Draft Final Report

A Scenario Tool for Assessing the Health Benefits of Conserving, Restoring and Managing Natural and Working Lands in California

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I. Acknowledgments

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II. Abstract

California's natural and working lands (NWL) are integral to achieving carbon neutrality, and effective land management strategies in response to increasing wildfires and other climate-related events could impart health co-benefits. This study evaluates the impacts that resilient NWL regions could have on various health outcomes through different management scenarios. We quantify the effects of wildfires and urban green space on human health through scoping reviews, health impact assessments, and validated atmospheric exposure modeling, with an overarching goal to incorporate all findings into a public-facing NWL Health Scenario Tool. We found evidence of increased risk of adverse health outcomes with increased wildfire smoke exposure and reduced risk of adverse health outcomes with increased urban green space exposure. We estimated 7,378 avoided deaths, 20,649,279 years of life expectancy gained, and 5,385 avoided low birth weight deliveries with increased urban green space exposure, and between 52,600 to 56,140 premature deaths attributable to wildfire $PM_{2.5}$, particulate matter with a diameter equal to or less than 2.5 micrometers. These estimates were consolidated into the tool, which allows users to quantitatively assess the potential health and economic benefits associated with various management scenarios for urban green space and wildfires through two separate interfaces. Results will help to inform future policy-making and development of appropriate management strategies for these NWL-specific environmental exposures.

III. Executive Summary

Background

California's NWL, consisting of grasslands, shrublands, and forests, hold an important role in the state's efforts to achieve carbon neutrality. Such NWL regions could serve as a potential source of carbon sequestration; however, recently, these regions have been subject to more carbon loss than sequestration due to the impacts from wildfires and other climate change-related events. Effective land management strategies can help to reduce these wildfires and the resulting emissions. As such, there is a growing need to assess the health impacts that certain interventions could impart to more comprehensively understand the benefits from different scenarios. Specifically, the focus of this study is to evaluate the human health impacts of wildfires and urban green spaces in California. Greening interventions, as climate adaptation and mitigation pathways, can aid in the benefits accruing from land management strategies by reducing climate-related exposures and promoting health co-benefits. We aim to quantify the effect that resilient NWL regions can impart through minimizing climate- and wildfire-related emissions, and thereby contributing to benefits for a wide range of human health outcomes. Results would inform policy-makers and stakeholders working towards the development of future climate mitigation policies and land management strategies.

Objectives and Methods

The objectives of this study are to assess the quantitative effects of wildfires and urban green spaces on human health through comprehensive scoping reviews and health impact assessments and to incorporate such findings into a public-facing and adaptable NWL Health Scenario Tool. This tool offers users the opportunity to quantitatively evaluate how different NWL management scenarios in urban green space and wildfire regions within California could yield health and economic costs and benefits.

The scoping reviews focus on examining the health impacts of wildfires and urban green spaces. Specifically, we aim to broaden our knowledge on mortality and several cause-specific morbidity outcomes associated with wildfire smoke particulate matter (PM) exposure and urban green space exposure in California. Once we identified literature that specified relationships between NWL-specific exposures and health outcomes, we extracted quantitative dose-response values from the literature that could be used to inform health impact research relevant to these topic areas.

We conducted health impact assessments to quantify the health benefits from reduced wildfire smoke $PM_{2.5}$ emissions and increased urban green space exposures. Applying the dose-response values identified from the scoping reviews, we used the U.S. Environmental Protection Agency's (EPA) Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) platform and geographic specific (census tract and zip code) models to estimate the changes in health outcomes from wildfire smoke events and different urban green space scenarios in California, separately. We quantified the benefits to mortality, life expectancy, and adverse birth outcomes with increased green space exposure and the impacts on mortality and morbidity outcomes from wildfire smoke $PM_{2.5}$.

Specifically for wildfire exposures, we employed STILT (Stochastic Time-Inverted Lagrangian Transport Model), a receptor-oriented atmospheric transport model, to simulate the transport of wildfire smoke $PM_{2.5}$ emissions through the atmosphere. We combined STILT with fire emissions estimates from the Fire Inventory from the National Center for Atmospheric Research (NCAR) (FINNv2.5) in 2018 and compared the STILT-FINNv2.5 simulated $PM_{2.5}$ concentrations to observed $PM_{2.5}$ concentrations at station monitors as a validation analysis.

Health, population, and environmental datasets are aggregated to inform the development of the NWL Health Scenario Tool, which assesses the potential health benefits garnered from different NWL management scenarios. The tool is split into two interfaces, one for wildfires and another for urban green space, and was developed in Google Earth Engine (GEE).

Results

The scoping reviews found evidence of strong associations between both urban green space and wildfire smoke exposure with several health outcomes. For urban green space, the literature review was focused on both peer reviewed meta-analyses and review papers and found evidence for effects on mortality, birth outcomes, mental health, and cardiovascular health, with inconsistent evidence for physical activity and respiratory health. For wildfire smoke, few reviews and meta-analyses were identified, but several primary epidemiological studies found consistent evidence for effects on mortality and respiratory health, with mixed evidence for cardiovascular health, though there is a growing trend for a positive association. Further good-quality longitudinal studies are needed to more thoroughly quantify the relationships between NWL-specific environmental exposures and health outcomes. Such results would help inform future climate-related interventions, such as wildfire management planning and various greening scenarios.

We developed exposure estimates from various environmental datasets and validated, when necessary. Modeled concentrations from the STILT-FINNv2.5 simulation were significantly correlated with observed station monitor concentrations at 8 of the 16 selected STILT receptors, with varying correlation strength. Receptors with a larger fire influence had stronger and more significant correlations between modeled and observed concentrations. Uncertainties with this model do exist, particularly in areas with a smaller fire influence and larger contributions from other emission sources.

The health impact assessment for urban green space found that increases in green space can contribute to large health benefits for mortality, life expectancy, and low birth weight (LBW). We estimated 7,378 avoided deaths, 20,649,279 years of life expectancy gained, and 5,385 LBW deliveries avoided from increased green space exposure. These results show that urban greening interventions through climate mitigation and adaptation strategies can yield health benefits, with a majority of those benefits arising in disadvantaged areas. Between 52,600 to 56,140 premature deaths were estimated to be attributable to wildfire $PM_{2.5}$, with an estimated economic impact of $432 to $460 billion, suggesting that wildfires contribute a considerable mortality and economic burden.

The NWL Health Scenario Tool was developed using the GEE platform and comprises both an urban green space and a wildfire component. The urban green space tool quantitatively evaluates the potential health and economic benefits linked with urban greening management strategies and is mapped at zip-code and census tract levels. The wildfire tool quantitatively evaluates the health impact of wildfire $PM_{2.5}$ using two atmospheric modeling simulations: (1) zip code-level health and economic costs from historical fire emissions using CMAQ (the Community Multiscale Air Quality Modeling System), and (2) county-level health and economic benefits from possible wildfire management strategies using STILT (additional work using the Goddard Earth Observing System chemical transport model [GEOS-Chem] will be detailed in final report).

Conclusions

NWL-specific environmental exposures, such as wildfires and urban green space, contribute to human health impacts across several health outcomes, including mortality, life expectancy, birth outcomes, respiratory health, and more. Reduced wildfire exposure and increased urban green space exposure impart substantial health benefits, underscoring the influence that climate-related interventions could have on improving health. Our tool allows users to quantitatively explore these health impacts through various intervention scenarios, with the aim that it will help inform future policy-making and development of management strategies. Future research could further strengthen the evidence base of quantitative dose-responses of various health categories from NWL-specific environmental exposures.

IV. Introduction

California's NWL comprise approximately 90 percent of the state's landmass and includes a biologically diverse landscape including grasslands, shrublands, and forest. The state's NWL areas is a major source of carbon sequestration by providing the land area capable of capturing carbon through plants, trees, and soils; however, some estimates suggest that California's NWL are currently a net greenhouse gas (GHG) source, losing more carbon than they sequester. In a recent assessment, wildfires were the largest cause of carbon loss but other losses can occur from drought, tree and shrub disease, and soil disturbances, conversion, and harvesting. Additionally, NWL can also be susceptible to climate change impacts of sea level rise, drought, and increased temperatures, which may further exacerbate the net GHG source from the state's lands.

In the currently funded California Air Resources Board's (CARB) project (19RD015), we found that the 2018 California wildfires, which burned nearly two million acres throughout the state, were responsible for approximately 11,500 premature deaths from wildland fire related $PM_{2.5}$. We estimate an economic impact of approximately $100 billion for the mortality burden from the 2018 wildland fires. Recognizing the potentially important role of NWL the state's carbon neutrality goals, the recent CARB Scoping Plan has included cutting edge modeling tools used to estimate the quantitative ability of NWL to remove and store carbon under different scenarios. This analysis showed that by applying various land management scenarios to land-use, land management, and eco-unit areas resulted in reductions in wildfire emissions when compared to business as usual. To understand more completely the benefits of various scenarios taken in California to reduce environmental and health impacts from wildfires in the state's NWL, it is critical to measure the potential health impacts of these initiatives. In this project we have developed methodology to better quantify how resilient landscapes can reduce wildfire related emissions in the state's NWL, with a detailed workflow depicted in Figures 4.1a - 4.1c.

We conduct an in-depth literature review to identify all health impacts from greenspace exposures in California's urban natural working lands (Task 1) which is further detailed in Section V (Scoping Review: Urban Greenspace). The literature review reveals several coefficients that may be used for the current tool (Subtask 2.2), allowing for subsequent analysis of health impacts from various greenspace exposures on health (Subtasks 2.1, 2.3 – 2.4) as detailed in Section VII (Health Impact Assessment: Urban Greenspace). During this time, and with careful discussion and guidance from various partners and CARB staff, we identified various greenspace scenarios expected to impact dose-response relationships for model inclusion (Subtask 2.5). We analyze identified greenspace management scenarios to identify various health impacts through the NWL Health Scenario Tool (Subtask 2.6) in Section XII (Final Tool Product Paper: A Decision-Support Tool To Evaluate Health Benefits Of Natural And Working Lands Scenarios).

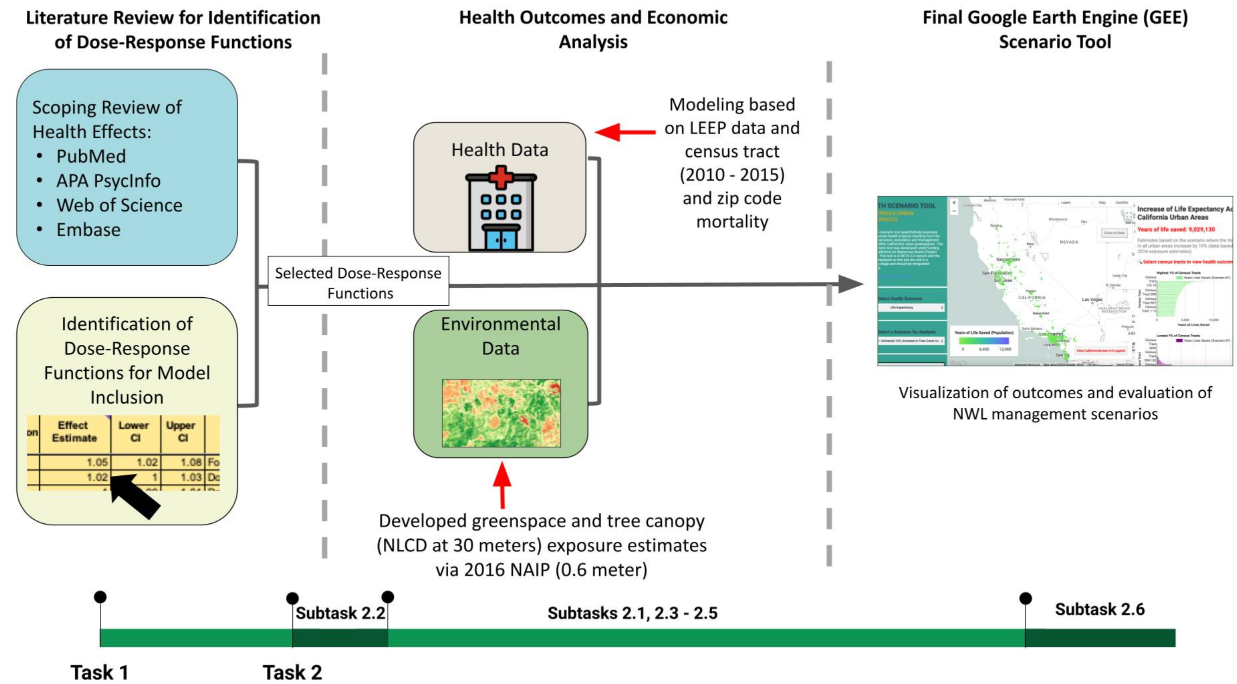


Figure 4.1a. *Workflow of project tasks for Greenspace on NWL*

Additionally, we conduct an in-depth literature review to identify all health impacts from wildfire specific $PM_{2.5}$ exposures in California's natural working lands (Task 1) which is further detailed in Section VI (Scoping Review: Wildland Fires). The literature review reveals several coefficients that may be used for the current tool (Subtask 2.2), allowing for subsequent analysis of health impacts from various wildfire exposures on health (Subtasks 2.1, 2.3 – 2.4) as detailed in Section VIII (Health Impact Assessment: Wildland Fire Mortality and CMAQ Validation) and Section IX (Health Impact Assessment: Wildfire Fire Morbidity). This included validation of exposure estimates (CMAQ Validation in Section IX and FINN validation work in Section X) and development and validation of modeling tools (STILT validation in Section X). During this time, and with careful discussion and guidance from various partners and CARB staff, we identified several wildfire scenarios expected to impact dose-response relationships for model inclusion (Subtask 2.5). Preliminary estimates from prescribed burning are provided in Section XI (STILT Scenario: Prescribed Burning) and further detailed in Section XII (Final Tool Product Paper: A Decision-Support Tool to Evaluate Health Benefits of Natural and Working Lands Scenarios) (Subtask 2.6). Scenarios specific to the recent CARB Scoping Plan are currently in the analysis phase and will be provided at the end of the contract (Subtask 2.6).

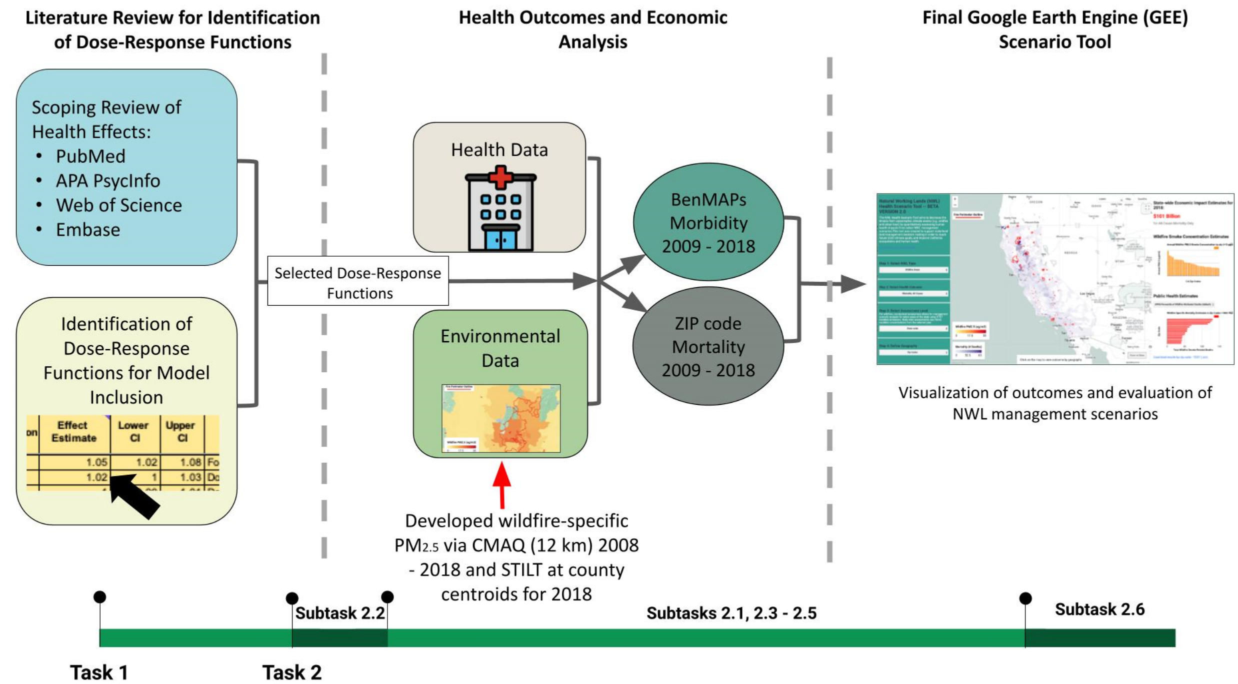


Figure 4.1b. *Workflow of project tasks for Wildfires on NWL*

Tasks and subtasks details and glossary of terms for the greenspace and wildfire workflows in Figures 4.1a and 4.1b, respectively, are provided in Figure 4.1c below.

Tasks & Subtasks

Task 1: In-Depth Literature Review

Task 2: In-depth Review of the NWL Policies, Programs, Activities, Models, and Other Tools

Subtask 2.1: Data Development for Use in the Scenario Tool

Subtask 2.2: Coefficient Identification

Subtask 2.3: Exploratory Analysis, Validation of Population Data, and Baseline Development

Subtask 2.4: Data Aggregation and Calculation of Input Variables

Subtask 2.5: Identify all Current and Proposed NWL Programs and Policies that are Expected to Impact Dose-Response Relationships

Subtask 2.6: Identify the Priority, Program, and/or Policy that are Likely to Yield the Greatest Health Impacts

Glossary

CMAQ	Community Multiscale Air Quality Model
GEE	Google Earth Engine
LEEP	Life Expectancy Estimates Project
NAIP	National Agriculture Imagery Program
NLCD	National Land Cover Database
NWL	Natural and Working Lands
STILT	Stochastic Time-Inverted Lagrangian Transport Model

Figure 4.1c. *Tasks & subtasks and glossary of terms for greenspace and wildfire workflows*

The results of this project aid in the development of future climate policies and implementation of NWL management strategies that maximize health benefits, reduce the risk of wildfire, and promote resilience to climate change.

V. Scoping Review: Urban Green Space

Abstract

California faces several serious climate hazards that can adversely affect human health, some of which are already occurring. Here we focus on four of California's leading climate risks where urban green space management could play a role in reducing exposures and generating health co-benefits. Specifically, we review the recent literature to qualitatively examine the role that green space could play in reducing adverse health effects associated with extreme heat exposure, flooding risk during extreme precipitation events, wildfire smoke air pollution, and infectious disease risk linked to dust pollution. We then quantitatively estimate the benefits to mortality, life expectancy, and adverse birth outcomes of increased green space in urban areas across California. Our findings indicate that achievable increases in urban green space could result in substantial health benefits, including approximately 7,378 avoided deaths and 20,649,279 years of life expectancy gained, with the majority of the benefits accruing to non-white populations. We also estimate up to 5,385 LBW deliveries avoided. Taken together, our findings show that urban and peri-urban green space provides direct health benefits that accrue from exposure reductions and health co-benefits as part of a suite of climate mitigation and adaptation strategies in California, with benefits concentrated in disadvantaged areas. The severity of future risks to population health in California will depend on atmospheric greenhouse gas concentrations, underlying population vulnerabilities, and local adaptation efforts, which to varying degrees can be influenced by effective green space interventions and policies.

Urban green space and associated infrastructure is a mitigation and adaptation pathway for promoting climate resilience and generating substantial health co-benefits. Here we review several of the most serious climate-related public health threats in California and possible green space solutions. Our conceptual framework illustrates the possible effects of greening interventions on climate-related exposures, health co-benefits, and possible unintended consequences. We illustrate the magnitude of possible health benefits of expanding urban green space on premature mortality, life expectancy, and adverse birth outcomes. For all outcomes, realistic increases in green space would likely result in substantial health benefits, especially for socially disadvantaged groups.

Introduction

A rapidly expanding body of literature on green spaces and public health consists of studies primarily falling into three research domains: physical health, mental health, and ecosystem health (J. Zhang et al., 2020). An abundance of recent studies provide evidence that access to urban green spaces is associated with positive health outcomes such as decreased mortality, reduced incidence of poor birth outcomes such as low birth weight and premature birth, and improved mental health, measured through metrics such as reductions in depressive symptoms (Callaghan et al., 2020; Gascon et al., 2016, 2018; Hu et al., 2021; Rojas-Rueda et al., 2019). Proposed mechanisms through which green spaces likely impact these health outcomes include social connectedness, stress reduction, increased physical activity, and environmental buffering (e.g. against air pollution, heat, and noise) (Nieuwenhuijsen et al., 2017).

Along with a plethora of primary analyses characterizing the dose-response relationship between access to urban green spaces and health outcomes, there is an expansive literature of systematic reviews and meta-analyses attempting to summarize the state of knowledge. However, many different meta-analyses report on the same health outcomes, often due to multiple research groups conducting the analyses concurrently, or variations in analytical methods. Synthesizing the findings of multiple meta-analyses can support the establishment of robust dose-response values for use in health impact assessments. To our knowledge, no umbrella review of existing dose-response meta-analyses currently exists, and this review attempts to bridge that gap.

Therefore, the aim of the scoping review is twofold: (1) summarize existing quantitative synthesizes of peer-reviewed literature examining the human health impacts associated with urban green and blue space exposure, and (2) identify empirical research that can be used to inform future modeled health impact research. These results will provide critical information for the management of the state of California's natural and working lands (see ***Figure 4.1a)***. Though green space is the primary focus of this review due to the expansive literature on the topic, studies evaluating the health impacts of urban blue spaces are briefly reported as well.

Methods

We conducted a scoping review of the global peer-reviewed epidemiological literature using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) between June - September 2020 within the following databases: PubMed, Web of Science, American Psychological Association (APA) PsycInfo, and Embase. We followed the Arksey and O'Malley's framework for scoping reviews and the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) which include the following five phase process: (1) identifying the research questions, (2) identifying relevant publications, (3) selecting the publications, (4) charting the data, and (5) collating, summarizing, and reporting the results (Arksey & O'Malley, 2005; Tricco et al., 2018). In collaboration with the University of California, Los Angeles' data librarians and project partners at CARB, we developed search terms to form keywords for the scoping review that would be inclusive of all potential health outcomes from exposures to urban green or blue spaces. A full list of search terms is included in Table 5.1 below.

Table 5.1a. *Search Strategy 1: Capture articles using most relevant keywords*

Concept	Text Keywords
Green/blue space	"public park*" OR "greenspace*" OR "green space*" OR "greenness" OR "blue space*" OR "nature contact" OR "NDVI" OR "normalized difference vegetation index"
Health	"health" OR "mortality"
Review	review OR meta-analy* *(used database restrictions for article type, as well as conducted a separate title search with these keywords to ensure no articles were missed)*

Table 5.1b. *Search Strategy 2: General search with "urban" restriction*

Concept	Text Keywords
Green/blue space	"greenspace*" OR "green space*" OR "greenness" OR "natural environment*" OR "nature contact" OR "blue space*" OR "NDVI" OR "normalized difference vegetation index" OR "open space*" OR "natural space*" OR "forest*" OR "public park*" OR "vegetation" OR "tree*" OR "outdoors"
Health	"health" OR "life expectancy" OR "mortality"
Urban	"urban" OR "city" OR "cities" OR "municipal" OR "urbanization" OR "built environment*" OR "residential" OR "residence*" OR "neighbo*hood"
Review	review OR meta-analy* *(used database restrictions for article type, as well as conducted a separate title search with these keywords to ensure no articles were missed)*

Criteria included empirical human-health studies of all age groups, sexes and genders which evaluated the health impacts from green or blue space exposures. Due to a rapidly growing and evolving body of literature on green spaces and health, we limited our search to the last ten years of published articles. All health impacts were included in the scoping review search. Since this study aims to quantify the human health impacts of the general population, occupational exposures were not included. We limited our search to studies published in a peer-reviewed journal written in English, French, or Spanish. Ineligible studies included those using non-human subjects or exposure studies that did not empirically examine the relationship between green or blue spaces to human health to provide a quantitative impact estimate (Table 5.2).

Table 5.2. *Inclusion criteria*

Inclusion Criteria	*Exclusion Criteria*
Primary peer-reviewed literature that was published in the last ten years (2010 – 2020) in English, Spanish, or French language	Non-peer reviewed literature (e.g. abstract only, conference proceedings, articles from the media, letters to the editor, reports, thesis, textbooks, etc.) published prior to 2010 and not in the English, Spanish, or French language
Literature that explicitly describes urban green or blue space-specific exposures	Literature that explicitly describes the inclusion of other environment types without including urban, real-life exposures (as opposed to virtual reality or laboratory conditions)
Primary or secondary health data used to examine relationships with green or blue space exposures	Surveillance data lacking an assessment of impact
Empirical studies that estimate quantifiable impacts	Non-empirical studies or studies that do not quantify exposure impacts
Studies that explicitly investigate the relationship between human health outcomes and green or blue space exposures	Literature that does not investigate the impacts of green or blue space exposures to human health

After removing duplicates, we analyzed titles and abstracts for significance, then removed studies that did not fit the above criteria. Once the relevant literature was identified, we systematically extracted and organized the data into an Excel spreadsheet that included relevant information, including authors, publication year, publication title, journal, study location, exposure measurement, and health outcome examined.

The initial database searches yielded a total of 775 review articles across all four databases after we reviewed duplicates. After screening titles and abstracts, we identified 59 with quantitative data presented in tabular format within the review article for full extraction. We extracted meta-analysis results, as well as primary article results as presented in summary tables within each review paper, focusing primarily on quantitative analyses.

We conducted additional screening searches in 2023 in PubMed and Web of Science to extract solely meta-analyses to include in the report and/or NWL tool. Articles from these searches are not included in the original extraction workbook, but the relevant data are included in this chapter. These searches were designed to supplement the first round of search in 2020 to ensure no recent articles with potentially useful dose-response values were missed.

As the final step, we identified 46 meta-analyses to focus on in this report. Therefore, this chapter serves to highlight the main, highly studied outcomes and statistical associations, and includes brief discussion of the resulting NWL tool, but does not encompass all possible health outcomes, or all of the extractions included in the spreadsheet, many of which are from primary literature.

A short narrative summary of each major health outcome category was developed, after which, we discussed the potential pathways between green space and each health outcome category and how we may incorporate identified dose-response values into a health impact assessment. A second reviewer reviewed all the listed articles and worked with the first reviewer to ensure data were extracted properly and accurately represented the data from the articles.

Results and Discussion

Health Outcomes

Mortality

Table 5.3. *Mortality: Summary of Review Studies Presenting a Quantitative Meta-Analysis of Urban Green or Blue Space Impacts*

Authors/ Year	Publication Title	Specific Health Outcomes	Green or Blue Space Exposure(s)	Quantitative Dose-Response/Pooled Effect Estimate	Main Findings
(Bertrand et al., 2021)	*Do we know enough to quantify the impact of urban green spaces on mortality? An analysis of the current knowledge*	All-cause mortality; cardiovascular mortality; respiratory mortality	NDVI	Pooled RR for 0.1 unit increase in NDVI: **All-cause mortality:** 0.96 (95% CI: 0.94, 0.97)* **Cardiovascular mortality:** 0.98 (95% CI: 0.96, 0.99) **Respiratory mortality:** 0.97 (95% CI: 0.92, 1.02) *extracted from Rojas-Rueda D. et al. (2019)	This study found that an increase in green space resulted in reduced risks of cardiovascular mortality, but not respiratory mortality. Authors reported a significant effect for all-cause mortality, extracted directly from Rojas-Rueda D. et al. (2019).
(Bianconi et al., 2023)	*Impacts of urban green on cardiovascular and cerebrovascular diseases—a systematic review and meta-analysis*	Cardiovascular disease mortality; ischemic heart disease mortality; cerebrovascular mortality	NDVI	Pooled HR for each IQR (0.10 to 0.24) unit increase in NDVI at a 250-m to 500-m buffer: **Cardiovascular disease morality:** 0.94 (95% CI: 0.91, 0.97) **Ischemic heart disease mortality:** 0.96 (95% CI: 0.93, 0.99) **Cerebrovascular mortality:** 0.96 (95% CI: 0.94, 0.97)	This study found that an increase in urban green resulted in reduced hazards of cardiovascular disease mortality, ischemic heart disease mortality, and cerebrovascular disease mortality.
(Gascon et al., 2016)	*Residential green spaces and mortality: A systematic review*	All-cause mortality; cardiovascular mortality; lung cancer mortality	NDVI & green space percentage by residential address	Pooled RR for a 10% increase in greenness: **All-cause mortality:** 0.992 (95% CI: 0.976, 1.008) **Cardiovascular mortality:** 0.993 (95% CI: 0.985, 1.001) **Lung cancer mortality:** 0.997 (95% CI: 0.980, 1.013)	This study did not find evidence of a relationship between greenness and all-cause, cardiovascular, or lung cancer mortality.
(Kua & Lee, 2021)	*The influence of residential greenness on mortality in the Asia-Pacific region: a systematic review and meta-analysis*	All-cause mortality	NDVI	Pooled HR for an exposure unit increase in NDVI at a 500-m buffer: **All-cause mortality**: 0.97 (95% CI: 0.93, 1.02)	This study did not find evidence of a relationship between surrounding greenness and all-cause mortality.

(X.-X. Liu et al., 2022)	*Green space and cardiovascular disease: A systematic review with meta-analysis*	Cardiovascular disease (CVD) mortality, ischemic heart disease (IHD) mortality, cerebrovascular disease (CBVD) mortality	NDVI	Pooled OR for a 0.1 unit increase in NDVI: **CVD mortality**: 0.97 (95% CI: 0.96, 0.99) **IHD mortality**: 98 (95% CI: 0.96, 1.00) **CBVD mortality**: 0.98 (95% CI: 0.97, 1.00)	This study found evidence of a protective effect of NDVI on CVD mortality, IHD mortality, and CBVD mortality, with 2-3% lower odds.
(Rojas-Rueda D. et al., 2019)	*Green spaces and mortality: a systematic review and meta-analysis of cohort studies*	All-cause mortality	NDVI	Pooled HR for a 0.1 unit increase in NDVI at a 500-m buffer: **All-cause mortality**: 0.96 (95% CI: 0.94, 0.97)	This study found that an increase in surrounding greenness resulted in reduced hazards of all-cause mortality.
(N. Smith et al., 2021)	*Urban blue spaces and human health: A systematic review and meta-analysis of quantitative studies*	All-cause mortality	Blue space	Pooled HR for presence of blue space within 500-m: **All-cause mortality**: 0.986, 95% CI (0.973, 0.999)	This study found that the presence of blue space within 500m of peoples' home address was associated with a 1.4% risk reduction in all-cause mortality.
(Twohig-Bennett & Jones, 2018)	*The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes*	All-cause mortality; cardiovascular mortality	Multiple, including NDVI, land cover maps, tree canopy and street tree data, and subjective measures of greenness	Pooled OR for a comparison of high to low green space exposure: **All-cause mortality:** 0.69 (95% CI: 0.55, 0.87) **Cardiovascular mortality:** 0.84 (95% CI: 0.76, 0.93)	This study found that exposure to high green space resulted in reduced odds of all-cause and cardiovascular mortality.
(Yuan et al., 2020)	*Green space exposure on mortality and cardiovascular outcomes in older adults: a systematic review and meta-analysis of observational studies*	All-cause mortality; stroke mortality	NDVI	Pooled HR for 0.1 unit increase in NDVI: **All-cause mortality:** 0.99 (95% CI: 0.97, 1.00) **Stroke mortality:** 0.77 (95% CI: 0.59, 1.00)	This study found that an increase in green space resulted in reduced hazards of all-cause and stroke mortality in older adults.

Notes: HR = hazard ratio; OR = odds ratio; RR = risk ratio; IQR = interquartile range; NDVI = normalized difference vegetation index; CVD = cardiovascular disease; IHD = ischemic heart disease; CBVD = cerebrovascular disease; CI = confidence interval.

We identified eight peer-reviewed meta-analyses that calculated dose-response estimates of the relationship between exposure to urban green space and mortality, including all-cause and cause-specific mortality. Studies included in these meta-analyses were conducted in the United States (U.S.), Canada, Europe, Asia, Australia, and Oceania. All meta-analyses used normalized difference vegetation index (NDVI) as a green space exposure metric, with two meta-analyses also including other exposure indicators such as residential green space and land cover (Gascon et al., 2016; Twohig-Bennett & Jones, 2018). Several meta-analyses found a significant, inverse association between green space and mortality, supporting evidence for a reduction in mortality with increased green space exposure (Bianconi et al., 2023; X.-X. Liu et al., 2022; Rojas-Rueda D. et al., 2019; Twohig-Bennett & Jones, 2018; Yuan et al., 2020). Although, some meta-analyses did not find statistically significant results (Gascon et al., 2016; Kua & Lee, 2021). Additionally, we identified one meta-analysis that investigated the relationship between urban blue space and mortality, which found reduced risk of mortality associated with increased blue space exposure (N. Smith et al., 2021).

All-cause Mortality

The Rojas-Rueda D. et al. (2019) study is a recent meta-analysis of cohort studies conducted to improve upon existing analyses, such as Gascon et al. (2016) and Twohig-Bennett & Jones (2018), that incorporated observational data into their pooled estimates. The authors focused solely on all-cause mortality and found a significantly decreased risk (Hazard ratio [HR]: 0.96, 95% confidence interval [CI]: 0.94 to 0.97) per 0.1 unit increase in NDVI within a buffer of 500-m or less of an individual's residence. The dose-response values from this study have also been applied in a recent health impact analysis for European cities (Barboza et al., 2021). However, the authors noted some limitations. Heterogeneity between the included studies restricted comparability (Rojas-Rueda D. et al., 2019). Additionally, NDVI was selected as the primary green space exposure; however, NDVI does not provide information about the quality or accessibility of such green spaces (Rojas-Rueda D. et al., 2019), which was also a limitation of all analyses using a greenness metric derived from satellite imagery.

Within the existing literature, five other meta-analyses also studied urban green space and all-cause mortality (Bertrand et al., 2021; Gascon et al., 2016; Kua & Lee, 2021; Twohig-Bennett & Jones, 2018; Yuan et al., 2020), though Rojas-Rueda D. et al. (2019) is still the most recent study that did not limit population or geographic region. Two found significant effects of green space exposure on all-cause mortality (Twohig-Bennett & Jones, 2018; Yuan et al., 2020), while two found effects that were non-significant (Gascon et al., 2016; Kua & Lee, 2021). One meta-analysis studied urban blue space and all-cause mortality and found significantly reduced risk of all-cause mortality associated with increased urban blue space (N. Smith et al., 2021). Bertrand et al. (2021) aimed to identify exposure-response functions for quantitative health impact assessments of green space on mortality and directly extracted the Rojas-Rueda D. et al. (2019) estimate because it included all of the studies that the authors had identified in their analysis. The authors ultimately reported a significant association between green space exposure and reduced risk for all-cause mortality based on this extracted estimate. Twohig-Bennett & Jones (2018) found a significantly lower risk for all-cause mortality associated with high compared to low green space, a much larger estimate than the dose-response value that Rojas-Rueda D. et al. (2019) reported. This was likely due to differences in the studies included, with the former meta-analysis including fewer and older studies, of which one of the studies found an effect for older adults that was transformed by the meta-analysis into an estimate of large magnitude (Odds ratio [OR]: 0.23, 95% CI: 0.14 to 0.40) (Sulander et al., 2016). Similarly, Yuan et al. (2020) also found a significant association between NDVI and reduced risk for all-cause mortality in older adults only; however, the upper confidence interval for the effect estimate was 1.00, which is on the border of conventional tests of statistical significance. Gascon et al. (2016) did not find evidence of a statistically significant association between greenness and all-cause mortality. Consequently, the authors suggested that more cohort studies should be analyzed, which ultimately prompted the meta-analysis led by Rojas-Rueda D. et al. (2019).

Overall, the recent meta-analysis from Rojas-Rueda et al. (2019) provides evidence of a causal relationship between greenness and all-cause mortality, with an available dose-response value for application in health impact assessments, as asserted by Bertrand et al. (2021). Further research would continue to strengthen this evidence.

Cause-specific Mortality

Six meta-analyses studied cause-specific mortality (Bertrand et al., 2021; Bianconi et al., 2023; Gascon et al., 2016; X.-X. Liu et al., 2022; Twohig-Bennett & Jones, 2018; Yuan et al., 2020). Five of the six studies found significant effect estimates between greenness and cardiovascular mortality, ischemic heart disease mortality, cerebrovascular mortality, and stroke mortality (Bertrand et al., 2021; Bianconi et al., 2023; X.-X. Liu et al., 2022; Twohig-Bennett & Jones, 2018; Yuan et al., 2020), with significance varying across different types of cause-specific mortality in Bertrand et al. (2021). Bertrand et al. (2021) found significantly reduced risk for cardiovascular mortality (Relative risk [RR]: 0.98, 95% CI: 0.96 to 0.99) but non-significant effects for respiratory mortality. Similarly, Twohig-Bennett & Jones (2018) found a significant effect for cardiovascular mortality associated with high compared to low green space levels. Both Bianconi et al. (2023) and X.-X. Liu et al. (2022) also found evidence of statistically significant relationships between urban green exposure and reduced risk of cardiovascular mortality, ischemic heart disease mortality, and cerebrovascular mortality. While Bertrand et al. (2021) found a small effect for cardiovascular mortality, Bianconi et al. (2023) found an effect of larger magnitude but with a wider confidence interval (HR: 0.94, 95% CI: 0.91, 0.97). Yuan et al. (2020) estimated lower risk of stroke mortality associated with increased NDVI, with an upper confidence interval on the border of conventional tests of statistical significance. Gascon et al. (2016) did not find evidence of an association between greenness and cardiovascular and lung cancer mortality.

Several of the meta-analyses shared limitations that also apply to the other health outcomes discussed throughout this report. Heterogeneity between the studies (e.g. variations in study population, exposure assessment, outcome estimations) was a common limitation reported by all meta-analyses (Bertrand et al., 2021; Bianconi et al., 2023; Gascon et al., 2016; Kua & Lee, 2021; X.-X. Liu et al., 2022; Rojas-Rueda D. et al., 2019; N. Smith et al., 2021; Twohig-Bennett & Jones, 2018; Yuan et al., 2020). Bianconi et al. (2023) and Kua & Lee (2021) reported similar issues regarding NDVI as a nonspecific measure. Other limitations included high statistical heterogeneity for associations between green space and mortality and issues of generalizability due to influences by urbanicity and culture (Bertrand et al., 2021; Bianconi et al., 2023; X.-X. Liu et al., 2022; Yuan et al., 2020). Despite these limitations, several meta-analyses also had notable strengths. Similar to Rojas-Rueda D. et al. (2019), Yuan et al. (2020) reported the inclusion of cohort studies as a strength to support the causal relationship between green space and health. Other strengths included comprehensive literature searches, rigorous critical appraisal, and quality scoring (Kua & Lee, 2021; Twohig-Bennett & Jones, 2018; Yuan et al., 2020).

To summarize, the existing meta-analyses suggest an association between urban green space and mortality, though confidence in these relationships varies across meta-analyses and different causes of mortality. The associations between urban green space and cardiovascular mortality and all-cause mortality are generally consistent across included meta-analyses. More research is required to confidently understand the effects of urban green space on respiratory mortality and other types of cause-specific mortality, such as stroke mortality and lung cancer mortality, as well as to explore the mechanisms behind these effects.

Birth Outcomes

We identified six systematic reviews including meta-analyses that focused on exposure to urban green space and birth outcomes (Akaraci et al., 2020; Dzhambov et al., 2014; Hu et al., 2021; K. J. Lee et al., 2020; Twohig-Bennett & Jones, 2018; Zhan et al., 2020), with Akaraci et al. (2020) also examining urban blue space (all included in Table 5.4). All reviews including meta-analyses were published between 2014-2021. All reviews analyzed NDVI as the green space exposure, with two of the studies analyzing other green space exposures in addition to NDVI (Dzhambov et al., 2014; Twohig-Bennett & Jones, 2018). The most analyzed birth outcomes were birth weight, LBW, preterm birth, and small for gestational age (SGA), with four of the studies analyzing all four outcomes (Akaraci et al., 2020; Hu et al., 2021; K. J. Lee et al., 2020; Zhan et al., 2020).

Table 5.4. *Birth Outcomes: Summary of Review Studies Presenting a Quantitative Meta-Analysis of Urban Green or Blue Space Impacts*

Authors/ Year	**Publication Title**	**Specific Health Outcomes**	**Green or Blue Space Exposure(s)**	**Quantitative Dose-Response/Pooled Effect Estimate**	**Main Findings**
(Akaraci et al., 2020)	*A systematic review and meta-analysis of associations between green and blue spaces and birth outcomes*	Birth weight, LBW, preterm birth, small for gestational age (SGA), term birth weight, term LBW	NDVI; blue space	Pooled standardized ß coefficient for an increase in NDVI at a 250-m/300-m buffer: **Birth weight:** 0.001 (95% CI: <0.001, 0.002) **Term birth weight:** 0.0009 (95% CI: –0.0002, 0.002) Pooled OR for an increase in NDVI at a 250-m/300-m buffer: **LBW:** 0.96 (95% CI: 0.91, 1.01) **SGA:** 0.95 (95% CI: 0.92, 0.97) **Preterm birth:** 0.99 (95% CI: 0.97, 1.02) **Term LBW:** 0.97 (95% CI: 0.80, 1.18)	This study found that an increase in residential greenness is associated with increased birth weight and resulted in reduced odds of SGA. No associations were found between blue space and birth outcomes.
(Dzhambov et al., 2014)	*Association between residential greenness and birth weight: Systematic review and meta-analysis*	Birth weight	NDVI and tree canopy (aerial imagery)	**Birth weight**: For an increase in greenness at a 100-m buffer under a quality effects model: Pooled standardized ß coefficient: 0.001 (95% CI = -0.001–0.003) For an increase in greenness at a 100-m buffer under a random-effects model: Pooled standardized ß coefficient: 0.002 (95% CI: 0.001, 0.003)	This study found that an increase in neighborhood greenness is associated with higher birth weight under the random-effects model, but not under the quality effects model.
(Hu et al., 2021)	*Residential greenness and birth outcomes: a systematic review*	Birth weight, LBW, preterm birth, SGA	NDVI	For 0.1 unit increase in NDVI: **Birth weight:** Green exposure buffers in six groups: (50-m, 100-m, 250-m, 300-m, 500-m, 1000-m)	This study found that an increase in residential greenness is associated with increased birth weight in all

	and meta-analysis of observational studies			Pooled ß coefficient and 95% CI: 11.22 (3.11, 19.33), 15.22 (8.75, 21.69), 7.99 (4.29, 11.70), 15.35 (11.41, 19.29), 13.42 (6.57, 20.27), and 14.77 (2.45, 27.09), respectively Green exposure buffers in five groups: (100-m, 250-m, 300-m, 500-m, 1000-m): **LBW:** Pooled OR and 95% CI: 0.87 (0.77, 0.98), 0.93 (0.86, 1.00), 0.79 (0.65, 0.96), 0.90 (0.83, 0.99), and 0.87 (0.62, 1.22), respectively **Preterm birth:** Pooled OR and 95% CI: 0.98 (0.96, 1.00), 0.99 (0.97, 1.01), 1.00 (0.81, 1.23), 0.99 (0.97, 1.00), and 0.98 (0.97, 0.99), respectively **SGA:** Pooled OR and 95% CI: 0.96 (0.90, 1.02), 0.99 (0.97, 1.01), 0.78 (0.61, 0.99), 1.00 (0.91, 1.09), and 0.97 (0.90, 1.03), respectively	buffer groups and resulted in reduced odds of LBW in some buffer groups. Significant associations were observed in only one buffer group for preterm birth and SGA, with the others being non-significant.
(K. J. Lee et al., 2020)	*Greenness, civil environment, and pregnancy outcomes: perspectives with a systematic review and meta-analysis*	Poor pregnancy outcomes (LBW, very low birth weight, and SGA), preterm birth, birth weight and term birth weight	NDVI	For an increase in NDVI: Green exposure buffers in four groups: (100-m, 250-m, 500-m, overall): **Term birth weight:** Pooled ß coefficient and 95% CI: 0.0022 (0.0005, 0.0038), 0.0026 (0.0005, 0.0048), 0.0034 (0.0010, 0.0058), and 0.0025 (0.0015, 0.0035), respectively **Birth weight:** Pooled ß coefficient and 95% CI: 0.0022 (0.0005, 0.0038), 0.0026 (0.0005, 0.0048), 0.0034 (0.0010, 0.0058), and 0.0025 (0.0015, 0.0035), respectively **Poor pregnancy outcomes:** Pooled OR and 95% CI were 0.90 (0.79,	This study found that an increase in greenness is associated with increased term birth weight in all buffer groups and resulted in reduced odds of poor pregnancy outcomes in only the overall group and preterm birth.

				1.01), 0.97 (0.95, 1.00), 0.91 (0.80, 1.03), and 0.94 (0.92, 0.97), respectively **Preterm birth** at a 100-m buffer: Pooled OR: 0.98 (95% CI: 0.97, 0.99)	
(Twohig-Bennett & Jones, 2018)	*The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes.*	Gestational age, preterm birth, and SGA	Multiple, including NDVI, land cover maps, tree canopy and street tree data, and subjective measures of greenness	Pooled OR for a comparison of high to low green space exposure: **Preterm birth:** 0.87 (95% CI: 0.80, 0.94) **SGA:** 0.81 (95% CI: 0.76, 0.86) Pooled mean difference for a comparison of high to low green space exposure: **Gestational age:** <–0.01 (95% CI: –0.05, 0.05)	This study found that exposure to high green space resulted in reduced odds of preterm birth and SGA.
(Zhan et al., 2020)	*Influence of residential greenness on adverse pregnancy outcomes: A systematic review and dose-response meta-analysis.*	Birth weight, gestational age, gestational diabetes, gestational hypertension, head circumference, LBW, mental health disorders, preeclampsia, preterm birth, SGA	NDVI	Pooled ß coefficient for a comparison of highest to lowest greenness exposure at a 100-m buffer*: **Birth weight:** 20.22 grams (95% CI: 13.50, 26.93) Pooled OR for a comparison of highest to lowest greenness exposure at a 100-m buffer*: **LBW:** 0.86 (95% CI: 0.75, 0.99) **SGA:** 0.93 (95% CI: 0.88, 1.00) **Preterm birth:** 0.98 (95% CI: 0.95, 1.02) Green exposure buffers in at least one of two groups: (≤300-m, >300-m) **Gestational age:** Pooled ß coefficient and 95% CI were –0.01	This study found that exposure to high greenness is associated with increased birth weight, increased head circumference, and reduced odds of LBW, SGA, and mental health disorders. No statistically significant associations were observed for preterm birth, gestational age, gestational diabetes, gestational hypertension, and preeclampsia.

	(–0.02, 0.01) and –0.02 (–0.07, 0.03), respectively **Head circumference:** Pooled ß coefficient at a >300-m buffer was 1.73 (95% CI: 0.69, 2.76) **Gestational diabetes:** Pooled OR at a ≤300-m buffer was 0.81 (95% CI: 0.57, 1.15) **Mental health:** Pooled OR at a >300-m buffer was 0.87 (95% CI: 0.77, 0.99)	

Notes: OR = odds ratio; NDVI = normalized difference vegetation index; LBW = low birth weight; SGA = small for gestational age; CI = confidence interval.
*Additional estimates were calculated at 250-m, 300-m, 500-m, and 1,000-m buffers but not included in the table for brevity.

Three of the six meta-analyses shared similar results, though had notable differences in their methodologies (Akaraci et al., 2020; Hu et al., 2021; Zhan et al., 2020). All three studies included birth outcomes with similar definitions, had no restrictions on the study types included, and used similar heterogeneity and publication bias tests. While Zhan et al. (2020) focused on both birth and pregnancy outcomes, Akaraci et al. (2020) and Hu et al. (2021) only assessed birth outcomes. Akaraci et al. (2020) also investigated the relationship between blue space and birth outcomes, but did not find evidence of an association. Hu et al. (2021) discussed the differences in exposure analysis between the three studies, emphasizing the use of more comprehensive and specific methods in comparison to the other two studies. Hu et al. (2021) maintained that their statistical analysis was more comprehensive as well, since they employed both random-effect and quality effects models, while Zhan et al. (2020) and Akaraci et al. (2020) only used one of the two. Additionally, Hu et al. (2021) assessed risk of bias and gauged certainty of evidence, neither of which the other two studies considered.

While Twohig-Bennett & Jones (2018) did evaluate some birth outcomes, their analysis spanned several other health outcomes as well, which added value to the literature with its expansive topic area within one study. However, this type of approach resulted in substantial pooling of green space exposures, and fewer modeling resources designated to investigating specific outcomes in depth. Their meta-analyses for birth outcomes only pooled together three to six studies for different birth outcomes, which was fewer than the number of pooled studies in the other meta-analyses within this health category (Akaraci et al., 2020; Dzhambov et al., 2014; Hu et al., 2021; Zhan et al., 2020), with some variation across buffer groups for Akaraci et al. (2020) and Zhan et al. (2020).

Birth Weight and Low Birth Weight (LBW)

All of the five studies that evaluated birth weight, a continuous outcome, found evidence of a significant relationship between urban green space and birth weight (Akaraci et al., 2020; Dzhambov et al., 2014; Hu et al., 2021; K. J. Lee et al., 2020; Zhan et al., 2020). Akaraci et al. (2020) and Zhan et al. (2020) found a significantly positive relationship between urban green space exposure and birth weight at buffers of 250-m/300-m and 100-m, respectively. Hu et al. (2021) and Lee et al. (2020) also found similar relationships for all buffer groups analyzed. Dzhambov et al. (2014) found that increased urban greenness exposure was significantly associated with increased birth weight under random-effects model, but not under the quality effects model.

Three of the four studies that examined LBW (infants less than 2,500 grams at birth, a dichotomous outcome), found evidence of an association between urban green space and LBW (Hu et al., 2021; K. J. Lee et al., 2020; Zhan et al., 2020). One of the studies evaluated LBW in combination with other poor pregnancy outcomes as shown in Table 5.4 (K. J. Lee et al., 2020), while the other two studies focused on LBW as an individual outcome indicator (Hu et al., 2021; Zhan et al., 2020). Lee et al. (2020) found a significant relationship between NDVI and a combination of poor pregnancy outcomes (including LBW, very LBW, and SGA) overall, but not for stratified buffers. Zhan et al. (2020) stratified the meta-analysis by buffer groups and found a significant association between NDVI and LBW at a 100-m buffer at highest greenness exposure (OR: 0.86, 95% CI: 0.75 to 0.99). The authors also estimated a dose-response value at a 300-m buffer and observed a very small but significant effect estimate (OR: 0.98, 95% CI: 0.97 to 0.99) per 0.1 unit increase in

NDVI (Zhan et al., 2020). Hu et al. (2021) found a significant association between NDVI and LBW in some buffer groups, with an OR of 0.93 (95% CI: 0.86 to 1.00) and OR of 0.79 (95% CI: 0.65, 0.96) per 0.1 unit increase in NDVI at 250-m and 300-m buffers, respectively. Akaraci et al. (2020) did not find a statistically significant relationship between NDVI and LBW (OR: 0.96, 95% CI: 0.91 to 1.01) per NDVI increase, although this study only used 250-m or 300-m buffers.

In comparing their LBW analyses, both Zhan et al. (2020) and Akaraci et al. (2020) included very similar studies. However, Zhan et al. (2020) presented pooled results stratified by five buffer groups (for the estimates comparing highest versus lowest greenness exposure), while Akaraci et al. (2020) presented a singular pooled result at a buffer of 250-m/300-m. The heterogeneity in buffer groups and how these two studies presented their results contributed to the difficulty in comparing the meta-analyses. If we were to compare the estimate from Akaraci et al. (2020) with the singular dose-response estimate at a 300-m buffer from Zhan et al. (2020) instead of their stratified estimates, Akaraci et al. (2020) found a larger effect estimate, but it was not quite statistically significant. Ultimately, it was challenging to determine what factors contributed to the different results between the two studies.

The literature on birth weight and LBW is consistent, with most studies in agreement of an association between green space and birth weight and LBW. Specifically, Hu et al. (2021) explicitly aimed to improve upon the methods of Zhan et al. (2020) and Akaraci et al. (2020) and was more recently conducted, and thus serves as the recommended dose-response estimate between green space and LBW.

Preterm Birth

Three of the five studies that analyzed preterm birth found significant associations between urban green space exposure and preterm birth (Hu et al., 2021; K. J. Lee et al., 2020; Twohig-Bennett & Jones, 2018). Hu et al. (2021) found a significant association between NDVI and preterm birth at a 1000-m buffer, but it was a very small effect estimate. The authors also found borderline significant results at 100-m and 500-m buffers (Hu et al., 2021). Similarly, Lee et al. (2020) found a statistically significant relationship between NDVI and preterm birth at a 100-m buffer, but the effect estimate was also very small (OR: 0.98, 95% CI: 0.97 to 0.99). Contrastingly, Twohig-Bennett & Jones (2018) observed a large effect estimate for preterm birth when comparing high to low green space exposure. Both Akaraci et al. (2020) and Zhan et al. (2020) did not find evidence of a relationship between urban green space exposure and preterm birth. Both meta-analyses assigned the highest weight to insignificant effect estimates from different primary studies (Cusack et al., 2017; Laurent et al., 2013).

The literature on preterm birth is inconsistent, with several studies reporting small or insignificant estimates, including the most recent meta-analysis available (Hu et al., 2021). At this stage, there is not sufficient evidence to include preterm birth in health impact assessment analyses.

Small for Gestational Age

All of the five studies that evaluated SGA found evidence of a significant relationship between urban green space and SGA (Akaraci et al., 2020; Hu et al., 2021; K. J. Lee et al., 2020; Twohig-

Bennett & Jones, 2018; Zhan et al., 2020). Again, Lee et al. (2020) found a significant relationship between NDVI and poor pregnancy outcomes (including SGA, LBW, and very LBW) overall, but not for stratified buffers. Both Akaraci et al. (2020) and Twohig-Bennett & Jones (2018) found statistically significant associations between green space exposure and SGA (OR: 0.95, 95% CI: 0.92 to 0.97 and OR: 0.81, 95% CI: 0.76 to 0.86 for an NDVI increase and high green space exposure, respectively), with the former study observing effects at a 250-m or 300-m buffer and the latter study observing effects when comparing high to low green space exposure. Hu et al. (2021) found a significant relationship between NDVI and SGA at a 300-m buffer, but not for all other buffer groups. Finally, Zhan et al. (2020) found evidence of an association between urban green space and SGA, although the estimated upper confidence interval for the SGA analyses is 1.00, which is on the border of statistical significance (Zhan et al., 2020).

To summarize, the existing meta-analyses suggest a protective but relatively small effect on adverse birth outcomes, although the certainty of these effects varies between the meta-analyses, likely due to methodological differences in the selection of studies and exposure buffers. The relationships between urban green space with LBW and SGA are generally consistent across the meta-analyses; however, significant effects were mostly found at certain exposure buffers and not others, which also varied across the meta-analyses. This could suggest that the relationship between greenness and birth outcomes changes with changing greenness for different radii around the residence. More analysis is needed for the relationship between urban green space and preterm birth, as well as other less commonly analyzed birth outcomes, such as gestational age and head circumference.

Mental Health

The body of literature on green spaces and mental health spans many different health outcomes, including mood, depression, anxiety, stress, restoration, and other indicators of mental distress. Studies evaluated short-term impacts of nature-based interventions in urban and rural settings on biological indicators of mental health challenges, as well as the effect of long-term exposures on clinical conditions. The challenges in quantitatively synthesizing the extensive body of research on urban green and blue spaces on mental health has been characterized in a systematic review from 2015, citing a lack of estimates and confidence intervals included in primary literature, and acknowledging the importance of meta-analyses of long-term impacts for providing information to policy-makers (Gascon et al., 2015).

An overview of relevant meta-analyses focused on mental health outcomes has been incorporated into Table 5.5.

Table 5.5. *Mental Health: Summary of Review Studies Presenting a Quantitative Meta-Analysis of Urban Green or Blue Space Impacts*

Authors/ Year	Publication Title	Specific Health Outcomes	Green or Blue Space Exposure(s)	Quantitative Dose-Response/Pooled Effect Estimate	Main Findings
(Bowler et al., 2010b)	*A systematic review of evidence for the added benefits to health of exposure to natural environments*	Self-reported emotions (energy, anxiety, tranquility, anger, fatigue, sadness), attention, cortisol levels	Activity in natural environment (natural environment ranged between studies but had to be reasonably 'green') versus synthetic environment (non-green outdoor built environments or indoor environments).	Effect size (Hedges' g, 95% CI): **Attention**: 0.23 (-0.30, 0.76) **Energy:** 0.76 (0.30, 1.22) **Anxiety:** 0.52 (0.25, 0.79) **Tranquility:** 0.07 (-0.42, 0.55) **Anger:** 0.35 (0.07, 0.64) **Fatigue:** 0.76 (0.41, 1.11) **Sadness:** 0.66 (0.16, 1.16) **Cortisol:** 0.57 (-0.43, 1.57)	Health-positive associations were found for energy, anxiety, anger, fatigue, and sadness. No significant effects were found for attention, tranquility, and cortisol.
(Coventry et al., 2021)	*Nature-based outdoor activities for mental and physical health: Systematic review and meta-analysis*	Depressive mood, reducing anxiety, improving positive affect, reducing negative affect	Nature-based interventions (NBIs, e.g., gardening, green exercise, nature-based therapy)	Standardized mean difference (SMD) for NBIs: **Depressive mood**: 0.64 (95% CI: 1.05, 0.23) **Reducing anxiety**: 0.94 (95% CI: 0.94, 0.01) **Improving positive affect**: 0.95 (95% CI: 0.59, 1.31) **Reducing negative affect**: 0.52 (95% CI: 0.77, 0.26)	This study found evidence of a positive impact of NBIs on mental health outcomes.
(Georgiou et al., 2021)	*Mechanisms of Impact of Blue Spaces on Human Health: A Systematic Literature Review and Meta-Analysis*	Restoration, social interaction	Living closer to blue space and having larger amounts of blue space in a geographic area	Cohen's d (standardized effect size), *Shorter distance to blue space:* **Restoration:** 0.123 (95% CI: –0.037, 0.284) **Social interaction:** –0.214 (95% CI: -0.55, 0.122) *Larger amounts of blue space within a geographical area* **Restoration:** 0.339 (95% CI: 0.072, 0.606) **Social interaction:** 0.405	Shorter distance to blue space was not associated with restoration or social interaction. Larger amounts of blue space within a geographical area, as well as being in more contact with blue space, were both significantly associated with higher levels of restoration.

				(95% CI: –0.214, 1.024) *Being in contact with blue space:* **Restoration:** 0.191 (95% CI: 0.084, 0.298)	
(Z. Liu et al., 2023)	*Green space exposure on depression and anxiety outcomes: A meta-analysis*	Depression, anxiety	Proportion of green space and NDVI	Merged OR (95% CI) for 10% increase in the proportion of green space: **Depression:** 0.963 (0.948, 0.979) **Anxiety:** 0.938 (0.858, 1.025) Merged OR (95% CI) for 0.1 unit increase in NDVI: **Depression**: 0.931 (0.887, 0.977)	Both increasing proportion of green space and increasing NDVI levels were found to be associated with lower risk of depression. Increasing proportion of green space was also found to be associated with lower anxiety, but results were not statistically significant.
(McMahan & Estes, 2015)	*The effect of contact with natural environments on positive and negative affect: A meta-analysis*	Positive and negative affect	Exposure to natural environments (includes urban and rural green space) compared to control conditions	Effect size (r): **Positive affect**: 0.31 (95% CI: 0.24, 0.37) **Negative affect**: –0.12 (95% CI: –0.17, –0.07)	This study found a significant relationship between exposure to natural environments and both increases in positive affect (moderate) and decreases in negative affect (small)
(Mygind et al., 2021)	*Effects of Public Green Space on Acute Psychophysiological Stress Response: A Systematic Review and Meta-Analysis of the Experimental and Quasi Experimental Evidence*	High frequency heart rate variability (HF HRV), cortisol	Seated relaxation and walking in natural environments (only included studies considering public green space, excluding private gardens, indoor nature, views of nature, and virtual nature)	Effect size (Hedges' g): *For seated relaxation* **HF HRV**: 0.51 (95% CI: –0.01, 1.03) **Salivary Cortisol**: –0.72 (95% CI: –1.19, –0.25) *For walking* **HF HRV**: 0.31 (95% CI: 0.06, 0.55) **Serum and Salivary Cortisol**: –0.27 (95% CI: –0.85, 0.30)	Both seated relaxation and walking in natural environments enhanced heart rate variability (though technically not statistically significant for the former). For cortisol, levels of salivary cortisol were lower after seated relaxation in a natural environment versus control, but there was no effect found for walking in a natural environment.
(Noordzij et al., 2021)	*Green spaces, subjective health and depressed affect in middle-aged and older adults: a cross-country*	Depressed affect (self-reported Indicator based on whether a participant felt	Distance to the nearest green space and amount of neighborhood green space	**Depressed affect**: Pooled OR for: *Distance to the nearest green space*: 0.98 (95% CI: 0.96, 1.00) *Amount of green space within 800-m buffer*: 1.00 (95% CI: 0.98, 1.03)	This study found no evidence for a relationship between green space and depressed affect in older adults.

	comparison of four European cohorts	sad, downhearted or blue)			
(H. Roberts et al., 2019)	*The effect of short-term exposure to the natural environment on depressive mood: A systematic review and meta-analysis*	Depressive mood (current emotional state)	Natural environments (defined by a high level of greenery, and not been extensively modified by human activity)	Summary effect from random-effect meta-analysis: –0.30 (95% CI: –0.50, –0.10)	This study found a small effect for reduction in depressive mood associated with exposure to the natural environment, but authors reported a high risk of bias and low quality of studies, with low confidence in the results.
(N. Smith et al., 2021)	*Urban blue spaces and human health: A systematic review and meta-analysis of quantitative studies*	Self-reported mental health and wellbeing	Blue space	**Mental health and wellbeing:** Pooled HR for presence of blue space within 500-m: Cohen's d = –0.25 (95% CI: 0.44, –0.07), $p < 0.001$	This study found that the presence of blue space within 500m of peoples' home address was associated with improved mental health and wellbeing.
(Song et al., 2022)	*Restorative Effects from Green Exposure: A Systematic Review and Meta-Analysis of Randomized Control Trials*	Restorative effects – psychological and physiological, including fatigue, vitality, heart rate levels, among other metrics	Green space settings vs. non green space settings	Effect sizes (statistically significant only): **Fatigue:** –0.84 (95% CI: –1.15, –0.54) **Tension**: –0.89 (95% CI: –1.21, –0.58) **Anger:** –0.48 (95% CI: –0.70, –0.26) **Confusion:** –0.65 (95% CI: –0.96, –0.33) **Vitality/vigor**: 0.85 (95% CI: 0.52, 1.18) **Positive affect**: 0.57 (95% CI: 0.27, 0.86) **High-frequency heart rate variability (HF)**: 0.52 (95% CI: 0.30, 0.74) **Natural logarithm of low-frequency/HF ratio (ln LF/HF)**: –0.55 (95% CI: –0.76, –0.34) **Heart rate levels:** –0.60 (95% CI: –0.90, –0.31)	Green space exposure was associated with less fatigue and tension, and increased vigor (large effect sizes), and less anger and confusion (moderate effect sizes). Evidence also indicates green space exposure can lower physiological indicators such as HF, ln LF/HF, and heart rate levels (moderate effect sizes).
(Weeland et al., 2019)	*A dose of nature: Two three-level meta-analyses of the beneficial effects of*	Self-regulation	Nature exposure – various, including residential greenness and	**Self-regulation**: Effect size for correlational studies: Pearson's r: 0.099; 95% CI: 0.056, 0.141; p < .001	Small, but significant positive overall associations were found for nature with children's self-regulation for

	exposure to nature on children's self-regulation		nature-based interventions	Effect size for quasi-experimental studies: Cohen's d: 0.151; 95% CI: 0.079, 0.244; p < .01	both correlational and quasi-experimental studies. Additionally, strength of the associations varied by instrument used to report green space; stronger effects were found for green space as quantified by parent-reports rather than via an objective index such as NDVI.
(Yao, Chen, et al., 2021)	*Impact of Exposure to Natural and Built Environments on Positive and Negative Affect: A Systematic Review and Meta-Analysis*	Positive and negative affect	Natural environments (categorized into biodiverse areas, forests, urban parks, and university campuses) compared to the built/physical environment.	Effect size (standardized mean difference) Main estimates for *natural environments*: **Positive affect:** 0.61 (95% CI: 0.41, 0.81) **Negative affect**: −0.47 (95% CI: −0.71, −0.24) *Urban park stratification*: **Positive affect**: 0.452 (95% CI: 0.147, 0.758) **Negative affect**: −0.006 (95% CI: 0.170, 0.158)	Exposure to the natural environment was associated with increased positive affect and decreased negative affect. More significant impacts were found for older populations. While urban parks vs. other nature types demonstrated a similar impact for positive affect, for negative affect, there was no significant impact for urban parks, meaning wild natural environments may be better for alleviating negative emotions.
(Yao, Zhang, et al., 2021)	*The effect of exposure to the natural environment on stress reduction: A meta-analysis*	Psychological and physiological stress indicators	Natural environments compared to built environments	Mean differences between natural environment and built environment (statistically significant only): **Total mood disturbance**: –6.42 (95% CI: –12.20, –0.63) **Negative affect**: –0.65 (95% CI: –1.16, –0.15) **State of anxiety:** –12.48 (95% CI: –26.61, 1.66) **Self-reported stress:** –0.33 (95% CI: –0.78, 0.13)	This study found an improvement in several psychological and physiological stress indicators following exposure to a natural environment.

	Systolic blood pressure (SBP): -3.82 (95% CI: –6.77, –0.86) **Natural logarithm of low-frequency/HF ratio (ln LF/HF)**: –0.29 (95% CI: –0.41, –0.18) of heart rate variability (HRV) **Increased restorative outcomes:** 4.82 (95% CI: –1.87, 11.51)

Notes: HR = hazard ratio; OR = odds ratio; NDVI = normalized difference vegetation index; LF = low-frequency; HF = high-frequency; HRV = heart rate variability; SBP = systolic blood pressure; CI = confidence interval.

It is important to note that our analysis did not incorporate studies focused entirely on mental health impacts associated with rural green space indicators such as forest bathing, which does have a substantial evidence base in the literature (Antonelli et al., 2019; Oh et al., 2017; Wen et al., 2019), but was beyond the scope of this review. However, several of the reviews included in this analysis did incorporate rural environments as part of a larger "natural environment" exposure.

There are different types of primary studies evaluating the mental health impacts of green and blue spaces, including short-term interventions or activities occurring in natural environments, as well as long-term exposures measured through residential conditions. While the former is important for understanding the capacity of natural environments to facilitate near-term improvements in mental health, studies evaluating the latter are vital for understanding implications for urban planning-related decision-making (Gascon et al., 2015).

Short-term Exposures

For the purposes of this report, short-term exposures include exposure to natural environments through various pathways, comprising specific nature-based interventions such as gardening, walking, or seated relaxation, and pre- and post-intervention measurement of biological indicators and self-reported mood states.

Eight studies evaluated the relationship between the natural environment and various psychological and physiological metrics associated with mental health outcomes, including depressive mood, positive and negative affect, and other indicators of stress (Bowler et al., 2010b; Coventry et al., 2021; McMahan & Estes, 2015; Mygind et al., 2021; H. Roberts et al., 2019; Song et al., 2022; Yao, Chen, et al., 2021; Yao, Zhang, et al., 2021). Cardiovascular outcomes are included here when listed as an indicator of a mental health condition, but blood pressure is explored in more depth in the *Cardiovascular Health* section.

Two studies expressly focused on stress (Mygind et al., 2018; Yao, Zhang, et al., 2021), two broadly on mental and physical health (Bowler et al., 2010b; Coventry et al., 2021), two on positive and negative affect (McMahan & Estes, 2015; Yao, Chen, et al., 2021), one on depressive mood (H. Roberts et al., 2019), and one on restoration (Song et al., 2022). Despite different stated focuses, many of these studies overlapped in the indicators evaluated for these mental health outcomes. Exposures evaluated were mostly labeled as the "natural environment" as compared to various controls, typically spending time in a managed environment.

Results from studies on positive and negative affect found exposure to the natural environment had the expected impact of increased positive affect and decreased negative affect (McMahan & Estes, 2015; Yao, Chen, et al., 2021), with more substantial impacts for positive affect and with larger effect sizes in the more recent study by Yao et al (2021). The two studies differed in a few ways; the more recent study included all empirical studies (Yao, Chen, et al., 2021), while the 2015 study only included randomized controlled trials (McMahan & Estes, 2015). Additionally, the former also evaluated study quality, and reported low confidence in the pooled estimates due to between-study heterogeneity (Yao, Chen, et al., 2021). One additional insight resulting from a stratified environment-type analysis was that effects of managed green space, namely urban parks, as opposed to wild nature, were similar with respect to positive affect, whereas there was no significant impact found for negative affect resulting from urban parks exposure impact (Yao, Chen, et al., 2021). This indicated that urban green spaces may be less effective at reducing negative emotions. These findings reflected a need for a stronger evidence base with better quality studies exploring mechanisms of impact (Yao, Chen, et al., 2021). The study on depressive mood, comparable to negative affect, had similar findings, reporting a small effect for reduction in depressive mood associated with exposure to the natural environment, but also citing poor quality and high risk of bias, resulting in low confidence in the estimates (H. Roberts et al., 2019).

Coventry et al. (2021) also evaluated affect and depressive mood and anxiety within its larger review of other health outcomes, finding improved mental health outcomes resulting from nature-based outdoor activities, such as gardening or green exercise (Coventry et al., 2021). Bowler et al. (2010) evaluated various self-reported emotions, finding health-protective associations of activity in green natural environments for outcomes of energy, anxiety, anger, fatigue, and sadness. No significant effects were found for attention, tranquility, and cortisol (Bowler et al., 2010b). A study focused on restorative effects of green space limited its analysis to randomized controlled trials (Song et al., 2022). The authors explored both psychological and physiological indicators and found that exposure was associated with less fatigue, tension, anger, and confusion, and increased vigor and positive affect (Song et al., 2022). Associations for depression and negative affect, while in the expected direction, were not statistically significant, which does not align with the previous studies discussed; this may be a function of the decision to only include randomized controlled trials, but requires further study. The authors also found evidence that green space exposure can lower heart rate-associated indicators, though no significant effects were found for blood pressure (Song et al., 2022).

