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Green Space, Wildfires, and Access to Clean Vehicles: Characterizing Public Health and Equity Outcomes Associated with Environmental Exposures and Policy Implementation across California

A dissertation submitted in partial satisfaction

of the requirements for the degree Doctor of Philosophy

in Environmental Health Sciences

by

Rachel Emma Connolly

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ABSTRACT OF THE DISSERTATION

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Characterizing Public Health and Equity Outcomes Associated with

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Doctor of Philosophy in Environmental Health Sciences

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Professor Yifang Zhu, Chair

Despite a growing body of research and policy action to increase environmental equity in California, vulnerable populations remain disproportionately environmentally disadvantaged, experiencing a wide spectrum of environmental injustices. Though California is a national leader in combating climate change, with ambitious climate change targets and priorities, the vulnerability of disadvantaged populations also has the potential to increase with impending climate impacts. Ultimately, this dissertation aims to identify pathways to improve environmental health and attain equity across California. We use various methods in the environmental health sciences field – including geospatial techniques, dose-response analysis, qualitative thematic analysis, and predictive modeling – to characterize environmental health impacts from various

exposures and identify evidence-based strategies to improve environmental conditions, providing action-oriented research that can result in policy change. This dissertation includes three aims, each of which has a distinct motivation stemming from California's climate priorities and environmental justice concerns throughout the state. This work is divided into the following five chapters: an introduction (Chapter 1), three chapters of primary research (Chapters 2-4) and the conclusions and future research directions (Chapter 5).

First, we used recently released small-area life expectancy data to quantify the relationship between life expectancy and green space in Los Angeles County, a large diverse region with inequities in park access. Our predictive models analyzing remote sensing and satellite imagery-based greenness metrics demonstrated that neighborhood-level greenness is positively associated with life expectancy. Additionally, we found evidence that access to higher park acreage is only predictive of longer life expectancy for populations residing in neighborhoods with a lower percentage of tree canopy cover than the county median. This finding suggests that parks become a more important component of green infrastructure when other sources of green space are unavailable, which within the Los Angeles context is often in neighborhoods with lower socioeconomic status and more communities of color. We found that more than 110,000 years of life expectancy could be saved for just Hispanic/Latinx and Black residents if park acreage were to be increased to the median level in less green areas. This has distinct environmental justice implications.

Then, we quantified the total mortality burden for exposure to fine particulate matter ($PM_{2.5}$) due to wildland fires in California using eleven years of Community Multiscale Air Quality (CMAQ) modeling system fire $PM_{2.5}$ estimates. We applied ZIP code level mortality data and an estimated wildfire-specific chronic dose-response coefficient accounting for the likely toxicity of wildfire smoke, estimating between 47,100 and 50,360 premature deaths are attributable to wildland fire $PM_{2.5}$ over the eleven-year period. This mortality burden for 2008-2018 equates to an economic impact of $387 to $413 billion. These findings extend evidence on climate-related health impacts, suggesting that wildfires account for a substantial mortality and economic burden.

Finally, we analyzed procedural equity in household-level just transition policies and associated programs, which are designed to increase the uptake of novel technologies through the provision of incentives and rebates. We accomplished this through a case study of a longstanding equity-focused electric vehicle incentive program in the United States, the Clean Cars 4 All (CC4A) program offered in California. We used the academic literature to develop a broader conceptual procedural equity framework for household-level just transition policies. We then conducted interviews with program stakeholders and benefit recipients to analyze the extent to which various regional CC4A program implementation strategies have achieved procedural equity outcomes, using the framework we developed. We find that while regionally distinct strategies are valuable in tailoring approaches to meet community heterogeneity, the decentralized program implementation structure has resulted in inconsistency in the realization of procedural equity outcomes. These procedural impacts also influence the distributive dimension of equity. The framework developed in this study can be applied in future procedural equity analyses of other policies, and our findings have significant implications for ensuring a just transition to clean energy more broadly.

The dissertation of Rachel Emma Connolly is approved.

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University of California, Los Angeles

2023

DEDICATION

To my family, for their unwavering support.

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International Association of Wildland Fire: Fire and Climate Conference. "Mortality and Morbidity Attributable to Wildfire Smoke in California from 2008-2018" [Oral Presentation, Co-Author]. Panel Title: Firefighter Health and Public Safety. 26 May 2022.

Nature and Health Virtual Conference. "The impact of green space, tree canopy and parks on life expectancy in neighborhoods of Los Angeles" [Oral Presentation]. Panel Title: The big picture: Comprehensive urban greening and health. 13 October 2021.

American Public Health Association Annual Meeting. "Estimating mortality impacts from vehicle emission reduction efforts: The Tune In and Tune Up program in the San Joaquin Valley" [Poster Presentation]. Environmental Health Student Achievement Poster Award Track. 13 November 2018.

1. INTRODUCTION

1.1. EQUITY, ENVIRONMENTAL HEALTH, AND CLIMATE PRIORITIES IN CALIFORNIA

Despite a growing body of research and policy action to increase environmental equity in California, vulnerable populations[1] remain disproportionately environmentally disadvantaged, experiencing a wide spectrum of environmental injustices. Low-income populations and communities of color are exposed to poor environmental conditions, including air pollution from transportation corridors and less access to green spaces such as parks. These types of exposures adversely impact public health (Pope and Dockery, 2006; Rojas-Rueda et al., 2019) and contribute to health disparities (Cushing et al., 2015), which are well-established between populations of different races, ethnicities, and income levels in California and throughout the United States (U.S.) (Brown et al., 2019; LaVeist et al., 2011; Office of Health Equity, 2015; O'Keefe et al., 2015). Existing environmental and health inequities extend to the effects of climate change, with vulnerable populations disproportionately impacted by extreme weather events, increases in local air pollution, and energy insecurity, as well as adaptation barriers such as lower community resiliency to climate impacts more broadly (Office of Environmental Health Hazard Assessment, 2022; Shonkoff et al., 2011; USGCRP, 2018).

The state of California, with a diverse population of more than 39 million, is a national environmental leader in the fight against climate change, with ambitious emissions targets, including a reduction in greenhouse gas emissions to 85% below 1990 levels by 2045. The state's

[1] For the purposes of this dissertation, *vulnerable or disadvantaged populations* include low-income populations and communities of color, as well as California's state-identified priority populations more broadly, which encompasses Senate Bill (SB) 535 disadvantaged communities [DACs] and Assembly Bill (AB) 1550 low-income households and low-income communities [LICs].

priorities for climate action span multiple sectors, and include zero-emission vehicles, wildfires, community resilience, and drought (California Environmental Protection Agency, 2023), with specific goals and targets to reduce environmental and health impacts associated with climate change outlined in the state's *Scoping Plan for Achieving Carbon Neutrality* (California Air Resources Board, 2022a).

Though existing literature assesses the magnitude of disproportionate exposures and explores methods to improve environmental conditions and mitigate climate impacts (Cushing et al., 2015; Mohai et al., 2009; Morello-Frosch et al., 2001; Pastor and Morello-Frosch, 2014; Shonkoff et al., 2011), there is a critical need to continue growing this body of research to support policy action, improve environmental health, and reduce health disparities throughout the state. Therefore, the pursuit of environmental justice and California's climate priorities are two key motivations for the research included in this dissertation. In its entirety, this dissertation aims to characterize pathways to improve public health and attain environmental equity across California**.**

This dissertation includes three aims, each of which has a distinct motivation stemming from California's climate priorities and environmental justice issues throughout the state. **Chapter 2** is focused on access to green spaces and life expectancy, which is connected to the climate priority of *community resilience*. Access to urban green spaces has a multitude of well-established health benefits achieved through several mediating pathways, including stress reduction and buffering of environmental exposures, such as extreme heat resulting from climate change (California Air Resources Board, 2022a; Nieuwenhuijsen et al., 2017). However, low-income populations and communities of color have less access to green spaces, including parks (Klompmaker et al., 2023; Rigolon, 2016), so this is a distinct equity concern, which is discussed and quantitatively analyzed throughout the chapter. **Chapter 3** is focused on wildland fires, air pollution, and mortality in

California, which is directly associated with the climate priority of *wildfires.* A brief discussion of the potential equity implications of wildfire exposure, related knowledge gaps, and future research directions are included. **Chapter 4** is focused on achieving procedural equity in household-level just transition policies, with a specific case study of an incentive program for clean vehicle uptake in California. This chapter is aligned with the *zero-emission vehicles* climate priority and has a sole focus on equity.

1.2. SUMMARY OF AIMS

In this dissertation, we use various methods in the environmental health sciences field – including predictive modeling, geospatial techniques, dose-response analysis, and qualitative thematic analysis – to characterize public health and equity outcomes associated with environmental exposures and policy implementation across California. This work provides action-oriented research that can result in policy change. Each of the three aims in this dissertation, presented in **Chapters 2, 3**, and **4**, is centered on a separate dimension of the environment. These aims investigate a spectrum of environmental, health, and equity topics with distinct and approachable implications.

In **Chapter 2**, we quantified the dose-response relationship between exposure to green spaces and life expectancy, with an emphasis on health equity dimensions. While there are significant disparities in life expectancy across neighborhoods in the U.S. by socioeconomic status and race and ethnicity (Singh et al., 2017; Woolf and Schoomaker, 2019), as well as established inequities in park and green space access (Klompmaker et al., 2023; Rigolon, 2016), there are no existing studies evaluating the impact of green spaces on life expectancy at the small-area level in the U.S. We used predictive modeling to quantify the effect of park access and other measures of green spaces, including normalized difference vegetation index (NDVI, a metric of greenness derived from satellite imagery), and tree canopy coverage, on life expectancy in Los Angeles County. This research presents an opportunity to consider environmental health equity during decision-making processes for the distribution of parks and green space funding.

In **Chapter 3**, we quantified the long-term impact of exposure to wildland fire-associated air pollution on mortality in California. Wildfires have increased in frequency and severity in the western U.S. in recent years, due to climate change (Hurteau et al., 2014; Westerling et al., 2006; Williams et al., 2019), an expansion of the wildland-urban interface (Burke et al., 2021; Radeloff et al., 2018), and questionable wildfire management practices emphasizing fire suppression (Jerrett et al., 2022). However, the long-term impact of fires on premature mortality in California has not been previously quantified. Using eleven years of Community Multiscale Air Quality (CMAQ) modeled data, we quantified the total impact of wildland fire-associated fine particulate matter ($PM_{2.5}$) on mortality, using an estimated chronic wildfire exposure dose-response function accounting for the likely toxicity of wildfire smoke (Aguilera et al., 2021). These findings have significant implications for California, a state at the forefront of climate policy with many fire-prone regions and a diverse population to protect. Continuing to grow the evidence on health impacts from wildfires and other climate-related exposures is critical in mitigating the impacts of climate change and protecting vulnerable populations throughout the state.

In **Chapter 4**, we characterized evidence-based methods to increase procedural equity in limited-funding household-level just transition policies and associated programs. There has been a historical focus on the distributive component of environmental justice (Bell and Carrick, 2017; Lake, 1996; Reed and George, 2011), but it is critical to consider equity in procedures regardless of the distribution of outcomes. To date, no studies have done so in the context of the implementation of environmental benefit policies and associated programs, which are increasingly authorized to support vulnerable households in just transition efforts to achieve a clean and equitable energy future. Our work bridges this gap through a qualitative case study of a longstanding equity-focused electric vehicle incentive program in the U.S., the Clean Cars 4 All (CC4A) program offered in California. We used academic literature to propose a broader conceptual procedural equity framework, and conducted interviews with program stakeholders and benefit recipients to analyze the extent to which various regional CC4A program implementation strategies have achieved procedural equity outcomes. The framework developed in this study can be applied in future procedural equity analyses of other similar policies and associated programs, and our findings have significant implications for ensuring a just transition to clean energy more broadly.

In sum, the three aims in this dissertation characterize public health and equity outcomes associated with environmental exposures and policy implementation across California. These findings can inform future research, community advocacy, and policy change.

2. THE ASSOCIATION OF GREEN SPACE, TREE CANOPY AND PARKS WITH LIFE EXPECTANCY IN NEIGHBORHOODS OF LOS ANGELES

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2.1. ABSTRACT

Substantial evidence suggests that access to urban green spaces and parks is associated with positive health outcomes, including decreased mortality. Few existing studies have investigated the association between green spaces and life expectancy (LE), and none have used small-area data in the U.S. Here we used the recently released U.S. Small-Area Life Expectancy Estimates Project data to quantify the relationship between LE and green space in Los Angeles County, a large diverse region with inequities in park access. We developed a model to quantify the association between green space and LE at the census tract level. We evaluated three green space metrics: normalized difference vegetation index (NDVI, 0.6-meter scale), percent tree canopy cover, and accessible park acres. We statistically adjusted for 15 other determinants of LE. We also developed conditional autoregressive models to account for spatial dependence. Tree canopy and NDVI were both significantly associated with higher LE. For an interquartile range (IQR) increase in each metric respectively, the spatial models demonstrated a 0.24 to 0.33-year increase in LE. Tree canopy and NDVI also modified the effect of park acreage on LE. In areas with tree canopy levels below the county median, an IQR increase in park acreage was associated with an increase of 0.12 years. Although on an individual level these effects were modest, we predicted 155,300 years of LE gains across the population in LA County if all areas below median tree canopy were brought to the county median of park acres. If tree canopy or NDVI were brought to median levels, between 570,300 and 908,800 years of LE could be gained. The majority of

potential gains are in areas with predominantly Hispanic/Latinx and Black populations. These findings suggest that equitable access to green spaces could result in substantial population health benefits.

2.2. 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 (Zhang et al., 2020). 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 (Akaraci et al., 2020; Callaghan et al., 2020; Gascon et al., 2018, 2016; 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). Although abundant literature exists on several key health outcomes associated with green space access, and evidence suggests that life expectancy (LE) can vary significantly at a small spatial scale (Chetty et al., 2016; National Center for Health Statistics et al., 2018), few studies have investigated the association between small-area LE and urban green spaces.

LE represents a critical measure of human development, and it is a core component of the United Nations' Human Development Index (United Nations Development Programme, 2022). LE is associated with social and environmental determinants of health (Pope et al., 2009), and considerable disparities between populations exist within the United States (Singh et al., 2017; Woolf and Schoomaker, 2019). While LE in the U.S. steadily increased from the late-1950s to mid-2010s, it has subsequently declined in three consecutive years since 2014 (Woolf and

Schoomaker, 2019), for reasons such as the opioid epidemic and an increase in suicide rates (Harper et al., 2021). Further declines have occurred in recent years, likely due to the COVID-19 pandemic (Masters et al., 2022; Woolf et al., 2022). Considering this downward trend, it is critical to understand underlying factors that can increase LE. As a modifiable risk factor, access to green spaces could help extend LE in the U.S. and elsewhere; therefore, a more comprehensive understanding of the relationship is potentially important to population health and well-being.

The two existing studies evaluating the effects of green space on small-area LE focused on the European continent (de Keijzer et al., 2017; Jonker et al., 2014). One study solely evaluating the relationship between green space and small-area LE in the Netherlands found that residential green space was associated positively with LE, though distance to the nearest urban green space did not have an impact on LE (Jonker et al., 2014). The other study from Spain evaluated both air pollution and greenness and associated impacts on mortality and LE and reported that higher levels of greenness improved health outcomes, but exclusively in disadvantaged areas with lower socioeconomic position (SEP) (de Keijzer et al., 2017).

Other studies have investigated these relationships using much larger areas. One study assessed natural resource amenities and LE in the U.S. at the county scale, finding that counties with more natural amenities — including forests, water bodies, and state parks — had longer LEs (Poudyal et al., 2009). In Mexico, an analysis at the state scale found that a combination of several aspects of ecological resilience, including tree cover and vegetation levels, was positively associated with LE at birth (Idrovo, 2011). Studies using relatively large-area data, however, may have exposure measurement error in terms of proximity of the population to green spaces within a region such as a city or county (Bixby et al., 2015; Perchoux et al., 2016), and more small-area studies are needed to strengthen the evidence base. Currently, no studies have been conducted in the U.S. linking small-area LE to green space. Filling this knowledge gap presents an associated opportunity to elucidate pathways to extend LE and support health equity. Additionally, while a European study (de Keijzer et al., 2017) demonstrated varying impacts of greenness for socially vulnerable populations, to our knowledge, no existing studies explore whether added park space in less green areas has a differential impact on LE. We hypothesize that in areas with less green space or tree canopy, parks are of additional value because they are supplying proportionately more of the green space exposure than in areas with more green space. Consequently, expected benefits to LE will associate more strongly with park access in less green areas.

This study was motivated by the (i) previously identified knowledge gap on how green space affects LE, (ii) regional inequalities in green space access throughout LA County (Los Angeles County Department of Parks and Recreation, 2016), and (iii) recent release of a novel small-area dataset on LE (National Center for Health Statistics et al., 2018). We achieve two key research objectives: first, we characterize the relationship between access to greenness and small-area LE, and second, we explore whether differential greenness in a neighborhood modifies the relationship between park access and health, while controlling for potential confounding factors.

2.3. METHODS

2.3.1. Study Setting

In this study, we used recently developed U.S. Small-Area LE Estimates Project (USALEEP) data – a novel, census tract (CT) level LE dataset for the years 2010-2015 – to quantify the relationship between green space and LE in LA County. LA County is part of the second largest metropolitan area in the U.S. It is a diverse region with a population of about 10 million people covering more than 4,000 square miles (more than 10,000 square kilometers) of land (US Census Bureau, 2015). Throughout the county, substantial variations in green spaces and parks exist by neighborhood (Los Angeles County Department of Parks and Recreation, 2016), and low-income populations and communities of color have less access to parks (Wolch et al., 2005). There are also stark health disparities within the region (Lewis and Burd-Sharps, 2018; Los Angeles County Department of Public Health, Office of Women's Health, 2017; PolicyLink and PERE, 2017), and this extends to LE, with CTs in affluent areas such as Beverly Hills reporting life expectancies as high as 90 and South LA communities less than 15 miles away with a median LE of 77, 13 years less (National Center for Health Statistics et al., 2018).

2.3.2. Outcome: Novel Life Expectancy Data

The USALEEP data has LE estimates for 94% of all LA County CTs (n = 2,177 used in our final analysis – see Figure 2.1 (left) for the spatial distribution of LE estimates). The abridged life tables used to compile these estimates were developed using National Vital Statistics System mortality data, decennial census counts, and American Community Survey census data (Arias et al., 2018). The LE estimates are computed using a "period" method that uses 2010-2015 as the period to estimate mortality rates that are then applied to a hypothetical birth cohort to estimate LE. Several novel modeling techniques were applied to impute mortality rates in census tracts with sparse data (Arias et al., 2018).

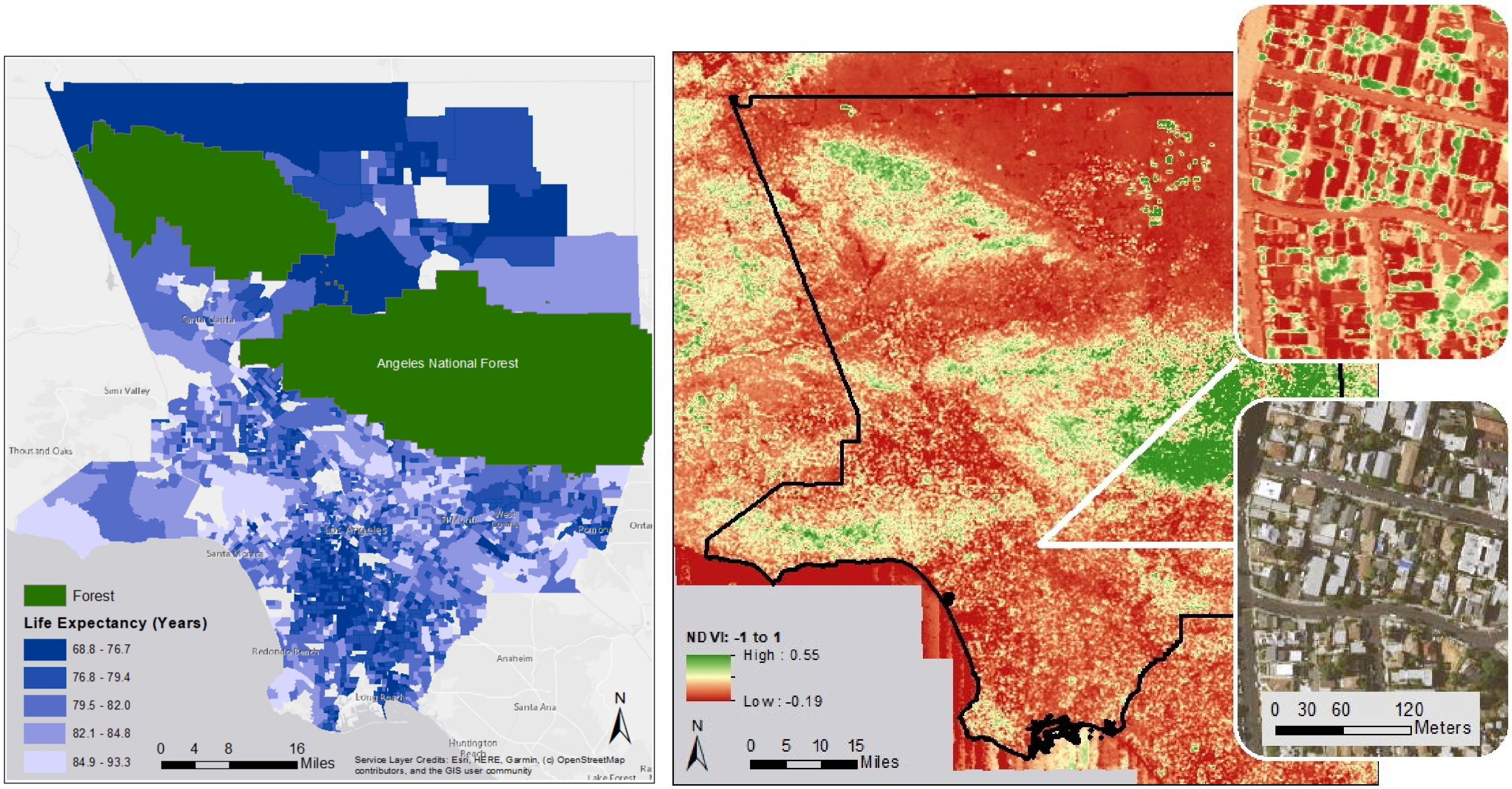

Figure 2.1. USALEEP LE estimates for LA County, 2010 – 2015 (left) and normalized difference vegetation index (NDVI) in Los Angeles, 2016 (right). Angeles National Forest was excluded from the analysis.

2.3.3. Green Space and Parks Exposure Metrics

We included three metrics of green space exposure at the CT level: normalized difference vegetation index (NDVI), tree canopy coverage, and park access.

NDVI. 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 for LA County (U.S. Department of Agriculture Farm Service Agency, 2016). First, we mosaicked the images into a single raster, and calculated NDVI for the entire coverage. We then removed water bodies and extracted the average NDVI value for each CT, using raster calculations. Figure 2.1 (right) shows the geographic coverage and spatial resolution of the NDVI data. We conducted preliminary analyses using 2012 NDVI data instead of 2016 but found that a major drought had severely impacted the NDVI estimates; therefore, we used 2016 data in our main analysis to represent a typical chronic exposure. NDVI estimates for 2012 and 2016 were nonetheless highly correlated (r = 0.82).

Tree canopy. We used a recently created Los Angeles tree canopy dataset for the year 2016, provided by TreePeople and the Loyola Marymount Center for Urban Resilience (TreePeople et al., 2019). This dataset was developed using remote sensing methods – imagery and light detection and ranging (LiDAR) technology. We used the percent tree canopy coverage in each CT as the tree canopy indicator in our analysis.

Park access. We used publicly available geospatial data from the 2016 Los Angeles Countywide Comprehensive Parks and Recreation Needs Assessment (PNA) for the park acreage metric; we estimated the average number of available park acres from any particular point within each CT (using raster calculations), based on the "available acres" raster layer (Los Angeles County Department of Parks and Recreation, 2016). The PNA developed this raster as a function of the number of park acres that individuals living within a certain area have access to, based on the buffers of how much people are willing to travel for parks of different sizes, with a two-mile maximum distance (the assumption being that people will travel further for a larger parks). This dataset was one factor used to determine the final park need for the assessment (see Appendix E of the PNA for additional details (Los Angeles County Department of Parks and Recreation, 2016)]). We selected this as the primary park access metric to capture any variations dependent on the size of green spaces (Mitchell et al., 2011). We also conducted a supplementary analysis using one additional parks metric: the distance to the nearest publicly available park, as used in the PNA (Los Angeles County Department of Parks and Recreation, 2016).

2.3.4. Analytical Methods

Initially, we ran several linear regression models for each metric of green space (Section 2.3.3), with LE as the outcome variable in each model. We adjusted for CT-level covariates potentially associated with LE, all listed in Table 2.1,[2] including lifestyle factors such as smoking, obesity, and physical inactivity; environmental factors, including fine particulate matter, ozone, and nitrogen dioxide air pollution estimates, transportation-specific noise, and heat exposure; SEP and demographic factors, including income, race/ethnicity, linguistic isolation, health insurance status, and education; and finally, social and environmental vulnerability, using two aggregated vulnerability indices, the CDC's Social Vulnerability Index and the California Office of

[2] Though several variables are outside of the life expectancy period of 2010-2015, they are well aligned with the exposures, which are all using 2016 data. For lifestyle variables as well as social vulnerability data, we elected to use more recent datasets with respect to continuously improving data collection techniques and methodology.

Environmental Health Hazard Assessment's CalEnviroScreen 3.0[3] (see Appendix Table A.1 for a correlation matrix). The PLACES data supplying the lifestyle variables (Table 2.1) were only available for approximately three quarters of CTs in LA County, so the median values for the lifestyle variables were applied to tracts with missing estimates (after testing the analyses for sensitivity to such changes).

[3] CalEnviroScreen 4.0 was released in October 2021. We ran several updated models incorporating the new estimates, but the change did not impact the analysis significantly.

Table 2.1. List of datasets, metric type, sources, and timeframes

Dataset	Metric type	Source (Reference)	Timeframe
Life expectancy (years)	Health – main outcome variable	United States Small Area Life Expectancy Estimates Project (USALEEP) (National Center for Health Statistics et al., 2018)	2010-2015
Tree canopy (percent cover)	Green space	TreePeople and the Loyola Marymount Center for Urban Resilience (TreePeople et al., 2019)	2016
NDVI (-1 to 1 scale)	Green space	National Agriculture Imagery Project (NAIP)	2016
Park access	Green space	Los Angeles Countywide Comprehensive Parks & Recreation Needs Assessment (Los Angeles County Department of Parks and Recreation, 2016)	2016
Smoking in adults (percent)	Lifestyle	U.S. Centers for Disease Control and Prevention (CDC) 500 Cities Project, renamed PLACES as of late 2020 (Centers for Disease Control and Prevention et al., 2019)	2017
Obesity in adults (percent)	Lifestyle		2017
Physical inactivity in adults (percent)	Lifestyle		2017
Fine particulate matter ($PM_{2.5}$, micrograms per cubic meter)	Environmental	Center for Air, Climate, & Energy Solutions (CACES) (Center for Air, Energy, and Climate Solutions, 2015; Kim et al., 2020) [4]	2015
Ozone (parts per billion)	Environmental		
Nitrogen dioxide (parts per billion)	Environmental	Health Effects Institute Report (Meng et al., 2021)	2012
Noise (transportation-specific, decibels A equivalent)	Environmental	U.S. Department of Transportation (US Department of Transportation: Bureau of Transportation Statistics, 2019)	2018
Heat (cooling degree days)	Environmental	Lawrence Berkeley National Laboratory (Vahmani, 2015; Vahmani et al., 2019)	2011-2015 averages
Median household income (U.S. dollars)	Social	U.S. American Community Survey (ACS) (US Census Bureau, 2015)	2011-2015 5-year estimates
Race/ethnicity (percent of the population with Hispanic ethnicity or non-white race)	Social		
Linguistic isolation (percent of households not speaking English)	Social		
Health insurance status (percent of uninsured adults ages 18 – 64)	Social		
Education (percent of the population that is a high school graduate or has higher education)	Social		
CDC Social Vulnerability Index score	Social vulnerability	CDC (Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry: GRASP Program, 2016)	2016
CalEnviroScreen 3.0 environmental health screening tool score	Social vulnerability	California Office of Environmental Health Hazard Assessment (Office of Environmental Health Hazard Assessment, 2018)	2018

[4] This article includes concentration estimates developed by the Center for Air, Climate and Energy Solutions (CACES) using v1 empirical models as described in (Kim et al., 2020).

Preliminary models had multicollinearity because several of the previously listed socioeconomic and demographic variables were highly correlated. Therefore, we reduced the dimensionality by applying Principal Component Analysis (PCA), allowing us to transform the potential confounders into a set of uncorrelated principal components for inclusion in the regression models along with the green space metrics (Luginaah et al., 2001).

We initially fit linear regression models by regressing the LE estimates onto green space metrics using the first six extracted principal components as controls. To determine if the linear regression models were meeting the assumption of independently distributed errors, we conducted local and global spatial clustering tests (Anselin Local Moran's I and Global Moran's I) on the unstandardized residuals in ArcMap. Residuals from the linear models demonstrated significant spatial autocorrelation, so we used a Gaussian model in a Bayesian framework with a conditional autoregressive (CAR) prior on the random effects to account for spatial dependence, developing a second set of models (Jonker et al., 2014; Lipsitt et al., 2021). We used the CARBayes package in R to develop these CAR models (Lee, 2013), referred to as spatial models within the text; we consider these spatial models to be the primary result, given the residual autocorrelation in the linear regression models.

Based on the conceptual hypothesis that parks may differentially impact health in greenness-deprived versus heavily green areas, we also explored multiplicative interactions between the park access metric and both the tree canopy and NDVI metrics.

Accordingly, we developed five linear and spatial models (ten primary models total) demonstrating the impact of various green space metrics on LE: (A) NDVI, (B) tree canopy, (C) park access, (D) park access in areas below the median level of tree canopy, and (E) park access in areas above the median level of tree canopy. The median level was selected for stratification after conducting both tertile- and median-specific analyses with similar results.

As mentioned in Section 2.3.3, we also conducted a supplementary analysis using one additional parks metric from the LA PNA dataset, included in the Appendix (Table A.2). Finally, we developed a full set of supplemental linear and spatial models estimating the impact of adjusting for chronic health conditions in the model, including asthma, diabetes, high blood pressure, cancer, and coronary heart disease (Centers for Disease Control and Prevention et al., 2019). Some of these health outcomes could be on the causal pathway between green space and LE (i.e., some of these outcomes have been related to green space in the literature) (Wu et al., 2022; Yu et al., 2022; Zhao et al., 2022). Therefore, including these variables as confounders could result in over-control bias. Consequently, we do not consider these to be the primary results, but they are included in Table A.2 as sensitivity analyses.

We used R 4.2.0 for all statistical analyses, and ESRI's ArcMap 10.8 (ESRI, 2020) for spatial analysis.

