Supporting Equitable Land Management Decisions Through the Characterization of Different Sources of Smoke Exposure for At-Risk Communities

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Abstract

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Communities across the western United States experience hazardous smoke exposures from multiple fire sources. As wildfires become more frequent and severe, smoke exposures stemming from these fires are also worsening. Prescribed burning is a promising forest management strategy that can mitigate future wildfire risk, but also contributes to biomass burning emissions and human exposure impacts. Agricultural burning is another commonly used management tool, implemented on agricultural landscapes across the West, but also contributes to ambient air pollution. Despite these multiple sources of smoke exposure, few studies have examined their differential exposure impacts, particularly among communities most at-risk. This dissertation seeks to address this gap, by characterizing smoke exposures from each of these fire types in the recent past and by examining how these exposures may change due to the implementation of new forest management strategies in the future.

First, we generate a fire type-specific 1 km biomass burning emissions inventory, using the Fire INventory from NCAR (FINN) and a series of federal and state-level fire and fuel treatment inventories to distinguish between wildfire, prescribed, and agricultural burn emissions across Washington, Oregon, and California. We then use that emissions inventory to model surface-level $PM_{2.5}$ concentrations and population-level exposures, using the GEOS-Chem atmospheric chemical transport model at a 0.25° x 0.3125° resolution from 2014-2020. We identify distinct spatiotemporal exposure patterns for each fire type, which differentially impact population sub-groups within states. For example, we observed disproportionately higher exposures to wildfire smoke among Native communities and higher exposures to agricultural burn smoke among lower socioeconomic groups in California.

Next, we specifically focus on the relationship between wildfires and prescribed burns to assess the exposure and health impacts of six forest management scenarios proposed for a 2.4 million acre landscape in the Central Sierra, California. Using wildfire and prescribed burn emission estimates generated using a landscape forecasting model, we modeled fire type-specific smoke exposure impacts using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model at a 27 km resolution. Among the general population, we estimated that moderate amounts of prescribed burning can reduce wildfire-specific smoke exposures and asthma-related health impacts. We observed a similar pattern when examining exposure impacts among outdoor agricultural workers in California, in which total smoke exposure is lowest under scenarios that call for moderate amounts of prescribed burning; however, we also observe a decreasing exposure benefit under scenarios that call for greater amounts of prescribed burning due to the smoke contributions from the fuel treatment themselves.

Together, this two-part analysis describes the distinct exposure patterns from different types of fire on the landscape and what role management can play in reducing exposure burdens. The results of this dissertation emphasize the need for more tailored exposure reduction strategies that consider the source of smoke. Additionally, it highlights the importance of increased collaboration between public health and natural resource management agencies in a way that can optimize the achievement of management objectives, while simultaneously minimizing harmful exposure burdens among at-risk communities.

Table of Contents

List of Figures

List of Tables

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Chapter 1: INTRODUCTION

Wildfire trends in the western U.S.

Wildfires are a natural ecosystem regulator. Regular wildfire regimes promote forest equilibrium and recovery and are integral components of the life cycle of various plant and animal species (Barros et al., 2018; Hessburg et al., 2015; McCauley et al., 2019). Despite their ecological benefits, wildfires can pose serious threats to human life and property. This is of particular concern given that the total area burned annually has been steadily increasing across the western U.S. for decades (North et al., 2015; Parks & Abatzoglou, 2020). This worsening wildfire trend can largely be attributed to three factors, the first being climate change. Increasing temperatures and aridity, as a result of human-driven climate change, are contributing to longer wildfire seasons across the western U.S. A study of the impacts of climate trends over the past several decades found that climate change was responsible for an additional 4.2 million hectares of wildfire from 1984-2015, which is almost double what would be expected in the absence of worsening climate conditions (Abatzoglou & Williams, 2016). Looking to the future, studies have estimated a doubling or tripling of total area burned by wildfires by the middle of the century (McKenzie et al., 2004; L. Westerling, 2018).

Another factor contributing to the growing annual burn area across the western U.S. is the expansion of the wildland-urban interface (WUI). Areas where forested wildlands and human development intersect, the WUI in the fastest growing land use type in the U.S., with a 41% increase in the number of new houses built, and a 33% increase in total land area from 1990 to 2010 (Radeloff et al., 2018). Both accidental and intentional human-caused ignitions are some of the most important causes of wildfires and occur more frequently in the WUI, due to increased population density, contributing to increased wildfire risk in these areas (Radeloff et al., 2018; Theobald & Romme, 2007).

The final factor responsible for the worsening wildfire trend in the western U.S. is historical forest management policies. From its establishment in 1905, the U.S. Forest Service (USFS) relied heavily on prevention and suppression as its primary fire management strategy (van Wagtendonk, 2007). Throughout the 20th century, forest managers across the country restricted any sort of controlled burning for land management purposes and responded to any wildfires that did occur with swift action to put them out as quickly as possible (van Wagtendonk, 2007). This strategy sharply contrasts a long history of Indigenous forest management practices, which are rooted in the recognition of fire as a vital ecosystem regulator and favor the use of human-managed fire (Kimmerer & Lake, 2001; Storm & Shebitz, 2006). Over time, in the absence of regular fire, tree density began to increase, filling dry western forests with excess fuels (Ryan et al., 2013). This buildup of low-lying, dense vegetation would ultimately provide fuel for the larger and higher severity wildfires we see each summer and fall in the western U.S. (Ryan et al., 2013; Williams, 2013).