Finally, the two studies evaluating the relationship between green space and stress both identified a statistically significant relationship for several psychological and physiological indicators (Mygind et al., 2021; Yao, Zhang, et al., 2021), some of which were also evaluated in previously discussed studies not explicitly focused on stress. Mygind et al. (2021) found that seated relaxation and walking in natural environments enhanced heart rate variability (though the association was not statistically significant for the former, but on the borderline of significance). They also found mixed results for cortisol; levels of salivary cortisol were lower after seated relaxation in a natural environment versus a control environment, but there was no effect found for walking in a natural environment. Challenges in evaluating changes to cortisol levels were discussed in depth within the article, and the authors suggested that heterogeneity in cortisol measures merits further research (Mygind et al., 2021), citing conflicting results with another study by Twohig-Bennett & Jones (Mygind et al., 2021; Twohig-Bennett & Jones, 2018). Two other meta-analyses also found no significant impacts for cortisol (Bowler et al., 2010b; Yao, Zhang, et al., 2021), indicating that this merits further analysis, which was echoed by another systematic review focused entirely on cortisol (R. Jones et al., 2021).

The reviewed studies present evidence of improved mental health outcomes associated with short-term exposure to natural environments, including urban green space, especially improvements in mood and other psychological indicators, as well as heart rate variance. Most of these studies were not able to isolate the effects for solely urban environments, which is a limitation of this review and merits further investigation. Ultimately, as for the other health outcomes evaluated in this report, the authors of the studies we reviewed cited challenges with low study quality and high levels of heterogeneity (Mygind et al., 2021; H. Roberts et al., 2019; Yao, Zhang, et al., 2021).

Long-term Exposures

For the purposes of this report, long-term exposures to green and blue spaces refer to exposures surrounding the residence, such as neighborhood NDVI or blue spaces within a specific buffer, rather than short-term interventions.

One recent meta-analysis evaluated depression and anxiety outcomes associated with several green space indicators, including the proportion of available green space, and NDVI (Z. Liu et al., 2023). The authors found that both increasing proportion of green space (OR: 0.96, 95% CI: 0.95 to 0.98) and increasing NDVI levels (OR: 0.93, 95% CI: 0.89 to 0.98) were found to be associated with a lower risk of depression. Additionally, an increasing proportion of green space was also found to be associated with lower anxiety (OR: 0.94, 95% CI: 0.86 to 1.03), but the results were not statistically significant. There was an insufficient number of studies (n=2) to conduct a meta-analysis for NDVI and anxiety (Z. Liu et al., 2023), but the two primary studies discussed within the review both found health-protective effects of NDVI on anxiety (N. Di et al., 2020; Maas et al., 2009).

Though we only identified one meta-analysis evaluating long-term impacts of urban green space on depression and anxiety in the general population, additional reviews and primary literature provide additional insights. Liu's findings are consistent with a previous review on urbanicity and depression (Sampson et al., 2020). Sampson et al. (2020) also reported that some existing evidence supported a relationship between green space and depression in urban areas, but not in rural areas (Sampson et al., 2020), based on the findings of two primary studies, one in children and one in adults (Bezold et al., 2018; Sarkar et al., 2018). Additionally, a recent primary analysis focused on the adult population provided further evidence on both depression and anxiety, finding surrounding greenness (NDVI) to be associated with reduced odds of taking benzodiazepines for anxiety, and access to large green spaces to be associated with self-reported history of depression (Gascon et al., 2018). Other primary studies provide evidential support for these health outcomes using different metrics, such as a recent study that found the view of green spaces from the residence was associated with lower risk of depression and anxiety (Braçe et al., 2020).

Another recent study presented pooled estimates for depressed affect (feeling sad, downhearted, or blue) in older adults (Noordzij et al., 2021). The authors evaluated two exposure metrics: distance to the nearest green space, and the amount of green space within 800-m buffers. The results were not statistically significant, though the pooled OR for the distance metric bordered significance, with ORs of 0.98 (95% CI: 0.96 to 1.00) and 1.00 (95% CI: 0.98 to 1.03) for the two metrics, respectively (Noordzij et al., 2021). However, this study was not a traditional meta-analysis in that it did not involve the synthesis of research results from multiple studies; rather, the authors pooled effects from multiple cohorts (Noordzij et al., 2021). This study also found no impacts of green space on subjective, self-rated health, and reported that further longitudinal studies are needed to characterize potential impacts in the older population, and determine whether other exposure metrics may have more significant impacts for this specific group (Noordzij et al., 2021).

Another study was the first to pool estimates of nature's effects on self-regulation in children, an outcome with important implications for the management of emotions and other cognitive processes (Weeland et al., 2019). The meta-analysis included both correlational and quasi-experimental studies (of which several of the latter fall into the short-term exposures category; this meta-analysis is only described in this section for simplicity). The authors found small but statistically significant positive overall associations between nature exposures – including residential greenness and various nature-based interventions, among other metrics – and children's self-regulation for both types of study designs. The authors did highlight several limitations, including methodological inconsistencies between studies, publication bias, and small samples sizes, as well as identified areas for future research, but also suggested that their findings have important implications for the development of nature-based intervention and prevention efforts for children (Weeland et al., 2019).

Two recent meta-analyses focused on urban blue space exposures, one including evaluations of restoration and social interaction (Georgiou et al., 2021) and the other on mental health and wellbeing (N. Smith et al., 2021). Both meta-analyses reported results in the form of an effect size, so specific dose-response relationships were not reported in Table 3.5. Both studies found health-protective impacts of blue space exposures. Georgiou et al. was focused on identifying the pathways through which blue spaces can affect health outcomes, and therefore evaluated physical activity, restoration, social interaction, and environmental factors. We limit this discussion to restoration and social interaction as mental health-associated outcomes. The authors found that larger quantities of blue space within a geographical area, as well as being in more contact with blue space, were both significantly associated with higher levels of restoration. However, living with a shorter distance to blue spaces was not associated with restoration or social interaction (Georgiou et al., 2021). While there was substantial evidence for restoration for two out of the three exposure metrics, this analysis found that the social interaction literature is mixed and requires further study (Georgiou et al., 2021). Smith et al. found that the presence of blue space within 500-m of peoples' home address was associated with improved self-reported mental health and wellbeing (N. Smith et al., 2021), finding relatively small effect sizes. Though not specific to mental health, apart from other outcomes explored in other sections of this report, Smith et al. also reported a positive relationship between blue spaces and general health (N. Smith et al., 2021). Both of these studies add to a growing body of evidence characterizing a positive relationship between urban blue spaces and population health, though further studies on blue space are needed, considering the evidence base was primarily composed of cross-sectional studies with substantial limitations, and though studies were of good quality, there was significant heterogeneity (Georgiou et al., 2021; N. Smith et al., 2021).

Overall, evidence from the meta-analyses builds upon the findings of a previous review on general mental health effects associated with long-term exposures to green and blue spaces which found limited evidence for surrounding greenness and mental health in adults (Gascon et al., 2015). They did not find sufficient evidence to draw conclusions for other greenness indicators (Gascon et al., 2015), and the Liu meta-analysis also only evaluated surrounding greenness, so more research is needed to explore other exposure metrics and uncover mechanisms of impact. Additionally, while the previous review was inconclusive on blue space impacts, the two meta-analyses we evaluated both provide more recent evidence of positive impacts of access to blue spaces on mental health (Georgiou et al., 2021; N. Smith et al., 2021).

In terms of potential dose-response values to use in health impact analysis, with access to the appropriate baseline health datasets for depression, the ORs developed in the meta-analysis from Liu et al. could be applied to evaluate the impacts of potential changes in greenness on depression outcomes in the general population (Z. Liu et al., 2023).

Cardiovascular Health

Table 5.6. *Cardiovascular Health: Summary of Review Studies Presenting a Quantitative Meta-Analysis of Urban Green or Blue Space Impacts*

Authors/ Year	**Publication Title**	**Specific Health Outcomes**	**Green or Blue Space Exposure(s)**	**Quantitative Dose-Response/Pooled Effect Estimate**	**Main Findings**
(Bowler et al., 2010b)	*A systematic review of evidence for the added benefits to health of exposure to natural environments*	Blood pressure (BP)	Activity in natural environment (ranged between studies, but had to be reasonably 'green') versus synthetic environment (non-green outdoor built environments or indoor environments).	Effect size (Hedges' g): **SBP:** 0.02 (95% CI: 0.42, 0.38) **DBP**: 0.32 (95% CI: –0.18, 0.82)	No effect was found on systolic or diastolic BP.
(Chandrabose et al., 2019)	*Built environment and cardio-metabolic health: systematic review and meta-analysis of longitudinal studies*	Obesity (only outcome pooled), type 2 diabetes, and hypertension	Built environment attributes: recreational facilities (including green space/parks)	**Obesity:** Weighted Z-value: 1.034 ($p = 0.301$)	Only obesity had sufficient longitudinal studies for a pooled analysis. While recreational facilities more broadly had a significant relationship with obesity outcomes in a health-protective direction, the isolated effect of green spaces and parks was not statistically significant.
(X.-X. Liu et al., 2022)	*Green space and cardiovascular disease: A systematic review with meta-analysis*	Stroke	NDVI	Pooled OR for 0.1 unit increase in NDVI: **Stroke incidence/prevalence**: 0.98 (95% CI: 0.96, 0.99)	This study found evidence of a protective effect of NDVI on stroke incidence (as well as cardiovascular mortality – see *Mortality* section).
(N. Smith et al., 2021)	*Urban blue spaces and human health: A systematic review and meta-analysis of quantitative studies*	Obesity	Blue space	Pooled β coefficient for presence of blue space within 500-m: **Obesity**: –0.34. (95% CI: –0.19, –0.09), $p < 0.001$	This study found that the presence of blue space within 500m of peoples' home address was associated with decreased levels of obesity.
(Twohig-Bennett & Jones, 2018)	*The health benefits of the great outdoors: A systematic review and meta-analysis*	Heart rate, diastolic and systolic blood pressure, HDL cholesterol, low frequency heart	Multiple, including NDVI, land cover maps, tree canopy and street tree data, and	Pooled mean difference for a comparison of high to low green space exposure (only significant, health protective results shown here):	This study found statistically significant associations between high levels of green space exposure and improved heart rate, diastolic blood pressure,

	of greenspace exposure and health outcomes	rate variability (HRV), increased high frequency HRV, hemoglobin, blood glucose, total cholesterol, LDL cholesterol, triglycerides, type 2 diabetes, hypertension, stroke, dyslipidaemia, and coronary heart disease	subjective measures of greenness	**Heart rate**: −2.57 (95% CI: −4.30, −0.83) **Diastolic blood pressure:** −1.97 (95% CI: −3.45, −0.19) **HDL cholesterol:** −0.03 (95% CI: −0.05, <-0.01) **LF HRV:** −0.06 (95% CI: −0.08, −0.03) **Increased HF HRV:** 91.87 (95% CI: 50.92, 132.82) Pooled OR for a comparison of high to low green space exposure: **Type 2 diabetes:** 0.72 (95% CI: 0.61, 0.85)	HDL cholesterol, low frequency HRV, increased high frequency HRV, and type 2 diabetes. Incidence of stroke, hypertension, dyslipidaemia, and coronary heart disease were also reduced but did not have statistically significant associations.
(Ye et al., 2022)	*Greenspace and health outcomes in children and adolescents: A systematic review*	Obesity/overweight	NDVI	Pooled OR for a 0.1 unit increase in NDVI: **Obesity/overweight**: 0.91 (95% CI: 0.84, 0.98)	This study found a statistically significant association between an increase in NDVI and reduced obesity/overweight outcomes.
(Zhao et al., 2022)	*Association between greenspace and blood pressure: A systematic review and meta-analysis*	Diastolic and systolic blood pressure, and hypertension	NDVI and distance to the nearest green space	Pooled coefficients for *0.1 unit increase in NDVI within 500m*: **SBP**: −0.77 mmHg (95% CI: −1.23, −0.32) **DBP**: −0.32 mmHg (95% CI: −0.57, −0.07) **Hypertension**: *NDVI in different buffers* was significantly associated with lower odds (2–9%) of hypertension. Pooled ORs for: *1% increase in proportion of green space:* 0.99, 95% CI: 0.99, 1.00 *Per 500 m increase in residential distance to the nearest green spaces:* 1.03, 95% CI: 0.96, 1.10	This study found evidence of a relationship between increased NDVI and decreased blood pressure. For hypertension, NDVI in different buffers was significantly associated with lower odds (2-9%) of hypertension, as was an increased proportion of green space. However, no relationship was found for the distance to nearest green space. The authors reported low confidence in all the pooled estimates.

Notes: OR = odds ratio; NDVI = normalized difference vegetation index; LF = low-frequency; HF = high-frequency; HRV = heart rate variability; DBP = diastolic blood pressure; SBP = systolic blood pressure; CI = confidence interval.

We identified seven systematic reviews including meta-analysis that evaluated cardiovascular health-related outcomes, described in Table 5.6 (excluding mortality outcomes which are included in the *Mortality* section above, see Table 5.3). The most commonly evaluated outcomes were blood pressure (Bowler et al., 2010b; Twohig-Bennett & Jones, 2018; Zhao et al., 2022) and obesity (Chandrabose et al., 2019; N. Smith et al., 2021; Ye et al., 2022), which were each evaluated in three studies. One of the studies on obesity was solely focused on urban blue space access (N. Smith et al., 2021). One study evaluated various cardiovascular mortality outcomes (discussed previously) as well as stroke (X.-X. Liu et al., 2022). Stroke (X.-X. Liu et al., 2022; Twohig-Bennett & Jones, 2018) and hypertension (Twohig-Bennett & Jones, 2018; Zhao et al., 2022) were also each included in two of the seven studies. We also note that some cardiovascular-related indicators such as blood pressure and heart rate are associated with mental health outcomes; articles focused on acute physiological responses of stress and similar outcomes are contained within the *Mental Health* section.

Blood Pressure

Of the three studies evaluating the relationship between green space access and blood pressure, two found a statistically significant impact. The Bowler et al. article was focused on short term exposures. The authors evaluated exposure to natural environments (also discussed in the *Mental Health* section) and investigated blood pressure, finding no effect on systolic or diastolic measurements (Bowler et al., 2010b). Also previously discussed, the review by Twohig-Bennett & Jones (2018), which was not limited to green interventions, found a statistically significant impact on diastolic blood pressure for a comparison of high to low green space exposures. Finally, a recent meta-analysis focused entirely on the effects of residential greenness (using NDVI) on blood pressure, characterizing changes in blood pressure measurements associated with various exposure metrics (Zhao et al., 2022). The authors found evidence of a relationship between increased residential NDVI (0.1 unit) and decreased systolic (pooled coefficient: −0.77 mmHg), 95% CI: −1.23 to −0.32) and diastolic (pooled coefficient: −0.32 mmHg, 95% CI: −0.57 to −0.07) blood pressure (Zhao et al., 2022). They also found that NDVI in different buffers was significantly associated with lower odds (2-9%) of hypertension, as was an increased proportion of green space. However, no relationships were identified for the distance to nearest green space (Zhao et al., 2022), which has been found in studies focused on other health outcomes as well (Connolly et al., 2023).

Zhao et al. explicitly compared their results to the Twohig-Bennett & Jones study, which also reported on blood pressure and hypertension. Zhao et al. (2022) identified a significant relationship between both systolic and diastolic blood pressure as well as hypertension, while Twohig-Bennett & Jones only found a significant relationship for diastolic blood pressure. The former expressed confidence in their own more recent estimates since their study design focused on specific green space exposures rather than pooling multiple types of exposures as Twohig-Bennett & Jones did in their analysis of 24 health outcomes (Twohig-Bennett & Jones, 2018). Regardless, the authors reported low confidence in the pooled estimates and called for further exploration of mediating factors as well as longitudinal studies, since most included in the meta-analysis were cross-sectional and therefore presented challenges in evaluating causality (Zhao et al., 2022).

More research is needed, but recent pooled estimates provide preliminary evidence that living in greener areas is associated with improved blood pressure outcomes, with coefficients derived from meta-analysis that could be utilized in health impact assessment studies (Zhao et al., 2022).

Obesity

Three meta-analyses evaluated obesity outcomes (Chandrabose et al., 2019; N. Smith et al., 2021; Ye et al., 2022). The previously cited study from Smith et al. (2021) was focused on urban blue spaces, and found the presence of blue space within 500-m of peoples' home address was associated with decreased levels of obesity (pooled β: -0.34, 95% CI: -0.19 to -0.09).

The other two studies evaluated green spaces. Chandrabose et al. (2019) was focused more broadly on the built environment, did not consider greenness metrics such as NDVI, and only included (1) longitudinal studies to inform causal inference, and (2) studies considering a physical activity pathway (i.e., not considering potential impacts of air quality or stress on obesity outcomes) (Chandrabose et al., 2019). The authors found that while recreational facilities more broadly had a significant relationship with obesity outcomes in a health-protective direction, the isolated effect of green spaces and parks was not statistically significant. The authors cited this as consistent with what was found in (Lachowycz & A. P. Jones, 2011) which included cross-sectional studies in their systematic review.

Finally, Ye et al. (2022) focused on residential greenness and obesity outcomes in children, supplementing a recent systematic review (Jia et al., 2021). The authors found a statistically significant association between an increase in NDVI and reduced obesity/overweight outcomes (for a 0.1 unit increase in NDVI, OR: 0.91, 95% CI: 0.84 to 0.98) for children and adolescents.
The Jia et al. (2021) review was also focused on children and found evidence of a positive association between access to green space and physical activity, as well as negative associations for television use, body mass index (BMI) and weight status (Jia et al., 2021).

There is growing evidence of a relationship between living in greener areas and obesity outcomes in children and adolescents, though findings are mixed for other green space outcomes. The evidence for children could be associated with outdoor play occurring more often in greener areas, but further analysis on mechanisms would be valuable. Additionally, there is limited positive evidence for impacts of living near blue spaces on obesity outcomes. Pooled estimates from the recent obesity meta-analysis (Ye et al., 2022) could be considered for health impact analyses of various greenness scenarios on obesity in children and adolescents, though again baseline small-area health estimates for the population of interest would be needed for this analysis.

Other Cardiovascular Outcomes

Several other cardiovascular outcomes were evaluated as well. One meta-analysis evaluated stroke incidence (alongside other mortality outcomes; see the *Mortality* section), finding evidence of a protective effect of NDVI on stroke incidence (for 0.1 unit increase in NDVI, OR: 0.98, 95% CI: 0.96 to 0.99), as well as various cardiovascular mortality outcomes (X.-X. Liu et al., 2022).

As described previously and referenced in other sections (see *Mortality, Mental Health,* and *Respiratory Health*), Twohig-Bennett & Jones (2018) studied multiple health outcomes, conducting 24 meta-analyses total (Twohig-Bennett & Jones, 2018). In terms of cardiovascular impacts (apart from what has been previously discussed), the authors found statistically significant health-protective associations between high levels of green space exposure and improved heart rate, high-density lipoprotein cholesterol, low frequency heart rate variance (HRV), increased high frequency HRV, and type 2 diabetes. Incidence of stroke, hypertension, dyslipidaemia, and coronary heart disease were also reduced but did not have statistically significant associations (Twohig-Bennett & Jones, 2018). Additionally, the previously mentioned study by Song et al. (2022) (see *Mental Health* and Table 5.5) focused on restoration and evaluated several of the same outcomes. Compared to Twohig-Bennett & Jones, Song et al. estimated a stronger impact for heart rate. The authors suggested several reasons for these discrepancies, including that while Twohig-Bennett & Jones did include more studies in their meta-analyses, they did not limit to randomized controlled trials as Song et al. (2022) did (to minimize meta-analysis heterogeneity).

Overall, while this evidence suggests protective effects for several cardiovascular outcomes, more focused analyses with improved study designs are needed on some of these less studied outcomes with inconsistent findings. While not discussed in this section, the existing literature does suggest a consistent association between urban green space and cardiovascular mortality across reviewed meta-analyses (see *Mortality* section).

Physical Activity

Due to a paucity of meta-analytic studies characterizing the dose-response relationship between urban green space and physical activity (Table 5.7), the discussion in this section incorporates findings from several relevant, U.S.-based systematic reviews as well.

Table 5.7. *Physical Activity: Summary of Review Studies Presenting a Quantitative Meta-Analysis of Urban Green or Blue Space Impacts*

Authors/ Year	Publication Title	Specific Health Outcomes	Green or Blue Space Exposure(s)	Quantitative Dose-Response/Pooled Effect Estimate	Main Findings
(Barnett et al., 2017)	*Built environmental correlates of older adults' total physical activity and walking: a systematic review and meta-analysis*	Total physical activity (PA), walking	Parks/public open space, greenery and aesthetically pleasing scenery	N/A – results not presented in dose-response form	This study found statistically significant evidence of positive associations between (1) total physical activity and (2) total walking with access to both parks/public open space and the presence of greenery and aesthetically pleasing scenery.
(Cerin et al., 2017)	*The neighbourhood physical environment and active travel in older adults: a systematic review and meta-analysis*	Active travel	Parks/public space/recreation, greenery and aesthetically pleasing scenery	N/A – results not presented in dose-response form	This study found no association between greenery and aesthetically pleasing scenery with any active travel outcomes. Positive associations were found between parks/public space/recreation with total and within-neighborhood walking, and all active travel, but not with walking/cycling or just cycling. Associations for parks/public space/recreation only hold for perceived environmental measures, not objective.
(Georgiou et al., 2021)	*Mechanisms of Impact of Blue Spaces on Human Health: A Systematic Literature Review and Meta-Analysis*	PA levels	Living closer to blue space and having larger amounts of blue space in a geographic area	**Physical activity levels**: For *living closer to blue space*: Cohen's d (standardized effect size): 0.122 (95% CI: 0.065, 0.179) For *having larger amounts of blue space in a region*: Cohen's d: 0.144 (95% CI: 0.024, 0.264)	This study found that (1) living closer to blue space and (2) having larger amounts of blue space within a geographical area are both associated with statistically significantly higher physical activity levels.
(McGrath et al., 2015)	*Associations of objectively measured built-environment attributes with youth moderate-vigorous physical activity: a systematic review and meta-analysis*	Moderate to vigorous PA levels	Built environment features (including parks)	N/A – results not presented in dose-response form	Play facilities, parks, playgrounds and features that facilitate walking had negative effects on children's activity but positive effects on adolescents' activity. Effects of parks and green spaces were not isolated.
(Van Cauwenberg et al., 2018)	*Relationships Between Neighbourhood Physical Environmental Attributes and Older Adults' Leisure-*	Leisure-time walking	Parks/public open space, greenery and	N/A – results not presented in dose-response form	This study found statistically significant evidence of positive associations between leisure-time walking with access to aesthetically pleasing

	Time Physical Activity: A Systematic Review and Meta-Analysis	aesthetically pleasing scenery	scenery, as well as between overall leisure-time physical activity and parks/open space.

Notes: PA = physical activity; CI = confidence interval.

Of the four meta-analyses included in Table 5.7, one was focused on blue space access (Georgiou et al., 2021), and the rest focused on neighborhood environment features (Barnett et al., 2017; McGrath et al., 2015; Van Cauwenberg et al., 2018). Of the latter, Barnett et al. (2017) and Van Cauwenberg et al. (2018) focused on older adults, and McGrath et al. (2015) focused on the youth population. Though all presented meta-analysis results, none of these studies presented a dose-response relationship for a specific increase in urban green or blue spaces resulting in a change in physical activity.

The three studies focused on the older adult population were conducted by the same research groups using the same methodologies, but focused on associations between the built/physical environment and three separate outcomes: active travel (Cerin et al., 2017), total physical activity and walking (Barnett et al., 2017), and leisure-time physical activity (Van Cauwenberg et al., 2018). While parks/public open space and the presence of greenery and aesthetically pleasing scenery were found to be statistically significantly associated with more total physical activity and walking (Barnett et al., 2017), results for active travel were less consistent, with no association found for greenery and aesthetically pleasing scenery, and positive associations found for parks/public space/recreation with several active travel outcomes (Cerin et al., 2017). Van Cauwenberg et al. (2018) found evidence of a positive relationship between access to aesthetically pleasing scenery with leisure-time walking, and between parks/open space with overall leisure-time physical activity, but not the inverse (Van Cauwenberg et al., 2018). While these studies provide mixed evidence of the relationship between access to green spaces and physical activity, they did not present quantitative dose-response values for the relationships and did not evaluate specific quantifiable and isolated green space exposures.

The meta-analysis by McGrath et al. (2015) also evaluated built environment characteristics, but for youths rather than older adults (McGrath et al., 2015). The authors found that play facilities, parks, playgrounds and features that facilitate play and walking had negative effects on children's moderate to vigorous activity but small positive effects on adolescents' activity. The authors cited potential causes for this disparity, including parental intervention in young children's activity for safety reasons (McGrath et al., 2015). Regardless, the effects of parks and green spaces were not isolated, so it is challenging to characterize the extent to which those features have significant impacts for the purposes of our analysis. The author's systematic review of the literature also found that more outdoor activity was associated with physical environment features such as streets, parking lots, shopping centers, and hard surface play areas, rather than greenness (McGrath et al., 2015).

Finally, the study focused on access to blue spaces and mechanisms of potential salutogenic effects found that both living closer to blue space and having large amounts of blue space within a geographical area were both associated with statistically significantly higher physical activity levels (Georgiou et al., 2021). These positive findings align with a 2017 systematic review on outdoor blue space exposure and the levels of physical activity, though the authors assigned a classification of "limited" to the evidence, mainly based on study heterogeneity (Gascon et al., 2017). There were multiple articles included in both syntheses (Karusisi et al., 2012; Perchoux et al., 2015; Wilson et al., 2011; Ying et al., 2015), though the study by Georgiou et al. (2021) incorporated several primary analyses published after the previous review.

An early systematic review evaluating obesity-related indicators found mixed evidence on green space and physical activity; though sixty-six percent of studies presented evidence of a positive association, many of the results were classified as ambiguous (Lachowycz & A. P. Jones, 2011). A 2015 review focused entirely on park access evaluated twenty years of studies in the U.S., again finding inconsistent evidence of the relationship between park density and proximity and objectively measured physical activity, citing variation in exposure measurement types as well as variation in the reporting of physical activity outcomes as important limitations (Bancroft et al., 2015). Seventy-five percent (15 out of 20) primary studies included in this particular review reported no association or a mixed association (Bancroft et al., 2015). Another review focused on the built environment more broadly found evidence of a positive effect of the provision of quality parks and playgrounds on physical activity and active transport (M. Smith et al., 2017), though they did not evaluate greenness specifically, with the exception of considering the retrofit of existing green space into pocket parks (Cohen et al., 2014). The review suggested its findings support further built environment interventions for increasing physical activity (M. Smith et al., 2017). Finally, a more recent systematic review on green space exposure and diabetes mellitus, physical activity, and obesity found evidence that the likelihood of physical activity increases with added exposure to neighborhood green space (De la Fuente et al., 2021). However, this assessment was based on only five studies with inconsistent exposure measurements, including nature experience, frequency of green space visits, and having a higher area of green space in the neighborhood. One of these primary studies did include an objective NDVI measurement, finding physical activity to be higher in adults who lived in an area with the highest quintile of greenness versus the lowest, and also higher for populations living closer to a park entrance (Klompmaker et al., 2018).

Results are inconsistent for the relationship between urban green space and physical activity, with mixed findings and no quantifiable dose-response values available for use in health impact assessment. There are several known challenges associated with characterizing the relationship between urban green space and physical activity, the most commonly cited being methodological heterogeneity (Bancroft et al., 2015; De la Fuente et al., 2021; M. Smith et al., 2017). There is also a need for longitudinal and quasi-experimental analyses that could evaluate causality (Barnett et al., 2017). This is an area for future study; potential methodological improvements to reduce heterogeneity, including the measurement of objective measures of greenness such as NDVI, would facilitate the development of dose-response values that could be used to evaluate potential physical activity increases associated with built environment interventions. Currently, we do not recommend specific dose-response values to be used for health impact assessment, due to inconsistent evidence and a scarcity of well-established dose-response values associated with a quantitative change in greenness such as NDVI or tree canopy coverage.

The existing evidence on blue spaces, though limited compared to the expanse of green space literature, supports the hypothesis that exposure to blue spaces is associated with increased physical activity. Previous reviews called for further longitudinal studies and a need for further multidisciplinary collaborations to improve upon challenges with methodological heterogeneities commonly seen in green and blue space analyses (Gascon et al., 2017; Georgiou et al., 2021).

The scope of this report does not include the impacts of other health outcomes resulting from physical activity in green space as an intervention, though results from some studies were incorporated in the extraction workbook (Shin et al., 2020). There is also recent meta-analytic evidence of increased positive impacts of physical activity in green and blue spaces on multiple health outcomes (H. Li et al., 2022; Yen et al., 2021), though evidence indicates differential impacts in "wild" versus urban settings (H. Li et al., 2022).

Respiratory Health

We identified seven systematic reviews including meta-analyses focused on access to urban green spaces and respiratory health, primarily in children and adolescents (Cao et al., 2023; Lambert et al., 2017; Parmes et al., 2020; Twohig-Bennett & Jones, 2018; X. Wang et al., 2022; Wu et al., 2022; Ye et al., 2022). Though the literature search included manuscripts published as early as 2010, all reviews including meta-analyses were published between 2017-2023. Asthma and allergic rhinitis were the most evaluated outcomes, with six out of the seven studies analyzing both. Table 5.8 provides an overview of the relevant studies.

Table 5.8. *Respiratory Health: Summary of Review Studies Presenting a Quantitative Meta-Analysis of Urban Green or Blue Space Impacts*

Authors/ Year	Publication Title	Specific Health Outcomes	Green or Blue Space Exposure(s)	Quantitative Dose-Response/Pooled Effect Estimate	Main Findings
(Cao et al., 2023)	*The effect of greenness on allergic rhinitis outcomes in children and adolescents: A systematic review and meta-analysis*	Allergic rhinitis	NDVI	For a 10% increase in NDVI: Main pooled OR: 1.00 (95% CI: 0.99, 1.00). 500-m buffer pooled OR: 0.99 (95% CI: 0.97, 1.01)	This study did not find evidence of a relationship between greenness and allergic rhinitis in children and adolescents.
(Lambert et al., 2017)	*Residential greenness and allergic respiratory diseases in children and adolescents – A systematic review and meta-analysis*	Asthma, allergic rhinitis	NDVI	Pooled OR for 0.1 unit increase in NDVI: **Asthma** at a 100-m buffer: 1.01 (95% CI: 0.93, 1.09) **Allergic rhinitis** at a 500-m buffer: 0.99 (95% CI = 0.87, 1.12)	This study did not find evidence of a relationship between greenness and asthma or allergic rhinitis in children and adolescents.
(Parmes et al., 2020)	*Influence of residential land cover on childhood allergic and respiratory symptoms and diseases: Evidence from 9 European cohorts*	Wheezing, asthma, allergic rhinitis, eczema	Proportion of land covered by green space	Pooled OR for 10% increase in green cover: **Wheeze:** 1.059 (95% CI: 1.008, 1.114) **Asthma:** 1.092 (95% CI: 1.011, 1.178) **Allergic rhinitis**: 1.081 (95% CI: 1.008, 1.160) **Eczema**: 1.009 (95% CI: 0.957, 1.064)	This study found that an increase in green space coverage resulted in greater odds of wheezing, asthma, and allergic rhinitis, but not eczema. Secondary analysis also found increased odds associated with living in areas with surrounding coniferous forests.
(Twohig-Bennett & Jones, 2018)	*The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes*	Asthma	Multiple, including NDVI, land cover maps, tree canopy and street tree data, and subjective measures of greenness	**Asthma**: Comparison of lowest green space to highest green space exposure: OR: 0.93 (95% CI: 0.57, 1.52)	This study did not find evidence of a statistically significant impact of greenness on asthma outcomes.
(X. Wang et al., 2022)	*Association between exposure to greenness and atopic march in children and adults-A systematic review and meta-analysis*	Asthma, allergic rhinitis	NDVI	Pooled ORs for exposure at birth and childhood outcomes, 0.1 unit NDVI increase: **Allergic rhinitis*:*** 0.83 (95% CI: 0.72, 0.96) **Asthma**: 0.96 (95% CI: 0.94, 0.98)	Increase in NDVI was associated with decreased odds of current asthma, but no significant association was found between residential greenness exposure and ever asthma, regardless of buffer distance.

				Current exposure and outcome, IQR NDVI increase: **Current asthma**: 0.94 (95% CI: 0.88, 1.00) **Ever asthma:** 1.00 (95% CI: 0.93, 1.08)	Results for exposure at birth suggest that living close to a greener environment at birth has a protective effect on the development of both childhood asthma and allergic rhinitis.
(Wu et al., 2022)	*Association of individual green space exposure with the incidence of asthma and allergic rhinitis: a systematic review and meta-analysis*	Asthma, allergic rhinitis	NDVI	For 0.1 unit increase in NDVI: **Current asthma:** Green exposure buffers in four groups (0 < radius ≤ 100 m, 100 < radius ≤ 300 m, 300 < radius ≤ 500 m, and 500 < radius ≤ 1000 m) Pooled OR (95% CI): 0.98 (0.90, 1.07), 0.99 (0.91, 1.07), 1.00 (0.91, 1.09), and 0.98 (0.90, 1.08), respectively **Ever asthma:** green exposure buffers in three groups (0 < radius ≤ 100 m, 100 < radius ≤ 300 m, and 300 < radius ≤ 500 m). Pooled OR (95% CI): 1.04 (0.92, 1.16), 1.00 (0.99, 1.02), and 1.04 (0.90, 1.22), respectively **Allergic rhinitis:** Pooled OR (95% CI): 0.98 (0.95, 1.02) for NDVI-100 m, 0.99 (0.94, 1.04) for NDVI-500 m, and 1.00 (0.95, 1.05) for NDVI-1000 m	This study did not find evidence of a significant relationship between greenness exposure and respiratory outcomes.
(Ye et al., 2022)	*Greenspace and health outcomes in children and adolescents: A systematic review*	Asthma, allergic rhinitis	NDVI	Pooled OR for 0.1 unit increase in NDVI: **Asthma**: 0.94 (95% CI: 0.84, 1.06) **Allergic rhinitis**: 0.95 (95% CI: 0.73, 1.25)	This study did not find evidence of a significant relationship between greenness exposure and respiratory outcomes.

Notes: OR = odds ratio; NDVI = normalized difference vegetation index; IQR = interquartile range; CI = confidence interval.

Five out of the seven studies did not find evidence of a relationship between urban green space and any respiratory health outcome (Cao et al., 2023; Lambert et al., 2017; Twohig-Bennett & Jones, 2018; Wu et al., 2022; Ye et al., 2022). Two of these studies included meta-analyses for other health outcomes unrelated to respiratory health (Twohig-Bennett & Jones, 2018; Ye et al., 2022). Twohig-Bennett & Jones conducted a meta-analysis for asthma using only two primary studies, and was part of a larger study evaluating more than fifteen health outcomes; the authors did not find a statistically significant relationship between exposure to high versus low levels of green space and asthma outcomes. This is unsurprising considering the two primary studies included in the meta-analysis (Andrusaityte et al., 2016; Škarková et al., 2015) both found statistically insignificant results, with associations in different directions. Ye et al. (2022) included obesity in their analysis alongside asthma and AR (Ye et al., 2022). The authors did not find evidence of a significant relationship between greenness exposure and respiratory outcomes in children and adolescents, citing largely inconsistent outcomes in the primary literature (Ye et al., 2022), which was a theme amongst all of the studies we reviewed.

Of the remaining three studies reporting no statistically significant findings (Cao et al., 2023; Lambert et al., 2017; Wu et al., 2022), the most recent was focused entirely on AR in children and adolescents (Cao et al., 2023). It included eleven studies in the meta-analysis, and found no significant relationships for the main pooled analysis or any of the buffer-specific analyses, including 500-m, which encompassed the largest number of primary studies. The studies by Lambert et al. (2017) and Wu et al. (2022) both included asthma and AR at various residential buffers. The latter study included both "current" and "ever" asthma (Wu et al., 2022).

The two remaining studies presented conflicting results. Wang et al. included an evaluation of exposures at birth and found evidence of protective effects of greenness at birth on asthma and allergic rhinitis developed in childhood (X. Wang et al., 2022). The authors suggested their findings may be different from the Lambert et al. (2017) and Wu et al. (2022) studies due to methodological limitations, including a lack of primary studies included in the analysis (Lambert et al., 2017) and the combining of birth cohorts and cross-sectional studies into one pooled analysis (Wu et al., 2022). It is challenging to state with certainty the reasons for these inconsistent findings, but the findings from Wang et al. (2022) do suggest potential differential and beneficial impacts of early life exposures, which should be further explored.

The final remaining study by Parmes et al. found the opposite of Wang et al. (2022): increased odds of both "lifetime" (synonymous with "ever") and "current" asthma, wheeze, and allergic rhinitis (though not eczema) associated with a 10% increase in green space cover (Parmes et al., 2020). The authors suggested their findings may be a function of allergies and other issues caused by emissions from vegetation, though the authors also noted several mechanisms through which green space can potentially be protective of health (Parmes et al., 2020). It is worth noting that this study is not a traditional meta-analysis, but includes nine cohorts (all from Europe), so we included it here for completeness. This study had several strengths, including the use of a standardized measure of European land cover for all of the cohorts included in the analysis; however, the use of this land cover metric means that it is challenging to compare these outcomes to those of other meta-analyses using NDVI. More research is needed to identify if these findings are widely applicable to other regions and populations.

As suggested by several of the studies we discussed here, these inconsistent results may be due to challenges in standardizing green space exposures, differences between populations studied and associated age groups, and confounding (Parmes et al., 2020). The study by Parmes et al. (2020), though not a traditional meta-analysis, was able to distinguish between forest types and found that living near coniferous forest was associated with greater odds of adverse respiratory outcomes (Parmes et al., 2020). Though future analyses are needed to further establish the specific relationship between the type of green space and respiratory impacts, this finding suggests that incorporating the type of green space in a given residential neighborhood into future analyses may be a key to characterizing the relationship between green spaces and respiratory health. The measure of NDVI was the most commonly used metric of green space in existing studies and can be standardized for summary analyses, but does not measure the vegetation type. Additionally, all of the meta-analyses (apart from the Parmes et al. cohort analysis) also included observational studies, and were potentially affected by confounding.

To summarize, in terms of recommended dose-response values for health impact assessment purposes, the existing meta-analyses do not present consistent supporting evidence of an association between green space and respiratory outcomes that would merit inclusion of such outcomes in an urban green space health impact assessment.

Implications

Considering the expansive green space literature, and a substantial knowledge gap in the establishment of specific dose-response values to be used in health impact assessments to evaluate various future natural and working land management scenarios, this review focused solely on meta-analyses with pooled estimates for green space and health outcomes. With several recent studies evaluating on the same or similar health outcomes, this review serves to consolidate the existing, recent literature and discuss potential alignments or inconsistencies.

This review illuminated common challenges in pooling exposures and outcomes for meta-analyses. Many of the meta-analyses reviewed cited high heterogeneity impacting confidence in the estimates. Some authors aimed to reduce this effect by limiting meta-analyses to primary studies with specific study designs to support causal inference, such as longitudinal studies or randomized controlled trials. Additionally, as is a general limitation in studies evaluating green space access, the quality of green spaces was not incorporated into these pooled estimates and is an area for future study. Several of the studies evaluating short-term health effects from exposure to the natural environment did not distinguish between urban and rural green space exposures, including both types in the meta-analysis, which limits inference about the mechanisms of impact.

Despite these challenges, the reviewed meta-analyses had several strengths. Some studies limited the inclusion of primary effect estimates to randomized controlled trials or longitudinal cohort studies, providing evidence of a causal relationship between urban green space and various health outcomes. Several studies also evaluated and improved upon previous meta-analyses, citing more comprehensive exposure metrics and statistical analyses, which strengthened confidence in their estimates.

This review itself has several limitations. Again, due to the nature of the growing body of literature on urban green spaces, we limited our review to six common categories of health effects, and did not incorporate all possible specific outcomes. We were also not able to include a general scoping overview of associations of all health outcomes, or all types of green space exposures, which was not the main focus of the review.

Ultimately, this review enabled us to determine the strength of the evidence for various dose-response relationships between access to urban green space and health outcomes. Due to limitations in available dose-response values and baseline health data, as well as baseline green space exposures, the NWL tool is currently limited to evaluating all-cause mortality, low birth weight, and life expectancy (the latter of which is not discussed in this review, but a California-specific dose-response estimate developed by our research team has been applied in the tool to supplement mortality and birth outcomes (Connolly et al., 2023). Depending on data availability in the future, several other health outcomes could be added to this tool and/or used in quantitative health impact assessments.

Conclusions

This review found substantial evidence of an association between urban green (and blue) spaces with impacts falling within various broad categories of health effects. However, not all specific outcomes within each given category presented sufficient meta-analytic evidence of a dose-response relationship. While there is growing evidence for impacts on various outcomes in the groupings of mortality, birth outcomes, mental health, and cardiovascular health, the evidence for physical activity and respiratory outcomes was more inconsistent. For all health effect categories, further longitudinal studies of good quality will be vital in the continued development of dose-response values quantifying the relationship between long-term exposure to urban green and blue spaces and health. Such dose-response values can be used to evaluate the potential health effects of future urban planning scenarios considered by policy-makers.

VI. Scoping Review: Wildland Fires

Introduction

Wildfires have been increasing in the western United States and are associated with higher temperatures and earlier spring snow melt (Westerling et al., 2006). The frequency and severity of wildfires are projected to increase globally due to alterations of temperature and precipitation patterns related to climate change (Moritz et al., 2012). Convincing evidence links wildfires to increases in $PM_{2.5}$ and, to a lesser extent, ozone (O_3) exposures; other species of particles, toxic air contaminants, and other gases such as nitrogen dioxide (NO_2) may also increase during wildfire events. While there has been a keen focus on the injuries caused by direct fire exposures, wildfire smoke exposures have the ability to negatively impact communities located at the urban wildland interface and beyond.

Compared to $PM_{2.5}$ from urban sources, wildfire-specific $PM_{2.5}$ has been found to have a greater negative impact on human health as it is more prone to large spikes in concentrations, varying and, in some cases, more toxic chemical compositions, and smaller particle size (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a; Makkonen et al., 2010). Furthermore, co-exposures between wildfire-specific $PM_{2.5}$ with other harmful environmental factors, particularly extreme heat, have been found to increase mortality (Shaposhnikov et al., 2014); an issue of increasing concern as temperatures are expected to rise further as a result of climate change and $PM_{2.5}$ smoke from wildfires are expected to increase 190% in in the continuous United States by 2100 (Ford et al., 2018). A recent study found short-term exposure to wildfire-specific $PM_{2.5}$ was associated with 65.6 million all-cause deaths globally, of which, approximately 8.6 million were within the United States (2000-2006) (G. Chen et al., 2021). Additional studies have attributed landscape fires to 677,745 premature deaths annually (G. Roberts & Wooster, 2021).

Substantial general evidence links elevated exposures of wildfire-specific pollution species, particularly $PM_{2.5}$, to numerous adverse morbidity outcomes including respiratory exacerbation from asthma, and other respiratory disease symptoms such as chronic obstructive pulmonary disease (COPD) (Reid, Brauer, et al., 2016a). Recent research from California has identified a significant relationship between wildfire-specific $PM_{2.5}$ and respiratory hospitalizations and emergency room (ER) visits (Reid, Jerrett, et al., 2016b). Acute exposures to wildfire-specific $PM_{2.5}$ have been associated with over 40,000 respiratory and cardiovascular related hospitalizations across the contiguous United States between 2008-2012 (Fann et al., 2018).

The current study aims to expand our knowledge on the mortality and morbidity impacts associated with wildfire exposure in California. There are few studies that have evaluated the short-term morbidity impacts or the statewide distribution of exposure to wildfire-specific $PM_{2.5}$ over a long-term period. The aim of the scoping review is two-fold: (1) to identify and summarize the peer-reviewed literature examining the human health impacts associated with wildfire-specific smoke exposure, specifically PM and; (2) identify and extract primary empirical research that can be used to inform future modelled health impact research (see **Figure 4.2b)**. These results will provide critical information for the State wildfire management planning and is especially relevant for quantifying impacts from natural working land policies, programs, and activities that decrease the threats from current catastrophic wildfires.

Methods

We conducted a scoping review of the global peer-reviewed epidemiological literature using the PRISMA between June - September 2020 on the following databases: PubMed, Web of Science, APA PsycInfo, and Embase. We followed the Arksey and O'Malley's framework for scoping reviews and the PRISMA-ScR which include the following five phase process: (1) identifying the research questions, (2) identifying relevant publications, (3) selecting the publications, (4) charting the data, and (5) collating, summarizing, and reporting the results (Arksey & O'Malley, 2005; Tricco et al., 2018). In collaboration with the University of California, Los Angeles' data librarians and project partners at CARB, we developed search terms to form keywords for the scoping review that would be inclusive of all potential health outcomes from exposures to wildfire related events. A full list of search terms is included in the Table below.

Table 6.1. *Keyword search*

Concept	Text Keywords
Natural & working lands	"Natural and Working Land*" OR "Natural Working Land*" OR NWL OR Chaparral* OR Settlement* OR "Woody Vegetation*" OR "Non-grass Vegetation*" OR "Woody Biomass" OR "Coastal Area*" OR Wilderness OR Forest* OR Pasture* OR Agroforestry OR Riparian OR Savanna* OR Meadow* OR Prairie* OR Steppe* OR Biomass OR Estuar* OR Connectivity OR Habitat OR Grassland* OR Woodland* OR Shrubland* OR Wetland* OR Rangeland* OR "Preservation Land*" OR Wildland* OR "State Park*" OR "Community Park*" OR "Recreational Park*" OR "National Park*"
Burn/Fire	Burn* OR Fire*
Wildfires	Wildfire* OR "Wild Fire*" OR "Controlled Burn*" OR "Prescribed Fire*" OR "Prescribed Burn*" OR "Experimental Fire*" OR "Experimental Burn*" OR "Burn Strategy" OR "Burning Strategy" OR "Wildland Fire*" OR "Peat Fire*" OR "Bush fire*" OR Bushfire* OR "Brush Fire*" OR Brushfire* OR "Landscape Fire*" OR "Biomass Burn*" OR "Forest Fire*"
Health	"Health Outcome*" OR "Health Impact*" OR "Rural Health" OR "Urban Health" OR "Mental Health" OR "Health Status" OR "Health Effect*" OR Adult* OR Child* OR Infant* OR Fetal OR Fetus* OR Human* OR Subject* OR Participant* OR Mortality OR Morbidity OR Exposure*
Review	Review OR Meta-Analy*

Criteria included primary empirical human-health studies of all age groups (including prenatal), sexes and genders which evaluated the health impacts from wildfire-specific PM smoke exposures. Due to the rapidly changing landscape of wildfires over the past decade that include more intense and severe fire events and, thus, exposures, we limited our search to articles published between 2010–2020. All health impacts including but not limited to respiratory, cardiovascular, mental health, maternal and child health, and cancers were included in the scoping review search. Since this study aims to quantify the human health impacts of the general population, occupational exposures, including those from wildland firefighters, were not included. We limited our search to studies published in a peer-reviewed journal written in English, French, or Spanish. One of the primary aims of the scoping review is to extract primary empirical research that can be used to inform future modelled health impact research; thus, we focused on wildfire-specific PM smoke as the primary exposure since particles are a commonly used wildfire exposure metric and provide several exposure modeling products (e.g. CMAQ, FINN, etc.) options for future modeled health impact research. While we prioritize review and meta-analysis articles in our search terms, we extracted articles from the search that also included primary research. Ineligible studies included those using non-human subjects, exposures in a laboratory setting, or exposure studies that did not empirically examine the relationship between wildfire-specific PM to human health to provide a quantitative impact estimate.

Table 6.2. *Inclusion and exclusion criteria*

Inclusion Criteria	*Exclusion Criteria*
Primary peer-reviewed literature that was published between 2010–2020 in English, Spanish, or French language	Non-peer reviewed literature (e.g. abstract only, conference proceedings, articles from the media, letters to the editor, reports, thesis, textbooks, etc.) published prior to 2010 and after 2020, and not in the English, Spanish, or French language
Literature that explicitly describes wildfire-specific exposures identified through measured and reported PM	Literature that explicitly describes the inclusion of other or mixed fire sources including prescribed burns, agricultural burning, non-descript regional haze, etc.
Primary or secondary health data used to examine relationships with wildfire-specific exposures	Surveillance data lacking an assessment of impact
Direct health impacts in non-occupational settings	Occupational exposures (e.g., firefighters) or secondary impacts (e.g., stress from displacement)
Empirical studies that estimate quantifiable impacts	Non-empirical studies or studies that do not quantify exposure impacts
Studies that explicitly investigate the relationship between human health outcomes and wildfire-specific exposures	Literature that does not investigate the impacts of wildfire-specific exposures to human health

After removing duplicates, we analyzed titles and abstracts for significance, then removed studies that did not fit the above criteria. We then conducted a reverse snowballing literature search by using the citations in the collected literature to identity additional relevant work to ensure all relevant articles were included within the review. Once the relevant literature was identified, we systematically extracted and organized the data for analysis into an Excel spreadsheet that included relevant information including: authors, publication year, publication title, journal, study location, exposure measurement, and health outcome examined.

A short narrative summary of each major health outcome categories was developed, after which, the authors discussed the potential pathways between wildfire smoke and each health outcome category and how we may incorporate them into a health impact analysis. A second reviewer looked at all the listed articles and worked with the first reviewer to ensure data were extracted properly and accurately represented the data from the articles.

Results

The scoping review yielded over 700 health endpoints. Most of these articles were from the United States, with the largest portion focused within California. While many of the health outcomes focused on respiratory and cardiovascular health end points, there were also articles that evaluated other impacts including birth outcomes and mental health outcomes. The strongest evidence that exists to date, of impact from wildfire emissions exposure, is for respiratory outcomes, particularly asthma hospital admissions or ER visits, more mixed or suggestive evidence for other respiratory health outcomes including pneumonia, as well as other outcomes like all-cause mortality. The results of this scoping review represent key findings and insights relevant to the impacts of wildfire smoke on human health and the state of the literature in terms of dose-response values. The articles were categorized into broad health outcome groups and summarized in more detail in the following section.

Summary of Health Outcomes

Birth Outcomes

Birth weight is often used as a population-level indicator of general health and future outcomes. Low birth weight has been associated with increased risk for mortality and morbidity outcomes including risk of cancer, adverse respiratory health outcomes, cardiovascular disease, and other chronic health outcomes. Available evidence supports a plausible causal relationship between air pollutants and birth outcomes (Lamichhane et al., 2015; Nyadanu et al., 2022), and studies examining impacts from combustion-related impacts suggest a link to inflammation, oxidative stress, and endothelial dysregulation in the maternal-fetal unit (Basilio et al., 2022). Similar impacts are expected for wildfire smoke exposures; however, recent reviews have only found limited evidence for the association between wildfire exposures, low birth weight and preterm birth, and inconclusive associations between wildfire exposures and small for gestational age and infant mortality (Amjad et al., 2021).

The current scoping review identified six peer-reviewed articles that examined the relationship between wildland fire exposures and various birth outcomes including, but not limited to, birth weight, preterm birth, and small for gestational age. The majority of these articles focused on birth weight, were based in the United States, and estimated exposures by distance to wildfire. Of the six peer-reviewed articles, five found an association with wildfire exposure and decreased birth weight, particularly when the exposure occurred later in the pregnancy (Abdo et al., 2019; Holstius et al., 2012; Mccoy & Zhao, 2021; O'Donnell & Behie, 2013, 2015; Prass et al., 2012).

Three U.S.-based peer-reviewed articles found significant impacts between low birth weight and wildfire exposures when mothers were exposed to both wildfire $PM_{2.5}$ and particulate matter with a diameter of 10 micrometers or less (PM_{10}), although the strength and significance of the association varied over trimesters (Abdo et al., 2019; Holstius et al., 2012; Mccoy & Zhao, 2021). Holstius et al. (2012) identified a 9.7 g weight difference in babies born to mothers residing in California's South Coast Air Basin (SoCAB) during a wildfire exposure timeframe that coincided with their second trimester compared to babies born to mothers outside that exposure window.

While similar results were found for exposure in the first trimester, they were not significant (Holstius et al., 2012). Abdo et al. (2019) found that exposure to wildfire $PM_{2.5}$ smoke was significantly associated with 5.7 g reduction in birth weight during the first trimester, while the other trimesters varied in their direction of association or were found to be insignificant. In addition, researchers identified an increased risk to preterm birth, gestational diabetes, gestational hypertension, SGA, neonatal intensive care unit (NICU) admissions, and assisted ventilation from wildfire $PM_{2.5}$ during the various trimesters; however, NICU admissions and assisted ventilation directionality was contrary to expectation (Abdo et al., 2019).

The literature based outside the U.S. were similarly heterogenous in their outcomes (O'Donnell & Behie, 2013, 2015; Prass et al., 2012). Studies in Australia and Brazil suggested wildfire exposure impacted birth weight; however, the significance and direction of impact varied between studies. O'Donnell & Behie (2015) found that male infants born in severe wildfire-affected regions exhibited notably greater average birth weights compared to less exposed counterparts, suggesting that heightened maternal stress may impact male fetal growth patterns (O'Donnell & Behie, 2015). In a previous study conducted in 2013, the authors had found that mothers exposed to wildfires during the late second trimester or third trimester gave birth to infants with increased preterm birth and decreased birth weight (O'Donnell & Behie, 2013).

Overall, the peer reviewed literature suggests an association between select birth outcomes with some noting profound outcomes that may have both wide-ranging and long-term public health implications; however, there is a lack of available evidence within the peer-reviewed literature to conclude an association (Adetona et al., 2016; Evans et al., 2022; Reid, Brauer, et al., 2016a). Additional epidemiological studies are needed to better understand the impacts of wildfire PM smoke exposures on birth outcomes (Amjad et al., 2021).

Table 6.3. *Relevant scoping review articles examining wildfire impacts on birth outcomes*

Author (Year)	***Title***	***Health Outcomes Included***	***Location***
Holstius et al. (2012)	*Birth weight following pregnancy during the 2003 Southern California wildfires.*	Birth weight	California, USA
Prass et al. (2012)	*Amazon forest fires between 2001 and 2006 and birth weight in Porto Velho.*	Birth weight	Brazil
O'Donnell and Behie (2013)	*Effects of bushfire stress on birth outcomes: A cohort study of the 2009 Victorian Black Saturday bushfires*	Birth weight, preterm birth, sex-ratios	Australia, Victoria
O'Donnell and Behie (2015)	*Effects of wildfire disaster exposure on male birth weight in an Australian population.*	Birth weight, gestational age	Australia

Mccoy and Zhao, 2021 (Early Access 2020)	*Wildfire and infant health: a geospatial approach to estimating the health impacts of wildfire smoke exposure*	Birth weight, gestational age	USA, Colorado
Abdo et al. (2019)	*Impact of wildfire smoke on adverse pregnancy outcomes in Colorado, 2007-2015.*	Primary: Preterm birth, birth weight birth weight Secondary: Gestational hypertension, gestational diabetes, neonatal intensive care unit admissions, assisted ventilation, small for gestational age, low birth weight	USA, Colorado

Cancer Outcomes

Polycyclic aromatic hydrocarbons (PAHs), metals, formaldehyde, and other wildfire pollutants are known human carcinogens, suggesting that wildfire exposure can increase risk of cancers in affected populations (Korsiak et al., 2022). Epidemiological studies examining the impacts of wildfire exposure on cancer risks can be challenging due to the long-term progression of the disease. Furthermore, the chemical composition of wildfire PM is difficult to characterize and can be affected by different ecosystems, limiting the ability to generalize constituents across geographies (J. C. Liu & Peng, 2019). A total of two peer-reviewed articles that examined the impacts of wildfire PM smoke and cancer risks and matched our inclusion criteria were identified in the current scoping review. These two articles spanned the range of Indonesia and the Western United States and focused on trace metals and hazardous air pollutants (HAPs) in wildfire smoke (Betha et al., 2013; O'Dell et al., 2020).

Betha et al. (2013) estimated the deposition of carcinogenic trace metals in peat fire related PM in Southeast Asia and performed Excessive Lifetime Cancer Risk (ELCR) assessments using particle-bound trace metals with known toxicity values (Betha et al., 2013). Applying concentrations of the carcinogenic trace metals speciated from peat fire related PM (cadmium, chromium, nickel, and cobalt), researchers found that approximately 0.4–0.5% of individuals could have an increased risk of cancer after being exposed to PM emissions from the Indonesian peat fires. Looking at HAPs and PM in western U.S. wildfire smoke plumes, O'Dell et al. (2020) found that acrolein, benzene, formaldehyde, and hydrogen cyanide are the major contributors to HAP risk in smoke plumes, and these risks decrease as a function of smoke age (O'Dell et al., 2020). Specifically, chronic exposure to 0.45 $\mu g/m^3$ of $PM_{1.0}$ smoke aged < one day or 0.77 $\mu g/m^3$ of $PM_{1.0}$ smoke aged > 3 days is associated with one excess cancer risk per one-million population.

While studies have investigated associations between biomass and non-specific haze events, there are few studies that have examined the impacts of wildfire-specific PM exposures on cancer risks (Ramakreshnan et al., 2018; Reid, Brauer, et al., 2016a); however, a recent longitudinal population-based observational cohort study on more than 2 million Canadian adults found a 5% higher lung cancer incidence and 10% higher brain tumor incidence compared to unexposed population (Korsiak et al., 2022). Future research should incorporate longitudinal studies and detailed demographic data to evaluate the effects of chronic exposures to wildfire PM, especially within susceptible populations.

Table 6.4. *Relevant scoping review articles examining wildfire impacts on cancer outcomes*

Author (Year)	***Title***	***Health Outcomes Included***	***Location***
Betha et al. (2013)	*Chemical speciation of trace metals emitted from Indonesian peat fires for health risk assessment.*	All cancers	Indonesia, Kalimantan
O'Dell et al. (2020)	*Hazardous Air Pollutants in Fresh and Aged Western US Wildfire Smoke and Implications for Long-Term Exposure*	All cancers	United States, Western US

Cardiovascular Health Outcomes

In a 2021 article, the researchers found 25 of the 38 epidemiological studies identified in the review process reported a positive associated between wildfire smoke exposure and increased healthcare needs for a range of cardiovascular, circulatory, and cerebrovascular diseases (H. Chen et al., 2021). Specifically, wildfire smoke exposures were found to increase risk of cardiac arrest, cardiovascular illness, hypertension, and congestive health failure, among other cardiac, circulatory, and cerebrovascular related healthcare needs (Crabbe, 2012; Haikerwal et al., 2015; F. H. Johnston et al., 2014; Jones C.G. et al., 2020; T.-S. Lee et al., 2009; Parthum B. et al., 2017; Rappold et al., 2012; Tinling et al., 2016).

Crabbe (2012) found a non-significant increased risk of cardiovascular admissions from same-day exposure to wildfire fine particulate matter in Darwin, Australia (Crabbe, 2012). Another study in Australia estimated increased risk of out-of-hospital cardiac arrests (percentage change in risk: 6.98%, 95% CI: 1.03%–13.29%) and ischemic heart disease-related ED visits and hospital admissions with increased $PM_{2.5}$ exposure at various lags (Haikerwal et al., 2015). F. H. Johnston et al. (2014) also found a significantly increased risk of ischemic heart disease ED visits at lag 2 (OR: 1.07, 95% CI: 1.01–1.15) but observed an inverse association for arrhythmias at lag 2 in Sydney, Australia (F. H. Johnston et al., 2014).

Based in the US, Rappold et al. (2012) found that on the day following exposure to wildfire smoke in North Carolina, ED visits for congestive heart failure increased 42% (95% CI: 5%–93%) (Rappold et al., 2012). Another study in North Carolina observed increased risk of hypertension and cardiac outcomes associated with increased $PM_{2.5}$ within adults (Tinling et al., 2016).

Despite these findings, additional articles failed to identify a positive association between related health outcomes and wildfire smoke exposures (Alman et al., 2016; DeFlorio-Barker et al., 2019; Delfino et al., 2009; H. Liu et al., 2017; Reid, Brauer, et al., 2016a; Reid, Jerrett, et al., 2016b).

While there was no clear consensus on the impacts to cardiovascular health, several initiating biological pathways have been identified and an increasing pool of evidence exists between short-term exposures and key cardiovascular outcomes (Hadley et al., 2022); however, interpretation of the resulting heath estimates should account for these uncertainties.

Table 6.5. *Relevant scoping review articles examining wildfire impacts on cardiovascular outcomes*

Author (Year)	***Title***	**Health Outcomes Included**	**Location**
Alman et al. (2016)	*The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: a case crossover study.*	Cardiovascular disease; Ischemic Heart Disease, Acute myocardial infarction, Dysrhythmia, Congestive heart failure, Ischemic Stroke, Peripheral vascular disease	USA, Colorado
Crabbe (2012)	*Risk of respiratory and cardiovascular hospitalisation with exposure to bushfire particulates: new evidence from Darwin, Australia.*	Cardiovascular conditions	Australia, Darwin
DeFlorio-Barker et al. (2019)	*Cardiopulmonary effects of fine particulate matter exposure among older adults, during wildfire and non-wildfire periods, in the United States 2008–2010.*	All-cause	USA, statewide
Dennekamp et al. (2015)	*Forest fire smoke exposures and out-of-hospital cardiac arrests in Melbourne, Australia: a case-crossover study.*	Cardiac arrest	Australia, Melbourne
Gan et al. (2017)	*Comparison of wildfire smoke estimation methods and associations with cardiopulmonary-related hospital admissions.*	Arrhythmia, myocardial infarction, ischemic heart disease, heart failure, cardiovascular disease	USA, Washington
Haikerwal et al. (2015)	*Impact of fine particulate matter ($PM_{2.5}$) exposure during wildfires on cardiovascular health outcomes.*	Acute myocardial infarction, angina, ischemic heart disease, cardiac arrest	Australia, Victoria
Henderson et al. (2011)	*Three measures of forest fire smoke exposure and their associations with respiratory and cardiovascular health outcomes in a population-based cohort.*	Cardiovascular morbidity, hypertension	Canada, British Columbia
Hutchinson et al. (2018)	*The San Diego 2007 wildfires and Medi-Cal emergency department presentations, inpatient hospitalizations, and outpatient visits: An observational study of smoke exposure periods and a bidirectional case-crossover analysis.*	Cardiovascular morbidity, ischemic heart disease, dysrhythmia, congestive heart failure, diseases of peripheral circulation	California, San Diego

Johnston et al.	*Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996-2007: A case-crossover analysis.*	Ischemic heart disease, cardiac failure, cardiovascular diseases, arrhythmias,	Australia, Sydney
Kollanus et al. (2016)	*Effects of long-range transported air pollution from vegetation fires on daily mortality and hospital admissions in the Helsinki metropolitan area, Finland.*	Cardiovascular morbidity	Finland
Le et al. (2014)	*Canadian forest fires and effects of long-range transboundary air pollution on hospitalizations among the elderly.*	Cardiovascular morbidity, acute MI, heart failure, hypertension; ischemic heart disease; acute pulmonary heart disease; acute heart disease; heart rhythm disturbances; peripheral vascular disease	USA, Northeastern & Mid-Atlantic States
Martin et al. (2013)	*Air pollution from bushfires and their association with hospital admissions in Sydney, Newcastle and Wollongong, Australia 1994-2007.*	Congestive heart failure, arrhythmia, cardiovascular morbidity, ischemic heart disease	Sydney, Australia
Morgon et al. (2010)	*Effects of bushfire smoke on daily mortality and hospital admissions in Sydney, Australia.*	Cardiac morbidity, ischemic heart disease, cardiovascular morbidity	Sydney, Australia
Rappold et al. (2012)	*Cardiorespiratory outcomes associated with exposure to wildfire smoke are modified by measures of community health.*	Cardiovascular heart failure	USA, North Carolina
Reid et al. (2016)	*Differential respiratory health effects from the 2008 northern California wildfires; a spatiotemporal approach.*	Cardiovascular disease, congestive heart failure, dysrhythmias, hypertension, ischemic heart disease	USA, California
Resnick et al. (2015)	*Health outcomes associated with smoke exposure in Albuquerque, New Mexico, during the 2011 Wallow fire.*	Cardiovascular morbidity; hypertensive disease; ischemic heart disease; diseases of pulmonary circulation; diseases of veins, lymphatics, and circulatory system	USA, New Mexico
Salimi et al. (2017)	*Ambient particulate matter, landscape fire smoke, and emergency ambulance dispatches in Sydney, Australia.*	Cardiovascular disease	Sydney, Australia
Stowell et al. (2019)	*Associations of wildfire smoke $PM_{2.5}$ exposure with cardiorespiratory events in Colorado 2011–2014.*	Ischemic heart disease; acute myocardial infarction; congestive heart failure; dysrhythmia; peripheral/cerebrovascular disease; cardiovascular disease	USA, Colorado

Tinling et al. (2016)	*Repeating cardiopulmonary health effects in rural North Carolina population during a second large peat wildfire.*	Heart failure; hypertension, cardiac morbidity, cardiac dysrhythmia	USA, North Carolina
Wettstein et al. (2018)	*Cardiovascular and cerebrovascular emergency department visits associated with wildfire smoke exposure in California in 2015.*	Cardiovascular disease; hypertension; myocardial infarction, ischemic heart disease; pulmonary embolism; dysrhythmia and conduction disorder; heart failure; peripheral arterial disease	USA, California
Yao et al. (2016)	*Evaluation of a spatially resolved forest fire smoke model for population-based epidemiologic exposure assessment.*	Cardiovascular morbidity	Canada

Cerebrovascular Outcomes

Cerebrovascular disease encompasses a range of conditions that impact the blood vessels within the brain and includes such health outcomes as stroke, aneurysms, and vascular malformations. Over the last ten years, there have been few studies that have examined the association between wildfire related PM smoke and cerebrovascular health outcomes. The current scoping review identified a total of eight peer-reviewed articles that investigated the association between cerebrovascular disease and wildfire PM smoke that fit our inclusion criteria. Of these eight peer-reviewed articles, six spanned across the Northeastern & Mid-Atlantic States, as well as the Western U.S. including California, Washington, and New Mexico; and two focused within the area of Sydney, Australia (Gan et al., 2017; Hutchinson et al., 2018; F. H. Johnston et al., 2014; Le et al., 2014; Morgan et al., 2010; Reid, Jerrett, et al., 2016b; Resnick et al., 2015; Wettstein et al., 2018).

There was inconclusive evidence and mixed directions of association between wildfire PM smoke and increased risk for stroke (Le et al., 2014; Morgan et al., 2010; Wettstein et al., 2018). Similar results were found for cerebrovascular disease. Studies in New Mexico, Washington, and California identified increased risk for cerebrovascular disease with exposures to the 2011 Wallow Fire (RR: 1.69, 95% CI: 1.03–2.77), the 2012 Washington complex fire (OR: 1.046, 95% CI: 1.004–1.090), and the 2015 California wildfire season (RR: 1.22, 95% CI: 1.00–1.48), respectively; however, between these three studies, there was heterogeneity between sex and age stratified sub-groups (Gan et al., 2017; Resnick et al., 2015; Wettstein et al., 2018). Martin et al. (2013) found no association between smoke events and cerebrovascular disease risk in three eastern Australian cities (Martin et al., 2013). Contrary to the other studies, Johnston et al. (2014), Reid et al. (2016), and Stowell et al. (2019) found a weak negative association between wildfires PM smoke exposures and cerebrovascular disease (F. H. Johnston et al., 2014; Reid, Jerrett, et al., 2016b; Stowell et al., 2019). Hutchinson et al. (2018) found significant negative associations between wildfire $PM_{2.5}$ smoke exposure and stroke risk in San Diego, California (Hutchinson et al., 2018). The overall evidence between cerebrovascular health outcomes and wildfire PM smoke is inconclusive, and more research is needed to elucidate the full range of outcomes associated with cerebrovascular health (Cascio, 2018).

Table 6.6. *Relevant scoping review articles examining wildfire impacts on cerebrovascular outcomes*

Author (Year)	***Title***	***Health Outcomes Included***	***Location***
Morgan et al. (2010)	*Effects of bushfire smoke on daily mortality and hospital admissions in Sydney, Australia.*	Stroke	Sydney, Australia
Martin et al. (2013)	*Air pollution from bushfires and their association with hospital admissions in Sydney, Newcastle and Wollongong, Australia 1994-2007.*	Cerebrovascular disease	Sydney, Australia
Johnston et al. (2014)	*Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996-2007: A case-crossover analysis.*	Cerebrovascular disease	Sydney, Australia
Le et al. (2014)	*Canadian forest fires and effects of long-range transboundary air pollution on hospitalizations among the elderly.*	Stroke	USA, Northeastern & Mid-Atlantic States
Resnick et al. (2015)	*Health outcomes associated with smoke exposure in Albuquerque, New Mexico, during the 2011 Wallow fire.*	Cerebrovascular disease	USA, New Mexico
Reid et al. (2016)	*Differential respiratory health effects from the 2008 northern California wildfires; a spatiotemporal approach.*	Cerebrovascular disease	USA, California
Gan et al. (2017)	*Comparison of wildfire smoke estimation methods and associations with cardiopulmonary-related hospital admissions.*	Cerebrovascular disease	USA, Washington
Hutchinson et al. (2018)	*The San Diego 2007 wildfires and Medi-Cal emergency department presentations, inpatient hospitalizations, and outpatient visits: An observational study of smoke exposure periods and a bidirectional case-crossover analysis.*	Cerebrovascular disease including stroke	USA, San Diego
Wettstein et al. (2018)	*Cardiovascular and cerebrovascular emergency department visits associated with wildfire smoke exposure in California in 2015.*	Cerebrovascular disease, ischemic stroke, intracerebral/ intraventricular hemorrhage, precerebral vascular occlusion	USA, California
Stowell et al. (2019)	*Associations of wildfire smoke $PM_{2.5}$ exposure with cardiorespiratory events in Colorado 2011–2014.*	Peripheral/cerebrovascular disease	USA, Colorado

Mental Health Outcomes

Over the past few decades, climate-induced environmental events have increased in both intensity and frequency across the globe. The devastation and displacement experienced from these events combined with the anticipation of future catastrophic exposures can have profound repercussions on the psychological well-being of individuals that persist for years after the event. The increasing distress produced by changes in our surrounding natural environment and the chronic fear of environmental cataclysm have prompted new terms like solastalgia and eco-anxiety to detail these emerging phenomena. Various review articles examining the impact of wildfires on human health and well-being have identified increased prevalence of conditions such as post-traumatic stress disorder (PTSD), depression, and anxiety during multiple stages of post-wildfire assessment in both adult and pediatric populations (To et al., 2021). Wildfire events have also been linked to increased substance abuse and exacerbation of physical and mental health symptoms (Woodland et al., 2023). While most research has focused on the impacts of exposure to the actual fire (e.g. flames), having property destroyed by fire, or events associated with escaping fires or displacement, there is evidence that wildfire smoke may also have impacts on mental health and well-being, particularly when the exposures are both chronic and persistent (Eisenman & Galway, 2022).