2.3.5. Simulation: Population Life Expectancy Impacts

To explore potential population impacts, we conducted a supplementary simulation to quantify the impact of increasing tree canopy and NDVI to the county median, as well as increasing park levels to the county median in less green areas (below median tree canopy levels). To estimate the potential years of life gained from added LE by increasing tree canopy, NDVI, or park space in less green tracts, we applied our calculated dose-response values for LE to CT population estimates using Eqn. 1 below.

$$Y_{LE} = \beta * GSj * Pop_{total,j} \quad (1)$$

where, β represents the one-unit dose-response value for green space and LE (linear regression model coefficient/median value for spatial model), GS_j represents the increase in green space to reach the county median in CT j, $Pop_{total,j}$ represents the population in each CT j, and Y_{LE} is the total years of LE gained. We apply Eqn. 1 to the population across LA County, using the American Community Survey (ACS) 2019 5-year estimates (US Census Bureau, 2019).

Additionally, we apply Eqn. 1 to the Black and Hispanic/Latinx populations in each tract to develop a race/ethnicity-specific assessment to evaluate how many years of life could potentially be saved from added LE in those populations. To assess whether we could apply the dose-response value developed for the entire population to the Black and Hispanic/Latinx populations specifically, we tested a multiplicative interaction between the percent of the population that is Black or Hispanic/Latinx and the greenness exposures. We did not find any significant relationship present in the linear or spatial models, so the same dose-response value as for the general population is applied to all groups.

2.4. RESULTS

Results from the linear and spatial models are shown in Table 2.2. Each model contained the first six principal components developed from our control variables, which explained 89% of the variance in the data (see the Appendix, Figures A.1 and A.2, Tables A.3 – A.6). In terms of the specific loadings for each component included in the analysis (Table A.4), for the full model (no stratification) we found moderate loadings on almost all variables for the first principal component, accounting for 54% of the total variance. The second component had loadings mostly on lifestyle and environmental factors (with slightly larger loadings for the environmental factors), including all eight of the variables in those two categories, and accounted for 13% of the total variance (see Figure A.1 for a visual plot of the loadings of components 1 and 2). The third component was also influenced by lifestyle factors and was focused on socio-demographic and social vulnerability, with some influence from environmental variables as well, accounting for 7.4% of the total variance. The other three components included in the analysis were less interpretable and accounted for relatively less of the total variance. The loadings were similar for the stratified models (Tables A.5 and A.6); we used each model's individual components to have more complete control for the strata, though results are similar when using the components from the full model on the two stratified models.

Our tests of interaction were significant for park access with the tree canopy variable at the 0.05 level, and the NDVI variable at the 0.1 level (for the linear models). We therefore present stratified results for park access above and below the median of tree canopy.

Table 2.2. Adjusted association of greenness (scaled by the interquartile range [IQR] of the respective green space metrics) with LE (in years) from five models with differing greenness metrics, for Los Angeles County CTs (total n = 2,177).

Model/Covariate of Interest	**Linear Model**		**CAR Gaussian model with spatial random effects**	
	Coefficient	*p-value*	*Median*	*Credible Interval*
A. Tree Canopy	0.383	<.0001***	0.244	0.053 – 0.432
B. NDVI	0.356	<.0001***	0.325	0.139 – 0.512
C. Park access	0.077	0.01*	0.015	-0.060 – 0.089
D. Park access: below median tree canopy (stratified model)	0.260	0.0006***	0.117	-0.062 – 0.296
E. Park access: above median tree canopy (stratified model)	-0.064	0.07	-0.074	-0.158 – 0.008

A. Tree canopy (Percent cover, IQR = 9.1%); B. NDVI (scale of -1 [least green] to 1 [most green], IQR = 0.053); C. Park access (available acres, IQR = 87.5); D. Stratified model: park access in areas with below median tree canopy (available acres, with respect to the same IQR = 87.5; n = 1,088 for the stratified analysis); and E. Stratified model: park access in areas with above median tree canopy (available acres, with respect to the same IQR = 87.5; n = 1,089 for the stratified analysis). Significance codes: * < 0.05, ** < 0.01, *** < 0.001 (linear models only).

Both sets of models demonstrate that tree canopy and NDVI, as measured through satellite imagery, are statistically associated with LE (as seen in Figure 2.2,[5] a visual representation of the fully adjusted linear models). The relationships were strong for both green space metrics independently, with the spatial models demonstrating that an increase in the IQR of tree canopy, or 9.1% cover (for the specific data subset included in the model), is associated with a 0.24-year (credible interval: 0.05 – 0.43) increase in LE, or approximately 2.9 months. An increase in the IQR of NDVI vegetation levels is associated with a 0.33-year (0.14 – 0.51), or 3.9-month, increase in LE.

[5] The R package used to develop Figure 2.2 is not compatible with CARBayes, so marginal effects for the spatial models are not plotted here.

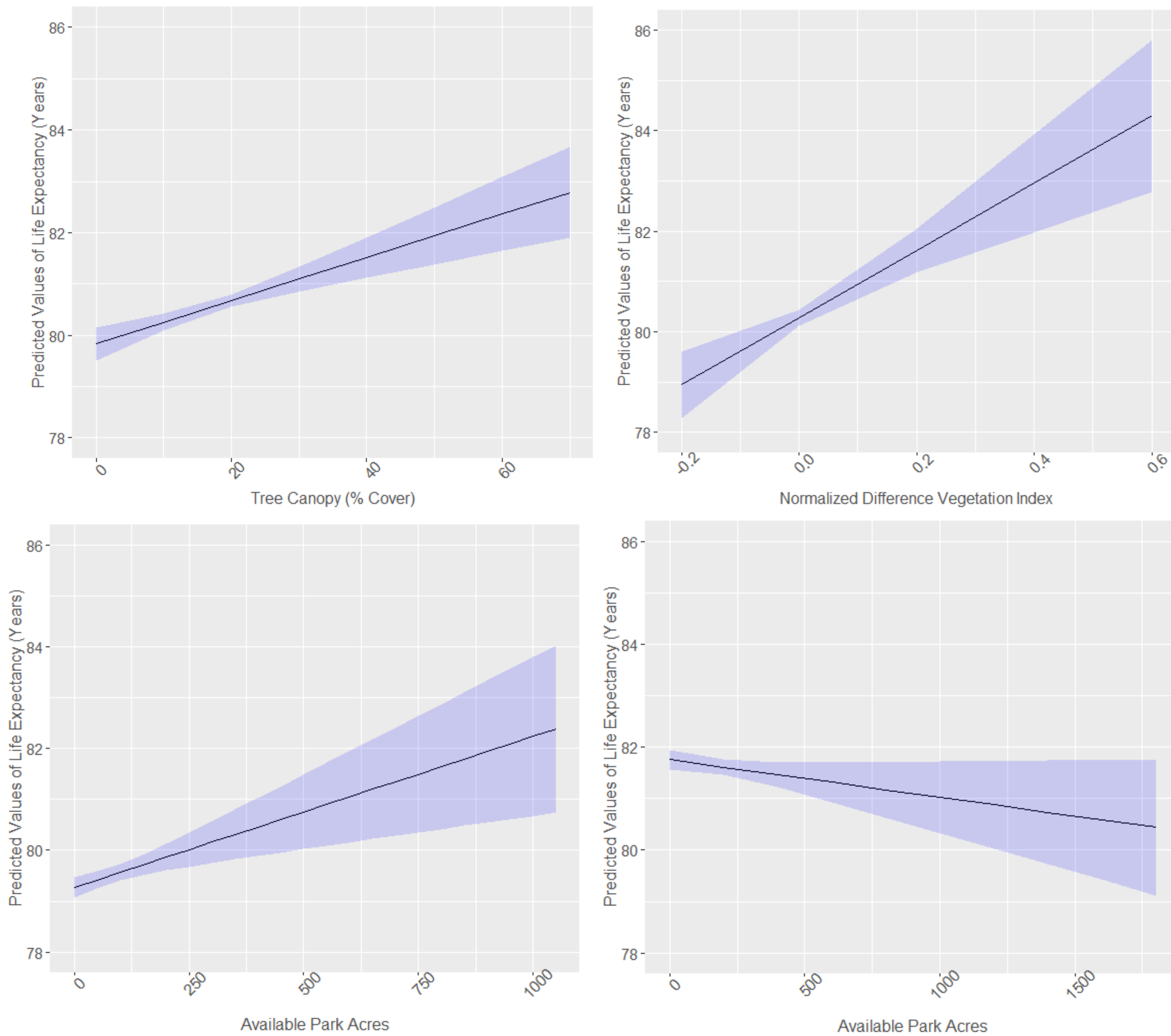

Figure 2.2. Predicted values of life expectancy for the fully adjusted linear tree canopy model (top left), NDVI model (top right), linear park access model for census tracts with below median tree canopy (bottom left), and linear park access model for census tracts with above median tree canopy (bottom right).

Findings regarding the impact of available park acreage on LE were less consistent, both with respect to the full versus stratified models and the linear models compared to the spatial models. While the linear model investigating an association between increasing park acreage and LE found that increased access to parks was significantly associated with longer LE, this relationship did not persist as evidently in the spatial model; the credible interval (indicating that the value lies within a 95% probability in the interval), includes zero and the effect estimate is also reduced from the linear model.

By separating tracts where the tree canopy is above or below the median level, we demonstrate that the relationship between increasing park access and longer LE only holds in regions with low greenness (as represented by tree canopy). This relationship is evident in the linear model (Figure 2.2), though not as strong in the spatial model, with the median estimate less than 50% of the magnitude of the linear coefficient, and the low end of the credible interval landing slightly below zero when scaled by the IQR (the low end of the credible interval is approximately 0 for the unscaled model). These results demonstrate that an IQR-level increase in access to available park acres (approximately 88 acres) in regions that are less green – with tree canopy below the median level for LA County – is associated with a 0.12-year increase in LE (-.06 – 0.30), which is equivalent to approximately 1.4 months. For the same model without the linear IQR scaling – representing the change in LE from one added acre of park access – the lower end of the credible interval is very close to zero.

These results indicate that in areas with less surrounding green space, having access to higher amounts of park acres is associated with longer population LE, though the range of the credible interval does lend less confidence to the strength of the results as compared to the other greenness metrics. We also developed supplemental models with one additional metric of park access developed for the LA PNA – the distance to the nearest publicly available park (Table A.2). Both the linear and spatial models indicate that the distance to the nearest park show no significant relationship with LE.

Results of a supplementary simulation where we apply our calculated dose-response values to CT population estimates are presented in Table 2.3. The results from the linear simulation are included as a reference point, but we only discuss the results for the fully adjusted spatial models here, as we consider those more reliable estimates. If tree canopy and NDVI were brought to their relative median levels throughout the county, between 570,300 and 908,800 years of LE could potentially be gained from added LE across the population in LA County living in less green CTs (Table 2.3), with a substantial portion of gains (between 61 - 69%) for Hispanic/Latinx and Black residents. Additionally, we estimate that if all the tracts in LA County with park deficits (below the median level) and below median tree canopy had an increase in available park acreage up to the county median (54 acres), approximately 155,300 years in LE could be gained across the county. These results for park access are presented in Figure 2.3 alongside CalEnviroScreen cumulative environmental vulnerability (Office of Environmental Health Hazard Assessment, 2021) to highlight the areas that could potentially benefit. This includes a gain of 111,500 years of LE for just Hispanic/Latinx and Black residents.

Table 2.3. Results of the simulations for added green space to the existing median level in LA County (using dose-response values from both linear and spatial models).

Simulation	**Total years added**		**Years added: Hispanic/Latinx and Black residents**	
	Linear	Spatial	Linear	Spatial
Tree Canopy	895,100	570,300	619,800	394,900
NDVI	995,500	908,800	603,500	550,900
Park Access: below median tree canopy	345,100	155,300	247,700	111,500

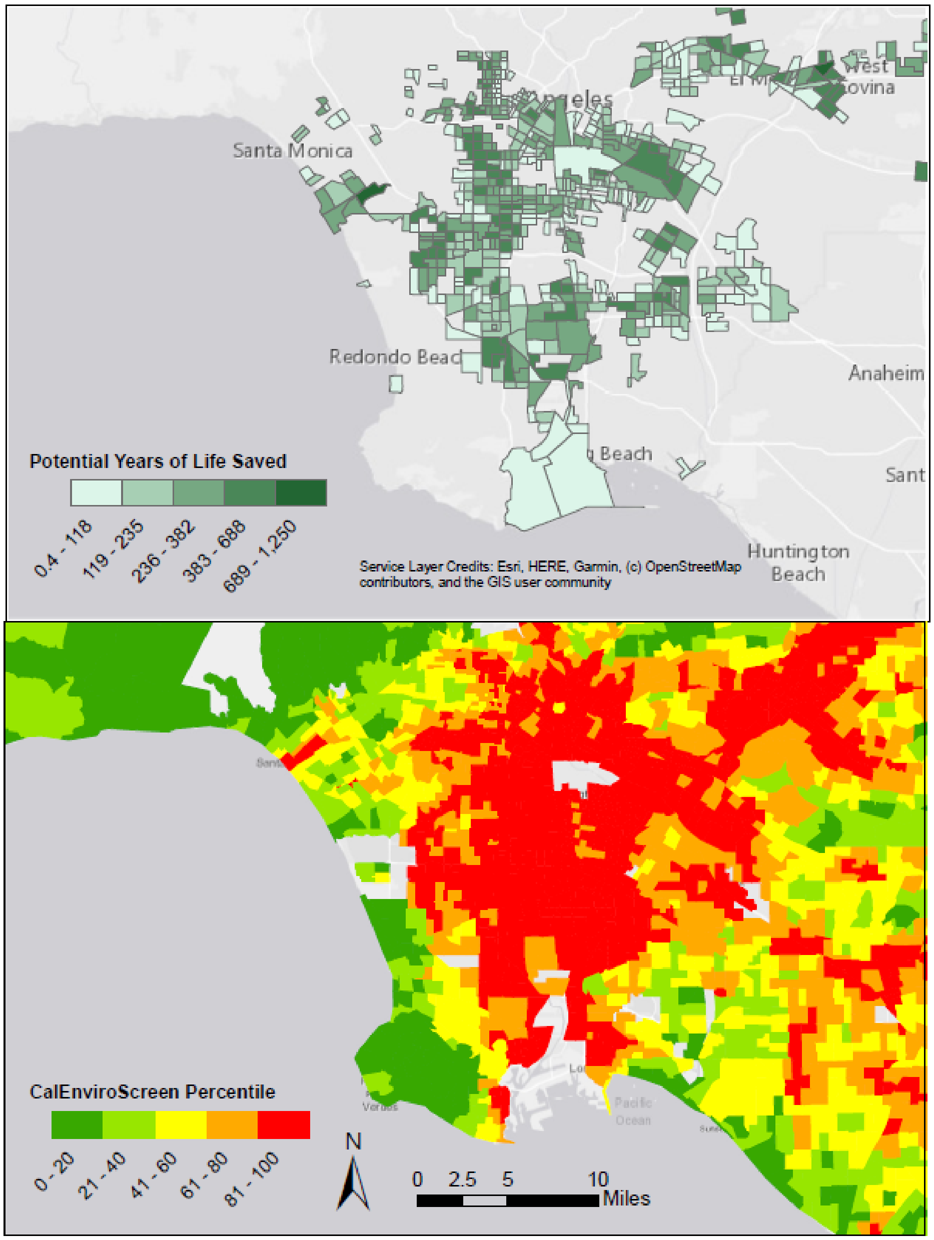

Figure 2.3. Potential years of life saved from added park space in greenness-deprived census tracts in the southern portion of LA County (top) and CalEnviroScreen 4.0 environmental justice vulnerability percentiles (bottom).

2.5. DISCUSSION

This is the first study in the United States to associate LE with access to green spaces, including parks and tree canopy, in small areas. We incorporate green space metrics that focus on surrounding neighborhood greenness and physical access to green spaces (parks), two characterization methods commonly utilized in the literature (Dadvand and Nieuwenhuijsen, 2019).

Our results based on the remote sensing and satellite imagery-based greenness metrics demonstrate that neighborhood-level greenness, as represented by tree canopy coverage and NDVI (vegetation greenness), is positively associated with LE. An IQR-level increase of each green space metric is associated with an average increase of several months of LE on an individual basis, which is substantial in magnitude when considering the population of 10 million in LA County (US Census Bureau, 2015).

These findings contribute to the body of evidence demonstrating that exposure to surrounding residential greenness improves health outcomes, including reducing population mortality (Rojas-Rueda et al., 2019) and yielding other positive effects on physical and mental health (Akaraci et al., 2020; Kondo et al., 2018; Nieuwenhuijsen et al., 2017; Twohig-Bennett and Jones, 2018; van den Berg et al., 2015). The body of literature on green space and LE is, however, limited. One comparable study focused on evaluating small-area LE in the Netherlands found a modest but statistically significant positive impact of an increase in urban green space; one standard deviation of percent green cover, which in this case was 11.5%, was associated with a 0.1-year longer LE (just over one month) (Jonker et al., 2014). The percentage of green space used in the Netherlands analysis was calculated using satellite imagery at a 25-meter scale (this is less spatially resolved than NAIP NDVI, at the 0.6-meter scale). We can compare these findings to (1) our spatial tree canopy model, where we see an increase in 9.1% coverage is associated with an increase of 0.24-years of LE, and (2) the similar finding for our spatial NDVI model, where the impact of an IQR change in NDVI on LE is 0.33-years (Table 2.2). The Netherlands study adjusted for income and spatial autocorrelation, but they did not control for other variables known to be associated with LE as we have here, with the authors identifying this as a limitation of their analysis (Jonker et al., 2014). This may explain why our results differ somewhat from the Netherlands study.

The only other comparable study used a similar approach to the Netherlands study to investigate the impact of air pollution and greenness on mortality and LE in Spain (de Keijzer et al., 2017). The authors present models that also adjust for spatial autocorrelation and socioeconomic vulnerability, as well as education levels and lung cancer as a proxy for smoking prevalence. This study found no association between greenness (NDVI at a 30-meter scale) and LE for the entire study area (de Keijzer et al., 2017). They found, however, an increase of 0.34 years with an IQR increase in NDVI in more economically deprived regions, which is very close to our finding of 0.33 years, though it must be noted that ours is for the entire study area and not just regions with low SEP. Additionally, when they stratified their analysis by community type, the statistical association was in an unexpected direction for urban areas, providing evidence that more greenness is associated with lower LE in urban areas. The authors cite several potential confounders and limitations associated with the analysis, including residual confounding by SEP, that may have led to this unexpected finding (de Keijzer et al., 2017). We did not explore urban and rural stratification in this study because most of our study area was urbanized, but these inconsistencies between urban and rural areas merit investigation in future research.

In terms of park access, after adjusting for spatial random effects, we found evidence that access to higher park acreage is only predictive of longer LE for populations residing in CTs with a lower percentage of tree canopy cover than the county median, though the effect estimate for parks is less robust than the estimates for tree canopy and NDVI. This finding suggests that parks become a more important component of green infrastructure when other sources of green space are unavailable, which within the Los Angeles context is often in neighborhoods with lower SEP and more people of color. When we evaluated one additional park access metric, distance to the nearest publicly available park (Los Angeles County Department of Parks and Recreation, 2016), we found no relationship with LE, which is consistent with findings from the Netherlands study (Jonker et al., 2014). A study comparing various green space indicators in Britain found preliminary evidence that larger green spaces may be disproportionately important for health impacts, and the authors also clarified that these larger spaces are less common in economically deprived regions, which is consistent with our study area as well (Mitchell et al., 2011). This may partially explain why our findings indicate that available park acreage is more beneficial to health than average distance to a park regardless of its size.

One emerging theme in the literature is the differential impacts of green space on vulnerable populations. A literature review on the health benefits of greenness identified multiple studies reporting a stronger relationship between greenness and health outcomes in populations of lower SEP (James et al., 2015). As mentioned previously, the Spain LE study found that greenness was only health-protective – predicting longer life expectancies – in areas with low SEP (de Keijzer et al., 2017). Though we explore green space stratifications and do not stratify by SEP specifically, CTs in LA County with lower levels of green space (below the county median) have lower median incomes (US Census Bureau, 2015). Therefore, our findings regarding park access contribute to the evidence that residential greenness is a potential health-protective built environment attribute for vulnerable communities. Again, our findings differ from those of the Spain-based study in several ways, considering we did find a significant impact of green space on LE for our entire study area, while the Spain study did not (de Keijzer et al., 2017). As suggested previously, our results may vary for several reasons, including the limited number of control variables in their analysis. While our findings are not directly comparable, our results provide additional evidence that socially disadvantaged areas with fewer environmental amenities may disproportionately benefit from increased access to green spaces and parks.

The modest but significant effect of park access on LE in less green areas highlights the substantial potential health benefits of adding park space in disadvantaged areas with less green space. The average green space (both tree canopy and NDVI) levels used in our analysis (TreePeople et al., 2019; U.S. Department of Agriculture Farm Service Agency, 2016) in state identified disadvantaged communities (as defined by California Senate Bill 535, 2012) are substantially lower than in other communities; for example, the average tree canopy coverage is 20.5% in non-disadvantaged communities versus 13.6% in disadvantaged communities. The median income for LA County tracts with tree canopy below the median level is an average of $58,900, as compared to $87,400 for tracts with tree canopy above the median level (TreePeople et al., 2019; US Census Bureau, 2019). Additionally, Hispanic/Latinx and Black communities have disproportionately less green coverage and therefore could potentially experience greater health benefits (via LE increases) from increased access to parks. About 60% of LA County's Hispanic/Latinx population and 67% of the county's Black population live in an area with tree canopy below the median level, while only 31% of the non-Hispanic White population does (TreePeople et al., 2019; US Census Bureau, 2019).

Assuming our associative model is predictive of changes in LE, the supplementary simulation for park access found that more than 110,000 years of LE could be saved for just Hispanic/Latinx and Black residents if park acreage were to be increased to the median level in less green areas. Additionally, increasing tree canopy coverage and greenness (measured by NDVI) up to the median level throughout LA County could add between 570,300 and 908,800 years of LE to the population living in less green CTs. Considering that the areas where the county's low-income populations and communities of color live are less green than other areas of the county, these regions and residents might receive substantial health benefits through the addition of park space.

This study is innovative in several ways. First, to our knowledge, no analysis investigating the relationship between green spaces and LE has been conducted using small-area data in the United States, and no studies have explored tree canopy specifically. The only existing comparable studies on small-area LE did not adjust for several variables known to be associated with LE (de Keijzer et al., 2017; Jonker et al., 2014). Existing LE studies in North America use a larger unit of analysis (Idrovo, 2011; Poudyal et al., 2009), which can be prone to aggregation bias and measurement error in the exposure to green spaces as considerable variation exists in most U.S. counties with respect to the distribution of green space. Additionally, we use several high-resolution datasets for NDVI (U.S. Department of Agriculture Farm Service Agency, 2016) and tree canopy (TreePeople et al., 2019), derived from satellite imagery. An added strength of this analysis is the use of PCA for data dimensionality reduction, which we used to transform our covariates into a set of uncorrelated principal components. This allowed us to control for many variables to strengthen the models without the statistical limitations accompanying multicollinearity.

This study also has several limitations. The findings are to be interpreted as associative, not causal, due to the nature of the observational datasets and statistical modeling, with one consideration being that certain populations may self-select into specific neighborhoods to benefit their already active lifestyles (Jerrett and van den Bosch, 2018). Likewise, financial constraints may limit the ability of low-income people to move into greener areas. Additionally, the LE estimates used in the analysis are modeled and therefore not as precise as LE estimates at a broader spatial level, such as by county, which would be based on observed mortality and population counts. Moreover, though we used a park access metric from the LA County PNA, we do not have sufficient individual or population data on how far people are actually willing to travel to reach different types of parks, so it is challenging to confirm if the buffers used within the PNA analysis are appropriate to be used to derive the metric. Further, this park access metric does not include factors that may influence park usage such as availability of programming at the parks, which may present added value and affect the likelihood of traveling to any specific park.

There are a few other limitations associated with the variables used in our analysis. First, our exposure metrics and covariates had some degree of temporal misalignment, though all fell within or close to the 2010-2015 range of the LE estimates. Considering most included variables are relatively stable and will likely vary similarly by CT (and we tested the sensitivity of changes in several of the variables over time), we do not anticipate this has substantially impacted our results.

Second, our results are also subject to a limitation faced in many epidemiological studies regarding latency periods of confounding factors included in our analysis. The LE estimates were based on "period" life tables that record the mortality experience of a population during a particular temporal point or period, in this case 2010-2015 (Arias et al., 2018). Such period tables then apply age-specific death rates in the period population to a hypothetical birth cohort. This requires the assumption that the hypothetical cohort will experience the same mortality rates by age as the actual population from the period throughout their entire lifetime. This has implications for confounders with different latencies. For example, factors such as smoking and obesity in the past (rather than contemporaneous behaviors) could affect current mortality rates and period LE. Thus, inclusion of these variables cross-sectionally in the model may not fully capture the confounding effect, although in a highly developed urban area such as Los Angeles it is unlikely that spatial patterns across neighborhoods would change dramatically over a 10–15-year latency period. Longer latency diseases such as some cancers in older groups, however, could still result in some residual confounding for which contemporaneous confounders do not fully control.

Finally, this analysis relies on ecological regression, but this is in a special class because of the LE outcome variable. Morgenstern (1995) refers this type of ecological model as a global measure because it lacks an individual analogue (Morgenstern, 1995). This type of global variable eliminates the major limitation of ecological analysis, known as ecological bias. Ecological bias occurs when the application of ecologic group-level effect estimates fails to represent actual, individual level impacts (Morgenstern, 1995). We have conducted extensive sensitivity analysis to account for many of the typical problems of ecological study design, a design which in this instance was unavoidable due to the global measure of population health – life expectancy – which was the dependent variable.

2.6. CONCLUSION

This study provides evidence that access to higher levels of green space and tree canopy is positively associated with longer LE. Additionally, in areas with less surrounding green space, access to more park acres is predictive of longer LE. The similar effect sizes in this study when compared to the Netherlands and Spain studies indicate that these findings could be generalizable to diverse regions, particularly as a tool for evaluating the impact of green space access on population longevity. The dose-response values presented here could be used for health impact assessment, applying similar techniques as a recent analysis quantifying mortality impacts from green space access in European cities (Barboza et al., 2021). Our results provide evidence that access to green space is a modifiable risk factor for LE, which is a key aspect of the United Nations' Human Development Index and used to evaluate developmental success. Ultimately, interventions that can improve LE could have widespread implications for health impact analyses and policy more broadly.

Both within and outside of Los Angeles, this research presents an opportunity to consider environmental health equity during decision-making processes for the distribution of parks and green space funding. This also presents an opportunity for recovery in the post-COVID-19 pandemic era by building community health resilience through parks and green space access. A recent study on racial inequalities in U.S. COVID-19 infections found substantial potential for increased green space access to reduce racial health disparities (Lu et al., 2021). Efforts to reduce green space inequalities should involve partnerships with stakeholders such as local community-based organizations to prevent green gentrification and displacement (Rigolon, 2019; Wolch et al., 2014; Yanez et al., 2020; Zuniga-Teran and Gerlak, 2019). Additionally, decision-making could consider the fact that park acreage and neighborhood greenness are not always highly correlated, but there could be benefits to adding surrounding greenness, such as planting trees, as well as developing additional park space; the findings we present here also highlight the potential benefits of building greener parks.

Numerous future research directions could be explored. With the development of spatially resolved park access and tree canopy datasets, this study could be replicated in other regions. Additionally, future research in the field is necessary to further characterize the nature of the association between green spaces and LE. Future studies should also investigate other metrics of park access, including the utilization of parks through park programming (e.g., recreational offerings), and the quality of parks more broadly. Others could build upon our findings and further explore the differential impacts of park access on LE in populations with varying SEPs, race and ethnicity, and exposure to environmental factors (such as surrounding greenness), which has distinct implications for health equity and urban planning.

CHAPTER 2 APPENDIX

Table A.1. Correlation matrix

	Smoke	Obesity	Physical inactivity	% Uninsured	Income	Education	Linguistic isolation	Race/ ethnicity	CDC index	CES	NO_2	NDVI	Available park acres	Tree canopy	Noise	Heat	$PM_{2.5}$	O_3
Smoke	1.00	0.91	0.92	0.76	-0.77	-0.83	0.55	0.68	0.83	0.68	0.35	-0.35	-0.23	-0.51	0.18	0.19	0.32	-0.29
Obesity	0.91	1.00	0.87	0.66	-0.67	-0.78	0.36	0.68	0.76	0.66	0.28	-0.26	-0.21	-0.43	0.22	0.09	0.39	-0.28
Physical inactivity	0.92	0.87	1.00	0.81	-0.77	-0.92	0.65	0.83	0.90	0.75	0.40	-0.29	-0.25	-0.51	0.17	0.17	0.43	-0.24
% Uninsured	0.76	0.66	0.81	1.00	-0.74	-0.83	0.77	0.70	0.78	0.69	0.52	-0.32	-0.22	-0.43	0.17	0.08	0.38	-0.25
Income	-0.77	-0.67	-0.77	-0.74	1.00	0.69	-0.61	-0.69	-0.82	-0.71	-0.56	0.46	0.31	0.59	-0.22	-0.11	-0.40	0.26
Education	-0.83	-0.78	-0.92	-0.83	0.69	1.00	-0.67	-0.80	-0.84	-0.75	-0.42	0.24	0.21	0.44	-0.16	-0.12	-0.42	0.24
Linguistic isolation	0.55	0.36	0.65	0.77	-0.61	-0.67	1.00	0.50	0.65	0.55	0.51	-0.27	-0.14	-0.35	0.10	0.09	0.25	-0.17
Race/ ethnicity	0.68	0.68	0.83	0.70	-0.69	-0.80	0.50	1	0.82	0.71	0.42	-0.28	-0.31	-0.53	0.17	0.06	0.54	-0.22
CDC index	0.83	0.76	0.90	0.78	-0.82	-0.84	0.65	0.82	1.00	0.78	0.45	-0.35	-0.27	-0.51	0.18	0.13	0.43	-0.23
CES	0.68	0.66	0.75	0.69	-0.71	-0.75	0.55	0.71	0.78	1.00	0.57	-0.30	-0.20	-0.48	0.28	-0.01	0.54	-0.31
NO_2	0.35	0.28	0.40	0.52	-0.56	-0.42	0.51	0.42	0.45	0.57	1.00	-0.37	-0.41	-0.44	0.26	-0.30	0.61	-0.43
NDVI	-0.35	-0.26	-0.29	-0.32	0.46	0.24	-0.27	-0.28	-0.35	-0.30	-0.37	1.00	0.37	0.72	-0.17	-0.19	0.01	0.18
Available park acres	-0.23	-0.21	-0.25	-0.22	0.31	0.21	-0.14	-0.31	-0.27	-0.20	-0.41	0.37	1.00	0.42	-0.15	-0.01	-0.25	0.11
Tree canopy	-0.51	-0.43	-0.51	-0.43	0.59	0.44	-0.35	-0.53	-0.51	-0.48	-0.44	0.72	0.42	1.00	-0.16	-0.08	-0.34	0.32
Noise	0.18	0.22	0.17	0.17	-0.22	-0.16	0.10	0.17	0.18	0.28	0.26	-0.17	-0.15	-0.16	1.00	-0.09	0.15	-0.07
Heat	0.19	0.09	0.17	0.08	-0.11	-0.12	0.09	0.06	0.13	-0.01	-0.30	-0.19	-0.01	-0.08	-0.09	1.00	-0.54	0.42
$PM_{2.5}$	0.32	0.39	0.43	0.38	-0.40	-0.42	0.25	0.54	0.43	0.54	0.61	0.01	-0.25	-0.34	0.15	-0.54	1.00	-0.45
Ozone (O_3)	-0.29	-0.28	-0.24	-0.25	0.26	0.24	-0.17	-0.22	-0.23	-0.31	-0.43	0.18	0.11	0.32	-0.07	0.42	-0.45	1.00

Table A.2. Results of supplemental analyses

Model/Covariate of Interest	Linear Model		CAR Gaussian model with spatial random effects	
	Coefficient	*p-value*	*Median*	*Credible Interval*
A. Tree Canopy (*including chronic health conditions*)	0.626	<.0001***	0.371	0.181 – 0.562
B. NDVI (*including chronic health conditions*)	0.543	<.0001***	0.446	0.264 – 0.624
C. Park Access (*including chronic health conditions*)	0.121	<.0001***	0.016	-0.064 – 0.093
D. Park access: below median tree canopy (*stratified model, including chronic health conditions*)	0.231	<.0001***	0.126	-0.050 – 0.300
E. Park access: above median tree canopy (*stratified model, including chronic health conditions*)	0.013	0.72	-0.012	-0.094 – 0.071
F. Distance to Nearest Park	0.0047	0.95	0.048	-0.097 – 0.189

A. Tree canopy (Percent cover, IQR = 9.1%);
B. NDVI (scale of -1 [least green] to 1 [most green], IQR = 0.053);
C. Park access (available acres, IQR = 87.5);
D. Stratified model: park access in areas with below median tree canopy (available acres, with respect to the same IQR = 87.5; n = 1,088 for the stratified analysis);
E. Stratified model: park access in areas with above median tree canopy (available acres, with respect to the same IQR = 87.5; n = 1,088 for the stratified analysis); and
F. Distance to nearest park (miles, IQR = 0.33).
Note: chronic health conditions are prevalence-based and include cancer, diabetes, asthma, coronary heart disease, and high blood pressure prevalence from the 500 Cities/PLACES project.
Significance codes: * < 0.05, ** < 0.01, *** < 0.001 (linear models only).