Fire for management purposes

Prescribed burning

The current trajectory towards more frequent and intense wildfires is driving large scale forest restoration and climate resilience planning. As the forest and fire communities' understanding of fire ecology improves, there is growing consensus that in order to achieve long-term forest health, natural fire regimes should be restored (Ryan et al. 2013). As a result, in the latter half of the 20th century, forest and fire managers shifted away from full-blown fire suppressions towards fuel reduction efforts, which include a combination of mechanical thinning and controlled fires, otherwise known as prescribed burning. The idea behind the implementation of prescribed burning is that more frequent, smaller scale fires in the near term can help reduce excess fuel availability and mitigate uncontrollable, mega fires in the long term (Kalies & Yocom Kent, 2016; Prichard et al., 2020; Tubbesing et al., 2019)

This shift towards the reintroduction of fire onto the landscape is rooted in the role of wildfires as natural ecosystem regulators (Barros et al., 2018; Hessburg et al., 2015). This is something that Indigenous communities have known for generations and have integrated into burning practices intended to accomplish a variety of land management goals, including pest control, game attraction, and biodiversity maintenance, among others (Storm and Shebitz 2004, Kimmerer and Lake 2001). It is generally accepted that reducing fuel loads through the use of prescribed fire can reduce the severity of future wildfires by mitigating factors such as the likelihood and rate of fire spread, ignition potential, and intensity (Fernandes, 2015; Fernandes & Botelho, 2003). Effectiveness of fuel treatments is often context specific, but multiple studies have documented the impacts of fuel treatments on fire severity. A study of the effects of prescribed burn treatments in mixed conifer forests in central Idaho found lower wildfire severity in treated areas within three years post-treatment, relative to untreated plots (Arkle et al., 2012). Another study on the effects of prescribed burn fuel treatments on the 2006 Tripod Complex Fires in north central Washington found that recent treatments, particularly targeting surface fuels, were highly correlated with reduced burn severity (Prichard & Kennedy, 2014). Similar reductions in fire severity were observed in plots where fuel treatments were applied prior to the 2014 Carlton Complex Fire (Prichard et al., 2020). The optimal frequency of prescribed burn treatments varies by vegetation type, local topography, meteorology, and historical fire return intervals, but fire managers often target repeated treatments every 3 to 15 years (Knapp et al., 2015; Westlind & Kerns, 2017).

Exposure and health tradeoffs

Given the growing push to use prescribed burns to address the wildfire crisis, as is evidenced by increased state and federal funding (CA Forest Management Task Force, 2021; DNR, 2018, Infrastructure Investment and Jobs Act, 2021), there is interest in exploring smoke exposure and health tradeoffs and the role that public health may play in forest management moving forward (Blades et al., 2014; D'Evelyn et al., 2022; Haikerwal et al., 2015; Jaffe et al., 2020; Jones et al., 2022; Lyth et al., 2018; Williamson et al., 2016). A handful of recent studies have sought to quantify these tradeoffs at national or regional scales, mostly focusing on high-level, hypothetical representations of fuel treatment increases across the landscape (Burke et al., 2021; Carter et al., 2023; Rabin et al., 2022; Ravi et al., 2018). While these studies tend to simplify the application of prescribed burns and subsequent wildfire impacts, they describe the potential smoke exposure and health co-benefits that could result through wildfire mitigation via prescribed burning.

Agricultural burns

Agricultural burning is another practice commonly used across the U.S.. Growers often burn crop residues after the harvest season to clear fields or before seeding new crops as a way to mitigate pests and weeds, ward off disease, and fertilize in preparation for the growing season. (Kumar & Goh, 1999; McCarty et al., 2009). Rice, grass seed, cereals (e.g. barley and wheat), and nuts (e.g. walnuts, almonds, and pecans) are commonly managed by agricultural residue burning in Washington, Oregon, and California, which are the focus of this dissertation (CARB, 2023; Hart et al., 2012). Burning crop residues has agricultural benefits for growers, but also releases pollutants into the atmosphere, including particulate matter and organic pollutants, which can degrade ambient air quality in surrounding areas (Santiago-De La Rosa et al., 2018).

Health impacts of smoke exposure

There is a growing body of epidemiological evidence documenting the health effects of wildfire smoke at the population level. In a regulatory context, fine particulate matter ($PM_{2.5}$) from wildfire smoke is considered the same as $PM_{2.5}$ from any other anthropogenic source; however, a recent study of respiratory health effects of smoke-specific $PM_{2.5}$ exposure in southern California found that hospitalizations linked to wildfire-specific exposures were up to 8.7% higher than those associated with $PM_{2.5}$ exposures from other sources (Aguilera et al., 2021). These results suggest that $PM_{2.5}$ from wildfires could be more harmful than from other sources, which highlights the importance of continued wildfire smoke exposure and epidemiological studies.

Multiple studies have found a significant association between wildfire smoke exposure and all-cause mortality (Analitis et al., 2012; Doubleday et al., 2020a; Hänninen et al., 2009; Kollanus et al., 2017; Vedal & Dutton, 2006). Studies that have looked at cause-specific mortality outcomes have found significant associations between smoke exposure and respiratory-related mortality, including a study from Washington state which estimated a 9% increase in the odds of mortality due to respiratory complications, as well as a 14% increase in mortality due to chronic obstructive pulmonary disease (COPD) (Doubleday et al., 2020b). Multiple studies have also linked wildfire smoke exposure to respiratory morbidities, such as asthma and COPD exacerbations, pneumonia, and bronchitis (Alman et al., 2016; Kondo et al., 2019; Reid et al., 2019; Reid & Maestas, 2019; Stowell et al., 2019), including a study of respiratory morbidities in the mid-Atlantic U.S states resulting from long-range transport of wildfire smoke from Quebec, Canada (Le et al., 2014).

Despite the extensive evidence that links total ambient $PM_{2.5}$ exposure to adverse cardiovascular outcomes (Du et al., 2016), the results of studies examining the relationship between wildfire smoke-specific $PM_{2.5}$ and cardiovascular morbidities are still mixed, with a handful of studies citing positive associations (Dennekamp et al., 2015; Haikerwal et al., 2015; Mahsin et al., 2022; Wettstein et al., n.d.), and others finding no association or mixed results (Delfino et al., 2009; Doubleday et al., 2023; Heaney et al., 2022; Henderson et al., 2011; F. H. Johnston et al., 2007; Yao et al., 2016).