The current scoping review did not find any articles that examined the health impacts from wildfire smoke PM to mental health outcomes. While there were multiple empirical peer-reviewed articles that examined exposures in the population, most used self-reported smoke exposures as a proxy for exposure. Ho et al. (2014) examined the Asian haze crisis on psychological symptoms, and perceived dangerousness of pollution level using the Pollution Standard Index (PSI) to estimate wildfire exposures (Ho et al., 2014). Caamano-Isorna et al. (2011) examined the number of wildfires which had occurred in the Galician municipality of north-west Spain in August 2006 and assigned a high, medium, and low exposure to daily dose of anxiolytics-hypnotics (Caamano-Isorna et al., 2011). Other qualitative peer-reviewed studies examining the impacts of wildfire smoke and mental health and well-being were assessed using self-reported exposure inputs and did not include air quality metrics specific to particles or particular matter (De Pretto et al., 2015; Dodd et al., 2018; Mottershead et al., 2020; Whitefish Lake First Nation 459 et al., 2019). Overall, few studies have investigated smoke exposure as a cause of mental health impacts, and as of this review, no studies have investigated the relationship between particulate matter exposure in wildfire-specific smoke and mental health outcomes. In the peer reviewed articles that were published between 2010–2020 that examined smoke, Reid et al. (2016) has identified them as having higher potential for bias (Caamano-Isorna et al., 2011; Ho et al., 2014). Overall, for broad qualitative smoke exposure studies, there is limited and inconsistent evidence of impact to mental health outcomes (Eisenman & Galway, 2022; Reid, Brauer, et al., 2016a). It is important that future research focuses on the application of more rigorous exposure methods including metric for particulate matter and other air pollutants, standardizing and differentiating between mental health outcomes through diagnostic criteria and instrumentation consensus, and identifying causal processes (Eisenman & Galway, 2022; Y. Zhang et al., 2022).

Respiratory Health Outcomes

While there were no consistent definitions of all-cause respiratory outcomes (also referred to as combined respiratory outcomes or respiratory morbidity), there was a general consensus that increased exposures to wildfire-specific $PM_{2.5}$ results in increased risk of ER visits or hospitalizations for broadly defined respiratory morbidity across California (Hutchinson et al., 2018; Reid, Jerrett, et al., 2016b; Reid & Maestas, 2019). Overall, relationships between wildfire smoke and respiratory health outcomes were mostly positively associated for the broader population. ER visits were associated with a 4% increased risk per 10 $\mu g/m^3$ increase in wildfire-specific $PM_{2.5}$ (Reid et al. 2019; Hutchinson et al. 2018). Furthermore, articles that investigated the Impacts of wildfire smoke PM on asthma outcomes for either ER visits or hospitalizations within California found similar results (Hutchinson et al., 2018; Reid, Jerrett, et al., 2016b; Reid & Maestas, 2019; Wettstein et al., 2018). Reid et al. (2016 & 2019) examined six specific regions of Northern and Central California and found an increased risk of asthma-related ER visits and hospitalizations from wildfire-specific $PM_{2.5}$ exposures during the 2008 Northern California wildfire complex (Reid, Jerrett, et al., 2016b; Reid & Maestas, 2019). Similarly, Wettstein et al. (2018) found an increased risk of asthma-related ER visits during the 2015 wildfire season across multiple lags and smoke categories across Northern and Central California areas; however, individuals aged 18 years and younger were not included in the analysis (Wettstein et al., 2018). The impacts of larger complex fires, like those that burned nearly 1 million acres in San Diego County in October 2007, was associated with increased risks of both asthma-related ER visits and hospitalizations over a three and five-day lagged period, respectively, for all-age Medi-Cal beneficiaries (Hutchinson et al. 2018). For two and three-day lagged exposures, studies in Northern California during the 2008 and 2015 wildfire seasons identified an increased risk of hospitalizations and ER visits for chronic lung disease in adult populations exposed to wildfire related $PM_{2.5}$ (Reid, Jerrett, et al. 2016b; Reid et al. 2019; Wettstein et al. 2018). Specifically, researchers found a significant 18% increased risk of ER visits from wildfire-specific $PM_{2.5}$ exposure among adults over 18 years of age; however, this risk increased to 29% in areas exposed to higher smoke densities (Wettstein et al. 2018). Similar results were found in Southern California, but researchers failed to find a significant difference among the dataset investigating the impacts of the 2007 San Diego County fires for either ER visits or hospitalizations (Hutchinson et al. 2018; Delfino et al. 2009).

U.S.-based studies outside of California also found similar results. Rappold et al. (2012) and Tinling et al. (2016) both found evidence of a positive association between exposure to wildfire smoke and increased risk of several respiratory health outcomes in North Carolina, including asthma, respiratory symptoms, and upper respiratory infections (Rappold et al., 2012; Tinling et al., 2016). Two studies based in Western states found a 7.2% increased risk (95% CI: 0.25%–15%) of respiratory morbidity in elderly populations during high smoke $PM_{2.5}$ days (Liu et al., 2017) and higher FEV1 in older children two days after exposure to wildfire $PM_{2.5}$ (Lipner et al., 2019). However, Lipner et al. (2019) did not observe any associations for FEV1 and asthma control in younger children (Lipner et al., 2019). Alman et al. (2016) and Stowell et al. (2019) estimated increased risk of asthma, COPD, and respiratory disease associated with increases in wildfire PM2.5 in Colorado, with significant effects from Stowell et al. and near-significant effects from Alman et al. (Alman et al., 2016; Stowell et al., 2019). In other Western states, increased risk of asthma was associated with increased wildfire $PM_{2.5}$ from the 2012 Washington wildfires (Gan et al., 2017), the 2013 Oregon wildfire season (Gan et al., 2013), and the presence of wildfire smoke in Nevada from 2013-2018 (Kiser et al., 2020). A statewide analysis found similar increased risks of respiratory morbidity on both smoke $PM_{2.5}$ and non-smoke $PM_{2.5}$ days, but higher risk of asthma (percentage change in risk: 6.9%, 95% CI: 3.71%–10.11%) on smoke $PM_{2.5}$ days among elderly populations (DeFlorio-Barker et al., 2019).

Overall, there was a vast amount of literature examining the impacts from wildfire exposures and respiratory outcomes with many reporting positive associations.

Table 6.8. *Relevant scoping review articles examining wildfire impacts on respiratory outcomes*

Author (Year)	***Title***	***Health Outcomes Included***	***Location***
do Carmo et al. (2010)	*Association between particulate matter from biomass burning and respiratory diseases in the southern region of the Brazilian Amazon.*	Respiratory visits	Brazil
Ignotti et al. (2010)	*Impact on human health of particulate matter emitted from burnings in the Brazilian Amazon region.*	Respiratory morbidity	Brazil, Amazon
Morgan et al. (2010)	*Effects of bushfire smoke on daily mortality and hospital admissions in Sydney, Australia.*	Asthma, COPD, Pneumonia and Acute Bronchitis, Respiratory morbidity	Sydney, Australia
Schranz et al. (2010)	*The 2007 San Diego Wildfire impact on the Emergency Department of the University of California, San Diego Hospital System.*	Shortness of breath, cough, others	USA, California
Caamano-Isorna et al. (2011)	*Respiratory and mental health effects of wildfires: An ecological study in Galician municipalities (north-west Spain).*	Medication	Spain
Henderson et al. (2011)	*Three measures of forest fire smoke exposure and their associations with respiratory and cardiovascular health outcomes in a population-based cohort.*	Acute upper respiratory infections, respiratory morbidity, Asthma	Canada, British Columbia
Rappold et al. (2011)	*Peat bog wildfire smoke exposure in rural North Carolina is associated with cardiopulmonary emergency department visits assessed through syndromic surveillance.*	Respiratory morbidity, asthma, COPD, pneumonia & acute bronchitis, upper respiratory infections	USA, North Carolina
Vora et al. (2011)	*2007 San Diego wildfires and asthmatics.*	Lung function, medication	USA, San Diego

Wiwatanadate & Liwsrisakun (2011)	*Acute effects of air pollution on peak expiratory flow rates and symptoms among asthmatic patients in Chiang Mai, Thailand.*	Lung function, PEFR and asthma symptoms	Thailand
Crabbe (2012)	*Risk of respiratory and cardiovascular hospitalization with exposure to bushfire particulates: new evidence from Darwin, Australia.*	Respiratory morbidity	Darwin, Australia
Rappold et al. (2012)	*Cardiorespiratory outcomes associated with exposure to wildfire smoke are modified by measures of community health.*	Asthma	USA, North Carolina
Dohrenwend et al. (2013)	*The impact on emergency department visits for respiratory illness during the Southern California wildfires west.*	Asthma, cough, respiratory syndrome, dyspnea, bronchitis, COPD	USA, California
Elliott et al. (2013)	*Time series analysis of fine particulate matter and asthma reliever dispensations in populations affected by forest fires.*	Asthma medication	Canada, British Columbia
Martin et al. (2013)	*Air pollution from bushfires and their association with hospital admissions in Sydney, Newcastle and Wollongong, Australia 1994-2007.*	Asthma, COPD, non-trauma, pneumonia and acute bronchitis, respiratory morbidity	Sydney, Australia
Silva et al. (2013)	*Particulate matter originating from burnings and respiratory diseases.*	Respiratory diseases	Brazil
Thelen et al. (2013)	*Modeling acute respiratory illness during the 2007 San Diego wildland fires using a coupled emissions-transport system and generalized additive modeling.*	Respiratory morbidity	USA, San Diego
Yao et al. (2013)	*Evaluation of a wildfire smoke forecasting system as a tool for public health protection.*	Asthma visits, pharmaceutical dispensing counts	Canada, British Columbia
Johnston et al. (2014)	*Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996-2007: A case-crossover analysis.*	Asthma, COPD, pneumonia and bronchitis, respiratory morbidity	Australia, Sydney
Le et al. (2014)	*Canadian forest fires and effects of long-range transboundary air pollution on hospitalizations among the elderly.*	Asthma, COPD, respiratory morbidity, respiratory tract infection, acute	USA, Northeastern & Mid-Atlantic States

		respiratory tract infections	
Trang et al. (2014)	*Spatial correlation analysis between particulate matter 10 (PM10) hazard and respiratory diseases in Chiang Mai Province, Thailand.*	Respiratory morbidity	Thailand
McLean et al. (2015)	*An evaluation of the British Columbia asthma monitoring system (BCAMS) and $PM_{2.5}$ exposure metrics during the 2014 forest fire season.*	Medicine counts	Canada, British Columbia
Resnick et al. (2015)	*Health outcomes associated with smoke exposure in Albuquerque, New Mexico, during the 2011 Wallow fire.*	Asthma, respiratory morbidity, other diseases of the respiratory system	USA, New Mexico
Tse et al. (2015)	*Effect of catastrophic wildfires on asthmatic outcomes in obese children: Breathing fire.*	Asthma, medication	USA, California
Alman et al. (2016)	*The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: a case crossover study.*	Asthma/wheeze, COPD, Upper Respiratory Infections, Pneumonia, Bronchitis, Combined Respiratory Conditions	USA, Colorado
Haikerwal et al. (2016)	*Fine particulate matter ($PM_{2.5}$) exposure during a prolonged wildfire period and emergency department visits for asthma.*	Asthma, COPD	Victoria, Australia
Kollanus et al. (2016)	*Effects of long-range transported air pollution from vegetation fires on daily mortality and hospital admissions in the Helsinki metropolitan area, Finland*	Asthma or COPD, Combined respiratory conditions	Finland, Helsinki
Morrison et al. (2016)	*A latent process model for forecasting multiple time series in environmental public health surveillance.*	Medication counts	Canada
Reid et al. (2016)	*Differential respiratory health effects from the 2008 northern California wildfires; a spatiotemporal approach.*	Asthma, COPD, pneumonia, respiratory morbidity	USA, California
Tinling et al. (2016)	*Repeating cardiopulmonary health effects in rural North Carolina population during a second large peat wildfire.*	Respiratory morbidity, upper Respiratory infections,	USA, North Carolina

		respiratory/other chest symptoms, asthma, COPD, acute respiratory infections	
Vicedo-Cabrera et al. (2016)	*Health effects of the 2012 Valencia (Spain) wildfires on children in a cohort study.*	Asthma	Spain, Valencia
Yao et al. (2016)	*Evaluation of a spatially resolved forest fire smoke model for population-based epidemiologic exposure assessment.*	Asthma, medication, upper respiratory infection, lower respiratory infection, COPD	Canada, British Columbia
Yuchi et al. (2016)	*Blending forest fire smoke forecasts with observed data can improve their utility for public health applications.*	Respiratory visits, medication counts	Canada, British Columbia
Gan et al. (2017)	*Comparison of wildfire smoke estimation methods and associations with cardiopulmonary-related hospital admissions.*	Respiratory morbidity, asthma, COPD, pneumonia, acute bronchitis	USA, Washington
Kim et al. (2017)	*Long-run health consequences of air pollution: Evidence from Indonesia's forest fires of 1997.*	Lung function	Indonesia
Liu et al. (2017)	*Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties.*	COPD & respiratory tract infections	USA, Western
Liu et al. (2017)	*Who among the elderly is most vulnerable to exposure and health risks of $PM_{2.5}$ from wildfires smoke?*	COPD & respiratory tract infections	USA, Western
Salimi et al. (2017)	*Ambient particulate matter, landscape fire smoke, and emergency ambulance dispatches in Sydney, Australia.*	Breathing problems	Sydney, Australia
Sheldon et al. (2017)	*The Impact of Indonesian Forest Fires on Singaporean Pollution and Health.*	Respiratory infections combined	Singapore
Fann et al. (2018)	*The health impacts and economic value of wildland fire episodes in the U.S.: 2008–2012.*	Respiratory morbidity	USA, multiple states
Hutchinson et al. (2018)	*The San Diego 2007 wildfires and Medi-Cal emergency department presentations, inpatient hospitalizations, and outpatient visits: An observational study of smoke exposure periods and a bidirectional case-crossover analysis.*	Acute bronchitis, asthma, bronchitis, COPD, pneumonia, respiratory index, respiratory	California, San Diego

		symptoms, upper respiratory infections	
Wettstein et al. (2018)	*Cardiovascular and cerebrovascular emergency department visits associated with wildfire smoke exposure in California in 2015.*	Asthma, COPD, other non-cardiac chest pain or respiratory syndrome, pneumonia	USA, California
Arriagada et al. (2019)	*Association between fire smoke fine particulate matter and asthma-related outcomes: systematic review and meta-analysis.*	Asthma	USA and Australia
DeFlorio-Barker et al. (2019)	*Cardiopulmonary effects of fine particulate matter exposure among older adults, during wildfire and non-wildfire periods, in the United States 2008–2010.*	Asthma, bronchitis, and wheezing; Respiratory morbidity	USA, statewide
Kondo et al. (2019)	*Meta-Analysis of Heterogeneity in the Effects of Wildfire Smoke Exposure on Respiratory Health in North America*	Asthma, COPD, respiratory morbidity, pneumonia	USA
Lipner et al. (2019)	*The associations between clinical respiratory outcomes and ambient wildfire smoke exposure among pediatric asthma patients at National Jewish Health, 2012–2015.*	FEV1/FVC, ACT/CACT	Western USA
Reid et al. (2019)	*Associations between respiratory health and ozone and fine particulate matter during a wildfire event.*	Asthma, pneumonia, acute bronchitis, acute respiratory infections, COPD, respiratory morbidity	USA, California
Stowell et al. (2019)	*Associations of wildfire smoke $PM_{2.5}$ exposure with cardiorespiratory events in Colorado 2011–2014.*	Asthma, bronchitis, COPD, upper respiratory infection, combined respiratory disease	USA, Colorado
Gan et al. (2020)	*The association between wildfire smoke exposure and asthma-specific medical care utilization in Oregon during the 2013 wildfire season.*	Asthma, medication	USA, Oregon

Kiser et al. (2020)	*Particulate matter and emergency visits for asthma: a time-series study of their association in the presence and absence of wildfire smoke in Reno, Nevada, 2013–2018.*	Asthma	USA, Nevada
Landguth et al. (2020)	*The delayed effect of wildfire season particulate matter on subsequent influenza season in a mountain west region of the USA.*	Influenza	USA, Montana
Leibel et al. (2020)	*Increase in pediatric respiratory visits associated with Santa Ana wind–driven wildfire smoke and PM2. 5 levels in San Diego County.*	Respiratory morbidity	USA, California

Mortality

Several review papers have identified a strong association between wildfire smoke and mortality outcomes, with stronger evidence for all-cause mortality compared to respiratory or cardiovascular specific deaths (Cascio, 2018; J. C. Liu et al., 2015; Reid, Brauer, et al., 2016a; Youssouf et al., 2014). A majority of peer-reviewed epidemiological studies examining the impacts from wildfire smoke exposures and cause-specific mortality reported non-statistically significant associations for cardiovascular in the United States (Doubleday et al., 2020; Xi et al., 2020; Zu et al., 2016) or abroad (Kollanus et al., 2016; Linares et al., 2015, 2018; Morgan et al., 2010); with only a few that identified statistically significant positive associations (Faustini A. et al., 2015; F. Johnston et al., 2011; Nunes et al., 2013). Similar results were reported for respiratory-related mortality, with few articles reporting a positive and statistically significant association (Augusto et al., 2020; Doubleday et al., 2020).

In an epidemiological study based in the state of Washington, Doubleday et al. (2020) found 1.3% increased odds (95% CI: 0.2 – 2.4%) for non-traumatic mortality wildfire smoke (Doubleday et al., 2020). A study on hemodialysis patients had an even higher risk of death after exposure with a 4% increase in daily mortality per 10 μg/m^3 increase in wildfire $PM_{2.5}$; the risk doubled if $PM_{2.5}$ was greater than 10 μg/m^3 (Xi et al., 2020). The most evidence for the relationship between wildfires and all-cause mortality exists in Australia and Europe, where air quality is further impacted by Saharan dust. The majority of these article exampled PM_{10}-specific wildfire smoke, finding positive associations with all-cause mortality, and a smaller number with statistically significant results (Augusto et al., 2020; Faustini A. et al., 2015; Kollanus et al., 2016; Linares et al., 2015, 2018). Linares et al. (2015) examined the impacts of biomass advection from 2004 – 2009 on the Madrid population and found that on days with biomass advection, where the mean PM_{10} was 44.2 μg/m^3, there was a 3.5% (95% CI: 1.1–- 6.0%) increased risk in all-cause mortality which doubled those over 75 years of age (Linares et al., 2015). In a later study, researchers examined impacts over broader regions in Spain over the same timeframe and found spatially varying effects with 8% (95% CI: 2.36–13.81%) increased risks for every 10 μg/m^3 increase in regions where wildfires were most frequent (Linares et al., 2018). Other studies found positive associations between wildfire exposures and all-cause mortality but lacked statistical significant (Augusto et al., 2020; Faustini A. et al., 2015; F. Johnston et al., 2011; Morgan et al., 2010).

Short-term non-wildfire specific $PM_{2.5}$ dose-response exposures have been estimated to be responsible for over 11,000 excess deaths within Malaysia, Singapore and Indonesia during the 2015 Indonesian fires which were the largest emissions of carbon dioxide from Equatorial Asia since the El Niño fires of 1997 (Crippa et al., 2016). Using a longer-term dose-response function via methods applied by Driscoll et al. 2015 (Driscoll et al., 2015) for non-wildfire specific $PM_{2.5}$, researchers estimated a much higher mortality total of over 100,000 deaths from the same region for a similar timeframe (Koplitz et al., 2016).

Table 6.9. *Relevant scoping review articles examining wildfire impacts on mortality*

Author (Year)	***Title***	***Mortality Outcomes Included***	***Location***
Morgan et al. (2010)	*Effects of bushfire smoke on daily mortality and hospital admissions in Sydney, Australia.*	Cardiovascular, respiratory, all-cause	Australia, Sydney
Johnston et al. (2011)	*Extreme air pollution events from bushfires and dust storms and their association with mortality in Sydney, Australia*	Cardiovascular, respiratory, all-cause, cardio-respiratory	Australia, Sydney
van Donkelaar et al. (2011)	*Satellite-based estimates of ground-level fine particulate matter during extreme events: a case study of the Moscow fires in 2010.*	All-cause	Russia
Marlier et al. (2013)	*El Niño and health risks from landscape fire emissions in Southeast Asia*	Cardiovascular	Southeast Asia
Nunes (2013)	*Circulatory disease mortality rates in the elderly and exposure to $PM_{2.5}$ generated by biomass burning in the Brazilian amazon in 2005*	Cardiovascular, acute myocardial infarction, cerebrovascular	Brazilian Amazon
Linares et al. (2015)	*Influence of advections of particulate matter from biomass combustion on specific-cause mortality in Madrid in the period 2004-2009.*	All-cause, cardiovascular, respiratory	Spain, Madrid
Sahani et al. (2014)	*A case-crossover analysis of forest fire haze events and mortality in Malaysia.*	All-cause, respiratory	Malaysia
Shaposhnikov et al. (2014)	*Mortality related to air pollution with the Moscow heat wave and wildfire of 2010.*	Non-accidental mortality	Russia, Moscow
Faustini et al. (2015)	*Short-term effects of particulate matter on mortality during forest fires in southern Europe: Results of the MED-PARTICLES project*	Cardiovascular, respiratory, natural	Spain, Italy, Greece

Crippa et al. (2016)	*Population exposure to hazardous air quality due to the 2015 fires in Equatorial Asia*	Mortality	Singapore
Kollanus et al. (2016)	*Effects of long-range transported air pollution from vegetation fires on daily mortality and hospital admissions in the Helsinki metropolitan area, Finland*	Non-accidental, respiratory, cardiovascular	Finland, Helsinki
Koplitz et al. (2016)	*Public health impacts of the severe haze in Equatorial Asia in September–October 2015: demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure.*	Mortality	Singapore, Malaysia, Indonesia
Zu et al. (2016)	*Long-range fine particulate matter from the 2002 Quebec forest fires and daily mortality in Greater Boston and New York City*	All-cause, respiratory, cardiovascular	USA, Boston and New York
Fann et al. (2018)	*The health impacts and economic value of wildland fire episodes in the U.S.: 2008–2012.*	Mortality	USA, Multiple states
Linares et al. (2018)	*Impact on mortality of biomass combustion from wildfires in Spain: A regional analysis*	All-cause	Spain
Augusto et al. (2020)	*Population exposure to particulate-matter and related mortality due to the Portuguese wildfires in October 2017 driven by storm Ophelia*	Cardiorespiratory, natural causes	Portugal
Doubleday et al. (2020)	*Mortality associated with wildfire smoke exposure in Washington state, 2006-2017: a case-crossover study*	Non-traumatic, respiratory, cardiovascular, ischemic heart disease, asthma, COPD, pneumonia, cerebrovascular	USA, Washington
Xi et al. (2020)	*Mortality in US Hemodialysis Patients Following Exposure to Wildfire Smoke*	Cardiac, vascular, infection, all-cause, other	USA

Discussion and Conclusion

In general, the scoping review yielded few reviews or meta-analyses but did locate multiple primary epidemiological studies that examined the health impacts from wildfire PM smoke. Most of the studies identified examined impacts from single wildfire events and focused on acute exposures. Few studies examined long-term impacts and those that did, were limited in scope (Gao et al., 2023; Grant & Runkle, 2022). Several review papers have identified a strong association between wildfire smoke and mortality outcomes, with stronger evidence for all-cause mortality compared to respiratory or cardiovascular specific deaths (Cascio, 2018; J. C. Liu et al., 2015; Reid, Brauer, et al., 2016a; Youssouf et al., 2014), suggesting a growing trend. There was consistent evidence between wildfire smoke exposure and multiple respiratory outcomes including asthma, chronic obstructive pulmonary disease, and general respiratory morbidity. In general, the strongest evidence of impact from wildfire emissions was found for respiratory outcomes, particularly asthma hospital admissions or ER visits.

While the evidence for impacts on cardiovascular health is mixed, there is a growing trend for positive association; however, it is recommended that researchers conduct additional reviews to confirm prior to including estimates into the final tool. While the majority of the health outcomes found in our review focused on respiratory and cardiovascular health endpoints, there were also articles that evaluated other impacts (e.g. birth outcomes); however, these additional health did not have sufficient evidence to support inclusion into the final NWL Health Scenario Tool. Specifically, literature on mental health outcomes from wildfire related exposures often focuses on small cohorts, relies on qualitative dataset collected via self-reported questionnaires (sometimes conducted months after exposure), or lacks standardized exposure estimate methods and outcomes limiting our ability to estimate future outcomes (Duclos et al., 1990; Eshel, 2016; Felix & Afifi, 2015; Ho et al., 2014; R. T. Jones et al., 1994; Kolbe & Gilchrist, 2009; Langley & Jones, 2005; Lewis et al., 2015; Marshall et al., 2007; McDermott et al., 2005; Papadatou et al., 2012; Pujadas Botey & Kulig, 2014). We provide additional (follow-up review) in Section IX to identify relevant coefficents for inclusion into the final model.

VII. Health Impact Assessment: Urban Green Space

Introduction

California has been a global leader in climate mitigation policies with the adoption of the world's first legally binding limits on carbon dioxide emissions (Mazmanian et al., 2020). Due to California's Mediterranean climate and additional pressures associated with resource management, however, the State also sits at the vanguard of those places experiencing some of the most severe health effects of climate change (Bedsworth et al., 2018). This presents numerous cross-sectoral challenges that can make integrative climate solutions difficult to identify and implement. One promising approach is through urban green space and related infrastructure. In California, many areas lack adequate access to green infrastructure (Connolly et al., 2023; Sister et al., 2010), which creates inequalities in climate hazard exposure and in the co-benefits that green space can afford to health (James et al., 2015; M. C. Kondo et al., 2018; Nieuwenhuijsen et al., 2017).

The expansion and better management of green spaces can help California address climate hazard exposures by storing carbon, adapting to the adverse consequences of climate-generated adverse exposures, and contributing substantial health co-benefits. Because green space is often undersupplied in socially-disadvantaged neighborhoods (Jennings et al., 2021), strategic investments for greening in disadvantaged neighborhoods can help address concerns about environmental injustices that affect health. Thus, urban greening offers the potential to enhance climate change mitigation and adaptation, while conferring health co-benefits to the general population, and particularly to socially disadvantaged groups (Connolly et al., 2023; Rigolon et al., 2021).

We have organized the paper into the following sections: (1) a conceptualization of potential green space solutions to climate change in California; (2) a general framework for prioritizing the health effects of climate change in California; (3) a review of key climate change exposures that affect health in California and how green space solutions; and (4) an empirical study that estimates the health benefits of increased urban green space and tree canopy on mortality, life expectancy, and adverse birth outcomes in California. We conclude the paper with a synthesis of findings and suggestions for future research and effective policy action on green solutions to climate change and public health in California.

Conceptualizing Green Space Solutions to Climate Change and Health

No standard definition for urban green space exists in the literature, yet several sources define urban green spaces as land covered with some type of vegetation or having "natural" features (Taylor & Hochuli, 2017). For example, the U.S. EPA defines green space as all vegetated land, including agriculture, lawns, forests, wetlands, and gardens but excludes barren land and impervious surfaces (Pickard et al., 2015; Taylor & Hochuli, 2017). Comprehensive reviews have emphasized the need to orient the definition to specific research questions that include both quantitative (i.e., percent vegetative cover) and qualitative aspects (i.e., natural areas). For this paper, we adopt a similar definition to the U.S. EPA as all vegetated land, but we qualify this as urban and peri-urban areas with some aspects being natural, as for example, coastal beaches could be considered another form of green space even with relatively little vegetative cover because they are perceived as natural.

There are several pathways from green space to specific climate change exposures of importance in California and elsewhere (James et al., 2015; Nieuwenhuijsen et al., 2017; Pickard et al., 2015). Climate change creates and magnifies numerous direct and indirect risks to human health in California. Direct effects are confined to actual changes to the climate. In California, this includes extreme heat, which generates direct biophysical effects on humans; extreme weather that threatens health through wind and flooding events; and drought, although this exerts effects largely through indirect means such as increases in wildfire or dust air pollution or water supplies. We classify indirect risks as those that are proximal or distal in terms of their potential or realized impact on human health. Within the set of indirect risks, flooding endangers low-lying communities with loss of property, mental health (stress and anxiety), and heightened infectious disease risk (Paterson et al., 2018). Likewise, climate change can exacerbate wildfire risks (Abatzoglou & Williams, 2016; Turco et al., 2023), with many adverse effects on human health. Other indirect risks are more distal, such as reductions in food production, economic activity, or long-term sea level rise. These distal categories are beyond the scope of this review.

Green space also stores and sequesters carbon, which contributes to the mitigation of worsening climate change with anticipated health benefits in the future (McPherson et al., 2013). For example, a study of carbon storage in Los Angeles and Sacramento estimated that urban forests accounted for 2% of total stored carbon and 12% annually sequestered in California (McPherson et al., 2013). When the authors also considered avoided emissions due to shading and reduced need for energy to power heating and cooling, urban forests accounted for about 20% of annual total reductions in carbon emissions.

Importantly, from a health perspective, in California where 94.2% of the population lives in urbanized areas (Cox, 2023), urban green spaces can also generate numerous health co-benefits throughout the life course via numerous pathways, with varying levels of support in the literature (James et al., 2015; M. C. Kondo et al., 2018; Nieuwenhuijsen et al., 2017). These include several mechanisms with major population health burdens impacted, including: (a) mental and physical health benefits via stress reduction and attention restoration; (b) increased opportunity for social interaction with the ensuring possibility for greater support through heightened formation of social capital; (c) physical activity while in or near green space with many possible improvements to health including obesity reduction and diabetes prevention; (d) reductions in other potentially adverse environmental exposures such as noise or light pollution; andI) with the most limited evidence, changes to the gut microbiome with potential benefits for reducing inflammation and related health conditions or physiological signally affecting, for example, blood pressure and heart rate variability. Likely via some combination of these pathways, hundreds of studies have reported associations of green space metrics with birth and pregnancy outcomes (Akaraci et al., 2020; Hu et al., 2021; Zhan et al., 2020), early childhood development and wellbeing (Davis et al., 2021), general and mental health (Gianfredi et al., 2021), cardiovascular disease (Nguyen et al., 2021), respiratory outcomes (Nguyen et al., 2021), physical activity (Gianfredi et al., 2021), obesity (Luo et al., 2020), diabetes (De la Fuente et al., 2021), cognitive decline in older adults (Zagnoli et al., 2022), premature mortality (Rojas-Rueda et al., 2019), and life expectancy (Connolly et al., 2023). Several systematic reviews of these outcomes noted overall associations, albeit with limitations such as cross-sectional study designs (M. C. Kondo et al., 2018), uncertain exposure metrics (Su et al., 2019), and heterogeneous measures of health outcomes ranging from self-reported to objectively measured. Despite these limitations, it appears highly likely that green space influences several of these health outcomes, with variation in the certainty and size of the association.

Green space can also elicit several potential unintended consequences. Enhanced green space can increase property values (Conway et al., 2010; Schinasi et al., 2021) with higher incomes being consistently associated with increased levels of green space in major cities in California and elsewhere (Jenerette et al., 2013). Higher property values and rents related to green space can drive out lower income populations and lead to an influx of wealthier people into "gentrifying" neighborhoods, with empirical evidence suggesting modest effects across major metropolitan areas of the U.S., with elevated but insignificant effects in major metropolitan areas of California (Schinasi et al., 2021). This potential has led prominent scholars to suggest the need to make cities just "green enough" to avoid this problem (Wolch et al., 2014). In addition, improperly maintained or located green spaces can increase vector-borne infectious disease risk (Dadvand & Nieuwenhuijsen, 2019); for example, standing water in a stormwater facility may increase habitat for mosquito breeding, which could increase risks of West Nile virus in California (Hartley et al., 2012). Expanded green space may also increase pollen, depending on the species planted, although available evidence on associations between green space and asthma or allergy symptoms is inconclusive (Dadvand & Nieuwenhuijsen, 2019). Recent studies comparing long-term trends in $PM_{2.5}$ in Los Angeles suggest that as much as 25% of $PM_{2.5}$ mass on hot days may derive from organic aerosols with precursors originating from plants (Nussbaumer & Cohen, 2021). In contrast, other studies demonstrate that urban forests can result in minor reductions in air pollution in major American cities (Nowak et al., 2014), and another body of evidence identifies potential improvements in local air pollution due primarily to deposition and deflection off of leaf structures (Baldauf, 2017). The impact of urban trees and green spaces on air pollution appears to be highly dependent on the location of the trees and the species, with some species emitting much higher precursors of air pollution than others and some being more efficient at reducing pollution than others. Finally, some evidence shows that women in major U.S. cities, including Los Angeles, are less likely to use urban trails with substantial tree and shrub cover than areas that are more open, with the hypothesized reason being a perceived loss of safety in green areas (Reynolds et al., 2007).

Avoiding these unintended consequences and maximizing the benefits of green space interventions on health necessitates an integrated approach that meshes green solutions effectively with other climate change mitigation and adaptation measures. In addition, when possible, green space interventions should account for the interactions between climate change exposures. Heat impacts in disadvantaged neighborhoods of Los Angeles, for example, can be worsened during drought periods when vegetation is desiccated more in poorer areas than in wealthier ones that have more irrigation (Dong et al., 2023). Heat can also amplify the health effects of wildfire smoke in California, and other studies have shown interactions between ozone and heat effects can vary spatially and depend on underlying social and demographic conditions in a neighborhood (Heaney et al., 2022; Schwarz et al., 2021).

Variations in the response to exposures based on underlying social or demographic conditions suggests a need for additional equity analyses to understand the uneven burden that falls on these groups, who have historically borne the brunt of conventional environmental risks such as air pollution, noxious facilities, and pesticide exposures in California (L. Cushing et al., 2015; Su et al., 2012). In designing effective green space policies and others to address climate risks, it is critical to focus measures that will affect those groups who are disproportionately impacted already and may lack the resources — economic or social — to adapt to worsening exposures in the future. Another key consideration in both the efficacy and equity dimensions of the response to climate change is the co-benefits that can accrue from measures aimed at mitigation or adaptation. For example, efforts to reduce heat by greening may also have some of the health co-benefits discussed above, which may benefit poorer neighborhoods more because they are underserved in green space (Connolly et al., 2023; Sister et al., 2010).

Estimating the Health Co-Benefits of Green Space in California.
Green space provides a wide array of possible health benefits across the life course. In this section of the paper, we conduct a quantitative health impact assessment of the benefits of expanding urban green space and tree canopy across California. We focus on three important beneficial health effects: (a) mortality, (b) life expectancy, and (c) birth outcomes. This health impact assessment (HIA) illustrates the magnitude of health benefits that can accrue from green space and tree canopy expansion and helps identify the groups who will benefit from increased green spaces. The empirical analysis also illustrates some of the complexities associated with conducting small-area health impact assessments for benefits associated with climate change mitigation and adaptation.

Health Benefits of Green Space. Dozens of studies have investigated the links between green space exposure during pregnancy and adverse birth outcomes, with preterm birth and low birth weight being two common outcomes studied (Akaraci et al., 2020; Hu et al., 2021; Zhan et al., 2020), including in California specifically (Y. Sun et al., 2020). Recent meta-analyses have suggested a positive but relatively small effect on adverse birth outcomes, although the certainty of these effects varies between the meta-analyses (Akaraci et al., 2020; Hu et al., 2021; Zhan et al., 2020) probably due to methodological differences in the selection of studies and exposure buffers. Adverse birth outcomes can affect the healthy development of the child and might have lifelong consequences on health, make these health outcomes particularly important (Linsell et al., 2015).

Mortality has also been studied extensively, with the overall finding that higher exposure to green space lowers premature mortality. Most studies employed satellite retrievals to estimate the NDVI around the residence as the primary exposure assessment metric, although some have used tree canopy. Pooled meta-analyses indicate moderately large effects on the order of a 4% reduction per a 0.1 unit increase in NDVI (Rojas-Rueda et al., 2019). Premature mortality is also a critical population health indicator that often has large associated social and economic costs.

Life expectancy has received relatively less attention in small-area studies, probably due to the difficulty of estimating this outcome. Life expectancy is a critical indicator of human development. It is a core component of the United Nations Human Development Index and is often used to compare overall population health across places, times, and nations. To date only three studies have investigated the links between life expectancy and green space in smaller areas that vary within cities (Connolly et al., 2023; de Keijzer et al., 2017; Jonker et al., 2014). One from the Netherlands reported modest increases in life expectancy associated with green space exposure (Jonker et al., 2014). Another study from Spain showed a relationship but only in socially disadvantaged groups (de Keijzer et al., 2017). A recent study from Los Angeles reported associations between life expectancy and green space or tree canopy (Connolly et al., 2023). Effect sizes showed individual gains on the order of 2-3 months. Summed across the population, however, large benefits were observed with Black and Latinx communities benefitting the most.

Materials and Methods

We used dose-response functions from primary studies and meta-analyses to estimate changes in mortality, life expectancy, and low birth weight incidence from various green space exposure scenarios within the urban areas of California (Table 7.1). We used statewide annual mortality data from the California Department of Public Health (Aragón, 2022), census data for life expectancy population impact analyses (US Census Bureau, n.d., 2019a), geocoded live births at the census tract level (Goldberg et al., 2008; Texas A&M Geoservices, n.d.), and CalEnviroScreen percent low birth weight infant data (Office of Environmental Health Hazard Assessment, 2021a). Remote sensing datasets were used to develop baseline greenness estimates of NDVI and tree canopy (Dewitz, 2019)

Table 7.1. *Dose-response functions used in the HIA.*

Health Outcome	**Green Space Metric**	**Dose-Response**	**Estimate Type**	**Exposure Unit**	**Source**
Mortality	NDVI	0.96 (0.94 – 0.97) *Hazard Ratio*	Meta-analysis	0.1 Increment*	Rojas-Rueda et al. 2019 (Rojas-Rueda et al., 2019b)
Life Expectancy (Years)	NDVI	0.61 (0.26 – 0.97) *Median (Credible Interval)*	Individual Estimate	0.1 Increment*	Connolly et al. 2023 (Connolly et al., 2023b)
Life Expectancy (Years)	Tree Canopy	0.027 (0.006 – 0.047) *Median (Credible Interval)*	Individual Estimate	1% Increment	Connolly et al. 2023 (Connolly et al., 2023b)
Low Birth Weight	NDVI	300-meter buffer: 0.79 (0.65 – 0.96) 500-meter buffer: 0.90 (0–83 - 0.99) *Odds Ratio*	Meta-analysis	0.1 Increment*	Hu et al. 2021 (Hu et al., 2021b)

* Scale of -1 to 1

Materials.

Mortality Data Source and Compilation. Statewide annual mortality data (total number of deaths) by zip code and age for 2016 are managed by the California Department of Public Health (CDPH) and publicly available on the California Health and Human Services Open Data Portal website (California Department of Public Health, 2022). For several zip code and age categories, the count of deaths is suppressed for confidentiality reasons (i.e., counts < 11). Therefore, we implemented substitution procedures to fill in the missing deaths. First, since we only apply the dose-response values to ages 25+ (due to the nature of the epidemiological analysis from which the dose-response values were derived), we calculated the percentage of deaths in people over 25 for the entire state for each year, which is approximately 98%. For the zip codes where the total number of deaths is available, but the total number of deaths by age group were suppressed due to low counts in each group, we multiplied that percentage (98%) by the total number of deaths to estimate the number of deaths for the applicable age group. For zip codes where even the total number of deaths are suppressed, we conservatively assume the zip code contains ½ of the suppression threshold and applied the percentage to that estimated value. We compared our final death count to the reported deaths in the state as a metric of quality assurance, and the total estimates varied by less than 0.35%.

Census Population and Urban Areas Data. For the life expectancy analyses (see Eqn. 3), we applied the American Community Survey (ACS) 2019 5-year estimates for the total population as well as the race- and ethnicity-specific populations for each tract (US Census Bureau, 2019b). Additionally, we used the U.S. Census Bureau's urban area classification (US Census Bureau, n.d.) to extract the urban areas for our analysis.

Birth Outcome Data. We extracted the percent of low birthweight infants (less than 2,500 grams) at the census tract level from CalEnviroScreen 4.0 (Office of Environmental Health Hazard Assessment, 2021b). Additionally, we were provided with the number of live births geocoded and assigned to the census tract level to use for the analysis (Goldberg et al., 2008; Texas A&M Geoservices, n.d.).

Green Space.

Normalized Vegetation Index. We used NDVI, an established measure of neighborhood vegetation greenness, which represents differences in land type reflectance and is calculated using red and near-infrared multispectral imagery bands (Rhew et al., 2011). We used publicly available National Agriculture Imagery Program (NAIP) satellite imagery data for the year 2016 at the 0.6-meter scale to derive NDVI estimates (U.S. Department of Agriculture Farm Service Agency, 2016b). We used GEE for all analyses. We masked water bodies from the NAIP raster and extracted the average NDVI value for each census tract and ZIP code, using raster calculations. We also estimated the mean value of NDVI for urban areas over the entire state (aggregated at the 1-meter scale rather than 0.6-meter due to computational limitations) to use for the development of green space scenarios applied in the analysis.

Tree Canopy. We used United States Geological Survey (USGS) National Land Cover Database (NLCD) percent tree cover at the 30-meter scale (Dewitz, 2019) to derive mean percent tree canopy estimates for each census tract and ZIP code using GEE. We also estimated the mean value of percent tree canopy for urban areas over the entire state to use for the development of green space scenarios used in the analysis.

Estimation Methods.

Mortality. To estimate mortality impacts throughout urban areas of the state resulting from various scenarios (Table S7.2) in which green space (NDVI) levels are increased, we used Eqn. 1:

$$\Sigma\Delta y = \left(1 - \left(\frac{1}{e^{(\beta \times \Delta E j)}}\right)\right) \times D_{\text{j}} \tag{1}$$

where, β represents the one-unit dose-response coefficient for NDVI and mortality from a recent meta-analysis of cohort studies (Rojas-Rueda et al., 2019b), ΔE_j represents the change in NDVI exposure for each ZIP code j within an urban area, Dj represents the total number of deaths in adults for each ZIP code j, and ΣΔy represents the change in the health outcome (mortality) for each scenario for the urban areas of California for 2016. We used ZIP codes for all mortality analyses since that is the most spatially resolved areal unit with the total number of deaths publicly available.

We also estimated the associated economic valuation attributable to decreased mortality from added green space exposure using Eqn. 2 below:

$$\text{Economic valuation} = \Sigma\Delta\text{y} * \text{V} \tag{2}$$

where, ΣΔy is the result of Eqn. 1 (mortality change for added green space), and V is the EPA's Value of a Statistical Life (VSL), which is $8.7 million in 2015 dollars (inflation year). We accounted for income growth to the year 2015 using publicly available income growth factors used in the U.S. EPA's BenMAP-CE tool (US EPA, 2021), since changes in income can impact willingness to pay for reduced risk of mortality.

Life Expectancy. To estimate the potential years of life saved resulting from varying green space (both NDVI and tree canopy) exposures throughout urban areas of the state, we used Eqn. 3:

$$\Sigma Y_{LE} = \beta \text{ x } \Delta GS_j \text{ x } Pop_{total,j} \tag{3}$$

where, β represents the one-unit dose-response coefficient for green space and life expectancy extracted from a recent study (Connolly et al., 2023), ΔGS_j represents the change in green space exposure for each census tract j within an urban area (NDVI or tree canopy, dependent on scenario), $Pop_{total,j}$ represents the population of interest in census tract j, and ΣY_{LE} represents the total years of life saved throughout the urban areas of California. We also multiplied Y_{LE} for each census tract by the percent of the non-white population in the tract to determine the total benefits that would be distributed to communities of color within the urban areas of the state.

Low Birth Weight. To estimate the potential changes to low birth weight outcomes resulting from varying green space exposures throughout urban areas of the state, we used Eqn. 4 (Malley et al., 2017):

$$\Sigma\Delta y = y0_{\mathrm{j}} \times \left(1 - \left(\frac{1}{(1-y0\mathrm{j})*e^{(\beta\times\Delta E j)}+y0\mathrm{j}}\right)\right) \times B_{\mathrm{j}} \qquad (4)$$

where, $y0_j$ represents the baseline frequency of low birth weight in each census tract j within an urban area, β represents the one-unit dose-response coefficient for green space and low birth weight extracted from a recent meta-analysis (Hu et al., 2021b), ΔE_j represents the change in NDVI exposure for each census tract j in an urban area, B_j represents the total number of live births for each census tract j, and $\Sigma\Delta y$ represents the change in the total cases of low birth weight throughout the urban areas of California for 2016.

The meta-analysis from which the low birth weight dose-response value is extracted is the most recent (Hu et al., 2021) of several available systematic review studies (Akaraci et al., 2020; Zhan et al., 2020). Some inconsistency exists in the literature with respect to the relationship between greenness and low birth weight; of two previous meta-analyses, one found a significant relationship between NDVI and low birth weight, but with a very small effect estimate (Zhan et al., 2020), and the second did not find a statistically significant relationship between NDVI and low birth weight (Akaraci et al., 2020), although this study only used 300-meter buffers. The study we used here from Hu et al. explicitly aimed to improve upon the methods of these two pre-existing meta-analyses, so we applied the dose-response functions from this study.

Results and Discussion

We conducted a quantitative health impact assessment of health co-benefits from urban green space and tree canopy expansion on premature mortality, life expectancy, and low birth weight (see Materials and Methods below for datasets and methodology; see Appendix A for a review of why these health outcomes are important indicators of population health as shown in previous studies).

We focused on several scenarios for expanding green space across urban areas of California. These scenarios involve either overall increases in green space of 0.1 units of NDVI (U.S. Department of Agriculture Farm Service Agency, 2016a) or bringing all areas up to the statewide mean of NDVI in urban areas for both mortality and low birth weight outcomes. With life expectancy, we used the same NDVI estimates, but we were also able to estimate potential benefits from tree canopy (Dewitz, 2019). Here we used an increase of 10% in statewide tree canopy and another estimate that involved bringing the tree canopy up to the statewide mean in all urban areas of California.

As shown in Table 7.2, benefits for increasing NDVI by 0.1 units could lead to a decrease of -7,378 (95% CI: -5,476 to -11,301) deaths per year. Deaths prevented from bringing all areas up to the mean statewide NDVI for urban areas (Figure 7.1) were smaller with -2,456 avoided (95% CI:

-1,819 to -3,782). For context, in 2016 California recorded some 261,867 deaths (State of California, Department of Public Health, 2023), so the lives saved would amount to about 2.8% of total deaths in California. This estimate is well aligned with a large HIA of mortality impacts from expanding green space in Europe to meet the World Health Organization (WHO) minimum recommendations of 0.5 hectares of green space within 300 meters of a residence, which reported a 2.3% reduction in all-cause mortality for the hypothesized intervention (Barboza et al., 2021). The economic analysis of deaths avoided suggests monetary benefits of approximately $74 billion (2015 dollars, 95% CI: $55 - $114 billion) for increasing NDVI by 0.1 and almost $25 billion (95% CI: $18 - $38 billion) for increasing NDVI to the statewide mean for urban areas.

Table 7.2. *Health Impact Assessment for urban green space scenarios for statewide urban areas. Perfect of effect in communities of color is estimated for life expectancy only.*

Health Outcome	**Description**	**Estimated Effect**		**Percent of Effect in Communities of Color**
		Value (95% CI)	**Unit**	
Mortality	Deaths Prevented from 0.1 unit increase in NDVI (2016)	-7,378 *(-5,476 to -11,302)*	Deaths (avoided)	N/A
	Deaths Prevented from Increase in NDVI to Urban Areas Mean (2016)	-2,456 *(-1,819 to -3,782)*	Deaths (avoided)	N/A
Life Expectancy	Life Expectancy Population Impa–ts - Years of Life Added from Universal 10% Increase in Tree Cover (e.g., 10% --> 20% tree cover)	9,029,130 *(1,961,245 – 15,985,999)*	Years added (across the population)	65%
	Life Expectancy Population Impa–ts - Years of Life Added from Increase in Tree Cover to Urban Areas Mean	2,632,154 *(571,738 – 4,660,204)*	Years added (across the population)	72%
	Life Expectancy Population Impa–ts - Years of Life Added from 0.1 unit increase in NDVI	20,649,279 *(8,831,538 – 32,530,559)*	Years added (across the population)	65%
	Life Expectancy Population Impa–ts - Years of Life Added from Increase in NDVI to Urban Areas Mean	8,533,201 *(3,649,585 – 13,443,075)*	Years added (across the population)	64%
Low Birth Weight	Reduced Cases of Low Birth Weight from 0.1 unit increase in NDVI (2016)	300-meter NDVI buffer: -5,385 *(-854 to -10,748)* 500-meter NDVI buffer: -2,270 *(-208 to -4,163)*	Reduced cases of LBW	N/A

	Reduced Cases of Low Birth Weight from Increase in NDVI to Urban Areas Mean (2016)	300-meter NDVI buffer: -2,589 *(-386 to -5,533)* 500-meter NDVI buffer: -1,046 *(-93 to -1,969)*	Reduced cases of LBW	N/A

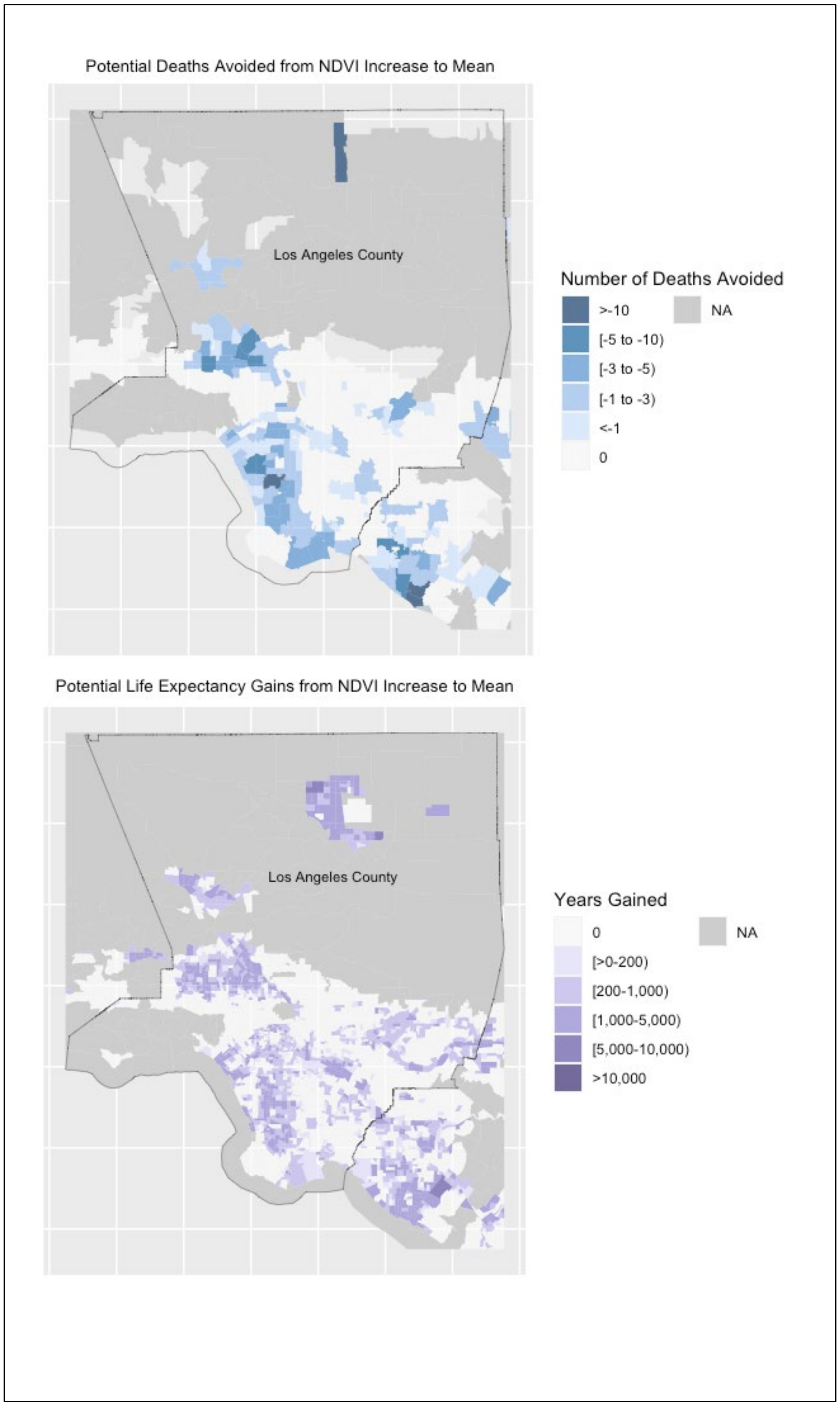


Figure 7.1. *Predicted changes in health impacts from a scenario where NDVI is increased to the mean of urban areas throughout California (effects for the Los Angeles County region shown here), resulting in decreased mortality (top) and increased life expectancy (bottom).*

In terms of life expectancy, we estimate 9,029,130 (95% Credible Interval (CrI): 1.96 – 15.99 million) extra years of life expectancy could be gained for increasing tree cover by 10%, while increasing tree canopy to match the average urban level across the state would be associated with 2,632,153 extra years of life expectancy (95% CrI: 571,738 – 4,660,204). Larger gains could be realized by increasing NDVI by 0.1 across the urban areas of California, with more than 20 million years of life gained (95% CrI: 8–83 - 32.5 million). Additionally, bringing the NDVI to the statewide mean would be associated with 8,533,201 (95% CrI: 3,649,585 – 13,443,075) years of increased life expectancy (Figure 7.1). We also used census data to estimate the population life expectancy impacts for communities of color (Table 7.2). Here we observe that in all scenarios, communities of color experience the majority of the benefits, ranging from 64-72% of the total benefits in years of life gained.

For low birth weight, using a dose-response value for a 300-meter buffer (typically around the maternal residence), we estimate reductions of -5,385 (95% CI: -854 to -10,748) associated with increasing NDVI by 0.1 and -2,589 (95% CI: -386 to -5,533) for increasing NDVI to the statewide mean of urban areas (Table 7.2). For a dose-response value applying to a larger 500-meter buffer reported in the same meta-analysis, estimated reductions are slightly less than half of the smaller buffer size, with an estimated reduction of -2,589 (95% CI: -208 to –4,163) and -1,046 (95% CI: -93 to -1,969) for an increase in 0.1-unit NDVI and an increase to the statewide mean, respectively. Different buffer sizes can reflect different exposure pathways (Hu et al., 2021; Yin, 2019). These findings indicate that though still statistically significant, the relationship between greenness and low birth weight is less strong for changing greenness in a larger radius around the residence.

The large effects on mortality, life expectancy, and low birth weight outcomes underscore the importance of conducting empirical studies to estimate the magnitude of potential benefits from increasing green space specifically and undertaking other climate change mitigation and adaptation strategies more broadly. Importantly, such estimates give policymakers and others some useful information on the likely population health gains that might accrue from different interventions.

Our empirical analysis has several limitations worth noting. First, we did not identify specific mechanisms associated with the health gains. It is possible that these resulted from some combination of direct exposure reductions such as the cooling effects of green space and the health co-benefits pathways. Recent European studies have shown that thousands of lives could be saved with increases in green cover and ensuring reductions in the urban heat island (Lungman et al., 2023). Such assessments are useful for benchmarking the relative size of health benefits, which could be pursued in California. Relatedly, knowing the specific pathways would help direct policy interventions to where they would likely have the most benefit. Second, many of the studies used to assess associations between green space and health outcomes are cross-sectional, which precludes causal determinations and leaves open the possibility of reverse causation. As noted, several studies have shown a positive association between either income or property values and green space. It is therefore possible that wealthier people who can afford to live in greener areas, have healthier lifestyles and relatively few health conditions would move into these areas, although a study reporting on a randomized trial intervention on greening vacant lots observed significant improvements in mental health compared to people living in areas that did not receive this intervention (Jerrett & Van Den Bosch, 2018). Limitations of this kind have led some to suggest that emphasis should be placed on experimental, quasi-experiments, and longitudinal studies for understanding the health benefits from green space (M. C. Kondo et al., 2018).

Our analysis also has several strengths. First, for two of our health effects (mortality and birth outcomes), we relied on meta-analyses that pooled numerous studies from different locations and populations. Moreover, most of the mortality studies used longitudinal designs that examined survival in relation to long-term exposure. Thus, the chance that all of these studies suffered from the reverse causality problem noted above is reduced. Second, we used high-resolution exposure and health data capable of estimating effects at small-areas across the urbanized areas of California. Third, we developed scenarios that are achievable. For example, earlier assessments of the million-tree initiative in Los Angeles concluded that a million trees could be accommodated by expanding the treed area of the city by 12% (McPherson et al., 2011). Hence, our 10% estimate is likely achievable in most urban areas across California, although achieving such ambitious goals requires confronting many challenges in implementation because of the complex public-private partnerships that are needed and the issues of maintenance (Pincetl, 2010). The 0.1 increase in NDVI amounts to an approximate increase of vegetation of about 10%, although recent studies have modeled how this percentage could be higher or lower depending on levels of initial vegetation (Martinez & Labib, 2023; Pincetl, 2010). The type of vegetation also influences what a 0.1 unit increase would mean on the ground. These heterogeneities necessitate interventions amenable to local conditions.

Conclusions and Synthesis

In this paper, we focused on extreme heat and precipitation, wildfires, and some infectious diseases likely to be affected now or in the future by climate change. To structure our review on the leading climate-health threats in California, we considered several factors, including: (1) direct and indirect proximal climate-related health threats, (2) the leading causes of disability and death in California which will have a higher disease burden than more rare diseases, and (3) climate exposure pathways where urban green space is, or could become, an adaptation or mitigation measure. We also reviewed how urban green space can generate solutions to climate change in the form of carbon storage, reduced direct and indirect exposures from climate change, and health co-benefits.

Several key findings result from our review and empirical analysis. First, of the major climate risks we reviewed in detail, the attribution certainty ranges from highly certain for extreme heat to low or moderate for Valley fever. Other things being equal, priority in the mitigation and adaptation response should be given to those effects with higher certainty. Future research needs to investigate attribution certainty in more detail. Second, high-quality impact assessments estimating the health burden from various climate risks are generally lacking for California. While often necessitated by data availability or other research constraints, this makes comparisons of health burdens across different climate hazards problematic because mitigation and adaptation measures could have huge variations in the potential health benefits. Our empirical study underscores this issue with large population gains on mortality, life expectancy, adverse birth outcomes. Detailed information of this kind will be critical for making informed policy interventions that maximize health benefits from greening and other policy measures. Third and relatedly, we found inconsistencies in methods to report health benefits. Efforts to standardize climate health reporting will benefit from other comprehensive assessments such as the upcoming Fifth California Climate Assessment. Fourth, populations in California can be exposed to overlapping or sequential climate hazards (AghaKouchak et al., 2020; Rosenthal et al., 2022; Schwarz et al., 2021). Our review did not consider exposure to cumulative impacts and possible interactions as the evidence for tracking exposures and health outcomes research is currently more limited (Dong et al., 2023; Schwarz et al., 2021).

Green solutions to climate change appear likely to yield substantial population health benefits, particularly for socially disadvantaged groups. Our empirical analysis indicates that a majority of the health benefits for life expectancy would go to non-white populations. Other studies showed that greening strategies to mitigate heat would benefit socially disadvantaged areas the most (Dong et al., 2023). Additional research is required to understand the unintended consequences of green space solutions and interactions with future climate change. For example, depending on specific plant characteristics, vegetation may worsen ambient air pollution by emitting ozone precursors (Wolf et al., 2020), or possibly offer improvements through dispersion or deposition effects.

Californians face numerous serious threats to their health and wellbeing from climate change. Ongoing initiatives in local communities to the state level are leveraging the co-benefits of green space to improve population health, and these strategies can also play a role in reducing climate-related exposures and generating health co-benefits.

VIII. Health Impact Assessment: Wildland Fire Mortality and CMAQ Validation

Abstract

In California, wildfire risk and severity have grown substantially in the last several decades. Research has characterized extensive adverse health impacts from exposure to wildfire-attributable $PM_{2.5}$. Few studies have quantified long-term health impacts from wildfires, and none have used a wildfire-specific chronic dose-response coefficient for mortality. We quantified the total mortality burden for exposure to $PM_{2.5}$ due to wildland fires in California from 2008 – 2018 using CMAQ modeling system wildland fire $PM_{2.5}$ estimates. We used a concentration response function for $PM_{2.5}$, applying ZIP code level mortality data and an estimated wildfire-specific chronic dose-response coefficient accounting for the likely toxicity of wildfire smoke. We find that modeled wildland fire $PM_{2.5}$ accounts for approximately half of all $PM_{2.5}$ in high fire years in California. We estimate between 52,600 to 56,140 premature deaths are attributable to wildland fire $PM_{2.5}$ over the eleven-year period. The mortality burden for 2008-2018 equates to an estimated economic impact of $432 to $460 billion. These findings extend evidence on climate-related health impacts, suggesting that wildfires account for a substantial mortality and economic burden. To our knowledge, this is the first health impact analysis applying chemical transport model estimates of wildland fire $PM_{2.5}$ to estimate mortality impacts using high-resolution health data.

Introduction

Wildfire risk and severity have grown in the last several decades across the western U.S.. Climate change (Hurteau et al., 2014; Westerling et al., 2006; Williams et al., 2019), an expansion of the wildland-urban interface (WUI) (Burke et al., 2021; Radeloff et al., 2018), and questionable wildfire management practices emphasizing fire suppression have all contributed to this increased risk (Jerrett et al., 2022). In California, the traditional wildfire season has lengthened, causing peak impacts to occur in earlier months (S. Li & Banerjee, 2021). California's recent wildfire seasons have caused extensive environmental, health, and economic damages within and outside of the state (Jerrett et al., 2022; D. Wang et al., 2021).

Wildfire smoke contributes to $PM_{2.5}$, with recent studies finding smoke can account for one-quarter to one-half of $PM_{2.5}$ throughout the U.S., and particularly high levels in western regions (Burke et al., 2021; Childs et al., 2022). $PM_{2.5}$ levels have generally improved throughout the country over the last several decades except for in fire-prone regions in the northwest U.S. (McClure & Jaffe, 2018), and the western U.S. more broadly, which have experienced increases in summer smoke $PM_{2.5}$ (O'Dell et al., 2019).

Scholars use various methods for estimating air quality during wildfires, including chemical transport models (CTMs), machine learning algorithms, in-situ monitoring data and satellite data, and combinations of these tools and datasets (Aguilera et al., 2023; Burke et al., 2021; Childs et al., 2022; O'Dell et al., 2019; O'Neill et al., 2021; Reid et al., 2015, 2021; D. Wang et al., 2021; Wilkins et al., 2020, 2022). Several of these methods have the ability to distinguish wildfire smoke from undifferentiated $PM_{2.5}$, with various strengths and limitations associated with each approach. In situ air quality monitoring is often sparse in fire-affected areas, and even with dense coverage, monitoring alone cannot isolate smoke $PM_{2.5}$ concentrations from total $PM_{2.5}$ from all sources.

Consequently, analyses modeling wildland fire air quality remain vital for characterizing the spatial distribution, magnitude, and temporal trends of wildfires, as well as understanding population exposures to smoke $PM_{2.5}$, which adversely impact public health (Black et al., 2017; Cascio, 2018; D'Evelyn et al., 2022; J. C. Liu et al., 2015; Reid, Brauer, et al., 2016a).

Exposure to $PM_{2.5}$ in urban air is associated with a multitude of health risks, including premature mortality and respiratory and cardiovascular morbidity outcomes (Pope & Dockery, 2006). In terms of wildfire-associated $PM_{2.5}$ specifically, there is relatively well-established evidence for the impact of wildfire smoke exposure on morbidity, such as respiratory illness and hospitalizations (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a; Cascio, 2018; J. C. Liu et al., 2015; Reid, Brauer, et al., 2016a). Evidence for mortality resulting from $PM_{2.5}$ exposure during wildfire events is more mixed (Black et al., 2017; Cascio, 2018; Casey et al., 2020; Reid, Brauer, et al., 2016a), though recent studies have quantified the relationship between short-term exposure to wildfire smoke and mortality (Doubleday et al., 2020; Magzamen et al., 2021) and estimated health impacts during wildfire events, applying both wildfire-specific $PM_{2.5}$ dose-response coefficients as well as urban $PM_{2.5}$ dose-response coefficients to concentration changes to calculate premature deaths (Y. Liu et al., 2021; Matz et al., 2020).

Such studies have largely found that exposure to $PM_{2.5}$ due to wildfires has substantial impacts on mortality and resulting economic burdens, with adverse effects reported in North America more broadly, the western U.S., as well as California specifically, which is the study area for this analysis. One long-term analysis in Canada found that the estimated economic impact for chronic health effects over a five-year period was between four and nineteen billion dollars annually, associated with 570 to 2,500 annual attributable premature deaths across the population of more than 35 million individuals (Matz et al., 2020). An analysis across the U.S., with a population of approximately 300 million, estimated wildfire impacts from a five-year period to result in tens of thousands of deaths annually and a total of hundreds of billions of dollars for chronic impacts over the entire period (Fann et al., 2018). Another recent study analyzed mortality impacts from April – October in 2012, 2013, and 2014, and found 4,000 annual deaths attributable to wildfires, alongside an economic valuation of $36 billion, with significant air quality impacts and mortality burden in the western states (Pan et al., 2023). In a western U.S.-focused study, a short-term analysis examining a specific wildfire event in the fall of 2020 in Washington state found that for the population of around 7.7 million, a 13-day period of increased $PM_{2.5}$ exposure from smoke was associated with more than 1,000 premature deaths from the marginal contribution of wildfire smoke to chronic exposures, and approximately 90 deaths from short-term exposures (Y. Liu et al., 2021). Finally, a recent study focused on 2018 California wildfires found more than 3,600 deaths to be associated with the fires, and more than $148 billion in total damages from health costs and capital and other indirect losses (D. Wang et al., 2021).

While the California population of nearly 40 million is at a heightened risk of wildfire exposure, no long-term epidemiological studies have directly assessed the mortality impacts resulting from years of increasing wildfire exposures within the state. Existing studies are also limited by the use of county-level health data. Further, no studies apply a chronic dose-response coefficient developed specifically for wildfire exposures; for long-term evaluations beyond a specific fire event, existing research solely utilizes undifferentiated $PM_{2.5}$ concentration-response coefficients, which do not capture differences in $PM_{2.5}$ smoke composition that could impact the dose-response effect (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a; B. A. Jones et al., 2016).

To bridge these knowledge gaps, we use modeled wildland fire-associated $PM_{2.5}$ concentrations, high-resolution CDPH mortality data, and a calculated chronic dose-response coefficient for wildfire $PM_{2.5}$ exposures and mortality to estimate premature deaths due to wildland fires over an eleven-year period from 2008-2018. The importance of wildfire management will only grow in the coming decades as aridification intensifies and more regions are susceptible to fires. Growing the evidence on health impacts from wildfires and potential health savings from wildfire management will be critical in ensuring the mitigation of wildfire impacts throughout the state and other regions.

Methods

Data

Modeled Wildland Fire $PM_{2.5}$ Concentrations

We used daily modeled $PM_{2.5}$ concentrations for 2008-2018 for the state of California at a 12-km grid spatial resolution, estimated using the U.S. EPA's CMAQ, v. 5.0.1- 5.3 – see Table B6.9) modeling system.

These wildland fire emissions estimates (which include wildfires and prescribed burns [but exclude agricultural burns], hereafter referred to as simply "fire") incorporate multiple sources of fire activity (see Table B8.9 for a full list of all data sources and specifications). SMARTFIRE2 (Sullivan et al., 2008) was used to reconcile the sources of fire activity data. Fuel consumption was calculated using the U.S. Forest Service's CONSUME ver. 3.0 fuel consumption model and the Fuel Characteristic Classification System (FCCS) fuel-loading database in the BlueSky Framework (Ottmar et al., 2007). Emission factors were taken from the Fire Emission Production Simulator (FEPS) model. Non-fire emissions sources are from the National Emissions Inventory (NEI). The model was run with all emissions (fire and non-fire sources) and again without fires. The calculated difference between these simulations ('all sources $PM_{2.5}$' and 'non-fire $PM_{2.5}$') isolates the fire contribution, or 'fire-only $PM_{2.5}$'. The model simulations for 2008-2012 are the same as those used by Rappold 2017 (Rappold et al., 2017) and Fann 2018 (Fann et al., 2018).

The first five years of data from 2008-2012 have been published by Wilkins et al. (Wilkins et al., 2018) and compared to other models in the literature (Burke et al., 2021); the remaining six years of data for 2013-2018 have not yet been reported in published studies. Therefore, we present a summary of all eleven years of data alongside the mortality and valuation analysis in this study. We compiled descriptive statistics for all eleven years of data, comparing all sources, fire-only, and non-fire $PM_{2.5}$ concentrations throughout the state and estimating the contribution of fires to total $PM_{2.5}$. We also investigate the impacts on air quality from fires within the context of days exceeding the NAAQS of daily $PM_{2.5} > 35$ μg/m^3 and years exceeding the annual NAAQS of 12 μg/m^3 (Wilkins et al., 2018).

Additionally, a supplemental validation analysis comparing monthly average modeled concentrations to observed concentrations from ground station data is included in Appendix B (Model Validation for $PM_{2.5}$ Estimates).