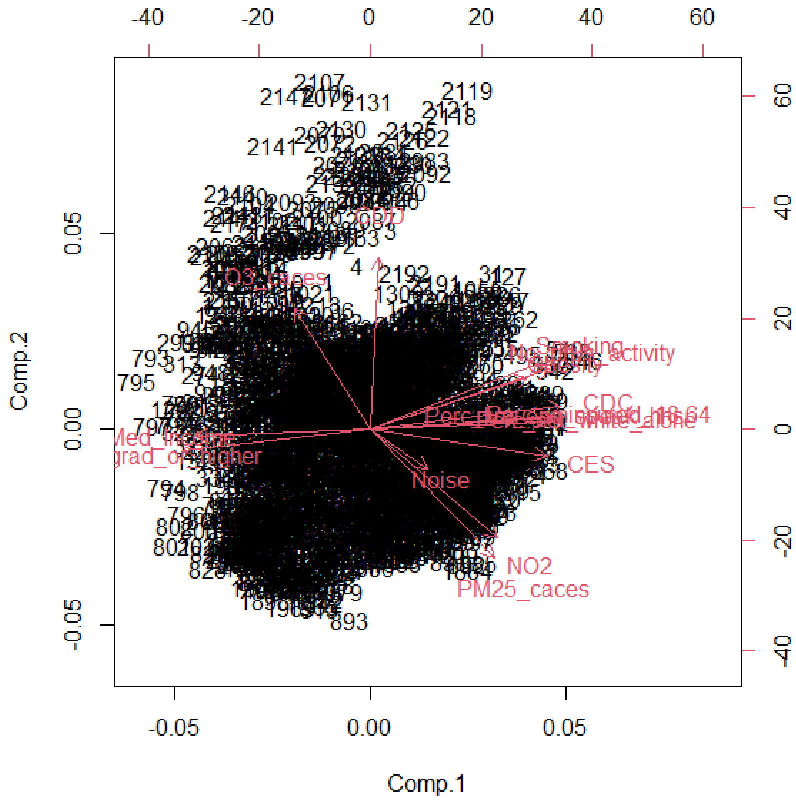

Figure A.1. Principal components loadings plot depicting the two components accounting for most of the variance in the data.

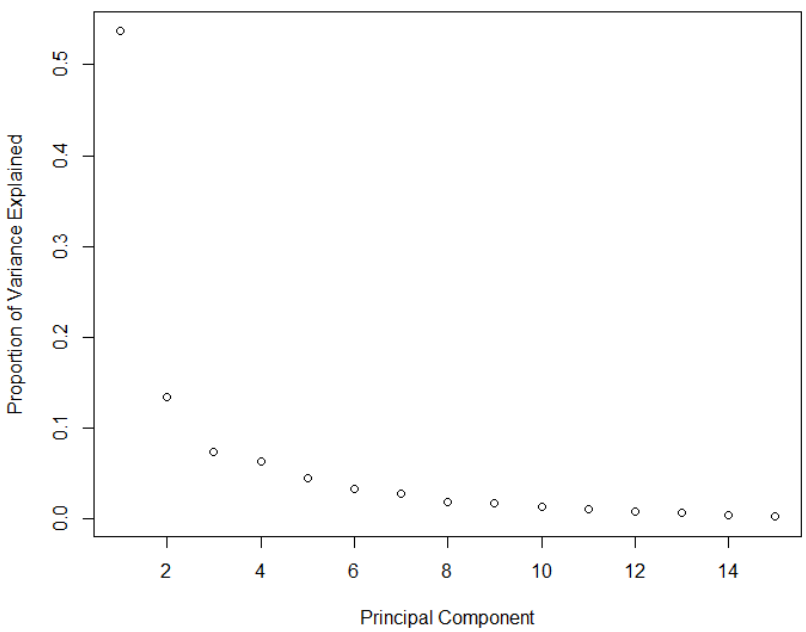

Figure A.2. Scree plot depicting the amount of variance explained by the principal components.

Table A.3. Proportion of variance explained by principal components (full model)

	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7	Comp. 8	Comp. 9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Standard Deviation	2.84	1.42	1.06	0.97	0.82	0.71	0.65	0.53	0.51	0.45	0.41	0.36	0.31	0.27	0.20
Proportion of Variance	0.54	0.13	0.074	0.063	0.045	0.034	0.028	0.019	0.018	0.013	0.011	0.0086	0.0065	0.0050	0.0028
Cumulative Proportion	0.54	0.67	0.75	0.81	0.85	0.89	0.92	0.93	0.95	0.97	0.977	0.986	0.992	0.997	1.0

Table A.4. Loadings for each individual variable (full model)

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Smoke	**0.286**	**0.225**	**0.381**	0.015	**0.122**	0.066	**0.275**	0.056	0.026	0.061	**0.105**	0.053	0.010	**0.262**	**0.733**
Obesity	**0.268**	**0.177**	**0.506**	0.081	-0.088	0.013	**0.195**	0.064	0.090	-0.074	0.042	**0.118**	-0.044	**-0.700**	**-0.250**
Physical inactivity	**0.304**	**0.205**	**0.278**	-0.037	-0.025	**0.201**	0.086	**0.167**	**-0.111**	**0.175**	**-0.127**	-0.068	0.027	**0.563**	**-0.574**
% Uninsured	**0.311**	0.039	**-0.168**	-0.056	**0.199**	**0.184**	**-0.129**	**-0.109**	**0.219**	**-0.623**	0.076	**0.403**	**0.385**	**0.101**	-0.075
Income	**-0.299**	-0.023	**0.175**	-0.039	-0.068	**0.320**	**-0.299**	**0.591**	**0.288**	0.078	**-0.246**	-0.067	**0.393**	-0.082	**0.131**
Education	**-0.318**	-0.072	0.068	0.037	0.024	**-0.108**	**0.358**	**-0.127**	**-0.300**	**0.295**	-0.062	**0.530**	**0.516**	0.002	-0.060
Linguistic isolation	**0.251**	0.034	**-0.369**	**-0.167**	**0.415**	**0.518**	-0.024	0.086	**-0.190**	**0.428**	**0.124**	0.082	-0.074	**-0.274**	0.020
Race/ ethnicity	**0.297**	0.025	-0.083	-0.078	**-0.408**	-0.056	**-0.307**	**0.132**	**-0.491**	-0.074	**-0.463**	**0.310**	**-0.139**	-0.063	**0.191**
CDC index	**0.325**	0.078	-0.073	-0.031	-0.077	**-0.121**	-0.073	**-0.332**	-0.090	**0.133**	**-0.164**	**-0.554**	**0.600**	**-0.146**	0.065
CES	**0.302**	-0.091	**-0.122**	0.075	**-0.120**	**-0.272**	**-0.147**	-0.098	**0.630**	**0.492**	**-0.125**	**0.318**	-0.047	0.054	-0.008
NO_2	**0.218**	**-0.367**	**-0.290**	0.008	0.076	**-0.141**	**0.619**	**0.408**	0.081	**-0.160**	**-0.326**	**-0.139**	0.000	-0.034	-0.007
Noise	0.098	**-0.134**	-0.038	**0.955**	0.071	**0.122**	**-0.121**	0.054	**-0.133**	0.012	0.040	-0.017	0.036	0.026	0.011
Heat	0.014	**0.585**	**-0.297**	0.066	0.078	**-0.491**	-0.053	**0.458**	-0.084	0.019	**0.285**	0.018	**0.118**	-0.028	-0.048
$PM_{2.5}$	**0.211**	**-0.436**	0.007	**-0.117**	**-0.472**	0.034	-0.022	**0.214**	**-0.104**	0.062	**0.663**	-0.002	**0.159**	0.045	0.003
Ozone (O_3)	**-0.129**	**0.411**	**-0.346**	**0.126**	**-0.577**	**0.412**	**0.348**	**-0.136**	**0.185**	-0.023	-0.004	-0.003	-0.020	-0.003	0.038

Table A.5. Loadings for each individual variable (stratified: below median tree canopy model)

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Smoke	**0.280**	**0.268**	**0.348**	**0.137**	**0.169**	**0.208**	0.045	0.092	0.002	0.034	0.072	0.011	0.064	**0.151**	**0.771**
Obesity	**0.257**	**0.208**	**0.499**	0.022	-0.020	**0.200**	0.071	0.069	0.023	**-0.157**	-0.021	**0.243**	**-0.113**	**-0.625**	**-0.320**
Physical inactivity	**0.312**	**0.226**	**0.206**	**0.109**	0.028	**0.167**	**0.199**	0.073	**0.110**	**0.330**	-0.044	**-0.129**	0.057	**0.574**	**-0.502**
% Uninsured	**0.312**	0.051	**-0.238**	0.078	**0.207**	**-0.174**	**0.260**	0.055	**-0.190**	**-0.585**	**-0.356**	**0.222**	**0.344**	**0.136**	-0.056
Income	**-0.312**	-0.080	**0.119**	0.005	**-0.130**	**-0.149**	**0.470**	**0.514**	**0.166**	**0.245**	**-0.217**	**-0.123**	**0.399**	**-0.204**	0.084
Education	**-0.321**	-0.097	**0.120**	0.042	**0.100**	**0.356**	**-0.220**	**-0.332**	**0.153**	**0.176**	**-0.375**	**0.490**	**0.364**	0.084	-0.004
Linguistic isolation	**0.234**	0.043	**-0.506**	**0.156**	**0.382**	0.023	**0.244**	-0.024	-0.024	**0.520**	0.093	**0.290**	**-0.104**	**-0.285**	0.028
Race/ ethnicity	**0.292**	-0.016	-0.080	**-0.115**	**-0.513**	**-0.174**	**0.228**	**-0.311**	**0.444**	0.056	**-0.364**	**0.105**	**-0.271**	0.006	**0.190**
CDC index	**0.333**	0.090	-0.062	-0.031	**-0.155**	-0.057	**-0.239**	**-0.338**	**-0.153**	**0.207**	-0.042	**-0.444**	**0.572**	**-0.291**	-0.004
CES	**0.295**	**-0.134**	-0.033	**-0.179**	**-0.179**	-0.092	**-0.519**	**0.542**	**-0.230**	**0.230**	**-0.295**	**0.236**	-0.073	0.057	0.026
NO_2	**0.221**	**-0.375**	**-0.219**	0.058	**0.168**	**0.468**	**-0.152**	**0.234**	**0.546**	**-0.216**	-0.016	**-0.282**	0.036	-0.088	-0.015
Noise	0.094	-0.093	**0.145**	**-0.876**	**0.386**	-0.081	**0.118**	-0.081	0.094	0.052	0.050	0.004	0.056	0.033	0.010
Heat	-0.064	**0.560**	**-0.209**	-0.090	-0.090	**-0.207**	**-0.265**	**0.169**	**0.479**	-0.097	**0.339**	**0.244**	**0.253**	0.020	-0.047
$PM_{2.5}$	**0.208**	**-0.440**	0.035	-0.035	**-0.387**	**0.123**	**0.195**	-0.007	**-0.104**	-0.018	**0.569**	**0.359**	**0.288**	**0.104**	0.008
Ozone (O_3)	**-0.132**	**0.361**	**-0.347**	**-0.333**	**-0.318**	**0.619**	**0.180**	0.090	**-0.282**	-0.065	-0.076	-0.060	-0.040	-0.011	0.037

Table A.6. Loadings for each individual variable (stratified: above median tree canopy model)

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Smoke	**0.294**	**0.222**	**0.266**	**0.243**	0.017	**0.252**	**0.260**	0.003	0.018	**0.141**	0.047	0.095	0.063	**0.355**	**0.665**
Obesity	**0.286**	**0.190**	**0.355**	**0.241**	**0.159**	**0.227**	0.050	0.047	**0.136**	0.061	0.003	0.044	-0.089	**-0.751**	**-0.144**
Physical inactivity	**0.306**	**0.227**	**0.282**	**0.126**	**0.117**	0.048	0.087	**-0.195**	-0.009	-0.081	**-0.106**	-0.034	0.044	**0.491**	**-0.660**
% Uninsured	**0.317**	-0.002	**-0.112**	-0.025	**-0.153**	**-0.206**	-0.032	**0.270**	**0.265**	-0.086	**0.650**	**0.263**	**0.406**	0.011	**-0.108**
Income	**-0.293**	**0.109**	**0.211**	0.057	0.051	**-0.244**	**-0.144**	**-0.445**	**0.634**	-0.023	**-0.127**	**-0.104**	**0.357**	-0.028	**0.129**
Education	**-0.325**	-0.027	-0.014	0.049	0.062	**0.242**	**0.256**	-0.055	**-0.357**	**0.189**	**-0.115**	**0.324**	**0.671**	**-0.107**	**-0.129**
Linguistic isolation	**0.267**	-0.002	-0.098	-0.075	**-0.283**	**-0.538**	**0.557**	**-0.366**	**-0.132**	**0.194**	-0.090	0.019	-0.065	**-0.180**	0.013
Race/ ethnicity	**0.301**	0.020	0.044	**-0.238**	**0.185**	**-0.109**	**-0.350**	**-0.317**	**-0.278**	**-0.484**	**-0.161**	**0.438**	0.069	-0.084	**0.201**
CDC index	**0.329**	0.032	-0.050	-0.078	-0.046	-0.055	-0.077	**0.233**	**-0.163**	**-0.163**	**-0.266**	**-0.668**	**0.478**	-0.091	0.099
CES	**0.305**	**-0.104**	**-0.176**	-0.054	-0.058	-0.041	**-0.298**	**0.223**	**0.256**	**0.533**	**-0.512**	**0.311**	0.045	0.069	-0.047
NO_2	**0.178**	**-0.456**	**-0.282**	**-0.102**	0.058	**0.425**	**0.409**	**-0.108**	**0.401**	**-0.346**	**-0.159**	0.028	0.010	-0.003	-0.028
Noise	0.089	**-0.217**	**-0.393**	**0.757**	**0.355**	**-0.187**	**-0.122**	**-0.151**	**-0.107**	0.007	0.055	-0.053	0.021	0.008	0.022
Heat	**0.109**	**0.441**	**-0.501**	-0.076	**-0.239**	**0.411**	**-0.208**	**-0.435**	-0.008	**0.166**	**0.172**	**-0.122**	0.005	-0.066	-0.028
$PM_{2.5}$	**0.175**	**-0.447**	**0.208**	**-0.334**	**0.375**	0.085	**-0.122**	**-0.299**	-0.098	**0.440**	**0.331**	**-0.218**	0.044	0.020	0.020
Ozone (O_3)	-0.044	**0.435**	**-0.304**	**-0.297**	**0.696**	**-0.156**	**0.260**	**0.185**	**0.116**	0.048	-0.010	0.004	-0.029	0.006	0.030

3. MORTALITY ATTRIBUTABLE TO $PM_{2.5}$ FROM WILDLAND FIRE SMOKE IN CALIFORNIA FROM 2008-2018

3.1. ABSTRACT

In California, wildfire risk and severity have grown substantially in the last several decades. Existing research has characterized extensive adverse health impacts from exposure to wildfire-attributable fine particulate matter ($PM_{2.5}$). Few existing studies, however, have quantified long-term health impacts from wildfires, and none have used a wildfire-specific chronic dose-response coefficient for mortality. In this project, we aimed to quantify the long-term mortality impacts and associated economic valuation attributable to population exposure to wildland fire $PM_{2.5}$ from 2008 – 2018 in California. We quantified the total mortality burden for exposure to $PM_{2.5}$ due to wildland fires in California using eleven years of Community Multiscale Air Quality (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 47,100 and 50,360 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 \$387 to \$413 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. 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.

3.2. INTRODUCTION

Wildfire risk and severity have grown in the last several decades across the western United States (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, and peak impacts now occur in earlier months (Li and 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; Wang et al., 2021).

Wildfire smoke contributes to fine particulate matter ($PM_{2.5}$), 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 and 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., 2021, 2015; Wang et al., 2021; Wilkins et al., 2022, 2020). Several of these methods have limited ability to distinguish wildfire smoke from undifferentiated $PM_{2.5}$. In situ air quality monitoring is often sparse in fire-affected areas, and even with dense coverage, monitoring 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; Liu et al., 2015; Reid 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 and 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 hospitalizations and respiratory illness (Aguilera et al., 2021; Cascio, 2018; Liu et al., 2015; Reid 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 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 (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 our 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). 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 (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 (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 (Jones et al., 2016).

To bridge these knowledge gaps, we use modeled wildland fire-associated $PM_{2.5}$ concentrations, high-resolution California Department of Public Health (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.

3.3. METHODS

3.3.1. Data

3.3.1.1. Modeled Wildland Fire $PM_{2.5}$ Concentrations

For this analysis, we used modeled $PM_{2.5}$ concentrations for 2008-2018 for the state of California at a 12-kilometer (km) grid spatial resolution, estimated using the U.S. Environmental Protection Agency's (EPA) Community Multiscale Air Quality (CMAQ, v. 5.0.1 - 5.3 – see Table A.1) modeling system. Daily model results from 2008-2018 were provided.

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 A.1 in the Supplemental Material 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 (hereafter referred to as '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 (Rappold et al., 2017) and Fann (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 U.S. EPA's National Ambient Air Quality Standards (NAAQS) of daily $PM_{2.5} > 35$ $\mu g/m^3$ and years exceeding the annual NAAQS of 12 $\mu g/m^3$ (Wilkins et al., 2018). Additionally, a supplemental validation analysis comparing daily concentrations to observed concentrations from ground station monitoring data is included in Appendix B.

3.3.1.2. 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%.

3.3.2. 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 scale, 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) *Scenario 1,* with no outliers removed, to characterize the potential impact of extremely high wildfire concentrations on mortality and (2) *Scenario 2,* capping fire-only $PM_{2.5}$ concentrations falling outside of the 99.9^{th} percentile of modeled values (at 143 $\mu g/m^3$ - see Table A.2), 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[6] dose-response coefficient (Eqn. 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 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; Jones et al., 2016; Reid 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 (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). 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 (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 et al., 2021).

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

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 Eqn. 1 below, which accounts for potential added toxicity of wildfire smoke as is suggested in several California-specific analyses (Aguilera et al., 2021; Wegesser et al., 2009):

$$\beta wL = \frac{\beta ws}{\beta s} \times \beta L \qquad (1)$$

where, β_{WS} is the short-term wildfire $PM_{2.5}$ dose-response from the Washington wildfires study (selected since it is recent and representative of western U.S. fire conditions) (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 A.3 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% confidence interval (CI) for the estimated dose-response value, though due to the confidence interval for the short-term wildfire dose-response odds ratio extending to 1.0, the calculated lower confidence limit of our resulting dose-response value extends to zero.

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

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

where, β_{WL} is the result of Eqn. 1 (dose-response value), $\Delta PM_{2.5ij}$ represents the change in $PM_{2.5}$ concentration from wildland fire smoke in year *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 duplicated the mortality calculations in Eqn. 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 Eqn. 1).

Finally, we apply the EPA's value of a statistical life (VSL) to these mortality impacts to estimate the total valuation of the health burden, using Eqn. 3 below:

$$\text{Economic valuation} = \Sigma\Delta mij * V \tag{3}$$

where, Δm_{ij} is the result of Eqn. 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 US EPA's Environmental Benefits Mapping and Analysis – Community Edition (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, 2014).

3.4. RESULTS

3.4.1. 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. A supplemental model validation analysis using several established model evaluation metrics is included in Appendix B and contains Tables B.1 and B.2 and Figures B.1 through B.3.

Table 3.1 presents a summary of the modeled $PM_{2.5}$ estimates, which includes concentrations from the entire state, including in rural areas with minimal pollution. As shown in Table 3.1, 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 million - 2 million acres, 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 A.4. 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 3.1. Summary of Modeled $PM_{2.5}$ ($\mu g/m^3$) Values and Acres Burned by Year (2008-2018) Statewide in California

Year	**All Sources $PM_{2.5}$** (SD, $\mu g/m^3$)*	**Fire-Only $PM_{2.5}$** (SD, $\mu g/m^3$)	**Non-Fire $PM_{2.5}$** (SD, $\mu g/m^3$)	**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

Note: 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 A.5 for a breakdown by metropolitan statistical area (MSA).*

To visually review model outputs, we examine fire-only concentrations for the entire time period (Figure 3.1), 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 A.1), daily $PM_{2.5}$ concentrations greater than the US EPA's 24-hour (daily) NAAQS of 35 μg/m^3 and annual NAAQS of 12 μg/m^3 (Figures A.2a and A.2b, respectively), and daily $PM_{2.5}$ concentrations greater than 35 μg/m^3 for each individual year (Figure A.3).

Figure 3.1 demonstrates fire-only concentrations by year for all eleven years of data, showing significant regional variation in fire impacts over the long-term period (see Figure A.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 are 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 A.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 (Figure A.1, middle) demonstrate significant pollution throughout LA 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 (Figure A.1, right) impact more rural, forested areas throughout the state on average, though there are significant regional variations not captured by these annual averages (Figure 3.1).

As shown in Figure A.2a, most exceedances of the 35 μg/m^3 NAAQS standard over the eleven-year period are due to wildland fire $PM_{2.5}$. 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 daily exceedances of the 24-hour NAAQS. In Figure A.3, those exceedances are stratified by year, with the high fire years contributing a significant portion of the exceedances over much of the state, with more than 25 days exceeding the daily NAAQS threshold. As far as the annual NAAQS analysis presented in Figure A.2b, exceedances 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 exceedances in the more rural regions in the northern part of the state. These fire-only sources (Figure A.2b, right panel) are responsible for average concentrations exceeding 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.

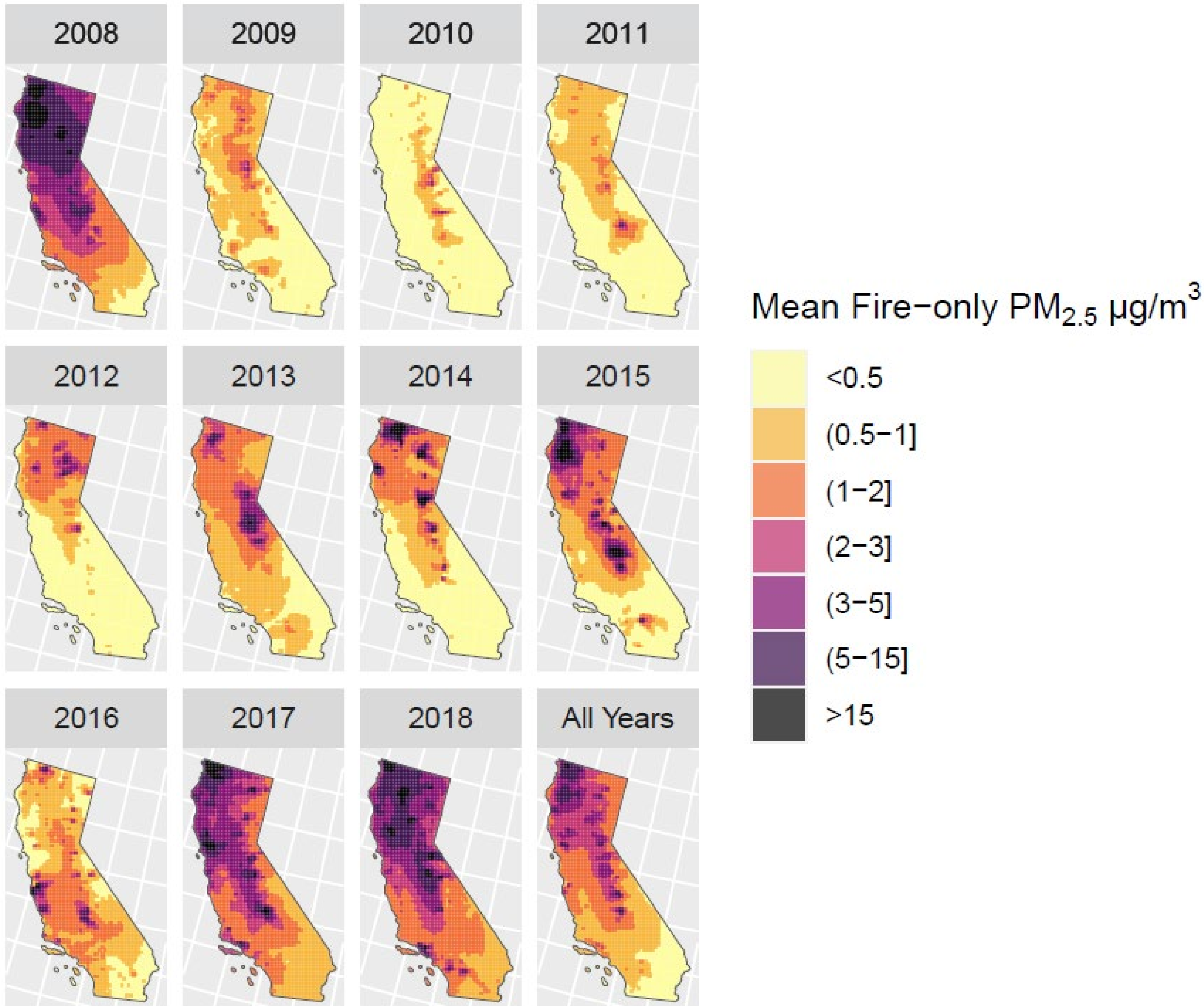

Figure 3.1. Community Multiscale Air Quality (CMAQ) mean fire-only $PM_{2.5}$ concentrations at 12-km resolution for 2008–2018.

3.4.2. Mortality and Associated Economic Valuation Impacts of Wildland Fires

The results for *Scenarios 1* and *2* using the calculated wildfire-specific dose-response value (β_{WL}) are presented in Table 3.2, along with 95% upper confidence limits (UCLs). We also include results using the preexisting chronic undifferentiated $PM_{2.5}$ dose-response value (β_L) (Pope et al., 2019) as a reference, along with 95% CIs.

For *Scenario 1*, 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 1,160 deaths in 2010 to a high of 11,560 in 2018 (Table 3.2), 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 50,360 deaths for *Scenario 1* over the eleven-year period, and 47,100 deaths for *Scenario 2* (see Table A.6 for a by-county breakdown of *Scenario 1* mortality results alongside total valuation).

When β_L from the Pope 2019 study is applied (Table 3.2) (Pope et al., 2019), which is an undifferentiated chronic $PM_{2.5}$ dose-response value not specific to wildfire smoke exposures, the total estimated mortality attributable to wildland fire $PM_{2.5}$ is approximately 36,470 for *Scenario 1*, and 33,960 for *Scenario 2*. These estimates are almost 28% less than projected mortality impacts when using the β_{WL} dose-response value accounting for wildfire-specific impacts.

Table 3.2. 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	**Scenario 1** *(No modeled values capped)*		**Scenario 2** *(Modeled values capped)*	
	Wildfire-specific dose-response (β_{WL}) *(95% UCL)*	**Undifferentiated $PM_{2.5}$ dose-response** (β_L) *(95% CI)*	**Wildfire-specific dose-response** (β_{WL}) *(95% UCL)*	**Undifferentiated $PM_{2.5}$ dose-response** (β_L) *(95% CI)*
2008	9,100 (*20,730*)	6,590 (*4,520 - 8,080*)	8,750 (*20,030*)	6,330 (*4,330 - 7,760*)
2009	2,020 (*4,800*)	1,450 (*990 - 1,790*)	2,010 (*4,770*)	1,440 (*980 - 1,770*)
2010	1,160 (*2,780*)	840 (*570 - 1,030*)	1,160 (*2,770*)	830 (*570 - 1,030*)
2011	1,360 (*3,250*)	980 (*660 - 1,210*)	1,360 (*3,240*)	980 (*660 - 1,200*)
2012	1,540 (*3,670*)	1,110 (*750 - 1,360*)	1,540 (*3,660*)	1,110 (*750 - 1,360*)
2013	3,070 (*7,240*)	2,200 (*1,500 - 2,710*)	3,060 (*7,230*)	2,200 (*1,500 - 2,710*)
2014	1,920 (*4,520*)	1,380 (*940 - 1,700*)	1,830 (*4,350*)	1,320 (*900 - 1,620*)
2015	3,210 (*7,530*)	2,310 (*1,580 - 2,850*)	3,100 (*7,310*)	2,230 (*1,520 - 2,740*)
2016	4,020 (*9,380*)	2,900 (*1,980 - 3,560*)	3,710 (*8,760*)	2,660 (*1,810 - 3,280*)
2017	11,390 (*25,240*)	8,330 (*5,760 - 10,150*)	9,690 (*22,430*)	6,990 (*4,780 - 8,590*)
2018	11,560 (*26,320*)	8,380 (*5,740 - 10,260*)	10,900 (*25,070*)	7,880 (*5,380 - 9,660*)
All Years	50,360 (*115,450*)	36,470 (*24,990, 44,700*)	47,100 (*109,620*)	33,960 (*23,180 - 41,740*)

Figure 3.2 depicts *Scenario 1* 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 A.5 for the full by-year breakdown for all years, and Figure A.6 for the spatial distribution of total mortality impacts over the eleven-year period). In 2010, the year with the fewest acres burned and lowest number of attributable deaths, most 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 A.5). In 2008, the largest fires were clustered in northern California, with more statewide spread of fires throughout 2017 and 2018.