There is a growing body of evidence that smoke exposures during pregnancy may contribute to lower birth weights and higher rates of preterm birth and potential increased susceptibility of infants, due to impacts on lung function and immune system regulation (Abdo et al., 2019; Black et al., 2017; Fernández et al., 2023; Heft-Neal et al., 2022; Holstius et al., 2012; Requia et al., 2022). Additionally, there is preliminary evidence that exposure to smoke may also be associated with adverse mental health outcomes (Eisenman & Galway, 2022; Humphreys et al., 2022; Mirabelli et al., 2022).

There has been very limited research on the differential health effects of exposure to smoke from prescribed or agricultural burns, relative to those from wildfire smoke. This gap highlights the need for more research in this space in order to better understand how different sources of smoke exposure impact health. The few studies that have been completed are summarized in Chapter 3 of this dissertation.

Disproportionately affected populations and environmental justice

Hazardous environmental exposures and resulting health effects are often not distributed equally across the population. These disparities were first unveiled in the early 1980s, when reports emerged of low-income communities and communities of color being exposed to elevated chemical exposures linked to industrial waste products (J. Johnston & Cushing, 2020). These communities' proximity to these sources of pollution, as well as the lack of corporate accountability and regulation, can be linked directly to racist infrastructure and housing policies, such as redlining, a policy which allowed financial institutions to deny mortgages to people of color in certain neighborhoods (Nardone et al., 2020; Pastor, 2007; B. Wilson, 2020). Although banned under the Fair Housing Act of 1968, the impacts of these racist policies persist today in the form of disproportionate exposures to harmful air pollution and increased burden of heat related illnesses due to urban heat islands in low income and communities of color (Nardone et al., 2020; B. Wilson, 2020).

The disproportionate burden of ambient air pollution exposures from anthropogenic emissions sources, such as traffic and energy generation, that is experienced by low income and communities of color across the U.S. has been well documented (Hajat et al., 2015; Mohai & Saha, 2015; Tessum et al., 2021). Less research has been done to examine the distribution of wildfire smoke exposure across environmental justice communities (Navarro et al., 2018). However, having a thorough understanding of how harmful exposures are distributed across demographics is crucial to be able to target effective exposure reduction interventions and policies. Populations could be disproportionately impacted by hazardous pollutant exposures through two primary mechanisms: 1) some populations may be more likely to be exposed to the hazard, due to the location of where they live or work, and 2) some may be more sensitive to health outcomes as a result of exposure, due to factors like underlying illnesses, age, genetics, co-exposures, and lack of adaptive capacity. In the case of smoke exposure, disproportionately impacted populations may include outdoor workers, such as agricultural workers, loggers, and those who work in outdoor recreation. Because these occupations require workers to be outside for most of the work shift, these populations spend more time, on average, than the general population inhaling ambient air, making them more likely to experience smoke exposures during wildfire events (Austin et al., 2020). Additionally, these occupations often require heavy physical labor, driving increased inhalation rates, which result in higher smoke doses per unit smoke inhaled (U.S.EPA 2011). Smoke exposure among agricultural workers is of particular concern in Washington, Oregon, and California, who employ up to 95,000, 82,000, and 407,000 workers respectively during the growing season, which usually aligns with peak wildfire season across the three states (EDD, n.d.; ESD, n.d.; OR Secretary of State, n.d.). Other disproportionately impacted populations could include communities in the WUI and Indigenous communities, who may live closer areas where wildfires occur and therefore may be more likely to experience smoke exposures. Populations that may be more susceptible to the health effects of wildfire smoke exposure include older adults (Delfino et al., 2009; Haikerwal et al., 2015), pregnant women and fetuses (Holstius et al., 2012), and those with preexisting respiratory conditions, such as asthma and COPD (Reid et al. 2016).

Low income and black, indigenous, and people of color (BIPOC) may also be disproportionately impacted by smoke exposure, due to increased risk of co-exposures and limited adaptive capacity. BIPOC communities are known to be disproportionately exposed to anthropogenic sources of air pollution throughout the U.S. (Hajat et al., 2015; Tessum et al., 2021). These communities may also be less likely to have access to the knowledge or resources to reduce their exposure to anthropogenic air pollution, and therefore may also have reduced access to smoke-specific exposure reduction strategies. Existing exposure disparities contribute to higher rates of air pollution-related adverse health outcomes in these communities, such as respiratory disorders and COPD, which as noted above, also contribute to wildfire smoke susceptibility. It follows that the known disparities in health care access, housing quality, and transportation access among low income and BIPOC communities may also contribute to reduced adaptive capacity to wildfire smoke (Davies et al., 2018; Rappold et al., 2017).

Wildfire smoke exposure assessment methods

Multiple different exposure assessment methods have been used in previous studies to examine population exposures and health impacts. In situ air quality measurements, including those from regulatory monitoring networks and temporary air pollution monitor deployments, are commonly used to characterize wildfire smoke exposure because they can provide highly temporally resolved, location-specific $PM_{2.5}$ concentrations (Dennekamp et al., 2015; F. H. Johnston et al., 2012; Shaposhnikov et al., 2014). However, these monitoring networks are often sparsely distributed, particularly in rural areas where heterogeneous meteorology and topography make it difficult to accurately interpolate between stations.

As an alternative to ground measurements, satellite data, such as aerosol optical depth (AOD) products, have been used to characterize wildfire smoke at high spatial resolutions (Krstic & Henderson, 2015; Rappold et al., 2011). Satellite AOD products can provide significantly better spatial coverage relative to ground monitors, though factors such as cloud cover and high surface reflectance can also contribute to exposure misclassification (Paciorek & Liu, 2009). Additionally, AOD does not provide information on the vertical distribution of aerosols within the atmospheric column and therefore does not directly reflect concentrations at the earth's surface (J. Li et al., 2015), though the development of new instruments such as Multi-Angle Imager for Aerosols (MAIA) will likely improve our ability to characterize aerosol concentrations in the breathing zone at fine spatial resolutions. A common limitation of using both ground measurements and satellite-derived AOD for wildfire research is that both data sources reflect contributions from all sources of $PM_{2.5}$, including traffic and industrial sources, making it challenging to separate out fire-specific exposures.