Mortality Data

Statewide annual mortality data (total number of deaths) by ZIP code and age for all 11 years are managed by the CDPH and are publicly available on the California Health and Human Services Open Data Portal website (California Department of Public Health, 2022). For several ZIP code and age categories, the count of deaths is suppressed for confidentiality reasons (i.e., counts < 11). Therefore, we implemented substitution procedures to fill in the missing deaths. First, since we only apply the dose-response values to ages 25+ (due to the nature of the epidemiological analysis from which the dose-response values were derived), we calculated the percentage of deaths in people over 25 for the entire state for each year, which is approximately 98%. For the ZIP codes where the total number of deaths was available, but the total number of deaths by age group were suppressed due to low counts in each group, we multiplied that percentage (98%) by the total number of deaths in the ZIP code to estimate the number of deaths for the applicable age group. For ZIP codes where even the total number of deaths are suppressed, we conservatively assume the ZIP code contains ½ of the suppression threshold and applied the percentage (98%) to that estimated value. We compared our final death count to the total reported deaths in the state (from the same CDPH data source) as a metric of quality assurance, and the total estimates varied by less than 0.35%.

Mortality and Associated Economic Valuation Calculations

We quantified the total mortality burden for exposure to $PM_{2.5}$ due to wildfires in California at the zip code level, using eleven years of CMAQ data (2008-2018). Based on the evaluation of the modeled data shown in Appendix B, we found that the highest modeled fire-only $PM_{2.5}$ values skew the correlations between the modeled and observed concentrations; thus, there is more uncertainty associated with those high concentrations. Therefore, we conducted two mortality analyses: (1) *Base case,* with no outliers removed, to characterize the potential impact of extremely high wildfire concentrations on mortality and (2) *Mod cap,* capping fire-only $PM_{2.5}$ concentrations falling outside of the 99.9th percentile of modeled values (at 143 $\mu g/m^3$–- see Table B8.9), considering the model is expected to perform less reliably far outside of the dataset.

We averaged the daily fire-only $PM_{2.5}$ values to develop estimates for each year and grid cell, and assigned exposures in each year to each ZIP code in California by identifying the nearest grid cell to each ZIP code centroid and assigning the associated $PM_{2.5}$ concentration to each ZIP code. If a given ZIP code contains one or more grid cells, the modeled $PM_{2.5}$ estimates were averaged for that ZIP code.

Then, we developed a wildfire-specific chronic[1] dose-response coefficient (Eq. 1). As mentioned previously, while there is substantial evidence regarding the impacts of exposure to wildfire-specific $PM_{2.5}$ on morbidity, such as respiratory outcomes (Delfino et al., 2009; Reid, Brauer, et al., 2016a), long-term mortality impacts from exposure to $PM_{2.5}$ from wildfire smoke – including how these impacts differ from exposure to ambient urban $PM_{2.5}$ – are not established and identified as a substantial knowledge gap in the literature (Black et al., 2017; B. A. Jones et al., 2016; Reid,

[1] Also referred to as "long-term" by some studies in the literature (e.g. Fann et al. 2018) (Fann et al., 2018).

Brauer, et al., 2016a). To our knowledge, no existing studies have attempted to characterize the dose-response between chronic wildfire $PM_{2.5}$ exposure and mortality. A limited number of studies focus on characterizing the short-term (or acute) wildfire-$PM_{2.5}$ mortality relationship (G. Chen et al., 2021; Doubleday et al., 2020), with one study focused on the west coast of the U.S. evaluating short-term impacts from days with heavy ground-level smoke from wildfire events in Washington state (Doubleday et al., 2020), and another global study, which presents a U.S.-specific dose-response estimate along with the main global estimate (G. Chen et al., 2021). Additionally, while there are no studies quantifying the relationship between chronic wildfire smoke exposure and mortality, several well-established dose-response values for the mortality impact of both chronic and short-term $PM_{2.5}$ exposures from undifferentiated (all sources) ambient $PM_{2.5}$ have been estimated. Existing short-term wildfire $PM_{2.5}$ dose-response values (G. Chen et al., 2021; Doubleday et al., 2020) demonstrate a more substantial impact on mortality than short-term undifferentiated dose-response values (Orellano et al., 2020), providing evidence of potential increased toxicity of wildfire smoke. Additionally, recent evidence from California has found differential increased impacts of wildfire $PM_{2.5}$ on health outcomes as compared to ambient $PM_{2.5}$ (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a).

Therefore, the application of an undifferentiated dose-response value to wildland fire-specific $PM_{2.5}$ exposures would likely underestimate mortality impacts. To address this concern, we calculated a novel chronic dose-response value using Eq. 1 below, which accounts for potential added toxicity of wildfire smoke as is suggested in several California-specific analyses: (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a; Wegesser et al., 2009)

$$\beta_{\mathrm{WL}} = \frac{\beta_{ws}}{\beta_{s}} \times \beta_{\mathrm{L}} \tag{1}$$

where, β_{WS} is the variance-weighted average of the two short-term wildfire $PM_{2.5}$ dose-response values (Washington and U.S.),(G. Chen et al., 2021; Doubleday et al., 2020), β_{S} is a short-term undifferentiated $PM_{2.5}$ dose-response value from a recent meta-analysis (Orellano et al., 2020), β_{L} is a chronic (annual) undifferentiated $PM_{2.5}$ dose-response value from a recent country-wide cohort study (Pope et al., 2019), and β_{WL} is the result: a chronic wildfire-specific $PM_{2.5}$ dose-response value (see Table B8.10 for a list of the dose-response values used in our analysis). We used a Monte Carlo distribution to estimate the final dose-response value used. We calculated a 95% CI for the estimated dose-response value.

Then, we calculated the mortality burden from exposure to $PM_{2.5}$ due to wildland fire smoke in the state of California using Eq. 2 below (US EPA, 2021):

$$\Sigma \Delta \mathrm{m_{ij}} = \left(1 - \frac{1}{e^{\left(\beta \mathrm{wL} * \Delta \mathrm{PM_{2.5ij}}\right)}}\right) * \mathrm{d_{ij}} \tag{2}$$

where, β_{WL} is the result of Eq. 1 (dose-response value), $\Delta PM_{2.5ij}$ represents the change in $PM_{2.5}$ concentration from wildland fire smoke in yIar *i* and ZIP code *j*, d_{ij} represents the total deaths in adults ages 25 and up, and Δm_{ij} represents the total mortality burden from wildland fires.
We also replicated the mortality calculations in Eq. 2 using solely the chronic undifferentiated $PM_{2.5}$ dose-response value from the U.S. national study conducted by Pope et al. (Pope et al., 2019)

to characterize the differences when the dose-response value is not adjusted for the potential added toxicity of wildfire smoke (as we did in Eq. 1).

Finally, we apply the EPA's VSL to these mortality impacts to estimate the total valuation of the health burden, using Eq. 3 below:

$$\text{Economic valuation} = \sigma\Delta m_{ij} * V \qquad (3)$$

where, Δm_{ij} is the result of Eq. 2 (mortality burden from wildland fires), and V is the EPA's VSL, which is $8.7 million in 2015 dollars (inflation year). We accounted for income growth to the year 2015 using publicly available income growth factors used in the U.S. EPA's BenMAP-CE tool (US EPA, 2021), since changes in income can impact willingness to pay for reduced risk of mortality. Finally, we applied a 3% discount rate over the eleven-year period to estimate the net present value of our economic estimates (US EPA, 2014a).

We also conducted two supplemental mortality analyses to further contextualize our primary results. First, we developed mortality estimates associated with all sources $PM_{2.5}$ exposure, using β_L, the same chronic undifferentiated $PM_{2.5}$ dose-response value used in our primary analysis (Pope et al., 2019). Second, we estimated β_{WL} using an alternative short-term wildfire $PM_{2.5}$ dose-response value developed in a recent global study (G. Chen et al., 2021), and used that to conduct a sensitivity analysis for the mortality estimates.

Results

Overview of Modeled Wildland Fire $PM_{2.5}$ Data

Here, we present a summary of the temporal, spatial, and overall distribution of the CMAQ modeled $PM_{2.5}$ concentrations at the 12-kilometer (km) grid scale. 'All sources $PM_{2.5}$' refers to total $PM_{2.5}$ concentrations, 'non-fire $PM_{2.5}$' refers to concentrations excluding wildland fires, and 'fire-only $PM_{2.5}$' describes the difference between those two simulations, the latter of which is the focus of our analysis. A supplemental model validation analysis at the monthly scale using several established model evaluation metrics is included in Appendix B (Appendix B, Model Validation for $PM_{2.5}$ Estimates).

Table 8.1 presents a summary of the modeled $PM_{2.5}$ estimates developed using the 12-km grid scale estimates, which includes concentrations from the entire state, including in rural areas with minimal background pollution. As shown in Table 8.1, Fire $PM_{2.5}$ contributes between 6.9% and 49% of $PM_{2.5}$ from all sources, depending on the severity of the fires in each particular year. In 2008, 2017, and 2018, years where California fires burned between 1.5 mill–on - 2 million acres (California Department of Forestry and Fire Protection (CAL FIRE), 2023), wildland fire $PM_{2.5}$ was responsible for almost half of all $PM_{2.5}$. The total $PM_{2.5}$ concentrations (all sources, including fires) were considerably higher in those years as well.

Expanded summary statistics for the independent grid cells (minimum, mean, and maximum annual concentrations by grid cell) for all eleven years are provided in Table B8.1 in Appendix B (Appendix B, Supplemental Tables). Substantial elevated maximum fire-only concentrations exist for several years due to extreme wildland fire events, and there are also low minimum annual concentrations from grid cells with little to no fire activity.

Table 8.1. *Summary of Averaged Modeled $PM_{2.5}$ (μg/m^3) Values and Acres Burned by Year (2008-2018) Statewide in California*

Year	**All Sources $PM_{2.5}$** (SD, μg/m^3)*	**Fire-Only $PM_{2.5}$** (SD, μg/m^3)	**Non-Fire $PM_{2.5}$** (SD, μg/m^3)	**Percent of $PM_{2.5}$ Attributable to Fire**	**Total Acres Burned**
2008	8.83 (5.49)	4.33 (5.04)	4.51 (3.34)	49.0%	1,593,690
2009	4.78 (3.03)	0.60 (0.39)	4.18 (3.00)	12.6%	451,969
2010	4.61 (3.21)	0.32 (0.29)	4.30 (3.21)	6.9%	134,462
2011	3.91 (2.23)	0.49 (0.34)	3.42 (2.25)	12.6%	228,599
2012	3.83 (2.10)	0.69 (0.74)	3.14 (2.14)	18.1%	829,224
2013	3.88 (2.36)	1.17 (1.26)	2.70 (2.17)	30.3%	601,635
2014	4.74 (3.95)	1.24 (3.73)	3.49 (2.06)	26.2%	625,540
2015	5.32 (4.85)	1.95 (4.75)	3.37 (1.93)	36.7%	880,899
2016	4.11 (2.37)	1.00 (1.46)	3.10 (1.76)	24.4%	669,534
2017	6.76 (5.50)	3.04 (5.28)	3.72 (1.85)	44.9%	1,548,429
2018	7.65 (4.68)	3.47 (4.42)	4.18 (1.78)	45.3%	1,975,086
All Years	5.31 (4.16)	1.66 (3.47)	3.65 (2.44)	31.3%	N/A

Notes: All sources = including fire and non-fire sources; fire-only = wildland fire sources only; non-fire = non-fire sources only. Acres burned were extracted from CAL FIRE Redbooks for each year (https://www.fire.ca.gov). National Interagency Fire Center (NIFC) estimates vary slightly (https://www.predictiveservices.nifc.gov/intelligence/intelligence.htm).
**Includes total land area with rural locations with lower $PM_{2.5}$; see Table S2 for a breakdown by metropolitan statistical area (MSA).*

To visually review model outputs, we examine fire-only concentrations for the entire time period (Figure 8.1), as well as compare (1) all sources, (2) non-fire, and (3) fire-only concentrations at the grid-cell level for mean $PM_{2.5}$ across the 11-year period (Figure B8.1). We also visualize locations with daily $PM_{2.5}$ concentrations greater than the U.S. EPA 24-hour (daily) National Ambient Air Quality Standards (NAAQS) of 35 μg/m^3 and annual NAAQS of 12 μg/m^3 over the entire eleven-year period (Figure B8.2a-b), and daily $PM_{2.5}$ concentrations greater than 35 μg/m^3 for each individual year (Figure B8.3). These figures demonstrate spatial and temporal trends in elevated $PM_{2.5}$ concentrations, but do not represent formal exceedances of the NAAQS standards or indicate nonattainment.

Figure 8.1 shows fire-only concentrations by year for all eleven years of data, with significant regional variation in fire impacts over the long-term period (see Figure B8.4 for the locations of fires greater than 300 acres in each year). Average annual fire-only concentrations exceed 15 μg/m^3 in several locations throughout the state in the high fire years. In contrast, during the least impacted year, 2010, the fire-only concentrations were less than 0.5 μg/m^3 throughout most of the state. The spatial distribution of all sources, non-fire, and fire-only concentrations (Figure B8.1) significantly vary, as anticipated due to differing pollution sources in different regions. Generally, wildfire smoke appears to expand the geographic areas affected by higher $PM_{2.5}$. The non-fire modeled values demonstrate significant pollution throughout two regions also prone to temperature inversions: Los Angeles County, a region known for significant traffic and industrial pollution, and the San Joaquin Valley, with two large highways running north-south and considerable agricultural pollution. The fire-only concentrations impact more rural, forested areas throughout the state on average, though there are significant regional variations not captured by these annual averages (Figure 8.1).

Most modeled concentrations higher than the 35 $\mu g/m^3$ NAAQS threshold over the eleven-year period are due to wildland fire $PM_{2.5}$ (Figure B8.2a). The most fire-impacted regions in the state, mostly in the vicinity of national forests in northwest California and east of the San Joaquin Valley, have grid cells with close to or more than 100 days with modeled concentrations higher than the 24-hour NAAQS threshold over the eleven-year period. The high-fire years contribute a significant portion of these elevated values over much of the state, with more than 25 days greater than the daily NAAQS threshold within a given year (Figure B8.3). With respect to the annual averages of the modeled values, concentrations greater than the annual NAAQS in the more populated, urban regions of the state (such as Los Angeles) are due primarily to non-fire sources, with fire-only sources accounting for values higher than the NAAQS thresholds in the more rural regions in the northern part of the state (Figure B8.2b). These fire-only sources are responsible for average concentrations greater than the annual thresholds in several regions and for multiple years during the eleven-year period, which demonstrates the magnitude of air pollution impacts during fire events.

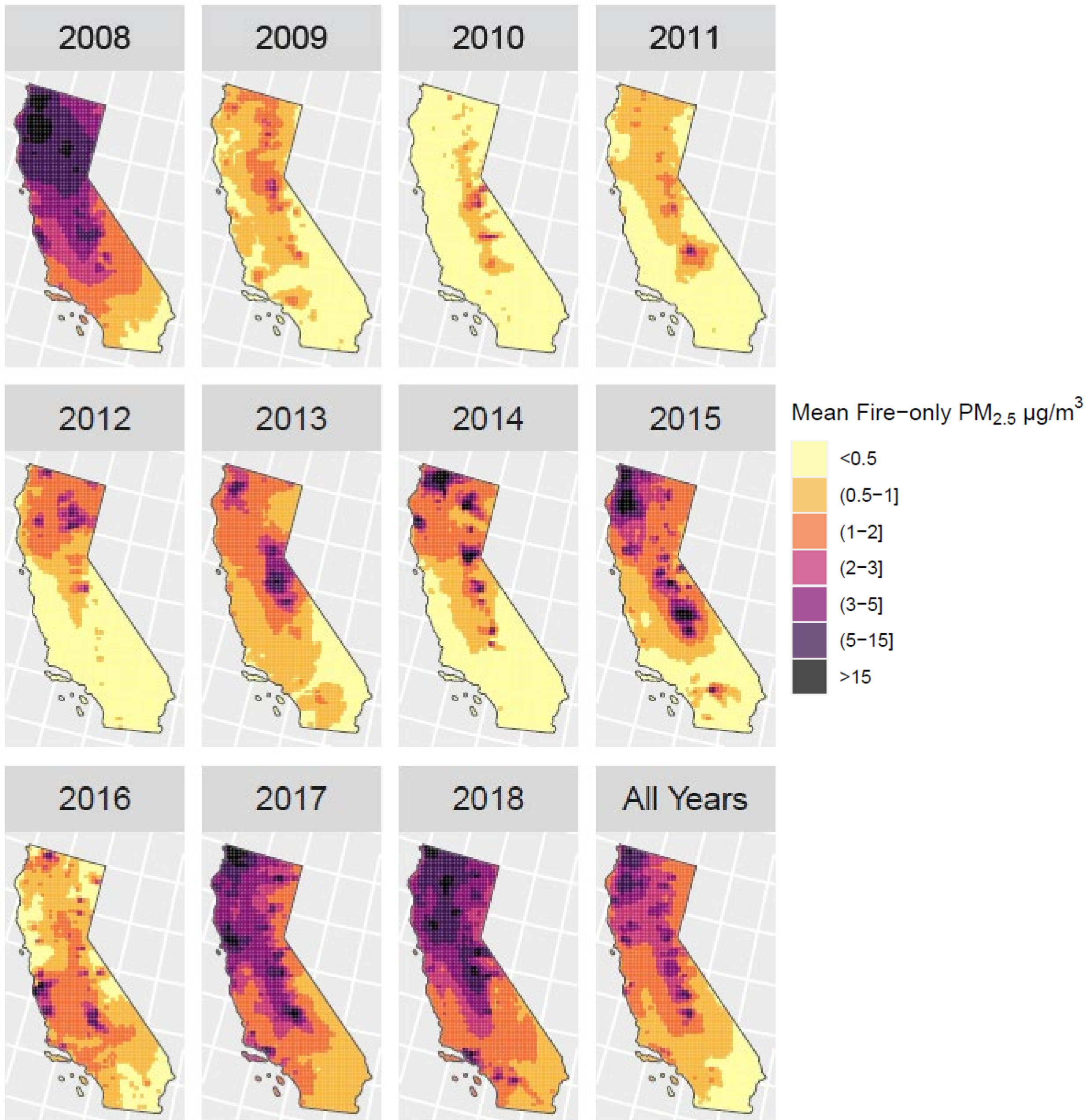


Figure 8.1. *CMAQ average daily fire-only $PM_{2.5}$ concentrations (µg/m^3) at 12-km resolution for 2008–2018 and the average value for all years, computed as the average over all days in each grid cell in each time period.*

Mortality and Economic Valuation Impacts of Wildland Fires

The total mortality burden for exposure to $PM_{2.5}$ due to wildfires in California, estimated for two exposure scenarios using a calculated chronic wildfire-specific dose-response value (β_{WL}), is presented in Figure 8.2 (Table B8.3), along with 95% CIs. In the *base case scenario*, no outliers are removed, to characterize the potential impact of extremely high wildfire concentrations on mortality. In the *modified cap (mod cap) scenario,* fire-only $PM_{2.5}$ concentrations falling outside of the 99.9th percentile of modeled values are capped to account for potentially skewed concentrations. The wildfire-specific dose-response value applied here, β_{WL}, was calculated to account for the potential increased toxicity of wildfire smoke using preexisting dose-response values from primary literature (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a; Wegesser et al., 2009). We also include results using a preexisting chronic undifferentiated $PM_{2.5}$ dose-response value (β_L) (Pope et al., 2019) as a point of comparison. For *base case*, including all of the original modeled fire-only values for all eleven years and applying β_{WL}, annual mortality impacts due to fire-only $PM_{2.5}$ exposure range from a low of approximately 1,300 deaths (95% CI: 130 – 2,490) in 2010 to a high of 12,880 (95% CI: 1,150 – 23,760) in 2018 (Figure 8.2), the latter of which is the year with the highest number of wildfire acres burned during our analysis period. This equates to a total of approximately 56,140 (95% CI: 5,–40 - 104,060) for base case over the eleven-year period, and 52,600 (95% CI: 4,–30 - 98,590) for *mod cap* (see Table B8.4 for a by-county breakdown of *base case* mortality results alongside total valuation).

As previously mentioned, we also present estimated mortality impacts using an undifferentiated chronic $PM_{2.5}$ dose-response value not specific to wildfire smoke exposures, β_L (Pope et al., 2019), to compare to our estimates using the calculated chronic wildfire-specific dose-response value (Figure 8.2). When using β_L, the total estimated mortality attributable to wildland fire $PM_{2.5}$ is approximately 36,470 (95% CI: 24,–90 - 44,700) for *base case*, and 33,960 (95% CI: 23,180 – 41,740) for *mod cap*. These estimates are approximately 35% less than projected mortality impacts when using the β_{WL} dose-response value accounting for wildfire-specific impacts, demonstrating that regardless of the added wildfire toxicity assumption (see Methods section), mortality impacts from wildfire smoke are substantial.

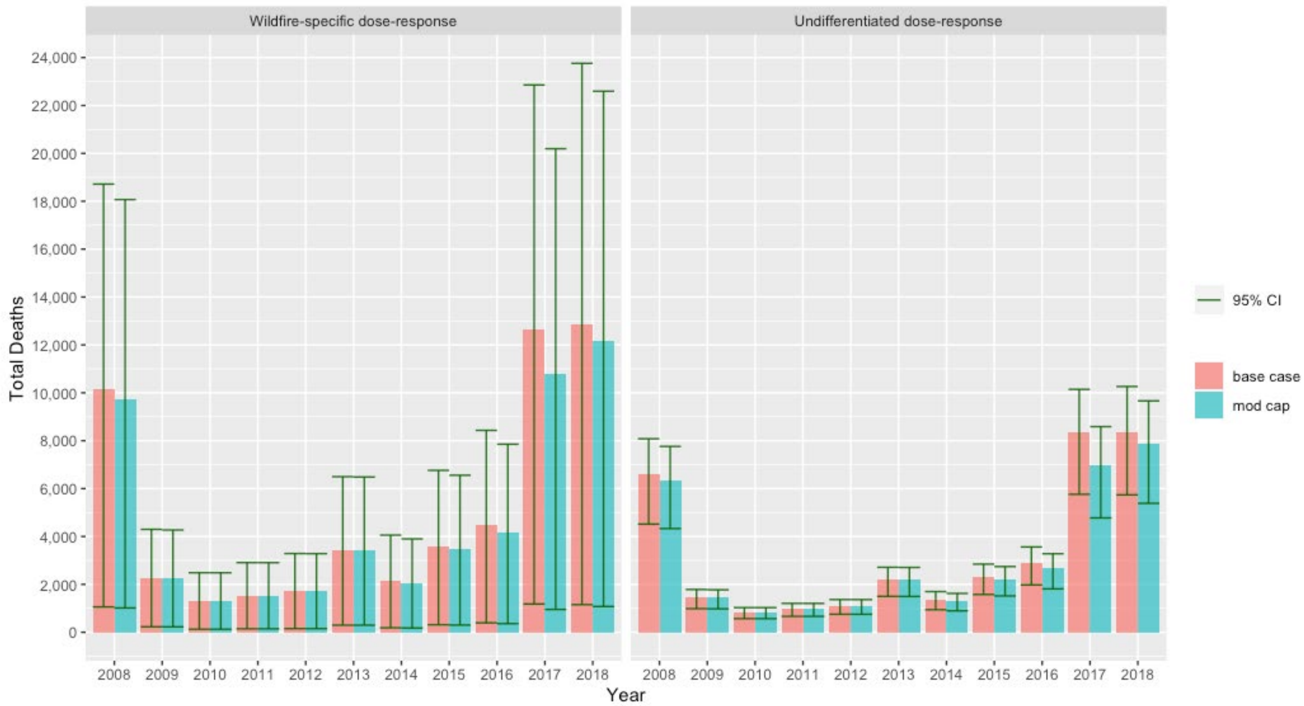


Figure 8.2. *Summary of long-term mortality impacts across California due to fire-only $PM_{2.5}$ for ages 25+, using wildfire-specific (left panel) and undifferentiated (right panel) chronic dose-response values, 2008-2018 (total deaths attributable to fire-only $PM_{2.5}$).*
Base case = no modeled $PM_{2.5}$ concentrations capped; mod cap = modeled $PM_{2.5}$ concentrations capped at the 99.9th percentile value of all fire-only concentrations.

Figure 8.3 depicts *base case* mortality impacts across California for the year with the lowest number of deaths attributable to wildland fire (2010), highest number (2018), and the average over the eleven-year period (see Figure B8.5 for the full by-year breakdown for all years, and Figure B8.6 for the spatial distribution of total mortality impacts over the eleven-year period). In 2010, a low-fire year with the least number of attributable deaths, approximately 90% of all ZIP codes were estimated to experience between 0-2 deaths. In contrast, in 2018, the highest fire year with the largest number of deaths attributable to wildland fire $PM_{2.5}$, almost 10% of ZIP codes experienced more than 15 deaths.

The elevated number of fires in 2008, 2017, and 2018 – along with significantly increased mortality impacts, represented by dark blue on the maps – are particularly striking, and there are clearly visible temporal and spatial trends (Figure B8.5). In 2008, the largest fires were clustered in northern California, with more statewide spread of fires throughout 2017 and 2018. Though fires throughout 2008 contributed a higher percent of total $PM_{2.5}$ than in 2017 and 2018 (Table 8.1), the attributable deaths were higher for the later years since the fires in those years expanded to more to high population areas.

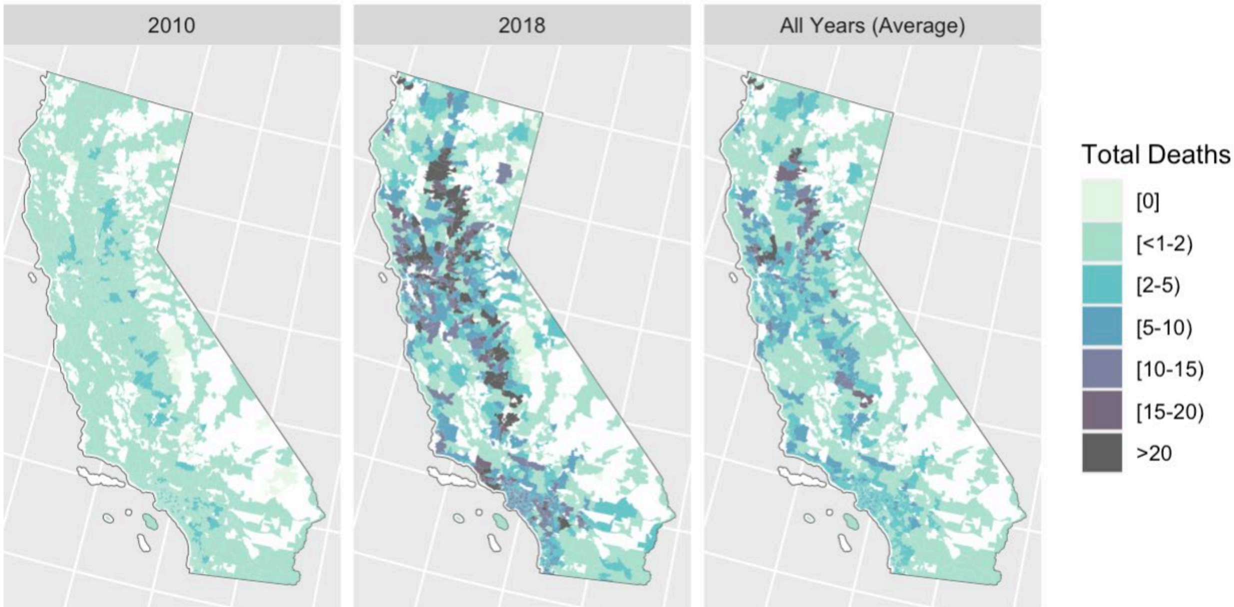


Figure 8.3. *Total deaths attributable to fire-only $PM_{2.5}$ (base case) in the year with the fewest deaths attributable to wildland fire (2010), most deaths attributable to wildland fire (2018), and the annual average over the eleven-year period (2008-2018). Darker colors indicate more deaths occurred in a given ZIP code, and white areas are outside of ZIP code designations.*

Though the fires are in more rural, forested regions (Figure B8.4, Figure 8.1), the mortality impacts are more widespread throughout population centers such as Los Angeles County in southern California, the San Joaquin Valley in central California, and the Bay Area in northern California, as smoke can be transported to these areas, and there are fewer individuals living in forested regions and therefore fewer premature deaths proportionally. For example, the Rough Fire of 2015 burned more than 150,000 acres in a more rural area of Fresno County, but most mortality impacts (represented by dark blue on the map) are west of the fire in a more populated area of the county, and throughout the San Joaquin Valley more broadly.

These mortality impacts can be considered in the context of two supplemental analyses. First, the mortality attributable to all sources $PM_{2.5}$ is presented in Table B8.5. Premature deaths attributable to all sources $PM_{2.5}$ are five times larger than the mortality impacts from solely wildland fire impacts, with a total of 296,300 deaths attributable to undifferentiated $PM_{2.5}$ from all sources over the eleven-year period of the analysis. Such results demonstrate that while other sources of $PM_{2.5}$ may dominate in urban population centers, and therefore result in disproportionately higher attributable mortality as compared to the overall contribution of wildland fire smoke to all sources $PM_{2.5}$ (Table 8.1), wildland fires are still responsible for nearly 19% of $PM_{2.5}$-associated deaths overall, and up to 41% in high fire years.

Second, the mortality attributable to wildland fire $PM_{2.5}$ estimated using a different short-term dose response value to estimate β_{WL} (a global estimate (G. Chen et al., 2021) as opposed to the average of the U.S. estimate from the same global study and the Washington wildfires study (Doubleday et al., 2020), see Table B8.6) is approximately twice as high as the results presented in Figure 8.2, with total estimate of 104,610 for all eleven years, versus 56,140 for our primary results. This is reflective of a significantly higher short-term dose-response value for wildfire impacts for the global estimate as compared to the two U.S.-specific values used in the primary analysis.

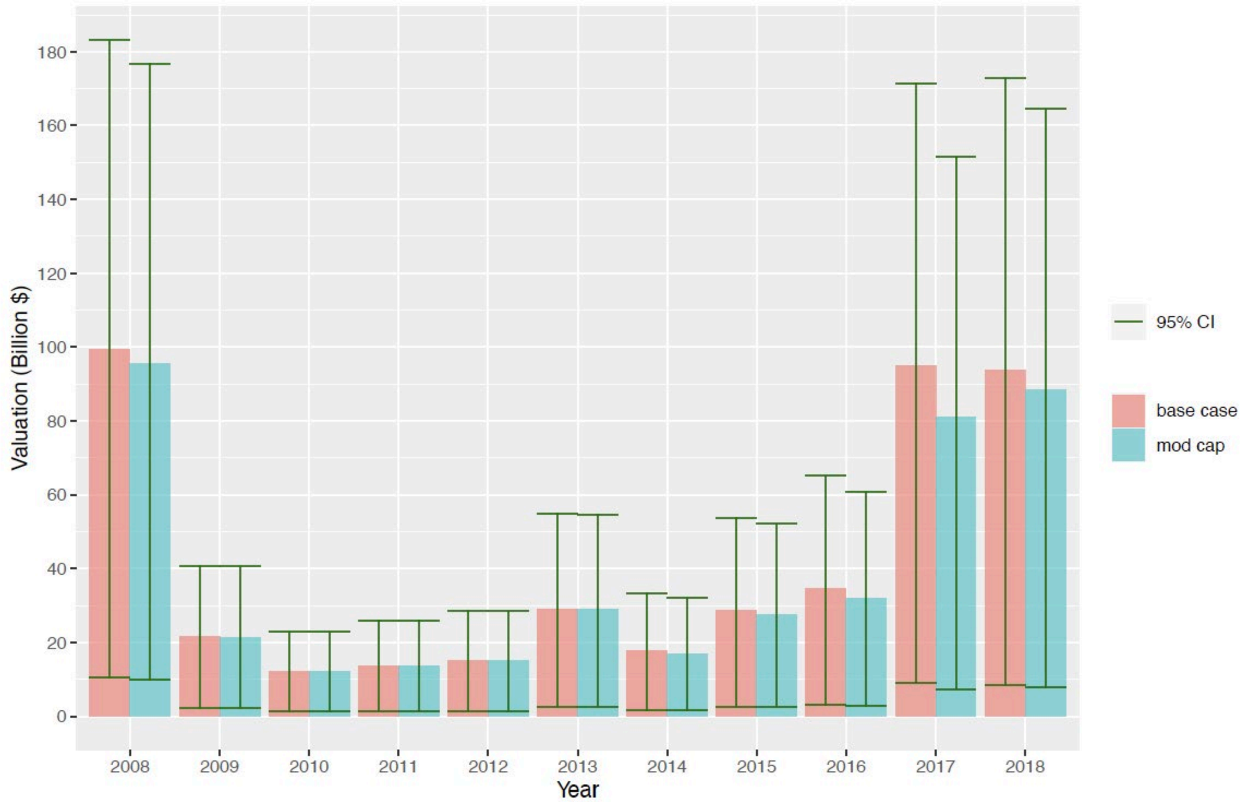


Figure 8.4. *Economic valuation of mortality impacts from wildland fires and 95% CIs for the base case and mod cap scenarios, using the wildfire-specific dose-response value (β_{WL}; 2015 dollars, 3% discount rate, 2015 income year)*

The valuation estimates for *base case and mod cap* (and CIs), using only the primary wildfire-specific dose-response value, are presented in Figure 8.4 and Table B8.7. The net present value of the estimates for all years is approximately 460 billion dollars (95% CI: $43.2 – $853 billion) for *base case*, and 432 billion dollars (95% CI: $40.0 - $810 billion) for *mod cap*.

Discussion

Here, we report on modeled wildland fire $PM_{2.5}$ estimates at the 12-km grid scale for 2008-2018, estimate associated premature mortality using a novel chronic dose-response value for wildfire exposure and calculate the associated economic valuation. We find the modeled wildland fire $PM_{2.5}$ estimates follow anticipated spatial and temporal trends with respect to the patterns of fire activity in the state. An estimated 52,600 to 56,140 premature deaths are attributable to fire-only $PM_{2.5}$ in California from 2008-2018, with an associated economic valuation of $432-$460 billion dollars (2015$). These deaths account for nearly 19% of total deaths attributable to all sources $PM_{2.5}$ in the state during this eleven-year period. To our knowledge, this is the first analysis to characterize mortality impacts in the state over a long eleven-year period, to apply a chronic dose-response value for wildfire-specific $PM_{2.5}$ exposure, and to use highly resolved health data in concert with a CTM (CMAQ) capable of isolating wildfire-related fine particle concentrations. These findings add to a growing body of literature on California-specific wildfire health effects (Delfino et al., 2009; Reid, Jerrett, et al., 2016b; Wettstein et al., 2018), and more broadly to evidence on past and projected wildfire and other climate-related health impacts occurring in California, the U.S., and globally (Deschênes & Greenstone, 2011; Ebi, Capon, Berry, Broderick, de Dear, et al., 2021; Ganesh & Smith, 2018; Neumann et al., 2021; Shonkoff et al., 2011; U.S. Global Change Research Program [USGCRP], 2018).

Modeled Fire-only $PM_{2.5}$ Estimates

The spatial distribution of fire-only $PM_{2.5}$ from our CMAQ model outputs aligns with general trends observed in analyses of historical fire records (S. Li & Banerjee, 2021; Williams et al., 2019) and other environmental health-focused studies using modeled data (Koman et al., 2019), though the model can overpredict concentrations in the high-fire years (other studies have reported similar CMAQ tendencies toward overprediction during wildfire events, due to challenges in modeling the distribution of fire emissions (Baker et al., 2016; Wilkins et al., 2018, 2022). As anticipated, the high fire years of 2008, 2017, and 2018 demonstrated elevated $PM_{2.5}$ concentrations, with many daily and annual values greater than the associated NAAQS thresholds (Table 8.1, Figure B8.2a-b, Figure B8.3). A recent wildland fire modeling analysis by Koman et al. used CMAQ to evaluate modeled exposure to wildland fire smoke from 2007-2013 in California and estimated all sources and fire-only $PM_{2.5}$ concentrations consistent with the results we present in Table 8.1 for the years overlapping with our analysis (Koman et al., 2019). This was expected considering the data inputs were similar, including the use of the BlueSky framework and SMARTFIRE2 to develop emissions to use within CMAQ. Additionally, studies incorporating machine learning algorithms in estimating wildfire $PM_{2.5}$ are becoming more common as an alternative to CTMs (Aguilera et al., 2023; Childs et al., 2022; Reid et al., 2015); two recent studies have used machine learning techniques to parse out wildfire smoke $PM_{2.5}$ across the contiguous U.S. Childs et al. found that smoke $PM_{2.5}$ can contribute approximately half of annual all sources $PM_{2.5}$ in certain high-fire locations in the Western U.S. (equating to an increase in annual $PM_{2.5}$ of 5 $\mu g/m^3$ in certain regions). This aligns with our modeled results for the high fire years of 2008, 2017, and 2018 (Table 8.1) (Childs et al., 2022).

Mortality Impacts of Exposure to Wildland Fire $PM_{2.5}$

We present a range of potential mortality impacts from two exposure scenarios (one with no modeled values altered [*base case*] and one with modeled values capped [*mod cap*]) to account for uncertainties in the modeled $PM_{2.5}$ estimates. Our use of a wildfire-specific chronic dose-response value (as opposed to an undifferentiated dose-response, which we also present as a form of sensitivity analysis) results in an increase in the magnitude of our findings, as is shown in the comparison to the premature mortality estimated using a chronic undifferentiated $PM_{2.5}$ dose-response value from Pope et al. (Figure 8.2) (Pope et al., 2019). We selected the Pope et al. study since it is a recent, representative U.S. sample.

Several studies quantify health impacts from exposure to $PM_{2.5}$ during wildfires, but few examine mortality in California specifically. A recent study by Wang et al. evaluating the economic footprint of the 2018 California wildfires conducted a health impact assessment for one portion of the analysis (D. Wang et al., 2021). They estimated 3,652 premature deaths associated with wildfire $PM_{2.5}$ exposure (D. Wang et al., 2021), which is significantly lower than our estimates of 12,160 – 12,880 for 2018. While the discrepancy is likely partially due to varying modeled $PM_{2.5}$ exposure used in the two studies, it is primarily due to the use of differing dose-response values. Wang et al. estimated mortality using a combination of a 2013 California specific dose-response estimate (Jerrett et al., 2013), and a well-established U.S. dose-response value from 2009 (Krewski et al., 2009) commonly used in U.S. health impact analyses. Their analysis used BenMAP-CE, which utilizes county level health estimates. Our study builds on this California-specific analysis by (1) using more highly resolved health data, which can reduce potential misclassification of exposures associated with using spatially coarse health data; (2) extending the temporal period of the health analysis; and (3) applying a chronic wildfire-specific dose-response value.

Fann et al. quantified long-term mortality and morbidity impacts throughout the entire country for 2008-2012, using the same commonly used U.S. dose-response value mentioned previously, and the same CMAQ simulation we apply in this study (Fann et al., 2018; Krewski et al., 2009). Though results for California are not explicitly presented, the authors reported that California is one of several states in the country with the most significant mortality and respiratory morbidity impacts over the five-year period (Fann et al., 2018). They estimated 14,000 premature deaths in the U.S. for the high fire year of 2008 as compared to our estimates of approximately 10,000 (for both scenarios) in California alone. Again, our use of the wildfire-specific dose-response coefficient has also increased the magnitude of our results. Additionally, similar to the California economic footprint study discussed previously, the U.S. study was limited by the use of county-level health data, which is again less spatially resolved than the ZIP code-level data used here.

Implications of Using Modeled Air Quality Estimates for Health Impact Assessment

The scenario-specific analysis has several implications as well. We find that capping fire-only concentrations at the 99.9th percentile (exceeding 143 μg/m^3 – see Table B8.8) of values results in several hundreds to thousands of fewer wildfire $PM_{2.5}$ attributed deaths per year, but the overall magnitude of impacts is still substantial with the peak concentrations capped. The results vary little between *the base case* and *mod cap* scenarios in the lower fire years (especially 2009-2014), which indicates that these higher concentrations are occurring primarily in the high fire years and likely driven by severe fire events. As it is certainly possible for concentrations to reach and exceed 143 μg/m^3 (the 99.9th percentile value) during fire events, capping these values would lead to an underestimate for *mod cap*. Additionally, the observed CMAQ model overprediction during fire events would lead to an overestimate for *base case*. This is an uncertainty in using modeled data for health impact assessment, particularly for analyses in which the results can be affected by high concentration averages applied in dose-response analysis.

This variation in results between *base case and mod cap* and the differing magnitude of our findings with the wildfire-specific versus undifferentiated dose-response value (Figure 8.2) highlights several considerations and challenges associated with using modeled data for health studies. The implications and sensitivity associated with the choice of wildfire smoke exposure data and potential misclassification in relation to quantifying health impacts has been discussed in recent studies (Cleland et al., 2021; Gan et al., 2017; Lassman et al., 2017; J. C. Liu et al., 2015). One study found differing odds ratios for morbidity outcomes using three different methods of wildfire smoke estimation (WRF-Chem, kriging, and geographically weighted ridge regression) (Gan et al., 2017). Another analysis that was focused on acute health impacts during the 2017 California wildfires used varying dose-response values and exposure surfaces to test the sensitivity of results (Cleland et al., 2021). The authors found that there were no statistically significant differences in results for the variation in either input, but the differing magnitude in outcomes resulting from the use of a range of dose-response values supported the use of context-specific dose-response values, as we have applied in this study (Cleland et al., 2021).

Novelty, Strengths, and Limitations

This study has several strengths and presents a unique contribution to the literature. The use of eleven years of CMAQ data enabled us to report on a long-term period of wildfire impacts in California, with several high fire years with substantial impacts. The use of fire-only $PM_{2.5}$ estimates from the CMAQ model is a distinct strength of this study. Though recent machine learning analyses have parsed out wildfire-specific $PM_{2.5}$ at slightly more spatially resolved levels than our 12-km grid (10-km (Childs et al., 2022) and ZIP code (Aguilera et al., 2023)), there is uncertainty in these estimates due to a series of assumptions in the methodology. Both studies intersect the Hazard Mapping System Fire and Smoke Product (HMS Smoke) hand-drawn smoke plumes from satellite imagery with the various grids as a primary method of identifying smoke days. The HMS Smoke product, however, characterizes the density of smoke plumes in the atmospheric column, and accordingly is not precisely aligned with ground-level $PM_{2.5}$ concentrations (Fadadu et al., 2020). Further, the studies characterize the fire-only concentrations using undifferentiated $PM_{2.5}$ concentrations (from all sources) and the binary smoke day classification, which again requires several assumptions to extract fire-only $PM_{2.5}$ using counterfactual non-smoke concentrations (Aguilera et al., 2023; Childs et al., 2022). The CMAQ modeled estimates applied in this study are subject to typical limitations associated with use of a CTM, but these values are based on actual all sources and non-smoke modeled $PM_{2.5}$ and do not involve the use of imputation. The use of highly-resolved health data at the ZIP code level is another key novel aspect. Less spatially resolved county-level mortality rates are used in BenMAP-CE (US EPA, 2021) and many existing health impact assessments, which can result in potential exposure misclassification, as mentioned previously. We also apply a fire-specific dose-response coefficient accounting for increased toxicity of wildfire smoke, which gives a first estimate of chronic wildfire-specific mortality impacts. Additionally, the inclusion of two exposure scenarios enables us to evaluate the sensitivity of the magnitude of health impacts to high $PM_{2.5}$ concentrations from severe wildfire events.

Several limitations deserve mention. The CMAQ model is affected by typical challenges associated with the use of data inputs and procedures for modeling wildfire smoke using CTMs (Fann et al., 2018; Jaffe et al., 2020; Koplitz et al., 2018). We address model overprediction concerns by including *mod cap,* in which we remove modeled data outside of the 99.9th percentile of all values and develop a second set of mortality and valuation estimates to consider and discuss. Additionally, the CMAQ model runs do not isolate wildfire emissions from prescribed burns. Therefore, the results presented here include mortality associated with all wildland fires (not including agricultural burns, which are not incorporated in the isolated fire-only fraction), and do not solely represent wildfires. However, prescribed burns in California account for a very small proportion of the total acres burned (CAL FIRE, 2022), though this may change in the future with ambitious targets for increased land management practices (California Wildfire & Forest Resilience Task Force, 2022). For this study period, we do not anticipate a significant portion of the mortality impacts to be attributable to prescribed burning.

Additionally, we estimated a wildfire dose-response value, which enables us to account for the potentially increased toxicity of wildfire smoke. There is some uncertainty in this approach, since this dose-response value was not developed through primary research, but instead was calculated using existing dose-response values. With respect to the short-term wildfire-specific dose-response function used to estimate the final coefficient, we chose to use the variance-weighted average of two dose-response values for the short-term wildfire-specific dose-response coefficient, one from a Washington wildfires study (representative of wildfire conditions, $PM_{2.5}$ composition, and population in the western U.S.). We drew the second from a global study that estimated short-term mortality risk attributable to wildfire smoke exposures in 749 cities, and provided a supplemental estimate for solely U.S. cities (G. Chen et al., 2021). The main dose-response value presented in the global study, however, found mortality risk estimates of a higher magnitude than the Washington study and its own U.S.-based estimate; results using this dose-response value are included as a sensitivity analysis (Table B8.6) and demonstrate approximately twice the mortality impact, with more than 100,000 deaths attributable to fire-$PM_{2.5}$ over the eleven-year period (G. Chen et al., 2021). While the application of two U.S. dose-response values – as we have done here – is the most appropriate approach for this analysis, the inconsistencies between global and U.S. estimates highlight the need for further analysis to characterize the relationship between wildfire $PM_{2.5}$ exposure and both acute and chronic mortality impacts.

Key Areas for Future Study

Further study on these topics will be crucial as the state continues to make efforts to reduce the widespread impacts of climate change on the environment and human health. Future work on air pollution modeling to parse out wildfire concentrations will enable more precision in health impact assessments. While a growing number of machine learning analyses discuss total $PM_{2.5}$ results in the context of wildfire smoke (Q. Di et al., 2019; L. Li et al., 2020; Reid et al., 2021), only recently have models isolating fire-specific $PM_{2.5}$ been built (Aguilera et al., 2023; Childs et al., 2022). This is an area for research and development, including further comparison against typical CTMs to determine the best approaches to develop exposure surfaces for health analyses. Finally, evaluating the equity dimensions of exposure and health outcomes is an area for future study. Another key implication of the substantial health and associated economic impacts from wildfires presented in this study is the importance of cultivating community resilience (D'Evelyn et al., 2022; McWethy et al., 2019) and protecting vulnerable populations throughout California who have less access to wildfire mitigation resources and reduced adaptive capacity (Davies et al., 2018; D'Evelyn et al., 2022). While many wildfire-prone regions are home to communities with lower social vulnerability (Wigtil et al., 2016), the intersection of wildfire health effects and equity will continue to grow in importance in the coming years as wildfires increase in severity and populations become more vulnerable to subsequent impacts. Considering the magnitude of the mortality impacts estimated here and the diverse population living in California, including many communities with pre-existing vulnerability, this presents an opportunity for future research and evidence-based policy action to protect public health and promote equity.

In conclusion, this analysis characterizes the harmful impacts of $PM_{2.5}$ from wildland fire smoke on the health of the California population during the eleven-year period of 2008-2018. To our knowledge, this is the first health impact analysis applying CTM estimates of wildland fire $PM_{2.5}$ to estimate mortality outcomes using high-resolution health data. This analysis is also novel with respect to the long-term nature of the evaluation over an eleven-year period, and estimation and application of a chronic dose-response value for wildfire-specific $PM_{2.5}$ exposure. We estimate between 52,600 to 56,140 premature deaths are attributable to fire $PM_{2.5}$ exposures, with an associated economic valuation of \$432 to \$460 billion. These findings have direct implications for California, a state at the forefront of climate policy development with many fire-prone regions and a diverse population to protect. Growing the evidence base on health impacts from wildfires and other climate-related exposures is critical in motivating future investments to mitigate the impacts of climate change and protect vulnerable populations.

IX. Health Impact Assessment: Wildfire Fire Morbidity

Introduction

The prevalence of wildfires in the western United States has surged in recent decades, driven, in part, by elevated temperatures, change in participation patterns, and expanding wildfire seasons. Several of largest wildfires in California's history have occurred within the past decade, and changes to wildfire patterns are only expected to continue climate change continues to create dry, fuel rich landscapes. Wildfire events have been explicitly linked to a rise in $PM_{2.5}$, and recent evidence suggests that wildfire PM can be more harmful than PM from other sources, likely due to its broad concentration variations, chemical compositions, and finer particle sizes (Aguilera et al. 2021). Additionally, co-exposure of wildfire-specific $PM_{2.5}$ with other environmental factors can lead to additional negative health outcomes. A recent study found short-term exposure to wildfire-specific $PM_{2.5}$ was associated with 65.6 million all-cause deaths globally, of which, ~8.6 million were within the United States (Chen et al. 2021). Growing evidence within the peer-reviewed literature has also identified a relationship between wildfire-specific $PM_{2.5}$ emissions with multiple adverse morbidity outcomes including exacerbated respiratory symptoms, asthma, and COPD.

Overall, there is a lack of available epidemiological peer-reviewed literature examining the full impacts of wildfire exposures on health; however, as wildfire risks increase globally, the pace of newly published literature is rapidly expanding. There is a critical need to better understand the human health impacts from wildfire emissions, from both historic wildfire events and future predicted wildfires. A tool capable of quantifying impacts of wildfire exposures is needed, however, it is critical that it is flexible as to account for developing inputs. Therefore, using the U.S. EPA's BenMAP-CE program (https://www.epa.gov/benmap) with environmental and human inputs, we have developed the NWL Health Scenario Tool that is capable of estimating health impacts from wildfire exposures within the western US. This tool is flexible and can be updated to account for improved coefficients of exposure and emissions estimates. BenMAP-CE is an opensource program that relates air quality changes to human health benefits and estimates the number and economic value from health impacts resulting from changes in air pollution concentrations. In this work, we detail the process of estimating California-specific health impacts using coefficients available in the peer-reviewed literature and wildfire emission estimates from the 12km CMAQ model.

To examine state-specific health estimates, we conducted a review of the current epidemiological literature examining the various human health impacts from wildfire smoke episodes. From this comprehensive review, we identified relevant studies that assessed the relationship between health outcomes and wildfire-specific $PM_{2.5}$ concentrations. In the absence of a meta-analysis specific to wildfire $PM_{2.5}$ emissions in the western US, we extracted the most appropriate dose-response metrics (coefficients) of exposure from the primary literature. We used the U.S. EPA's BenMAP-CE program to estimate health impacts from wildfire-specific $PM_{2.5}$ using daily concentrations from the 12km CMAQ model. Resulting health impact estimates from wildfire exposures were presented from multiple studies to examine the variations over various dose-response metrics exposure. Finally, we included these results in the interactive, publicly available NWL Health Scenario Tool which allows users to visualize the results of various scenarios, as detailed in the later chapters.

Methods

Updated Literature Review
To understand the current state of the literature, and expanding on the previous scoping review detailed in earlier chapters, we first conducted a non-structured review to identify relevant review articles that have been published in the last few years. We used the identified literature to state, with confidence, the direction and strength of associations between wildfire specific $PM_{2.5}$ exposures and respiratory, cardiovascular, and mortality outcomes. With this information, we then conducted a more focused, outcome-specific structured literature review to identify and extract region-specific dose-response values that can be incorporated and modeled to estimate health impacts of exposure.

Expanding the timeframe of the previous scoping review, we focused the literature review on health outcome categories identified as having strong evidence of association with wildfire $PM_{2.5}$ emissions. We conducted searches on the PubMed and Web of Science databases in July 2023 and included all articles published from 2021 through the search date. Further, we developed an inclusion and exclusion criteria to limit the identified literature to the most appropriate studies of interest. Criteria included primary empirical human-health studies of all age groups, sexes and genders which evaluated human health impacts from wildfire-specific exposures in the western United States including Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming. We focused on studies that explicitly identified or measured health outcomes as a direct impact from wildfire-specific exposure and included studies with a quantifiable dose-response value detailed in the literature. We focused on wildfire-specific $PM_{2.5}$ as the primary exposure for two reasons: (1) particles, specifically particles with an aerodynamic size ≤ 2.5μm, are among the most commonly utilized wildfire-specific metric of exposure within the peer-reviewed literature; thus potentially providing a larger pool of relevant studies that can be used to develop health estimates and; (2) several wildfire products including the CMAQ provide $PM_{2.5}$ estimates that can be utilized to assess health burdens from their modelled emissions or concentrations. To develop the health estimates of exposure, and in absence of available medical data, we were limited to studies with International Classification of Diseases (ICD) codes that could be matched with health outcomes provided in the BenMAP-CE database.

For the review, ineligible studies included those using non-human subjects, exposures in a laboratory setting, or exposure studies that did not empirically examine the relationship between wildfire-specific $PM_{2.5}$ to human health to provide a qualitative impact estimate. Since the ultimate goal is to examine impacts statewide, occupational exposures, including those from wildland firefighters were excluded. We further limited our search to studies published in a peer-reviewed journal written in English, French, or Spanish. The full list of inclusion and exclusion criteria are provided in Table 9.1 below.

Table 9.1. *Inclusion and exclusion criteria applied to compressive peer review literature search*

Inclusion Criteria	*Exclusion Criteria*

Peer-reviewed literature that was published since the previous scoping review (2020 – 2023) in English, Spanish, or French language	Non-peer reviewed literature (e.g. abstract only, conference proceedings, articles from the media, letters to the editor, reports, thesis, textbooks, etc.) published prior to 2020 and not in the English, Spanish, or French language
Peer-reviewed research studies that collect non-occupational wildfire exposure data to examine the relationship to human health outcomes as identified by an ICD code	Studies that report on occupational exposures, or exposures from health outcomes that cannot be classified by an ICD code
Health outcomes are examined as a direct impact from wildfire exposures with a quantifiable dose-response value detailed in the literature	Health outcomes that are examined as a secondary impact from wildfire exposures (e.g. loss of livelihood and resulting stress) or does not provide a quantifiable dose-response value
Literature that examines populations impacted in Western United States including Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming	Literature that does not look at populations within the Western United States.
Literature that explicitly investigate wildfire exposures that are identified or measured by wildfire-specific $PM_{2.5}$ smoke	Literature that does not explicitly examine wildfire-specific PM smoke exposures (e.g. residential fires, prescribed burns, agricultural fires, anthropogenic biomass fires, vehicular emissions, etc.)

After removing duplicates, we analyzed titles and abstracts for significance, then remove studies that did not fit the detailed inclusion and exclusion criteria. We applied the same criteria to articles identified in the previous scoping review and conducted a reverse snowballing literature search by using citations in the collected literature to identity additional relevant work. We conducted a full article review on the resulting literature to determine inclusion in subsequent crosswalk.

Estimates of Health Impacts

BenMAP-CE Crosswalk. Once the target literature was identified, we systematically extracted and organized the data for analysis into an Excel spreadsheet that included relevant information including: authors, publication year, publication title, journal, study location, exposure measurement, and health outcome examined, and ICD-9 code(s). We evaluated each health outcome for inclusion based on the availability of existing prevalence data currently available within BenMAP-CE. We created a crosswalk of coefficients from the identified literature of high and medium certainty and compared them to the extensive health outcome prevalence data sets available in the BenMAP-CE program. We restricted our inclusion to only those with matching ICD codes and medical delivery method (e.g., hospitalizations, emergency department [ED] or ER visit, etc.) as the most defensible comparison and broaden the scope based on consultation with medical professionals. If more than one coefficient was identified for model inclusion, we prioritized dose-response values derived from studies that examined health outcomes within

California, prioritizing studies that examined impacts over larger geographic regions, included emissions from multiple wildfire events into exposure estimates, and examined more recent wildfire events.

Import Health Coefficient Database. Peer-reviewed literature on wildfire-specific $PM_{2.5}$ is expanding rapidly; thus, it is important to utilize a platform that can adapt to emerging findings, coefficients, and health outcomes. The health coefficients selected for the current project aim to characterize statewide exposures, specific to the project objectives; but the provided tool is flexible and can adapt to individual research needs. We extracted all relevant peer-reviewed literature (as detailed in Section VI and IX) and included dose response coefficients in the resulting extraction worksheet (Figure 9.1) for all eligible exposures within the western US. Depending on individual project needs, these coefficients included in the extraction worksheet can be evaluated for model inclusion and used for additional analyses, where appropriate.

Figure 9.1. *Extraction worksheet of additional coefficients for additional analyses in western U.S.*

		1			
Health Outcome	**ICD-9 Codes**	**Authors**	**Title**	**ournal Publish**	**ar Publi**
Hospital admission; Acute bronchitis and b	466	Delfino RJ, Brummel S,	The relationship of respiratory and ca	Occupational and	2009
Hospital admission; Asthma	493	Delfino RJ, Brummel S,	The relationship of respiratory and ca	Occupational and	2009
Hospitilizations & ED visits; Upper Respirat	460-466	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospital admission; Upper respiratory infe	460-465	Delfino RJ, Brummel S,	The relationship of respiratory and ca	Occupational and	2009
Hospitilizations & ED visits; Acute myocard	410	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Acute myocard	410	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Dysrhythmia	427	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Dysrhythmia	427	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Congestive he	428	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Congestive he	428	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospital admission; Pneumonia	480-487	Delfino RJ, Brummel S,	The relationship of respiratory and ca	Occupational and	2009
Hospital admission; COPD	491, 492, 496	Delfino RJ, Brummel S,	The relationship of respiratory and ca	Occupational and	2009
Hospitilizations & ED visits; Ischemic Heart	410-414	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Ischemic Heart	410-414	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Cardiovascular	410–414, 427, 428	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Cardiovascular	410–414, 427, 428	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Ischemic Strok	433–437	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Ischemic Strok	433–437	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Peripheral vas	440, 443, 444, 451	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Hospitilizations & ED visits; Peripheral vas	440, 443, 444, 451	Alman, B.L., Pfister, G.	The association of wildfire smoke with	Environ. Health	2016
Physician visits; Respiratory illness	460.0–519.9	Lee TS, Falter K, Meye	Risk factors associated with clinic	Int J Environ Hea	2009
Physician visits; Asthma	493.0–493.99	Lee TS, Falter K, Meye	Risk factors associated with clinic visi	Int J Environ Hea	2009
ED visits; Asthma	493	Rappold, A.G., et al.	Cardiorespiratory outcomes associate	Environ. Health: (	2012
Hospital Admission; Asthma	493	Le, G.E., Breysse, P.N	Canadian forest fires and effects of lo	ISPRS Int. J. Geo	2014

Health Coefficient of Exposure. We utilize the BenMAP-CE platform to populate the Health Impact Functions per the guidance from BenMAP-CE staff (See Figure 9.1). Selected coefficients were formatted for comma separated value datasheets using daily 24-hour metric (D24HourMean), annual and seasonal metrics remained undefined, and assigned an appropriate distribution.

Figure 9.2. *Selected coefficients formatted for BenMAP-CE Health Impact Function import.*

Endpoint Group	Endpoint	Pollutant	Metric	Seasonal Me	Metric Statis	Study Author	Study Year	Beta	Distribution I	Parameter 1	P
Emergency Room Visits, Respiratory	Emergency Room Visits, Asthma	PM2.5_Daily	D24HourMean		None	Arriagada (comparison only)	2019	0.00676586	Normal	0.00119788	
Emergency Room Visits, Respiratory	Emergency Room Visits, Asthma	PM2.5_Daily	D24HourMean		None	Malig et al (L: 02)	2021	0.01761152	Normal	0.00202735	
Emergency Room Visits, Respiratory	Emergency Room Visits, Asthma	PM2.5_Daily	D24HourMean		None	Reid et al (L: 1-2)	2019	0.01088544	Normal	0.00114415	
Emergency Room Visits, Respiratory	ER visits, respiratory	PM2.5_Daily	D24HourMean		None	Malig et al (L: 02)	2021	0.0084979	Normal	0.0014318	
Emergency Room Visits, Respiratory	ER visits, respiratory	PM2.5_Daily	D24HourMean		None	Reid et al (L: 1-2)	2019	0.00344014	Normal	0.00051787	
Emergency Room Visits, Respiratory	ER visits, respiratory	PM2.5_Daily	D24HourMean		None	Gould et al (comparison only)	2023	0.0036	Normal	0.00086735	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Aguilera et al (IM)	2021	0.00127188	Normal	0.00045843	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Delfino et al (Lag: 0-1)	2009	0.00276152	Normal	0.00067038	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Malig et al (L: 2)	2021	0.00484311	Normal	0.00175586	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Reid et al (L: 1-2)	2019	0.00382587	Normal	0.00108048	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Heaney et al (L: 01)	2022	0.0007616	Normal	0.00034171	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Gan et al	2017	0.00506931	Normal	0.00133338	
Hospital Admissions, Respiratory	HA, All Respiratory	PM2.5_Daily	D24HourMean		None	Gould et al (comparison only)	2023	0.0025	Normal	0.00084184	
Hospital Admissions, Respiratory	HA, Asthma	PM2.5_Daily	D24HourMean		None	Arriagada (comparison only)	2019	0.00582689	Normal	0.00169324	
Hospital Admissions, Respiratory	HA, Asthma	PM2.5_Daily	D24HourMean		None	Delfino et al (Lag: 0-1)	2009	0.00468836	Normal	0.00133847	
Hospital Admissions, Respiratory	HA, Asthma	PM2.5_Daily	D24HourMean		None	Malig et al (L: 0)	2021	0.0055995	Normal	0.00426456	
Hospital Admissions, Respiratory	HA, Asthma	PM2.5_Daily	D24HourMean		None	Reid et al (L: 1-2)	2019	0.01310283	Normal	0.00266182	
Hospital Admissions, Respiratory	HA, Asthma	PM2.5_Daily	D24HourMean		None	Heaney et al (L: 01)	2022	0.00229964	Normal	0.00090488	
Hospital Admissions, Respiratory	HA, Asthma	PM2.5_Daily	D24HourMean		None	Gan et al	2017	0.00732505	Normal	0.00277274	
Hospital Admissions, Respiratory	HA, Chronic Lung Disease (less Asthma)-4	PM2.5_Daily	D24HourMean		None	Delfino et al (Lag: 0-1)	2009	0.00372958	Normal	0.00174308	
Hospital Admissions, Respiratory	HA, Chronic Lung Disease (less Asthma)-4	PM2.5_Daily	D24HourMean		None	Reid et al (L: 1-2)	2019	0.00411419	Normal	0.00200663	
Hospital Admissions, Respiratory	HA, Chronic Lung Disease (less Asthma)-4	PM2.5_Daily	D24HourMean		None	Gan et al	2017	0.00806579	Normal	0.00279941	
Hospital Admissions, Respiratory	HA, Chronic Lung Disease (less Asthma)-4	PM2.5_Daily	D24HourMean		None	Malig et al (L: 0)	2021	0.00779152	Normal	0.00334591	

Selected coefficients were formatted for custom Health Impact Function import into the BenMAP-CE platform using the Database Import function in the Tools dropdown menu (Figure 9.3) and by selecting the appropriate file (Figure 9.4).

Figure 9.3. Option for importing custom coefficients into BenMAP-CE.

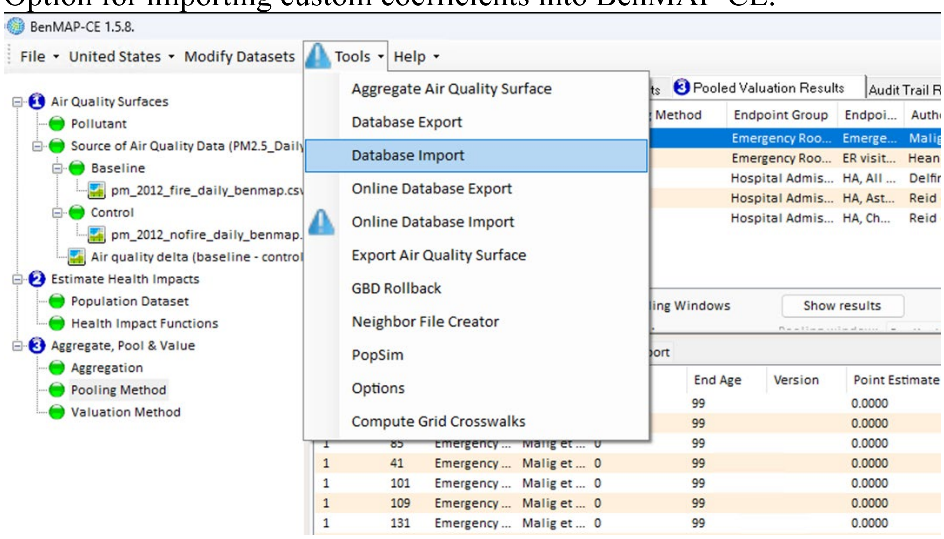
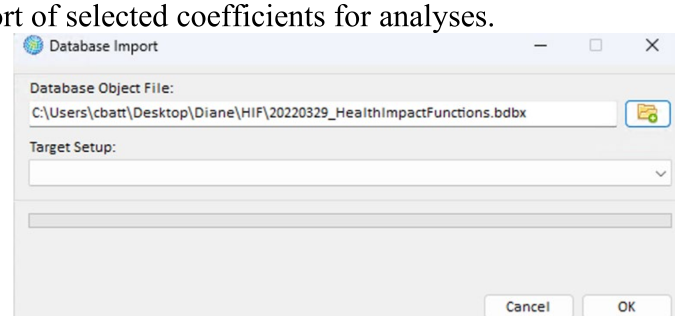
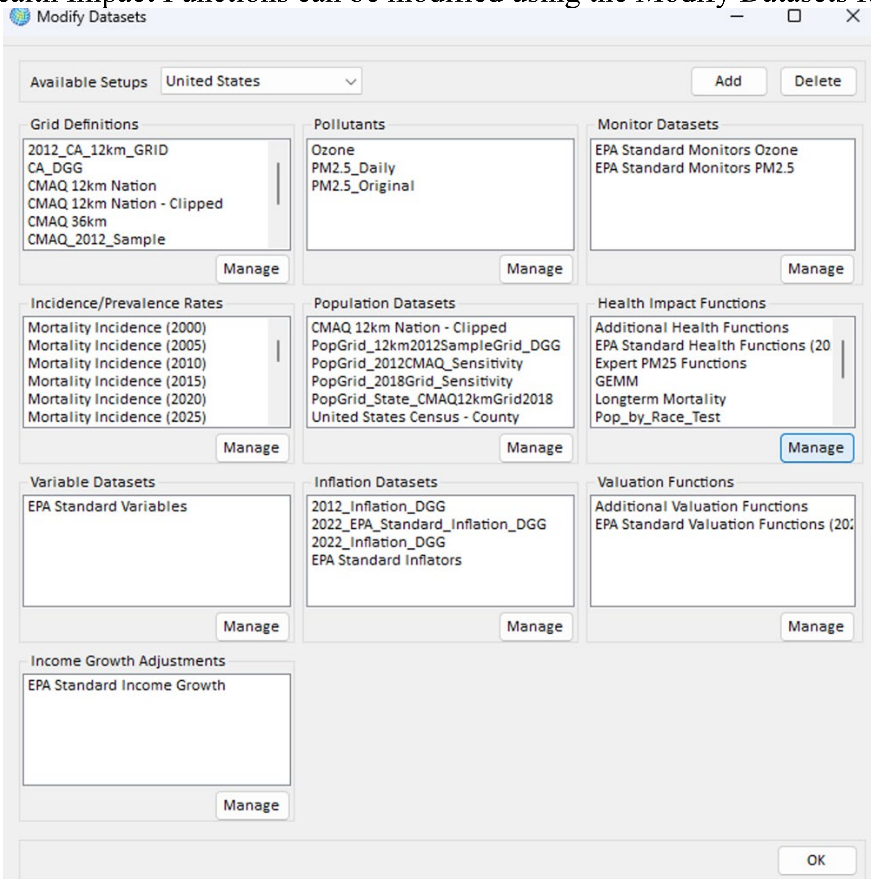


Figure 9.4. File import of selected coefficients for analyses.



Custom Health Impact Functions can be viewed in the Modify Datasets section and further updated as needed (Figure 9.5). Coefficients selected for the current study and the final extraction worksheet will be formatted and provided as a comma-separated values (CSV) file and provided as part of the final tool package.

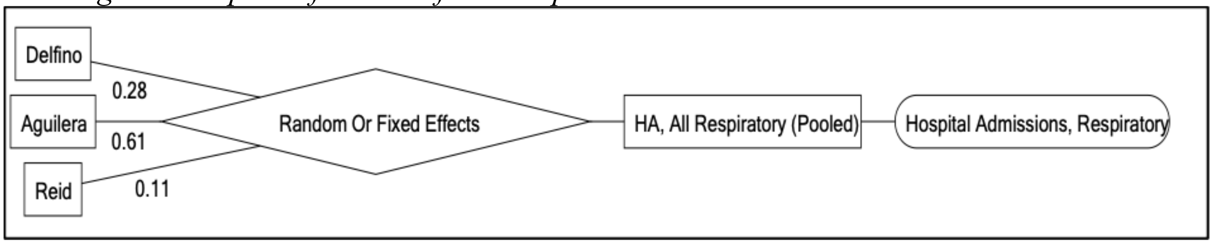
Figure 9.5. Health Impact Functions can be modified using the Modify Datasets function.



Pooling Function. For health outcomes with multiple coefficients with similar methodologies, we conducted pooling to aggregate the incidence results and place an economic value on the combined health estimates. The methods used to pool each of the health endpoints varies depending on the identified studies. The weighting scheme used for the dose-response coefficients are based on the U.S. EPA built-in pooling functions; to reference the weights applied to each dose-response coefficient in the current study, view the provided Forest Plots.

The random effects model was used to pool health estimates derived from individual study coefficients that sampled from two different populations. The random effects model assumes both within and between-study vulnerabilities; thus, the model accounts for and assigns weight based on these two factors.