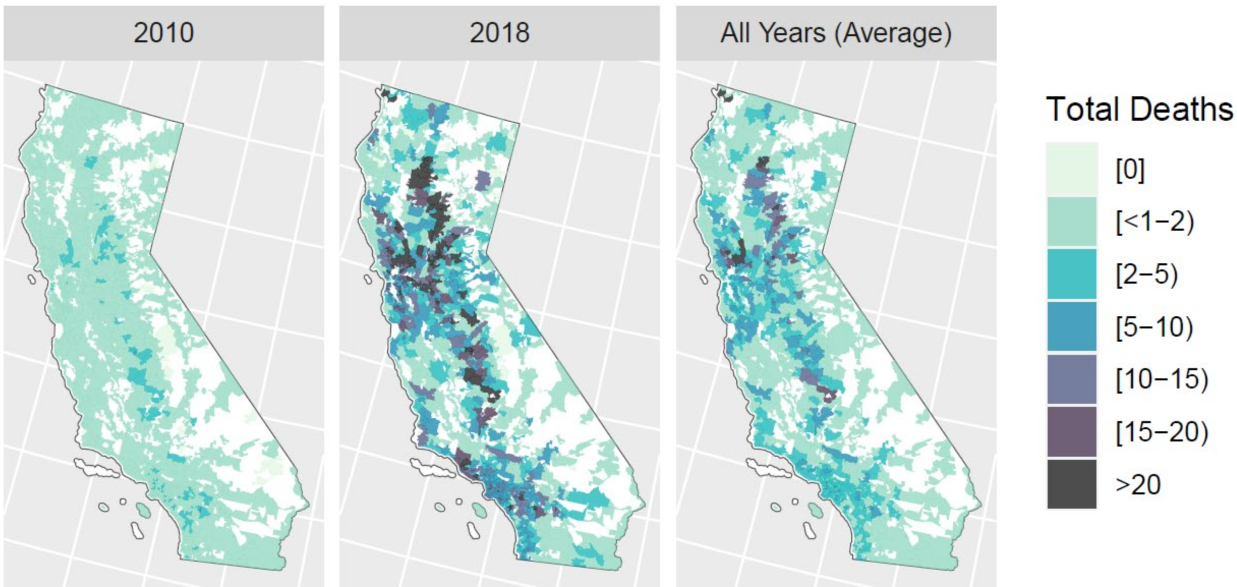

Figure 3.2. Total deaths attributable to fire-only $PM_{2.5}$ (*Scenario 1*) in the year with the fewest deaths attributable to wildland fire (2010), most deaths attributable to wildland fire (2018), and the annual average over the eleven-year period (2008-2018).

Though the fires are in more rural, forested regions, the mortality impacts are more widespread throughout population centers, as there are fewer individuals living in forested regions and therefore fewer premature deaths. 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 in Figure A.5) are west of the fire in a more populated area of the county, and throughout the San Joaquin Valley more broadly.

Table 3.3. 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% UCL)*	
	Scenario 1	**Scenario 2**
2008	$89.1 *(203)*	$85.6 (*196*)
2009	$19.2 *(45.6)*	$19.1 (*45.3*)
2010	$10.7 *(25.6)*	$10.7 (*25.6*)
2011	$12.2 *(29.1)*	$12.2 (*29.1*)
2012	$13.4 *(31.9)*	$13.4 (*31.9*)
2013	$25.9 *(61.2)*	$25.8 (*61.0*)
2014	$15.7 *(37.1)*	$15.0 (*35.6*)
2015	$25.6 *(59.9)*	$24.7 (*58.1*)
2016	$31.1 *(72.5)*	$28.6 (*67.6*)
2017	$85.4 *(189)*	$72.7 (*168*)
2018	$84.2 *(192)*	$79.4 (*183*)
All Years (Total)	$413 *(947)*	$387 (*901*)

The economic valuation estimates presented here are associated with premature mortality and only account for one aspect of the total economic damages caused by wildfires throughout the state (Feo et al., 2020; Wang et al., 2021). The valuation estimates for *Scenarios 1* and *2* (and associated UCLs), using the wildfire-specific dose-response value, are presented in Table 3.3. Economic valuation estimates using the undifferentiated $PM_{2.5}$ dose-response (β_L) are not presented here as those are not considered to be the primary results. The net present value of the estimates is approximately 413 billion dollars for *Scenario 1*, and 387 billion dollars for *Scenario 2,* with UCLs of more than 900 billion dollars.

3.5. DISCUSSION

Here, we report on modeled wildland fire $PM_{2.5}$ estimates at the 12-km grid scale for 2008-2018, quantify associated premature mortality using an estimated 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 fire patterns in the state. An estimated 47,100 to 50,360 premature deaths are attributable to fire-only $PM_{2.5}$ in California from 2008-2018, with an associated economic valuation of $387-$413 billion dollars (2015$). 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 $PM_{2.5}$ concentrations. These findings add to a growing body of literature on California-specific wildfire health effects (Delfino et al., 2009; Reid 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 and Greenstone, 2011; Ebi et al., 2021; Ganesh and Smith, 2018; Neumann et al., 2021; Shonkoff et al., 2011; USGCRP, 2018).

3.5.1. Modeled Fire-only $PM_{2.5}$ Estimates

The spatial distribution of fire-only $PM_{2.5}$ from our CMAQ model output aligns with general trends observed in analyses of historical fire records (Li and 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 [Baker et al., 2016]). As anticipated, the high fire years of 2008, 2017, and 2018 demonstrated elevated $PM_{2.5}$ concentrations and substantial exceedances of the daily and annual NAAQS (Table 3.1, Figures A.2a-b, Figure A.3). A recent 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 3.1 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 the fire inventory and 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; two recent studies have used machine learning techniques to parse out wildfire smoke $PM_{2.5}$ (Aguilera et al., 2023; Childs et al., 2022). Childs et al. found that smoke $PM_{2.5}$ can contribute approximately half of annual all sources $PM_{2.5}$ in certain fire prone 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 3.1) (Childs et al., 2022).

3.5.2. 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 [*Scenario 1*] and one with modeled values capped [*Scenario 2*]) to account for uncertainties in the modeled $PM_{2.5}$ estimates. Our use of a wildfire-specific chronic dose-response value results in an increase in the magnitude of our findings as compared to the premature mortality estimated using a chronic undifferentiated $PM_{2.5}$ dose-response value from Pope et al. (Table 3.2) (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 (Wang et al., 2021). They estimated 3,652 premature deaths associated with wildfire $PM_{2.5}$ exposure, which is significantly lower than our estimates of 10,900 – 11,560 for

2018 (Wang et al., 2021). While the discrepancy is likely partially due to varying modeled $PM_{2.5}$ exposure surfaces 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 avoid the 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 9,000 (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.

3.5.3. 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 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 hardly vary between *Scenario 1* and *Scenario 2* 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. Since it is certainly possible for concentrations to reach and exceed 143 $\mu g/m^3$ (the 99.9th percentile value) during fire events, capping these values would lead to an underestimate for *Scenario 2*. Additionally, the observed CMAQ model overprediction during fire events would lead to an overestimate for *Scenario 1*. 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 *Scenarios 1* and *2* as well as the differing magnitude of our findings with the wildfire-specific versus undifferentiated dose-response value (Table 3.2) 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; 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).

3.5.4. 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. However, the HMS Smoke product 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 novel 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 *Scenario 2*, 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. 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 Washington wildfires study for the short-term wildfire-specific dose-response coefficient because it is representative of wildfire conditions and $PM_{2.5}$ composition in the western U.S., and the two regions have comparable population characteristics (Doubleday et al., 2020). Another recent global study, however, estimated short-term mortality risk attributable to wildfire smoke exposures in 749 cities and found mortality risk estimates of a higher magnitude than the Washington study (Chen et al., 2021). If we had used this global estimate our results would have shown larger impacts, suggesting that our results might be an underestimation of the health and economic impacts.

3.5.5. 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 (Di et al., 2019; 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 residents of communities with pre-existing vulnerability, this presents an opportunity for future research and evidence-based policy action to protect public health and promote equity.

3.6. 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 47,100 and 50,360 premature deaths are attributable to fire $PM_{2.5}$ exposures, with an associated economic valuation of \$387 to \$413 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.

CHAPTER 3 APPENDIX

Appendix A. Supplemental Tables and Figures

<u>Tables</u>

Table A.1. 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		v3.4
2010	2008 NEI	v5.0.1	3.14	2010	CB05	AERO6		v3.4
2011	2011 NEI	v5.0.1	3.14	2011	CB05	AERO6		v3.4
2012	2011 NEI	v5.0.2	3.14	2012	CB05	AERO6		v3.4
2013	2011NEIv2	v5.2	3.6.1	2013	CB6r3	AERO6		v3.8
2014	2014NEIv1	v5.2	3.6.1	2014	CB6r3	AERO6		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		v3.8.1
2017	2014NEIv2	v5.2.1	3.6.1	2017	CB6r3	AERO7		v3.8.1
2018	2014NEIv2	v5.3	3.6.1	2018	CB6r3	AERO7		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 A.2. 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 A.3. $PM_{2.5}$ Dose-Response Estimates for All-Cause Mortality

Sources	**Time-frame**	**Risk Value**	**Value Type**	**Confidence Interval**	**Pollutant Increment**	**Standar-dized Beta** (1 µg/m^3 increment)	**Authors/ Year**
Wildfire	Short-term/Acute	1.02	OR	(1.00–1.05)	21.7 µg/m^3	0.00091	Doubleday et al. 2020
Undifferentiated/ All Sources	Short-term/Acute	1.0065	RR	(1.0044–1.0086)	10 µg/m^3	0.00065	Orellano et al. 2020
Undifferentiated/ All Sources	Chronic/ Long term	1.12	RR	(1.08–1.15)	10 µg/m^3	0.011	Pope et al. 2019

OR = Odds ratio, RR = Relative risk

Table A.4. 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 A.5. Summary of Modeled $PM_{2.5}$ ($\mu g/m^3$) Values by Metropolitan Statistical Area (MSA) in California

MSA	All Sources $PM_{2.5}$ (SD, $\mu g/m^3$)	Fire-Only $PM_{2.5}$ (SD, $\mu g/m^3$)	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 A.6. Mortality and Valuation Impacts from Wildland Fire in California by County, 2008-2018 (Scenario 1 - 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	363	56	32	53	47	128	61	107	47	574	419	1,885	154
Alpine	2.2	0.40	0.70	0.40	0.40	3.2	0.50	1.1	0.40	1.6	5.9	17	1.4
Amador	33	11	3.2	5.5	5.2	16	7.0	15	7.4	21	34	158	13.2
Butte	377	36	17	27	60	51	39	67	36	124	433	1,266	106
Calaveras	31	9.7	3.8	5.4	4.9	21	6.1	25	8.3	27	48	191	15.7
Colusa	16	2.0	0.80	2.0	2.7	3.0	2.1	5.8	1.9	8.3	21	65	5.4
Contra Costa	352	56	30	51	51	115	59	107	43	582	426	1,870	153
Del Norte	27	3.1	1.4	2.4	5.4	8.5	10	66	1.9	155	89	369	28.8
El Dorado	106	33	11	21	21	54	70	46	23	66	104	554	46.4
Fresno	429	60	54	51	47	125	86	223	137	330	441	1,982	164
Glenn	28	2.9	1.2	2.7	4.4	5.6	4.5	8.6	3.6	13	32	106	8.8
Humboldt	112	11	5.1	8.9	11	30	29	66	12	100	68	453	37.8
Imperial	5.4	4.5	2.7	3.4	3.9	7.2	2.9	3.5	6.3	12	12	64	5.2
Inyo	2.2	0.60	0.70	1.2	0.40	1.0	0.50	1.9	1.5	2.7	2.1	15	1.2
Kern	202	37	32	39	27	57	46	60	125	199	192	1,016	84.0
Kings	40	8.3	3.7	5.6	5.6	14	8.9	11	18	39	38	191	15.8
Lake	101	6.6	3.6	6.9	17	18	18	34	7.2	52	159	423	34.6
Lassen	21	3.1	1.2	1.7	9.3	3.2	7.0	5.0	2.6	8.9	18	81	6.8
Los Angeles	1,151	547	284	220	256	498	253	324	1,132	1,599	1874	8,138	665
Madera	60	9.5	8.4	10	8.1	29	15	31	22	57	79	328	27.0
Marin	96	11	8.1	13	13	26	14	28	7.7	173	98	487	39.7
Mariposa	14	2.5	2.3	2.8	3.0	10	4.1	6.9	5.6	22	38	112	9.0
Mendocino	106	6.0	3.2	5.2	12	17	26	23	5.2	46	48	297	25.5
Merced	84	16	9.8	15	13	29	18	32	35	85	102	437	35.9
Modoc	4.9	1.1	0.40	1.1	3.0	1.6	2.5	2.7	1.3	6.3	6.8	32	2.6

Mono	4.6	1.0	0.90	0.80	0.80	4.2	1.2	5.0	1.9	2.7	7.9	31	2.5
Monterey	83	17	8	10	8.6	29	11	25	364	94	72	722	57.9
Napa	107	11	5.2	10	15	21	17	36	17	240	98	577	46.6
Nevada	126	14	7.8	11	12	45	41	25	18	78	68	444	37.6
Orange	285	88	79	63	78	143	86	118	289	446	564	2,238	181
Placer	249	47	20	37	40	81	67	85	56	163	253	1,099	91.6
Plumas	23	2.7	1.7	2.0	6.9	4.7	7.3	5.7	3.3	11	11	80	6.8
Riverside	167	90	78	61	69	155	58	148	177	291	519	1,812	146
Sacramento	861	179	62	120	132	195	155	263	146	687	906	3,703	308
San Benito	11	2.4	1	1.6	1.5	3.5	1.9	3.3	19	13	12	70	5.7
San Bernardino	172	85	53	45	53	101	41	104	186	246	307	1,392	114
San Diego	258	76	69	54	75	128	82	105	202	341	381	1,769	145
San Francisco	145	30	26	33	24	70	29	63	24	371	221	1,036	83.5
San Joaquin	300	55	20	41	43	84	55	98	52	279	336	1,362	113
San Luis Obispo	55	14	7	10	10	19	11	22	61	71	67	346	28.2
San Mateo	151	23	21	25	20	62	24	52	19	236	184	816	66.7
Santa Barbara	70	23	8.1	9.6	12	23	12	20	65	147	84	473	38.3
Santa Clara	442	58	36	53	47	116	68	105	148	440	457	1,970	162
Santa Cruz	77	22	5.1	11	7.6	18	11	18	69	79	68	385	31.8
Shasta	287	23	12	20	51	48	45	83	23	115	454	1,161	95.4
Sierra	4.1	0.50	0.30	0.40	0.60	1.4	1.0	0.90	0.50	1.4	1.9	13	1.1
Siskiyou	49	8.3	3.9	5.8	11	14	51	24	12	53	56	287	23.6
Solano	177	23	15	23	27	45	31	54	25	324	218	961	78.0
Sonoma	306	30	16	31	33	64	46	79	26	1,412	235	2,278	180
Stanislaus	224	38	21	36	30	70	41	89	52	243	247	1,093	90.0
Sutter	66	12	4.6	10	12	14	14	23	14	46	83	298	24.7
Tehama	123	8.0	3.5	7.9	16	19	13	33	9.3	40	99	370	31.3
Trinity	45	1.8	0.70	2.1	2.8	5.7	4.8	37	1.8	11	19	131	11.2
Tulare	164	35	24	29	21	48	42	81	117	211	186	957	78.3
Tuolumne	41	11	9.3	8.0	7.5	80	13	31	12	41	51	304	25.2

Ventura	105	36	16	19	21	48	21	34	95	218	333	947	75.2
Yolo	111	14	6.2	12	18	23	20	34	18	94	118	468	38.7
Yuba	54	9.2	4.2	7.5	8.2	16	10	15	10	41	59	235	19.5

Figures

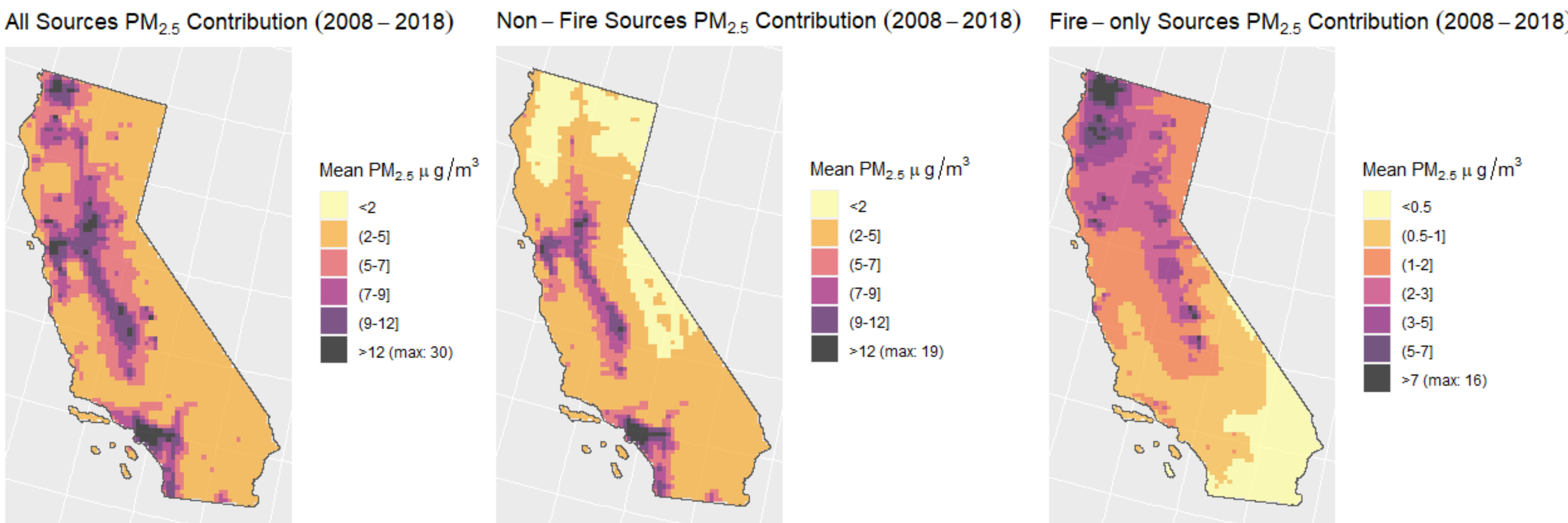

Figure A.1. Community Multiscale Air Quality (CMAQ) mean $PM_{2.5}$ concentrations at 12-km resolution for 2008–2018 for all sources (left), non-fire sources (middle), and fire-only sources (right). Note the differing scale for the fire-only map and differing maximum values for each panel.

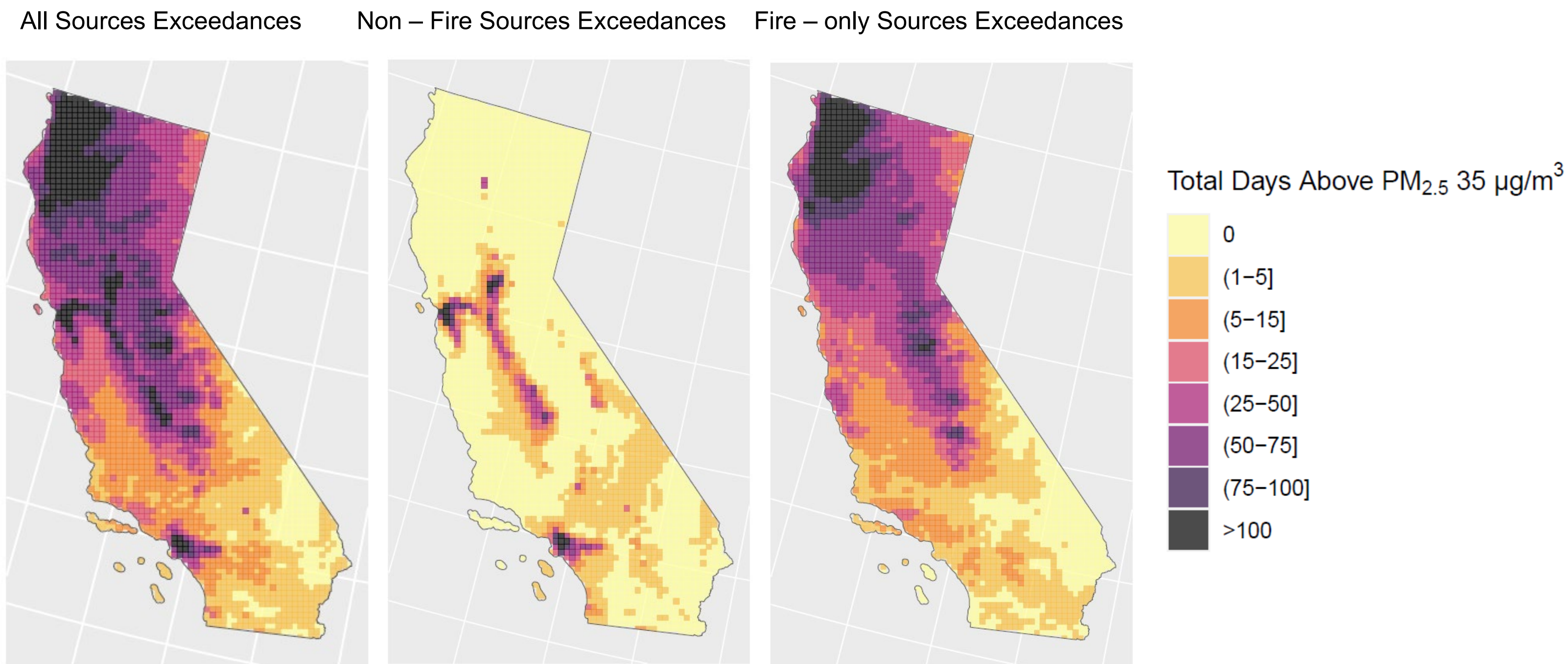

Figure A.2a. Community Multiscale Air Quality (CMAQ) simulations at 12-km resolution showing the number of days with $PM_{2.5}$ >35 µg/m^3 during the eleven-year period of 2008–2018 for all sources (left), non-fire sources (middle), and fire-only sources (right).

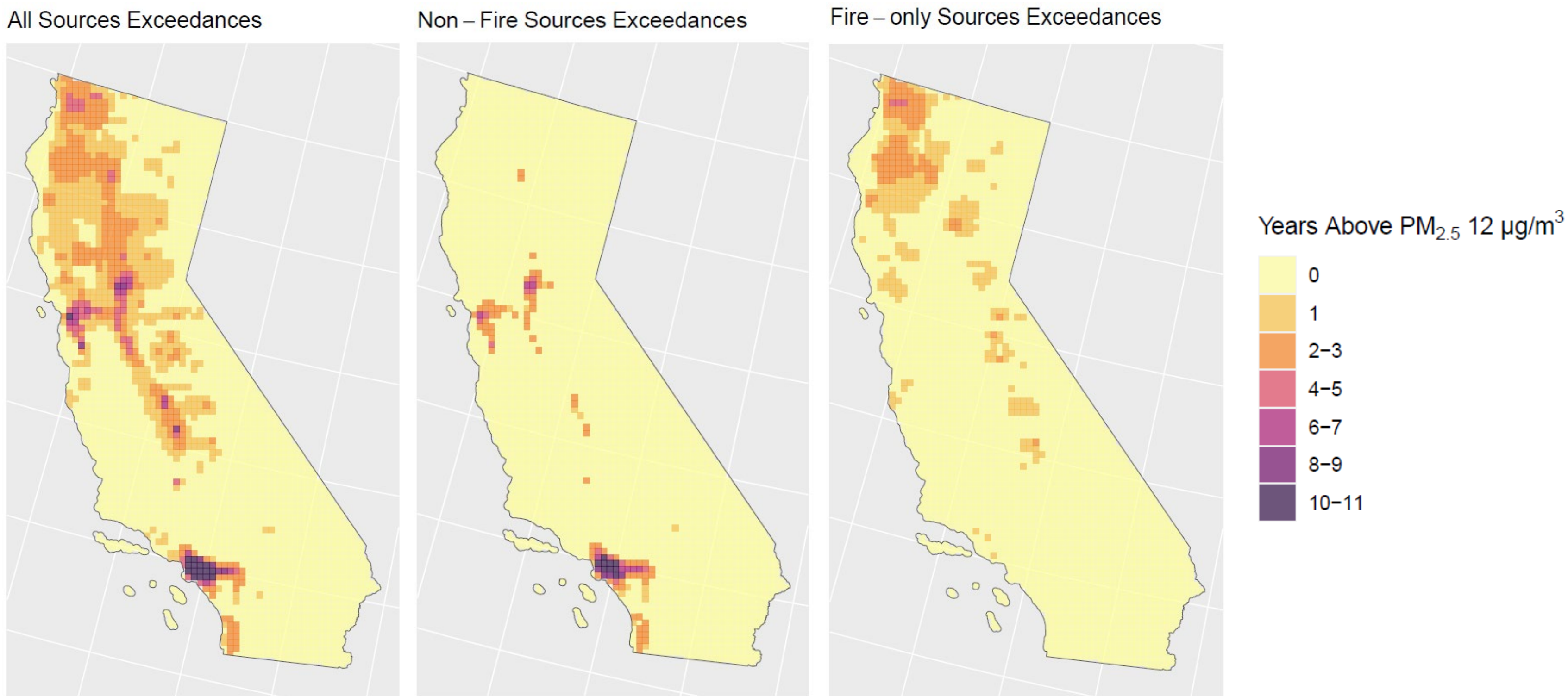

Figure A.2b. Community Multiscale Air Quality (CMAQ) simulations at 12-km resolution showing the number of years with average $PM_{2.5}$ >12 µg/m^3 during the eleven-year period of 2008–2018 for all sources (left), non-fire sources (middle), and fire-only sources (right).

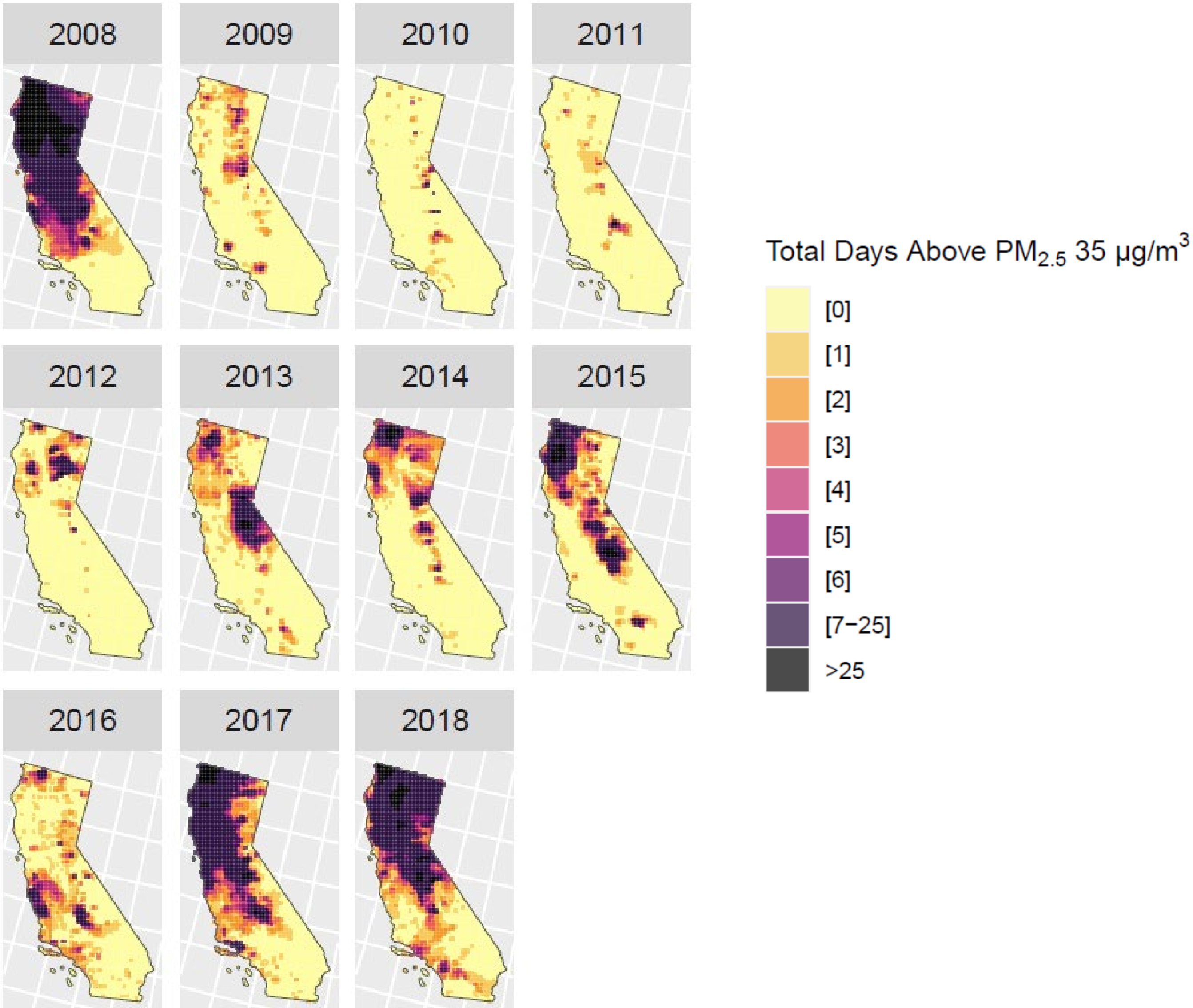

Figure A.3. Community Multiscale Air Quality (CMAQ)-simulated days with a wildland fire contribution (fire-only concentrations) to ambient $PM_{2.5}$ >35 μg/m^3, by year.