Modeling approaches for wildfire exposure assessment have included the use of chemical transport models (CTMs), such as The Community Multiscale Air Quality Modeling System (CMAQ) (Fann et al., 2018a; Koman et al., 2022; Meng et al., 2023; Rappold et al., 2017) and GEOS-Chem (Heaney et al., 2022; J. C. Liu et al., 2016; Marlier et al., 2022; Ye et al., 2022), which do not rely on ground measurements or satellite AOD. Other studies have sought to develop fusion models by integrating multiple sources of $PM_{2.5}$ data, including ground measurements, satellite data, and CTMs through machine learning methods in an attempt to overcome the limitations of each individual data source (Aguilera et al., 2023; Childs et al., 2022; Zou et al., 2019). A handful of studies have adapted land use regression (LUR) methods, which are commonly used in urban air quality studies, for wildfire smoke exposure assessment (Mirzaei et al., 2018; Reid et al., 2015; Yao & Henderson, 2014). This method allows for the use of land use covariates and other source-specific characteristics to improve model performance; however, models are often geographically specific and therefore must be re-fitted before use across various locations.

Dissertation Aims

The primary focus of the smoke-related exposure and health literature has been on wildfires, given their growing prevalence and catastrophic impacts. While smoke emissions from all sources of biomass burning are hazardous to health, exposures stemming from wildfire, prescribed burns, and agricultural burns should not always be considered under the same umbrella. Each has a different set of drivers (i.e. wildfires are naturally occurring while prescribed and agricultural burns are started intentionally by humans) and exist under different regulatory frameworks. For example, all fire types are not all considered equal under the Clean Air Act (i.e. wildfires and prescribed burns can be considered Exceptional Events, while agricultural burns typically are not) and prescribed and agricultural burns permits are often issued by different state-level regulatory agencies (EPA, 2019). Because of these differences, understanding the nuances of each smoke source may create the opportunity for more tailored, and thus more effective, exposure reduction strategies. In the case of prescribed burns, it is also becoming increasingly important to understand the role these fuel treatments have in specific ecological landscapes in the mitigation of future exposures to wildfire smoke . Throughout this dissertation, I explore these nuances from two directions, one looking retrospectively in time (Aims 1 and 2) and one forward in time (Aim 3), to form a more holistic understanding of how communities are impacted by smoke. This dissertation has three aims:

1. Characterize historical smoke-specific $PM_{2.5}$ exposure from wildfire, prescribed burns, and agricultural burns across Washington, Oregon, and California.
    a. Subaim 1a. Use a combination of remote sensing-based biomass burning emissions inventories and administrative data to estimate daily smoke emissions from wildfires, prescribed, and agricultural burns.
    b. Subaim 1b. Use GEOS-Chem to map the spatial and temporal distribution of fire type-specific $PM_{2.5}$.

c. Subaim 1c. Calculate population weighted exposures to wildfire, prescribed, and agricultural burn smoke across the general population.

2. Quantify the differential impacts of wildfire, prescribed, and agricultural burn-specific smoke exposure across at-risk populations.
3. Evaluate the estimated smoke-specific $PM_{2.5}$ exposure and health impacts of six forest management scenarios for the Tahoe Central Sierra Initiative in the central Sierra Nevada, California.
    a. Subaim 3a. Model the spatial and temporal distribution of smoke-specific $PM_{2.5}$ concentrations and population-level exposures for six forest management scenarios.
    b. Subaim 3b. Estimate the health impacts associated with each management scenario.
    c. Subaim 3c. Evaluate the distribution of wildfire and prescribed burn smoke exposures among outdoor agricultural workers.

These aims reflect an interdisciplinary approach to a problem that bridges the gap between the fields of public health and forest and fire management, which includes prescribed burn use on wildlands and agricultural burning for crop management. While immense progress has been made in these disciplines independently of one another to understand the ecological and human dimensions of fires and smoke, the goal of this dissertation is to leverage perspectives and methods from each in order to better understand how they can work together to achieve necessary management objectives, while protecting communities from hazardous smoke exposures. The remainder of this dissertation is broken down into four chapters. Chapters 2 and 3 establish a baseline understanding of the smoke exposure landscape across the three West Coast states in recent years, with Chapter 2 focusing on Subaim 1a and Chapter 3 on Subaims 1b-1c and Aim 2. Chapters 4 and 5 demonstrate how we can quantifiably incorporate public health considerations into future forest management planning. Chapters 2-5 are written in the form of scientific manuscripts, intended for publication. Chapter 6 reflects on both the backward and forward-looking perspectives together and suggests directions for future work.

Chapter 2: DEVELOPMENT OF A SOURCE-SPECIFIC BIOMASS BURNING EMISSIONS INVENTORY FOR WASHINGTON, OREGON, AND CALIFORNIA[1]

Abstract

While wildfires are the dominant source of biomass burning emissions across the U.S., prescribed and agricultural burns also contribute to emissions and ambient air quality. Understanding the differential impacts that these different sources of biomass burning have on air quality and public health is important in the development of effective exposure reduction strategies. We leverage the high-resolution Fire INventory from NCAR (FINN) to develop a source-specific biomass burning emission inventory that distinguishes between wildfire, prescribed burn, and agricultural burn sources across Washington, Oregon, and California. We describe the methodology for reclassifying FINN using multiple national and state-level fire and fuel treatment inventories and present the results of the emissions reclassification process for these three states from 2012-2020. This fire type-specific biomass burning emissions inventory can be used in air pollution transport models to better understand the impacts of each of these sources on air quality across the region along with downstream public health impacts.

Introduction

Biomass burning emissions are a significant source of air pollution exposures across the United States (U.S.) (McClure & Jaffe, 2018; O'Dell et al., 2019). While wildfires are the dominant source of biomass burning emissions, particularly across the fire-prone landscapes of the western U.S., other sources, such as prescribed and agricultural burns, also contribute to total

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emissions and ambient air quality (Jaffe et al., 2020; X. Liu et al., 2017). Prescribed burns are managed fires applied to the landscape to reduce excess fuel availability and mitigate higher severity wildfire (Kalies & Yocom Kent, 2016; Prichard et al., 2020; Tubbesing et al., 2019). Prescribed burning is a practice that has been used by Indigenous communities for generations to accomplish a variety of land management goals, including pest control, game attraction, and biodiversity maintenance (Kimmerer & Lake, 2001; Storm & Shebitz, 2006). Agricultural sources of biomass burning emissions largely stem from crop residue burning, which is a common strategy used prior to the growing season and after the harvesting season to clear fields for subsequent crops, manage pests, and control weeds (Brandt, 1966; McCarty et al., 2009).