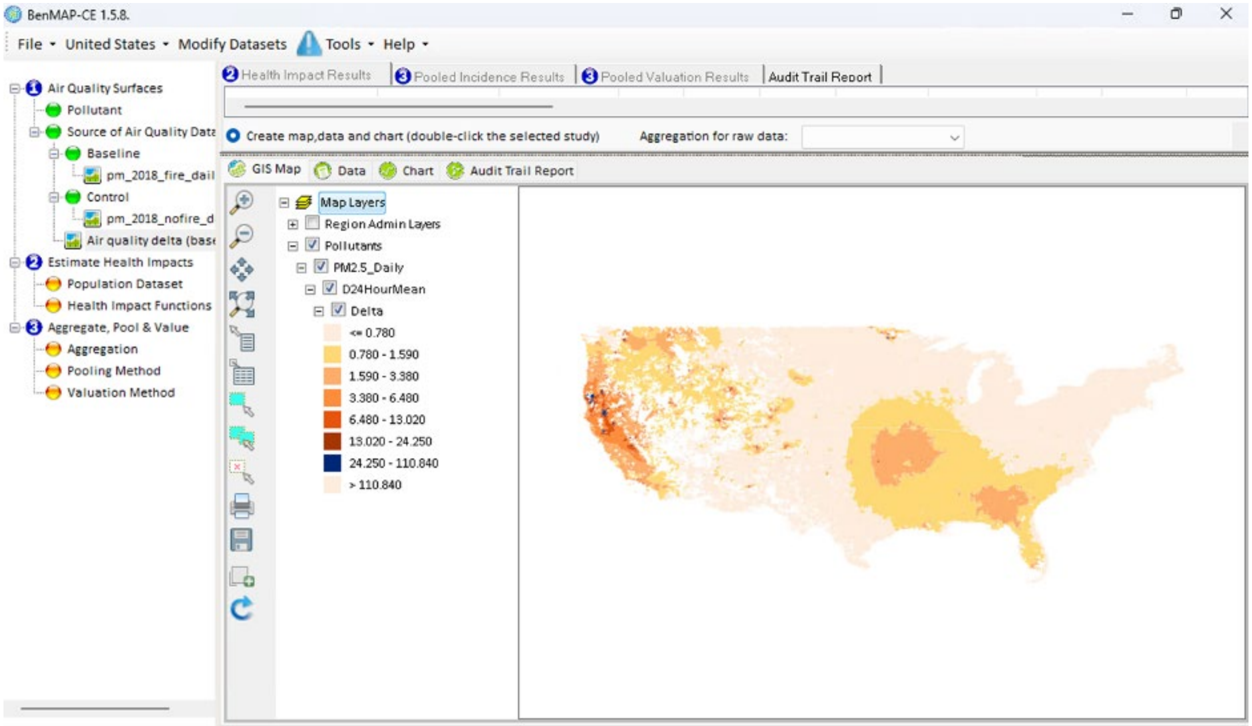
Figure 9.6. *Example pooling weights for all-cause respiratory hospital emissions in BenMAP-CE using dose-response functions from the peer reviewed literature.*



$PM_{2.5}$ Exposure Estimates. We used daily wildfire-specific $PM_{2.5}$ concentrations (µg/m^3) from 2008-2019 at a spatial resolution of 12 km developed from the CMAQ model using SMARTFIRE (Sullivan et al. 2008) emissions to simulate changes in air pollution concentrations with and without fires across the contiguous United States (Wilkins et al. 2018). Fuel consumption was calculated using the U.S. Forest Service's CONSUME version 3.0 fuel consumption model and the FCCS fuel-loading database in the BlueSky Framework (Ottmar et al. 2007). Wildland fire emissions estimates (which include wildfires, agricultural burns, and prescribed fires) incorporate multiple sources of fire activity, including Earth observations as well as federal, state, local, and tribal databases. Emission factors are taken from the FEPS model. Non-fire emissions sources are from NEI. CMAQ wildfire estimates have been reviewed and validated within the current report (see additional chapters).

Per consultation with BenMAP-CE personnel, we formatted the daily CMAQ inputs into comma separated files with columns identifying a daily 24-hour mean metric (D24HourMean), and none-specified annual statistic or seasonal metric for both all emissions (fire and non-fire sources) and without fire datasets. Once uploaded, the model is run with all emissions (baseline) and again without fires (control); the difference between the two simulations isolates the wildfire-specific $PM_{2.5}$ contribution. Wildfire-specific $PM_{2.5}$ CMAQ concentrations are shown as inputs into the BenMAP-CE program in Figure 9.2 (below).

Figure 9.7. *BenMAP-CE display with uploaded wildfire-specific $PM_{2.5}$ CMAQ concentrations for 2018 across the county.*



Population Data. In BenMAP-CE, population data is used to estimate population exposure and can be adjusted by race, ethnicity, gender, and age. When the spatial scale was not available in the BenMAP-CE platform, the population dataset was created using the PopGrid software application (www.epa.gov/benmap/benmap-community-edition), which aggregates block-level population data into a custom grid definition. For 2008 – 2012 estimates, we used PopGrid to forecast population at the specific 12-km grid definition. For years 2013 – 2018, we forecast population based on the existing 12-km national CMAQ grid pre-loaded in the BenMAP-CE software. Population for all years were estimated using the 2010 U.S. Census defined at the appropriate grid definition.

Health Data. BenMAP-CE uses 2012-2014 county-level mortality data from the Centers for Disease Control and Prevention (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER) database and use the data to generated age-, cause-, and county-specific mortality rates. Mortality rates in years 2015 through 2060, are calculated using annual adjustment factors, based on a series of Census Bureau projected national mortality rates. Hospitalization and ED visits, also referred to as ER visits, are calculated using data from the Healthcare Cost and Utilization Project (HCUP). Short-term morbidity and mortality outcomes are calculated by an existing BenMAP-CE equation (see below) but can be updated based on the needs of each unique coefficient.

$$Y= M \times (1-(1/e^{\wedge}(\times E))) \times P$$

Economic Data. We also estimated economic impacts from hospital admission and ER visits for each morbidity and mortality outcomes. Existing economic indices within BenMAP-CE are adjusted based on the 2015 currency year and scaled to the year of interest. Morbidity endpoints are based on willing to pay (WTP) and cost of illness (COI) measures and mortality endpoints are based on the VSL. Within the U.S. set-up, the valuation function has a dollar year of 2015 with inflation factors based on the All Goods, Medical Costs, and Wage Indices. For each health estimate, we used the pre-loaded U.S. EPA Standard Valuation Functions selected based on the information in the table below.

Table 9.2. *U.S. EPA Standard Valuation Function preloaded in BenMAP-CE and used for economic estimates of health impacts*

Health Outcomes	Dataset Name	Details	$ (114pprox..)
ER, Asthma	EPA Standard Valuation Functions (2021)	COI: Standford et al. (1999); mean medical cost 2015	$450
ER, Respiratory	EPA Standard Valuation Functions (2021)	Nationwide Emergency Department Sample (NEDS). Healthcare Cost and Utilization Project (HCUP). 2016	$900
HA, Chronic Lung Disease (less asthma)	Additional Valuation Functions	Mean hospital charge in 2015	$2,500
HA, Asthma	Additional Valuation Functions	Mean hospital charge in 2015	$18,600
HA, Respiratory	Additional Valuation Functions	Mean hospital charge in 2015	$32,600
Mortality	EPA Standard Valuation Functions (2021)	VSL, based on 26 value of life studies, with Cessation Lag 3% d.r.	$8,700,00

Results

A cursory, non-structured review of the direction and strength of association between wildfire exposure and health impacts in the peer-reviewed literature confirmed our initial scoping review results in terms of both respiratory and mortality impacts. We noted mixed and variable results for the association between wildfire exposures and cardiovascular outcomes as a result of the previous scoping review. While there was no clear consensus on the impacts to cardiovascular health, several initiating biological pathways have been identified and an increasing pool of evidence exists between short-term exposures and key cardiovascular outcomes (Hadley et al. 2022). The non-structured review of the literature failed to provide additional evidence for association; thus, due to the high level of uncertainty, and the lack of representative studies, we did not include cardiovascular outcomes in any further analyses.

Search keywords were tailored towards respiratory and mortality outcomes to identify additional articles with coefficients of interest. Applying the keyword to the PubMed and Web of Science databases resulted in 398 and 489 articles for respiratory and mortality outcomes, respectively (Table 9.3).

Table 9.3. *Outcome specific literature search*

Search Specific Health Outcome: Respiratory		
Database	Developed Search: Specific for Respiratory Outcomes	Date: Articles Identified

PubMed	((wildfire[Title/Abstract]) OR (“wild fire”[Title/Abstract]) OR (“controlled burn”[Title/Abstract]) OR (“prescribed fire”[Title/Abstract]) OR (“prescribed burn”[Title/Abstract]) OR (“experimental fire”[Title/Abstract]) OR (“experimental burn”[Title/Abstract]) OR (“wildland fire”[Title/Abstract]) OR (“peat fire”[Title/Abstract]) OR (“bush fire”[Title/Abstract]) OR (bushfire[Title/Abstract]) OR (“brush fire”[Title/Abstract]) OR (brushfire[Title/Abstract]) OR (“landscape fire”[Title/Abstract]) OR (“forest fire”[Title/Abstract]) OR (wildfires[MeSH Terms])) AND ((respiratory[Title/Abstract]) OR (lung[Title/Abstract]) OR (asthma[Title/Abstract]) OR (pneumonia[Title/Abstract]) OR (“respiratory tract diseases”[MeSH Terms])) Filtered by: Published in either French, English, or Spanish, 2021-2023	07/07/2023: 176
Web of Science	(TI=(wildfire*) OR TI=(“wild fire*”) OR TI=(“controlled burn*”) OR TI=(“prescribed fire*”) OR TI=(“prescribed burn*”) OR TI=(“experimental fire*”) OR TI=(“experimental burn*”) OR TI=(“wildland fire*”) OR TI=(“peat fire*”) OR TI=(“bush fire*”) OR TI=(bushfire*) OR TI=(“brush fire*”) OR TI=(brushfire*) OR TI=(“landscape fire*”) OR TI=(“forest fire*”)) AND (TI=(respiratory) OR TI=(lung) OR TI=(asthma) OR TI=(pneumonia)) Filtered by: Published in either French, English, or Spanish; 2021-01-01 – 2023-07-07; “Article”, “Review Article”	07/07/2023: 33
Web of Science	(AB=(wildfire*) OR AB=(“wild fire*”) OR AB=(“controlled burn*”) OR AB=(“prescribed fire*”) OR AB=(“prescribed burn*”) OR AB=(“experimental fire*”) OR AB=(“experimental burn*”) OR AB=(“wildland fire*”) OR AB=(“peat fire*”) OR AB=(“bush fire*”) OR AB=(bushfire*) OR AB=(“brush fire*”) OR AB=(brushfire*) OR AB=(“landscape fire*”) OR AB=(“forest fire*”)) AND (AB=(respiratory) OR AB=(lung) OR AB=(asthma) OR AB=(pneumonia)) Filtered by: Published in either French, English, or Spanish; 2021-01-01 – 2023-07-07; “Article”, “Review Article”	07/07/2023: 189
Search Specific Health Outcome: Mortality		
Database	Developed Search: Specific for Mortality	Date: Articles Identified
PubMed	((wildfire*[Title/Abstract]) OR (“wild fire*”[Title/Abstract]) OR (“controlled burn*”[Title/Abstract]) OR (“prescribed fire*”[Title/Abstract]) OR (“prescribed burn*”[Title/Abstract]) OR (“experimental fire*”[Title/Abstract]) OR (“experimental burn*”[Title/Abstract]) OR (“wildland fire*”[Title/Abstract]) OR (“peat fire*”[Title/Abstract]) OR (“bush fire*”[Title/Abstract]) OR (bushfire*[Title/Abstract]) OR (“brush fire*”[Title/Abstract]) OR (brushfire*[Title/Abstract]) OR (“landscape fire*”[Title/Abstract]) OR (“forest fire*”[Title/Abstract]) OR (wildfires[MeSH Terms])) AND ((mortality[Title/Abstract]) OR (mortality[MeSH Terms])) Filtered by: Published in either French, English, or Spanish, 2021-2023	07/14/2023: 143
Web of Science	(TI=(wildfire*) OR TI=(“wild fire*”) OR TI=(“controlled burn*”) OR TI=(“prescribed fire*”) OR TI=(“prescribed burn*”) OR TI=(“experimental fire*”) OR TI=(“experimental burn*”) OR TI=(“wildland fire*”) OR TI=(“peat fire*”) OR TI=(“bush fire*”) OR	07/14/2023: 32

	TI=(bushfire*) OR TI=("brush fire*") OR TI=(brushfire*) OR TI=("landscape fire*") OR TI=("forest fire*")) AND TI=mortality Filtered by: Published in English (was no French/Spanish), 2021-01-01 – 2023-07-14; "Article"	
Web of Science	(AB=(wildfire*) OR AB=("wild fire*") OR AB=("controlled burn*") OR AB=("prescribed fire*") OR AB=("prescribed burn*") OR AB=("experimental fire*") OR AB=("experimental burn*") OR AB=("wildland fire*") OR AB=("peat fire*") OR AB=("bush fire*") OR AB=(bushfire*) OR AB=("brush fire*") OR AB=(brushfire*) OR AB=("landscape fire*") OR AB=("forest fire*")) AND AB=mortality Filtered by: Published in either French, English, or Spanish, 2021-01-01 – 2023-07-14; "Article" "Review Article"	07/14/2023: 314

Each article was scanned for duplicates and reviewed according to the inclusion and exclusion criteria detailed in Table 9.1. After a full-text review, we identified a total of 19 peer-reviewed journal articles that were inclusive to our developed criteria. We extracted the author, publication title, respiratory or mortality ICD codes, area or region of study, wildfire timeline of interest, and main findings (Table 9.4). All relevant coefficients were formatted for inclusion into the BenMAP-CE platform for future Western U.S. specific wildfire analyses and provided in the supplementary material as a CSV document. It is important to note that all provided coefficients should be evaluated prior to inclusion into any future analyses to ensure they are appropriate for specific study aims. To demonstrate health estimates, we applied relevant dose-response values from Table 9.4 to the BenMAP-CE program to develop health and economic estimates from California- from wildfire emissions.

Table 9.4. *Respiratory and mortality health outcome articles evaluated for BenMAPs crosswalk.*

Author (Year)	Publication Title	Respiratory-specific ICD codes included	State/ Region	Wildfire Period/ Timeline	Exposure Method	Included in Analysis?
Delfino et al. (2009)	*The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003*	466; 493; 277, 460-466, 480-487, 490-496, 506, 508, 786; 460-465; 480-487; 491, 492, 496	Southern California	October 21 - 30, 2003 fire period	Spatial interpolation of $PM_{2.5}$ in fire polygons	Yes
Resnick et al. (2015)	*Health outcomes associated with smoke exposure in Albuquerque, New Mexico, during the 2011 Wallow fire.*	493; 460–519; 510-519	New Mexico; Albuquerque	June 1-13, 2011 fire period	Comparisons of $PM_{2.5}$ concentrations pre, during, and post wildfire event	No
Alman et al. (2016)	*The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: a case crossover study.*	460 - 466, 490 - 786.07	Colorado	June 5 - July 6, 2012 fire period	$PM_{2.5}$ estimates from WRF-Chem modeling using FINN emissions	No
Reid et al. (2016)	*Differential respiratory health effects from the 2008 northern California wildfires; a spatiotemporal approach.*	480 – 486, 491 - 493, 496	Northern California	May 6 - September 15, 2008 wildfire period	$PM_{2.5}$ derived using blended modeling	No; same dataset from Reid 2019
Gan et al. (2017)	*Comparison of wildfire smoke estimation methods and associations with cardiopulmonary-related hospital admissions.*	466; 493; 460-519; 480-486; 490-492, 494, 496	Washington	July 1 - October 31, 2012 wildfire period	$PM_{2.5}$ derived using WRF-Chem, kriging, and mixed methods	Yes
Hutchinson et al. (2018)	*The San Diego 2007 wildfires and Medi-Cal emergency department presentations, inpatient hospitalizations, and outpatient visits: An observational study of smoke exposure periods and a bidirectional case-crossover analysis.*	277, 460-464, 466, 480-487, 490 – 495, 496, 506, 508, 786	California; San Diego	October 2007 fire period	$PM_{2.5}$ HYSPLIT concentrations estimates	No, does not review impacts within general population
Wettstein et al. (2018)	Cardiovascular and cerebrovascular emergency department visits associated with wildfire smoke exposure in California in 2015.	480–486, 491– 493, 496, 786	California; Northern and Central CA Air Basins	May 1 - September 30, 2015 fire season	NOAA GOES smoke product grouped by light, medium, and dense smoke categories accompanied by	No; PM concentration in dense smoke categories not clearly defined

					modeled $PM_{2.5}$ estimates	
Reid et al. (2019)	*Associations between respiratory health and ozone and fine particulate matter during a wildfire event.*	460 - 466, 480 - 486, 491 - 493, 496	California; Northern and Central Air Basins	June 20–July 31, 2008 fire period	$PM_{2.5}$ estimates from spatiotemporal exposure models	Yes
Stowell et al. (2019)	*Associations of wildfire smoke $PM_{2.5}$ exposure with cardiorespiratory events in Colorado 2011–2014.*	466; 493; 460 – 465; 460 - 466, 480 - 486, 491 - 493, 496; 480-486; 496, 491 - 492	Colorado	Wildfire events from 2011 - 2014	$PM_{2.5}$ estimates from CMAQ with AOD model for smoke mask	No
Doubleday et al. (2020)	*Mortality associated with wildfire smoke exposure in Washington state, 2006-2017: a case-crossover study*	ICD-10: A01-V99, J01-J99, I05-I52, I60–67, A01-V99, J01-J99, I05-I52, I60–67	Washington state	Peak wildfire season June – September 2006 - 2017	Air Indicator Report for Public Awareness and Community Tracking (AIRPACT-4) modeled $PM_{2.5}$ using inputs from monitored daily $PM_{2.5}$ concentrations	Yes
Gan et al. (2020)	*The association between wildfire smoke exposure and asthma-specific medical care utilization in Oregon during the 2013 wildfire season.*	493	Oregon	July – August 2013	$PM_{2.5}$ estimates from kriged surface monitors, AOD, and WRF-Chem	No
Kiser et al. (2020)	*Particulate matter and emergency visits for asthma: a time-series study of their association in the presence and absence of wildfire smoke in Reno, Nevada, 2013–2018.*	493.00–493.92	Nevada; Reno	Wildfire events 2013 - 2018	Qualifying 24-h average $PM_{2.5}$ from four air quality monitors	No
Aguilera et al. (2021)	*Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California.*	460 - 519	California; Southern	Wildfire season between 1999-2012	$PM_{2.5}$ estimated via three approaches: imputation approach, interaction model, seasonal interpolation	Yes
Casey et al. (2021)	*Wildfire particulate matter in Shasta County, California and respiratory and circulatory disease-related emergency department visits and mortality, 2013-2018*	460 - 519	California; Shasta County	51 major wildfires from 2013 - 2018 in Shasta County & Carr Fire (2018)	Spatiotemporal multiple imputation approach	No, weekly averages may not be appropriate for pooling

Hahn et al. (2021)	*Wildfire Smoke Is Associated With an Increased Risk of Cardiorespiratory Emergency Department Visits in Alaska*	466, 480-486, 490-494, 496; 493; 466; 490-492, 494, 496; 480-486	Alaska, Anchorage, Fairbanks, and the Matanuska-Susitna Valley	2015–2019 wildfire seasons	$PM_{2.5}$ concentrations from wildfire days determined via established criteria using both PM and smoke plume data	No
Magzamen et al. (2021)	*Differential Cardiopulmonary Health Impacts of Local and Long-Range Transport of Wildfire Smoke*	460–519; 493; 490–492, 494, 496; 480–486; 466	Colorado; Front Range	May – October wildfire season from 2010-2015	Daily kriged $PM_{2.5}$ based on ground stations with satellite-based smoke plumes to identify smoke days	No
Malig et al. (2021)	*Examining fine particulate matter and cause-specific morbidity during the 2017 North San Francisco Bay wildfires*	ICD10: J00-J06; J45, R06.2; J40-J44, J47; J12-J18; J00-J99 J00-J06; J45, R06.2; J40-J44, J47; J12-J18; J00-J99	California; nine Northern counties	October 2017 North San Francisco Bay wildfires	38 PM monitors assigned population-weighted concentration at block group level	Yes
Heaney et al. (2022)	*Impacts of Fine Particulate Matter From Wildfire Smoke on Respiratory and Cardiovascular Health in California*	493; 460–466; 490–492; 460–519	California; statewide	May 1-October 31 fire season for years 2004-2009	$PM_{2.5}$ derived from Global Fire Emissions Database via GEOS-Chem modeling	Yes
Doubleday et al. (2023)	*Wildfire smoke exposure and emergency department visits in Washington State*	ICD10: A01-R99; J01-J99; J45	Washington	June-September from 2017-2020	Air Indicator Report for Public Awareness and Community Tracking (AIRPACT-4) used to model $PM_{2.5}$ on binary indicator of wildfire smoke-impacted day	No

BenMAP-CE Crosswalk

The crosswalk between the identified and relevant dose-response values within the western U.S. region and BenMAP-CE health datasets resulted in the selection and inclusion of a total of six studies to develop our state-specific health estimates from wildfire exposure (noted in Table 9.4). The results of the crosswalk are provided in Table 9.5 below with corresponding coefficients and detailed in the following sections for each specific health outcome.

Each article in Table 9.4 was reviewed in detailed and evaluated for inclusion in the BenMAP-CE crosswalk analysis as detailed in the methods section. Through the developed crosswalk, we identified the following health outcomes for tool inclusion: ER visits for all respiratory and asthma outcomes; hospitalizations for all respiratory, asthma, chronic lung disease (less asthma) and all-cause mortality. The outcome of this crosswalk with details on ICD value differences are included in Table 9.4.

Table 9.5. *Dose-response values selected from the BenMAP-CE crosswalk for California-specific health estimates for respiratory and mortality outcomes.*

Health Outcome	BenMAP-CE ICD-9 Code	Select Studies in Western US	Study-specific ICD Code	% Risk per 1 $\mu g/m^3$ [95% CI]
HA: Asthma	493	Southern California: Delfino et al (2009)	493	0.47 [0.21, 0.73]
		Northern California: Reid et al (2019)	493	1.31 [0.79, 1.83]
		Northern California: Malig et al (2021)	ICD10: J45, R06.2	0.56 [-0.26, 1.41]
		Washington: Gan et al. (2017)	493	0.73 [0.19, 1.28]
		Statewide: Heaney et al. (2022)	493	0.23 [0.05, 0.41]
HA: Chronic lung disease (less asthma)	490-492, 494, 496	Southern California: Delfino et al (2009)	491, 492, 496	0.37 [0.04, 0.72]
		Northern California: Reid et al (2019)	491, 492, 496	0.41 [0.02, 0.81]
		Northern California: Malig et al (2021)	ICD10: J40-44, 47	0.78 [0.13, 1.44]
		Washington: Gan et al. (2017)	490-492, 494, 496	0.81 [0.26, 1.35]
HA: All Respiratory	460-519	Southern California: Delfino et al (2009)	277, 460-466, 480-487, 490-496, 506, 508, 786	0.28 [0.14, 0.40]
		Southern California: Aguilera et al (2021)	460-519	0.13 [0.04, 0.22]

		Northern California: Reid et al (2019)	460 - 466, 480 - 486, 491 - 493, 496	0.38 [0.17, 0.59]
		Northern California: Malig et al (2021)	J00-J99	1.13 [0.30, 1.91]
		Statewide: Heaney et al. (2022)	460 - 519	0.08 [0.01, 0.14]
		Washington: Gan et al. (2017)	460-519	0.51 [0.25, 0.77]
ER visits: Asthma	493	Northern California: Reid et al (2019)	493	1.09 [0.86, 1.31]
		Northern California: Malig et al (2021)	ICD10: J45, R06.2	1.76 [1.35, 2.14]
ER visits: All Respiratory	460- 466, 477.0-477.9, 480-486, 491-493, 496, 786.07, 786.09	Northern California: Reid et al (2019)	460 - 466, 480 - 486, 491 - 493, 496	0.34 [0.24, 0.44]
		Northern California: Malig et al (2021)	J00-J99	0.85 [0.56, 1.12]
Mortality: All-cause	All	Washington: Doubleday et al (2020)	A01-V99 (ICD-10)	0.09 [0, 0.22]

Coefficients were scaled based on the PM changes per unit increase in risk and the resulting beta was added as a BenMAP-CE coefficient. The program was run with the inputs detailed in the methods section and the results are summarized in the table below.

Table 9.6a. *Health outcomes for all identified dose-response coefficients from 2008-2018 for emergency room visit morbidity and mortality.*

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
ER visits, Asthma											
Reid (2019)	4,039	1,012	556	692	742	1,505	903	1,415	1,751	4,309	4,964
Malig (2021)	6,039	1,585	868	1,108	1,187	2,373	1,426	2,206	2,709	6,425	7,536
Pooled Estimates	4,995 (3,287 - 6,821)	1,283 (808 - 1,821)	704 (444 - 995)	888 (547 - 1,284)	952 (588 - 1,374)	1,916 (1,198 - 2,733)	1,150 (719-1,643)	1,791 (1,132- 2,531)	2,205 (1,406 - 3,100)	5,320 (3,516 - 7,257)	6,190 (4,014- 8,556)
Value Estimates (USD $)	1,817,540	481,822	273,267	355,220	394,844	814,008	500,492	799,509	1,022,095	2,527,272	2,998,882
Arriagada (2019)	2,659	643	353	433	465	952	571	903	1,125	2,855	3,230
ER visits, Respiratory Morbidity											
Reid et al (2019)	8,535	1,994	1,107	1,325	1,448	2,931	1,787	2,842	3,639	9,105	10,292
Malig (2021)	19,455	4,788	2,657	3,247	3,538	7,069	4,289	6,756	8,523	20,490	23,755
Pooled Estimates	13,698 (6,066 - 23,442)	3,305 (1,400 - 5,872)	1,834 (777 - 3,258)	2,224 (926 - 4,011)	2,426 (1,012 - 4,368)	4,872 (2,056 - 8,685)	2,960 (1,257- 5,266)	4,680 (2,001- 8,264)	5,936 (2,580 - 10,390)	14,486 (6,526 - 24,668)	16,641 (7,309- 28,779)
Value Estimates (USD $)	9,762,488	2,430,388	1,394,953	1,742,625	1,970,608	4,054,387	2,522,630	4,093,172	5,387,934	13,479,317	15,790,252
Gould (2023)	8,906	2,085	1,157	1,386	1,515	3,065	1,868	1,558	3,800	9,493	10,292
Mortality											
Doubleday et al (2020)	8,787	2,023	1,083	1,373	1,560	2,890	1,856	2,946	3,804	11,266	10,958
Value Estimates in millions (USD $)	62,978	14,440	7,858	10,280	11,922	22,403	14,622	23,236	30,379	91,899	91,569

Table 9.7a. *Health outcomes for all identified dose-response coefficients from 2008-2018 for hospitalizations.*

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Hospitalizations, Asthma											
Delfino (2009)	316	81	45	52	56	117	69	109	153	372	414
Reid (2019)	796	216	119	144	153	317	187	289	400	921	1,059
Malig (2021)	373	96	53	62	66	139	82	129	181	437	489
Heaney (2022)	161	40	22	26	27	58	34	54	77	192	210
Gan (2017)	477	124	69	81	87	181	107	167	234	556	627
Pooled Estimates	410 (47 - 950)	106 (9 - 261)	59 (5 - 144)	69 (6 - 177)	73 (7 - 188)	154 (15 - 387)	92 (15-228)	143 (516-351)	203 (34 - 483)	487 (86 - 1,096)	548 (92-1,268)
Value Estimates (USD $)	6,437,654	1,718,047	985,257	1,188,445	1,311,058	2,823,411	1,730,010	2,754,658	4,052,127	9,949,505	11,408,116
Arriagada (2019)	387	100	55	65	69	145	86	134	188	453	508
Hospitalizations, Respiratory Morbidity											
Delfino et al (2009)	1,688	405	223	263	297	604	371	589	800	1,985	2,286
Gan (2017)	2,977	733	403	481	542	1,096	670	1,060	1,430	3,465	4,037
Reid et al (2019)	2,295	557	307	364	411	832	509	808	1,094	3,324	3,107
Malig et al (2021)	2,855	701	386	460	518	1,048	641	1,015	1,369	2,589	3,870
Aguilera et al (2021)	800	188	104	122	137	280	173	275	378	960	1,089
Heaney (2022)	484	113	62	73	82	168	104	166	229	590	662
Pooled Estimates	1,643 (225 - 3,903)	391 (52 - 978)	215 (29 - 539)	253 (34 - 647)	286 (38 - 729)	583 (78-1,466)	358 (49 - 894)	570 (77 - 1,411)	775 (108-1,896)	1,900 (470-3,800)	2,222 (311-5,311)
Value Estimates (USD $)	45,008,940	11,053,758	6,286,195	7,623,072	8,917,660	18,616,262	11,707,391	19,113,438	26,967,120	68,142,144	80,862,208
Gould (2023)	1,536	367	202	238	286	548	336	534	727	1,810	2,080
Hospitalizations, COPD											
Delfino et al (2009)	373	89	48	59	68	135	85	134	178	436	516
Gan (2017)	750	188	102	127	145	287	179	281	370	874	1,048

Reid et al (2019)	409	98	53	65	74	149	93	148	195	477	565
Malig (2021)	727	182	99	122	140	277	173	272	358	848	1,016
Pooled Estimates	502 (25 - 1,056)	120 (6 - 275)	65 (3 - 150)	79 (4 - 188)	91 (4 - 215)	182 (8 - 421)	114 (5 - 262)	180 (9-409)	239 (12 - 536)	584 (31 - 1,237)	681 (35-1,493)
Value Estimates (USD $)	10,537,459	2,587,259	1,455,160	1,820,971	2,166,411	4,445,558	2,849,159	4,630,381	6,352,915	15,956,077	18,963,560

Conclusion

The methods outlined here provide a flexible approach to estimate health outcomes from wildfire specific exposures in the absence of region-specific meta-analyses. It was important incorporate flexibility into the final tool to allow researchers to updates coefficients of exposure as new and relevant epidemiological studies emerge and/or the direction or the strength of association between exposure and health impacts shift. During or initial and follow-up review of the literature, both structured and unstructured, we identified a single meta-analysis in the peer-reviewed literature that would have allowed for an impact evaluation within the BenMAP-CE environment. In this work, authors evaluated multiple asthma presentations in hospital admissions and ER visits (Arriagada et al., 2019) and included global coefficients from non-Western U.S. regions including Canada, Australia, and the East Coast for pooling. While this meta-analysis was not appropriate for our specific aims, we did use the coefficient from Arriagada et al. 2019 and Gould et al. 2023 to compare outcomes to our own. For the two health outcomes that overlapped, we compared and noted our own pooled estimates to be higher than those estimated from the meta-analysis which may be due to the California-specific studies utilized in our work.

X. Scenario Development: STILT and FINN Validation

Abstract

Wildfire pollution in California has been growing as fires have become larger and more severe. Fine particulate matter ($PM_{2.5}$) pollution from fires poses an important health risk to exposed populations, and it is increasingly important to understand and mitigate health impacts. The Stochastic Time-Inverted Lagrangian Transport Model (STILT) is a receptor-oriented, atmospheric transport model, which is a powerful tool to quantify the influence of different emissions sources and to efficiently model the impact of multiple emissions scenarios on downwind air quality. In this study, we coupled STILT with high resolution fire emissions estimates from the Fire Inventory from NCAR (FINNv2.5) in 2018. The 16 selected STILT receptors are co-located with station monitors from government-regulated station networks and represent 14 of the 15 California Air Basins with two additional stations highly influenced by the 2018 fires. We compared the STILT-FINNv2.5 simulated $PM_{2.5}$ concentrations to observed $PM_{2.5}$ values at the station monitors. Modeled concentrations from STILT-FINNv2.5 were significantly correlated with station observations at 8 of the 16 receptors and the strength of these significant correlations varied ($0.38 \leq r \leq 0.86$). Because we did account for other emissions sources, receptors more influenced by fires typically had stronger, more significant correlations between modeled and observed $PM_{2.5}$ concentrations. This validation work supports the NWL Health Scenario Tool, which models the impact of the 2018 wildfires on $PM_{2.5}$ concentrations at California's 58 population-weighted county centroids. The uncertainties around this STILT-FINNv2.5 model framework, especially for areas with lower fire influence, where other emissions sources dominate, should be considered when using the NWL Health Scenario Tool.

Introduction

Wildfire burned area in California has increased dramatically in recent decades, with an eightfold increase in the summer season since the 1970s (Williams et al., 2019) with a corresponding increase in annual area burned at high severity (Parks & Abatzoglou, 2020). This growth in fire activity can be attributed to several interacting factors, including anthropogenic climate change (Parks & Abatzoglou, 2020; Williams et al., 2019), a history of fire exclusion policies that have promoted fuel build-up in forests (Stephens et al., 2009), and the expansion of the wildland-urban interface (Radeloff et al., 2018). As climate change accelerates, wildfire burned area in California will likely continue to increase and large wildfires will occur more frequently (Westerling, 2018). These fires emit harmful air pollutants, including $PM_{2.5}$ and hundreds of gaseous compounds (Jaffe et al., 2020). Depending on the severity of future climate change coupled with various development scenarios, wildfire emissions in California could increase 19-101% above the 1961-1990 baseline by 2100 (Hurteau et al., 2014). Population exposure to fire pollution, especially $PM_{2.5}$, poses important health consequences— resulting in an increased risk for respiratory-related hospitalization and ED visits (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a; Delfino et al., 2009; Hutchinson et al., 2018; Reid, Jerrett, et al., 2016b), adverse cardiovascular events (H. Chen et al., 2021), and mortality (Cascio, 2018). It is increasingly important to understand the impacts of fires on historical $PM_{2.5}$ population exposure and to predict and mitigate future wildfire pollution impacts under different fire management scenarios.

Numerous studies have estimated the impact of fires on ambient $PM_{2.5}$ levels and population exposure through several methods, including atmospheric and chemical transport models, machine learning statistical algorithms, other approaches utilizing satellite-based estimates of smoke transport and ground monitor data, and combinations of these approaches (Burke et al., 2021; Childs et al., 2022; Neumann et al., 2021; O'Dell et al., 2019). Each approach has strengths and weaknesses (Cohan & Napelenok, 2011; J. C. Liu et al., 2015; Reid, Brauer, et al., 2016a). Among the atmospheric transport modeling approaches, backward, receptor-oriented atmospheric models like STILT are useful tools to quantify the influence of various emissions sources and simulate multiple emissions scenarios. As a Lagrangian particle dispersion model, STILT also offers some advantages over gridded atmospheric modeling tools, like GEOS-Chem and CMAQ, because it can capture small-scale differences in the distribution of surface fluxes that are not captured by gridded transport models (Lin et al., 2003). It also offers a computationally efficient method for modeling the impact of multiple emissions scenarios on downwind air quality. Previous studies have successfully utilized STILT in conjunction with historical data from fire emissions inventories to estimate fire-derived pollutant concentrations and validated their estimates against station data (Cusworth et al., 2018; Mallia et al., 2015; Wilmot et al., 2022). With a receptor-oriented model like STILT, researchers can identify potential source regions contributing to the observed pollutant concentrations and determine how much a particular source, such as a fire, is contributing to pollution at the receptor site. In the context of NWL in California, STILT can evaluate how different potential land management scenarios— and their expected changes in fire emissions— could impact downwind pollutant concentrations. California is considering the trade-offs of local, short-term prescribed burning, which can potentially be utilized to fuel load and future fire emissions, against infrequent, large, and intense wildfires (B. A. Jones et al., 2022; Wiedinmyer & Hurteau, 2010; Williamson et al., 2016).

We currently lack information examining trade-offs between wildland fire management strategies on downwind air pollution, but STILT, as a receptor-oriented model, can be used to rapidly evaluate different emissions scenarios and their impact on downwind air pollution concentrations (Cohan & Napelenok, 2011). In this study, we evaluated the modeled concentrations produced by STILT, coupled with a highly spatially-resolved fire emissions inventory, FINNv2.5. Using government-regulated station monitors as STILT receptors, we compare the modeled, fire-specific $PM_{2.5}$ concentrations to the measured total $PM_{2.5}$ at the station monitors. This validation work supports the NWL Health Scenario Tool, which models the impact of the 2018 fires on $PM_{2.5}$ concentrations at California's 58 population-weighted county centroids. Furthermore, our tool leverages STILT's computational advantages to model hypothetical scenarios of increased prescribed burning and decreased wildfire emissions across the state.

Materials and Methods

2.1 Fire Emissions Inventory

We utilized emissions from FINNv2.5, which provides daily, finely spatially-resolved (1-km^2) global emissions estimates. FINN is a widely used fire emissions inventory that has been employed to determine the effects of fire activity on air quality and public health (Crippa et al., 2016; Nawaz & Henze, 2020). While previous iterations of FINN, such as FINNv1 and FINNv1.5, underestimated biomass burning emissions in California and the western U.S. (Koplitz et al., 2018;

Pfister et al., 2011), FINN is a 'bottom-up' inventory that estimates fire emissions based on satellite active fire detections, combined with fuel loads from land cover maps, biomass combustion estimates, and emissions factors for individual species (Wiedinmyer et al., 2011). In addition to the 1-km resolution Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 (MCD14DL) detections from version 1, FINNv2.5 incorporates 375-m resolution Visible Infrared Imaging Radiometer Suite (VIIRS) fire detections, which allows the inventory to account for smaller fires missed by MODIS (Wiedinmyer et al., 2023). FINNv2.5 uses an updated algorithm to calculate burned area based on fire detection points and their resolutions (375-m^2 rectangles for VIIRS and 1-km^2 rectangles for MODIS) with adjustments for fire aggregation and land cover type. Fire detections in proximity to one another are aggregated when satellite detection rectangles overlap and an extended fire polygon is generated to estimate burned area, which improves estimates for larger fires and utilizes multiple satellite products simultaneously without double-counting fires.

2.2 Atmospheric Model Simulations

2.2.1 STILT

To model the impact of fires on $PM_{2.5}$ concentrations at our receptors, we coupled an atmospheric model, STILT, with FINNv2.5 emissions. STILT is a receptor-oriented, Lagrangian particle dispersion model, meaning it tracks an ensemble of individual air parcels backward in time from a chosen receptor location to their respective source locations. The backward dispersion model is the heart of STILT, and it is responsible for calculating the trajectory of air parcels by simulating the complex interactions of winds, turbulence, and atmospheric stability. Meteorological data is the second key component of STILT, and it includes information on wind speed and direction, temperature, humidity, and atmospheric stability. With the modeling framework and the meteorological data simulating air parcel back trajectories, STILT generates a gridded 'footprint' quantifying the influence of upwind grid cells on the receptor at a given point in time (Lin et al., 2003). STILT footprints can be convolved with emission inventory data, which provides information on the spatial and temporal distribution of pollutant sources. Emissions fluxes are coupled with STILT footprints to estimate the concentrations of air pollutants provided by the inventory (i.e., $PM_{2.5}$) at the receptor site (Fasoli et al., 2018; T. Liu et al., 2020; Mallia et al., 2015; Nehrkorn et al., 2010).

In this study, STILT was driven by meteorological data from the High-Resolution Rapid Refresh (HRRR) model at 3km-resolution (Benjamin et al., 2016). The model was run on 99 selected days in the 2018 fire season at 6-hour intervals for each of the 16 receptors (Figure 10.1). The footprints generated at 6-hour intervals: morning (6 am), noon (12 pm), evening (6 pm), and night (12 am), were averaged to generate a daily mean footprint raster. The daily mean footprint was coupled with the daily FINNv2.5 emissions, which were aggregated up from 1km^2 to 3km^2 to match the model spatial resolution, to estimate the mean $PM_{2.5}$ concentrations at each receptor site for each day. The modeling days were chosen based on the overlap between station availability at our receptor sites and high-emissions fire days (classified as days in the 75th percentile or above for $PM_{2.5}$ emissions from a California-specific emissions inventory: the Wildfire Burn Severity and Emissions inventory) (Xu et al., 2022) (Figure 10.1).

2.2.2 Receptor Site Selection

To directly validate modeled fire $PM_{2.5}$ concentrations against observed data, we chose model receptors in California from station monitors within the EPA's Air Quality System (AQS) and Interagency Monitoring of Protected Visual Environments (IMPROVE) networks (*Improve – Interagency Monitoring of Protected Visual Environments*, 2022; US EPA, 2014b) (Figure 10.2). We prioritized the inclusion of stations with maximum data availability during the 2018 fire season (defined as June 1st to November 30th) from each of California's Air Basins to capture variation in the state's geography, meteorology, and ecology and any additional stations that were highly impacted by the 2018 fires (Figure 10.2). Within the air basins, we also prioritized receptor sites to include communities with significant population exposure and smaller communities with extreme fire pollution exposure. For each air basin, we chose one station with the greatest zip code population according to ACS data and any stations in the 90th percentile or greater for annual mean fire-derived $PM_{2.5}$ according to CMAQ modeling (US Census Bureau, 2019a). It is important to note that annual mean CMAQ fire-derived $PM_{2.5}$ concentrations are for all of 2018, not just the selected STILT dates, and that CMAQ is an imperfect representation of fire influence at a coarser 12 km resolution than STILT-FINNv2.5 model.

2.3 Validation with Station Monitor Data

We evaluated the model outputs for fire-derived $PM_{2.5}$ concentrations against EPA and IMPROVE observed $PM_{2.5}$. As we selected high fire days for STILT modeling, we expect that fire $PM_{2.5}$ will often be the dominant source of $PM_{2.5}$ and will explain much of the variability in our $PM_{2.5}$ concentrations during fire season. Some receptor sites, however, are located far from fire locations during the 2018 fire season, and other sources of pollution will dominate. For each receptor site in the 2018 fire season, we calculated Pearson Correlation Coefficients between modeled concentrations from STILT and FINNv2.5 and observed $PM_{2.5}$ concentrations. The modeled concentrations represent wildland fire-specific $PM_{2.5}$ concentrations, but the observed concentrations represent all sources of $PM_{2.5}$ contributing to pollution. Moreover, not all receptors will be affected by fires on each day of modeling. As a result, the modeled data will not perfectly match the observations, as discussed in other STILT modeling studies (Wilmot et al., 2022), especially for receptors impacted more strongly by other anthropogenic sources of pollution. The modeled concentrations should be less than or equal to the observed concentrations, depending on the relative strength of the contribution from non-fire pollution emissions compared to wildfire sources. To account for the differential impact of fires on our receptors, we ranked the receptors based on the 2018 annual mean fire-derived $PM_{2.5}$ concentrations from CMAQ; receptors with greater fire influence should have better correlations between the modeled and observed $PM_{2.5}$ concentrations. To account for receptor-specific systematic bias, we also grouped results from all receptors and examined the correlation between all STILT-FINNv2.5 estimates and observations.

Results

3.1 Model Validation

3.1.1 Time Series Evaluation

The STILT-FINNv2.5 modeling framework varied in its ability to replicate observed station $PM_{2.5}$ concentrations on high fire days and the level of agreement was highly dependent on the receptor and day. The station receptors also varied in their data availability and for most stations, we did not have station observations to match each day of modeling (minimum number of sample days = 27, maximum =99). For the time series in Figure 10.5, the receptors are shown in descending order for CMAQ-estimated fire influence. The station monitor concentrations were generally greater than the STILT-FINNv2.5 concentrations, especially for the receptors with less fire influence (as estimated by CMAQ) (Figure 10.5). In some instances, the STILT-FINNv2.5 model failed to simulate extreme $PM_{2.5}$ concentrations during the fire season, such as on 11/16/18 at Chico-East Avenue when the observed concentration was 411 $\mu g/m^3$ but the modeled concentration was only 28.7 $\mu g/m^3$ (Figure 10.5). The STILT-FINNv2.5 model, however, sometimes overestimated the observed concentrations at the receptors with greater fire influence, simulating extremely high $PM_{2.5}$ levels. For instance, at the Cortina Indian Rancheria receptor on 8/3/18, STILT-FINNv2.5 estimated that the daily mean fire-derived $PM_{2.5}$ concentration was 356 $\mu g/m^3$ while the station reported the daily mean $PM_{2.5}$ concentration as 62.5 $\mu g/m^3$ and on 7/31/18 at the Trinity National Forest receptor, the STILT-FINNv2.5 concentration was 611 $\mu g/m^3$ while the station observation was 43.4 $\mu g/m^3$ (Figure 10.5).

3.1.2 Correlations between Modeled $PM_{2.5}$ and Observations

The correlations between STILT-FINNv2.5 modeled concentrations and the observed concentrations varied by receptor (Figure 10.6). For 8 of the 16 receptors, there was a statistically significant correlation between the modeled and observed concentrations that had the expect sign ($p < 0.05$) (Table 10.1), but the strength of the correlations varied ($0.38 \leq r \leq 0.86$). When combining the data from all receptors, there was also a relatively weak but significant correlation between modeled and observed concentrations ($r = 0.28$, $p < 0.01$) due partly to the large sample size (n=1102) (Figure 10.7). For the correlation plots and corresponding table (Figure 10.6, Table 10.1), the receptors are shown in descending order by the CMAQ annual mean fire-derived $PM_{2.5}$ concentrations. The receptors with greater CMAQ fire-derived $PM_{2.5}$ were often more likely to have significant correlations (Figure 10.6, Table 10.1). Of the first eight receptors with the greatest CMAQ fire-derived $PM_{2.5}$ concentrations, seven had significant correlations between modeled and observed values (Table 10.1). The relationship between fire influence and correlation coefficient was not always consistent. When plotting the receptor's CMAQ fire $PM_{2.5}$ against their correlation coefficients, there was a positive but statistically insignificant relationship (Figure C10.8) ($r = 0.32$, $p = 0.22$). The regression was affected by a few outliers, such as Lake Tahoe Community College, where the CMAQ annual mean fire $PM_{2.5}$ was on the lower end at 2.28 $\mu g/m^3$ but correlation coefficient was very high ($r = 0.82$), and White Mountain Research Center, where CMAQ estimated the annual mean fire $PM_{2.5}$ was only 1.32 $\mu g/m^3$ but the correlation coefficient was 0.86— the highest for any receptor (Table 10.1).

Discussion

For the 2018 fire season in California, we used STILT to simulate how fire emissions from FINNv2.5 affected downwind $PM_{2.5}$ concentrations. With 16 stations from the EPA AQS and IMPROVE networks representing our receptors, we evaluated the modeled daily $PM_{2.5}$ concentrations against station observations. While we had 99 days of modeled concentrations in the 2018 fire season (representing high fire days between June 5th to November 21st), the station data availability was more limited and varied by receptor. We did not expect consistently-high correlations between modeled and observed values because we were only considering one emissions source, but to validate our modeling, we compared the modeled and observed concentrations as a time series, plotted the regression lines, and calculated the correlations coefficients. Half of the receptors had a significant correlation between modeled and observed concentrations, while receptors with greater fire influence, estimated by CMAQ, were more likely to have significant correlations. Anomalies, however, existed in the relationship between estimated fire influence and the correlation coefficient. Moreover, for some receptors with high fire influence, there were a few days when the STILT-FINNv2.5 greatly overestimated the observed $PM_{2.5}$ concentrations.

Our results generally fit our expectations regarding the relationships between receptor modeled and observed concentrations. We expected the STILT-FINNv2.5 modeled $PM_{2.5}$ concentrations, based on fire emissions alone, to be lower than the observed concentrations. This was generally true, but there were some exceptions, especially at receptors with very high estimated fire influence. These discrepancies between modeled and observed $PM_{2.5}$ could be at least partially attributed to vertical wildfire plume transport. While STILT assumes that all emissions are emitted at the surface and transported in the boundary layer of the atmosphere, the heat from wildfires can add buoyancy to the air and increases the vertical transport of wildfire plumes (Mallia et al., 2018). Underestimating the wildfire plume height can result in an overestimate of local air pollution (i.e., for these receptors closer to fires). In these cases where the fire was a greater source of air pollution, stations with higher estimated fire influence had stronger, more significant correlations between modeled concentrations and observations. Given our prioritization of statewide geographic coverage, station availability, and population size in our receptor selection, we have more receptors, especially in Southern California, with little fire influence and poor correlations. Still, the CMAQ-estimated fire influence did not always predict the strength and significance of the correlation coefficients, because CMAQ is an imperfect model run at a coarser resolution ($12km^2$ compared to $3km^2$ for STILT). In addition to fire influence, the impact of anthropogenic pollution on these receptors can also impact the correlations.

This study utilizes a powerful receptor-oriented, dispersion model with a finely resolved emissions inventory and meteorological grid, which better captures small spatial differences in surface fluxes and fine-scale transport. Moreover, the receptors are located at EPA AQS and IMPROVE station monitors, so the modeled and observed concentrations are spatially coincident. We sought maximum data availability and chose receptors geographically distributed across California to match the spatial distribution of our 58 county centroids in the NWL Health Scenario Tool. Our study nevertheless also had several limitations. Our STILT-FINNv2.5 model only accounts for fire emissions, not other sources contributing to the observed concentrations. Since we prioritized station data availability and geographic coverage when choosing receptors, several receptor locations had low fire influence— some likely had greater anthropogenic pollution contributions— and that resulted in poor correlations. Additionally, the STILT model did not account for wildfire plume rise, likely resulting in overestimates of local air pollution surrounding fires. It is important to note that STILT only considers primary fire emissions, not secondary aerosol formation contributing to $PM_{2.5}$ mass (Hodshire et al., 2019; Lin et al., 2003), which could contribute to underestimates in modeled $PM_{2.5}$ concentrations. Due to computational limitations, our backward simulations in STILT lasted 24 hours and did not capture the effect of more distant fires on air quality at our receptors, since aerosols can be transported over much larger distances (>1000 km) downwind of a fire (Sapkota et al., 2005).

Conclusions

In this study, we evaluated the STILT-FINNv2.5 model simulations for fire-derived $PM_{2.5}$ concentrations against EPA AQS and IMPROVE station monitor data. This study supports the NWL Health Scenario Tool, which models the impact of the 2018 fires on $PM_{2.5}$ concentrations at California's 58 population-weighted county centroids and the influence of potential management scenarios. We chose 16 receptors representing station monitors across California's air basins with high data availability in the 2018 fire season and higher population exposure or high fire impact. The stations with greater fire influence were more likely to have significant, stronger correlations between modeled and observed concentrations, because the modeled values only reflected fire $PM_{2.5}$ while the station observations represent all sources of $PM_{2.5}$. However, the estimated fire impact from CMAQ did not always predict the strength and significance of the correlation coefficient— likely because CMAQ has its own limitations and the degree of anthropogenic pollution at each receptor will also affect the correlation. It is important to keep in mind that STILT did not always simulate the extreme $PM_{2.5}$ concentrations observed at the stations during the fire season or overestimated the $PM_{2.5}$ levels. These uncertainties will affect the concentrations and health impacts in the NWL Health Scenario Tool.

Tables & Figures

Figure 10.1. *Daily California statewide emissions in the 2018 fire season (June 1st to November 30th) and the selected STILT days above the 75th percentile for annual $PM_{2.5}$ wildfire emissions. The emissions estimates from the WBSE (the Wildfire Burn Severity and Emissions) inventory, a California-specific data source.*

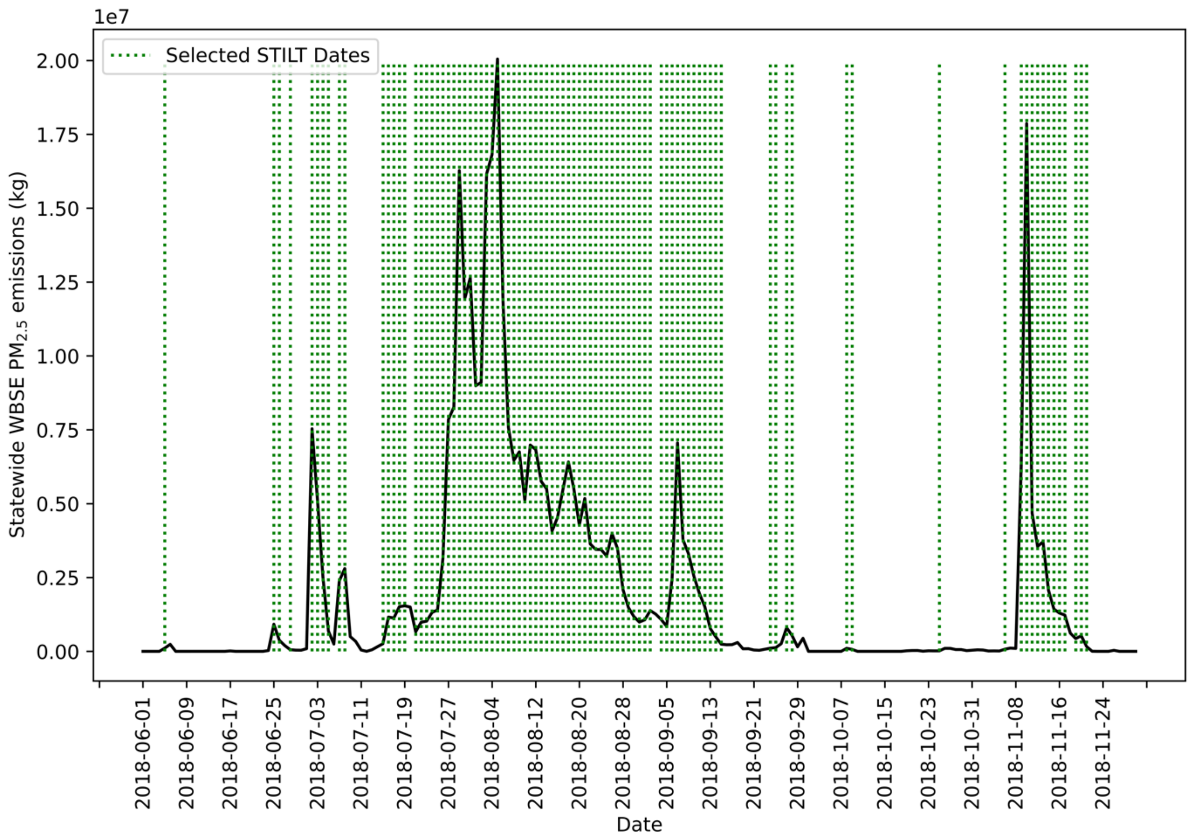


Figure 10.2. *Conceptual diagram of the selection process for selecting STILT receptor sites.*

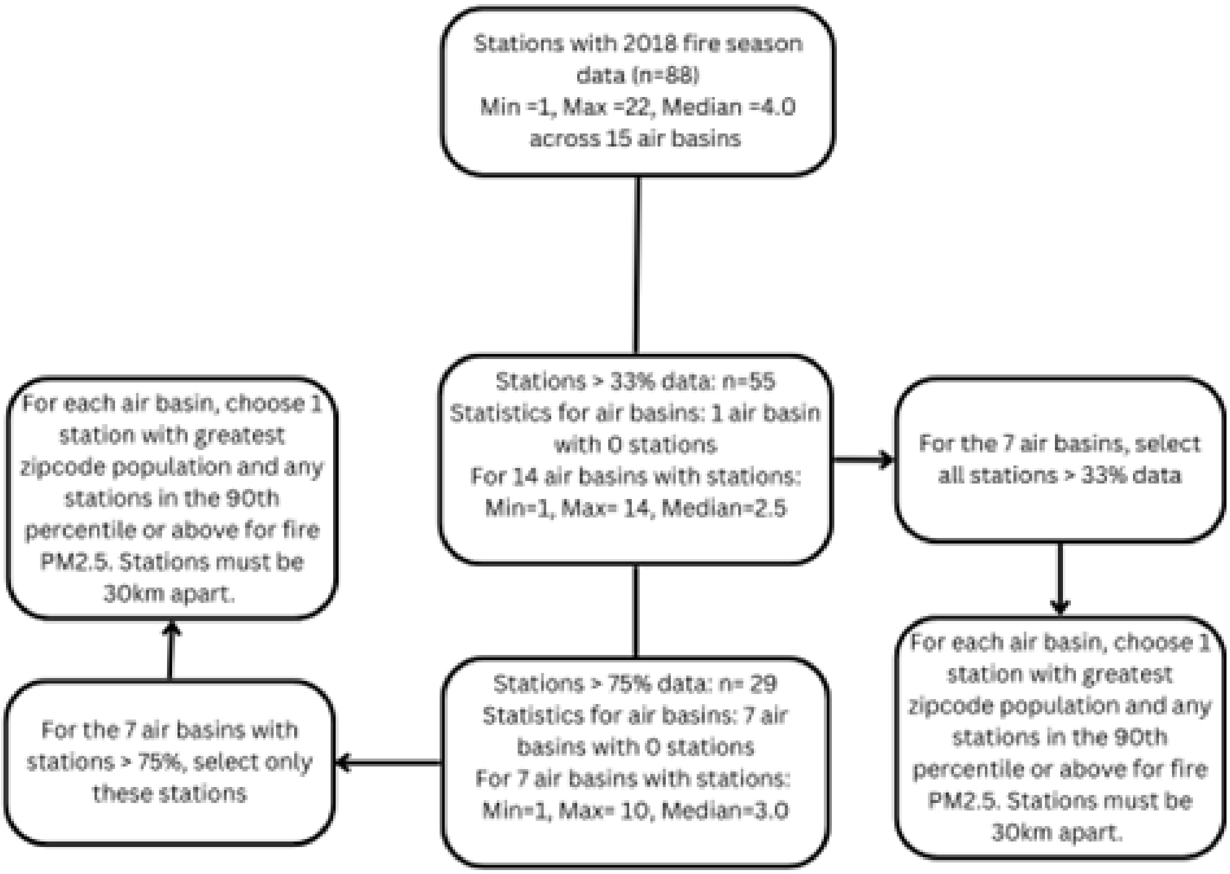


Figure 10.3. *Station monitor receptor locations are shown in blue, the boundaries and abbreviations for California Air Basins are in black, and the annual summed FINNv2.5 $PM_{2.5}$ emissions (kg) range from white (0 kg) to dark red (6.6 x 10^6 kg).*

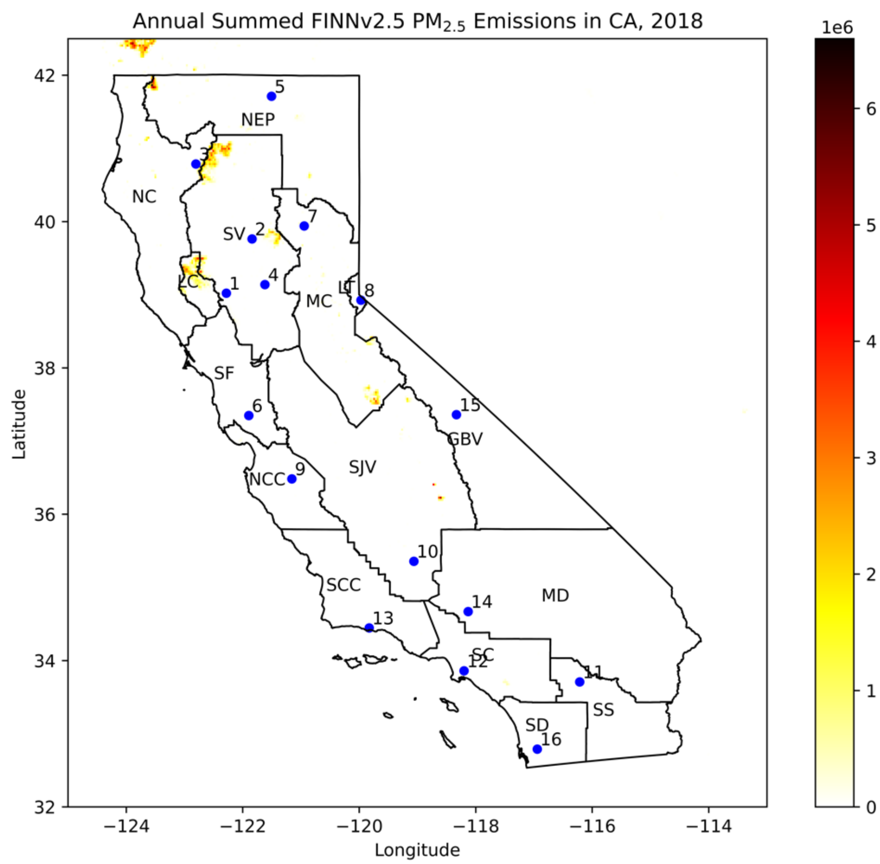


Table 10.1. *Air basin abbreviations shown in Figure 9.1 with the corresponding air basin name and the numbered station monitors shown in Figure 9.1 with their AQS or IMPROVE names. The station monitors are ranked according to annual mean fire-derived $PM_{2.5}$ concentrations from CMAQ, with 1 as the higher fire concentration. For each receptor, the Pearson's Correlation Coefficients (r value) and its significance (p value) was calculated between modeled data and the corresponding station observations.*

Site Name	**Air Basin Abbreviation**	**Air Basin Name**	**CMAQ 2018 Annual Mean Fire-Derived $PM_{2.5}$** ($\mu g/m^3$)	**r value**	**p value**
Cortina Indian Rancheria	SV	Sacramento Valley	15.95	0.55	1.0E-08
Chico-East Avenue	SV	Sacramento Valley	9.46	0.42	3.5E-05
Trinity National Forest	NC	North Coast	8.17	0.45	0.0018
Yuba City	SV	Sacramento Valley	7.12	0.43	5.4E-05
Lava Beds	NEP	Northeast Plateau	4.62	0.44	0.0019
San Jose - Jackson	SF	San Francisco Bay Area	3.02	0.28	0.11
Quincy-N Church Street	MC	Mountain Counties	2.87	0.38	1.1E-04
Lake Tahoe Community College	LT	Lake Tahoe	2.28	0.81	1.4E-08
Pinnacles	NCC	North Central Coast	2.14	0.03	0.88
Bakersfield-California	SJV	San Joaquin Valley	2.01	0.07	0.53
Indio	SS	Salton Sea	1.72	0.28	0.13
Long Beach-Route 710 Near Road	SC	South Coast	1.66	0.19	0.075
Goleta	SCC	South Central Coast	1.63	0.15	0.14

Lancaster-Division Street	MD	Mojave Desert	1.47	0.15	0.15
White Mountain Research Center - Owens Valley Lab	GBV	Great Basin Valleys	1.32	0.86	5.5E-30
El Cajon - Lexington Elementary School	SD	San Diego	1.17	-0.04	0.69

Figure 10.4. *Mean STILT Atmospheric Footprint for Cortina Indian Rancheria for 90 STILT modeling days between 6/5/18 and 11/21/18. The sensitivity is in units of ppm kg^{-1} m^{2} s. The locations with higher sensitivity values (darker red shades) have a greater contribution to pollution at the receptor site.*

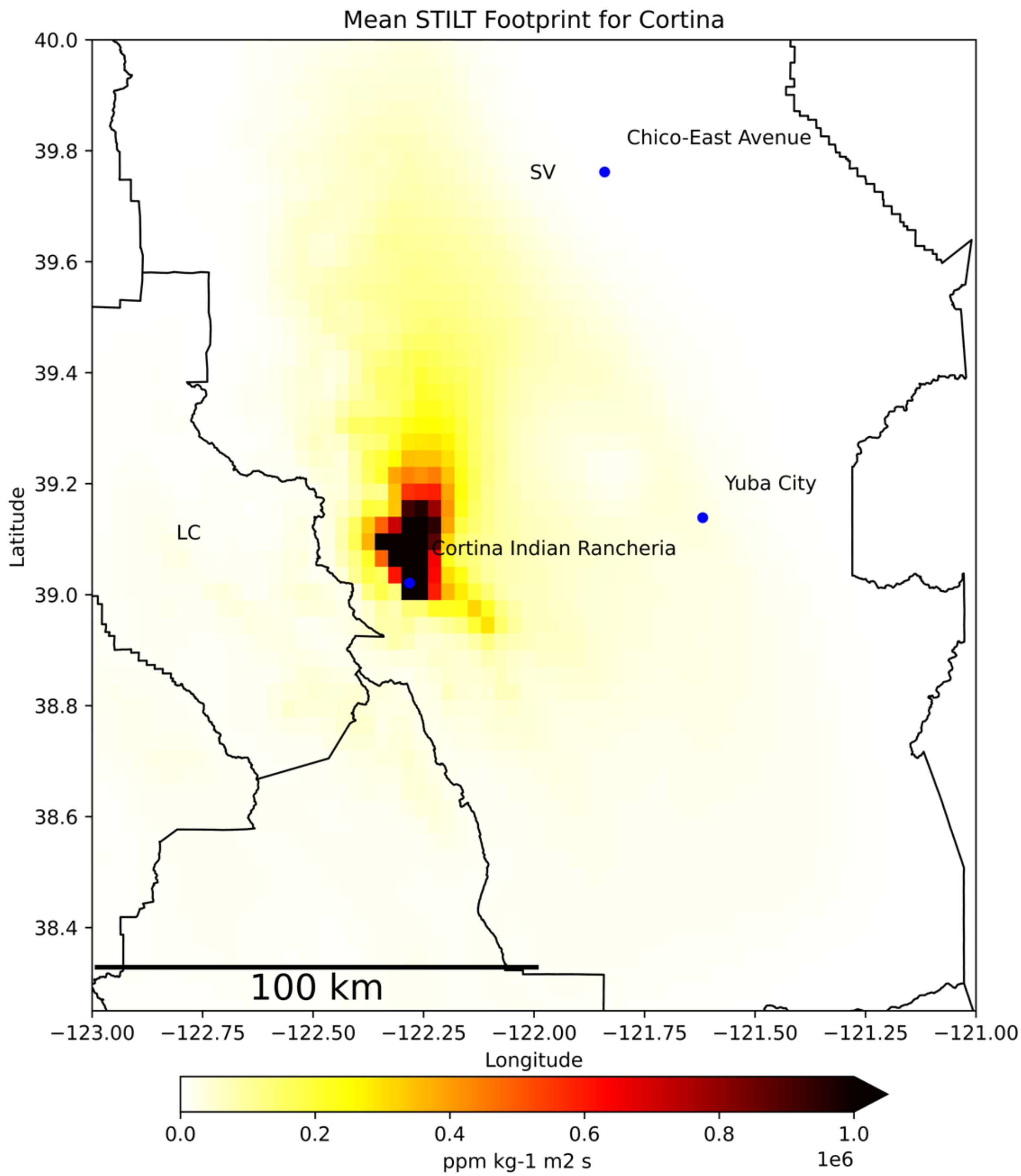
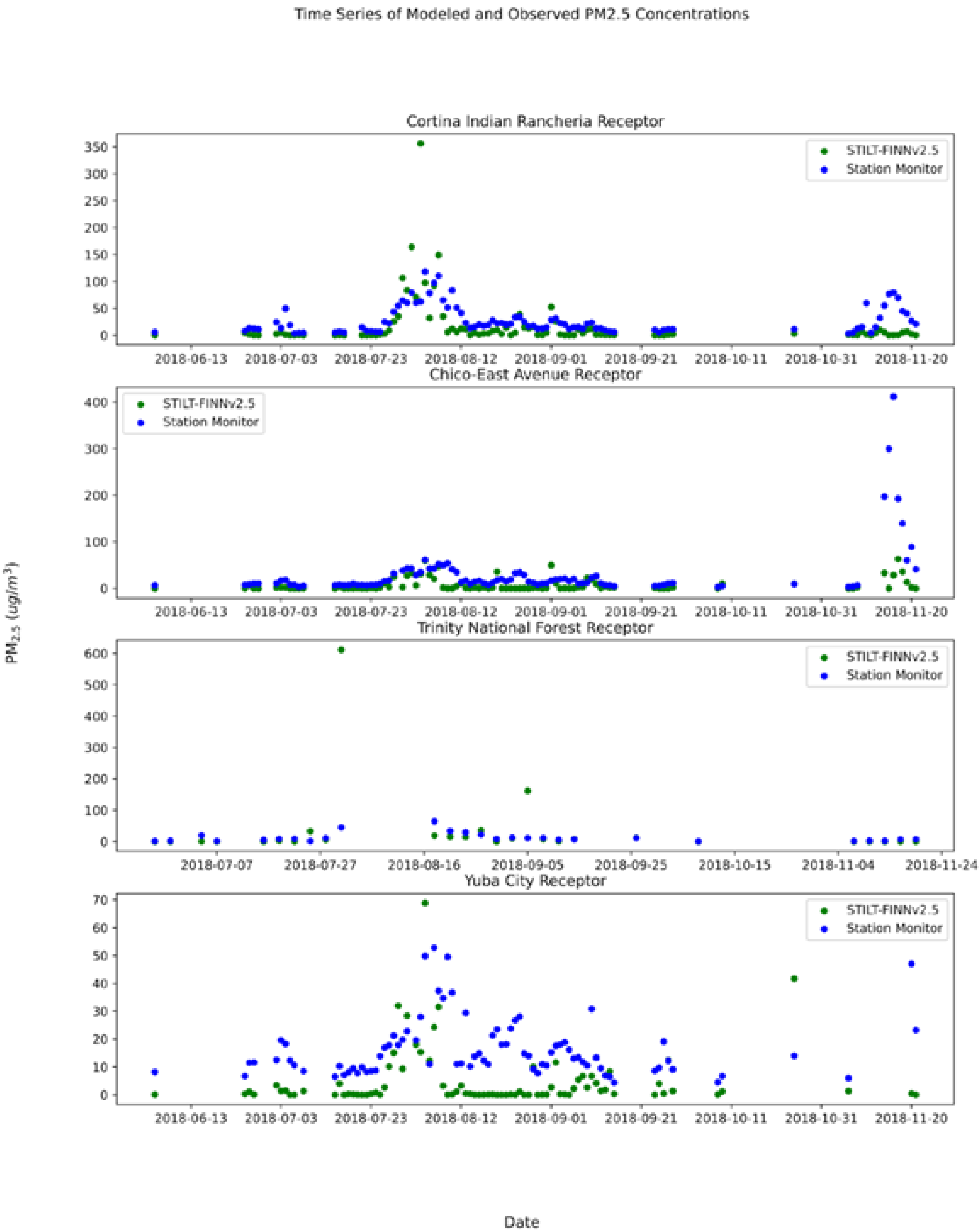
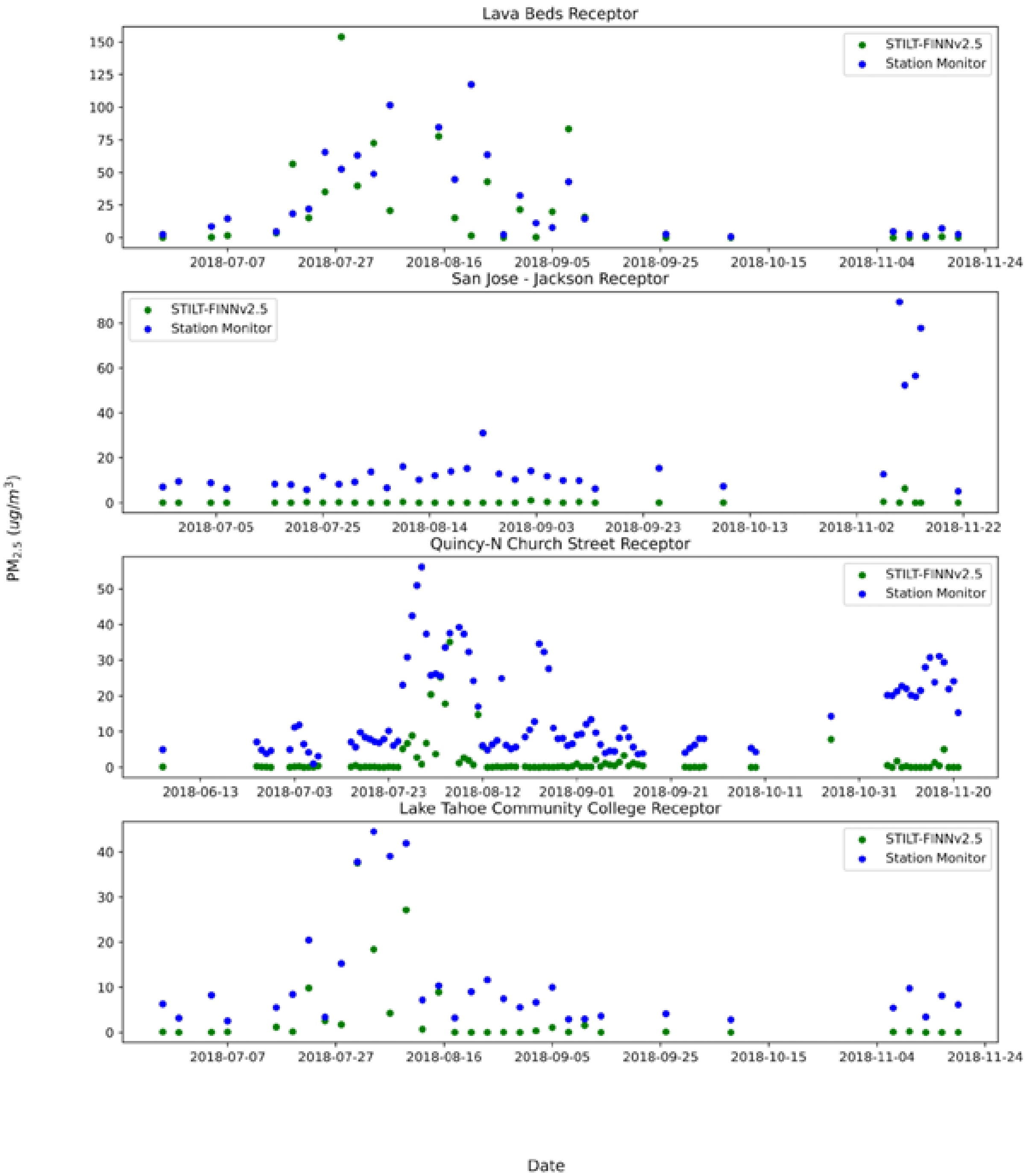
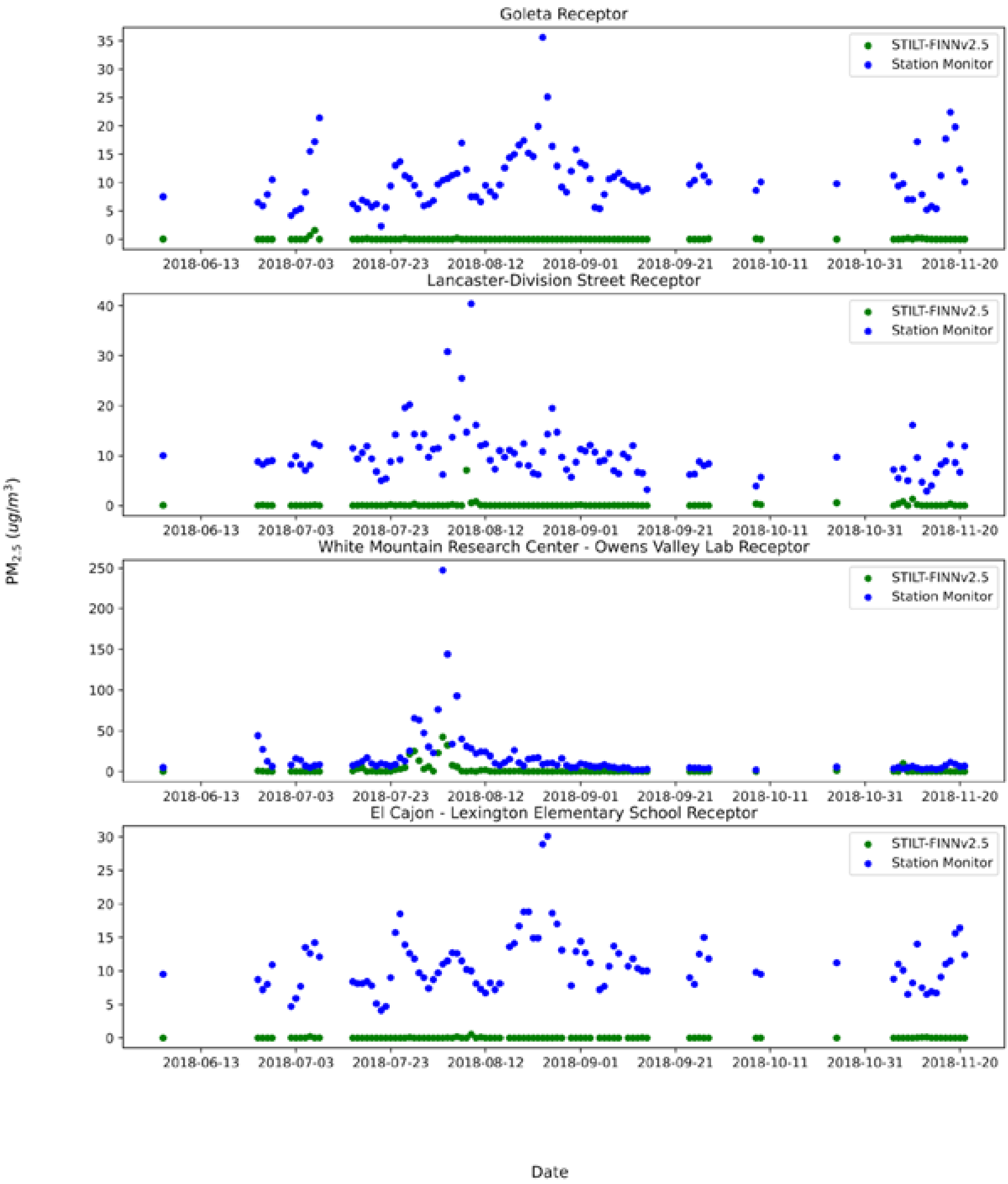