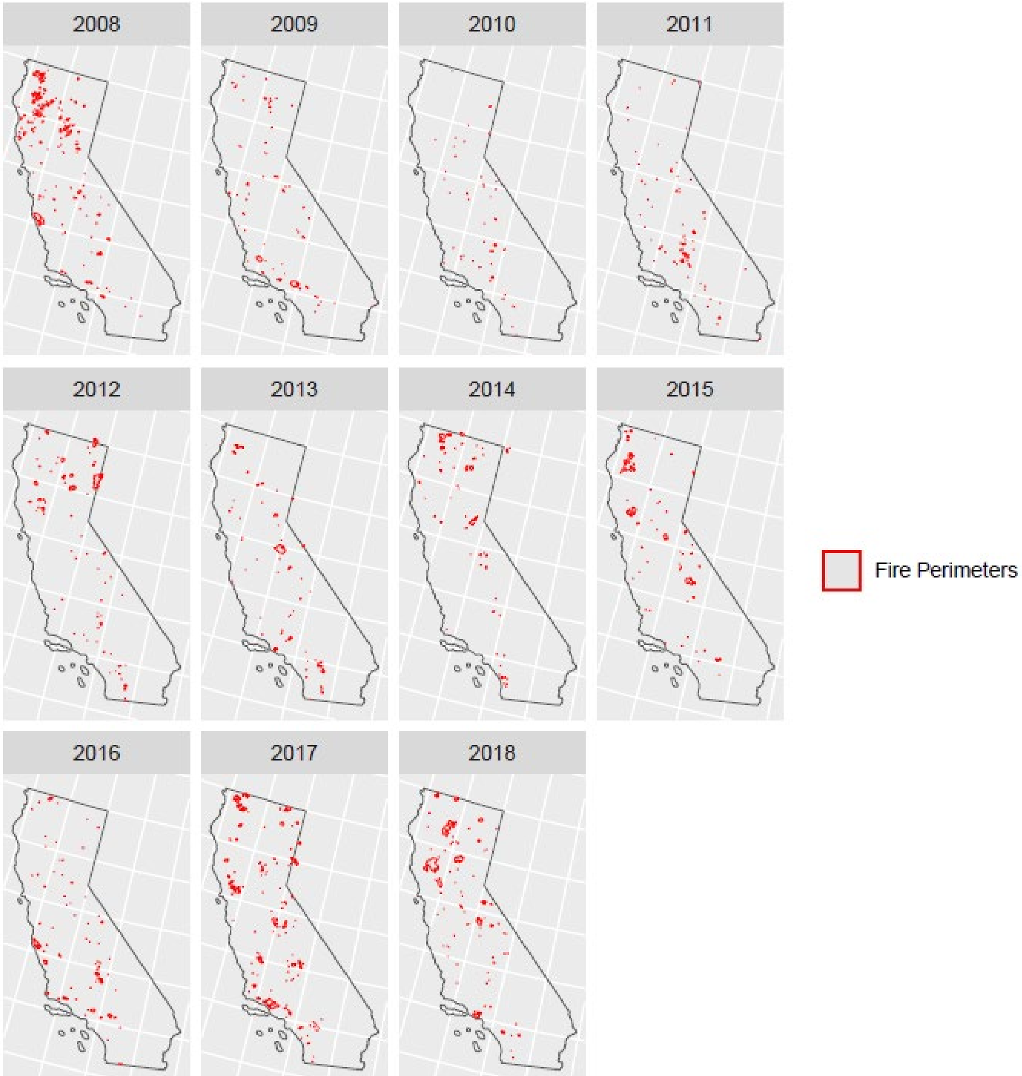

Figure A.4. California wildfire perimeters > 300 acres burned, by year.
Source for fire perimeters: CAL FIRE (https://frap.fire.ca.gov/frap-projects/fire-perimeters/) (CAL FIRE, 2022)

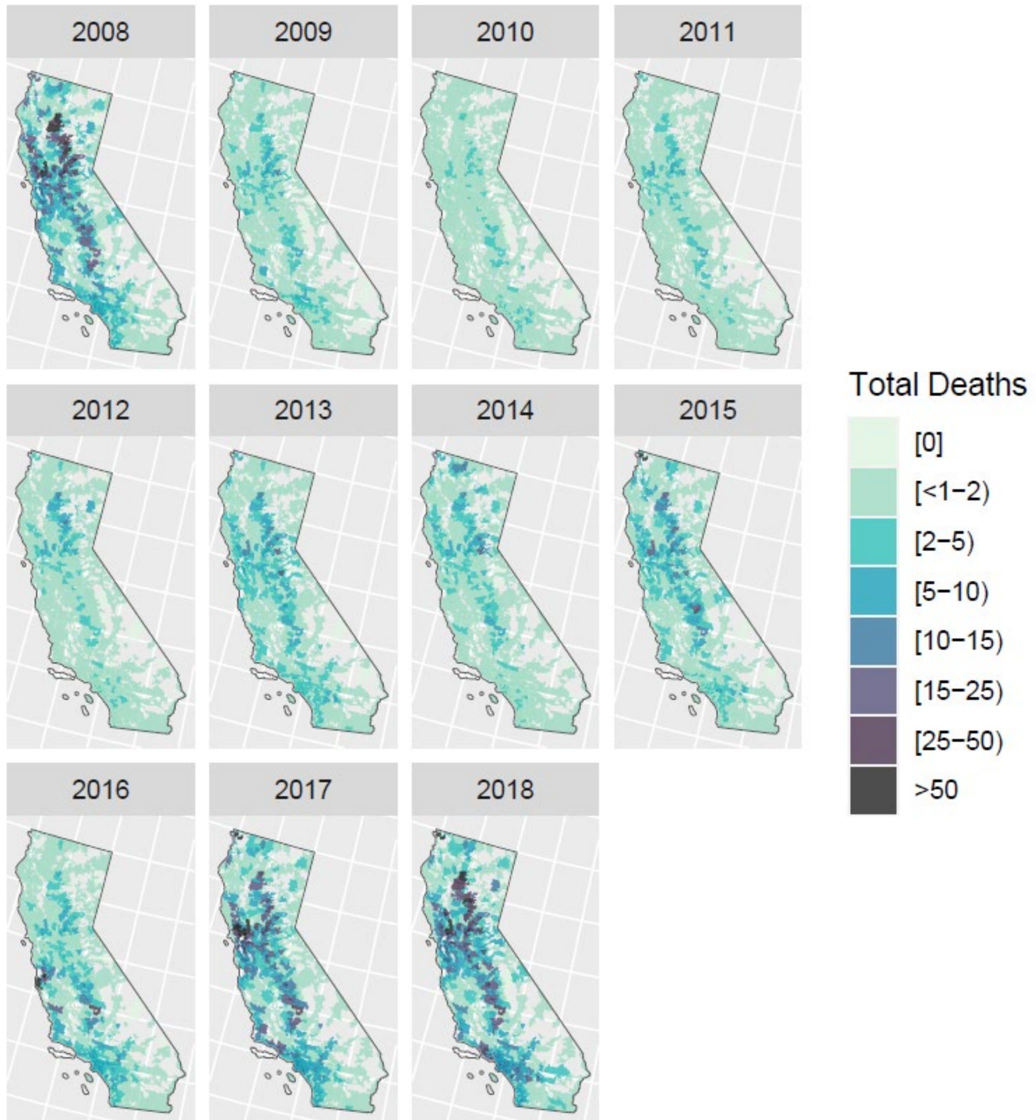

Figure A.5. Total deaths attributable to fire-only $PM_{2.5}$ (*Scenario 1*), by year.

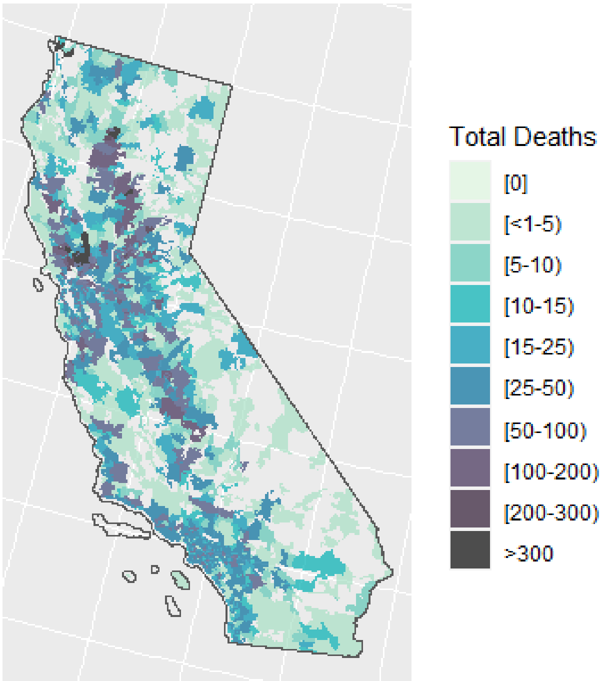

Figure A.6. Total deaths attributable to fire-only $PM_{2.5}$ over the eleven-year period of 2008 – 2018 (*Scenario 1*).

Appendix B. Model Validation for $PM_{2.5}$ Estimates

Methods

In this appendix, we include a supplementary validation analysis. To validate the modeled concentrations, daily modeled estimates were paired with observed values from ground stations from the EPA's Air Quality System (AQS; https://aqs.epa.gov/aqsweb/airdata/download_files.html) network, Interagency Monitoring of Protected Visual Environments (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 values were removed from the dataset prior to analysis (<0.4% of the total paired observations). A limited number of observed measurements with values of zero (<0.3% of the total paired 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 values were compared through the calculation of previously established metrics for evaluating atmospheric model performance during the fire season (June – October) (Koman et al., 2019; Wilkins et al., 2018).

Results

The validation statistics for the paired observations for each year's fire season (June – October) are presented in Table B.1, and the location of the monitoring stations included in the observed dataset are in Figure B.1 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 μg/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 μg/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 (see Table 3.1 for acres burned), the modeled means are higher than the observed means by approximately 1 - 4 μg/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.

Table B.1. Fire season (June – October) statistics summary of paired 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

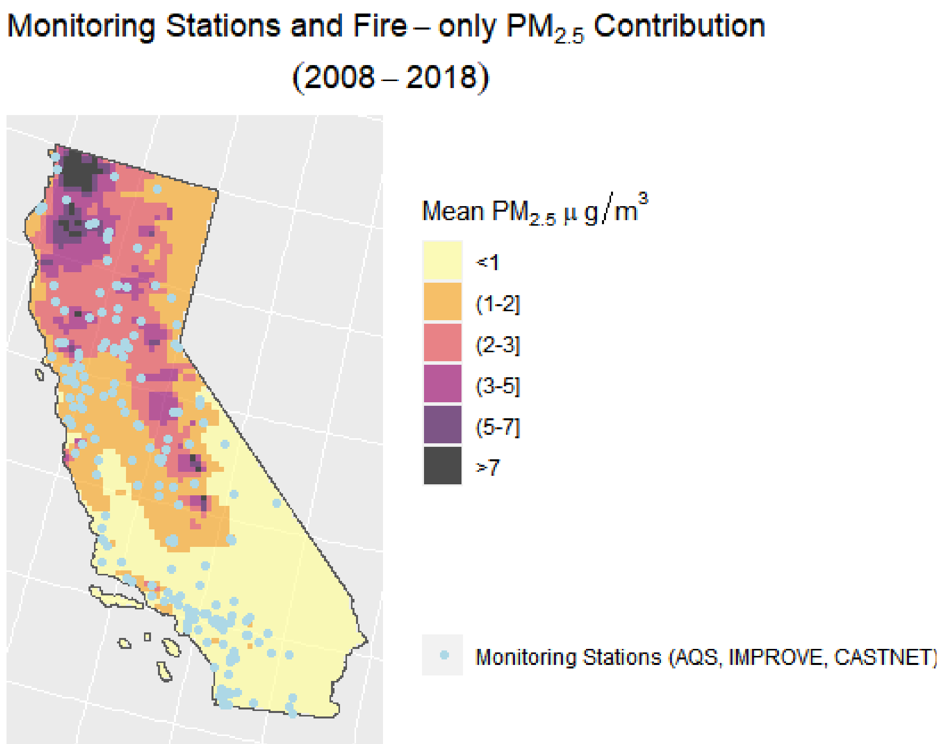

Figure B.1. Location of $PM_{2.5}$ monitoring stations (including AQS, IMPROVE and CASTNET networks) alongside fire-only sources $PM_{2.5}$ estimates.

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 B.2 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 B.2 and Table B.1. Some seasonal trends are apparent, including peaks in the fire season for the observed data and all sources concentrations.

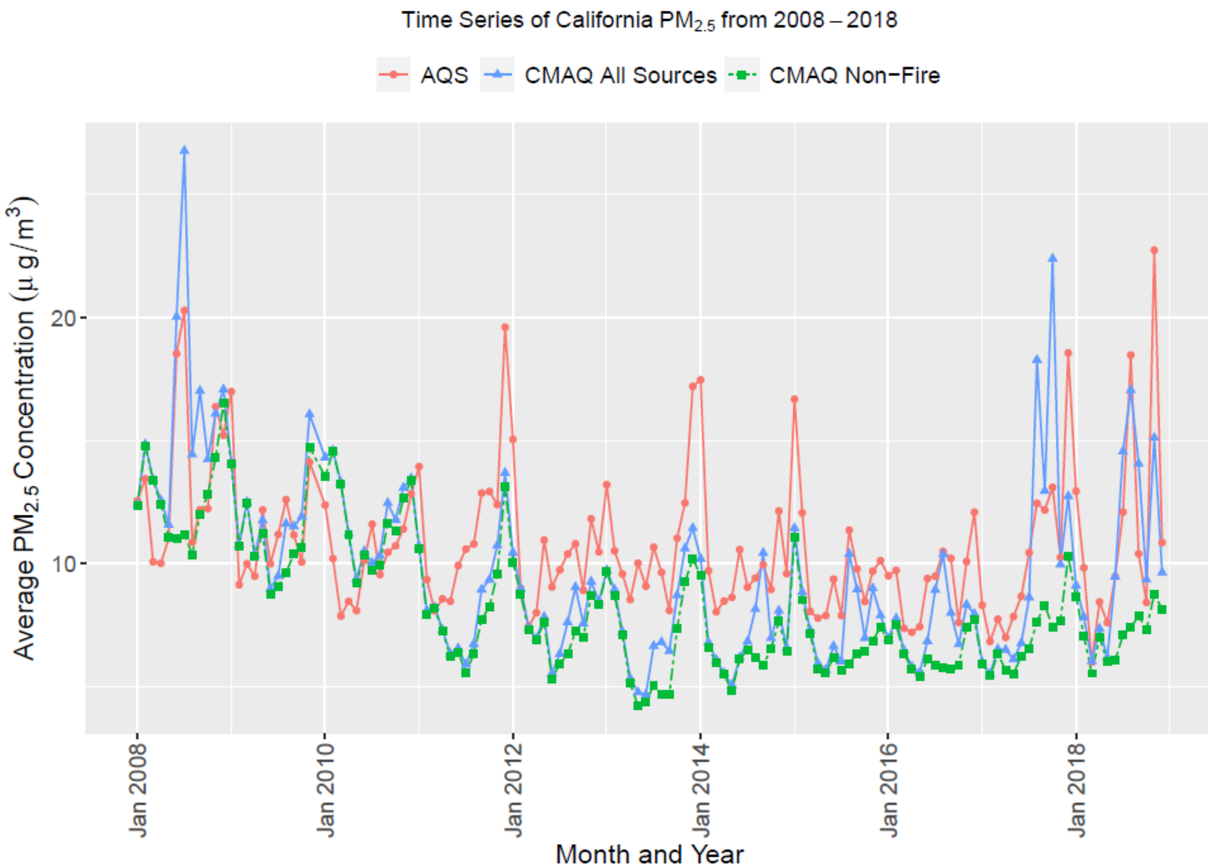

Figure B.2. Time series of California $PM_{2.5}$ from 2008 – 2018 with modeled all sources, non-fire, and observed data pairs. Monthly mean $PM_{2.5}$ concentrations across California for 2008-2018 for AQS observations (red line), Community Multiscale Air Quality (CMAQ) all sources (blue line) and CMAQ non-fire sources (green line). Only CMAQ concentrations paired with observations are included.

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 B.2 for fire season statistics and Figure B.3 for a monthly analysis) (Koman et al., 2019).

Table B.2. Fire season (June – October) statistics summary of paired 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).

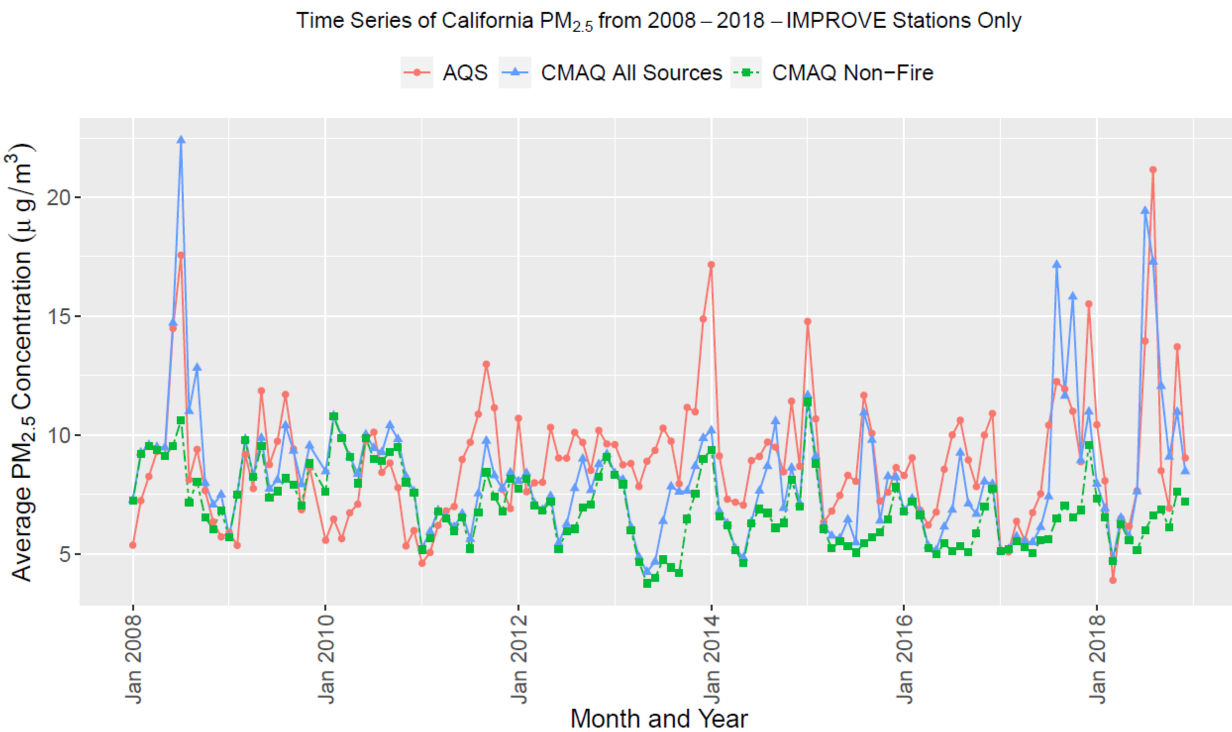

Figure B.3. Time series of 11-year $PM_{2.5}$ with observed, all sources, and non-fire concentrations for IMPROVE stations only. Monthly mean $PM_{2.5}$ concentrations across California for 2008-2018 for AQS observations (red line), Community Multiscale Air Quality (CMAQ) all sources (blue line) and CMAQ non-fire sources (green line). Only CMAQ concentrations paired with observations are included.

The IMPROVE monitors have consistently higher correlations for both all sources and non-fire values (Table B.2) than the combination of all stations (Table B.1). 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 B.3 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 B.1) 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).

4. PROCEDURAL EQUITY IN HOUSEHOLD-LEVEL JUST TRANSITION POLICY IMPLEMENTATION: CLEAN VEHICLE INCENTIVES IN CALIFORNIA

4.1. ABSTRACT

There has been an outsized focus on the distributive aspects of environmental justice compared to procedural aspects. Yet, procedure is equally important to assess in a just transition policy context, but there is no established framework through which to evaluate procedural elements of a growing number of household-level just transition policies. Such policies are designed to increase uptake of novel technologies through the provision of incentives and rebates. In this study, we analyze procedural equity in the context of such policies and associated programs, particularly those with large household benefits but limited total funding which are increasingly employed in just transition efforts. We accomplish this through a case study of a longstanding and the largest equity-focused electric vehicle incentive program in the United States, the Clean Cars 4 All (CC4A) program offered in California. CC4A is authorized at the state level but operated regionally by local air quality management districts. We used the academic literature to develop a broader conceptual procedural equity framework for household-level just transition policies, with respect to four aspects: (1) participation and inclusiveness, (2) community capacity building, (3) respect and recognition of diverse perspectives, and (4) decision-making influence. We then conducted interviews with fourteen program stakeholders and benefit recipients to analyze the extent to which various regional CC4A program implementation strategies have achieved procedural equity outcomes. We find that while regionally distinct strategies are valuable in tailoring approaches to meet community heterogeneity, the decentralized program implementation structure has resulted in inconsistency in the realization of procedural equity outcomes, with the most notable differences

appearing with respect to outreach approach and community partnerships. The extent, type, and collaborations involved in the outreach process varied widely across the districts. These procedural impacts also influence the distributive dimension of equity. The framework developed in this study can be applied in future procedural equity analyses of other policies. Our findings have significant implications for ensuring a just transition to clean energy more broadly.

4.2. INTRODUCTION

There has been a historical focus on the distributive component of environmental justice (Bell and Carrick, 2017; Lake, 1996; Reed and George, 2011), which attempts to measure fairness in the allocation of environmental benefits or risks to various sub-populations. While procedural equity – encompassing the equitable involvement of communities impacted by an environmental process – is equally important to assess within any policy implementation context, it is rarely studied, particularly alongside distributional impacts (McDermott et al., 2013).[7]

Previous studies have analyzed procedural elements of environmental policies, events, and decision-making, yet to our knowledge, no studies have done so in the context of the implementation of environmental benefit policies and associated programs increasingly authorized to support vulnerable households in just transition efforts to achieve a clean and equitable energy future. Existing literature on environmental benefit program offerings and methods to increase associated outputs is limited (Carley and Konisky, 2020). A recent review focused on the just transition highlighted successes and challenges associated with assistance program

[7] The term "procedural justice" is commonly used in the literature. However, the case analyzed within this study is focused on a state government-authorized and designed program with uniform eligibility requirements, a design which has certain advantages. This structure makes achieving justice goals of equal representation and treatment less plausible. Accordingly, since certain dimensions of justice are not applicable to this type of program and associated assessment, we focus our evaluation on equity, which can be feasibly achieved through such programs. Conceptual distinctions between justice and equity are further discussed in Section 4.5.1.

implementation more broadly, and emphasized a scarcity of existing literature on best practices, as well as a lack of knowledge on the extent of implementation of targeted interventions to reach the most underserved populations (Carley and Konisky, 2020).

As we strive to meet climate goals in California and the U.S., such policies and programs will continue to grow in importance, as shown by the passage of the Inflation Reduction Act of 2022, which includes significant funding for a myriad of clean energy rebates and tax credits. Entitlement programs, such as California Alternate Rates for Energy (CARE) and the Supplemental Nutrition Assistance Program (SNAP), are made available to all eligible individuals or households.[8] However, there is a growing suite of first come, first serve climate-related policies and associated programs providing larger financial benefits to a limited group of participants. These programs support household uptake of novel, evolving technologies, and include clean vehicle replacement, solar system installation, turf replacement, and heat pump installation, and are more complex since they involve in-home infrastructure and significant financial incentives. Equity is a particularly important consideration for these types of programs, since the benefit is not practically available to all who are eligible, and program implementation targets large per-household benefits to those who truly need them. Thus, it is important to study the program processes associated with the application and distribution of these limited financial resources. We refer to these policies as *household-level just transition policies* throughout this study.

Due to the paucity of relevant literature in this space, there is no established framework through which to evaluate procedural elements of such policies. In this study, we aim to begin to fill this

[8] Other well-known programs such as the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) and Low-Income Home Energy Assistance Program (LIHEAP) are not technically entitlement programs, but are available to all eligible individuals while funding is available.

knowledge gap and characterize pathways to the realization of procedural equity in the context of household-level just transition policies, particularly those with large available benefits and limited funding. We investigate the following research questions: *How should procedural equity be attained with respect to household-level just transition policies and programs? How does this play out in practice?*

We answer these questions by (1) adapting procedural equity concepts into an analytical procedural framework through which to analyze such policies, and (2) applying our proposed framework to perform a qualitative case study of the California Air Resources Board's (CARB) Clean Cars 4 All (CC4A) clean vehicle incentive program. Compared to the newest generation of environmental equity efforts in California, CC4A is a relatively mature program with about eight years of operation at scale, with $190 million allocated for the program as of the end of the 2021-2022 fiscal year (California Air Resources Board, 2022b). To date, CC4A is the largest equity focused electric vehicle program in the U.S.

Thus, in this study, we build on our own previous research (Pierce and Connolly, 2020, 2019), as well as environmental justice scholarship (Bell and Carrick, 2017; Holifield et al., 2017), to assess procedural equity in CC4A implementation. As the state continues to set necessarily ambitious environmental targets, including a rapid transition to zero emission vehicles, demand for environmental incentive programs will grow. Though the case study is focused on a specific program, the results of this study will be widely applicable to the pursuit of procedural equity in similar programs, which have greatly proliferated, especially since the passage of the Inflation Reduction Act. This research also characterizes equitable program implementation procedures, which, if implemented in future programs, will help ensure that the most in-need households have access to incentive dollars, and more broadly, will be crucial in enabling a just transition to clean energy (Carley and Konisky, 2020).

In the remainder of the manuscript, we describe the case study background (Section 4.3) and methods (Section 4.4). Then we present results (Section 4.5), including a review of the peer-reviewed literature in this space and the proposed analytical framework (Section 4.5.1), and the case study procedural equity analysis (Section 4.5.2). Then, we discuss implications (Section 4.6) and conclude (Section 4.7).

4.3. CASE STUDY BACKGROUND

4.3.1. CC4A Program Overview

To achieve its air quality and climate change goals, California must electrify its light-duty vehicle fleet, as exemplified by Governor Newsom's executive order (N-79-20) mandating the sale of only zero-emission light-duty vehicles by 2035. One of the enduring challenges of widespread adoption of clean light-duty vehicles in the state is overcoming the financial challenges of vehicle purchase faced by lower-income households who rely heavily on cars (Martens et al., 2012).

The CC4A program grew out of the Enhanced Fleet Modernization Program (EFMP). To meet clean transportation needs in low- and moderate-income populations (California Air Resources Board, 2018), CARB introduced the EFMP Plus-Up pilot program in June 2015, which expanded upon an existing EFMP vehicle retirement and replacement program which had limited uptake in its replacement offerings (California Air Resources Board, 2013; Ju et al., 2020). This new program was designed to better integrate vehicle retirement and replacement incentive programs which could be accessed by lower income households. After several years of growth, Assembly Bill (AB) 630 (2017) formally codified the pilot project as a stand-alone program and changed the name to CC4A.

The CC4A program has now been operating for approximately eight years, during which time the program has implemented over 14,000 vehicle replacements for eligible households through the 2021-2022 fiscal year (California Air Resources Board, 2022c). Based on the broad appeal of and demand for expansion of the program, the initial pilot has recently expanded from two regions, the San Joaquin Valley and South Coast, to five. Two additional regional branches of the program launched in the Bay Area in 2019 and in Sacramento in late 2020, with San Diego intending to launch in 2023, and a statewide program currently under development as well.

While the CC4A program maintains common eligibility and benefit criteria across the state, each operating air quality management district (also referred to as ‘air district’) has been granted and exercises discretion in implementation of the program regionally, particularly around outreach strategies. Moreover, as described in Section 4.2, CC4A offers access to a relatively complex environmental benefit with a high per-household benefit level (up to $9,500) to those who successfully enroll. The result has been, since the outset of the CC4A program, that there has been higher demand for incentives than supply of incentive funds (Pierce and DeShazo, 2017).

Previous studies have analyzed both distributional and procedural elements of program administration of various phases of preliminary CC4A implementation and provided evidence of distinct outreach approaches employed in the various districts, and by the same districts over time (Pierce & Connolly, 2019; Pierce & Connolly, 2020; Pierce & DeShazo, 2017). As discussed in Section 4.2, the design of CC4A makes the nature and efficacy of program implementation even more crucial to ensure equity in program outcomes. Strategies used by the air districts and program partners to provide both information about the program opportunity as well as support to help navigate the enrollment process to interested participants are critical, given the limited benefit dollars available compared to the pool of eligible households.

4.3.2. CC4A Benefit Allocation to Date: Distributional Equity Analysis

In this section, we provide further case study context by highlighting distributive equity outcomes of the program. Part of this analysis was first published in a 2021 report with distributive results through December 2020 (Pierce et al., 2021), and has since been updated to account for the distribution of incentives through June 2021 to better align with the timeframe of the interviews. The methods and data used, as well as additional tables and figures described here, are available in Appendix A. Our analysis focuses on the three districts that have been operating CC4A for more than two years: the South Coast Air Quality Management District (SCAQMD, which calls the program "Replace your Ride" locally), the San Joaquin Valley Air Pollution Control District (SJVAPCD), and the Bay Area Air Quality Management District (BAAQMD).

To support program implementation, each district receives funding from the state, and some districts pool or contribute minor amounts of local funding at their discretion as well. We find that the state has distributed more than $104 million in incentive funding (close to 80% from the Greenhouse Gas Reduction Fund [GGRF]), with nearly $1 million of additional funds contributed from local funding sources. There are large differences in funding distribution across districts, reflective of both their relative size and time implementing the program. Approximately 58% of state funding has been distributed through the SCAQMD, 27% through the SJVAPCD, 11% through the BAAQMD, and 3% through the Sacramento Metropolitan Air Quality Management District (SMAQMD) (Figures A.1 and A.2; SMAQMD is not shown on Figure A.2 since it only accounts for 3% of all funding).

We present different ways of looking at CC4A distributive equity outcomes across the three districts, using a variety of disadvantaged community (DAC, as defined by Senate Bill [SB] 535) statistics (see Table 4.1) as well as household income status (Table A.1) metrics presented in the appendix, so as to share a multi-faceted perspective on distributional outcomes. Keeping in mind key demographic and socioeconomic differences across California's regions, there remain notable trends in the number and proportion of incentives accessed among the absolute and relatively most disadvantaged and lowest income communities.

Nearly 13,000 incentives were distributed to households through June 2021, with almost half of all incentives distributed to residents in state-identified DACs (Table 4.1), and nearly two-thirds of all incentives distributed to state-identified AB 1550 low-income communities (LICs; Table A.1).[9] More than half of all incentives have been distributed in the South Coast region. Table 4.1 below shows the variation in distribution patterns by district, with respect to DAC-related metrics, as we compare incentive distribution to socioeconomic and environmental vulnerability. We would expect variation amongst the districts, since each region is comprised of different amounts of DAC tracts. In fact, almost 90% of the state's DAC tracts are in the South Coast and San Joaquin Valley regions, with a considerably smaller amount in the Bay Area. While the San Joaquin Valley has the largest percentage of tracts within any region that are considered DACs, it also has the highest percentage of incentives distributed to DAC tracts, and by far the least funding distributed to non-DAC tracts. It also has nearly double the proportion of CC4A funding distributed to the most disadvantaged (top 10% DAC) tracts than any other region.