While wildfire, prescribed burns, and agricultural burns all involve vegetation burning, prescribed and agricultural burns are planned and implemented by humans for management purposes and are therefore fundamentally different emissions sources from naturally occurring wildfires. Spatiotemporal patterns likely also vary across these fire types. When considering the downwind impacts of these emissions (i.e. air quality and human health impacts), these distinctions may be important in terms of planning and implementing exposure reduction strategies. For example, because prescribed and agricultural burns are planned, there is the opportunity for advanced coordination between burners and local health agencies to set up public communications channels and clean air centers to mitigate any potential exposure impacts (D'Evelyn et al., 2022).

Prior studies of the exposure and health impacts of smoke have largely focused on total biomass burning emissions as a proxy for wildfire smoke emissions due to a limited ability to distinguish between smoke from these different sources (Cleland et al., 2021; Fann et al., 2018b; J. C. Liu, Wilson, Mickley, Dominici, et al., 2017). This likely contributes to exposure misclassification by including other sources of biomass burning (i.e. prescribed and agricultural burns) under the umbrella of wildfire smoke. Additionally, prescribed burning is likely to ramp up across the western U.S. in the coming years as a result of increased federal and state funding for forest management activities (CA Forest Management Task Force, 2021; DNR, 2018, Infrastructure Investment and Jobs Act, 2021). This highlights a growing need to better understand how prescribed burn emissions may differentially impact air quality and public health relative to wildfire.

Air quality and health studies that utilize pollutant concentration outputs from various transport models rely on the availability of satellite-derived global or regional emissions inputs. Biomass burning emissions inventories commonly used include top down inventories, such as Global Fire Assimilation System (GFAS) and Quick Fire Emissions Dataset (QFED), which rely on satellite-derived estimates of fire radiative power and are available at 0.1 x 0.1° resolution (Kaiser et al., 2012; Koster et al., 2015). Bottom up inventories, such as Global Fire Emissions Database (GFED) and Fire INventory from National Center for Atmospheric Research (NCAR) (FINN), leverage satellite observations of active fires and/or burned areas, in combination with fuel loading estimates and emissions factors and are available at 0.25x0.25° and 1 km resolution, respectively (van der Werf et al., 2017; Wiedinmyer et al., 2011). Beyond GFED, which characterizes agricultural waste burning emissions, most inventories do not distinguish between different sources of biomass burning (van der Werf et al., 2017; Wiedinmyer et al., 2011). FINN's fine-scale resolution makes it a promising candidate to detect smaller prescribed burns, which are often 10s to 100s of acres in size, and agricultural burns which are often less than 10 acres or pile burns. While earlier versions of FINN (v1) were found to generate biased low pollutant emissions relative to other inventories (T. Liu et al., 2020), recent updates to the model (v2) have improved active fire detections through the inclusion of observations from the Visible Infrared Imaging Radiometer Suite (VIIRS). These updates have resulted in FINNv2 emission estimates that are in the upper range of emission estimates generated by the other inventories noted above (Wiedinmyer et al., 2023).

Given its high spatial resolution and these recent improvements to model performance relative to other emissions inventories, we leverage FINN to develop a source-specific biomass burning emission inventory that distinguishes between wildfire, prescribed burn, and agricultural burn sources. Here we describe our methodology for reclassifying FINN, using a series of national and state-level fire and fuel treatment inventories and present the results of that reclassification process along with a characterization of source-specific biomass burning emissions across Washington, Oregon, and California from 2012-2020.

Methods

Overview

We reclassified the 1 km FINN inventory to distinguish between emissions from wildfire, prescribed burns, and agricultural burns across Washington, Oregon, and California from 2012-2020. We spatially and temporally matched fire type information from several national, state, and tribal fire and fuel treatment datasets as well as the National Land Cover Database. All data processing was carried out in RStudio (version 4.2.2) and QGIS (version 3.22).

Fire INventory from NCAR

Biomass burning emissions were estimated using FINN version 2.2, which is a fire emissions product generated from active fire and burn area observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) (Wiedinmyer et al., 2011). FINN provides daily gridded fire emissions estimates at a 1 km resolution, which is more resolved than other available biomass burning emissions inventories that are available at 0.25 x 0.25 (GFED) and 0.1 x 0.1 degree (QFED and GFAS) resolutions. We selected FINN over other biomass burning emissions inventories because its high spatial resolution maximizes our ability to detect prescribed and agricultural burns, which are often in the range of 10s to 100s of acres.

Fire type input data

Monitoring Trends in Burn Severity

The Monitoring Trends in Burn Severity (MTBS) data product provides daily fire perimeter polygons for all fires greater than 1,000 acres in the western U.S. at a 30 m spatial resolution, derived from Landsat imagery. MTBS contains information on ignition type (i.e. wildfire, controlled wildfire, or prescribed burn), determined from federal and state agency fire occurrence data (Picotte et al., 2020). Because MTBS only contains information on larger fires, we employ the following federal and state-level datasets to further distinguish smaller prescribed burns.

Forest Service Activity Tracking System

The U.S. Forest Service (USFS) manages the Forest Service Activity Tracking System (FACTS) database, which includes Hazardous Fuel Treatment polygons on federal lands starting from 1990. The FACTS Hazardous Fuel Treatment database includes information on the location and timing of prescribed burns and mechanical fuel treatments carried out with the intention of manipulating vegetation on USFS land in order to maintain landscape resiliency and reduce high severity wildfire risk (USFS, 2023). For the purposes of reclassifying fire emissions, only records of prescribed burn fuel treatments were used. For fuel treatments carried out on non-federal lands, we turn to the following state-level datasets.