Figure 10.5. *Time series of the simulated fire $PM_{2.5}$ concentrations from STILT-FINNv2.5 at the receptor sites and the observed total $PM_{2.5}$ concentrations in the 2018 fire season.*




Lava Beds Receptor
STILT-FINNv2.5
Station Monitor
150
125
100
75
50
25
0
2018-07-07
2018-07-27
2018-08-16
2018-09-05
2018-09-25
2018-10-15
2018-11-04
2018-11-24
San Jose - Jackson Receptor
80
60
40
20
2018-07-05
2018-07-25
2018-08-14
2018-09-03
2018-09-23
2018-10-13
2018-11-02
2018-11-22
Quincy-N Church Street Receptor
50
40
30
10
2018-06-13
2018-07-03
2018-07-23
2018-08-12
2018-09-01
2018-09-21
2018-10-11
2018-10-31
2018-11-20
Lake Tahoe Community College Receptor
$PM_{2.5}$ (ug/m^3)
Date


Goleta Receptor
Lancaster-Division Street Receptor
White Mountain Research Center - Owens Valley Lab Receptor
El Cajon - Lexington Elementary School Receptor
STILT-FINNv2.5
Station Monitor
PM2.5 (ug/m3)
Date
2018-06-13
2018-07-03
2018-07-23
2018-08-12
2018-09-01
2018-09-21
2018-10-11
2018-10-31
2018-11-20

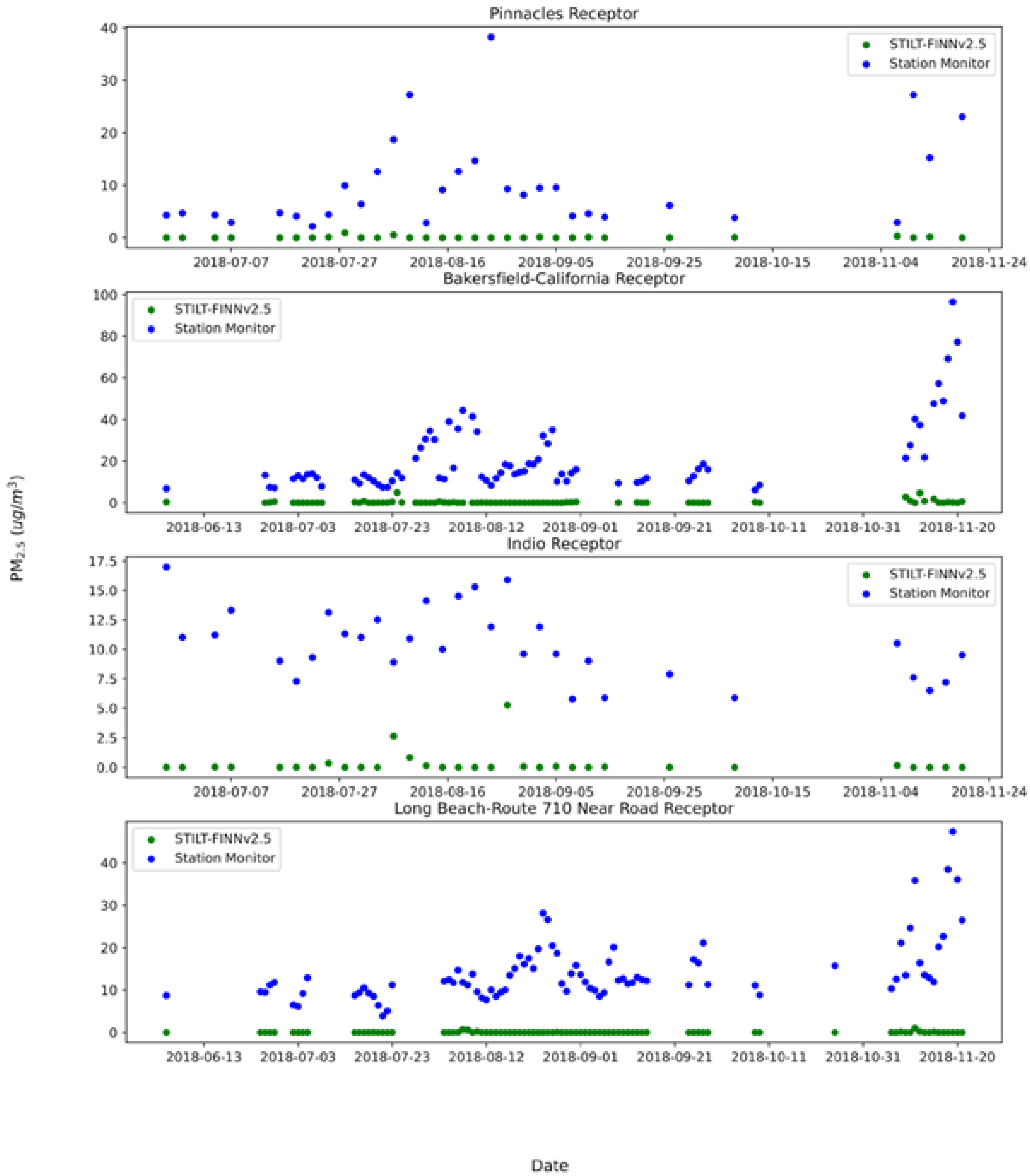
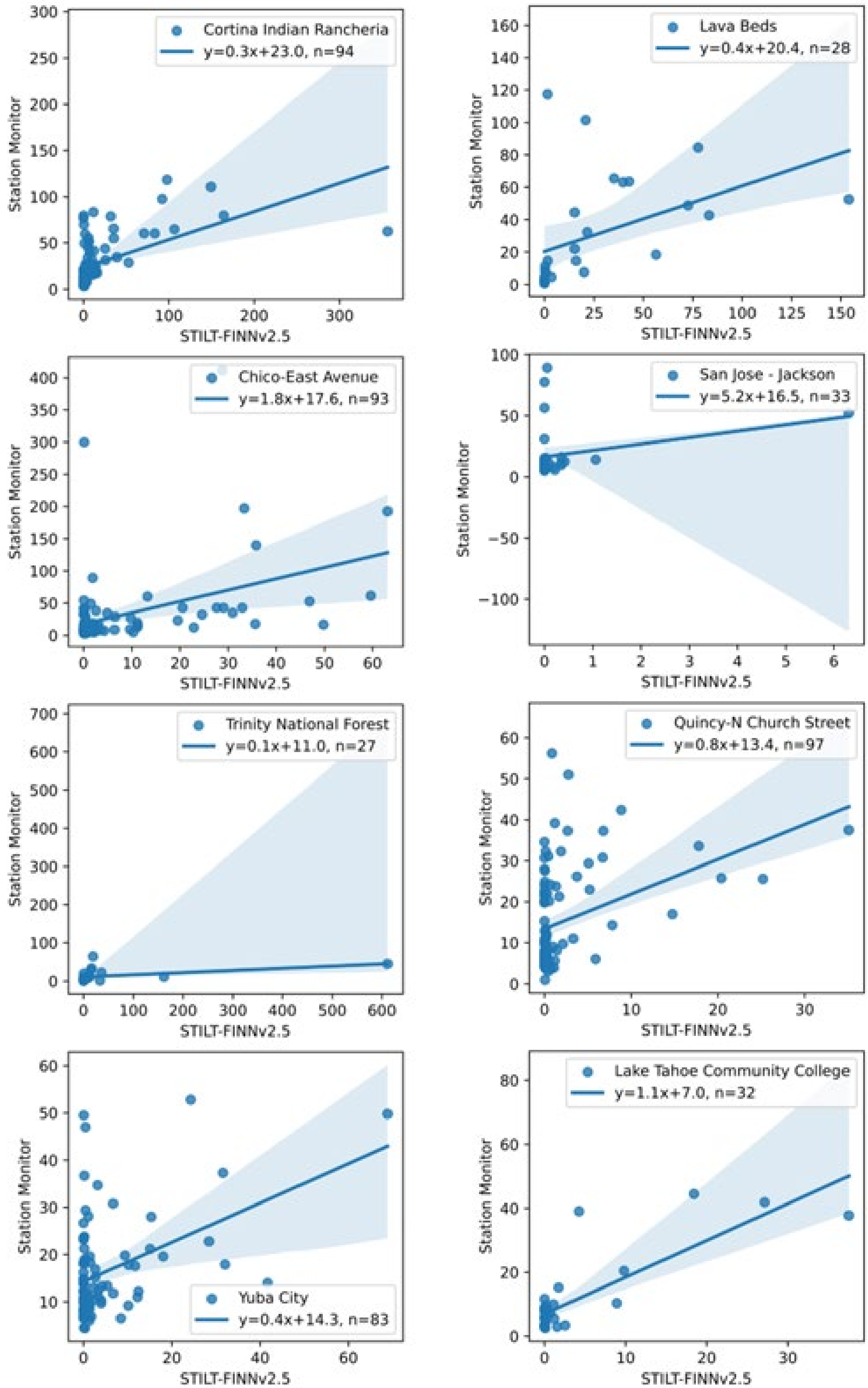

Pinnacles Receptor
STILT-FINNv2.5
Station Monitor
Bakersfield-California Receptor
Indio Receptor
Long Beach-Route 710 Near Road Receptor
$PM_{2.5}$ (ug/m^3)
Date

Figure 10.6. *The relationships between the STILT-FINNv2.5 simulated fire $PM_{2.5}$ concentrations and the observed $PM_{2.5}$ concentrations at each receptor.*


Cortina Indian Rancheria
y=0.3x+23.0, n=94
Lava Beds
y=0.4x+20.4, n=28
Chico-East Avenue
y=1.8x+17.6, n=93
San Jose - Jackson
y=5.2x+16.5, n=33
Trinity National Forest
y=0.1x+11.0, n=27
Quincy-N Church Street
y=0.8x+13.4, n=97
Yuba City
y=0.4x+14.3, n=83
Lake Tahoe Community College
y=1.1x+7.0, n=32
Station Monitor
STILT-FINNv2.5

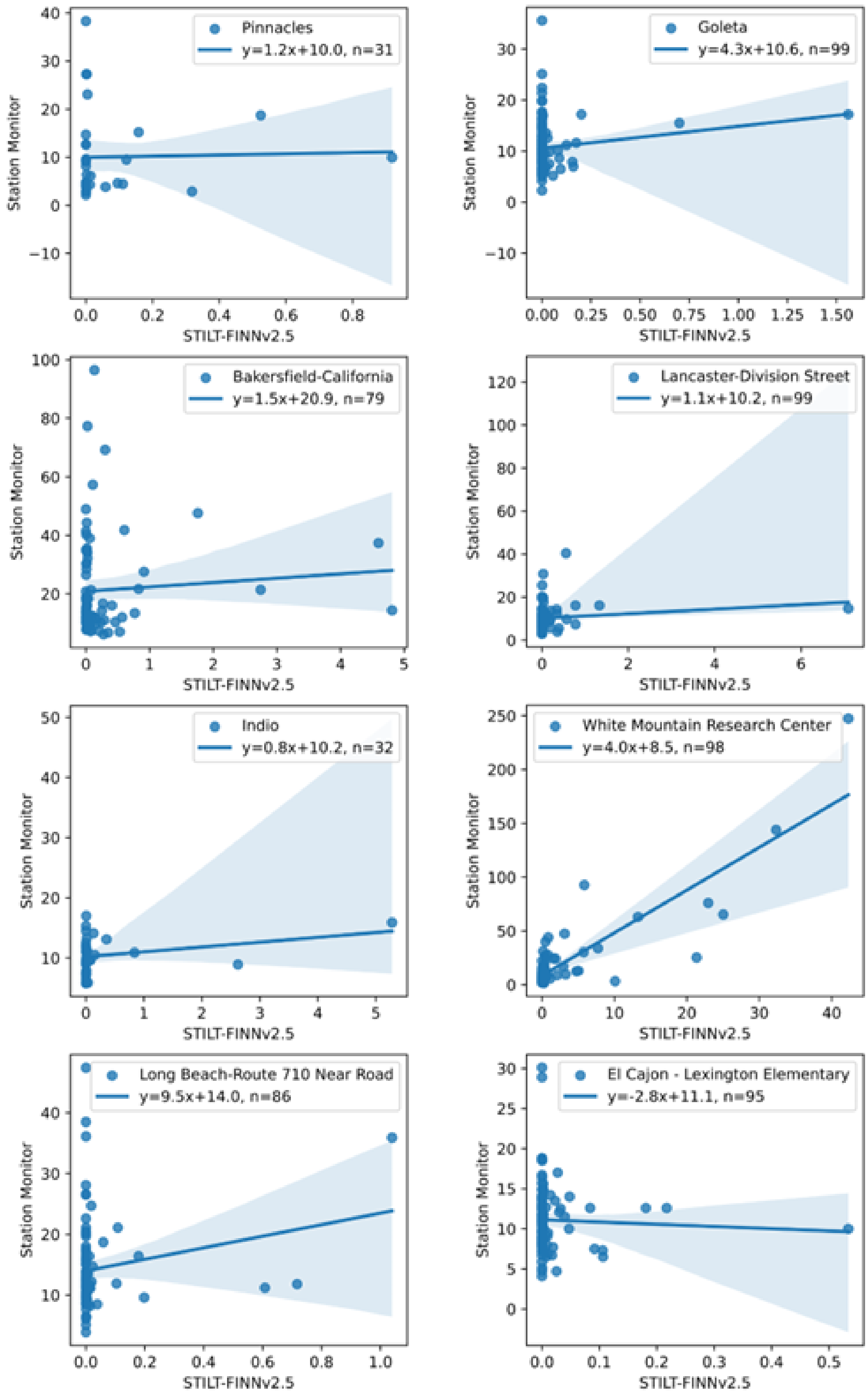

Pinnacles
y=1.2x+10.0, n=31
Goleta
y=4.3x+10.6, n=99
Bakersfield-California
y=1.5x+20.9, n=79
Lancaster-Division Street
y=1.1x+10.2, n=99
Indio
y=0.8x+10.2, n=32
White Mountain Research Center
y=4.0x+8.5, n=98
Long Beach-Route 710 Near Road
y=9.5x+14.0, n=86
El Cajon - Lexington Elementary
y=-2.8x+11.1, n=95
Station Monitor
STILT-FINNv2.5

Figure 10.7. *The relationship between the STILT-FINNv2.5 simulated fire $PM_{2.5}$ concentrations and the observed $PM_{2.5}$ concentrations for all receptors.*

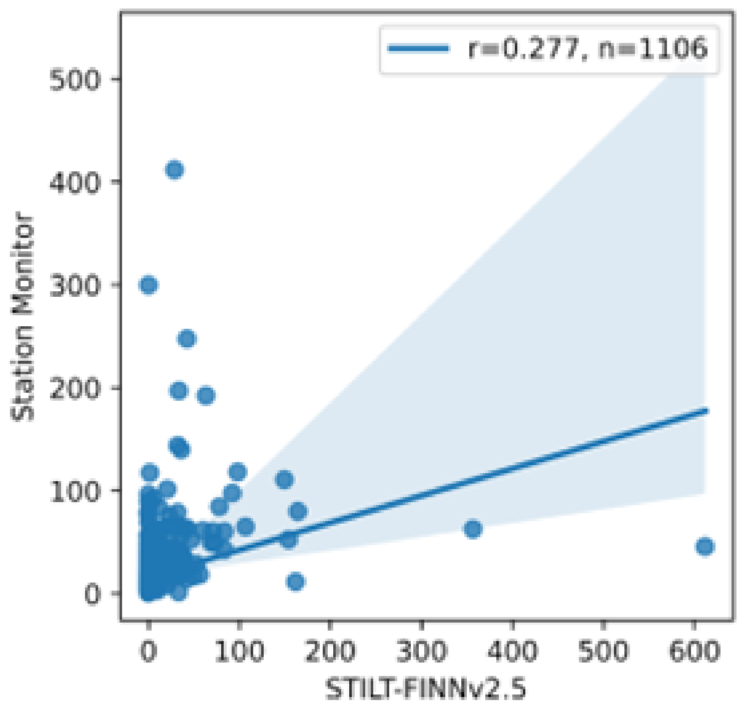
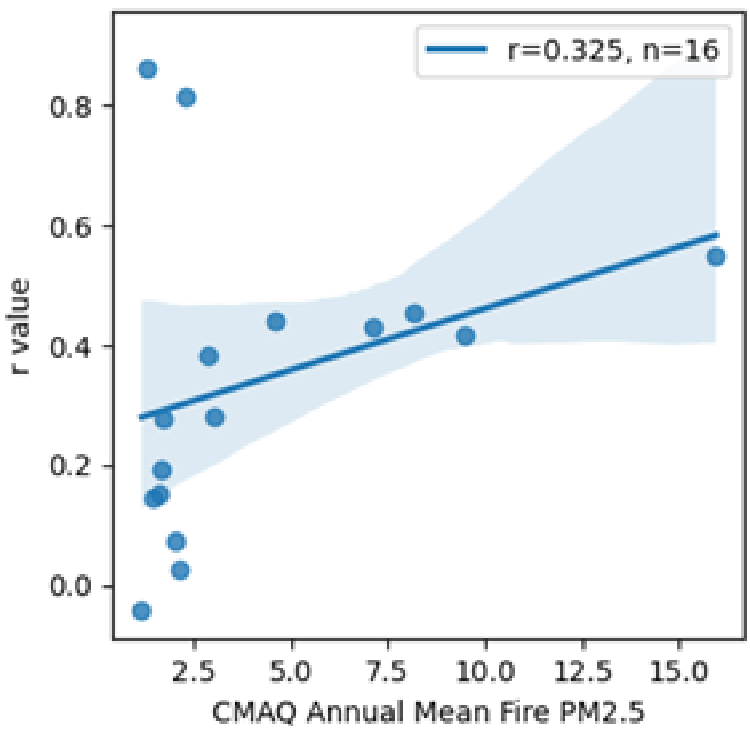


Figure 10.8. *The relationship between CMAQ annual mean fire $PM_{2.5}$ concentrations at each receptor and the correlation coefficient between the STILT-FINNv2.5 fired-derived $PM_{2.5}$ concentrations and the observed concentrations.*



XI. STILT Scenario: Prescribed Burning

Introduction

Wildfire activity in California and around the world is worsening due to climate change, increased development at the wildland urban interface, and too much fire suppression. Prescribed burning is a method to reduce the fuel load in forests by setting controlled fires at strategic locations to reduce the future possibility of larger uncontrolled wildfires igniting or spreading. The State of California and the Federal Government recently signed an agreement to dramatically increase fuel treatments, including mechanical thinning and prescribed burning, to 1 million acres per year. This would increase over current levels of prescribed burning by approximately 7-fold by 2025, based on levels that we estimated in 2018, which were about 71,166 acres per year in total. Little is known about the health effects of prescribed burning compared to those of wildfires. Our objective is to estimate the excess mortality due to prescribed burning in California for 2018.

Methods

We fit the STILT particle dispersion receptor-based model for fire and non-fire days in 2018 (79 days in total) to reflect various meteorological conditions. The model timeframe included three periods: pre-fire season (February 18-28), typical fire season (June 20-30, July 13-August 18), and late fire season (November 6-25). These were used to develop atmospheric sensitivity "footprints" that provide a flexible means of assessing various scenarios based on changes in the emissions from prescribed burns. Please see *Chapter X. Scenario Development: STILT and FINN Validation* for detailed information on STILT. We assembled data from CAL FIRE on the locations of prescribed burns throughout the state in 2018. Prescribed burns were identified from CAL FIRE's prescribed fire and fuel treatment GIS dataset, which provides burn areas in the form of polygons, based on reports from county, state, and federal agencies, including CAL FIRE's units and from cooperating agencies (Bureau of Land Management (BLM), California State Parks (CSP), National Park Service (NPS), United States Forest Service (USFS), United States Fish and Wildlife (USFW) (*Prescribed Fire Burns - California [Ds397] GIS Dataset*, n.d.). We selected the prescribed burning treatment types within the fuel treatment dataset. These burned area polygons were spatially joined with the FINNv2.5 database of fire emissions at the 3 km scale to isolate emissions associated with prescribed burning. These emissions were then applied to the STILT footprints to estimate $PM_{2.5}$ concentrations associated with prescribed burns in each county in California. This methodology enabled us to predict emission changes at receptor locations and to calculate county-wide mortality estimates. We quantified the health impacts attributable to prescribed burning using the following equation:

$$\sum \Delta m_{ij} = \left(1 - \frac{1}{e^{(\beta wL * \Delta PM_{2.5ij})}}\right) * d_{ij}$$

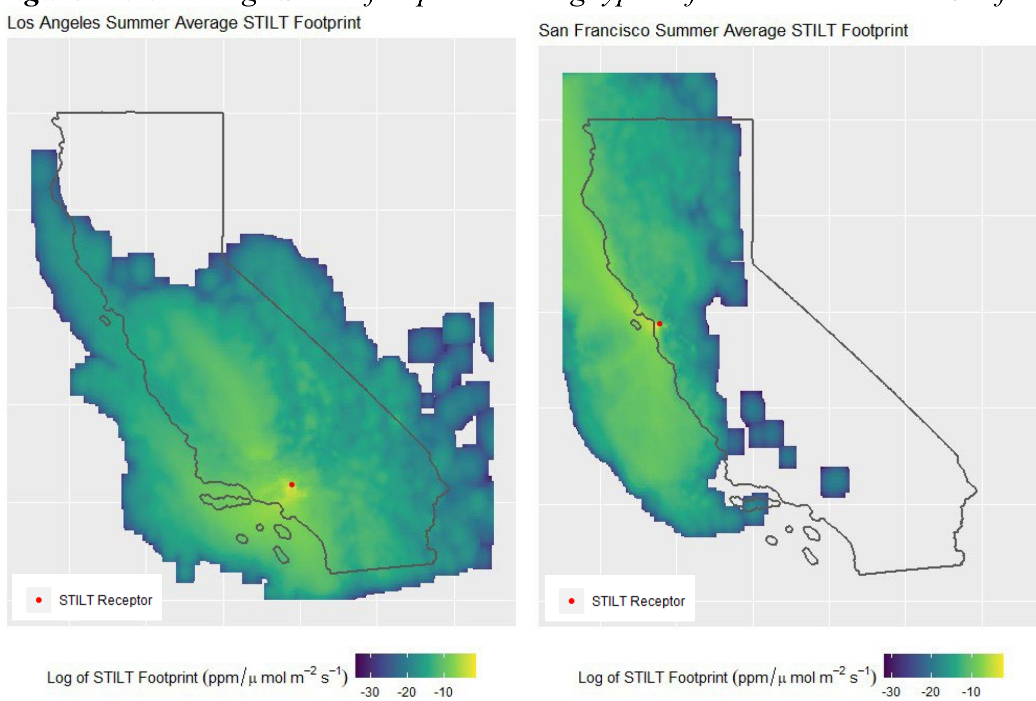
where M_{ij} is mortality in the *ith* county for the *j*th year; ßwL is the long-term effect of wildfire smoke based on the ratio of short-term wildfire effects over the short-term total $PM_{2.5}$ effects times the chronic estimate from Pope et al. (2019); $PM_{2.5}$ is the exposure change due to fires; and d_{ij} is the deaths occurring in the *ith* zip code for the *jth* year (as detailed in Section VIII).

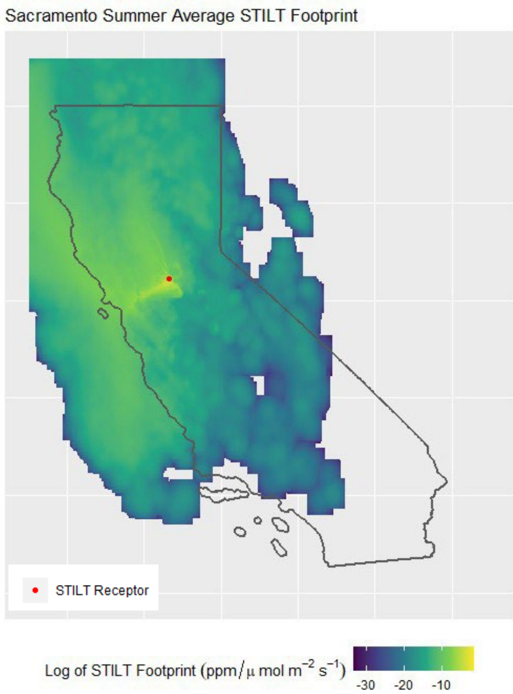
Preliminary Results

Wildfires burned an area of 6,430 km^2, while prescribed burns accounted for 288 km^2.

Figure 11.1 shows the results of the average STILT footprints in Los Angeles, San Francisco, and Sacramento during the typical fire season.

Figure 11.1. *Average STILT footprints during typical fire season in three California regions.*





Lighter shades (yellow) indicate where emissions will have a greater influence on downwind pollution.

Prescribed burning contributed minimally to ambient levels of $PM_{2.5}$, with concentrations increasing maximally by about 0.5 $\mu g/m^3$, with most areas experiencing little or no impacts from prescribed burnings. Figure 11.2 compares the spatial distribution of $PM_{2.5}$ contribution from wildfires to prescribed burns across California counties. Using ZIP-code level mortality data, and dose-response coefficient accounting for the increased toxicity of wildfire smoke, our preliminary[†] analyses estimated 25 excess deaths from prescribed burning in 2018. For the same year, we estimated about 1,684 excess deaths from wildfire-generated $PM_{2.5}$. Figure 11.3 displays the spatial distribution of mortality in 2018 attributable to wildfire smoke compared to smoke from prescribed burns across California counties.

[†] data is still preliminary due to on-going quality assurance and quality control measures.

Figure 11.2. *Wildfire vs. prescribed burns $PM_{2.5}$ contributions*

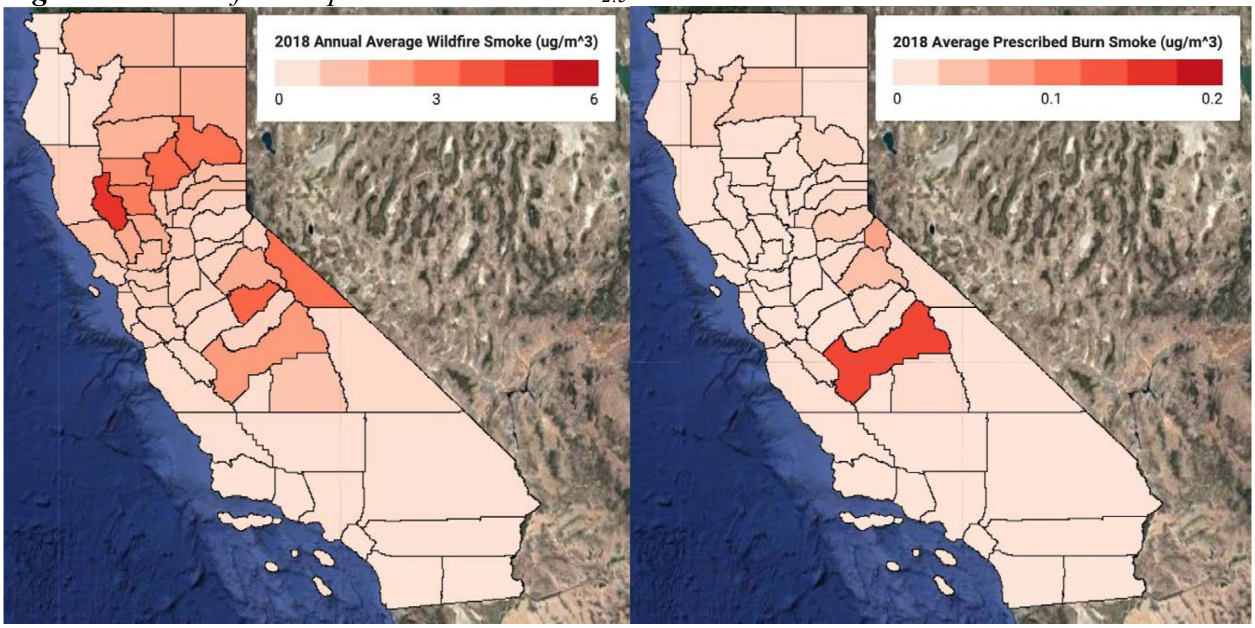
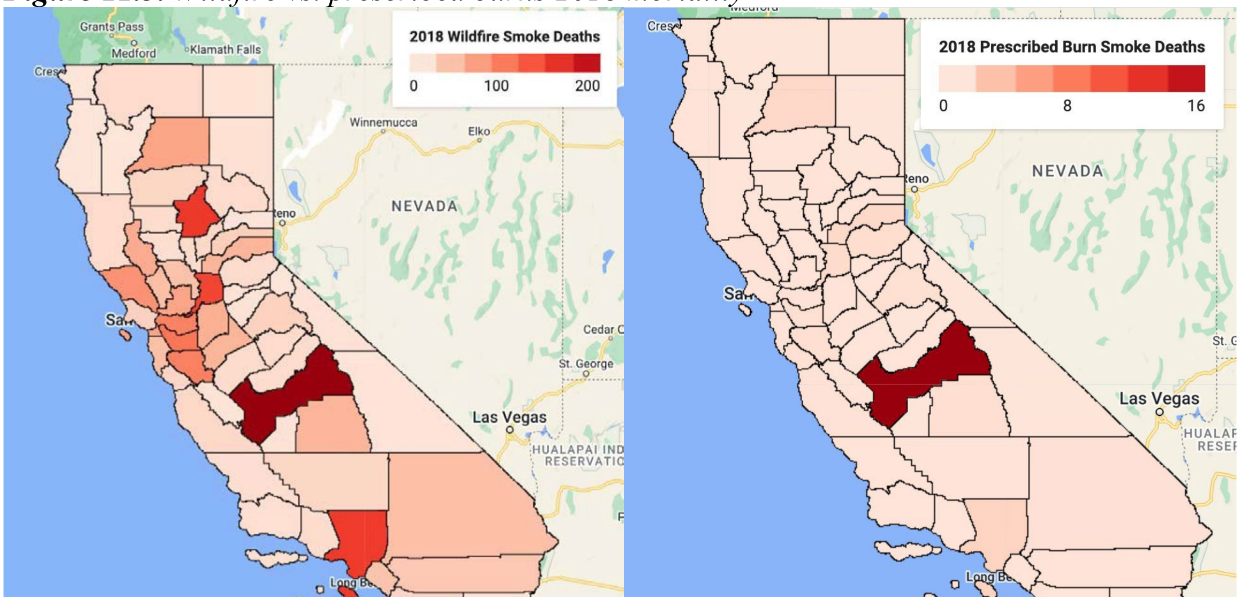


Figure 11.3. *Wildfire vs. prescribed burns 2018 mortality*



Conclusion

Our preliminary results demonstrate relatively small effects from prescribed burning in 2018 compared the deaths attributable to wildfire smoke. It is still uncertain how much wildfire activity can be prevented by prescribed burning, but even a 5% reduction would result in 84 deaths avoided, so net benefits would be more than 3 times greater than the deaths attributed to prescribed burns. Future research is needed to better understand this relationship. It is also critical to investigate what the 10-fold increase in prescribed burning will mean for health burdens going into the future.

XII. Final Tool Product Paper: A Decision-Support Tool to Evaluate Health Benefits of Natural and Working Lands Scenarios

Abstract

The purpose of this chapter is to describe the development of the Natural Working Lands Health Scenario Tool. The Health Scenario tool evaluates the potential health benefits associated with different NWL management scenarios. The tool has been divided into two separate online interfaces for urban green space and wildfire areas, respectively, both of which are available through GEE. In the sections that follow, we provide a technical description of the input datasets and methodology, along with a step-by step guide to select different scenarios, visualize output, and download datasets for further analysis.

Introduction

California's NWL encompass diverse landscape types, including grasslands, shrublands, and forests in both urban and rural settings. In addition to the role of California's NWL in storing carbon and therefore mitigating future climate-related exposures, these areas also provide direct and indirect health and economic benefits.

Urban green space provides direct health benefits and indirect benefits through mitigation of climate-related hazards. Among a myriad of health outcomes impacted through various pathways (Nieuwenhuijsen et al., 2017), there is substantial evidence for a dose-response relationship between access to urban green spaces and decreased mortality, as well as improved birth outcomes, both established in recent meta-analyses (Rojas-Rueda et al., 2019, Hu et al, 2021). Additionally, our research team has recently evaluated the relationship between green spaces and small-area life expectancy, finding that increased access to residential greenness and parks can substantially increase population longevity (Connolly et al., 2023). Our research and other studies suggest that increasing urban green space area could provide direct and indirect benefits for populations in California, particularly in disadvantaged communities. In the tool, we explore the health benefits associated with feasible increases in urban green space in California, based on past or ongoing efforts at the local to regional level.

Wildland fires can influence public health outcomes through contributions to fine particulate matter (hereafter referred to as "smoke $PM_{2.5}$"). Recent evidence suggests that smoke $PM_{2.5}$ may be more toxic than other sources of $PM_{2.5}$ pollution (Aguilera et al., 2023). This has consequences for respiratory outcomes, particularly asthma hospital admissions or ED visits, with growing evidence for all-cause mortality and cardiovascular effects (Chen et al., 2020; Reid, Brauer, et al., 2016a). Land management strategies to reduce the risk of future extreme wildfire events include prescribed burning, mechanical thinning, and other fuel reduction strategies. Despite potential benefits for reducing fuel loads and subsequent wildfire emissions (Wiedinmyer & Hurteau, 2010), prescribed burn use was stable or declined in most of the western U.S. over the past twenty years (except in lands managed by the Bureau for Indian Affairs) (Kolden, 2019). Widespread adoption of low-level prescribed burning has been proposed to reduce the future frequency and severity of uncontrolled wildfires. As reviewed by Hunter and Robles (2020), prior research has generally found that prescribed burning results in a lower extent and intensity of future wildfires. However, there are multiple uncertainties associated with assessing prescribed burning scenarios. This includes the wide range of spatial and temporal scales involved and challenges with simulating the future incidence of wildfire activity with and without prescribed burning (Hunter & Robles 2020). Quantifying public health trade-offs from smoke exposure to short-term, local pollution from prescribed burns versus longer time-scale, broad population exposure to smoke from wildfire events is also highly uncertain (Williamson et al. 2016). In the wildfire component of the NWL tool, we explore hypothetical future land management scenarios that could reduce wildfire emissions, as well as the consequences for smoke $PM_{2.5}$ exposures and health outcomes.

The NWL Health Scenario Tool provides quantitative estimates of the potential health benefits associated with multiple NWL management scenarios. In the sections that follow, we describe the online tool interfaces for two types of NWL, urban green space and wildfire areas. In the green space tool, users can quantitatively assess the potential human health impacts and economic benefits associated with management activities in California's urban green space areas at the ZIP code and census tract level. In the wildfire tool, users can evaluate the influence of wildfires on $PM_{2.5}$ and health outcomes with two complementary types of atmospheric modeling simulations: (1) ZIP code-level health burdens and economic costs associated with historical fire emissions based on 2008-2018 wildfire-specific $PM_{2.5}$ concentrations from CMAQ; (2) County-level health and economic benefits associated with potential wildfire management scenarios using the STILT model. In the remainder of this chapter, we describe the methods to quantify connections between NWL (focusing on urban green space and wildfires), health, and economic outcomes, and provide a step-by-step guide for how to visualize results and run additional scenarios in the online tools.

Methods

3.1 Urban Green Space

We examined three health outcomes associated with urban green spaces: mortality, life expectancy, and low birth weight. Current urban green space is measured with satellite metrics of NDVI from NAIP for 2016 at 0.6m resolution and tree canopy from the USGS NLCD percent tree cover at 30-m scale (Dewitz, 2019; U.S. Department of Agriculture Farm Service Agency, 2016). Baseline health status were from ZIP-code scale annual mortality data for 2016 from the CDPH (California Department of Public Health, 2022), life expectancy for 2019 from the ACS (US Census Bureau, 2019b), and the percent of low birthweight infants from CalEnviroScreen 4.0 (Office of Environmental Health Hazard Assessment, 2021b). Dose-response functions were identified through a scoping review of the peer reviewed literature. Please see *Chapter VII. Health Impact Assessment: Urban Green Space* for detailed methodology.

We developed eight scenarios, involving varying exposures to greenness in California's urban areas as measured by NDVI and tree canopy, summarized below. The scenarios are based on realistic increases in urban green space area. The Million Trees Initiative in Los Angeles, for example, could expand urban forest area by 12%, though under this type of scenario there would be local variations in green space changes (McPherson et al., 2011), which would influence the magnitude of health outcomes throughout the region.

1. Deaths Prevented from 0.1 unit increase in NDVI (2016)
2. Deaths Prevented from Increase in NDVI to Urban Areas Mean (2016)
3. Life Expectancy Population Impacts - Years of Life Added from Universal 10% Increase in Tree Cover (e.g., 10% --> 20% tree cover)
4. Life Expectancy Population Impacts - Years of Life Added from Increase in Tree Cover to Urban Areas Mean
5. Life Expectancy Population Impacts - Years of Life Added from 0.1 unit increase in NDVI
6. Life Expectancy Population Impacts - Years of Life Added from Increase in NDVI to Urban Areas Mean
7. Reduced Cases of Low Birth Weight from 0.1 unit increase in NDVI (2016)
8. Reduced Cases of Low Birth Weight from Increase in NDVI to Urban Areas Mean (2016)

3.2 Wildfires

3.2.1 ZIP Code Level Historical Analysis (CMAQ Model)

We quantified the total mortality burden for exposure to $PM_{2.5}$ due to wildland fires in California from 2008 – 2018 using CMAQ modeling system wildland fire $PM_{2.5}$ estimates. We used a concentration response function for $PM_{2.5}$, applying ZIP code level mortality data and an estimated wildfire-specific chronic dose-response coefficient accounting for the likely toxicity of wildfire smoke. The CMAQ estimates do not explore future management scenarios, but provide a retrospective analysis of smoke-specific health and economic impacts at the ZIP-code level. Please see *Chapter VIII. Health Impact Assessment: Wildland Fire Mortality and CMAQ Validation* for detailed methodology.

3.2.2 County Level Scenario Analysis (Receptor Model)

To model the impact of wildfires on $PM_{2.5}$ concentrations at our receptors, we coupled an atmospheric model, STILT, with FINNv2.5 emissions. STILT is a receptor-oriented, Lagrangian particle dispersion model, which means it tracks an ensemble of individual air parcels backward in time from a chosen receptor location to their respective source locations. The atmospheric transport model is the heart of STILT, and it is responsible for calculating the trajectory of air parcels by simulating the complex interactions of winds, turbulence, and atmospheric stability. Meteorological data is the second key component of STILT and it includes information on wind speed and direction, temperature, humidity, and atmospheric stability. With the modeling framework and the meteorological data simulating air parcel back trajectories, STILT generates a gridded ‘footprint’ quantifying the influence of upwind grid cells on the receptor at a given point in time (Lin et al., 2003). STILT footprints can be convolved with emission inventory data, which provides information on the spatial and temporal distribution of pollutant sources. Emissions fluxes are coupled with STILT footprints to estimate the concentrations of air pollutants provided by the inventory (i.e. PM) the receptor site (Mallia et al., 2015); (Wilmot et al., 2022). Please see *Chapter X. Scenario Development: STILT and FINN Validation* for detailed methodology.

Several illustrative, hypothetical management scenarios are available in the tool to compare against modeled historical emissions for 2018: 5%, 10%, and 15% across-the-board reductions in emissions state-wide, exclusion of all emissions from outside of California (may be relevant for northern counties near Oregon fires), exclusion of all emissions from outside of the selected county, and 100% and 10% reduction in emissions from the Sierra Nevada ecoregion. In addition, the tool can also consider just emissions from just 2018 prescribed burns, as well as +25%, +50%, and +100% increases to those emissions (preliminary results provided).

Wiedinmyer and Hurteau (2010) evaluated emissions changes from widespread prescribed burning in the western U.S. They simulated prescribed burning in specific forest types where prescribed burning would be appropriate by reducing fuel consumption to surface fuels only, but did not alter the seasonality or timing of future fire activity. They estimated an 18-25% reduction in carbon dioxide (CO_2) fire emissions under this prescribed burning scenario, with an average decline of 19% in California. After accounting for climate and prior fires on fuel availability and flammability in the Sierra Nevada Mountains (instead of climate alone), Hurteau et al. (2019) found that burned area is reduced by 14% and greenhouse gas and particulate matter emissions by a similar amount. Although not focused on prescribed burning specifically, this study points to dynamic climate and land use relationships. We can assess the air quality and public health implications of prescribed burning with the NWL tool through two broad strategies. In the first, we can assess a specified reduction in emissions through prescribed burning, without considering changes in seasonality or fire frequency (Wiedinmyer & Hurteau 2010). Users of the tool could explore how different proportional emissions reductions in different locations would influence population-level pollution exposure.

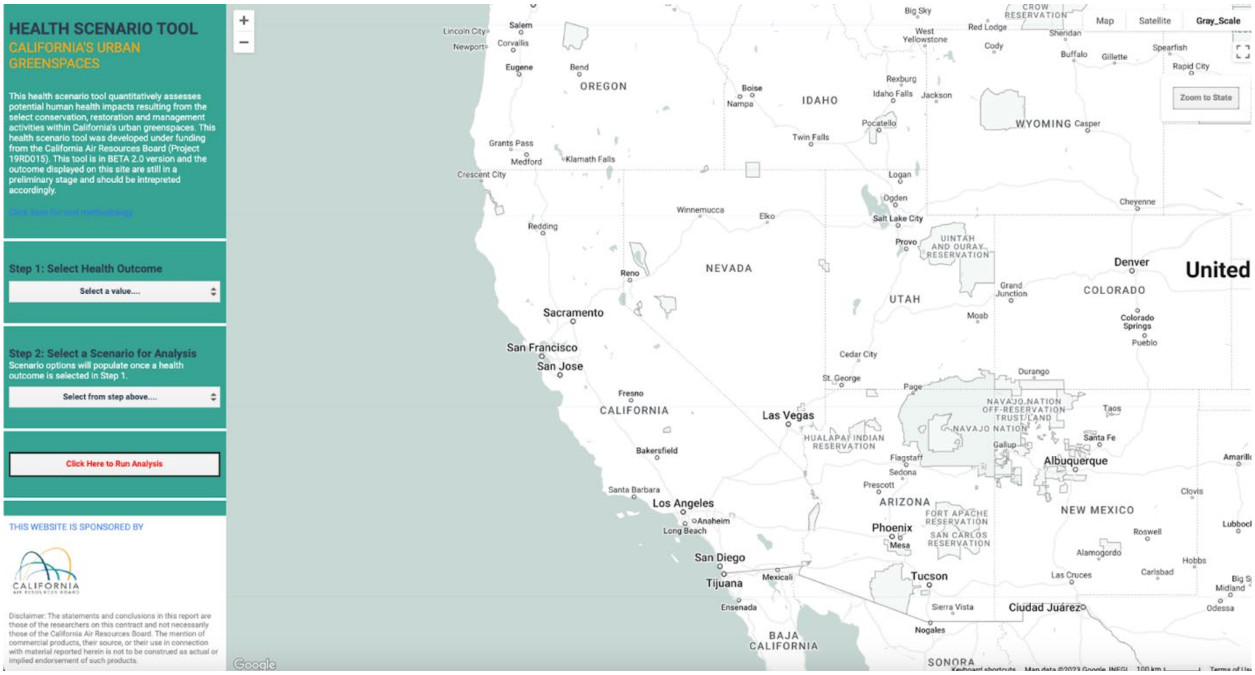
Results

Please see *Chapter VII. Health Impact Assessment: Urban Green Space, Chapter VIII. Health Impact Assessment: Wildland Fire Mortality and CMAQ Validation,* and *Chapter X. Scenario Development: STILT and FINN Validation* for detailed results on the urban green space and wildfire analyses, which we incorporated into the development of the tools.

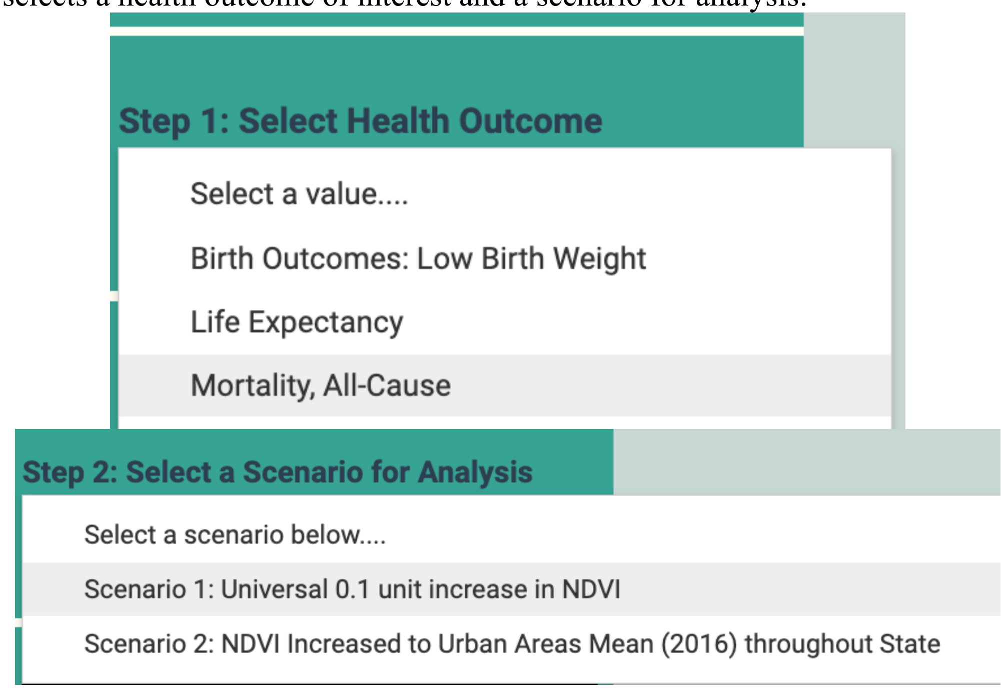
The sections to follow guide the user through the two online interfaces for the Urban Green Space and Wildfire NWL tools and various options available.

4.1 Urban Green Space (link)

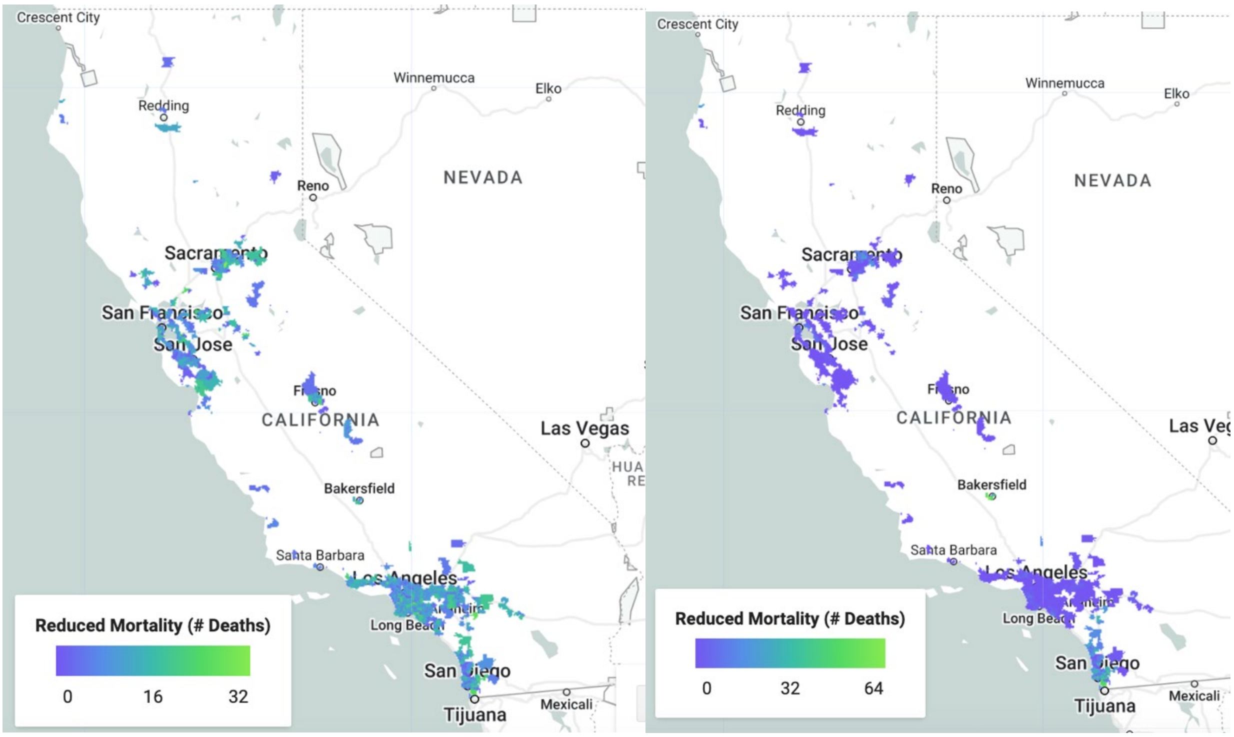
Green Space Tool when launched:



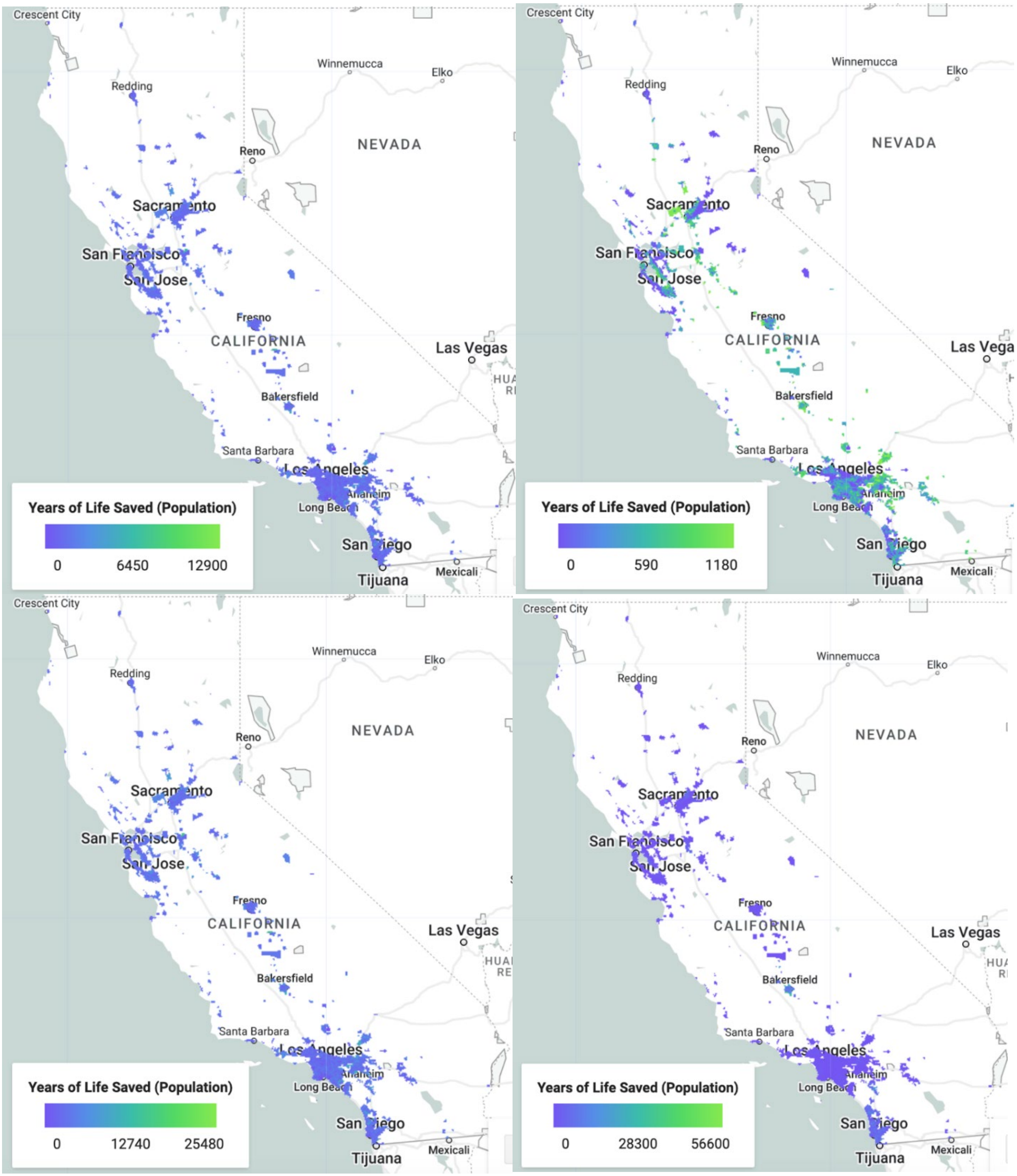
The user selects a health outcome of interest and a scenario for analysis:



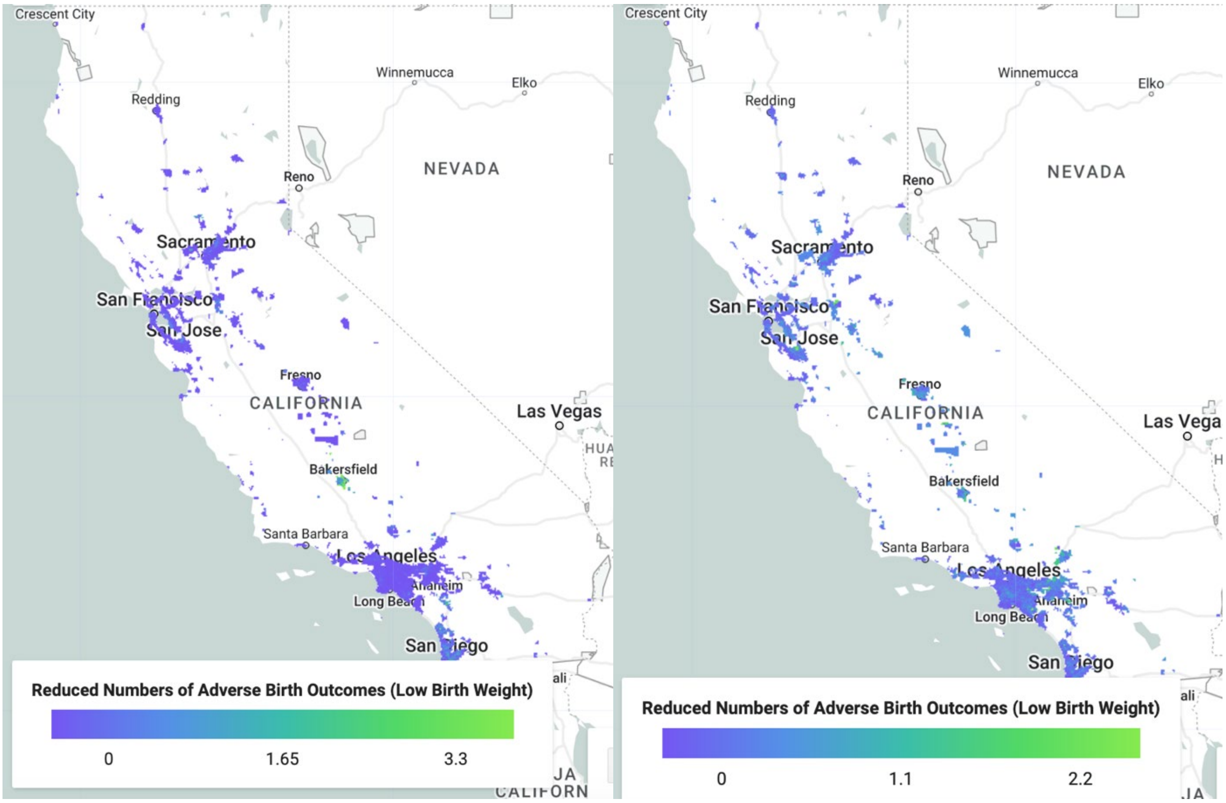
In response, the tool generates maps of how the selected health outcome changes for the selected scenario:



Change in mortality for universal 0.1 unit increase in NDVI (left) and NDVI increase to urban area mean (right).

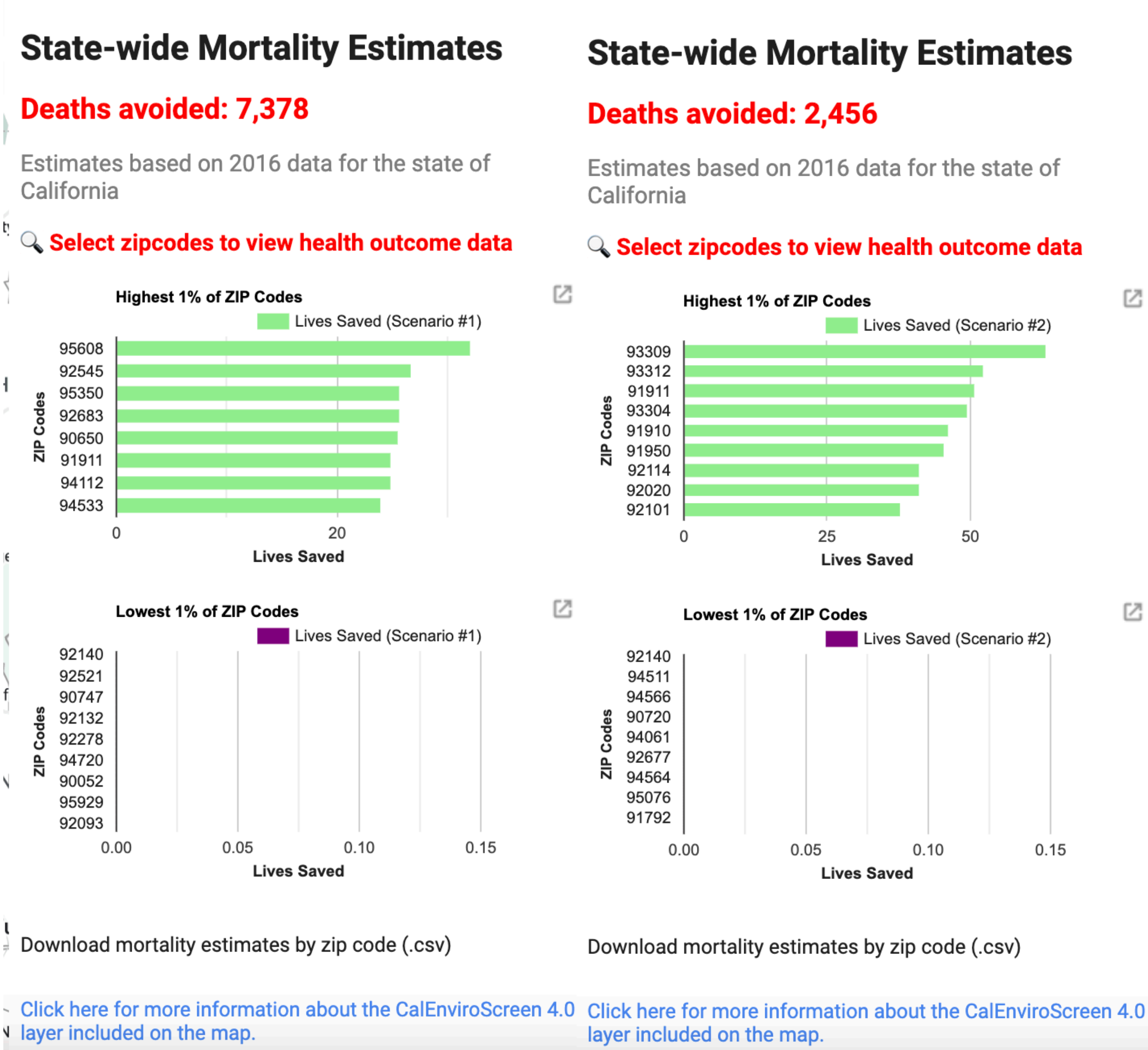


Changes in life expectancy for universal 10% increase in tree cover (upper left), increase in tree cover to urban area mean (upper right), universal 0.1 increase to NDVI (lower left), increase in NDVI to urban area mean (lower right).



Changes in low birth weight adverse outcomes for NDVI increase to urban area mean (left) and universal 0.1 increase to NDVI (right).

The tool also generates a results panel showing the total change in the outcome of interest for the scenario as well as highlighting the ZIP Codes most and least affected:



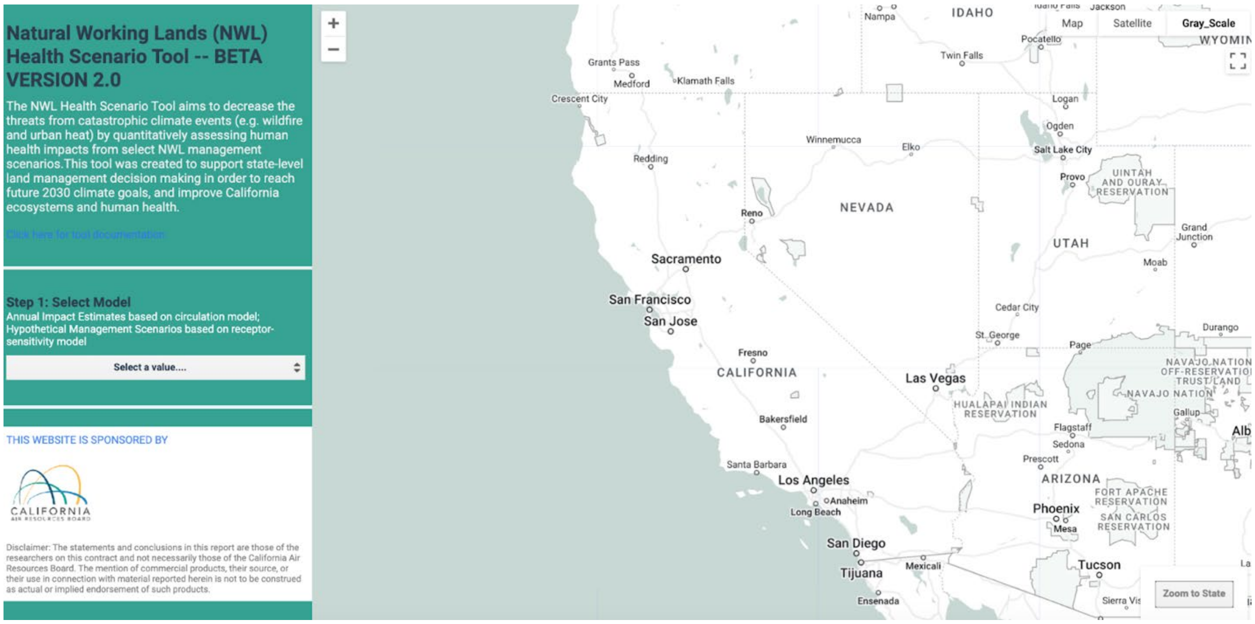
Results panel for mortality estimates for universal 0.1 unit increase in NDVI (left) and NDVI increase to urban area mean (right)

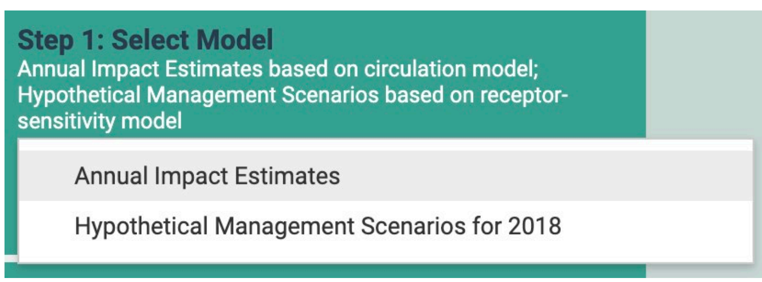
The user can also explore individual census tracts (life expectancy and birth outcomes) or ZIP Codes (mortality) by clicking them on the map:

Zipcode	Lives Saved (Scenario #1)	Lives Saved (Scenario #2)
92067	2.159	1.075
91754	11.935	0
90210	7.821	0

4.2 Wildfires (link)

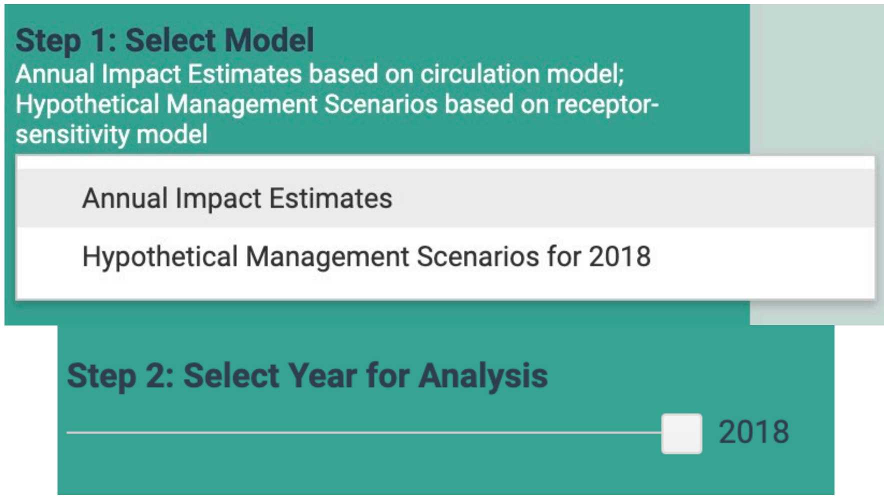
The NWL Health Scenario Tool interface allows users to select from two models and multiple outcomes. The first step is for users to determine the model selection of interest: (1) ZIP-code retrospective health and economic analysis based on the CMAQ model for 2008-2018 "Annual Impact Estimates", or (2) county-level management scenario analysis based on the STILT receptor model for the 2018 meteorological year "Hypothetical Management Scenarios for 2018".