[9] We do not report participant household income levels due to uncertainty about the reporting of extremely low incomes, including negative values. After incomes less than $100 were removed, mean household income is $28,140 and median household income is $24,140.

Table 4.1. Incentive distribution and participant characteristics by air district: disadvantaged community (DAC) metrics

District	Year Program Started	Total # Incentives	Average CES 3.0 Percentile: Participant Residential Locations	% of Tracts in Region That Are DACs (SB 535)	% of Incentives to DAC Tracts	% of Incentives to Top 10% DAC Tracts	% of DAC Tracts: No Incentives Received
SCAQMD	2015	7,657	68%	38%	43%	16%	28%
SJVAPCD	2015	3,587	81%	56%	72%	30%	4%
BAAQMD	2019	1,381	49%	6.9%	17%	1.8%	26%
All Districts (including SMAQMD)	2015	12,955	69%	25%	47%	18%	22%

Table A.1 displays outcomes with respect to pure income rather than broader disadvantage-related metrics. Again, each region is comprised of different amounts of AB 1550 LIC tracts. We find the distribution of CC4A funding to LICs is nearly identical in the San Joaquin Valley and South Coast, and slightly lower in the Bay Area. The percent of CC4A participants below 225% of the Federal Poverty Line, the lowest income bracket in the CC4A program, is high in all three of the districts, with almost 90% of all participants throughout the state meeting that threshold. We also find that all three of the districts have relatively high distribution to low-income households, using a county-specific, cost of living adjusted "low-income" threshold, with 96% of incentives distributed to such households for the SCAQMD and the BAAQMD, and 83% for the SJVAPCD, which reflects its comparatively lower cost of living.

Appendix Figures A.3a-c visually depicts incentive provision alongside CalEnviroScreen 3.0 percentiles in each census tract, where red indicates a higher environmental health vulnerability. This demonstrates relatively widespread incentive distribution, but also differences in concentration of the distribution in the South Coast and San Joaquin Valley. From the Bay Area map (Figure A.3c), it is evident that the program and incentive distribution is still in earlier stages in the region (particularly as of June 2021) than the other two districts.

The amount distributed to DAC versus non-DAC tracts has grown significantly over time as the program matured (Figure A.1), with a relatively steady distribution to DAC versus non-DAC tracts, though the DAC allocation dropped slightly in 2020. In terms of allocation of funding by district (Figure A.2), funding through the SCAQMD has rapidly grown in recent years, with a peak of greater than $16 million in 2019 (in incentive funding only, not including administrative costs). The BAAQMD and the SJVAPCD distributed similar amounts of state incentive funding in 2020. There is a considerably smaller proportion of DAC census tracts comprising the Bay Area region (Table 4.1), and the percent allocation of incentive funding to DACs is accordingly much smaller in this region.

These findings, including inconsistencies in distributional equity between the various air districts, provide context for the case study presented here and further highlight the importance of a careful analysis of procedures and characterization of the relationship between the two aspects of equity.

4.4. METHODS

4.4.1. Literature Review

To inform our analytical framework, we conducted a scoping literature review. This review served to characterize the limited literature available on household-level just transition policies and their associated intersection with procedural environmental justice and equity, including conceptual distinctions and theoretical advances. This review provided the necessary context through which to develop the procedural equity analytical framework. We used the Web of Science and Google Scholar databases, as well as a snowballing approach. Keywords were combined in various structures and included “environmental justice,” “procedural equity,” “procedural justice,” “environmental benefits, rebates, or incentives,” “clean energy,” and “just transition.”

The resulting review has two focus areas: (1) existing research on environmental benefit policies more broadly, including the household-level just transition policies of interest, and available evidence on equity implications, and (2) the concepts of procedural environmental justice and equity. These findings are applied in Section 4.5.1 in the development of the analytical framework.

4.4.2. Interview Procedures

We undertook a qualitative, case study research approach since there are a limited number of implementing air districts, and the process of CC4A program implementation is complex and has varied over time. The case study analyzes CC4A program implementation, focusing on differing program operation techniques in three implementing air quality management districts across the state, which have been given discretion in program implementation. Again, our analysis focuses on the three air districts that have been operating CC4A for more than two years: the SCAQMD, SJVAPCD, and BAAQMD.

We aimed to triangulate information and perspectives from different stakeholders involved in the implementation process in each district through 14 semi-structured interviews. These interviews were all conducted over Zoom using the audio function. The interview guides used for the semi-structured interviews can be found in Appendix B. We interviewed four types of stakeholders associated with each air district’s program implementation: (1) air district staff, (2) district contractors aiding in implementation and case management, (3) community-based organizations (CBOs), and (4) program participants. Interviews with staff, contractors, and CBOs were conducted in January – March 2021, and participant interviews were conducted in June – October 2022.

We interviewed staff from all three air districts and the associated contractors (six interviews total). The contractors that have assisted with program implementation and case management for each district are as follows: Green Paradigm Consulting (Green Paradigm) for the SCAQMD, Valley Clean Air Now (Valley CAN) for the SJVAPCD, and GRID Alternatives for the BAAQMD. We asked questions to district staff and the contractors across six implementation element themes, based on existing knowledge of the CC4A program and our literature review on procedural justice and equity: program structure and roles of stakeholders in outreach; outreach methods; in-person outreach events; partnerships; case management and direct assistance to participants; and program strengths and challenges, and feedback reported by program participants.

We conducted interviews with CBOs in two district regions: *Active San Gabriel Valley* in the South Coast region and *Lideres Campesinas* in the San Joaquin Valley.[10] The questions we posed in these interviews were focused on organizations' and members' knowledge of CC4A and direct experience with the program, and their perspectives on equitable clean transportation program outreach and implementation more broadly.

Lastly, we determined it was vital to supplement our analysis with participant perspectives in order to comprehensively analyze procedural equity. To connect with program participants, we first reached out to air districts and contractors, who provided the contact information of participants who were interested in having a 30-minute conversation about their experience with

[10] We contacted a relevant Bay Area CBO multiple times, but we did not receive a response regarding setting up an interview.

the program. We conducted interviews with six program participants (two from each of the three districts). Interview questions were focused on the participants' personal experiences with the program and their general perspectives on clean vehicle replacement and barriers to sustainable transportation in their communities.

4.4.3. Analytical Framework Development

Using findings from the literature review, we developed a procedural equity framework to apply to the CC4A case study. Other studies in the environmental field have taken a similar approach and developed context-specific procedural justice frameworks (Lecuyer et al., 2018; Ruano-Chamorro et al., 2022). The process involved reviewing the principles identified in procedural justice, equity, and just transition and environmental benefit policy literature more broadly, as well as assessing how procedural justice and equity frameworks have been applied to specific case studies, to help identify how we could apply appropriate criteria to relevant household-level just transition policies.

The developed procedural equity framework ultimately guided our analysis of interview data. The analytical framework we established includes four procedural equity aspects through which we consider the interview results (Table 4.2): (1) *participation and inclusiveness,* (2) *community capacity buildin*g, (3) *respect and recognition of diverse perspectives,* and (4) *decision-making influence*. Due to the top-down nature of decision-making for this type of statewide program, aspect (4) is less applicable for this analysis, and we will only briefly analyze it within the CC4A context.

While this case study is focused on one specific program, our proposed framework characterizes approaches to attain procedural equity in household-level just transition policies and associated environmental benefit programs more broadly. We present the analytical framework in Section 4.5.1.

4.4.4. Case Study Analysis

To analyze the interview findings within our framework, we drew from thematic analysis techniques. Thematic analysis is a qualitative research method used to characterize themes in a data set (Braun and Clarke, 2006; Nowell et al., 2017). It is a flexible analytic approach (Braun and Clarke, 2006; Dierckx de Casterlé et al., 2012; Nowell et al., 2017), which is advantageous considering it can be adapted to fit the needs of each individual analysis.

The analysis involved the following steps. First, we conducted data familiarization, involving interview transcription, reviewing the transcripts and documenting initial perspectives. Next, we developed categories through which to organize the data, and then we identified themes by linking interview excerpts to appropriate categories and identifying emerging patterns. From there, we reviewed the developed themes for suitability by returning to the raw data, as well as co-researcher triangulation. Lastly, we defined and characterized the apparent themes within the aspects of the analytical procedural equity framework (Table 4.2). This analysis was an iterative process (Nowell et al., 2017); though there are distinct steps to follow, the analysis involved traversing between these listed steps to meet the needs of the study.

Using these results, we characterized differences in each equity aspect between the three air districts to draw conclusions about the status of procedural equity in program implementation. This approach enabled us to explore how the equity implications of uptake of these programs can vary based on implementation approaches.

4.5. RESULTS

4.5.1. Literature Review and Framework Development

4.5.1.1. Household-level Environmental Benefit Policies and Equity Implications

Household-level environmental benefit policies are a critical aspect of achieving a just transition to a low-carbon future. Throughout the US, there are many environmentally focused benefit policies and programs that are offered uniformly to the population and available to all who are eligible, including entitlement programs such as monthly utility bill assistance offered through CARE, which enrolls over 80% of eligible households in California.

As mentioned previously, existing literature on environmental benefit program offerings and methods to improve outcomes is limited (Carley and Konisky, 2020). The authors of a recent study raised concerns about the extent to which environmental incentive program design (specifically targeting pro-environmental behavior) is based on evidence-based practices (Fontecha et al., 2022), and older studies have highlighted challenges in evaluating and designing such programs (Porse et al., 2016).

Much of existing literature has been focused on the implementation and impact of energy and transportation rebate and incentive programs, and secondarily, efficiency and technology transition programs (Choi et al., 2018; Houde and Aldy, 2017; Palmer et al., 2013; Pincetl et al., 2019; Porse et al., 2016; Spang et al., 2020). These programs have existed for several decades in various forms in the U.S. (U.S. Department of Energy, 2023), with the recently passed Inflation Reduction Act of 2022 allocating close to $9 billion for home energy rebates (The White House, 2023). Challenges in program design and incentive uptake have been identified (Carley and Konisky, 2020). Benefit program eligibility criteria can have the opposite of intended effects depending on policy design (Graff and Pirog, 2019), and a lack of information provision significantly impacts participation in such programs (Palmer et al., 2013). Unsurprisingly, the substantial upfront costs of residential energy improvements are a significant barrier to undergoing retrofits offered through such programs (Palmer et al., 2013; Porse et al., 2016), and one study identified that the existence of financial incentives for energy improvements in a particular region did not impact program uptake (Palmer et al., 2013). Additionally, this same study noted that while government programs do spend significant funding on the incentives themselves, not enough money is focused on information dissemination about the incentives, and community knowledge gaps persist (Palmer et al., 2013).

California has been a leader in climate policy, and has thus adopted and implemented a growing number of the limited-funding household-level just transition policies and associated programs that are the focus of this study. Such programs are increasingly valuable, as they reduce upfront costs of various environmental services for households to install technologies that support a clean energy transition but are generally not affordable for low-income populations. While there is substantial literature on the unequal adoption of earlier technologies in California and the U.S. context, such as the installation of solar photovoltaic (PV) systems, turf replacement, and clean vehicles, literature on the distribution of larger technology benefit efforts to support adoption in lower income populations is scarce (Carley and Konisky, 2020). To date, the limited evidence unsurprisingly indicates that lower income households are less likely to participate in more complex rebate programs, likely associated with a lack of existing capital to supplement incentives (Pincetl et al., 2019), a finding largely applicable to this category of benefits for significant household installations. This is echoed by several studies evaluating the distributional impacts of a variety of investment subsidies, as well as the just transition (Carley and Konisky, 2020; Lekavičius et al., 2020; Shen et al., 2022).

Several reports and articles have assessed the distributional impacts of California's clean vehicle incentive programs specifically (Guo and Kontou, 2021; Ju et al., 2020; Pierce and Connolly, 2019; Rubin and St-Louis, 2016). Clean vehicle transportation initiatives in California have operated for more than a decade in the form of the Clean Vehicle Rebate Project (CVRP), a program that distributes rebates for the purchase or lease of new zero-emission or plug-in hybrid vehicles meeting program criteria. However, CVRP rebates have not been equally distributed to low-income populations (Guo and Kontou, 2021; Ju et al., 2020; Rubin and St-Louis, 2016). More than 80 percent of CVRP recipients (2010 – 2015) reported annual incomes of more than $100,000 (Rubin and St-Louis, 2016), a finding echoed by a more recent analysis evaluating equity in clean vehicle rebate and incentive programs in California (Ju et al., 2020), as well as a recent CVRP-focused study which found participation clusters in high-income populations and metropolitan regions (Guo and Kontou, 2021). A recent study assessed equity in clean vehicle rebate and incentive distribution in CVRP compared to CC4A, finding that CC4A benefit distribution has been significantly positively associated with increased vulnerability and disadvantage as measured by various metrics, including California DAC status (Ju et al., 2020). CC4A's stringent eligibility criteria have led to the enrollment of more disadvantaged households than CVRP (Ju et al., 2020), as anticipated.

Alongside clean vehicles, as newer technologies such as heat pumps, induction stoves, and energy storage (Carley and Konisky, 2020; Kittner et al., 2017; Mai et al., 2018) emerge at the forefront of the climate technology landscape, they will be increasingly subject to similar just transition and environmental benefit policy considerations as well. This review of household-level environmental benefit programs – which include the limited funding just transition policies we focus on in this study – served to highlight the knowledge gap we aimed to fill with this analysis.

While there are several studies focused on the distribution of clean vehicle (Guo and Kontou, 2021; Ju et al., 2020) and other technology incentives (Pincetl et al., 2019), we found that no existing studies evaluate procedural elements of policy implementation. This is a distinct motivation for our analysis.

4.5.1.2. Procedural Environmental Justice and Equity

The concept of environmental justice has grown and evolved since it rose to prominence after several landmark studies exposing substantial racial environmental injustices in the late 1980s and 1990s (Bullard, 2019; United Church of Christ Commission for Racial Justice, 1987) and Executive Order 12898 in 1994. While there exist several frameworks with varying dimensions of justice to be considered depending on circumstances (Holifield et al., 2017; McDermott et al., 2013; Schlosberg, 2007), one commonly applied framework consists of distributive justice, procedural justice, and justice as recognition (Bell and Carrick, 2017; Blue et al., 2021; Schlosberg, 2007). The latter conceptually intersects with both procedural and distributive justice (Bell and Carrick, 2017; Lau et al., 2021), since for a group to be recognized and respected, relevant processes and outcomes must be just, and associated injustices can be interpreted as misrecognition (Bell and Carrick, 2017).

Procedural environmental justice encompasses the fair involvement of populations or communities who are impacted by an environmental process or event, including respecting and elevating community perspectives, facilitating participation, and involving them in decision-making to ensure the inclusion of diverse perspectives (Bell and Carrick, 2017; Blue et al., 2021; Schlosberg, 2007). While scholarship has primarily focused on the distributive impacts of environmental condition (Bell and Carrick, 2017; Reed and George, 2011), such analyses can overlook social and political factors driving such inequities (Blue et al., 2021; Foster, 1998), which are undeniably considerations of justice as well. Thus, it is critical to consider justice in procedures regardless of the distribution of outcomes.

The concept of procedural justice has wide applicability in the environmental policy field – within local decision-making processes, such as the siting of industrial facilities, but also in the development and implementation of environmental programs. Analyses range from case studies of biodiversity conflicts (Lecuyer et al., 2018) and the adoption of solar energy (Yenneti and Day, 2015), to evaluations of the justice implications of fracking policy (Clough, 2018; Cotton, 2017), analyses of procedural elements of environmental governance structures (Adeyeye et al., 2019; George and Reed, 2017), and the characterization of pathways to achieve procedural justice in ecological and conservation decision-making (Friedman et al., 2020; Ruano-Chamorro et al., 2022) as well as climate adaptation (Holland, 2017). However, to date, no studies have evaluated procedural elements of environmental benefit policies and programs.

Achieving procedural justice can present many layers of complexity. For instance, scholars have outlined barriers to procedural justice in sustainability organizations, which include the need for professionalization of environmental and other groups in order to attain funding, as well as a historical organizational focus on sustainability and environmental priorities, without making efforts to directly incorporate social and environmental justice aspects (George and Reed, 2017). In the context of decision-making, ensuring potentially impacted individuals have the knowledge necessary to participate can pose significant barriers, particularly in scenarios with complex science and health topics at the center of environmental crises, and with respect to the existence of knowledge gaps that are driven by societal power dynamics (Ottinger, 2013). An added challenge is the constantly evolving knowledge of science and environmental effects, which brings into question the potential to gain procedural justice through one decision-making process in a distinct moment in time (Ottinger, 2013). Attempts for community inclusion can also be ineffective; participation does not guarantee a genuine process where community perspectives are valued and insights are utilized (Deacon and Baxter, 2013). Finally, the definitions of justice-related terms are flexible, and can evolve (Holifield et al., 2017; Schlosberg, 2007), which is a positive characteristic, but can present an added challenge in assessing environmental justice in various scenarios. Scholars have theorized that expanding the definition of procedural justice to focus on community agency and "self-determination" is vital in realizing multiple dimensions of justice, instead of solely distributive changes that had been the previous focus of most studies (Lake, 1996).

As described in a study focused on democratic practice, early experts in the field distinguished between distributional outcomes and the resulting mechanisms, or processes, leading to such outcomes (Cutter, 1995; Lake, 1996; Torres, 1993), which are not solely related to decision-making. Many recent studies focus entirely on procedural environmental justice and equity exclusively in terms of participation in environmental governance and decision-making (Adeyeye et al., 2019; Deacon and Baxter, 2013; Friedman et al., 2020; Holland, 2017), as this is applicable to the study settings analyzed and reflects a definition presented in much of the procedural justice literature. However, several studies do reflect the inclusion of other principles encompassing procedural justice, such as recognition and inclusivity (McDermott et al., 2013), which highlights the subjective and multivalent nature of justice and equity concepts and the need for context-specific analyses. Indeed, we utilize a more multifaceted definition in this case study.

In this context, there is one additional important conceptual consideration mentioned briefly in Section 4.2 but worth highlighting in this discussion of the procedural environmental justice literature. While the concept of environmental justice refers to a systemic state of fair treatment and access to environmental benefits and involvement in decision-making, equity generally refers to fair outcomes – though we do note that these concepts of environmental equity and justice vary throughout the evidence base, with scholars highlighting the value of flexibility and general plurality in the definitions of key terms such as these, considering the constantly-evolving nature of social movements (Been, 1992; Holifield et al., 2017; Lake, 1996; Lecuyer et al., 2018; Schlosberg, 2007; Torres, 1993) – and some environmental literatures use the phrases interchangeably (Ruano-Chamorro et al., 2022). As primarily policy-developed government-run programs with specific eligibility requirements, certain equity goals can be achieved through just transition policies, but realizing justice goals of equal rights, representation, and treatment is less plausible.

Therefore, in this study, we adapt procedural justice concepts into a procedural equity framework, as has been done by other scholars noting distinctions between justice and equity terms (McDermott et al., 2013), using guidance from the procedural justice literature to pursue an analysis focused on procedural outcomes. We still focus largely on fair treatment and meaningful involvement, two core environmental justice concepts, but adapt them into the context of community participation and a focus on community inclusion and consideration in program implementation procedures.

4.5.1.3. Analytical Framework

As described in Section 4.4.3, the literature review was used to develop the analytical framework appropriate for this specific policy context (Table 4.2). The framework presented here draws from multiple literature sources, including established procedural environmental justice principles (Bell and Carrick, 2017; Schlosberg, 2007), and primary literature evaluating procedural justice and equity for various case studies. The framework is thus designed to be flexible and can be adapted for various contexts.

Table C.1 presents an illustrative (non-systematic) list of procedural justice and equity principles reported or considered in existing studies, including those not presenting a formal framework. This demonstrates the variation in themes depending on study context, though several common principles are evident.

The first aspect proposed here is *participation and inclusiveness*, reflecting the extent to which program outreach and processes influencing participation are equitable. Drawing from an academic framework on the justice of hazardous waste siting facilities (Hunold and Young, 1998), as stated in the Routledge Handbook of Environmental Justice, "'inclusiveness' requires equal recognition for all and a concerted effort to reach out" to vulnerable communities that face organizing challenges (Bell and Carrick, 2017). While the previously mentioned academic framework focuses on democratic decision-making, such definitions apply within this context as well. Achieving procedural equity can involve "affirmative action" to support groups that have been historically underserved (McDermott et al., 2013), or in this context, make focused efforts to include various communities in need who would otherwise remain unaware or untrusting of such policies and programs. Therefore, *participation and inclusiveness* is a key procedural equity consideration in the context of household-level just transition policies.

The second aspect is *community capacity building*, or empowerment and development through program implementation, which is cited as a core procedural justice criteria by environmental justice scholars (Schlosberg, 2007) and included in the framework utilized in a study on environmental governance and sustainability organizations (George and Reed, 2017). The value of community capacity enhancement with respect to environmental justice is well established

(Williamson et al., 2020), and applicable to the just transition policy context we analyze here. In addition to delivering direct benefits, program implementation procedures can indirectly engage communities and enhance their capacity for economic and environmental resilience.

The third aspect is *respect and recognition of diverse perspectives*, involving the acknowledgement of community differences and elevation of diverse perspectives and feedback on program implementation. As a component of the procedural equity framework, this aspect refers to the respect and recognition of communities within procedures. These considerations are included in some procedural assessments (George and Reed, 2017), but cited as often overlooked in examinations of procedural equity (McDermott et al., 2013). Household-level benefit programs are developed to reach communities with pre-existing vulnerabilities. Such communities have historically experienced discrimination and marginalization due to their differences, and the existence of such differences implicitly requires an approach to program implementation that acknowledges and respects community heterogeneity and elevates diverse perspectives (Whyte, 2017).[11]

The last aspect of the framework is *decision-making influence*, which is the involvement of affected community members or stakeholders in program decision-making processes. As highlighted previously, this is a well-established procedural justice principle (Bell and Carrick, 2017) and the most applicable procedural consideration to many environmental contexts, such as decisions regarding the siting of pollution hazards, and a focus of procedural justice theory more

[11] This deserves additional clarification, as 'justice as recognition' is one of the main components of an often cited environmental justice framework, along with procedural and distributive justice (Bell and Carrick, 2017).This component of the procedural equity framework does not intend to encompass the entirety of the concept of justice as recognition. Recognition as a branch of environmental justice involves the respect and acknowledgement of the differences between various populations and groups (Whyte, 2017). Justice as recognition conceptually intersects with both procedural and distributive justice, as injustices in procedures and distribution can be interpreted as "misrecognition or lack of respect" (Bell & Carrick, 2017).

broadly. Therefore, many procedural studies focus solely or almost entirely on participation in decision-making (Adeyeye et al., 2019; Deacon and Baxter, 2013; Friedman et al., 2020; Holland, 2017). Though this aspect also involves participation, it is distinct from the first aspect presented here – *participation and inclusiveness* – as decision-making influence refers specifically to the influence of community members on policy and program design, but does not refer to the processes driving equitable program participation and community involvement (the central concepts of the *participation and inclusiveness* aspect). Though decision-making influence is less applicable for the case study analysis presented here due to the top-down nature of decision-making for this type of statewide program, it remains a core component of the analytical framework as it is a central aspect of procedural equity.

These procedural equity aspects, as well as the CC4A-specific subcategories under each aspect that we characterize in Section 4.5.2, do not exist independently of one another, and conceptually intertwine. For example, respect and recognition is often a key factor in decision-making influence (Yenneti and Day, 2015). Achieving various aspects of procedural equity can influence the attainment of others, as is the case with the procedural, distributive, and recognition branches of environmental justice (Bell and Carrick, 2017).

4.5.2. Case Study: Procedural Equity in the CC4A Context

Here, we present the themes identified in the procedural equity analysis, including specific quotes and descriptions of interview responses. An overview of the framework and variations in each procedural equity aspect by district is presented in Table 4.2.

Table 4.2. Procedural equity framework and results overview

Procedural equity aspect	CC4A subcategories	Summary of by-district results		
		SCAQMD	**SJVAPCD**	**BAAQMD**
Participation and inclusiveness	(1) Maximizing incentive distribution (2) Outreach approach (3) Community partnerships and involvement in outreach (4) Innovation and adaptation	- Focus on reaching high-emitting vehicles to improve air quality - Maximizes incentive distribution - No targeted outreach	- Focus on reaching households in disadvantaged communities - Maximizes incentive distribution - Conducts targeted outreach	- Adapted approach to reach more households in disadvantaged communities - Maximizes incentive distribution - Conducts targeted outreach
Community capacity building	(1) Synergies with other programs (2) Provision of direct assistance to participants (3) Support for communities through established partnerships (4) Social and financial wellness opportunities	- Provides direct assistance to participants - Offers limited program bundling opportunities (emPOWER, though not offered through case management) - No existing community partnerships	- Provides direct assistance to participants - Offers multiple program bundling opportunities (vehicle programs and emPOWER) - Utilizes community partnerships	- Provides direct assistance to participants - Offers limited program bundling opportunities (solar) - Utilizes community partnerships
Respect and recognition of diverse perspectives	(1) Responsiveness to participant feedback (2) Efforts to overcome recognition and trust barriers (3) Community-based organization representation	- Attempts to overcome barriers through translation services - Community partnerships is an area for growth	- Attempts to overcome barriers through translation services and outreach in multiple languages - Respects and values community representation and engagement	- Attempts to overcome barriers through translation services and outreach in multiple languages - Respects and values community representation and engagement
Decision-making influence	No applicable CC4A subcategories; area for growth	No district specific points applicable – area for growth	No district specific points applicable – area for growth	No district specific points applicable – area for growth

4.5.2.1. Participation and Inclusiveness

We first analyze the themes of participation and inclusiveness in program implementation, as expressed in interview responses. Applicable CC4A subcategories include (1) maximizing incentive distribution, (2) outreach approach, (3) community partnerships and involvement in outreach, and (4) innovation and adaptation. We found the most notable differences in program implementation across districts lie in this aspect of procedural equity, with each district adopting a unique perspective on the necessity of targeted outreach and optimal methods to reach eligible participants.

Maximizing incentive distribution. The utilization of all available funding is a significant metric of program participation, independent of all other facets of participation. Generally, all districts have had great success in program uptake. There continues to be high demand among low- and moderate-income households for clean vehicle incentive programs such as CC4A that offer upfront incentives to participants (Pierce et al., 2019; Pierce and DeShazo, 2017).

As a result, CC4A program funding has been nearly or entirely exhausted in several of the districts across several funding cycles, as reported in every district interview. This is both a success, in terms of getting vehicles to participants quickly, and a challenge, since it leads to pauses in program offerings. Funding uncertainty and delays result in the use of waiting lists for CC4A, and long wait times for receiving vehicles and uncertainty throughout the process was mentioned by several program participants. This is particularly concerning given that the low-income households that the program aims to reach usually have less mobility and financial flexibility (Blumenberg and Agrawal, 2014) and thus waiting for several months to receive a vehicle has more of an adverse impact for potential program participants than it would for the broader population.

Program funding has repeatedly been exhausted in the SCAQMD, causing them to not be able to accept new applications; this theme has been recurring since the first year of implementation in this region. In the Bay Area, the BAAQMD was able to contribute $10 million of local funding to keep its program operating and "*avoid losing momentum*." Similarly, while this has not always been the case, the SJVAPCD reported *"getting more people to participate than funding can support.*" This is also a testament to the success of the program in maximizing participation and incentive distribution within the three districts.

Outreach approach. Each district's approach for outreach, including which communities are targeted and via which methods – such as events, social media, and radio – impacts the populations reached. The district and contractor interviews highlighted challenges in identifying the individuals most in-need of CC4A incentives among the much broader pool of eligible households, since there is no method applied to account for household wealth as opposed to income.

Preliminary findings from a report on in the pilot stage of CC4A identified two distinct outreach approaches adopted by the SCAQMD and the SJVAPCD (Pierce and DeShazo, 2017). These differences have largely persisted with time, with the newer BAAQMD approach falling in the middle.

As explicitly stated by both the district and Valley CAN, the primary goal of program implementation in the San Joaquin Valley is reaching DACs. Valley CAN uses its preexisting community relationships and fine-tuned outreach strategies to reach populations that would otherwise not learn about CC4A. Valley CAN holds weeknight clinics rotating throughout the sub-regions of the San Joaquin Valley, with a goal to reach communities in less populated regions (see also [Pierce and Connolly, 2019]), educate community members on the program, and help them walk through the initial stages of their applications. They also hold large bimonthly smog repair events throughout the San Joaquin Valley, where they advertise about CC4A as well. In terms of outreach methods, Valley CAN highlighted the value of "*being everywhere*" – this means swap meets, radio interviews, and outreach through word of mouth at churches, by meeting with city officials, and even reaching out to homeless shelters. Accordingly, both SJVAPCD participants that were interviewed heard about the program through the intended outreach, one over the radio, and one from a social media advertisement.

SJVAPCD staff stated that *"we have learned through our partnership with Valley CAN that in order to reach the community in the Valley driving older vehicles eligible for this program, traditional media and outreach methods [like] old school paid advertising doesn't really work, so we work closely with them to make sure we are getting to the communities."* They rely on social media as well; during the height of COVID-19, Valley CAN shifted from holding events to adjusting online outreach to get potential participants to call a designated phone bank to begin the application process. The district highlighted the value of this targeted community outreach performed by Valley CAN, stating that it is "*providing true emission reductions in those communities in the San Joaquin Valley where we are really focused, which are some of our CalEnviroScreen communities where we see the biggest need."*

Green Paradigm highlighted that the SCAQMD is primarily focused on emission reductions, so expending funding toward such reductions is the program's main objective. Accordingly, the SCAQMD reports taking a different approach to outreach, electing not to conduct targeted outreach due to (1) high program demand and (2) success in passing through incentive dollars to participants, as discussed previously. When the district first started the program, it did contract with an outreach organization for a few years to conduct targeted outreach to communities of color and low-income communities; this was discontinued due to program oversubscription. The district staff stated that while they always accept outreach invitations to promote the program and participate in annual events for Earth Day and car shows, the district has not actively implemented a formal CC4A outreach campaign for the last 2-3 years (as of the interview in 2021). There have been some informal outreach efforts, including an online campaign SCAQMD conducted as a response to interest from its Board. This campaign "*completely exploded the number of applicants*." SCAQMD also occasionally sent out program fliers to various nonprofits in recent years. Additionally, SCAQMD does not routinely hold outreach events, but (apart from the COVID-19 period) the district and contractors did host weekend workshops where participants could get their vehicle emissions tested free of charge and receive assistance from staff in completing their applications online.

Accordingly, the SCAQMD program participants both reported never seeing any advertisements for the program, with one suggesting this is to the district's "detriment" (see Table C.2, which includes key participant quotes related to all procedural equity impacts discussed throughout Section 4.5.2). One participant suggested that radio, YouTube, and social media advertisements would be effective ways to reach their community to spread knowledge about the program.[12] Green Paradigm also stated that increasing targeted outreach, and doing so through local CBOs, is an opportunity for improvement in CC4A implementation.