California Prescribed Burns

California tracks prescribed burn treatment polygons carried out by state, federal, and private entities as part of the California Strategic Fire Plan. Records contain burn perimeters for prescribed burns, machine pile burns, hand pile burns, and jackpot burns, which target high concentrations of vegetation in preparation for broadcast burns, carried out across the state (Fire, 2023). For the purposes of this emissions reclassification process, all fire use within this dataset (i.e. machine pile burns, hand pile burns, etc.) were considered prescribed burns.

Oregon Prescribed Burn Accomplishments

The Oregon Department of Forestry (ODF) tracks prescribed burn accomplishments by ODF district. This dataset includes date, point location (latitude and longitude), and burn area estimates for fuel treatments carried out by management agencies and private landowners. Burn areas polygons were created by generating a circular buffer around the point location based on the reported burn area.

Washington Prescribed Burn Permits

The Washington Department of Natural Resources (DNR) publicly provides prescribed burn permit information submitted from public and private burners across the state. This database includes information on accepted, rejected, and permits under review. Only accepted permits were used in this emissions reclassification process. The burn permits include date, point location (latitude and longitude), and burn area estimates for fuel treatments. Similar to the Oregon prescribed burn point data, burn areas polygons were created by generating a circular buffer around the point location based on the reported burn area.

Prescribed Burns on the Colville Reservation

Many tribal nations independently track fuel treatments carried out on reservation land. Because state-level permitting and reporting practices vary across tribal jurisdictions relative to the requirements on non-tribal lands, records of fuel treatments on tribal lands can be incomplete across the federal and state databases described above. For the purposes of this study, we did not compile individual inventories from all tribal nations across the study area, though an existing relationship with partners in the Natural Resource Department of the Confederated Tribes of the Colville Reservation in north central Washington allowed us to obtain prescribed burn records from that specific reservation. Fuel treatment data include date, point location (latitude and longitude), and burn area estimates, which were used to generate circular burn area polygons using the buffer method described above. The inclusion of fuel treatment locations from this specific reservation likely improves fire type reclassification in this region. While other tribal burns were not explicitly included in this analysis - unless already included in the fuel treatment inventories described above - similar prescribed burn records could be obtained from other tribal nations in the future to further improve fire type reclassification in other geographies.

Emissions inventory reclassification

An iterative process was used to spatially join each fire type input data layer to the FINN emissions inventory (Figure 2.1). A 100 m buffer was generated around each FINN emission location to account for the pixel geolocation biases of both MODIS and VIIRS (Wolfe, 2006; Wolfe et al., 2013). Prescribed burns and wildfire locations from each fire type input dataset were spatially joined to emissions events based on polygon intersection (Figure 2.2). Emissions locations that were matched to fires in each of the fire type input datasets were then checked for temporal consistency. To account for errors in fuel treatment reporting, a two week buffer was applied before and after the date of the FINN emission event. If the matching record from the fire input dataset was not within that time frame, the match was removed. Individual emission locations within FINN are assigned a FIREID. For larger fires, several emissions locations can be assigned the same FIREID. If an emission location matched to any of the fire type input records, that match was also assigned to all emissions locations with that same FIREID.

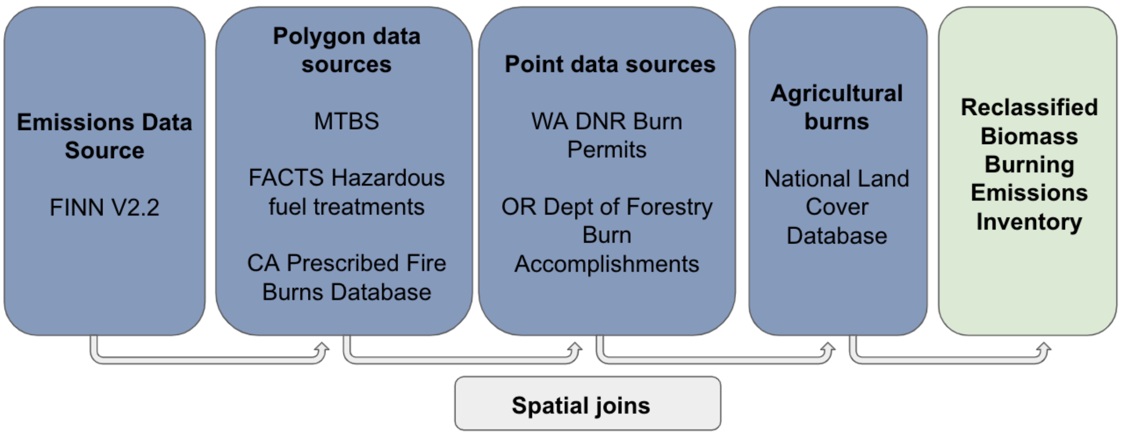

Figure 2.1 Schematic of iterative spatial join procedure to reclassify FINN, using MTBS, federal and state fuel treatment databases, and the NLCD.

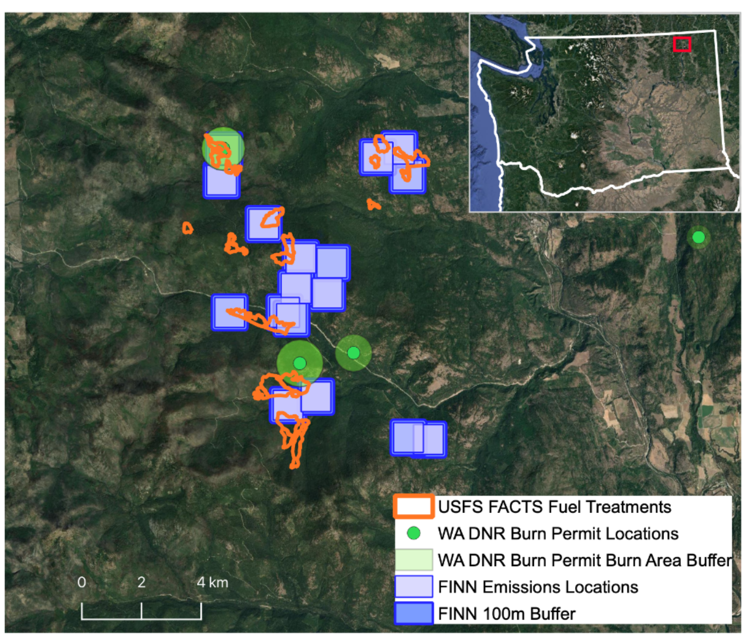

Figure 2.2. Example of FINN emissions locations with 100m buffer and 2020 fuel treatment inputs from FACTS and WashingtonDNR.