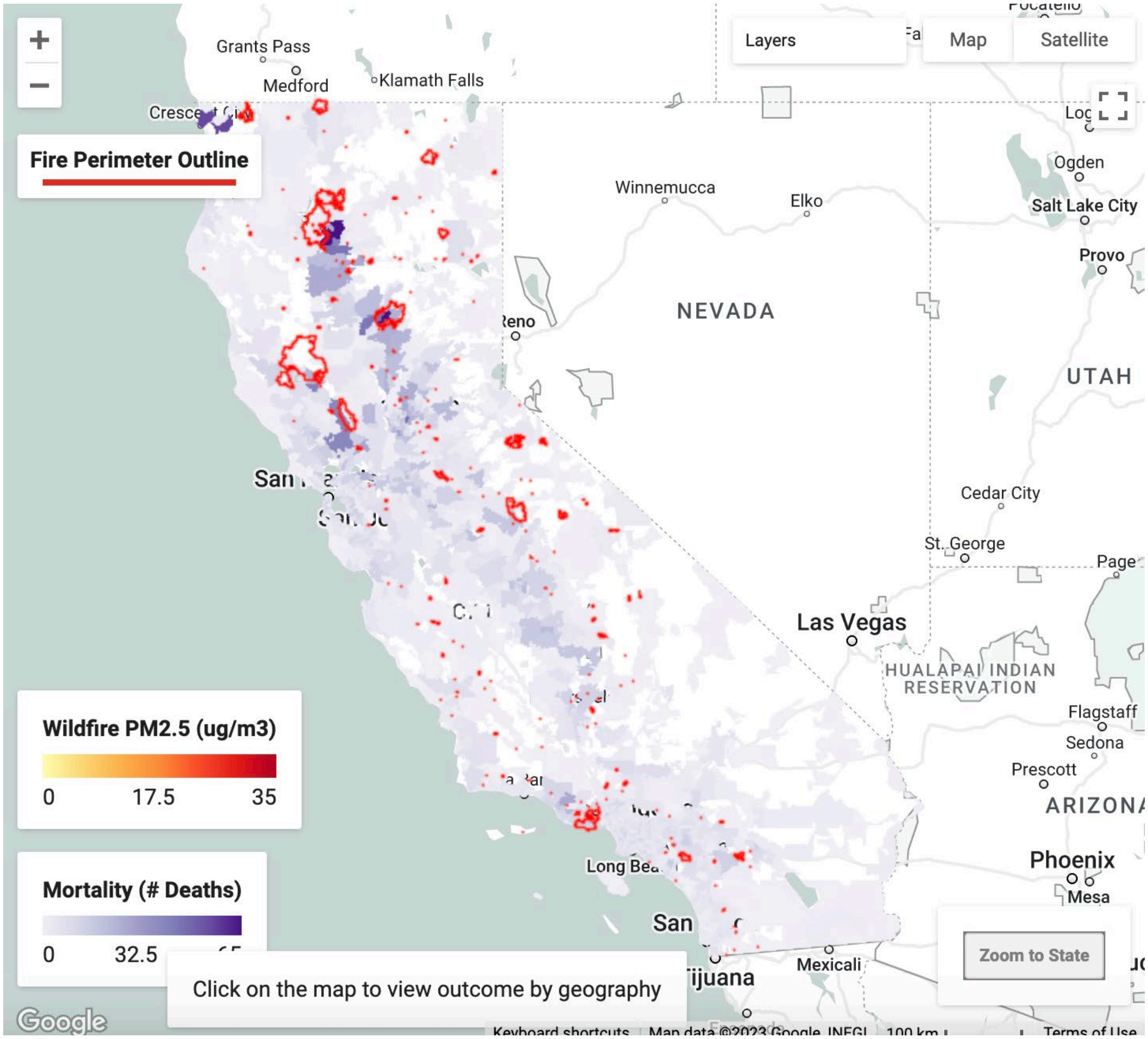


4.2.1 Annual Impact Estimates

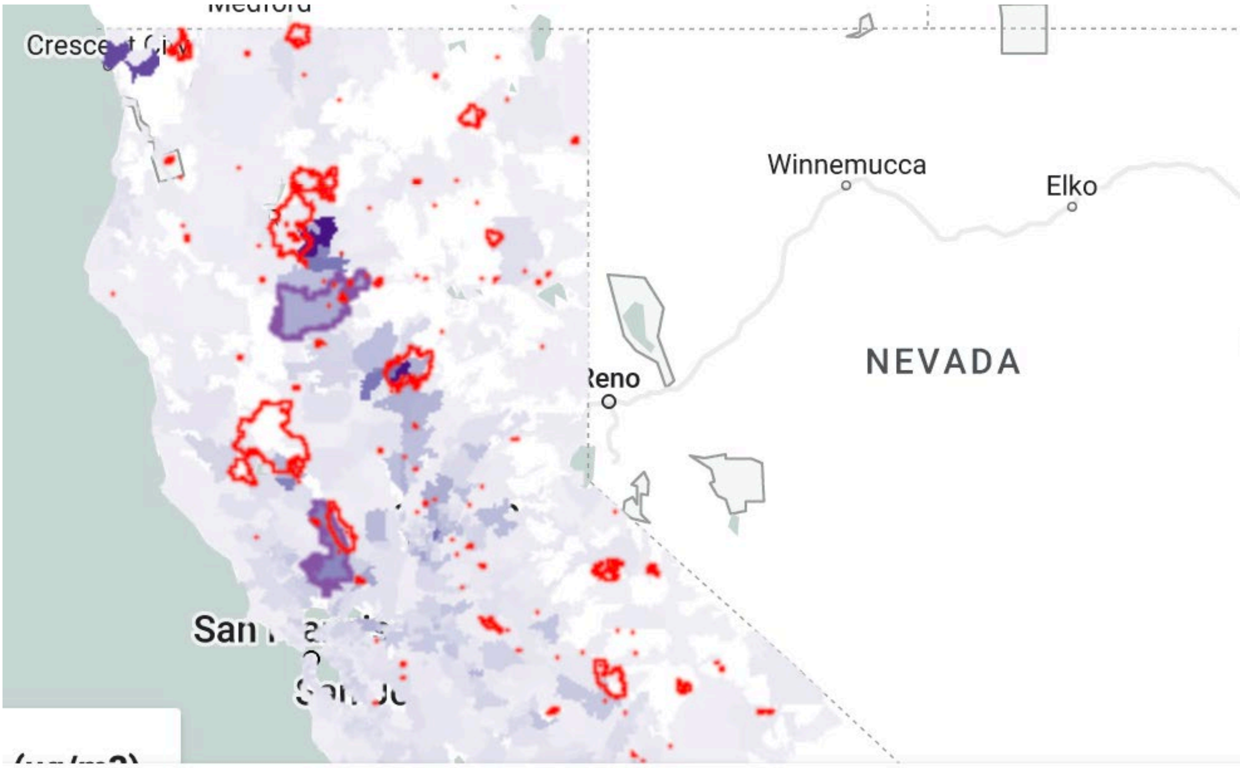
Users who select "Annual Impact Estimates" will be able to select various health outcomes of interest at the ZIP-code scale and a year of interest from 2008 to 2018 using the CMAQ model. Results are available across the state of California, but after running the analysis, users can select a ZIP code of interest for more detailed information.



Here we provide examples of the results provided in the tool with the above example selections, although this will vary depending on the user's selections at each step. First, a statewide map shows ZIP-code level annual fire-specific $PM_{2.5}$ concentrations and estimated mortality, with fire perimeters overlaid in red. Users can toggle between the concentrations and mortality using the "Layers" feature in GEE.



By selecting specific ZIP Codes on the map, more detailed information is provided on health and economic outcomes.



Zipcode	2018 Estimated Deaths	2017 Estimated Deaths	2016 Estimated Deaths	2015 Estimated Deaths	2014 Estimated Deaths	201 Estima Deat
94558	59.792	124.13	9.933	21.605	8.963	11.
96080	41.142	17.932	4.455	15.427	6.047	8.

Close Window

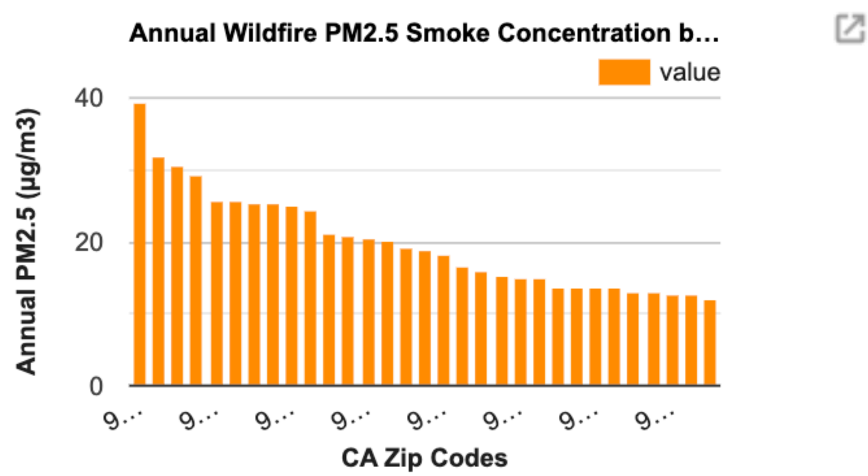
We also show here examples of aggregate economic impacts and ZIP-code rankings of the highest smoke $PM_{2.5}$ concentrations and mortality.

State-wide Economic Impact Estimates for 2018:

$101 Billion

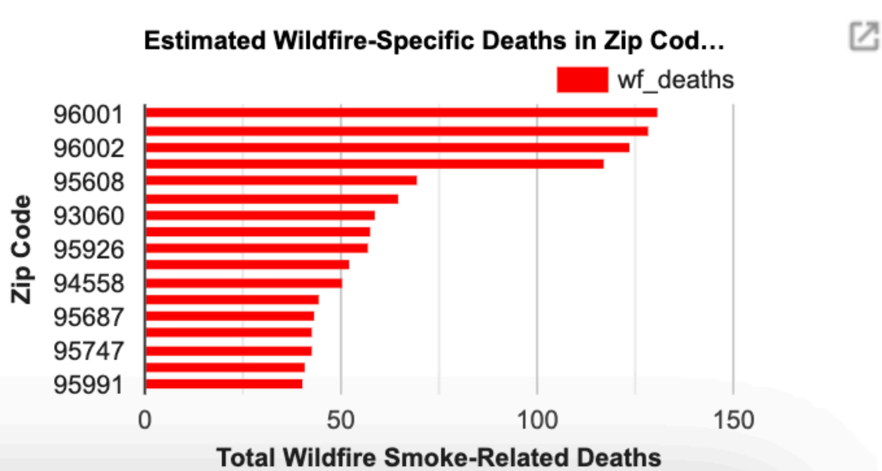
for All-Cause Mortality Only

Wildfire Smoke Concentration Estimates



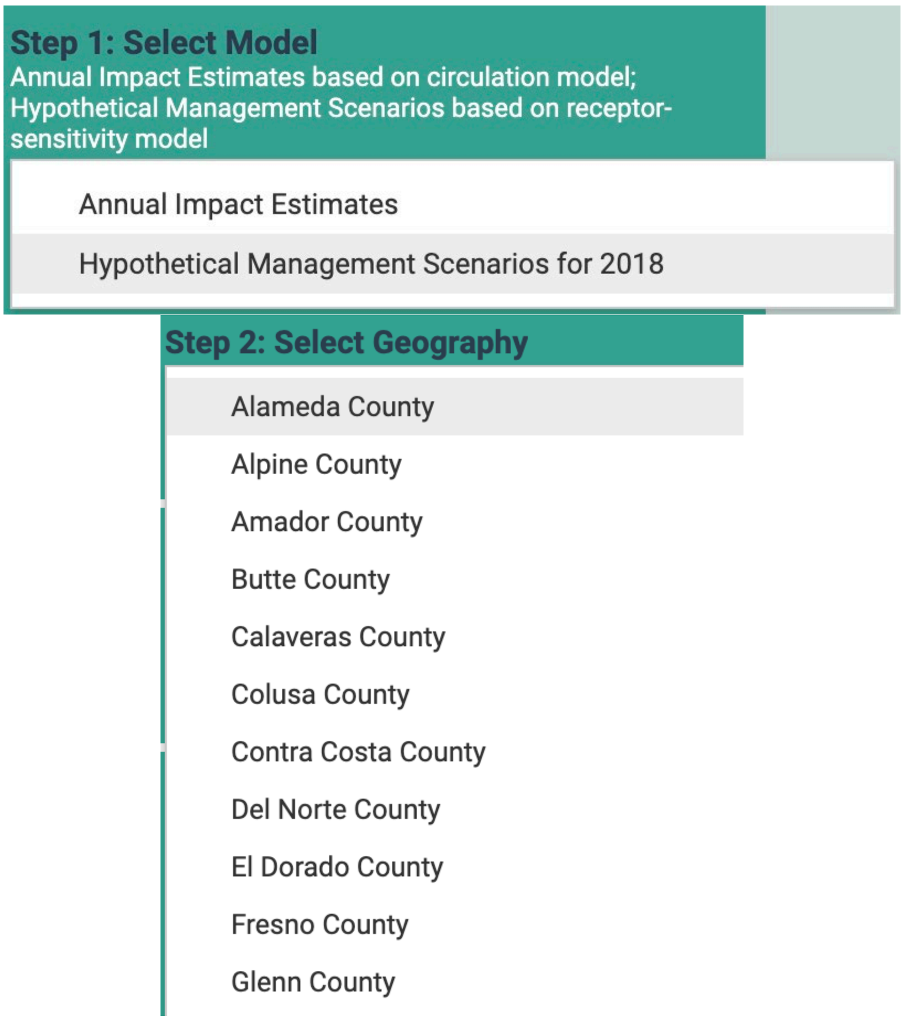
Public Health Estimates

≥99th Percentile of Wildfire Attributed Deaths

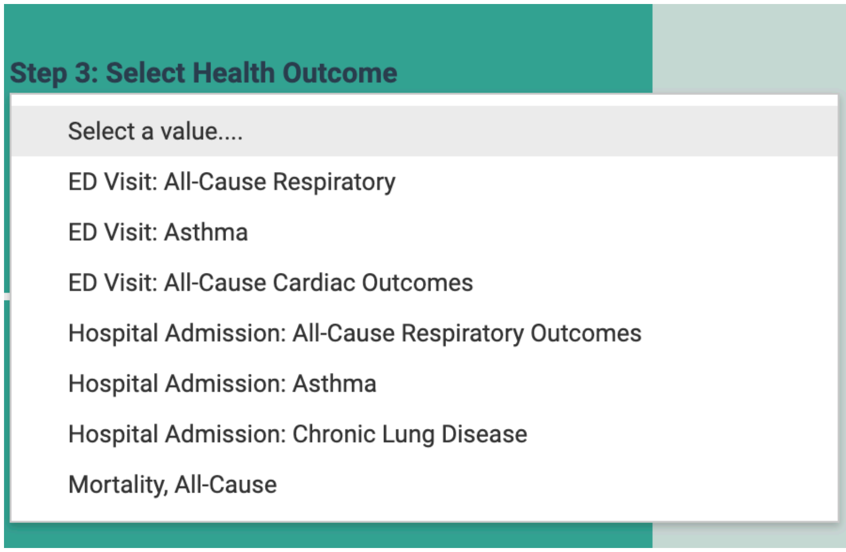


4.2.2 Hypothetical Management Scenarios for 2018

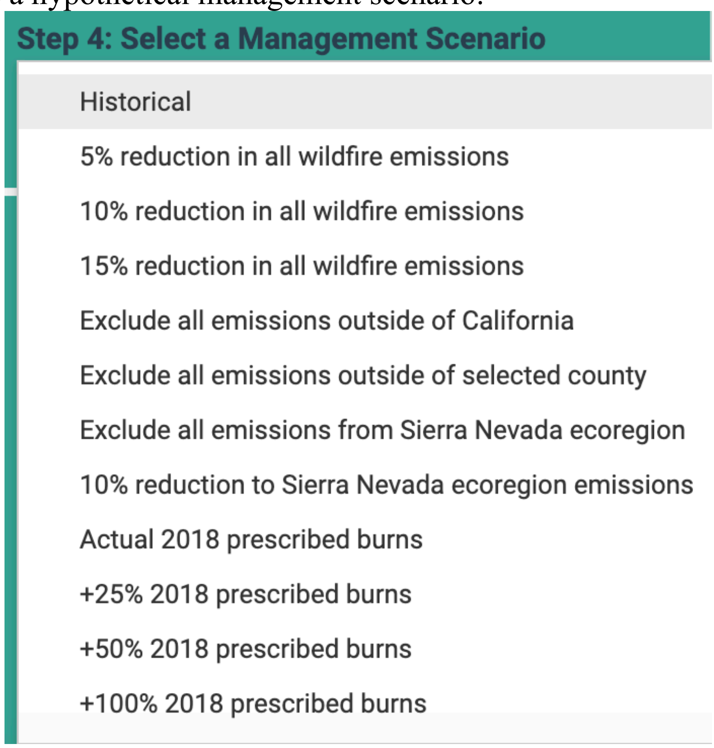
The second model option in the wildfire tool uses a receptor-oriented model (STILT) to allow users to rapidly examine the influence of potential NWL management scenarios on downwind $PM_{2.5}$ concentrations and health outcomes. By selecting the second model type in Step 1 (“Hypothetical Management Scenarios for 2018”), users are then directed to select a county of interest.



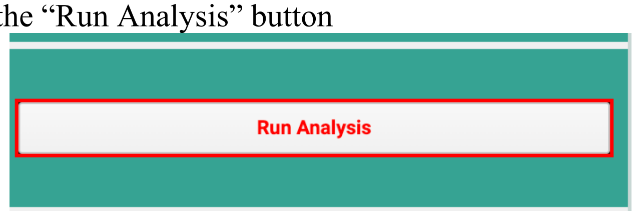
At present, the tool only provides estimates for impacts on mortality, but could be augmented with other health outcomes, such as:



The user then selects a hypothetical management scenario:



Finally, the user clicks the “Run Analysis” button



Once the user has made these selections, the tool displays county-specific average annual wildfire $PM_{2.5}$ emissions, number of health outcomes (e.g. deaths for all-cause mortality), and economic impact for both the chosen scenario and the modeled "historical" scenario for 2018.

Historical	10% reduction to Sierra
4.684 (ug/m^3)	4.217 (ug/m^3)
at population centroid	at population centroid
597 people	540 people
$5198 Million	$4699 Million
Mortality, All-Cause	Mortality, All-Cause

Example result for Fresno County comparing model result for historical (as it happened, left), and hypothetical 10% reduction of emissions from the Sierra Nevada ecoregion (right).

Discussion

The purpose of the NWL Health Scenario tool is to provide quantitative assessments of the potential health and economic benefits associated with urban green space and wildfires. The online interface in GEE allows users to select from multiple management scenarios, immediately quantify the potential health and economic outcomes, and download results for future analysis.

Our findings indicate that achievable increases in urban green space could result in substantial health benefits, including approximately 7,378 avoided deaths and 20,649,279 years of life expectancy gained, with the majority of the benefits accruing to non-white populations. We also estimate up to 5,385 low birth weight deliveries avoided. Please see *Chapter VII. Health Impact Assessment: Urban Green Space* for a detailed overview of strengths and limitations of this empirical analysis. Future work should continue to explore differential impacts between populations in California and the U.S. more broadly, as this has distinct implications for urban planning and environmental justice policy.

The ZIP-code level annual health impact analysis with the CMAQ model simulations found that wildland fire emissions contribute approximately half of total $PM_{2.5}$ in high fire years. We estimate 52,600 - 56,140 premature deaths associated with smoke $PM_{2.5}$ exposure from 2008-2018. The STILT model provides estimates of specific scenarios for specific counties, for example that reducing emissions from the Sierra Nevada ecoregion by 10% would have decreased 2018 average $PM_{2.5}$ in Fresno County from 4.68 to 4.22 $\mu g/m^3$, reducing modeled mortality from 597 to 540 deaths and associated economic impact from $5.2 to $4.7 billion. There are several limitations of this analysis. For the ZIP-code level estimates of the health and economic outcomes associated with smoke $PM_{2.5}$ exposure, the CMAQ model simulations include the influence of all wildfires, but cannot differentiate between the contributions of individual fire types or locations. The relatively coarse model grid cells (12-km) results in spatially averaging exposure estimates to link with population health data available at the ZIP-code scale. The county-level analysis based on

STILT simulations also has several limitations. Given computational constraints, we simulated atmospheric sensitivity footprints for a sample of 80 days in 2018 and for the population centroid of all 58 counties in California. We do not consider variation in exposures within counties or with different meteorological years, although future work could incorporate these additional analyses.

The NWL Health Scenario Tool provides users with the ability to quantitatively estimate the potential health and economic costs and benefits associated with historical and future NWL management scenarios in urban green space and wildfire areas across California. The tool framework has the built-in flexibility to accommodate the inclusion of additional scenarios if they were to become available at a future date.

CARB Future Scenarios (in progress)

We will develop future fire emissions based on the 2022 Scoping Plan NWL land management scenarios in a format that can be directly used as input to drive GEOS-Chem, a chemical transport model that provides wall-to-wall emissions outputs based on National Aeronautics and Space Administration (NASA) global modeling inputs. The impacts of future fire emissions on air quality and human exposure concentration of $PM_{2.5}$ are distinguished from climate factors by running GEOS-Chem with future fire emissions but present-day meteorology over selected future years. GEOS-Chem driven by present-day meteorological datasets, such as NASA Global Modeling and Assimilation Office's (GMAO) GEOS-FP ("forward-processing") meteorological data product (Lucchesi, 2018), supports global simulations as well as flexible nested grid definitions to study regional changes in air pollutants at down to a spatial resolution of 0.25° x 0.3125°. To investigate the instant and accumulated impacts of fire changes, we used cycled present-day meteorology in GEOS-Chem to simulate continuous wildfire smoke changes induced by future fire emissions throughout the mid-21st century. We will create spatially and temporally explicit maps of CARB's wildfire emissions scenarios that are available at the ecounit scale. In our ongoing research with CARB, we are developing unique scaling factors from past to future scenarios of wildfire factors for combinations of ecounits, land cover types, and land ownership. These scaling factors are applied to the average distribution of past wildfires from the Fire Inventory from NCAR version 2.5 (Wiedinmyer et al., 2023). We will adapt this approach to identify new locations for future wildfire emissions for each of scenarios provided by CARB through a spatial and temporal disaggregation process (Neumann et al., 2021; Yue et al., 2013). We will allocate future emissions across the landscape and month by randomly distributing 70% of emissions to 10% of grid cells and evenly distributing the remaining 30% to 90% of grid cells as in Neumann et al. This will produce a realistic emission distribution across the landscape by estimating a plausible distribution of individual wildfire events. We will keep observed historic seasonal patterns to estimate sub-annual emissions distribution for use in GEOS-Chem.

References

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Glossary of Terms, Abbreviations, and Symbols

ACS	**American Community Survey** An annual demographics survey on population and housing information, administered by the U.S. Census Bureau.
AMET	**Atmospheric Model Evaluation Tool** A software that is used to compare meteorological and air quality model predictions with observed data from monitor networks to assess model performance.
APA	**American Psychological Association** A U.S. scientific and professional organization of psychologists.
AQS	**Air Quality System** A repository from the EPA that contains ambient air pollution monitoring data collected by the EPA and state, local, and tribal air quality agencies.
AR	**Atmospheric river** Concentrated bands of water vapor in the atmosphere that can lead to heavy precipitation events.
BenMAP-CE	**Environmental Benefits Mapping and Analysis Program Community Edition** An open-source program of the EPA that relates air quality changes to human health benefits and estimates the number and economic value from health impacts resulting from changes in air pollution concentrations.
CAL FIRE	**California Department of Forestry and Fire Protection** The fire department of the California Natural Resources Agency that promotes fire protection of the state's wildlands and also provides emergency services.
CASTNET	**Clean Air Status and Trends Network** An air quality monitoring network that evaluates the impacts of air pollution emissions changes on the environment, such as pollutant concentrations and ecological effects.
CDC	**Center for Disease Control and Prevention** A U.S. federal public health agency that works to protect people from health threats and promote health security in the nation.
CDPH	**California Department of Public Health** A department of the state of California that oversees public health affairs in the state.
CI	**Confidence interval** Range of estimates for a parameter to fall in with a specific level of confidence in frequentist statistics.
CMAQ	**Community Multiscale Air Quality model** An open-source computational tool of the EPA that models air pollutants, such as ozone, particulates and more, and is used for air quality management.
CO_2	**Carbon dioxide**

	A greenhouse gas that is emitted into the atmosphere through human activities, such as fossil fuel burning, and contributes to increased global warming.
COI	**Cost of illness** A method of quantifying and measuring costs associated with a disease.
COPD	**Chronic obstructive pulmonary disease** A group of chronic lung diseases that prevent airflow, making breathing difficult.
CrI	**Credible interval** A range of estimates for a parameter to fall in with a specific probability in Bayesian statistics. Incorporates information from previous distribution to inform estimate.
C-Solutions	**Center for Healthy Climate Solutions** A center at UCLA that provides expertise on public health affairs and works with communities to implement solutions that protect people from the effects of climate change and generate several health, economic, and environmental co-benefits.
CSV	**Comma-separated values** A text file format that saves tabular data in plain text and separates data entries with commas.
CTM	**Chemical transport model** A computer numerical model that simulates dispersions, transformations, and chemical reactions of air pollutants to predict air pollution concentrations.
DALY	**Disability adjusted life year** A measure of the burden of disease, represented as the number of years of life lost due to mortality or other adverse health outcomes.
ED	**Emergency department** Similar to emergency room. Hospital area that provides treatment to people with immediate or acute illnesses.
ELCR	**Excessive Lifetime Cancer Risk** An estimate of an increased risk of cancer that can be acquired after exposure to carcinogenic substances.
EPA	**Environmental Protection Agency** A U.S. federal government independent agency that is responsible for environmental protection affairs.
ER	**Emergency room** Similar to emergency department. Hospital area that provides treatment to people with immediate or acute illnesses.
FCCS	**Fuel Characteristic Classification System** A fuel-loading database that stores wildland fuel characteristics in fuelbeds and estimates potential hazards and fire from environmental variables.
FEPS	**Fire Emission Production Simulator model** A software program that manages data on fuel consumption, emissions generation, and smoke plumes and can be used to simulate fire events.

FINN	**Fire INventory from NCAR** A highly spatially-resolved fire emissions inventory from NCAR that is used to determine the effects of fire activity on air quality and public health.
GEE	**Google Earth Engine** A planetary-scale platform comprised of catalogs of satellite imagery and geospatial datasets for Earth science data and analysis.
GEOS-Chem	**Goddard Earth Observing System chemical transport model** A chemical transport model that provides wall-to-wall emissions outputs based on NASA global modeling inputs.
GHG	**Greenhouse gas** Gases in the atmosphere that trap heat and contribute to warming effects.
GPS	**Global positioning system** A navigation system consisting of a network of satellites that transmit signals to Earth to provide global location data.
GSI	**Green stormwater infrastructure** An infrastructure system that employs vegetation and other nature-based systems to improve stormwater management and address water quality issues.
HAP	**Hazardous air pollutant** Toxic air pollutants that can cause major adverse health effects.
HCUP	**Healthcare Cost and Utilization Project** A collection of national hospital care databases, such as inpatient stays, emergency department visits and more, online tools, and reports.
HIA	**Health impact assessment** A tool that evaluates the potential human health impacts of a project or policy on populations.
HMS Smoke	**Hazard Mapping System Fire and Smoke Product** A product that maps smoke plumes that could indicate locations of fires, digitized from satellites across the U.S.
HR	**Hazard ratio** Ratio of the hazard rates. Explains the effect of an intervention or exposure variable on the hazard of an event in survival analysis.
HRRR	**High-Resolution Rapid Refresh model** A real-time, high-resolution, 3-kilometer, hourly-updating, convection-allowing atmospheric model by National Oceanic & Atmospheric Administration (NOAA).
HRV	**Heart rate variance** A measure of the time difference between heartbeats.
ICD	**International Classification of Diseases** A medical classification system, managed by WHO, that is used globally to code diseases, injuries, and mortality.
IHD	**Ischemic heart disease** Heart problems caused by damage to coronary arteries, which restricts blood flow and oxygen to the heart.

IHME	**Institute for Health Metrics and Evaluation** A global health research institute at the University of Washington that provides publicly-available measurements for several global health issues.
IMPROVE	**Interagency Monitoring of Protected Visual Environments** A network created by the EPA to monitor air pollution visibility and address visibility issues in areas such as national parks, wilderness areas, and more across the U.S.
IPCC	**Intergovernmental Panel on Climate Change** An intergovernmental body of the United Nations that focuses on assessing the state of scientific knowledge on climate change and its effects.
LBW	**Low birth weight** Infants less than 2,500 grams at birth.
MODIS	**Moderate Resolution Imaging Spectroradiometer** A satellite sensor on NASA satellites that monitors and collects data on Earth's lands, oceans, and atmosphere.
NAAQS	**National Ambient Air Quality Standards** Ambient air quality standards set by the EPA for six criteria air pollutants that can cause health and environmental harms.
NAIP	**National Agriculture Imagery Program** A program of the United States Department of Agriculture that collects aerial imagery of the nation during agricultural growing seasons.
NASA	**National Aeronautics and Space Administration** A U.S. federal government independent agency that leads the civil space program and research on aeronautics and space.
NASA GMAO's GEOS-FP	**NASA Global Modeling and Assimilation Office's GEOS-"forward processing" meteorological data product** A present-day meteorological dataset generated by the NASA Global Modeling and Assimilation Office in near-real time or reanalysis modes.
NCAR	**National Center for Atmospheric Research** A U.S. center specialized in research in Earth system science, established by the National Science Foundation.
NDVI	**Normalized difference vegetation index** An indicator that quantifies vegetation health and density using near-infrared and red light.
NEI	**National Emissions Inventory** A comprehensive estimate of air emissions of criteria air pollutants and precursors and HAPs, with data supplied from state, local, and tribal air agencies and the EPA.
NICU	**Neonatal intensive care unit** An intensive care nursery that provides medical care to newborn infants who are sick or preterm.
NLCD	**National Land Cover Database** A geospatial dataset from the USGS that provides mapping information on U.S. land cover and land cover change.
NO_2	**Nitrogen dioxide**

	A highly reactive gas that is emitted into the atmosphere through fuel burning, such as emissions from vehicles and power plants. Part of the nitrogen oxides group.
NWL	**Natural Working Lands** Includes a biologically diverse landscape of grasslands, shrublands, and forests.
O_3	**Ozone** A highly reactive gas composed of three oxygen atoms in the Earth's atmosphere. Can either be beneficial or adverse, depending on where in the atmosphere the gas is found.
OEHHA	**California Office of Environmental Health Hazard Assessment** A department of the California EPA that evaluates health risks from environmental contaminants.
OR	**Odds ratio** Ratio of the odds of exposure among people with a disease to the odds of exposure among people without a disease.
PAH	**Polycyclic aromatic hydrocarbon** A class of chemicals that can be released through fuel burning, such as coal, oil, and more, and can bind to or produce small airborne particles.
PM_{10}	**Particulate matter with a diameter of 10 micrometers or less** A type of air pollutant of inhalable particles that have diameters of 10 micrometers or less. $PM_{2.5}$ is a subset of PM_{10}.
$PM_{2.5}$	**Fine particulate matter with a diameter of 2.5 micrometers or less** A type of air pollutant of fine inhalable particles that have diameters of 2.5 micrometers or less.
PRISMA	**Preferred Reporting Items for Systematic Reviews and Meta-Analyses** An evidence-based checklist of 27 items to ensure transparent reporting for systematic reviews and meta-analyses.
PRISMA-ScR	**Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews** An extension of PRISMA specifically for scoping reviews, containing 20 necessary items and two optional items.
PSI	**Pollution Standard Index** A scale developed by the EPA that measures air pollution levels of six major air pollutants to determine air quality in specific regions.
PTSD	**Post-traumatic stress disorder** A mental health disorder that can arise after experiencing a traumatic and dangerous event.
RCP	**Representative Concentration Pathway** A set of greenhouse gas concentration scenarios used by the IPCC that attempt to model future climate trends, based on different human activities and emissions generation.
RR	**Relative risk** Ratio of the risks for an event in the exposed group to the risks for the event in the non-exposed group.

SGA	**Small for gestational age** Infants with a birthweight less than the 10th percentile of gestational age.
SLR	**Sea level rise** A rise in global average sea levels due to thermal expansion of seawater and melting of ice from increased global warming.
SoCAB	**California's South Coast Air Basin** An air basin area in California, identified by the state to be responsible for air quality management and air pollution control in the region.
STILT	**Stochastic Time-Inverted Lagrangian Transport model** A receptor-oriented, atmospheric transport model used to quantify the influence of different emission sources and model the impact of multiple emissions scenarios on downwind air quality.
U.S.	**United States of America** Country in North America.
USGCRP	**U.S. Global Change Research Program** A U.S. federal program leading federal research on global environmental and Earth system changes and their effects on people.
USGS	**United States Geological Survey** A U.S. governmental agency that collects, analyzes, and provides information on Earth, water, and biological science and mapping.
VIIRS	**Visible Infrared Imaging Radiometer Suite** An instrument on board a NASA-National Oceanic & Atmospheric Administration (NOAA) satellite that collects visible and infrared images of the Earth's lands, oceans, atmosphere and cryosphere.
VSL	**Value of a Statistical Life** An economic measure of additional costs people are willing to incur for small reductions in risk of mortality, often used in cost-benefits analyses.
WHO	**World Health Organization** A specialized health agency of the United Nations that works to promote global health and is involved in international public health affairs.
WONDER	**CDC Wide-ranging Online Data for Epidemiologic Research database** A directory of online and searchable public health datasets.
WTP	**Willing to pay** The maximum amount that a person would be willing to pay for a good.
WUI	**Wildland-urban interface** A transitionary zone between undeveloped wildland (natural environment) and land developed by humans (built environment), where risk of wildfires is increased.

APPENDIX A

Supplementary Information for *Chapter VII. Health Impact Assessment: Urban Green Space*

Review of Key Climate-Health Threats in California and Possible Green Space Solutions

Here we review climate change and important health risks specific to California through the lens of green space solutions. This complements existing climate change assessments already available for California (Bedsworth et al., 2018; Intergovernmental Panel On Climate Change (IPCC), 2023b; U.S. Global Change Research Program (USGCRP), 2016). We focus on the direct and proximal indirect health effects of key climate threats in California, including extreme heat, severe precipitation events, wildfire smoke, and infectious disease. We consider exposures that can affect highly ranked causes of disability and death will often have a higher burden of disease because of the larger populations affected (see Appendix A). To structure the review, we established a series of evaluative criteria for each selected climate risk (Table A7.1). This includes the attribution of exposure to climate change, the projected timing of the effects, the likely burden of disease related to the risk, vulnerable populations, available adaptation measures, and the possible co-benefits that can result from urban green space solutions. This review prioritizes California-specific studies (to the extent the literature is available) but also considers studies from other locations that describe biological mechanisms for climate-health pathways or potential adaptation solutions. We consider health effects in the general population, as occupational health risks are beyond the scope of this review.

Extreme Heat

Climate change is increasing the frequency and intensity of extreme heat events, and many factors influence the magnitude and nature of extreme heat health impacts (Ebi, Capon, Berry, Broderick, De Dear, et al., 2021). Although no standard definition of an extreme heat event exists, the consensus suggests that increasing heat from climate change is a major public health problem.

Attribution Certainty. Human influence has unequivocally impacted and warmed the atmosphere, oceans, and lands. Over the last twenty years, more than 150,000 deaths from heat waves have been recorded across the globe (Clarke et al., 2022; Intergovernmental Panel On Climate Change, 2023b). Within California, various models have attributed anthropogenic emissions to increased likelihood of extreme weather in Los Angeles and the Central Valley (Clarke et al., 2022; Mazdiyasni et al., 2019).

Timing of Effects. Annual temperatures within California have increased by 1°F to more than 2°F since the first half of the 20th century (Bedsworth et al., 2018). Statewide annual average maximum temperatures could increase by 4.4°F to 5.5°F compared to the 1961-1990 baseline by mid-century, under Representative Concentration Pathway [RCP] 4.5 and 8.5, respectively (Geospatial Innovation Facility, 2023), and by > 8°F by the end of the century (Bedsworth et al., 2018). The frequency and intensity of heat waves are also predicted to increase across California with some Central Valley heat waves lasting 4-9 days longer by mid-century (Vahmani et al., 2019). Extreme heat events are predicted to increase in inland areas already prone to heat waves, but also in coastal areas less accustom to extreme heat (Gershunov & Guirguis, 2012; Vahmani et al., 2019), which may result in a larger health burden in these less adapted areas (Cheng et al., 2019).

Likely Population Health Burden. Extreme heat is the leading weather-related cause of mortality in the U.S. and the burden of extreme heat on human health in California is already substantial and expected to increase rapidly along with rising climate change. Extreme heat can raise body temperature and result in increased breathing rates, elevated heart rates, and changes in blood coagulation and arterial pressures. These disruptions in key circulatory mechanisms can lead to negative cardiac outcomes because of the added demand induced by extreme heat exposures. Considerable evidence shows that extreme heat can exacerbate chronic conditions, increase the risk of heat-related illnesses, lead to multiple morbidities including cardiovascular, respiratory, renal, and in severe cases, death (Basu & Ostro, 2008; Cheng et al., 2019; Fletcher et al., 2012; Knowlton et al., 2009; Z. Sun et al., 2018). Extreme heat has also been associated with negative impacts on pregnancy, mental health outcomes, and an increased risk for hospitalizations and ED visits, especially in vulnerable populations (Anderson et al., 2013; Chersich et al., 2020; Nori-Sarma et al., 2022; S. Sun et al., 2021; Thompson et al., 2018).

Limited information exists on the overall health burden from extreme heat within California; however, a study found that each additional extreme heat day is associated with 0.07 additional deaths per 100,000 adults within the contiguous U.S. (Khatana et al., 2022). With California's roughly 30 million adult residents, this would correspond to 21 deaths across the state's adult population for each extreme heat day. Historic heat waves provide additional evidence to this potential health burden in California. For example, the July 2006 heat wave, characterized by two-weeks of elevated temperatures and humidity, resulted in an estimated 232 deaths across nine counties and increased all-cause mortality risks by 9% per 10°F increase (Ostro et al., 2009). In the absence of adaptation measures, the impact of extreme heat is expected to rise by the end of the century with models predicting approximately 400 deaths per one-million persons every year (values extracted from figure) throughout the state from extreme heat exposures (Shindell et al., 2020). When we consider morbidity impacts, the population burden rises even further. During the same 2006 heat wave, a total of 16,166 excess ED visits and 1,182 excess hospitalizations were estimated statewide (Knowlton et al., 2009).

Vulnerable Populations. High-risk populations include children and the elderly; pregnant, undocumented, economically disadvantaged, and unhoused individuals; individuals with preexisting conditions; and outdoor workers (Jung et al., 2021; Knowlton et al., 2009; Peters & Schneider, 2021; Qu et al., 2021). Children, the elderly, and those with pre-existing conditions are less likely to self-thermoregulate and can suffer from impaired thirst sensation or experience impaired glomerular filtration rates. During the 2006 California heat wave, Knowlton et al. (2008) found children (0-4 years) and elderly (≥ 65 years of age) at a higher risk of ED visits compared to other groups (Knowlton et al., 2009). Additional studies examining the impacts of extreme heat on mortality found that the Black racial/ethnic group had a higher risk of non-accidental mortality with 10°F increases in temperature compared with Whites (Basu & Ostro, 2008). In addition, extreme heat exacerbates existing inequities across the state by impacting low-income communities and communities of color who are disproportionately housed within some of the hottest census-tracts in the state (Gabbe & Pierce, 2020). These communities have a more difficult time adapting to extreme heat due to barriers around access to and use of air conditioning (O'Neill, 2005). Further, vegetation in vulnerable neighborhoods is often more sensitive to drought conditions, and thus, these areas are less likely to benefit from urban green space cooling effects likely due, in part, to barriers to water access and usage (Dong et al., 2023).

Adaptation Measures. Urban green space, specifically tree canopies, have been widely recognized for their role in reducing urban heat islands via evapotranspiration and shading from solar radiation (Bowler et al., 2010a; Rahman et al., 2020; Winbourne et al., 2020; Yan et al., 2020). Within Los Angeles, estimating the impacts of moderate tree cover and albedo mitigation scenarios (RCP 4.5) could delay climate-induced warming by 69 years; in effect, experiencing a climate in the year 2089 that was like the climate in the year 2020 (Kalkstein et al., 2022). Aggressive action to increase both tree canopy and urban reflectivity within urban Los Angeles can save one in four lives during extreme heat events; however, it is important to consider native vegetation to increase resiliency to local drought impacts and inequities in water related access and usage (Allen et al., 2021; Dong et al., 2023; Kalkstein et al., 2022). Cool and green roofs can also reduce urban temperatures with impacts highest in areas with more building density and, thus, roof surface area (Krayenhoff et al., 2018). Cool roofs, which are roofs designed to reflect more sunlight and absorb less heat relative to standard roofs, have been predicted to reduce future exposure to heat waves across the 29 most populous counties in California by up to 56% (Vahmani et al., 2019). The combination of cool and green roofs with street trees can decrease both projected regional and summer temperatures, with the highest impacts in the southwest U.S. (Krayenhoff et al., 2018).

Additional adaptive measures include well-communicated heat action plans at the local level, robust surveillance and monitoring programs, cooled spaces, and interventions aimed at the most vulnerable populations. Targeting adaptive actions within areas with limited access to either private or public cooled spaces could reduce heat-related health risks (Fraser et al., 2017). For example, shared-wall, multi-family dwelling units can reduce peak energy demand by up to 50% (Burillo et al., 2019). Furthermore, California-based tools like the California Health Places Index: Extreme Heat Edition (https://heat.healthyplacesindex.org/) and the Center for Healthy Climate Solutions (C-Solutions) Heat Maps (https://uclaheatmaps.org), provides a platform that can be used to visualize and understand the distribution of heat-related illness across the state, identify adaptation resources, and to prioritize the delivery of resources and programs (Public Health Alliance of Southern California, n.d.; UCLA Center for Healthy Climate Solutions & UCLA Center for Public Health & Disasters, n.d.).

Green Space Health Co-benefits. Studies have found that extreme heat can have multiplicative effects with air pollution and have varying impacts on specific geographies and groups of people, especially among vulnerable populations (Grigorieva & Lukyanets, 2021; Xu et al., 2014). Strategically placed vegetation within urban environments can mitigate urban heat islands and may improve local air quality by removing air pollutants via deposition; in some cases, urban green space deposition can account for street-level reductions of air pollutants up to 60% (Pugh et al., 2012), although uncertainty exists because of the possible precursors to particle formation emitted by plants. Additional co-benefits of adaptive measures include indirect health benefits associated with reducing climate forcing CO_2 emissions from measures like reflective roofs and urban vegetation (Z.-H. Wang, 2021). Compared to a single management action, combining heat related mitigation and adaptive measures has been shown to further reduce urban temperatures

(Santamouris et al., 2020) and providing the potential to further limit impacts on morbidity and mortality. The long-term mitigation strategies that address rising temperature and air pollution can be implemented via policies that reduce energy consumption in transportation, industry, and households and improve the built environment (Harlan & Ruddell, 2011).

Extreme Precipitation

Climate change alters the timing and severity of extreme precipitation events. Here we review health risks associated with wet precipitation extremes. The health burden associated with dry precipitation extremes (drought) is explored through the contribution to wildfires and Valley fever in subsequent sections.

Attribution Certainty. The connection between climate change and increased precipitation extremes is more certain than changes in annual precipitation totals (Berg & Hall, 2015). Most heavy precipitation events in California are linked to atmospheric river (AR) events (Gershunov et al., 2019), which are concentrated bands of water vapor (Ralph et al., 2018). AR events, such as the heavy precipitation that caused the Oroville Dam crisis in 2017, are enhanced to varying degrees by climate change (Michaelis et al., 2022). In addition to higher precipitation totals during individual events, as the climate warms, more precipitation will fall as rain rather than snow (Huang et al., 2020). Subsequent connections to flood risk depend on multiple factors, including the intensity of extreme precipitation events, soil moisture, and snowmelt (Sharma et al., 2018).

Timing. California currently experiences more compressed and severe rainy seasons than in the historical record (Luković et al., 2021). AR events are expected to intensify in the future, and there is strong model agreement that extreme precipitation events will increase in this century (Polade et al., 2017). The risk of megafloods associated with extreme storm sequences, runoff, and hydrologic outcomes has already doubled (Huang & Swain, 2022) and the extreme flood event is more likely than not in the next few decades (Huang & Swain, 2022; Swain et al., 2018). Some 1.39 million properties in California are currently at risk of flooding, which could increase to 1.54 million in the next 30 years; cities in the Central Valley are most vulnerable (Bates et al., 2021; First Street Foundation, n.d.).

Population Health Burden. Extreme precipitation events impact health through multiple pathways: trauma or drowning, displacement, water quality, vector borne diseases, or mental health impacts (Paterson et al., 2018). Simulations of a potential severe winter storm scenario that would be of a comparable magnitude to the historic 1861-1862 events in California would result in widespread flooding, extreme winds, and landslides. Given the location of development and residential areas, this would cause hundreds of billions of dollars in property damage, the evacuation of approximately 1.5 million residents, and disruption to critical infrastructure, particularly among Central Valley and coastal communities (Porter et al., 2011). Water management planning will also be challenged by the shifting nature of precipitation events (Siirila-Woodburn et al., 2021).

Stormwater runoff also accumulates pollutants that can negatively impact water quality. AR events, for example, are linked to three-quarters of fecal pollution spikes in California's coastal waters, including densely populated areas in Southern California (Aguilera et al., 2019). Drier summers could possibly reduce coastal water contamination through reduced runoff amounts, but increased population density in coastal areas and increased variability in precipitation could challenge surveillance that are used to mitigate health risks (Semenza et al., 2012). Precipitation extremes could also amplify the effects of climate-related sea level rise (SLR). This includes potential consequences such as coastal flooding, erosion, salinization of water sources, and storm surge (Rahimi et al., 2020). In coastal California, hazardous sites are vulnerable to flooding, which can release toxic chemicals into the environment. The risk, especially in socially marginalized communities, is expected to increase by the end of the century (L. J. Cushing et al., 2023). In general, however, while ample evidence of potential impacts on health of extreme precipitation, there is currently a dearth of literature that estimates the past, current, or future burden of morbidity and mortality from these extreme events.

Vulnerable populations. Vulnerable populations to extreme precipitation include communities that are lower income, have inequities in access to information systems to prepare for extreme events, or have increased incidence of chronic illnesses or other impairments that can reduce evacuation ability. Los Angeles County is one of the top ten counties in the U.S. for the population size at flood risk (Qiang, 2019). In addition, a recent study in Los Angeles found that approximately 425,000 people are at high risk of flooding, with disadvantaged and Black communities being disproportionately impacted (Sanders et al., 2023). Communities with limited English proficiency, including some in the Central Valley, are at risk for timely evacuation and access flood alerts (Qiang, 2019).

Adaptation Measures. Impervious surfaces increase the risk of flooding associated with climate change in California (KC et al., 2021). Retreating from flood-prone areas or prohibiting development in flood zones can limit future populations at risk of flooding. In addition, prediction of extreme events, including monitoring, flood alerts, and evacuation plans, can protect public health. Tree canopies or other green infrastructure can reduce the volume and intensity of stormwater runoff in urban areas (Berland et al., 2017; Kuehler et al., 2017). Other considerations include the intersection of extreme precipitation with additional climate hazards, such as flooding or landslides following wildfire events (AghaKouchak et al., 2020).

Green Space Health Co-Benefits. Urban greening could mitigate flood risk and bring additional health co-benefits. Urban green infrastructure, such as wetlands, re/afforestation, riparian buffers, and other green spaces could provide multiple benefits related to population health, including water supply, water purification, and extreme event moderation (Bertule et al., 2014). The literature on health effects directly associated with green stormwater infrastructure (GSI) is more limited than the economic (property values) or ecological benefits (Suppakittpaisarn et al., 2017; Venkataramanan et al., 2019). Stormwater harvesting can benefit health through non-potable water use and restoration of ecosystems, such as wetlands flood retention capacity and stormwater treatment (Jiang et al., 2015). Urban green stormwater infrastructure was associated with improved safety outcomes in Philadelphia (M. Kondo et al., 2016). A case study for siting vegetated areas to manage stormwater in Los Angeles found that social and public health and water quality benefits would be greatest if built in heavily developed areas and those with high density commercial and industrial uses (Jessup et al., 2021).

Wildfires

In California, climate change has affected the length of the fire season, annual burned areas, and the severity of wildland fires. Wildfires contribute to air pollution, including $PM_{2.5}$, ozone, nitrogen dioxide, and other trace gasses. Wildfires have also become an increasingly important source of carbon emissions (Jerrett et al., 2022). In this section, we review the health implications of wildfire smoke pollution.

Attribution Certainty. Climate change influences wildfire smoke pollution through increased fire activity and the enhancement of pollution formation in the atmosphere. In the western U.S., earlier snowmelt and rising temperatures associated with climate change have dried fuels and extended the wildfire season (Westerling, 2016). From 1984 to 2015, half of the forest wildfire burned area in the western U.S. was attributed to anthropogenic climate change (Abatzoglou & Williams, 2016). In California, Turco et al. (2023) found that anthropogenic climate change, not natural variability, was responsible for dramatic increases in summer burned area from 1971 to 2021 (Turco et al., 2023). By simulating different scenarios for climate change, population growth, and development in California, Hurteau et al. (2014) reported that climate change was the largest driving force behind projected increases in wildfire $PM_{2.5}$ emissions. The greatest increases in wildfire emissions are expected to occur in parts of northern California under federal management and unavailable for development (Hurteau et al., 2014).

Timing of Effects. Climate change is already contributing to increased wildfire activity, and it is expected to accelerate in the future. Annual area burned in California increased fivefold from 1972-2018 (Williams et al., 2019), at increasingly high severity (Parks & Abatzoglou, 2020). Under a high climate change emissions scenario (RCP 8.5), mean wildfire burned area in California is expected to increase 77% by the end of the century (compared to 1961-1990 baseline) and large wildfires would occur 50% more frequently (Westerling, 2018). Wildfire emissions in California are projected to increase 19 -101% above the baseline period by 2100 depending on climate change and land development scenarios (Hurteau et al., 2014). Other studies of the western U.S. project that the trend in increasing wildfire $PM_{2.5}$ emissions will continue, especially increases in maximum wildfire-specific $PM_{2.5}$ levels (J. C. Liu et al., 2016; Yue et al., 2013).

Population Health Burden. Exposure to wildfire smoke PM contributes to oxidative stress, inflammation, and cell toxicity (Reid & Maestas, 2019). Recent studies have found that wildfire smoke PM is more toxic than ambient urban PM due to greater oxidative potential (Verma et al., 2009; Wegesser et al., 2009). Wildfire smoke also increases concentrations of $PM_{2.5}$ indoors in California (Liang et al., 2021), which is another contributing factor to health effects given that people spend the majority of their time indoors. Wildfire smoke exposure is consistently associated with increased respiratory morbidity and all-cause mortality (Cascio, 2018). In California, researchers found positive associations between smoke exposure and ER visits and hospitalizations for respiratory symptoms among the general population and especially asthmatics (Delfino et al., 2009; Dohrenwend et al., 2013; Heaney et al., 2022; Hutchinson et al., 2018; Reid, Jerrett, et al., 2016b). Recent evidence from southern California wildfires also suggests that wildfire smoke pollution may be more harmful to respiratory health than other pollution sources (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021a). The effect of wildfire smoke exposure on cardiovascular effects is less conclusive. Some studies, including those from California, did not find an association between cardiovascular events or cardiovascular-related mortality (J. C. Liu, Wilson, Mickley, Dominici, et al., 2017a; Reid, Jerrett, et al., 2016b). Growing evidence, however, shows that wildfire PM exposure is a risk factor for cardiovascular morbidity and mortality (H. Chen et al., 2021). In their review, Chen et al. (2021) found that 25 out of 38 epidemiological studies on cardiovascular morbidity found a positive association between wildfire smoke exposure and cardiovascular disease impacts. There is also emerging evidence that wildfire exposure is linked to adverse birth outcomes, such as preterm births, via smoke or psychosocial stress but this requires further study (Amjad et al., 2021; Heft-Neal et al., 2022).

A recent study, which addressed the impact of the severe 2018 California wildfires, found that smoke pollution contributed to over 3,600 state-wide deaths that year. The total wildfire damages amounted to $148 billion in health costs, capital, and other indirect losses (D. Wang et al., 2021). For future smoke exposure mortality, limited information exists on the burden for California specifically. Focusing on future western U.S. wildfire activity, Neumann et al. (2021) project that wildfire $PM_{2.5}$-related mortality could increase by 3.7 times to 4.2 times by end of century under moderate (RCP4.5) and high (RCP8.5) emissions scenarios respectively (Neumann et al., 2021). Climate change accounts for 40% (for RCP4.5) to 60% (for RCP8.5) of the projected increases in wildfire mortality (Neumann et al., 2021).

Vulnerable Populations. The sensitive groups for wildfire smoke $PM_{2.5}$ exposure include children younger than 18 (particularly young children), older adults, people with chronic health conditions such as asthma, people with lower socioeconomic status, and potentially women and racial minorities. Most of the literature focuses on differential impacts by age group, where they found that children, especially under 5 years of age, were more susceptible to the respiratory health effects of wildfire smoke pollution, including ED visits for respiratory symptoms, asthma diagnoses, and asthma hospital admissions (Heaney et al., 2022; Hutchinson et al., 2018). Aguilera et al. (2021) also found that wildfire-specific $PM_{2.5}$ was 10 times more harmful to children's respiratory health compared to other $PM_{2.5}$ sources for emergency and urgent care respiratory care from 2011-2017 in San Diego (Aguilera, Corringham, Gershunov, Leibel, et al., 2021b). Older populations over age 65 are often more susceptible to respiratory and potentially cardiovascular impacts from smoke pollution exposure (Delfino et al., 2009; Heaney et al., 2022). People living in low-income communities are also more susceptible to smoke exposure health effects, such as for asthma, COPD, pneumonia, and all-cause respiratory-related ED visits (J. C. Liu, Wilson, Mickley, Dominici, et al., 2017a; Reid, Jerrett, et al., 2016b). Some evidence suggests that women and racial minorities, particularly Black populations, are more likely to experience health effects from wildfire smoke exposure (J. C. Liu, Wilson, Mickley, Ebisu, et al., 2017b). Recent research in California has reported that higher smoking prevalence rates modifies the effect of wildfire smoke on ER visits for asthma and pneumonia, with greater admissions in areas with higher smoking rates (Reid et al., 2023).

Adaptation Measures. In events of severe wildfire pollution, clear and consistent messages must be conveyed across several modes of communication, with special focus on vulnerable groups, to mitigate exposure (Fish et al., 2017). Providing clean air shelters and portable air cleaners may also reduce individual exposure (Barn et al., 2016).

Wildland management strategies, such as mechanical thinning, prescribed burns, and other fuel treatments, may reduce the scale and severity of future fires (Hunter & Robles, 2020). Westerling (2018) simulated large-scale fuels treatments and found that they substantially offset the increased burned area modeled under future climate change (Westerling, 2018). In the WUI, green space management in agricultural areas, parks, recreation areas, or other managed open spaces can create buffers around communities (in addition to providing primary health benefits) (Moritz et al., 2022). Moritz et al. (2022) emphasize how such landscape measures need to be coordinated with complimentary interventions in the built environment (e.g., fire-resistant construction) and across the community scale (e.g., community outreach to create social capital that increases mitigation efforts) (Moritz et al., 2022). Increasing defensible space reduces available fuel in proximity to homes and can reduce the risk of a home igniting (Syphard et al., 2014). The relationship between vegetation and wildfire risk (as measured through structure loss), however, is complex and varies from local to landscape scales (Syphard et al., 2021).

Green Space Health Co-benefits. Fuel management strategies, such as prescribed burning, can potentially reduce carbon emissions and mitigate climate change with long-term health benefits. Such measures can also reduce emissions of air pollutants that adversely affect human health. If widespread prescribed burning were to be implemented and replaced wildfire activity in the western U.S., biomass burning carbon emissions could be reduced by up to 25% (Wiedinmyer & Hurteau, 2010). Simulations of land management policy scenarios in California have studied the net impacts of land conservation, ecosystem restoration, forest fuel reduction (i.e., prescribed burning and mechanical thinning), and agricultural carbon sequestration on carbon dioxide and methane emissions (Simmonds et al., 2021). They found that although emissions from prescribed burning initially outweighed emissions reductions from other strategies, cumulative net emissions were reduced by mid-century and more significantly by the end of the 21st century. The quantifiable net impacts of prescribed burns on carbon and particulate emissions, however, remain uncertain, because research has yet to ascertain accurately the extent to which low level prescribed burns will prevent future emissions from extreme wildfires (B. A. Jones et al., 2022).

Infectious Disease: Dust Pollution and Valley Fever

Many paths exist from climate change to infectious disease, including changes in habit and range of vectors and human migration that can increase contact with vectors. In California, several infectious diseases are predicted to worsen due to climate change, including two of the more serious ones: West Nile Virus (Flaviviridae) (Morin & Comrie, 2013) and coccidioidomycosis or Valley fever (Weaver & Kolivras, 2018). Valley fever affects more people than West Nile Virus in terms of annual incidence (8,030 versus 149 new cases in 2021) (Aragón, 2022). Moreover, the California Office of Environmental Health Hazard Assessment (OEHHA) has tracked the incidence of West Nile Virus since 2001, after the virus became prevalent in California (Office of Environmental Health Hazard Assessment, 2018). Given this potentially larger and growing problem with evidence of no clear time trends from OEHHA, we focus on Valley fever as the most likely important climate-affected infectious disease risk in California.

Valley fever is a growing concern associated with dust mobilization in the southwestern U.S. Valley fever is caused by the inhalation of dust-carried fungus *Coccidioides immitis* (*C. immitis*) or *Coccidioides posadasii* (*C. posadasii*) (Kollath et al., 2019). It is endemic to California's Central Valley. In this subsection, we consider the link between climate change and health risks associated with both dust pollution and Valley fever. We also emphasize how greening solutions can limit dust exposure.

Attribution Certainty. The arid and semi-arid region of the southwestern U.S. is characterized by large concentrations of soil-derived dust particles in the lower atmosphere, especially in spring. Trend analysis indicates an increase in springtime dust concentration and an earlier onset of the dust season over past decades (Hand et al., 2016). Climate models predict with high confidence a warmer and drier environment in the southwestern U.S. through the 21st century (Intergovernmental Panel On Climate Change (IPCC), 2023b). This would bring more frequent and severe drought (Prein et al., 2016; Seager & Vecchi, 2010; Williams et al., 2020). Such conditions can modify vegetative cover and influence dust mobilization.

Coccidioides reproduce rapidly during the winter with moderate rainfall and mild temperature and then disperse easily during hot and dry summer conditions (del Rocío Reyes-Montes et al., 2016). When the soil is dry, spores of *Coccidiodes* can be picked up by wind and carried by dust particles, allowing them to be inhaled by humans (Matlock et al., 2019). The size of dust particles typically spans from less than 1 µm to 400 µm in diameter, with particles larger than 100 µm mostly settling down near the source of formation. PM_{10} can reach deep into human lung systems and bloodstreams, among which fine dust particles (e.g., $PM_{2.5}$) pose the greatest risk to health, thus having been mostly studied. *Coccidiodes* spores are about 2 µm to 5 µm in length, falling within both fine and coarse dust particle sizes (Akram & Koirala, 2023). *Coccidiodes* fungus can out survive other organisms and become dormant under drought conditions; the fungus can then be reactivated when ideal conditions (e.g., precipitation) return; this life cycle is followed by the release of infection fragments when the environment is dry and hot again and the contaminated soil is disturbed (Coates & Fox, 2018; Fisher et al., 2000; Gorris et al., 2018). Head et al. (2022) also found that Valley fever incidence in arid counties is more sensitive to precipitation fluctuations as drought years followed by wet winters increase Valley fever incidence in California, while the incidence in cool and wet counties, such as coastal regions, is more sensitive to temperature changes (Head et al., 2022). These regional differences create a heterogeneous spread across California.

Timing of Effects. Achakulwisut et al. (2018) identified the Standardized Precipitation-Evapotranspiration Index as a useful indicator of present-day dust variability, and predicted increases of 26 - 46% in fine dust concentrations over the southwestern U.S. in spring by 2100 (Achakulwisut et al., 2018). In contrast, Pu and Ginoux (2017) found that the frequency of extreme dust days decreases slightly in spring within this region due to reduced extent of bare land under 21st century climate change, highlighting the complex relationships between climate change and land use (Pu & Ginoux, 2017). Valley fever became more prevalent in recent decades and is projected to further expand north into the dry western U.S. (135, 136). Pearson et al. (2019) analyzed the threat of Valley fever to the general population in California due to climate change, land use, and population movement. California is expected to face increasingly dry conditions, which could allow the dominant Coccidioides species (C. immitis) to outnumber its microbial competitors (Pearson et al., 2019).

Likely Population Health Burden. Valley fever can infect the lung system, cause respiratory symptoms such as cough, fever, shortness of breath, and chest pain, and may spread to other parts of the body and be potentially fatal (CDC, 2021). In California, the number of reported valley fever cases has greatly increased from 719 since 1998 to 9,004 in 2019 (CDC, 2021). Originally, high Valley fever incidence in California was reported in the San Joaquin Valley, but the largest case increases in recent decades have occurred in the Northern San Joaquin Valley, the Central Coast, and South Coast regions (Cooksey et al., 2020). Correlated changes in Valley fever incidence with drought and temperature in California demonstrate that climate conditions are driving factors that control valley fever outbreak, leading to the expansion of valley fever cases to regions that experience prolonged dryness and drought in recent years and under future climate (Gorris et al., 2019; Head et al., 2022; Shriber et al., 2017).

Vulnerable Populations. Most cases have been contracted occupationally in construction, agricultural, military, archeological, and correctional institutional settings, possibly due to heightened exposure to dust. People over 60 years of age, pregnant women, those with depressed immune systems, women, and Black and Filipino populations are at higher risk of contracting coccidioidomycosis (Guevara et al., 2015; Niehaus et al., 2023; Rosenstein et al., 2001).

Adaptation Measures. Green space expansion in California could mitigate dust mobilization and its health consequences. Wind speed and vegetation cover are two key factors that determine soil erodibility and dust emissions (Zender et al., 2003). In addition, vegetation constrains dust emissions by preserving soil moisture through plant shade and root systems (Hillel, 1982). Under future climate scenarios, regions with higher temperature, reduced soil moisture, which is characteristic of drought, and enhanced anthropogenic land use practices could experience strengthened dust mobilization (Y. Li et al., 2021), as the loss of vegetative cover during drought increases soil erosion (Archer & Predick, 2008; Bestelmeyer et al., 2018). Additionally, developing early dust warning advisory and assessment systems, reducing personal exposure by reducing time spent outdoors and outdoor physical activities, and using devices such as wearable global positioning system (GPS) and activity sensors could reduce adverse health outcomes (Eleftheriou et al., 2023).

Green Space Health Co-Benefits. Dust particles, particularly $PM_{2.5}$, have a wide array of negative effects on human health across the life course (Tong et al., 2023). Green space can effectively hold soil, prevent dust mobilization, and intercept and filter suspended dust particles in the air. Distinct dust constituents such as crystalline silica and endotoxins have long been studied and are found to be highly associated with adverse respiratory outcomes, including a decline in lung function, pulmonary diseases, lung cancer, and silicosis (Baron et al., 2002; Nieuwenhuijsen et al., 1999). Dust may also transport harmful neurotoxic pesticides that can come into contact with sensitive human receptors such as children, with possible impacts on neurological development (Gunier et al., 2011). Exposure of farmers to endotoxin, a type of bioaerosol, as well as crystalline silica, has also been associated with allergy, respiratory, and lung diseases in California (Schenker et al., 2005, 2009; Seidel et al., 2023).

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Leading Causes of Death and Disability in California. Understanding public health risks to Californians also requires knowledge of the leading causes of disability and death. The top three causes of death and disability in California primarily result from chronic disease conditions, including ischemic heart disease, stroke, and chronic obstructive pulmonary disease (Figure A7.1). Lower respiratory tract infections, ranked seventh, are the only infectious diseases included in the top ten causes of death (Global Burden of Disease Collaborative Network & Institute for Health

Metrics and Evaluation (IHME), 2020). In terms of disability adjusted life years (DALYs, a combined measure of death and disability), infectious diseases do not rank in the top 10 causes, with ischemic heart disease (IHD), low back pain, and drug use disorders occupying the top three positions.