The BAAQMD reported a mixed approach to outreach since the program started in 2019. It began with a strategic focus on AB 617 communities,[13] DAC, and LICs, but eventually broadened its focus to more of the Bay Area. As of the timing of the interview in 2021, the district realized it

[12] Other suggestions included billboards and mailers included with utility bills.
[13] AB 617 is implemented through the Community Air Protection Program in California, and focuses on reducing air pollution and improving public health in the communities most in-need throughout the state (https://ww2.arb.ca.gov/our-work/programs/resource-center/ab-617-implementation).

was not getting high participation from disadvantaged and low-income tracts, and thus decided to focus back on targeted outreach to DACs with a goal to gain higher participation from these communities. In terms of outreach methods, it has used mailers, social media, and events; the BAAQMD has hosted several "ride and drives" and other events advertising multiple program offerings, including CC4A, with two events held in AB 617 communities. It found the most success in events hosted by CBOs and other groups, such as farmers markets. Similar to the SJVAPCD, the Bay Area team has found significant value in word of mouth or referrals. Indeed, one of the participants we interviewed heard about the program through word of mouth. The staff also noticed that radio programs (Spanish, Vietnamese, and English radio) were effective in advertising the program opportunity independently, without any funded ad placement.

Community partnerships and involvement in outreach. We highlight CBO representation in several procedural equity aspects, since these collaborations increase equity in a multitude of ways. With respect to participation and inclusiveness, partnering with local CBOs reflects a concerted effort from the air districts to increase equitable program participation. There are multiple benefits associated with such partnerships (Pierce and Connolly, 2020; Williamson et al., 2020), and CBOs have strong pre-existing connections with their communities, presenting an opportunity to effectively reach those populations.

The SJVAPCD and Valley CAN rely on community partnerships, often using CBOs and other local organizations such as churches and foundations as an essential outreach mechanism. This is a mutually beneficial partnership; Valley CAN also often has CBO representatives join their team at events, where the CBOs can help with program outreach, but also utilize Valley CAN's existing network to advocate and advertise for other causes and opportunities. The BAAQMD and GRID Alternatives also partner with similar types of community organizations, such as churches, CBOs, and city representatives, and leverage the existing partnerships that GRID Alternatives has in place, since it is a well-established organization and has strong community relationships and existing trust. This helps reduce barriers to participation. In South Coast, since the district is not actively conducting outreach, it does not have existing community partnerships for CC4A implementation.

Innovation and adaptation. The air districts have each made efforts to innovate and adapt to improve CC4A implementation, even before the COVID-19 pandemic led to necessarily drastic adjustments in program operation. One of the common strengths of CC4A program implementation is a dedication to experimentation and adaptation in pursuing the most effective ways to reach participants and replace vehicles as needs evolve.

In the South Coast region, the district recognized program demand was routinely outpacing supply, so staff incorporated a tailpipe emissions test into the district's eligibility criteria to target vehicles retired through CC4A which are particularly high emitters. This was used to further restrict eligibility, using emission thresholds based on statewide and historical data from the program. The district adjusted the thresholds to eliminate approximately 15% of the cleanest cars from qualifying, with the goal to remove the highest emitters and maximize emission reductions in the air basin.

The SJVAPCD and Valley CAN have made consistent efforts to adjust outreach to reach targeted communities throughout the region, instead of targeting high-emitting vehicles. They have focused on innovating and adapting to reach DACs in the San Joaquin Valley, for CC4A as well as their smog repair program, Tune In & Tune Up (TI&TU), which has been operating for almost 10 years. They have utilized and evolved the TI&TU network approach and outreach methods to reach participants for CC4A in a multifaceted fashion (Pierce and Connolly, 2019; Pierce and

DeShazo, 2017), including exploring various social media channels to find the most effective one to use to communicate with customers. Additionally, they have implemented a follow-up process to ensure participants are able to get all of their application documents completed, which involves emailing and text messaging participants on a specific schedule following each CC4A clinic (Pierce and Connolly, 2019). The district itself stated that "*as the landscape of outreach changes, we just need to continue to be flexible and understand how we can reach folks in these communities where there is the greatest need*."

Although operating for a shorter period, the BAAQMD has also evolved its outreach processes using demographic data they have collected to identify gaps in program participation and make necessary adjustments. GRID Alternatives also reported making significant shifts in its case management as its team recognized how to work most efficiently with the program participants and help them complete applications, including more active outreach to in-process applicants to walk them through each step of the application, and thus avoid attrition. GRID Alternatives reports subsequently receiving significant positive feedback on its case management, particularly regarding the availability of support from case managers throughout the pandemic.

4.5.2.2. Community Capacity Building

We identified several specific opportunities for capacity building in the CC4A context, including (1) synergies with other programs, (2) the provision of direct assistance to participants, (3) support for communities through established partnerships, and (4) social and financial wellness opportunities.

Synergies with other programs. Providing CC4A participants with opportunities to sign up for other programs is beneficial from a financial as well as environmental standpoint. Districts and contractors can support benefit "bundling" (the tendency to enroll in more than one assistance program [Frank et al., 2006; Higgins & Lutzenhiser, 1995; Murray & Mills, 2014]) by enabling participants to sign up for more than one incentive program at a time, through providing additional opportunities either through their organization or offerings from partnering organizations.

With respect to the South Coast region, the SCAQMD financially supported a small portion of the implementation of the emPOWER campaign, which was developed by Liberty Hill Foundation and funds CBOs to conduct outreach to their communities to help enroll residents in a much wider variety of environmental benefit programs (Pierce and Connolly, 2020). Using this tool, participants can learn about and apply for more than 45 environmental benefit programs offered in the region, including CC4A, at the same time.

In the San Joaquin Valley, Valley CAN operates multiple clean vehicle related programs, including CC4A, as well as TI&TU,[14] providing an opportunity for vehicle repair for individuals who will not be replacing their vehicle. It also recently operated a pilot program with Southern California Edison (SCE) in Kings and Tulare counties, using the previously mentioned emPOWER tool, through which participants can sign up for a range of benefit programs available through SCE (Pierce et al., 2022).

The BAAQMD similarly leverages GRID Alternatives' existing solar energy program, Energy for All, to get participants signed up for as many programs as they are eligible for and interested in. GRID Alternatives mentioned that it relies heavily on cross-referrals from the solar program; if an individual happens to not be eligible for solar specifically, the organization provides information on other clean mobility programs, including CC4A. Their team also conducts cross referrals through CARB's One-Stop-Shop pilot as appropriate.

[14] Additionally, at Valley CAN's large TI&TU smog repair events (with capacities around 500 vehicles), they include other organizations and community groups which provide a variety of opportunities including, but beyond, the bundling of environmental incentive programs.

Provision of direct assistance to participants. Through direct case management, the districts and contractors can further provide community members with the tools to follow through with the application process, as well as help them gain a broader understanding of how to apply for these types of programs, which can support them in the future. All three of the districts employ contractors to perform case management, with varying strategies.

The SCAQMD currently has three different contractors for case management, of which we interviewed one for this study. Once an application is submitted to the program, it is sent to one of the three contractors, which then communicates with the participant to let them know what is missing from their application. One participant from this district cited the importance of having a good case manager and support from the district, explaining that they believe the positive experience they had was “contingent” on having a good, dependable CC4A contact.

In the San Joaquin Valley, Valley CAN primarily handles the case management process. After initial contact with potential applicants, either after an event or a preliminary phone call, staff follow up with participants with an application in process on a specific schedule. Valley CAN mentioned that each participant has different needs, and highlighted that it is “*focused on helping people overcome any burden that would prevent them from attaining our incentives.*” One participant from this district echoed the perspective of the previously mentioned SCAQMD participant, indicating that they also had a very strong case manager and good support throughout the process, which was necessary due to the challenges in completing paperwork, confirming eligibility, and program delays.

Similarly, BAAQMD staff mentioned occasionally helping with direct assistance as needed but highlighted the importance of GRID Alternatives in providing direct case management support. The GRID Alternatives team stated they do face inherent challenges associated with the volume of applicants, but they aim to respond to participants within two days to a week. Staff also mentioned inviting participants into the office to help with the application process as needed, and they have also been able to streamline some processes, such as transitioning to the use of a video call for verifying retirement vehicles are still operating, which used to require a visit to the dismantler. The two BAAQMD participants both highlighted that they needed to be invested in enrollment on their end and keep in active communication with program staff to keep the process moving forward - which they were - and therefore they had a successful experience.

Support for communities through established partnerships. We highlight CBO representation in several procedural equity aspects, as previously mentioned. Community partnerships can not only enhance CC4A implementation and increase participation in targeted communities, but also support the partnering organizations (Pierce & Connolly, 2020b). Within this aspect, we briefly highlight the associated district approaches within the context of supporting capacity building through such partnerships. In the San Joaquin Valley, apart from outreach assistance, partnering organizations also often reach directly back out to Valley CAN for direct assistance with signing community members up for the program. Additionally, Valley CAN holds its weeknight clinics at local restaurants, which is a mutually beneficial partnership as well. Several local organizations attend the larger TI&TU events, and use these events to connect with community members about the organizations' other focuses as well; Lideres Campesinas highlighted that it helps with the promotion of Valley CAN's events, but is also able to provide community members with information on domestic violence, one of its main initiatives, through this channel. As reported previously, the BAAQMD partners with similar types of organizations as Valley CAN, and attended events hosted by CBOs, as well as events such as farmers markets, to promote CC4A, while also supporting local communities.

Social and financial wellness opportunities. In terms of participation more broadly, each of the organizations we interviewed has received consistent, positive feedback from participants who have completed the process and received their vehicle. The contractor associated with the SCAQMD stated that they "*believe that [the statewide CC4A program] is one of the best social justice as well as air quality programs"* available. This coheres with the information shared during the participant interviews. Additionally, program enrollment can support economic resilience. All participants interviewed expressed gratitude for the program, with one citing a significantly increased credit score, and another stating the program has been "*life-changing*" (Table C.2). Several of the participants report consistently encouraging family and friends in their social networks to participate in the program.

4.5.2.3. Respect and Recognition of Diverse Perspectives

Similar to decision-making influence, the aspect of respect and recognition is less applicable to a program that is operated in a top-down manner than the first two aspects described in Sections 4.5.2.1 and 4.5.2.2, but we have identified several considerations relevant to procedural equity.

Responsiveness to participant feedback. Apart from significant positive feedback received, the districts and contractors have occasionally received constructive or negative feedback on the CC4A process from participants. For the SCAQMD, this feedback mostly involved frustration around time on various waiting lists, which was also mentioned by participants from all three districts. There have also been frustrations voiced from dealerships in the South Coast region around delays in the process and a general incompatibility with how the dealerships typically do business.

In the San Joaquin Valley, Valley CAN has received feedback surrounding its use of certain languages in outreach (e.g., running an advertisement on a specific language radio station but not others), to which staff reported always responding transparently. Since the Valley CAN team conducts online outreach and has a substantial online presence, they do often receive feedback through their online platform, to which they aim to respond when possible, again to increase transparency. The BAAQMD and GRID Alternatives did not report receiving significant constructive feedback from participants.

Program participant comments, including suggestions about potential improvements for the program, are quoted in Table C.2.

Efforts to overcome recognition and trust barriers. Barriers to program enrollment faced by potential CC4A participants include language barriers within outreach materials and case management support, as well as community mistrust of government programs, and misconceptions about electric vehicles. The districts and contractors can impact equity outcomes by recognizing these disproportionate challenges and undertaking efforts to reduce these barriers.

Language-related barriers are a challenge in CC4A implementation as well. Overcoming such barriers means ensuring that materials and translations are available in as many languages as possible. The SCAQMD contracted with a translation company due to district staff lacking fluency in some languages, and they have also brought district and contractor staff with multilingual skills to weekend workshops to support the case management process. The SJVAPCD has case management in Spanish through Valley CAN, relies heavily on Spanish language outreach, and involves CBOs when Asian-language translation is needed. Valley CAN mentioned that its team has *"translated a lot of our materials to be able to cater to the first-generation communities we have [many] of in the Valley, to help with our [application] process.*" The BAAQMD has case management in Spanish and offers support in other languages as needed as well.

An established challenge associated with environmental benefit programs more broadly (Pierce and Connolly, 2020), is high levels of distrust of government programs in low-income communities and communities of color. One participant highlighted this as a barrier to enrollment, indicating that they were very suspicious of the program and believed it might be a scam prior to participating (Table C.2).

To reduce community mistrust and misconceptions about the program and electric vehicles more broadly, interventions can include experiential testimonials offered by respected local partners, as well as more generic education through outreach materials and events. Along with simply reducing language barriers, advertisements in languages other than English are also "*very successful because [they give] credibility to the program; inherently there is distrust from non-English speaking communities toward government programs…[the ads] really boosted credibility and trust*," as stated by GRID Alternatives, and echoed by a BAAQMD participant. Each of the contractors expressed the opportunity CC4A presents as far as increasing education on this type of program to reduce these barriers.

The CBOs we interviewed also highlighted a persistent disconnect in terms of community members' understanding of the financial considerations of program enrollment, as well as how these vehicles can fit into their lifestyles. Many potential participants still consider electric vehicles to be a "luxury" (Pierce and Connolly, 2020) that they cannot afford to incorporate into their budget, and the organizations cited recurring resident concerns regarding electric vehicle limitations such as mileage range and charging infrastructure. GRID Alternatives mentioned that in-person events were incredibly important for "*breaking down barriers and misconceptions about driving electric*."

CBO representation. Not only are CBO partnerships related to participation and capacity building, they are also important when considering the involvement of CBOs in CC4A program implementation. Meaningful involvement can take place through direct partnerships, bringing CC4A representation to community events, or including CBOs in public CC4A events such as "ride and drives," and demonstrates respect for community preferences. These organizations serve as stakeholders to represent the community and disseminate information, and can also provide valuable perspectives on program implementation. Here, we provide a brief overview of CBO involvement in each district's implementation process as it relates to community engagement and respect.

The SJVAPCD stated that it "*keeps and builds relationships with leaders in the community, and makes sure those relationships are strong*." Valley CAN echoed this sentiment, declaring that the success of its partnerships in the Valley "*boils down to community trust…once you gain the trust of leaders and organizations, you overcome a huge step in the outreach process*." The Valley CAN team reports that this community trust and associated partnerships took years to build and is a key factor in the success of their outreach. The BAAQMD has partnered with several CBOs as well, mentioning specific nonprofits in the San Jose area that engage with Latinx communities. Its team also works with churches in the area and leverages the existing relationships that GRID Alternatives has in the region. By contrast, the SCAQMD does not currently have any collaborations with CBOs, but the contractor highlighted that as an important goal for the program in the future, stating that "*there is a lot more that can and needs to be done [including] engaging with local community organizations*."

4.5.2.4. Decision-Making Influence

As mentioned previously, the design and funding for the CC4A program is top-down in many ways. Therefore, decision-making influence is the least relevant aspect of procedural equity for this case study. Accordingly, in this section, we only briefly discuss opportunities and challenges associated with shared decision-making for a program such as CC4A. There are certain benefits to a top-down approach, such as maintaining uniform eligibility requirements and common reporting practices for equity purposes. If certain aspects of decision-making were delegated entirely to districts or shared with communities at a local level, this could lead to less accountability at the state level to meet broader California Climate Investment (CCI) goals. More broadly, scholars have identified that shared decision-making authority is typically not achieved in the environmental context, so a shift to considering power and influence is often appropriate (Bell and Carrick, 2017).

The CC4A program is unlikely to transform into a community-led or co-designed program, but it may be feasible to provide opportunities for communities and other stakeholders to formally provide feedback on the program and more readily incorporate ideas for improvement, both at the state and air district level. CARB has for some time hosted public workshops on their various household-facing programs, including CC4A (https://ww2.arb.ca.gov/cc4a-meetings-workshops), during which the general public can attend, ask questions, and present perspectives on the program. However, the existence of an opportunity to attend workshops does not equate to fair and genuine public participation, particularly with respect to challenges faced by marginalized groups in terms of access to the knowledge and other tools necessary to engage in such discussions (Bell and Carrick, 2017; Butler and Adamowski, 2015). Program challenges identified in the interviews and discussed throughout Section 4.5.2 provide evidence that the perspectives of community members and other stakeholders have not been incorporated sufficiently into program design.

Increasing impactful public participation in decision-making presents an opportunity to increase the attainment of procedural equity goals. Every participant interviewed had suggestions to improve the program, through increasing ease of enrollment, stronger dealership-program relationships, increased case management and district responsiveness, and the adjustment of eligibility requirements.

4.6. DISCUSSION

This study is the first to propose an analytical framework for the equity analysis of environmental benefit policies. This framework can be used for future evaluations of just transition policies more broadly within and outside of California, as well as adapted to evaluate procedural equity in other contexts. Researchers have highlighted the importance of the relationship between theory and practice in informing the evolution of these concepts and surrounding discourses (Schlosberg, 2013), which is directly applied through tangible case studies such as ours of CC4A.

This analysis is distinct from much of existing scholarship with respect to several conceptual and methodological aspects. First, as mentioned previously, we focus our analysis on procedural equity, since achieving justice goals of equal rights, representation, and treatment is not plausible in the just transition policy context. Second, the analytical framework presented in this study considers decision-making to be one, but not the central, component in attaining procedural equity, with respect to the consideration that processes (often mechanisms affecting distribution) surrounding an environmental event or policy implementation are not limited to decision-making but include aspects of all procedures driving outcomes. This methodological choice is encouraged by support for the value in the flexibility of the definitions of justice and equity, as mentioned previously, and enables us to tailor our evaluation to the specific focus of the study, without overlooking aspects of implementation that may not fall within a typical procedural or distributive framework. As posited by McDermott et al., in practice, criteria for achieving procedural equity can vary from influence in decision-making and policy development to taking steps to foster inclusion and prioritize marginalized populations (McDermott et al., 2013).

Finally, we analyze a new generation of climate-focused household-level just transition policies and associated benefit programs for which this framework was specifically adapted. Such programs offer high financial benefits with limited available funding, such as clean vehicle and solar incentive and rebate programs, and can support a just transition to clean energy by providing financial support and other benefits to disadvantaged populations who would not otherwise be able to afford the opportunity. Since these programs are not readily available to all that are eligible (due to funding constraints), this presents a unique scenario in which the design and implementation of these programs can substantially impact equity outcomes. This includes which populations are involved and ultimately receive incentives, as well as the associated benefits apart from the incentive, such as community education, capacity building, economic resilience, and program bundling. The limited funding highlights the importance of ensuring equity in opportunity, and the analytical framework proposed here is a tool that can be used to facilitate the attainment of procedural equity.

4.6.1. Impact of Regionally Distinct Program Designs on the Achievement of Procedural Equity Goals

In this case study, we present a novel analysis of procedural equity in the implementation of just transition environmental benefit policies and associated programs. We qualitatively analyzed to what extent program models with consistent policy design elements but operated by governing agencies in different regions can result in similar or dissimilar outcomes. We did this by analyzing procedural equity through a framework built specifically for the CC4A context, with respect to three main aspects: (1) participation and inclusiveness, (2) respect and recognition of diverse perspectives, and (3) community capacity building. A fourth aspect, decision-making influence, is less applicable in terms of CC4A specifically, but remains a key aspect of the procedural equity framework proposed in this study.

Regionally distinct program designs can be valuable, with respect to diversities between communities and the need for community-tailored approaches to facilitate successful outreach and inclusion (Butler and Adamowski, 2015; Gorman et al., 2013; Ruano-Chamorro et al., 2022; Williamson et al., 2020; Yenneti and Day, 2015). For example, different communities utilize different forms of communication, such as radio, television, or social media. Some populations require more education on benefit programs when considering participation, to increase comfort with the concept of enrollment and the understanding of benefits.

However, our results indicate that the regionally distinct implementation structure has resulted in some inconsistency in procedural equity outcomes, with the most notable differences with respect to participation and inclusiveness. We found that the extent, type, and collaborations involved in the outreach process varied widely across the districts. Some of the major differences in program implementation procedures in the South Coast and San Joaquin Valley regions, first mentioned in a 2017 report on EFMP (the early stage of CC4A) (Pierce and DeShazo, 2017), have persisted, with resulting distinctions in the extent to which different procedural equity measures have been attempted and achieved in each region. These differences reflect diverse priorities adopted in the two regions regarding program objectives, beyond those which are laid out in state guidance and met by both districts. While SCAQMD successfully exhausted incentive funding, maximizing participation in one sense of the term, they did not conduct targeted outreach to reach the most in-need communities or partner with community groups. This can be considered in the context of a study on capacity building efforts in which the authors distinguish between more surface-level efforts that focus only on actual participation from community members, but do not focus on facilitating community knowledge-building and commitment to the efforts, citing the latter as vital for valuable engagement (Williamson et al., 2020). One previously mentioned study also pointed out the necessity of using funding not simply for the incentives, but for knowledge dissemination about the existence of the incentives (Palmer et al., 2013); along those lines, the SCAQMD program participants highlighted a lack of program advertising and a resulting lack of awareness about the program in their communities.

The importance of community capacity in various contexts is well-established (Goodman et al., 1998; Williamson et al., 2020). Capacity building was accomplished in terms of synchronizing offering CC4A benefits along with other assistance programs, involving and compensating CBO staff in outreach, and providing direct assistance to potential participants throughout the enrollment process, with each district achieving these to varying extents. The potential for energy and environmental program bundling enables community members to maximize financial benefits as well as learn about a myriad of environmental and energy issues, as previously mentioned. Additionally, the value of direct case management and enrollment support for targeted populations to increase uptake in assistance programs is highlighted in existing studies (Gorman et al., 2013; Pierce and Connolly, 2020). All three districts supported these two conditions to a certain extent, but only the SJVAPCD and BAAQMD engaged with CBOs, which can support the organizations through compensation, but also support communities through providing increased exposure to the community support campaigns (apart from CC4A) operated by partnering CBOs.

In this case study, all three districts made efforts in support of respect and recognition, though district responsiveness to participant feedback and active efforts to aid enrollment through the elimination of barriers and CBO partnerships again varied slightly, with all districts providing language translation services, but some not utilizing CBOs or conducting targeted outreach to reach specific populations with preconceived notions regarding CC4A and associated factors. Program efforts surmounted language and trust barriers, including general mistrust of government programs and misconceptions about electric vehicles that persist in some populations. In the context of CC4A, these efforts reflect accepting and valuing community differences, and support the procedural equity aspect of respect and recognition (Bell and Carrick, 2017; Ruano-Chamorro et al., 2022). One program participant from the BAAQMD suggested that the CC4A program may even present an opportunity to increase trust in government through the implementation of these programs (Table C.2). This is unsurprising, considering that existing procedural justice literature suggests that supporting participation with respect to a seat at the table in decision-making processes has the potential to increase trust in both the government (in this context, reduce mistrust of such governmental programs) and environmental technologies such as clean vehicles (Gross, 2007; Leach et al., 2005; Mitra, 2021; Renn et al., 1995; Zoellner et al., 2008), as cited in (Yenneti and Day, 2015).

The varying outcomes observed are reflective of the flexibility in program implementation, which we have shown here can be both beneficial and detrimental to equity impacts.

4.6.2. Exploring the Relationship Between Procedural and Distributional Outcomes

Apart from the distinct procedural equity goals, it is also important to discuss the relationship between procedures and distribution in this context, as it has significant implications for maximizing equity in program implementation. Studies have discussed the complexity of the connections between the two forms of justice in various contexts (Bell and Carrick, 2017; Blue et al., 2021; Hauenstein et al., 2001; Hunold and Young, 1998; Schlosberg, 2007; Simpson and Clifton, 2016). Procedural justice is an independent aspect of environmental justice and should be focused on independently, but achieving procedural justice can also lead to fairer outcomes (Bell and Carrick, 2017; Domingue and Emrich, 2019; Hunold and Young, 1998; Schlosberg, 2007); some scholars suggest procedural environmental justice must be achieved in order to successfully attain distributive environmental justice (Bell and Carrick, 2017; Schlosberg, 2007).

Our results present clear distributive patterns across air districts which likely reflect procedural differences. The differing approaches to program implementation between the SJVAPCD and SCAQMD presented in Section 4.5.2 and discussed in Section 4.6.1 can be considered with respect to differing distributive outcomes as well (see Section 4.3.2 and Appendix A for an overview of incentive distribution). These two regions contain almost 90% of the DAC census tracts in the entire state. The distributive results reflect these differing approaches; while the SCAQMD has successfully distributed more than half of all CC4A incentives, which is a success in terms of overall program participation, they have reached significantly fewer DAC tracts proportionally. Almost one-third of DAC tracts in the region have not received any incentives (Table 4.1), compared to only 4% for the San Joaquin Valley.

Along with the evidence base on the relationship between procedural and distributive justice cited previously, these patterns are also consistent with findings of limited peer-reviewed and gray literature on characteristics of successful outreach campaigns to access targeted communities (Gorman et al., 2013; Pierce and Connolly, 2020). A study on outreach efforts for the Supplemental Nutrition Assistance Program (SNAP) highlighted the importance of community partnerships, direct assistance, and adaptation of strategies to reach eligible potential participants that are the most in-need (Gorman et al., 2013). It can also be considered through the lens of factors to prioritize in community engagement and empowerment, such as the importance of valuing and accounting for "informal community structures" (Butler and Adamowski, 2015) and engaging in critical capacity building activities to prioritize community needs and development (Williamson et al., 2020). A recent review on the just transition to clean energy also highlighted the essential nature of community partnerships to facilitate successful program implementation (Carley and Konisky, 2020).

In the Bay Area, a region with fewer DACs and LICs to consider and with a much shorter timeframe of implementation, it is more challenging to make equivalent comparisons. Considering their plan to increase targeted outreach to DACs, this motivates the analysis of a future case study to evaluate procedural and distributive outcomes of the adaptation in the air district's program implementation strategies.

4.6.3. Case Study Strengths and Limitations

The case study analysis has several strengths. First, it is novel in its procedural evaluation of an environmental benefit program, which are typically analyzed for distributive elements; here, we focus on procedures, but also include a qualitative discussion of the relationship between procedures and distribution. Accordingly, these findings have distinct implications for environmental benefit policy in California and more broadly. Additionally, we interviewed multiple different types of stakeholders, including those with the most instrumental roles in program implementation, as well as individuals and organizations directly impacted by program operation, to develop comprehensive qualitative data to analyze within the analytical framework.

In terms of limitations, the CC4A program is currently expanding statewide, but to complete this analysis, there were only three districts that had been operating the program for several years that we could include in the analysis. Additionally, there may be bias associated with participants who self-selected into the interview process; this is not a limitation with the other stakeholders interviewed, as they represent the only (or one of few) organizations implementing or involved with the program. Finally, this analysis is subject to subjectivity concerns associated with qualitative thematic analyses, which we aimed to minimize through meeting the characteristics of a trustworthy thematic analysis (Nowell et al., 2017).

4.7. CONCLUSION

Procedural equity is a particularly important consideration for environmental benefit programs such as CC4A, which need to target relatively large per-household incentives to those who truly need them. Through this case study, we find that regionally-specific household-level just transition policy designs have significant impacts on the achievement of procedural equity goals.

This analysis demonstrates the value of a shift away from a sole focus on distribution to considering multiple dimensions of equity in the design and implementation of household-level environmental benefit programs, including many of those in the Inflation Reduction Act, as well as environmental processes more broadly. Though the distribution of benefits or environmental risks continues to be an important metric for evaluation, a more holistic assessment including an analysis of equity or justice in procedures can illuminate issues and inconsistencies in the development and implementation of policies, programs, or processes. These procedural concerns can also have a cascading impact across the equity dimensions of distribution and recognition, as they are all deeply intertwined. Such considerations should be incorporated into metrics for evaluation determined by program stakeholders.

We have developed a framework that can be used for future evaluations of similar just transition policies and associated large-scale environmental benefit programs, as well as adapted to analyze procedural equity or justice in other relevant environmental contexts. Future research in this space should utilize tailored analytical frameworks for evaluating multiple dimensions of equity and justice in various contexts, as well as analyze specific programs and processes as we have done for the CC4A case study here; such programs will continue to operate for years into the future and impact many individuals throughout the state and U.S. more broadly. This and similar evaluations have significant implications for increasing equity in environmental incentive policies and associated programs, identifying methods to ensure the social, environmental, and health benefits to priority populations are maximized.

These findings also present several policy implications. Our results suggest certain methods can better facilitate equitable procedural implementation of large, limited funding household-level incentive programs. First, it would be beneficial for main implementing agencies to provide more guidance and certainty around the timing and extent of program funding. Relatedly, guidance should be developed around the maintenance of regional waiting lists, and their associated equity implications. Additionally, such programs should consider the least burdensome, but still rigorous means of instituting eligibility verification procedures to ensure that the households that are the intended beneficiaries of such programs are those who benefit most easily and extensively from it in practice. Finally, and particularly in scenarios where funding gaps persist and program demand remains elevated, as is the case for CC4A, the state should consider instituting additional, evidence-based targets for advancing distributive equity beyond those currently used as eligibility standards.

To meet necessarily ambitious environmental targets and equity goals, more funding must be routed to such climate mitigation interventions through state and federal programs. In this process of scaling climate efforts, demand for household-level just transition policies and associated programs will continue to grow. Instituting evidence-based equitable program implementation procedures will help ensure that the most in-need households have the greatest opportunity and access to incentive dollars, and more broadly, will be crucial in enabling a just transition.

CHAPTER 4 APPENDIX

Appendix A. Case study background: Distributional equity analysis

Methods

Although this analysis is focused on procedural equity in implementation, we include a distributive equity analysis to inform our qualitative approach and a discussion of the relationship between procedural and distributive outcomes (Section 4.6.2). We developed descriptive statistics to broadly look at benefit distribution at the census tract level using participant-level enrollment data.

To assess distributive outcomes within the three districts, we analyzed anonymized, participant-level data (n = 12,955) for each CC4A incentive recipient through June 2021, to align the data as closely as possible with the timeframe in which most interviews were conducted (early 2021). These data were acquired through CARB's public records act (PRA) process. The dataset includes each participant's census tract of residence, year of incentive provision, household income level, low-income household and community status, incentive amount, and funding source. We joined the detailed participation data with other publicly available data on SB 535 DAC status[15] (as presented in CalEnviroScreen 3.0) and AB 1550 LIC status to enhance our analysis.

To determine the distributive equity impacts from the CC4A program, we quantified the following outcomes of the program in each air district:

- average CalEnviroScreen 3.0 score of participants' tracts;
- percent of incentives distributed to DAC census tracts;

[15] Though CalEnviroScreen 4.0 was released in late 2021, we present metrics from the 3.0 version since this specific version was applicable to incentive distribution during the timeframe of our analysis.

- percent of incentives distributed to top 10% DAC census tracts (highest level of CalEnviroScreen vulnerability);
- percent of DAC tracts that have not received incentives;
- percent of incentives distributed to LIC census tracts;
- percent of incentives distributed to households under 225% of the Federal Poverty Level (FPL); and
- percent of incentives distributed to low-income households (low-income designation based on county-specific thresholds).

These results are presented in Section 4.3.2 as a supplemental background analysis and discussed in the context of the procedural equity analysis.