Following previous studies that characterized crop residue burning, unmatched FINN emissions locations were then overlaid with the National Land Cover Database (NLCD) to determine which unmatched emissions locations overlapped with croplands (land cover types 81-Pasture/Hay Areas and 82-Cultivated Crops) across the study area (McCarty et al., n.d.; Pouliot et al., 2008). Emissions locations that overlapped with crop land cover and were otherwise unmatched to wildfires or prescribed burns were classified as agricultural burns. If a fire location was determined to be a wildfire or prescribed burn in one of the fire and fuel treatment inventories described above but also overlapped with agricultural land cover, the wildfire or prescribed fire classification took precedence. Similarly, if a fire was determined to be a wildfire in one fire or fuel treatment inventory but a prescribed burn in another, the prescribed burn classification took precedence. Any fire locations that showed up in the fire and fuel treatment inventories but not in FINN were not included in this analysis.

The remaining unmatched FINN emission locations were classified as wildfires. A characterization of the unmatched locations is presented in the Results.

Comparison with NEI

Because of the lack of pre-existing source-specific biomass burning emissions inventories for this region and the fact that air pollution data from ground monitoring networks do not distinguish between sources of $PM_{2.5}$, it is challenging to ground truth our reclassification protocol. The Environmental Protection Agency's (EPA) National Emission Inventory (NEI) does include estimates of $PM_{2.5}$ emissions by fire type, but is only available for a subset of years within our study period. County-level wildfire, prescribed burn, and agricultural burn emission estimates for the NEI were generated using a similar process of leveraging several satellite-based datasets and federal and state-level fire inventories to identify different sources of burning, making it useful for comparative purposes, but not validation. Thus, we obtained county-level monthly estimates of total wildfire, prescribed burn, and agricultural burn emissions for Washington, Oregon, and California from the 2014, 2017, and preliminary 2020 NEI. FINN emissions for each of these fire types were summed across each month and county and compared to NEI estimates using Pearson's correlation coefficients. We also obtained daily wildfire event data from the 2014, 2017, and preliminary 2020 NEI supporting data. Wildfire emissions were totaled across days for each state for both inventories and compared using Pearson's correlation coefficients by quantile.

Results

The process of spatially joining FINN emissions locations to the fire type input datasets followed by the NLCD resulted in a 71.75%, 78.36% and 81.38% emissions locations match rate in Washington, Oregon, and California, respectively. The average $PM_{2.5}$ emissions of unmatched fires were 78.2, 125.1, and 124.6 Mg/fire/day in Washington, Oregon, and California, which are all elevated relative to the average emission of wildfires identified through the spatial join process and greater than emissions from both prescribed and agricultural burns (Table 2.1). Across all three states, 90% of unmatched FINN fires fall between June 21st and October 3rd, with a median date of August 20th (Figure 2.3). The median date of wildfires identified through the spatial join process was August 28th across all three states (Figure 2.3). Given the high average $PM_{2.5}$ emissions and timing of unmatched fires, unmatched FINN observations were classified as wildfire emissions.

Table 2.1. Percent of FINN emissions locations matched to fires in the various fire type input databases or crop cover via the NLCD across each state along with the mean, standard deviation (SD), 95th percentile $PM_{2.5}$ emissions reported in Mg/fire/day for each fire type and unmatched fires. Fire is defined as a unique FIREID.

			PM2.5 (Mg/fire/day)		
		Percent of unique emissions locations	Mean	SD	95th percentile
WA	**Wildfire**	59.02%	45.3	202.4	184.9
	Rx Burns	2.45%	39.1	27.2	141.7
	Ag Burns	10.28%	3.2	8.0	11.7
	Unmatched	28.25%	78.2	330.7	356.3
OR	**Wildfire**	69.11%	74.7	787.0	260.0
	Rx Burns	3.47%	26.4	58.2	119.9
	Ag Burns	5.78%	4.2	13.1	13.2
	Unmatched	21.64%	125.1	514.7	544.8
CA	**Wildfire**	67.22%	81.2	577.0	310.1
	Rx Burns	1.00%	30.1	68.4	137.2
	Ag Burns	13.16%	3.2	14.6	10.5
	Unmatched	18.62%	124.7	413.4	637.9