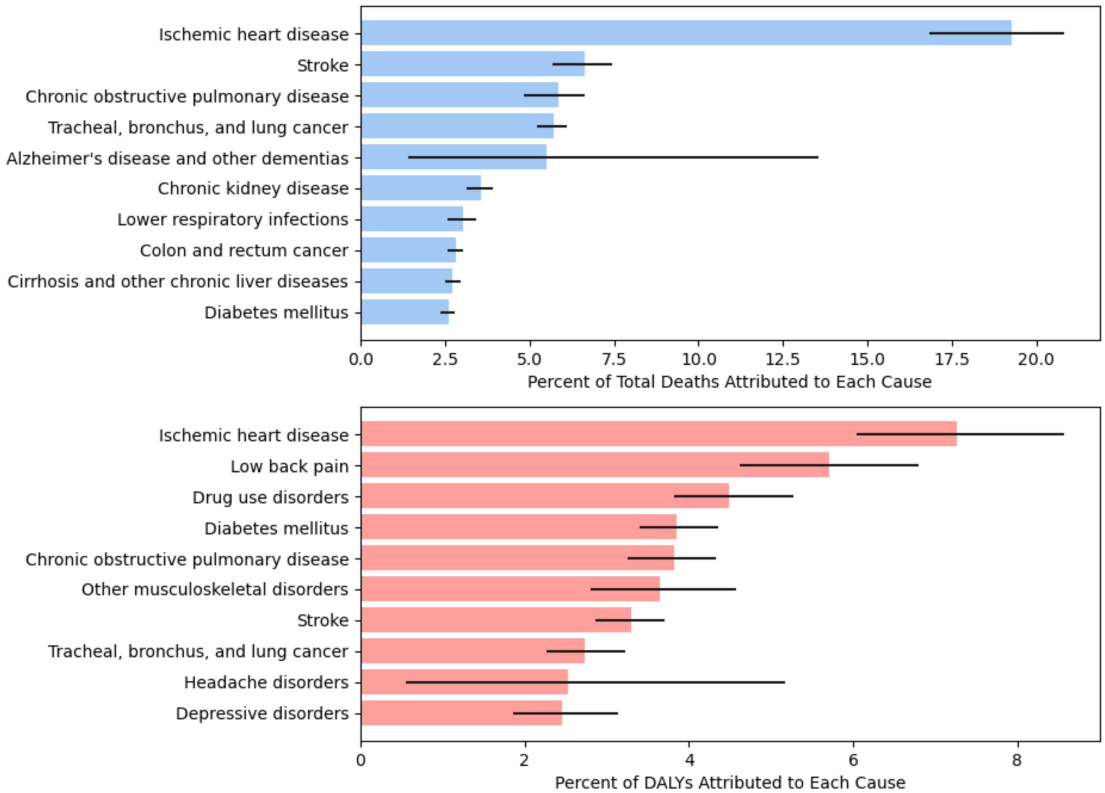

Figure A7.1. *Leading Causes of Death and Disability for California in 2019 with error bars representing 95% CIs for each cause (Global Burden of Disease Collaborative Network & Institute for Health Metrics and Evaluation (IHME), 2020).*

Table A7.1. *Evaluation criteria to assess the direct and proximal indirect health effects of climate change in California.*

Climate Pathway	**Attribution**	**Timing**	**Population Health Burden**	**Vulnerability**	**Adaptation**	**Green Space Solutions**
	How clearly linked is the exposure to climate change?	*What is the trend in exposure?*	*What is the projected health burden in California?*	*Are certain populations more vulnerable to health effects?*	*What adaptation measures are available?*	*What are the health co-benefits or unintended consequences of green space?*
Extreme heat	Highly certain	Warming	Respiratory, renal, and cardiovascular morbidity, heat-related illness, negative pregnancy and mental health outcomes, mortality	Children, elderly, pregnant women, preexisting conditions, low SES, outdoor workers	Urban green space, heat action plans, AC access, cool roofs, building design, albedo increases	Reduced air pollution and carbon emissions
Extreme precipitation	Medium-high certainty	Increasing	Trauma, drowning, displacement, mental health, water quality >1 million CA properties at risk of flooding	Low SES, Black populations, inequities in information access or ability to evacuate	Flood alerts and evacuation plans, green stormwater infrastructure	Increased water supply, improved water quality, public safety
Wildfires	Medium-high certainty	Increasing	Respiratory and potential cardiovascular morbidity and mortality; potential birth outcomes and mental health >3,600 deaths in 2018	Children, elderly, pregnant women, preexisting conditions, low SES, potentially Black populations and women	Air quality alerts, clean air shelters, wildland fuel management, defensive areas including green space such as parks, golf	Reduced carbon emissions, reduced exposure to other air pollution sources

					courses, and agricultural land at the WUI	
Valley Fever	Low-medium certainty	Increasing	Respiratory morbidity and mortality, fever 9,000 cases in 2019	Elderly, pregnant women, preexisting conditions, underrepresented groups such as Black or Filipino	Early dust warning advisory and assessments, personal dust exposure tracking, vegetation cover to mitigate dust pollution	Reduced dust mobilization and PM exposure that affects many other health outcomes

APPENDIX B

Supplementary Information for *Chapter VIII. Health Impact Assessment: Wildland Fire Mortality and CMAQ Validation*

Supplemental Tables

Table B8.1. *Summary Statistics of Annual Modeled $PM_{2.5}$ Estimates (California) by Grid Cell (mean, minimum, and maximum of all grid cell annual averages)*

Year	**All Sources $PM_{2.5}$**			**Non-Fire $PM_{2.5}$**			**Fire-only $PM_{2.5}$**		
	Mean	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
2008	8.83	2.89	51.4	4.51	1.56	34.2	4.33	0.35	49.7
2009	4.78	1.80	32.7	4.18	1.46	32.4	0.60	0.16	4.30
2010	4.61	1.75	36.6	4.30	1.55	36.4	0.32	-0.20	4.90
2011	3.91	1.82	18.3	3.42	1.38	17.9	0.49	0.13	8.30
2012	3.83	1.50	17.7	3.14	1.33	17.4	0.69	0.13	9.90
2013	3.88	1.26	18.0	2.70	0.89	17.2	1.17	0.29	15.2
2014	4.74	1.61	87.8	3.49	1.20	13.7	1.24	0.09	86.4
2015	5.32	2.27	94.0	3.37	1.57	14.9	1.95	0.15	91.9
2016	4.11	1.85	46.8	3.10	1.48	13.9	1.0	0.11	44.0
2017	6.76	2.59	102	3.72	1.93	14.3	3.04	0.48	97.5
2018	7.65	3.28	110	4.18	2.29	14.5	3.47	0.50	107

Table B8.2. *Summary of Annual Averaged Modeled $PM_{2.5}$ ($\mu g/m^3$) Values by Metropolitan Statistical Area (MSA) in California*

MSA	**All Sources $PM_{2.5}$** (SD, μg/m^3)	**Fire-Only $PM_{2.5}$** (SD, μg/m^3)	**Percent of $PM_{2.5}$ Attributable to Fire**
Anaheim-Santa Ana-Irvine	11.46 (3.38)	0.74 (0.70)	6.5%
Bakersfield	5.20 (1.86)	1.02 (0.86)	19.7%
Chico	7.06 (4.72)	3.03 (4.09)	42.9%
El Centro	3.97 (1.28)	0.35 (0.21)	8.9%
Fresno	6.29 (5.36)	1.96 (4.77)	31.2%
Hanford-Corcoran	7.60 (2.32)	1.22 (0.99)	16.1%
Los Angeles-Long Beach-Glendale	8.24 (4.76)	0.79 (0.77)	9.5%
Madera	6.35 (3.30)	1.98 (2.04)	31.2%
Merced	7.83 (2.44)	1.51 (1.31)	19.2%
Modesto	7.55 (2.91)	1.55 (1.40)	20.5%
Napa	6.56 (5.03)	2.85 (4.77)	43.4%
Oakland-Hayward-Berkeley	9.46 (3.50)	1.32 (1.39)	14.0%
Oxnard-Thousand Oaks-Ventura	5.18 (2.61)	0.96 (1.56)	18.6%
Redding	5.56 (4.97)	3.12 (4.53)	56.1%
Riverside-San Bernardino-Ontario	3.99 (2.04)	0.49 (0.42)	12.3%
Sacramento--Roseville--Arden-Arcade	7.54 (4.41)	2.45 (3.01)	32.6%
Salinas	4.61 (2.97)	1.37 (2.73)	29.7%
San Diego-Carlsbad	5.80 (2.82)	0.48 (0.31)	8.3%
San Francisco-Redwood City-South San Francisco	6.37 (2.15)	1.05 (1.05)	16.5%
San Jose-Sunnyvale-Santa Clara	5.76 (2.59)	1.09 (1.01)	19.0%
San Luis Obispo-Paso Robles-Arroyo Grande	4.71 (1.16)	0.92 (0.81)	19.6%
San Rafael	5.41 (2.19)	1.38 (1.92)	25.6%
Santa Cruz-Watsonville	6.55 (2.14)	1.30 (1.24)	19.9%
Santa Maria-Santa Barbara	4.16 (1.24)	0.84 (0.84)	20.2%
Santa Rosa	6.84 (7.51)	3.05 (7.30)	44.6%
Stockton-Lodi	9.67 (2.71)	1.59 (1.48)	16.4%
Vallejo-Fairfield	8.43 (2.92)	1.91 (2.15)	22.7%
Visalia-Porterville	6.35 (4.41)	1.95 (3.33)	30.8%
Yuba City	8.48 (3.54)	2.42 (2.27)	28.6%

Table B8.3. *Summary of long-term mortality impacts across California due to fire-only $PM_{2.5}$ for ages 25+, using wildfire-specific and undifferentiated chronic dose-response values, 2008-2018 (total deaths attributable to fire-only $PM_{2.5}$)*

Year	**Base Case Scenario Deaths** *(No modeled values capped)*		**Mod Cap Scenario Deaths** *(Modeled values capped)*	
	Wildfire-specific dose-response (β_{WL}) *(95% CI)*	**Undifferentiated $PM_{2.5}$ dose-response** (β_L) *(95% CI)*	**Wildfire-specific dose-response** (β_{WL}) *(95% CI)*	**Undifferentiated $PM_{2.5}$ dose-response** (β_L) *(95% CI)*
2008	10,150 *(1,060 - 18,720)*	6,590 (*4,520 – 8,080*)	9,750 *(1,010 - 18,070)*	6,330 (*4,330 – 7,760*)
2009	2,260 *(230 - 4,300)*	1,450 (*990 – 1,790*)	2,240 *(230 - 4,270)*	1,440 (*980 – 1,770*)
2010	1,300 *(130 - 2,490)*	840 (*570 – 1,030*)	1,300 *(130 - 2,480)*	830 (*570 – 1,030*)
2011	1,530 *(140 - 2,910)*	980 (*660 – 1,210*)	1,520 *(140 - 2,910)*	980 (*660 – 1,200*)
2012	1,730 *(150 - 3,290)*	1,110 (*750 – 1,360*)	1,720 *(150 - 3,280)*	1,110 (*750 – 1,360*)
2013	3,430 *(300 - 6,500)*	2,200 (*1,500 – 2,710*)	3,420 *(300 - 6,480)*	2,200 (*1,500 – 2,710*)
2014	2,150 *(190 - 4,060)*	1,380 (*940 – 1,700*)	2,050 *(180 - 3,900)*	1,320 (*900 – 1,620*)
2015	3,590 *(310 - 6,760)*	2,310 (*1,580 – 2,850*)	3,460 *(300 - 6,560)*	2,230 (*1,520 – 2,740*)
2016	4,490 *(390 - 8,430)*	2,900 (*1,980 – 3,560*)	4,140 *(360 - 7,850)*	2,660 (*1,810 – 3,280*)
2017	12,650 *(1,180 - 22,860)*	8,330 (*5,760 – 10,150*)	10,810 *(950 - 20,190)*	6,990 (*4,780 – 8,590*)
2018	12,880 *(1,150 - 23,760)*	8,380 (*5,740 – 10,260*)	12,160 *(1,080 - 22,590)*	7,880 (*5,380 – 9,660*)
All Years	56,140 *(5,240 - 104,060)*	36,470 (*24,990 - 44,700*)	52,600 *(4,830 - 98,590)*	33,960 (*23,180 – 41,740*)

Notes: Base case = no modeled $PM_{2.5}$ concentrations capped; mod cap = modeled $PM_{2.5}$ concentrations capped at the 99.9^{th} percentile value of all fire-only concentrations; β_{WL} = chronic wildfire-specific dose-response value; β_L= chronic undifferentiated dose-response value. Values rounded to the nearest ten.

Table B8.4. *Mortality and Valuation Impacts from Wildland Fire in California by County, 2008-2018 (Base case scenario - no modeled values capped)*

County	Deaths - 2008	Deaths - 2009	Deaths - 2010	Deaths - 2011	Deaths - 2012	Deaths - 2013	Deaths - 2014	Deaths - 2015	Deaths - 2016	Deaths - 2017	Deaths - 2018	Deaths - All Years	Total Valuation (2015 $, Hundreds of Millions)
Alameda	405	63.0	35.8	58.8	52.1	143	67.8	119	53.0	640	468	2,106	172
Alpine	2.5	0.5	0.7	0.4	0.5	3.6	0.5	1.2	0.5	1.8	6.5	18.7	1.5
Amador	36.2	12.6	3.6	6.1	5.8	17.8	7.8	16.6	8.2	23.6	38.3	177	14.8
Butte	418	40.0	18.8	30.3	67.0	56.5	43.0	74.3	40.2	139	477	1,404	118
Calaveras	34.4	10.8	4.3	6.1	5.5	23.9	6.8	27.7	9.3	30.2	53.3	212	17.5
Colusa	17.6	2.2	0.9	2.2	3.0	3.4	2.4	6.5	2.1	9.3	23.2	72.8	6.0
Contra Costa	393	62.5	33.5	56.5	56.8	129	65.6	119	47.5	648	476	2,088	170
Del Norte	29.9	3.5	1.6	2.7	6.0	9.5	11.3	72.4	2.1	167	96.8	403	31.4
El Dorado	118	36.7	12.3	23.0	23.3	60.0	77.7	51.0	26.0	73.3	116	618	51.7
Fresno	478	66.8	60.6	56.9	52.2	140	95.8	248	153	368	491	2,211	183
Glenn	30.6	3.3	1.3	3.0	4.9	6.3	5.0	9.6	4.0	14.0	36.1	118	9.8
Humboldt	125	12.0	5.7	9.9	12.6	33.2	32.5	73.5	12.9	111	76.3	505	42.1
Imperial	6.1	5.0	3.0	3.8	4.3	8.0	3.3	3.9	7.0	13.2	13.9	71.5	5.9
Inyo	2.5	0.7	0.8	1.3	0.4	1.1	0.6	2.2	1.7	3.0	2.3	16.7	1.4
Kern	226	41.2	35.3	44.1	29.9	64.0	51.1	66.9	140	222	214	1,135	93.9
Kings	44.9	9.2	4.2	6.3	6.3	15.2	10.0	12.7	19.9	43.0	41.9	213	17.7
Lake	112	7.4	4.1	7.8	19.1	19.9	19.9	37.8	8.0	58.5	175	468	38.4

Lassen	23.3	3.5	1.3	1.9	10.3	3.6	7.8	5.5	2.9	10.0	19.8	89.9	7.6
Los Angeles	1,287	612	317	246	286	557	284	362	1,265	1,788	2,094	9,098	744
Madera	66.6	10.7	9.4	11.5	9.1	32.5	16.9	34.1	24.7	63.2	87.9	367	30.1
Marin	106.7	12.5	9.1	14.1	14.2	29.1	16.0	31.5	8.7	193	109	543	44.3
Mariposa	16.0	2.8	2.5	3.2	3.4	11.4	4.5	7.7	6.3	24.3	42.1	124	10.0
Mendocino	117.6	6.7	3.6	5.8	13.2	18.4	28.7	25.9	5.8	51.7	53.6	331	28.3
Merced	93.2	17.5	11.0	17.1	14.4	31.9	19.8	35.5	38.5	95.2	114	488	40.1
Modoc	5.5	1.3	0.5	1.2	3.4	1.8	2.8	3.0	1.5	7.0	7.6	35.6	2.9
Mono	5.1	1.1	1.0	0.9	0.9	4.6	1.4	5.6	2.1	3.0	8.8	34.5	2.8
Monterey	93.0	18.8	8.9	11.5	9.6	31.8	12.4	28.1	401	105	80.5	801	64.3
Napa	119	11.8	5.8	11.7	16.8	23.2	18.5	40.1	18.5	266	110	641	51.8
Nevada	140	15.3	8.7	12.3	13.3	49.9	45.4	28.0	19.6	86.3	75.5	494	41.8
Orange	319	98.0	88.9	69.9	87.3	160	95.6	132	323	498	630	2,502	203
Placer	277	53.0	22.1	41.5	45.1	91.0	75.2	94.6	63.1	182	282	1,226	102
Plumas	25.1	3.0	1.9	2.2	7.7	5.2	8.2	6.3	3.7	12.8	12.4	88.6	7.6
Riverside	187	101	87.5	67.9	77.0	174	64.8	165	198	326	580	2,026	164
Sacramento	958	200	69.4	134	147	218	173	294	163	766	1,009	4,131	343
San Benito	11.9	2.7	1.1	1.8	1.7	3.9	2.1	3.6	21.7	14.4	13.6	78.5	6.4
San Bernardino	192	95.0	59.1	50.5	59.4	113	46.3	116	208	275	343	1,556	127
San Diego	288	85.0	76.9	60.4	83.5	143	91.7	117	226	381	426	1,978	162

San Francisco	162	33.6	29.5	36.6	27.2	77.7	32.4	70.2	27.3	414	247	1,157	93.3
San Joaquin	334	60.9	22.4	46.0	47.9	94.0	61.6	110	58.5	312	374	1,521	126
San Luis Obispo	61.8	15.1	7.8	11.3	11.3	20.8	12.2	24.4	68.3	79.1	74.4	387	31.5
San Mateo	168	26.1	23.5	27.4	22.4	69.6	26.6	57.6	21.3	264	205	912	74.5
Santa Barbara	78.2	25.4	9.1	10.8	12.8	25.8	13.1	22.3	73.1	164	93.6	528	42.8
Santa Clara	493	64.6	40.8	59.2	52.0	130	76.3	118	166	492	510	2,200	181
Santa Cruz	86.3	24.5	5.7	12.3	8.5	20.3	12.5	20.4	76.5	87.6	75.8	430	35.5
Shasta	318	25.6	12.9	22.7	57.3	53.9	50.1	92.5	25.7	128	500	1,288	106
Sierra	4.6	0.6	0.4	0.4	0.7	1.6	1.1	1.1	0.5	1.5	2.1	14.6	1.3
Siskiyou	53.9	9.3	4.3	6.5	12.7	15.6	56.3	26.6	12.9	59.1	61.8	319	26.2
Solano	197	25.7	16.5	25.4	29.9	50.6	34.8	60.3	28.1	361	243	1,072	87.0
Sonoma	341	33.8	17.7	34.4	37.1	71.4	51.4	88.1	29.6	1,522	262	2,489	197
Stanislaus	250	42.9	24.0	40.6	33.9	78.3	46.3	99.6	58.3	271	276	1,220	101
Sutter	73.5	13.3	5.1	11.3	13.3	16.1	15.4	25.1	16.1	50.8	92.5	332	27.5
Tehama	136	8.9	3.9	8.9	18.2	20.7	14.5	36.8	10.4	44.2	110	412	34.8
Trinity	49.1	2.0	0.7	2.3	3.1	6.3	5.4	40.5	2.0	12.5	20.8	145	12.3
Tulare	183	39.3	26.3	32.0	23.0	53.4	47.2	90.4	131	235	207	1,068	87.3
Tuolumne	45.9	11.7	10.4	8.9	8.4	88.5	14.7	34.8	12.8	45.1	57.2	339	28.1
Ventura	118	40.5	17.7	21.4	23.3	53.8	24.0	38.3	106	243	371	1,058	84.0
Yolo	124	15.8	6.9	13.5	20.6	25.6	22.5	37.9	19.7	105	131	522	43.2

Yuba	60.5	10.3	4.7	8.4	9.2	17.3	11.6	17.0	11.6	45.8	65.4	262	21.7

Table B8.5. *Summary of long-term mortality impacts across California due to all sources $PM_{2.5}$ for ages 25+, using undifferentiated chronic dose-response values, 2008-2018 (total deaths attributable to all sources $PM_{2.5}$)*

Year	Undifferentiated $PM_{2.5}$ dose-response (β_L)	
	Base Case Scenario Deaths *(No modeled values capped) (95% CI)*	**Mod Cap Scenario Deaths** *(Modeled values capped) (95% CI)*
2008	37,250 (26,130 – 44,880)	36,950 (25,910 – 44,530)
2009	29,060 (20,250 – 35,170)	29,030 (20,230 – 35,150)
2010	30,610 (21,370 – 37,010)	30,580 (21,340 – 36,980)
2011	23,390 (16,200 – 28,450)	23,390 (16,200 – 28,450)
2012	23,080 (15,980 – 28,070)	23,080 (15,980 – 28,070)
2013	22,040 (15,230 – 26,830)	22,030 (15,230 – 26,820)
2014	21,670 (14,970 – 26,400)	21,610 (14,920 – 26,320)
2015	24,050 (16,630 – 29,280)	23,970 (16,570 – 29,180)
2016	23,250 (16,070 – 28,310)	23,020 (15,910 – 28,040)
2017	30,440 (21,160 – 36,910)	29,140 (20,190 – 35,420)
2018	31,430 (21,820 – 38,150)	30,940 (21,470 – 37,570)
All Years	296,300 (205,800 – 359,477)	293,700 (204,000 – 356,500)

Table B8.6. *Sensitivity analysis: Summary of long-term mortality impacts across California due to fire-only $PM_{2.5}$ for ages 25+, using alternative short-term wildfire-specific dose-response value (Chen et al., 2021 global estimate) to calculate β_{WL}*

Year	Wildfire-specific dose-response (β_{WL})	
	Base Case Scenario Deaths *(No modeled values capped) (95% CI)*	**Mod Cap Scenario Deaths** *(Modeled values capped) (95% CI)*
2008	18,810 (10,520 – 26,550)	18,160 (10,110 – 25,720)
2009	4,320 (2,340 – 6,280)	4,290 (2330 – 6,240)
2010	2,500 (1,350 – 3,640)	2,500 (1350 – 3,640)
2011	2,920 (1,580 – 4,250)	2,920 (1580 – 4,250)
2012	3,310 (1,790 – 4,800)	3,300 (1790 – 4,800)
2013	6,530 (3,560 – 9,450)	6,520 (3,550 – 9,440)
2014	4,080 (2,230 – 5,900)	3,920 (2,130 – 5,690)
2015	6,800 (3,720 – 9,790)	6,590 (3,600 – 9,520)
2016	8,480 (4,660 – 12,170)	7,900 (4,300 – 11,430)
2017	22,970 (13,090 – 32,110)	20,300 (11,220 – 28,960)
2018	23,880 (13,360 – 33,720)	22,710 (12,610 – 32,270)
All Years	104,610 (58,210 – 148,670)	99,130 (54,570 – 141,960)

Table B8.7. *Economic valuation of mortality impacts from wildland fires, using the wildfire-specific dose-response value (β_{WL}; 2015 dollars, 3% discount rate, 2015 income year)*

Year	**Valuation Estimate in Billions** *(95% CI)*	
	Base Case	**Mod Cap**
2008	$99.3 (10.4 - 183.2)	$95.5 (9.9 - 176.8)
2009	$21.5 (2.2 - 40.8)	$21.3 (2.2 - 40.6)
2010	$12 (1.2 - 22.9)	$12 (1.2 - 22.9)
2011	$13.7 (1.3 - 26)	$13.7 (1.3 - 26)
2012	$15 (1.3 - 28.6)	$15 (1.3 - 28.5)
2013	$28.9 (2.5 - 54.9)	$28.9 (2.5 - 54.7)
2014	$17.6 (1.5 - 33.3)	$16.8 (1.5 - 32)
2015	$28.6 (2.5 - 53.8)	$27.6 (2.4 - 52.2)
2016	$34.7 (3 - 65.1)	$32 (2.8 - 60.7)
2017	$94.9 (8.9 - 171.5)	$81.1 (7.2 - 151.5)
2018	$93.8 (8.4 - 173)	$88.5 (7.8 - 164.5)
All Years (Total)	$460 (43.2 - 853.1)	$432.4 (40.1 - 810.4)

Table B8.8. *Quantiles of All Daily Modeled Fire-Only Values for CA, 2008-2018*

Quantile	**Fire-only $PM_{2.5}$ ($\mu g/m^3$)**	**Approximate Count of Observations**
25%	0.006	2.9 million
50%	0.075	5.9 million
75%	0.48	8.8 million
95%	5.0	11.2 million
98%	14	11.5 million
99%	27	11.6 million
99.9%	143	11.7 million

Table B8.9. *CMAQ Model Specifications*

Year	NEI year	CMAQ version	BEIS version	EGU CEM data	Gas phase chemistry	PM chemistry	Boundary inflow	WRF version
2008	2008 NEI	v5.0.1	3.14	2008	CB05	AERO6	GEOS-CHEM	v3.4
2009	2008 NEI	v5.0.1	3.14	2009	CB05	AERO6	GEOS-CHEM	v3.4
2010	2008 NEI	v5.0.1	3.14	2010	CB05	AERO6	GEOS-CHEM	v3.4
2011	2011 NEI	v5.0.1	3.14	2011	CB05	AERO6	GEOS-CHEM	v3.4
2012	2011 NEI	v5.0.2	3.14	2012	CB05	AERO6	GEOS-CHEM	v3.4
2013	2011NEIv2	v5.2	3.6.1	2013	CB6r3	AERO6	GEOS-CHEM	v3.8
2014	2014NEIv1	v5.2	3.6.1	2014	CB6r3	AERO6	GEOS-CHEM	v3.8.1
2015	2014NEIv2	v5.2.1	3.6.1	2015	CB6r3	AERO6	Hemispheric CMAQ	v3.8.1
2016	2014NEIv2	v5.2.1	3.6.1	2016	CB6r3	AERO7	Hemispheric CMAQ	v3.8.1
2017	2014NEIv2	v5.2.1	3.6.1	2017	CB6r3	AERO7	Hemispheric CMAQ	v3.8.1
2018	2014NEIv2	v5.3	3.6.1	2018	CB6r3	AERO7	Hemispheric CMAQ	v3.8.1

NEI = National Emissions Inventory, BEIS = Biogenic Emission Inventory System, EGU CEM = Energy Generating Unit Continuous Emission Monitoring, WRF = Weather Research and Forecasting

Table B8.10. *$PM_{2.5}$ Dose-Response Estimates for All-Cause Mortality*

Sources	Timeframe	Risk Value	Value Type	Confidence Interval	Pollutant Increment	Standardized Beta (1 µg/m^3 increment)	Authors/Year
Wildfire (Washington state)	Short-term/Acute	1.02	Odds Ratio	(1.00–1.05)	21.7 µg/m^3	0.00091	Doubleday et al. 2020
Wildfire (U.S.)	Short-term/Acute	1.010	Relative Risk	(1.001–1.020)	10 µg/m^3	0.000995	Chen et al. 2021
Wildfire (global)	Short-term/Acute	1.019	Relative Risk	(1.016–1.022)	10 µg/m^3	0.0019	Chen et al. 2021
Undifferentiated/All Sources	Short-term/Acute	1.0065	Relative Risk	(1.0044–1.0086)	10 µg/m^3	0.00065	Orellano et al. 2020
Undifferentiated/All Sources	Chronic/Long term	1.12	Relative Risk	(1.08–1.15)	10 µg/m^3	0.011	Pope et al. 2019

Supplemental Figures

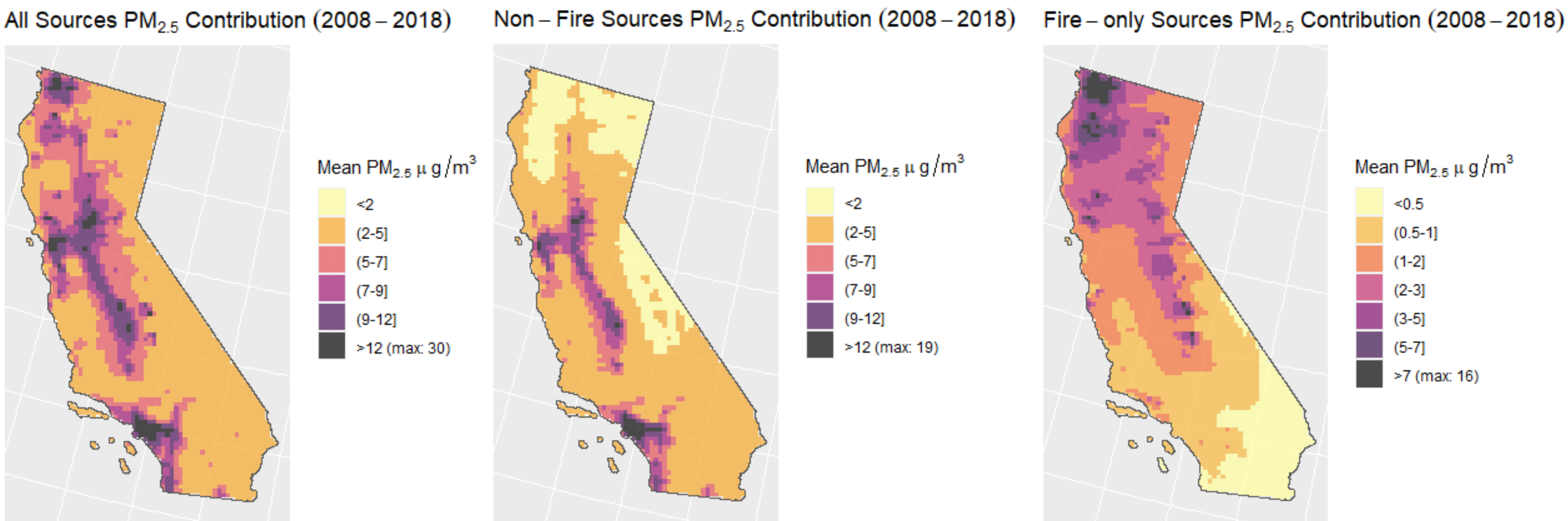

Figure B8.1. *Community Multiscale Air Quality (CMAQ) average daily $PM_{2.5}$ concentrations (μg/m^3) at 12-km resolution for 2008–2018 all sources (left), non-fire sources (middle), and fire-only sources (right). Values were computed as the average over all days in each grid cell in each time period. Note the differing scale for the fire-only map and differing maximum values for each panel.*

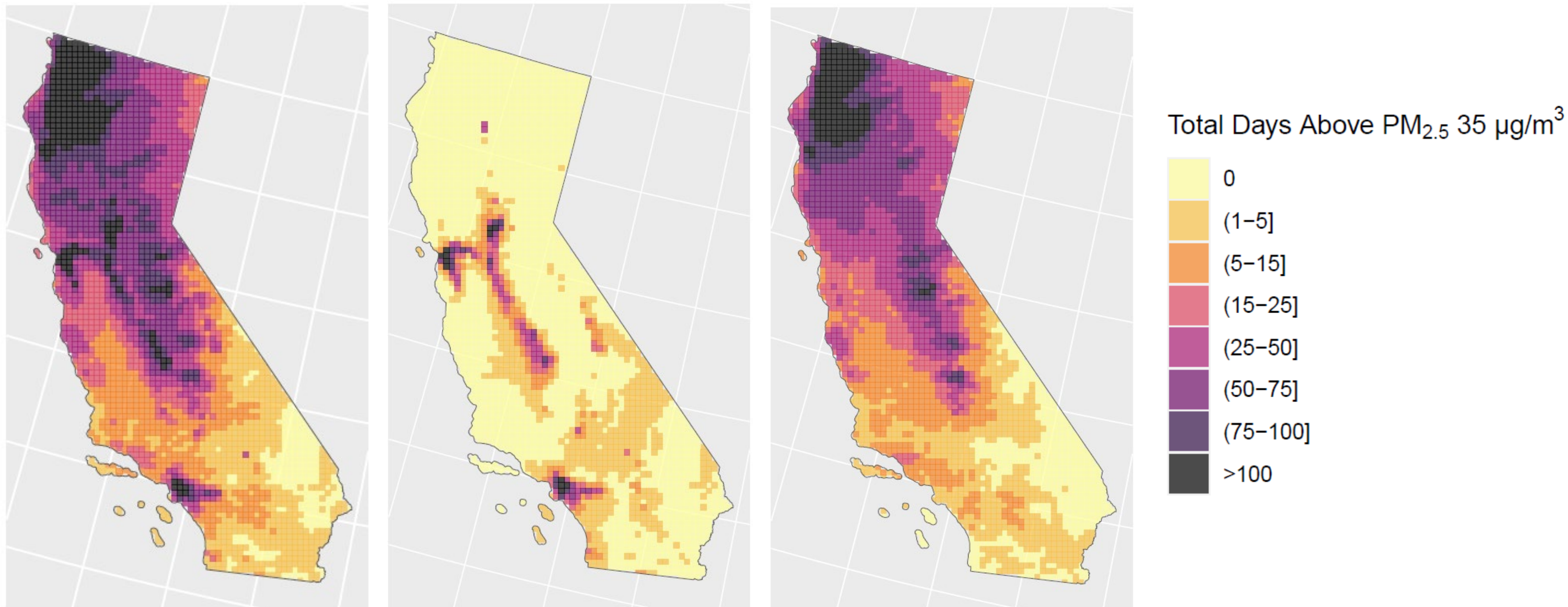

Figure B8.2a. *Community Multiscale Air Quality (CMAQ) simulations at 12-km resolution showing the number of days with $PM_{2.5}$ >35 µg/m^3 (higher than the 24-hour NAAQS threshold) during the eleven-year period of 2008–2018 for all sources (left), non-fire sources (middle), and fire-only sources (right).*

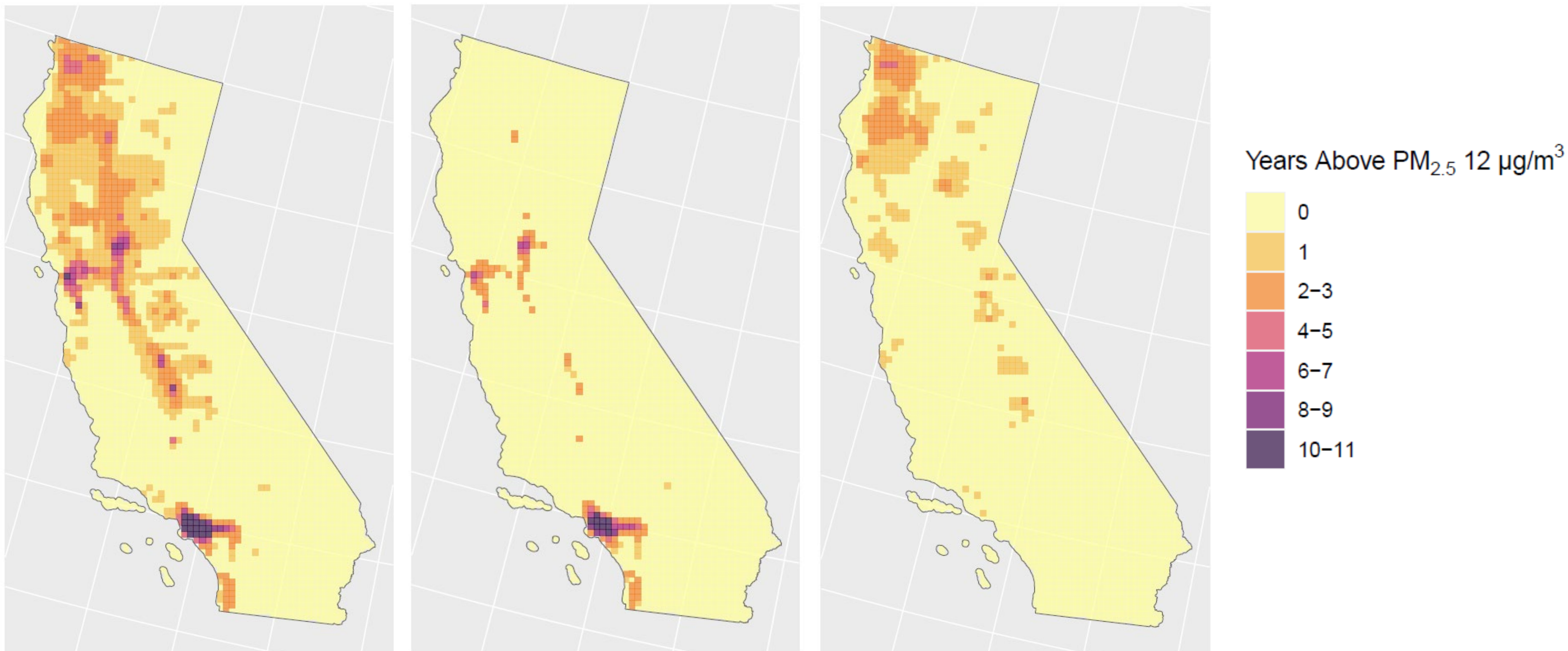

Figure B8.2b. *Community Multiscale Air Quality (CMAQ) simulations at 12-km resolution showing the number of years with average $PM_{2.5}$ >12 µg/m^3 (higher than the annual NAAQS threshold) during the eleven-year period of 2008–2018 for all sources (left), non-fire sources (middle), and fire-only sources (right).*

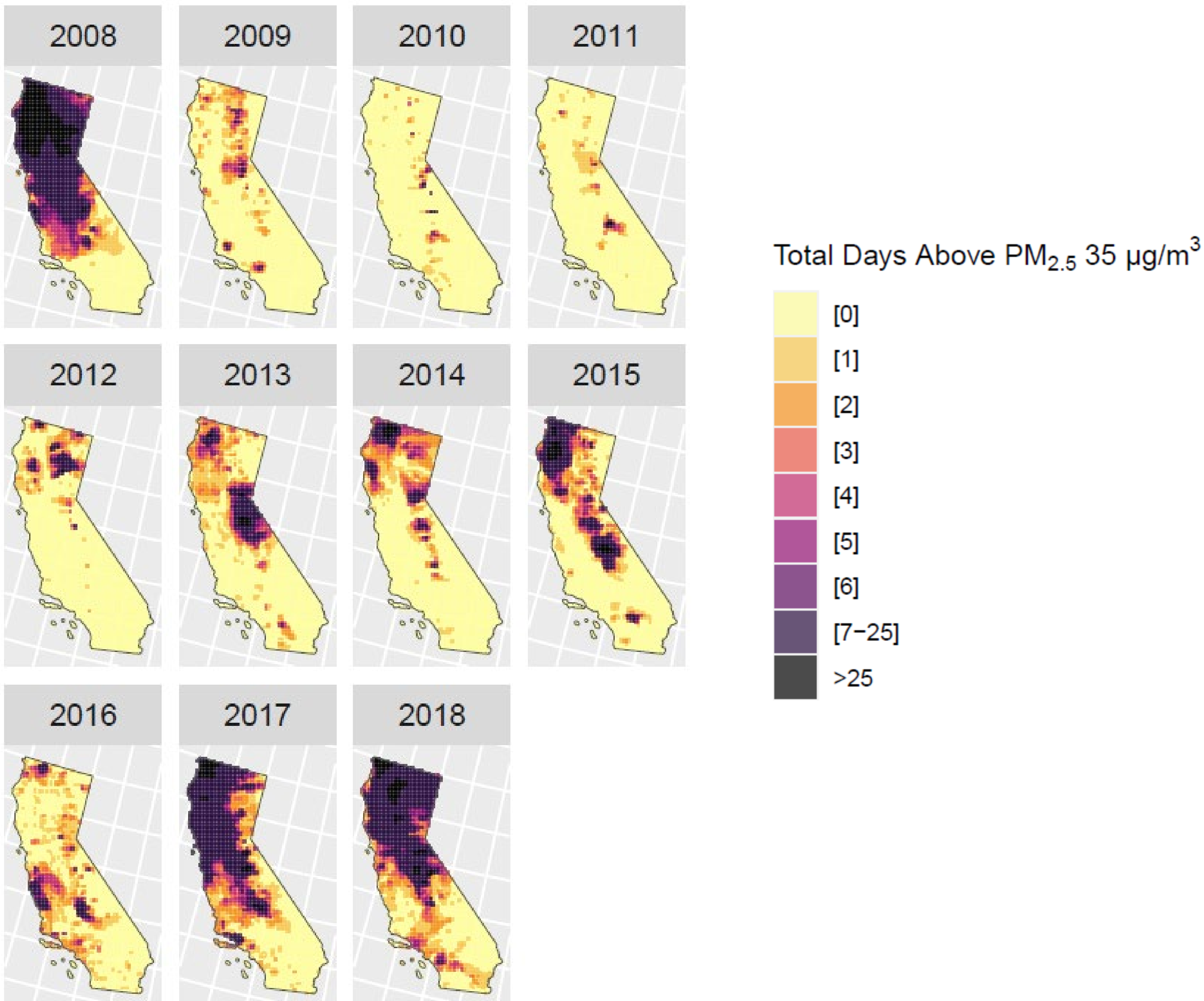

Figure B8.3. *Community Multiscale Air Quality (CMAQ)-simulated days with a wildland fire contribution (fire-only concentrations) to ambient $PM_{2.5}$ >35 μg/m^3 (higher than the 24-hour NAAQS threshold), by year.*

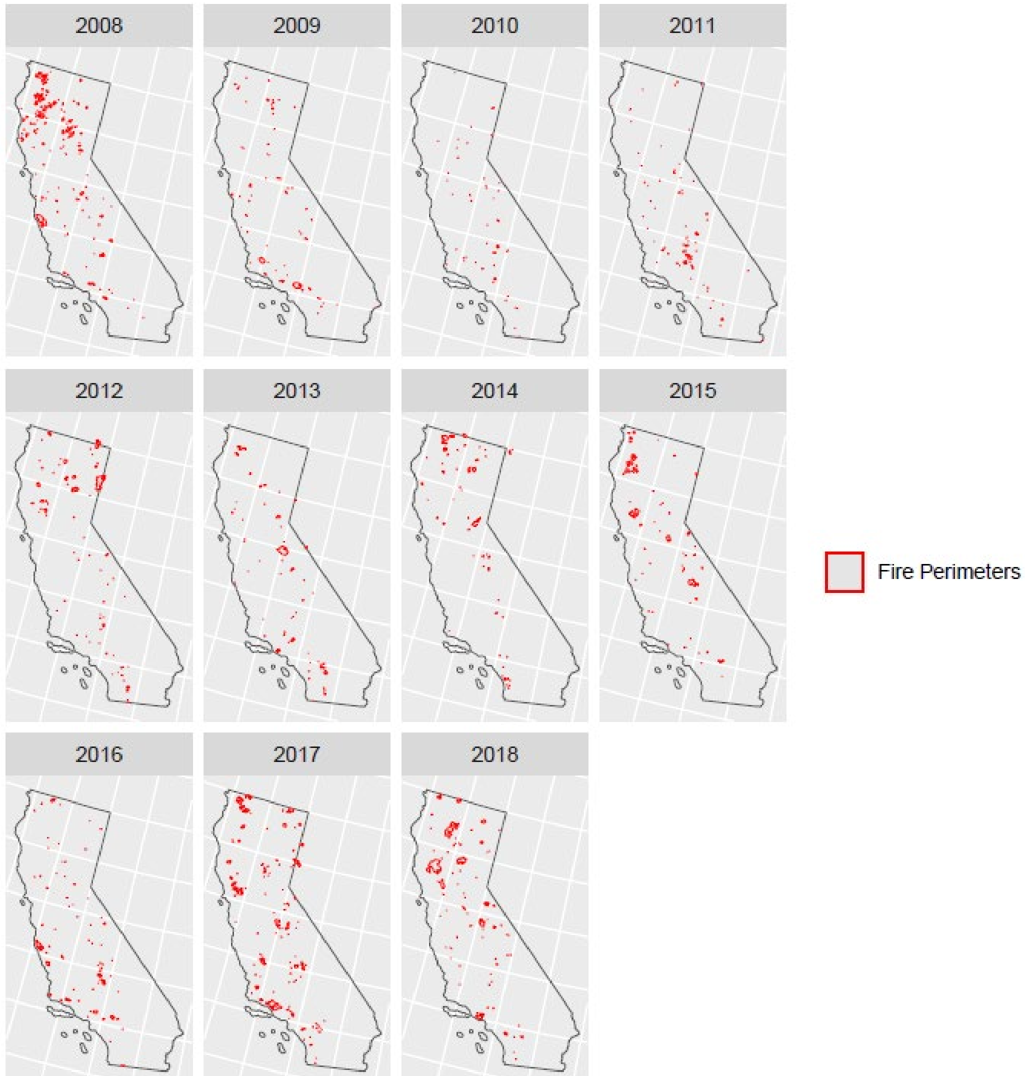

Figure B8.4. *California wildfire perimeters > 300 acres burned, by year.*
Source for fire perimeters: CAL FIRE (https://frap.fire.ca.gov/frap-projects/fire-perimeters/)(CAL FIRE, 2022)

Figure B8.5. *Total deaths attributable to fire-only $PM_{2.5}$ (Base case), by year.*

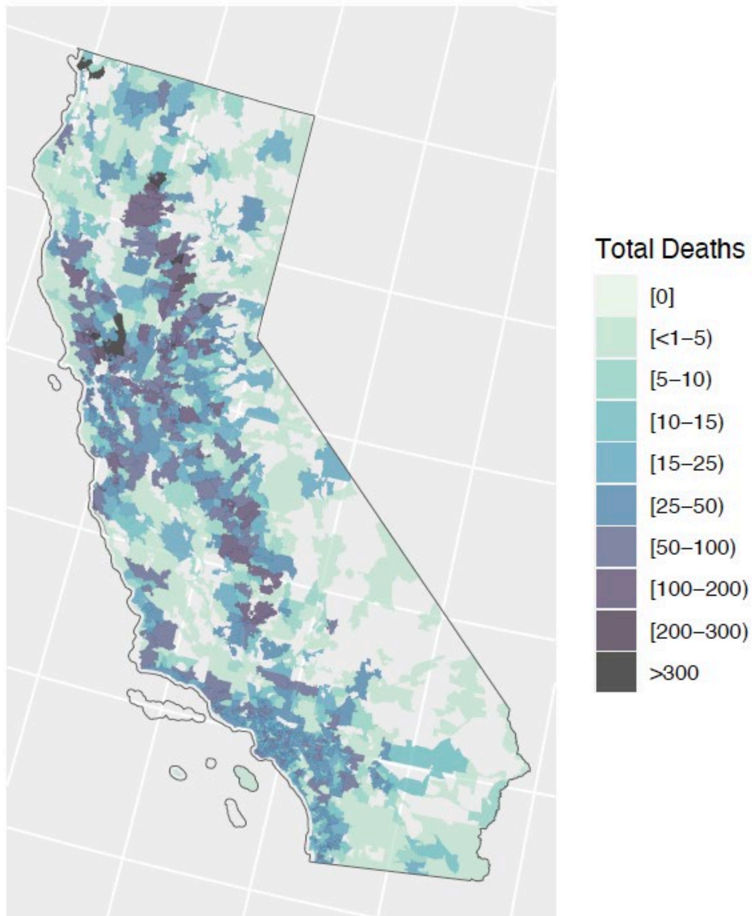

Figure B8.6. *Total deaths attributable to fire-only $PM_{2.5}$ over the eleven-year period of 2008 – 2018 (Base case).*

Model Validation for $PM_{2.5}$ Estimates

Methods

Monthly and daily modeled estimates were paired with monthly averaged observed values from ground stations from the EPA's AQS (https://aqs.epa.gov/aqsweb/airdata/download_files.html) network, IMPROVE (http://vista.cira.colostate.edu/improve/) network, and Clean Air Status and Trends Network (CASTNET; https://www.epa.gov/castnet). These observed values were compiled using the Atmospheric Model Evaluation Tool (AMET) software (Appel et al., 2011) and were provided to the research team by the U.S. EPA. A small number of negative observed daily values were removed from the dataset prior to monthly averaging and analysis (<0.4% of observations). A limited number of observed daily measurements with values of zero (<0.3% of the observations) were kept in the dataset after preliminary analysis demonstrated that results were not impacted by the inclusion or exclusion of zeroes. The paired modeled and observed monthly values were compared through the calculation of previously established metrics for evaluating atmospheric model performance (Koman et al., 2019; Wilkins et al., 2018) and results are presented in a series of tables and figures.

Results

Results for the daily validation analysis are described here. The validation statistics for the paired observations for each year's fire season (June – October) are presented in Table B8.11, and the location of the monitoring stations included in the observed dataset are in Figure B8.7 alongside average fire-only concentrations. Notably, there are more paired observations in the more recent years, as air monitoring has expanded throughout the state. A very small number of the fire-only daily modeled concentrations (n = 25) were significantly higher than the maximum observed value in the paired dataset for the entire timeframe, which was 557 $\mu g/m^3$. Inclusion of these values significantly impacted the correlations; to analyze the data without those exceptional cases (representing extreme fire events), we reassigned all higher estimates to the maximum observed concentration of 557 $\mu g/m^3$ prior to comparing the two datasets.

Overall, the correlation of the all sources model for the entire dataset (all years combined) is higher than the non-fire sources model (*r* of .44 vs. 0.33). While the root-mean-square error (RMSE) is higher for the all sources model, likely skewed by high concentrations predicted for extreme fire events, the mean bias (MB) is considerably lower for the all sources model and reflects a slight under-prediction of the model as compared to the observed measurement.

In the high fire years of 2008, 2017 and 2018, the modeled means are higher than the observed means by approximately 1 - 4 $\mu g/m^3$). For most of the lower fire years, the observed values are similar to or slightly higher than the modeled estimates. The correlation between observed and modeled data ranges from 0.24 – 0.69 for each individual fire season. The all sources correlations are consistently higher than the non-fire correlations in the high fire years, but trends are less consistent in low-fire years.

The RMSE values range widely from year to year and do not reflect consistent patterns between all sources and non-fire sources concentrations. The RMSE values are considerably higher for the high fire years, again likely a result of high modeled concentrations from extreme fire events during those years skewing the RMSE calculation. The mean bias, which is less sensitive to outliers, improves considerably for the all sources simulation for nine out of the eleven years of the analysis.

Figure B8.8 depicts a time series of monthly averages of observed (AQS) and CMAQ modeled $PM_{2.5}$ (both all sources and non-fire sources) across the state from 2008-2018. Peaks for the fire seasons in several of the years, particularly those previously identified high fire years, are substantial, and the all sources and AQS monthly averages both visibly increase in concert during those periods. In the early analysis years as well as the final two years of the analysis, the CMAQ model predicts well on average, but largely underpredicts for the middle years. This is reflected in both Figure B8.8 and Table B8.11. Some seasonal trends are apparent, including peaks in the fire season for the observed data and all sources concentrations.

We conducted a supplemental analysis including only the IMPROVE stations in the analysis, since these monitors are sited in National Parks and wilderness areas and can be considered a more direct measure of model performance for estimating wildland fire $PM_{2.5}$ concentrations in rural, fire-prone areas (see Table B8.14 for fire season statistics and Figure B8.9 for a monthly analysis) (Koman et al., 2019).

The IMPROVE monitors have consistently higher correlations for both all sources and non-fire values (Table B8.14) than the combination of all stations (Table B8.11). With the exception of several years in the middle of the analysis period, the all sources values are more highly correlated with observed data than the non-fire concentrations as expected. However, the eleven years of all sources values have a correlation range of 0.39 – 0.84, and Figure B8.9 demonstrates that the all sources modeled concentrations rise and fall consistently with observed IMPROVE concentrations in peak wildland fire smoke conditions as expected. Additionally, for the all sources simulation, the RMSE for pairs with IMPROVE monitors as compared to the entire dataset (Table B8.11) is lower in eight out of the eleven years of the analysis, and the MB is lower in eight of the years.

For further details on the model results and a detailed model evaluation for the contiguous United States for the first five years of the CMAQ analysis, see Wilkins et al., 2018 (Wilkins et al., 2018).

Table B8.11. *Fire season (June – October) statistics summary of paired daily averaged observations and all sources and non-fire sources modeled concentrations for 2008-2018*

Year	**Observed Mean**	**Fire Severity** (*1: most acres burned, 11: least acres burned; see Table 3.1*)	**Modeled Mean** (μg/m^3)		**Count of pairs**	**Correlation**		**RMSE** (μg/m^3)		**MB** (μg/m^3)	
			All Sources	*Non-Fire*		*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*
2008	14.9	2	18.6	11.5	10,353	0.69	0.15	14.2	15.3	3.69	-3.42
2009	10.9	9	10.7	9.72	12,722	0.50	0.45	7.65	7.62	-0.15	-1.16
2010	10.4	11	11.0	10.6	15,491	0.40	0.39	8.52	8.49	0.63	0.21
2011	11.5	10	7.53	6.89	16,818	0.54	0.53	7.49	7.84	-3.92	-4.57
2012	9.78	5	7.23	6.38	18,659	0.50	0.41	6.27	6.91	-2.55	-3.40
2013	9.73	8	6.68	5.25	19,738	0.44	0.41	7.26	7.43	-3.05	-4.48
2014	9.59	7	7.62	6.26	18,486	0.29	0.48	11.3	6.31	-1.98	-3.33
2015	9.39	4	7.78	6.13	20,328	0.50	0.35	8.35	7.09	-1.61	-3.27
2016	9.45	6	8.06	5.88	21,201	0.24	0.43	12.0	6.31	-1.39	-3.57
2017	11.4	3	13.1	7.25	21,238	0.42	0.25	21.9	10.9	1.71	-4.16
2018	11.8	1	12.8	7.17	21,982	0.40	0.26	14.5	11.4	1.00	-4.66
All Years	10.6	N/A	9.77	7.22	197,016	0.44	0.33	12.0	8.81	-0.85	-3.40

Note: modeled values capped at highest observed value: 557 μg/m^3

Table B8.12. *Fire season (June – October) statistics summary of paired monthly averaged observations and all sources and non-fire sources monthly modeled concentrations for 2008-2018*

Year	**Observed Mean**	**Modeled Mean** (μg/m³)		**Count of pairs**	**Correlation**		**RMSE** (μg/m³)		**MB** (μg/m³)	
		All Sources	*Non-Fire*		All Sources	*Non-Fire*	*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*
2008	13.0	16.9	9.32	583	0.76	0.18	9.2	10.3	3.9	-3.7
2009	9.13	8.80	7.86	633	0.56	0.51	4.7	4.9	-0.33	-1.3
2010	8.90	9.20	8.75	662	0.50	0.49	5.6	5.7	0.29	-0.16
2011	9.77	6.43	5.77	679	0.58	0.57	5.3	5.8	-3.3	-4.0
2012	8.64	6.39	5.39	723	0.54	0.46	4.4	5.1	-2.3	-3.3
2013	8.73	6.16	4.49	714	0.45	0.47	4.8	5.6	-2.6	-4.2
2014	8.80	7.39	5.77	679	0.47	0.57	5.4	4.7	-1.4	-3.0
2015	8.66	7.36	5.57	728	0.60	0.40	4.0	4.9	-1.3	-3.1
2016	8.80	7.43	5.32	748	0.47	0.50	4.4	4.8	-1.4	-3.5
2017	10.8	12.4	6.70	754	0.51	0.37	8.8	6.4	1.6	-4.1
2018	11.5	12.6	6.67	765	0.54	0.21	7.9	8.8	1.1	-4.8
All Years	9.67	9.10	6.43	7,668	0.59	0.38	6.1	6.3	-0.57	-3.24

Note: modeled values capped at highest observed value: 557 μg/m³

Table B8.13. *Annual (not limited to fire season) statistics summary of paired monthly averaged observations and all sources and non-fire sources monthly modeled concentrations for 2008-2018*

Year	Observed Mean	Modeled Mean (μg/m³)		Count of pairs	Correlation		RMSE (μg/m³)		MB (μg/m³)	
		All Sources	*Non-Fire*		All Sources	*Non-Fire*	*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*
2008	11.3	13.7	10.3	1,398	0.71	0.38	7.5	8.0	2.3	-1.1
2009	9.37	9.54	8.91	1,367	0.60	0.58	5.2	5.3	0.16	-0.47
2010	8.65	10.0	9.71	1,585	0.53	0.52	5.8	5.8	1.4	1.1
2011	9.73	7.27	6.81	1,624	0.61	0.60	5.6	5.9	-2.5	-2.9
2012	8.78	6.84	6.29	1,741	0.56	0.53	4.8	5.2	-1.9	-2.5
2013	9.58	6.67	5.67	1,714	0.61	0.61	5.9	6.3	-2.9	-3.9
2014	9.12	6.60	5.80	1,694	0.55	0.64	6.1	6.0	-2.5	-3.3
2015	8.94	7.18	6.14	1,753	0.68	0.66	4.5	5.0	-1.8	-2.8
2016	8.37	6.69	5.65	1,777	0.62	0.64	4.1	4.4	-1.7	-2.7
2017	9.50	9.15	6.22	1,793	0.57	0.59	6.9	6.1	-0.35	-3.3
2018	10.7	9.78	6.54	1,840	0.60	0.49	7.3	8.3	-0.87	-4.1
All Years	9.43	8.38	6.97	18,286	0.59	0.51	5.9	6.1	-1.1	-2.5

Note: modeled values capped at highest observed value: 557 μg/m³

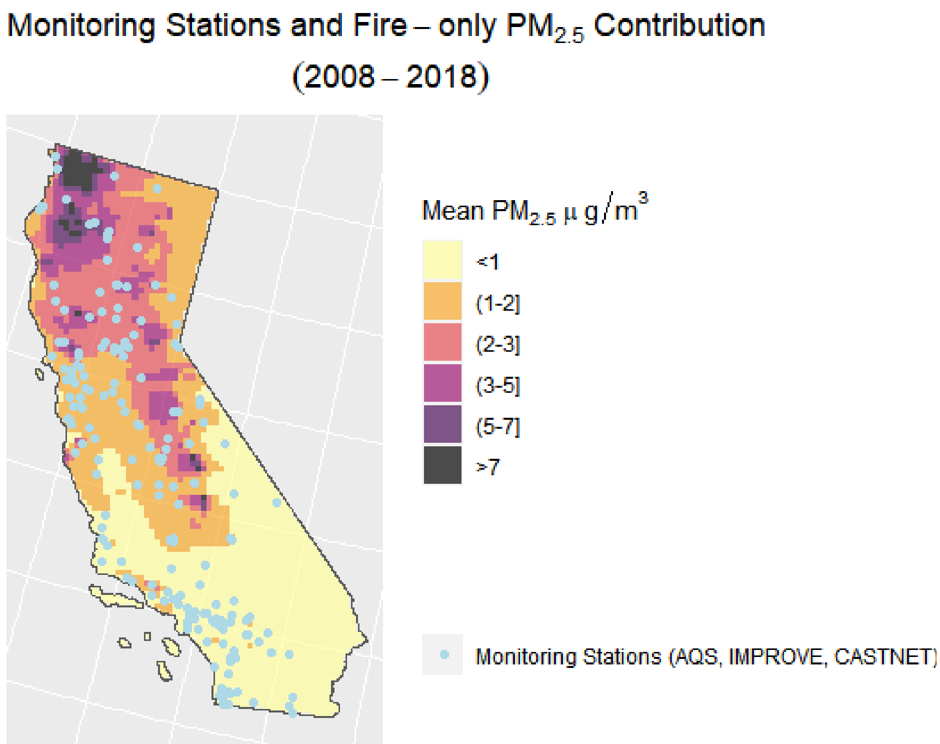

Figure B8.7. *Location of $PM_{2.5}$ monitoring stations (including AQS, IMPROVE and CASTNET networks) alongside fire-only sources $PM_{2.5}$ estimates.*

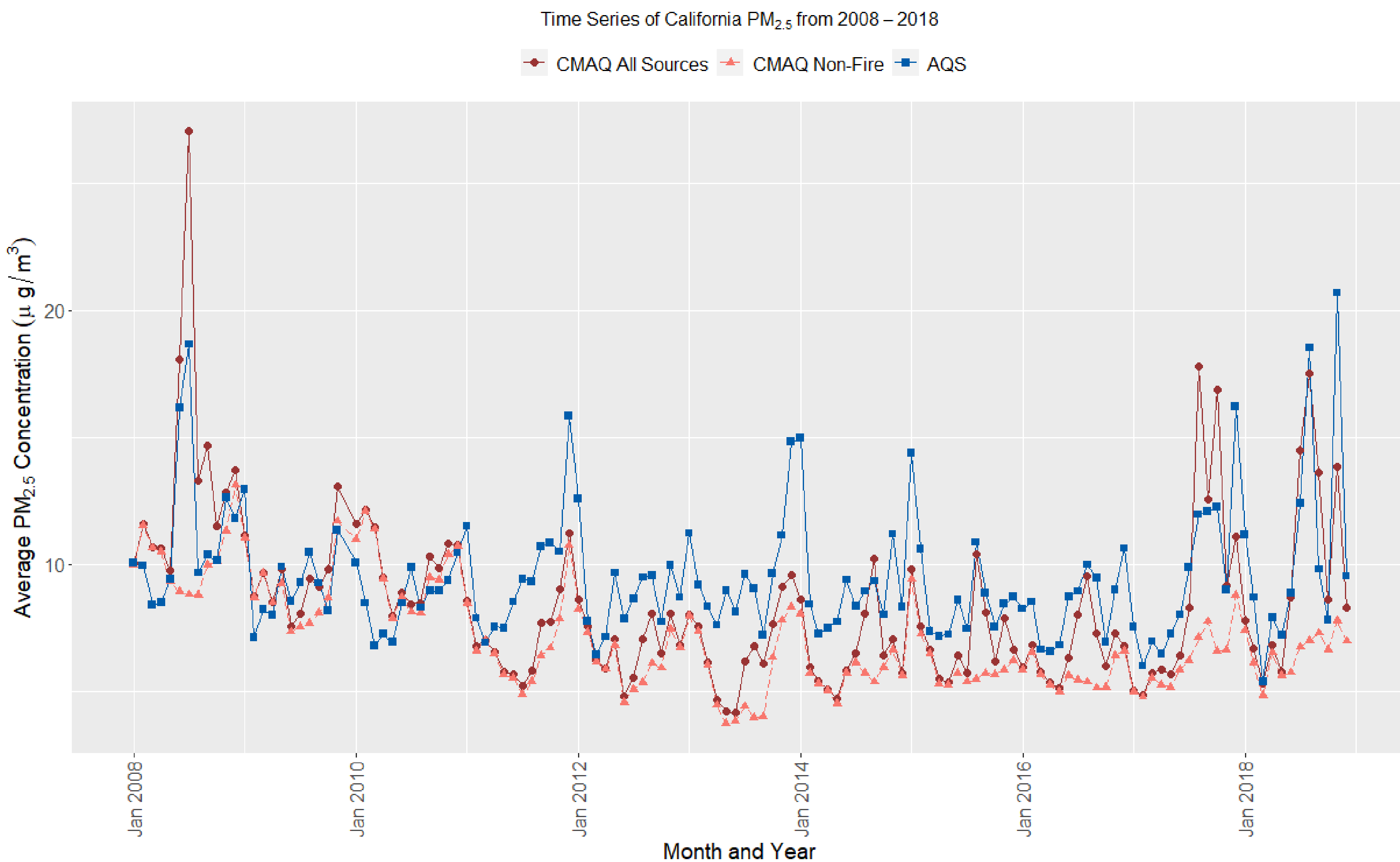

Figure B8.8. *Time series of California $PM_{2.5}$ from 2008 – 2018 with modeled all sources, non-fire, and observed data pairs. Monthly mean $PM_{2.5}$ concentrations across California for 2008-2018 for AQS observations (blue solid line, square symbol), Community Multiscale Air Quality (CMAQ) all sources (dark red line, circle symbol) and CMAQ non-fire sources (light red line, triangle symbol).*

Table B8.14. *Fire season (June – October) statistics summary of paired daily averaged IMPROVE station observations and all sources and non-fire modeled concentrations for 2008-2018*

Year	**Observed Mean**	**Modeled Mean (µg/m³)**		**Count of pairs**	**Correlation**		**RMSE (µg/m³)**		**MB (µg/m³)**	
		All Sources	*Non-Fire*		*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*
2008	11.6	13.9	8.43	1,182	0.75	0.48	11.6	11.5	2.35	-3.14
2009	9.29	8.70	7.63	1,290	0.84	0.78	4.74	5.49	-0.60	-1.67
2010	9.00	9.81	9.30	1,271	0.82	0.83	5.68	5.54	0.81	0.30
2011	10.8	7.66	6.92	1,375	0.84	0.85	6.85	7.1	-3.15	-3.89
2012	9.27	7.22	6.25	1,818	0.76	0.70	5.17	5.99	-2.04	-3.01
2013	9.69	6.84	4.76	1,827	0.48	0.68	8.78	7.71	-2.86	-4.93
2014	9.14	8.04	6.46	1,728	0.49	0.71	9.33	5.34	-1.09	-2.67
2015	9.11	7.85	5.48	1,958	0.52	0.51	8.53	6.91	-1.25	-3.63
2016	9.21	7.23	5.36	1,967	0.54	0.62	6.69	6.79	-1.99	-3.86
2017	10.6	11.7	6.24	1,847	0.53	0.38	14.6	10.1	1.05	-4.37
2018	11.7	12.4	6.16	1,841	0.39	0.23	19.1	16.2	0.74	-5.51
All Years	9.91	9.07	6.43	18,104	0.55	0.54	10.3	8.74	-0.84	-3.47

Note: One outlier capped at the maximum observed concentration for the entire dataset of paired observations (557 µg/m³).

Table B8.15. *Fire season (June – October) statistics summary of paired monthly averaged IMPROVE station observations and all sources and non-fire monthly modeled concentrations for 2008-2018*

Year	**Observed Mean**	**Modeled Mean (µg/m³)**		**Count of pairs**	**Correlation**		**RMSE (µg/m³)**		**MB (µg/m³)**	
		All Sources	*Non-Fire*		*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*	*All Sources*	*Non-Fire*
2008	9.07	11.3	3.96	95	0.94	0.29	7.3	9.3	2.2	-5.1
2009	5.94	4.66	3.55	95	0.85	0.75	2.3	3.4	-1.3	-2.4
2010	5.12	4.49	3.91	95	0.88	0.86	2.1	2.5	-0.63	-1.2
2011	5.61	3.81	2.95	97	0.87	0.86	2.8	3.4	-1.8	-2.7
2012	5.75	4.24	2.86	105	0.71	0.65	3.3	4.0	-1.5	-2.9
2013	5.95	5.34	2.37	99	0.48	0.70	5.5	4.4	-0.61	-3.6
2014	6.13	6.02	4.07	105	0.47	0.72	5.3	3.2	-0.11	-2.1
2015	6.57	6.12	3.38	102	0.68	0.48	4.4	4.7	-0.45	-3.2
2016	6.43	4.89	3.25	100	0.68	0.64	3.2	4.3	-1.5	-3.2
2017	8.67	10.3	4.57	105	0.48	0.37	11.0	6.9	1.6	-4.1
2018	9.97	11.3	4.55	105	0.56	0.27	11.6	11.3	1.3	-5.4
All Years	6.86	6.61	3.59	1,103	0.67	0.47	6.3	5.9	-0.24	-3.3

Note: One outlier capped at the maximum observed concentration for the entire dataset of paired observations (557 µg/m³)

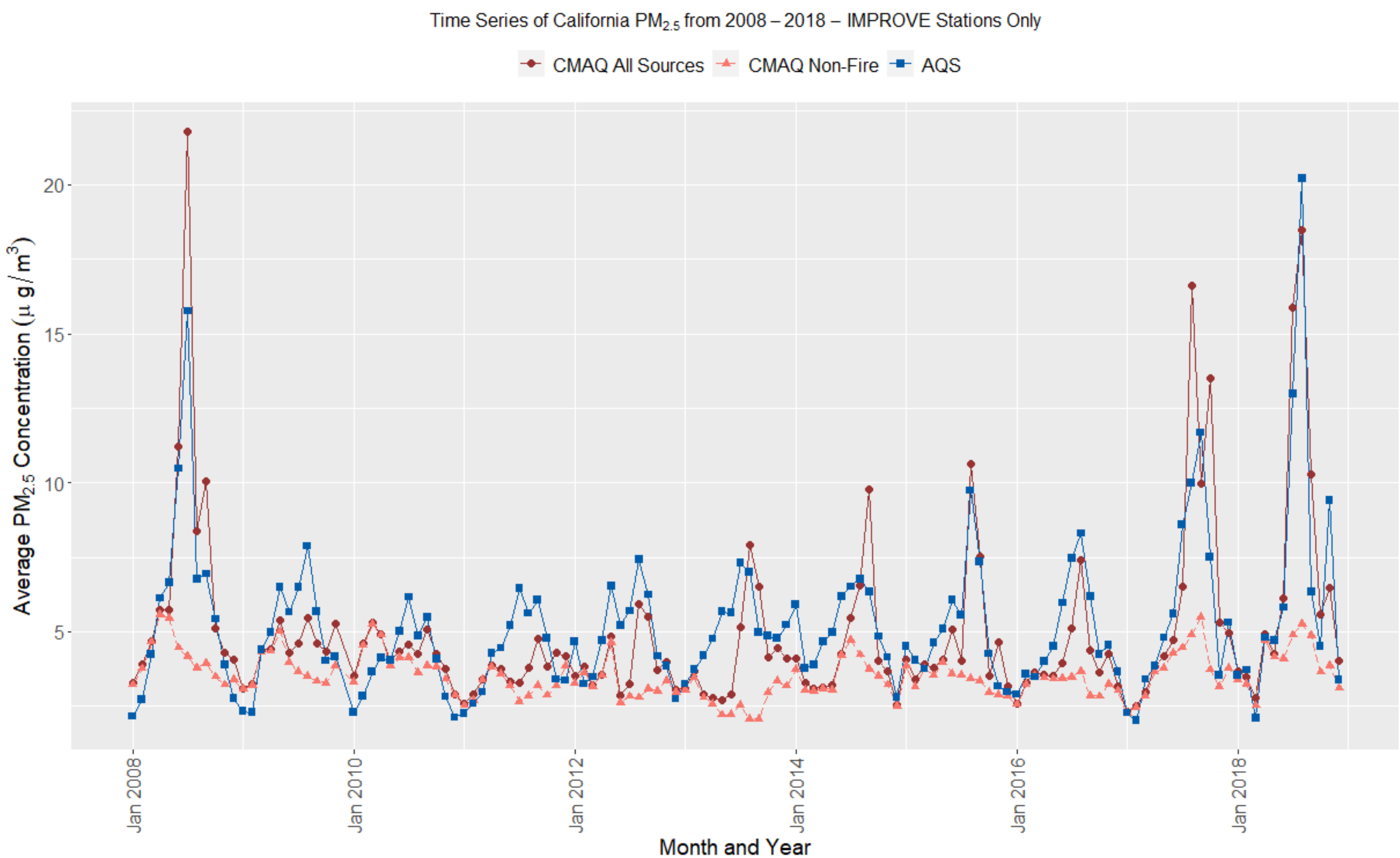

Figure B8.9. Time series of 11-year $PM_{2.5}$ with observed, all sources, and non-fire concentrations for IMPROVE stations only. Monthly mean $PM_{2.5}$ concentrations across California for 2008-2018 for AQS observations (blue solid line, square symbol), Community Multiscale Air Quality (CMAQ) all sources (dark red line, circle symbol) and CMAQ non-fire sources (light red line, triangle symbol).

Table B8.16. *Fire season (June – October) statistics summary of paired observations and with-fire and no-fire modeled concentrations for 2008-2018, no values capped*

Year	Observed Mean	Modeled Mean (µg/m³)		Count of pairs	Correlation		RMSE (µg/m³)		MB (µg/m³)	
		With-Fire	*No-Fire*		*With-Fire*	*No-Fire*	*With-Fire*	*No-Fire*	*With-Fire*	*No-Fire*
2008	14.9	18.6	11.5	10,349	0.69	0.15	14.2	15.3	3.69	-3.42
2009	11.0	10.8	9.74	12,568	0.50	0.45	7.63	7.61	-0.25	-1.27
2010	10.5	11.0	10.6	15,308	0.40	0.39	8.48	8.46	0.52	0.10
2011	11.5	7.53	6.89	16,816	0.54	0.53	7.48	7.84	-3.92	-4.57
2012	9.78	7.23	6.38	18,654	0.50	0.41	6.27	6.91	-2.55	-3.40
2013	9.73	6.68	5.25	19,738	0.44	0.41	7.26	7.43	-3.05	-4.48
2014	9.59	7.72	6.26	18,486	0.20	0.48	17.5	6.31	-1.87	-3.33
2015	9.39	7.84	6.13	20,328	0.35	0.35	13.2	7.09	-1.56	-3.27
2016	9.45	8.21	5.88	21,201	0.13	0.43	23.8	6.31	-1.24	-3.57
2017	11.4	13.9	7.25	21,238	0.20	0.25	64.0	10.9	2.50	-4.16
2018	11.8	13.0	7.17	21,982	0.29	0.26	21.0	11.4	1.11	-4.66

Table B8.17. *Fire season (June – October) statistics summary of paired IMPROVE station organic and elemental carbon $PM_{2.5}$ observations and fire-only modeled concentrations for 2008-2018*

Year	EC/OC Observed Mean	Fire-Only Modeled Mean (µg/m^3)	Count of pairs	Correlation	RMSE (µg/m^3)	MB (µg/m^3)
2008	3.46	6.57	996	0.74	14.8	3.11
2009	2.28	1.16	1,026	0.39	4.85	-1.12
2010	1.59	0.59	979	0.20	2.93	-1.00
2011	1.73	0.84	1,003	0.13	4.29	-0.89
2012	1.73	1.28	1,145	0.65	3.71	-0.45
2013	1.95	2.83	1,019	0.62	9.22	0.88
2014	1.72	1.95	1,114	0.48	10.5	0.24
2015	2.10	2.71	1,079	0.48	9.42	0.61
2016	1.93	1.75	1,020	0.19	4.96	-0.18
2017	3.46	5.92	1,065	0.53	16.8	2.46
2018	3.97	5.93	1,032	0.36	14.5	1.96
All Years	2.35	2.86	11,478	0.48	9.93	0.51

Notes: EC = elemental carbon, OC = organic carbon. One outlier capped at the maximum observed EC/OC concentration for the entire dataset of paired observations (205 µg/m^3)