Supplemental Results

Table A.1. Incentive distribution and participant characteristics by air district: income-related metrics

District	Total # Incentives	% of Tracts in Region That Are LICs (AB 1550)	% of Incentives to LICs (AB 1550)	% of Incentives to Households Below 225% FPL	% of Incentives to "Low-Income" Households (Cost of Living Adjusted)
SCAQMD	7,657	52%	67%	89%	96%
SJVAPCD	3,587	57%	69%	91%	83%
BAAQMD	1,381	36%	54%	78%	96%
All Districts (including SMAQMD)	12,955	48%	66%	88%	92%

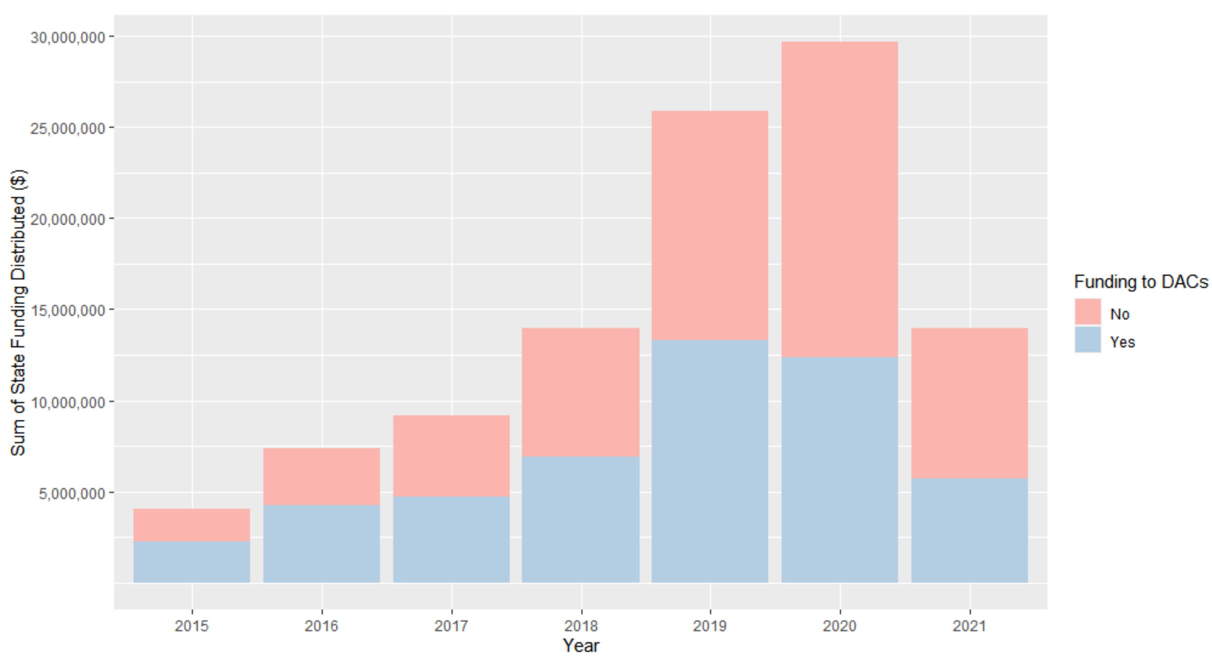

Figure A.1. Sum of state incentive funding distributed through CC4A to DAC and non-DAC census tracts through June 2021.

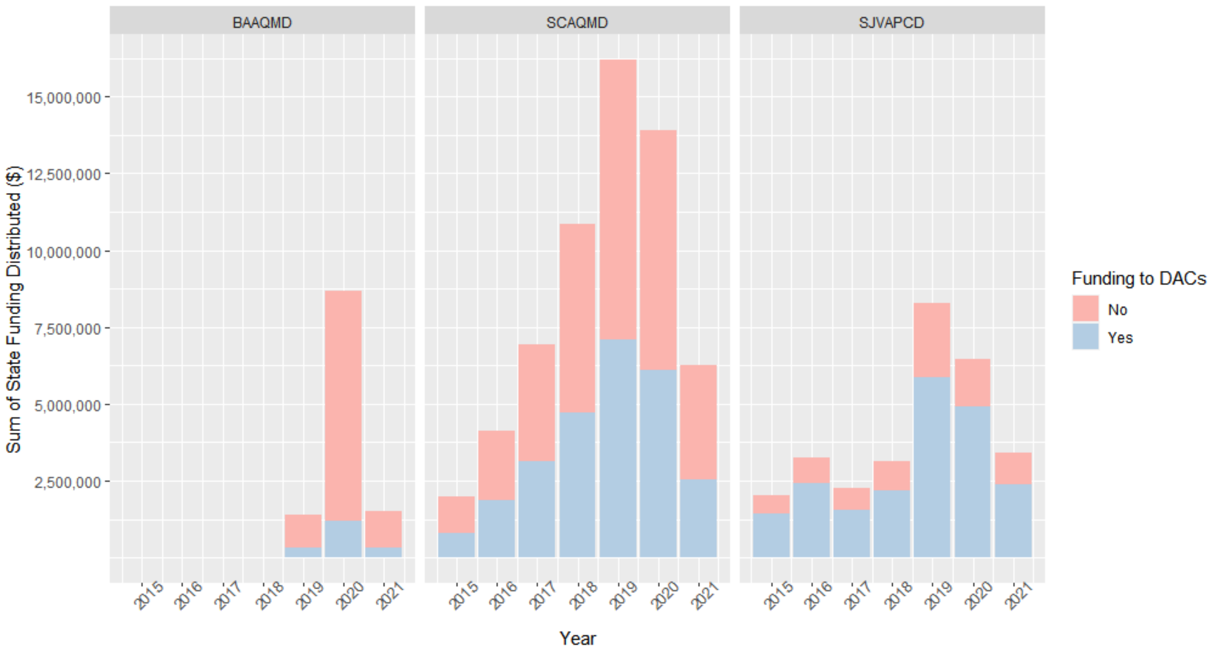

Figure A.2. Sum of state incentive funding distributed through CC4A to DAC and non-DAC census tracts through June 2021, by air district.

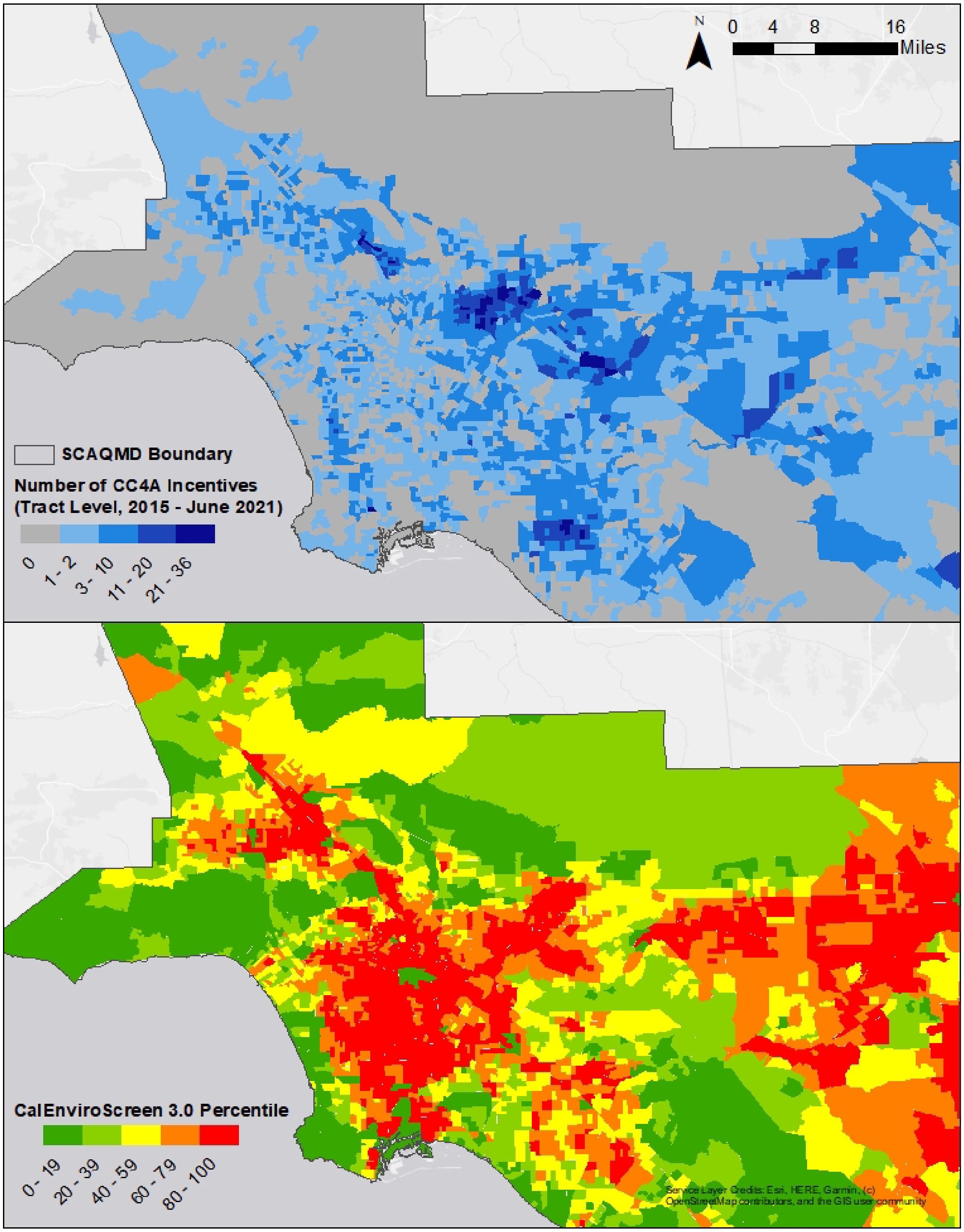

Figure A.3a. Distribution of CC4A incentives through June 2021 under jurisdiction of the SCAQMD.

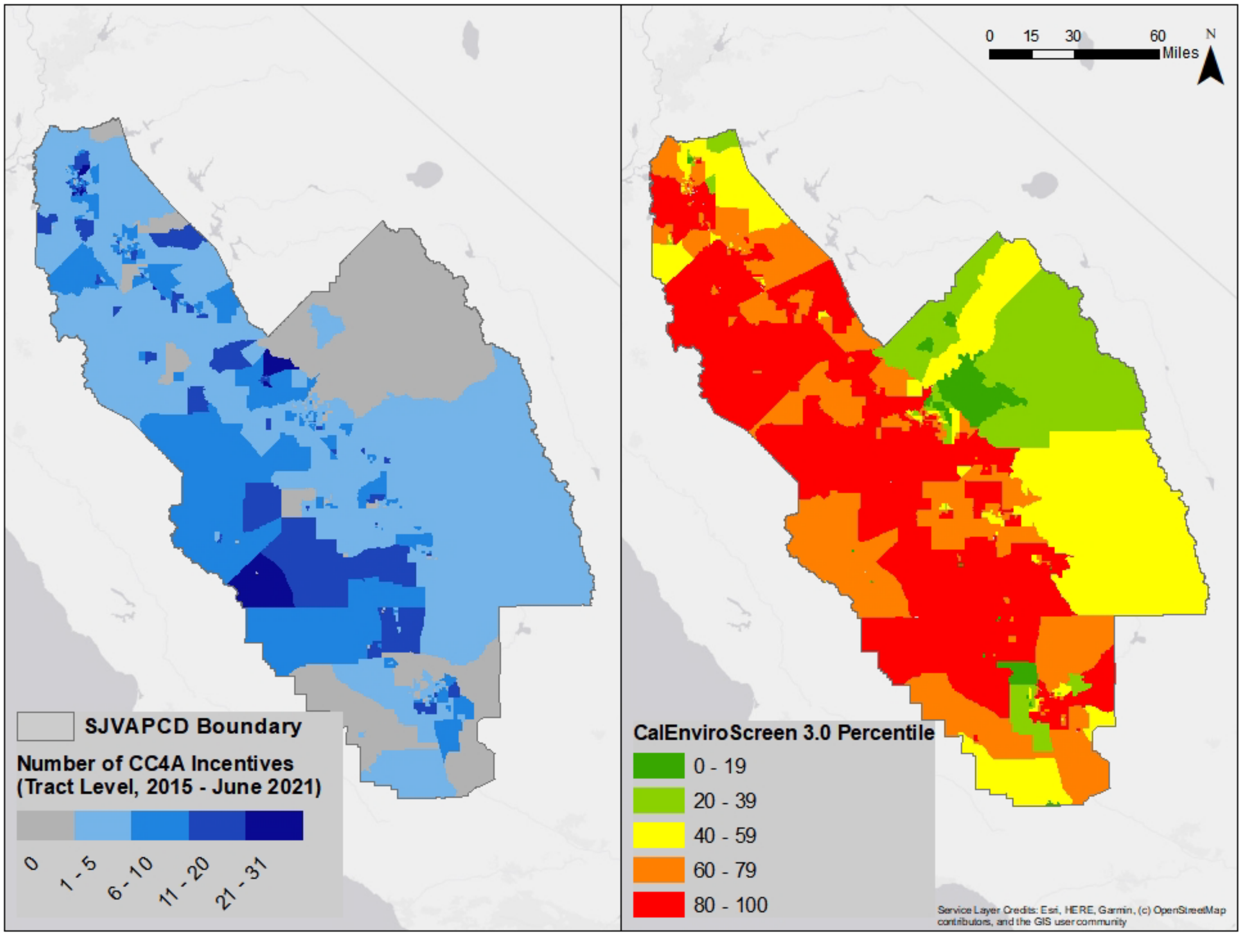

Figure A.3b. Distribution of CC4A incentives through June 2021 under jurisdiction of the SJVAPCD.

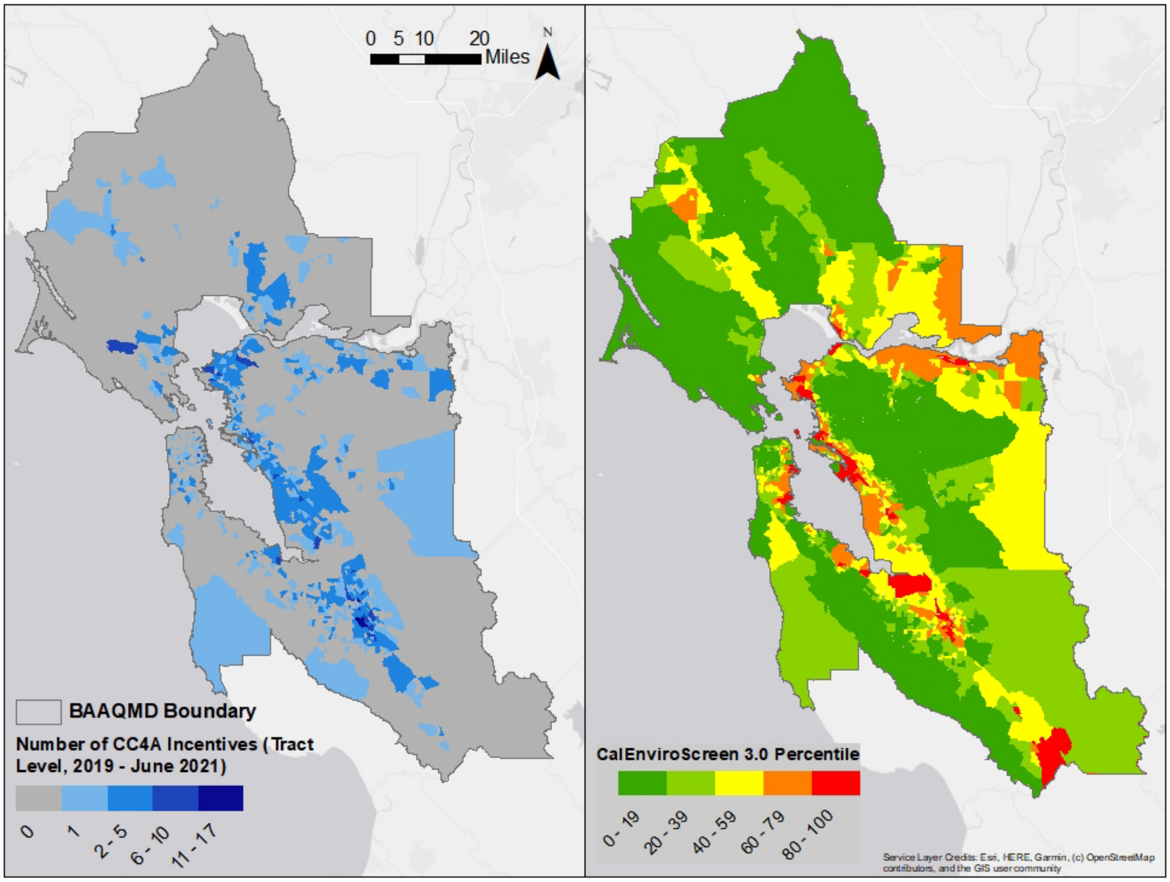

Figure A.3c. Distribution of CC4A incentives through June 2021 under jurisdiction of the BAAQMD.

Appendix B. Semi-structured interview instruments

Interview questions for district staff and contractors

- **Overview**
  - How would you describe the program outreach process in the district you work/worked with?
  - What role does the contractor play versus the district staff?
- **Physical Events**
  - Does the district hold public events focused on CC4A outreach and enrollment?
- **Partnerships**
  - What organizations does the district partner with in facilitating program implementation?
- **Other Forms of Outreach**
  - What methods of outreach does the district use to reach potential participants? (social media, radio, etc.)
- **Case Management/Direct Assistance**
  - Is there direct assistance available to participants in the district to help them through the application process?
- **Additional Questions**
  - Have you received any feedback from program participants on program outreach, positive or constructive, that you would be comfortable sharing?
  - In your opinion, what are the strengths of the district's CC4A implementation process?

  - In your opinion, what challenges has the district faced throughout program implementation?
  - Do you/the district have any plans to adjust program implementation?

Interview questions for community-based organizations

- What is the extent of your/your organization's knowledge about the Clean Cars 4 All (CC4A) program?
- What is the extent of your organization's involvement in program implementation, if at all? Has your organization participated in any public events involving CC4A (e.g. Ride and Drives)?
- In your organization's experience, what is the community outreach process for this program in your air district (e.g. social media, radio, etc.)? Do you have perspectives on the efficacy of different types of outreach within your community?
- Have you heard any general thoughts or feedback from your community members about the program?
- Have you noticed specific strengths or challenges in the district's approach to program implementation?
- What do you think are ideal characteristics for this program/type of program?

Interview questions for participants

- **General experience with CC4A**
  - Please describe your experience with the Clean Cars 4 All (CC4A) program.
  - What made you (or someone in your household) decide to ultimately participate in the program?
  - How has the replacement vehicle impacted you and your family's daily life?

- **Outreach**
    - In your experience, what is the community outreach process for this program in your region and what organization is conducting the outreach (e.g. social media, radio, etc.)?
    - Do you have perspectives on how well different types of outreach work for this and similar benefit programs (e.g. CARE) within your community?
- **Community perspectives**
    - Do you have feedback, positive or constructive, about the program?
    - Have you recommended the program or clean vehicles to anyone based on your experience?
    - Have you heard any thoughts or feedback from other community members about the program that you can share?
    - Have you noticed any common perceptions in your community regarding the uses and benefits of electric vehicles?
    - What do you believe are the largest barriers to clean vehicle uptake in your community?
- **Ideal program characteristics**
    - What are ideal characteristics for this program/type of program focused on sustainable transportation?
    - Would changes in program design/implementation make program enrollment more accessible for members of your community?
- **Big picture:** What would you identify as the major barriers to affordable transportation in your community?

Appendix C. Supplemental Tables

Table C.1. Examples of procedural justice or equity principles applied or identified in the environmental literature (non-systematic list)

Study subject matter	Procedural justice or equity terms used	Procedural justice or equity principles/aspects	Citation
Hazardous facility siting	Procedural 'conditions'	Inclusiveness; consultation over time; equal resources and access to information; shared decision-making authority; authoritative decision-making	(Hunold and Young, 1998)
Solar energy: case study of solar park development	Justice	Information exchange; inclusion and enfranchisement; representation	(Yenneti and Day, 2015)
Government-led community-based forest management	Equity	Measures of participation: Participation level; village institution membership; satisfaction with participation Defined procedural equity as: "the level and inclusivity of participation in village institutions and satisfaction with this level of participation"	(Friedman et al., 2020)
Ecology and criminology	Justice	Respect; neutrality/impartiality; voice	(Maxwell and Maxwell, 2020)
Environmental governance in sustainability organizations	Justice	Recognition of multiple perspectives; effective citizen participation (in the decision-making context); building capacity	(George and Reed, 2017)
Conservation	Justice	Presented eleven procedural justice criteria in three key domains. Process properties domain: Transparency, accountability, neutrality, correctability, ethicality, trustworthiness Agency of participants domain: voice, decision control, capabilities Interpersonal treatment: respect, politeness	(Ruano-Chamorro et al., 2022)
Environmental management: case study of biodiversity conflicts	Justice	Drew from literature and their case study to select the following "codes" through which to consider procedural justice in the context of decision-making and action implementation: Representation; consistency; respect; trust	(Lecuyer et al., 2018)

Table C.2. Key participant quotes

Region	Statement	Procedural equity aspect(s)
SCAQMD	*"That was the only disappointing thing – I would have liked to have seen it more well-advertised. Even during the process, I never heard about it, and then bringing it up in conversation to other people that might be eligible for it, and trying to pay it forward and let other people know…everybody was clueless to the program even existing. I mean, I've never seen any social media posts, any advertisement. I know that when you go through the [CC4A] website, they do have public events, but it's kind of like you have to look for it versus it being readily available or advertised."*	Participation and inclusiveness
BAAQMD	*"I have lots of ideas [on outreach]. Even sometimes ideas people might be thinking but are afraid to say…outside the box. I'm sure [the program operators] are thinking along those lines too, but they have to, if they really want to reach the targeted community. First off the top…people are so suspicious of the government and any type of program. When I first heard of this myself, I was like…no way…that is too good to be true…this has got to be a scam…Something new like this…[people] are always very suspicious of it. Has to be one of their own for them to be more open to it… [someone they know] really got [a vehicle]. Ok, it is legit. They would be less afraid"*	Participation and inclusiveness, respect and recognition of diverse perspectives, decision-making influence
SJVAPCD	*Regarding the most effective outreach methods in their community:* *"Social media I think is a big thing, because that's where I found it. Maybe if they did do TV commercials or maybe put flyers in with like water bill, or electric bill, whichever they are affiliated with – maybe some kind of flyers or note on bill itself to say that's available…I would just think social media would be the biggest thing."*	Participation and inclusiveness, respect and recognition of diverse perspectives, decision-making influence (opportunity for community input)
BAAQMD	*Regarding the most effective outreach methods in their community:* *"Word of mouth really…some people don't like to watch [tv] commercials. Facebook will reach more people…now whether they'll believe or notice or what not… or Instagram…but with all the controversy going on with all these social media things right now politically, I don't know what people would believe or not. As far as the Latin community, I think that would be more based on… Spanish-speaking [radio stations] …would probably reach them*	Participation and inclusiveness, respect and recognition of diverse perspectives, decision-making influence

	really well and that would be more trusting for them…not presented so much as a government program."	(opportunity for community input)
BAAQMD	*"This is the newest car I've ever had in my life…my credit score was like 420…and to this day now my credit score is like 721...that is how it benefited me…I'm very grateful."*	Community capacity building
BAAQMD	*"This program really has been life changing. Life changing for me and my kids to change the main source of transportation, I just appreciate it so much."*	Community capacity building
SCAQMD	*"All the staff was really willing to help and…going the extra mile... It was really dependent on me getting a good, competent, reliable representative at [CC4A] to have a good experience [with the dealership], so I think a lot of it was contingent on that"*	Community capacity building
SJVAPCD	*"I think it really does make a difference, the grant money that they give to go towards the car, the down payment offsets some major costs…not having to put so much down on a down payment makes a huge difference on our monthly payments."*	Community capacity building
SCAQMD	*The biggest ask or want would be for Tesla to be on the list. There are so many people this would help. I think for a lot of people Tesla would be a number one choice…I think that would be the biggest help for EV adoption…people wouldn't have a lot of the hindrances of a public charging station that doesn't work…* *And then also just having more dealerships participating in the program and having quicker turn times on the replace your ride side of funding.*	Decision-making influence (opportunity for community input)
SJVAPCD	*"Hardest part here…is the whole charging thing. They ask us not to run our air, and they ask us not to do all these things with our electricity during peak times when it's so hot here, but then they want us to buy electric cars which we can't charge at home and we don't have charging areas…They are pushing that on us but not providing adequate places for us to charge them if we need to. "*	Decision-making influence (opportunity for community input)
BAAQMD	*"I particularly know quite a few people that would have been perfect for this program but their car wasn't registered. If there was something on a case by case basis…[to allow people to participate in those cases]."*	Decision-making influence (opportunity for community input)

5. CONCLUSIONS AND FUTURE DIRECTIONS

In this dissertation, we characterize public health and equity outcomes associated with environmental exposures and policy implementation across California, with respect to three topics: (1) access to green spaces, (2) wildfire-associated air pollution exposure, and (3) procedural equity in the implementation of just transition policies. We use various methods in the environmental health sciences field – including predictive modeling, geospatial techniques, dose-response analysis, and qualitative thematic analysis – to quantify environmental health impacts from various exposures and identify evidence-based strategies to improve environmental conditions, providing action-oriented research that can result in policy change. This work is particularly relevant considering the state's ambitious climate change targets, as well as the priorities identified by the California Environmental Protection Agency, which include community resilience, wildfires, and zero-emission vehicles. Additionally, the topics in this dissertation are rising in importance as the vulnerability of disadvantaged populations increases with impending climate impacts. The changing climate is accompanied by a suite of environmental health concerns, as California's population is exposed to more extreme weather events, including catastrophic wildfires and extreme heat, as well as drought, and increases in local air pollution (Shonkoff et al., 2011; Watts et al., 2015). This research provides a unique perspective on multiple environmental and health topics to be considered by environmental justice advocates and policymakers when assessing the full suite of costs and benefits reaped from potential interventions, including climate mitigation approaches.

In **Chapter 2**, we used recently released small-area life expectancy (LE) data to quantify the relationship between LE and green space in Los Angeles County, a large diverse region with inequities in park access. To date, no other studies have investigated the association between green spaces and LE using small-area data in the U.S. Our predictive models analyzing the remote sensing and satellite imagery-based greenness metrics demonstrate that neighborhood-level greenness, as represented by tree canopy coverage and normalized difference vegetation index (NDVI), is positively associated with LE. An interquartile range-level increase of each green space metric is associated with an average increase of several months of LE on an individual basis, which is substantial in magnitude when considering the population of 10 million in LA County (US Census Bureau, 2015). In terms of park access, after adjusting for spatial random effects, we found evidence that access to higher park acreage is only predictive of longer LE for populations residing in census tracts with a lower percentage of tree canopy cover than the county median, though the effect estimate for parks is less robust than the estimates for tree canopy and NDVI. This finding suggests that parks become a more important component of green infrastructure when other sources of green space are unavailable, which within the Los Angeles context is often in neighborhoods with lower socioeconomic position and more people of color. A supplementary simulation found that more than 110,000 years of LE could be saved for just Hispanic/Latinx and Black residents if park acreage were to be increased to the median level in less green areas. Our findings from **Chapter 2** suggest that equitable access to green spaces could result in substantial population health benefits, which has distinct policy implications.

For **Chapter 2**, future research should extend and expand this study in other regions, as well as investigate other metrics of park access, including the utilization of parks through park programming (e.g., recreational offerings), and the quality of parks more broadly. Others could build upon our findings and further explore the differential impacts of park access on LE in populations with varying socioeconomic position, race and ethnicity, and exposure to environmental factors (such as surrounding greenness), which has distinct implications for health equity and urban planning.

In **Chapter 3**, we characterized the adverse impacts of fine particulate matter ($PM_{2.5}$) from wildland fire smoke on the health of the California population during the eleven-year period of 2008-2018. This analysis is novel with respect to the long-term nature of the evaluation over an eleven-year period, estimation and application of a chronic dose-response value for wildfire-specific $PM_{2.5}$ exposure, and use of highly-resolved health data at the ZIP code level. We estimate between 47,100 and 50,360 premature deaths are attributable to fire $PM_{2.5}$ exposures over the eleven-year period, with an associated economic valuation of $387 to $413 billion. These findings extend a growing body of evidence on climate-related health impacts, suggesting that wildfires account for a substantial mortality and economic burden in California, a state with many fire-prone regions and a diverse population to protect. Ultimately, continuing to grow the evidence on health impacts from wildfires and other climate-related exposures is critical in mitigating the impacts of climate change and protecting vulnerable populations throughout the state.

For **Chapter 3**, future research should prioritize the development of chronic wildfire mortality risk estimates to utilize in future health impact studies such as these. Additionally, the improvement of wildfire $PM_{2.5}$ modeling techniques will increase precision in health impact assessments. While several machine learning analyses discuss results in the context of wildfire smoke, the models typically solely predict total $PM_{2.5}$ (Di et al., 2019; Li et al., 2020; Reid et al., 2021); only recently have models isolating fire-specific $PM_{2.5}$ been built, with considerable limitations (Aguilera et al., 2023; Childs et al., 2022). This is an area for future research and development, including further comparison against typical chemical transport models to determine the best approaches to develop exposure surfaces for health analyses. Finally, examination of the sociodemographic trends in exposure to $PM_{2.5}$ and resulting health impacts associated with wildfires will be vital in protecting vulnerable populations in both California and across the U.S. as the climate continues to change.

In **Chapter 4**, we analyzed procedural equity in the context of household-level just transition policies. We accomplished this through a case study of the largest equity-focused electric vehicle incentive program in the United States, the Clean Cars 4 All (CC4A) program offered in California. We developed a conceptual procedural equity framework for household-level just transition policies, with respect to four aspects: (1) participation and inclusiveness, (2) community capacity building, (3) respect and recognition of diverse perspectives, and (4) decision-making influence. We find that though regionally distinct strategies are valuable in tailoring approaches to meet community heterogeneity, the decentralized program implementation structure has resulted in inconsistency in the realization of procedural equity outcomes. Additionally, these procedural impacts also influence the distributive dimension of equity. The framework developed in this study can be applied in future procedural equity analyses of other policies, and our findings have significant implications for ensuring a just transition to clean energy more broadly.

In terms of future research for **Chapter 4**, additional studies in this space should utilize tailored analytical frameworks for evaluating multiple dimensions of equity and justice in various contexts, including the analysis of specific programs and processes as we have done for the CC4A case study here. Such programs will continue to operate for years into the future and impact many individuals throughout the state. This and similar evaluations have significant implications for increasing equity in just transition policies and associated programs more broadly, identifying methods to ensure the social, environmental, and health benefits to vulnerable populations are maximized.

In sum, the research included in this dissertation can aid in developing a comprehensive understanding of the pathways to increase health and equity across California, through increasing beneficial environmental exposures, mitigating adverse environmental exposures, and supporting a just transition.

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