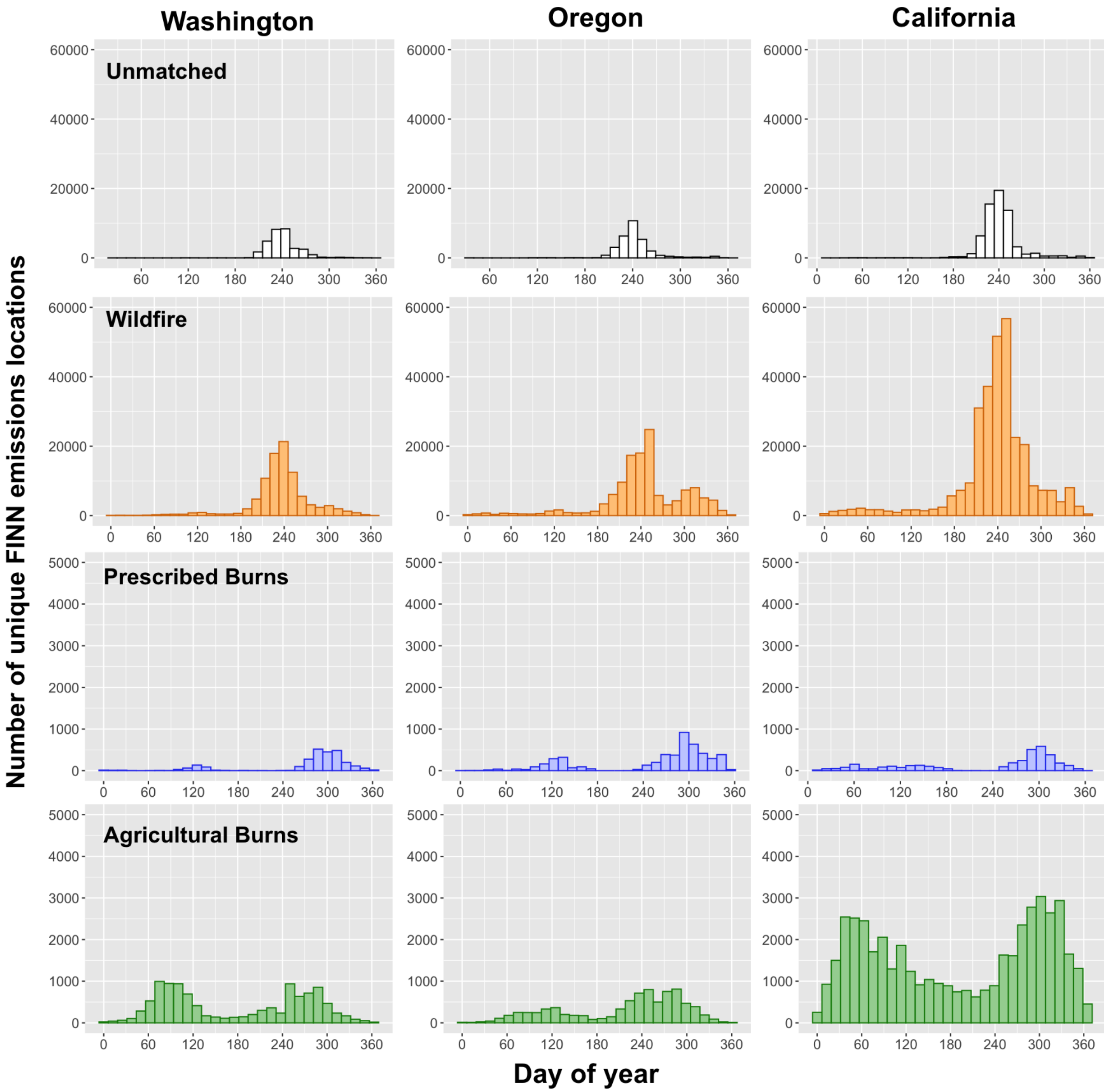

Figure 2.3. Distribution of the day of the year that fire emissions occurred for wildfire, prescribed burns, agricultural burns, and unmatched fires across Washington, Oregon, and California. Note the different y-axis scales for unmatched and wildfires versus prescribed and agricultural burns.

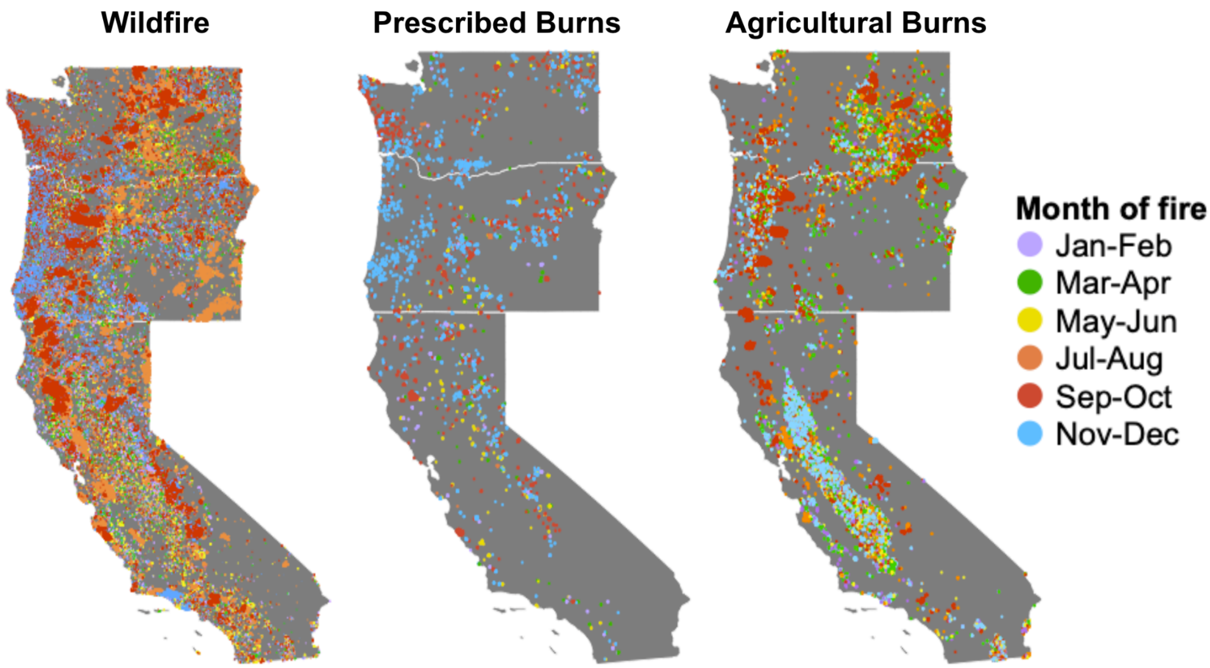

Figure 2.4. FINN emissions locations for each fire type. The colors represent the month of the year that the fires occur.

Figure 2.4 shows the spatiotemporal distribution of FINN emissions locations by fire type. As expected, there were many more wildfire emission locations across all three states relative to the other two fire types, with 82% wildfire emissions occurring during June-October. Prescribed burn emissions locations are more sparse across all three states, but clustered around northeast and southwestern Washington, western, and northeastern Oregon, and northcentral California, with most burns occurring during two main seasons: March - May (23%) and September - December (68%). As expected, agricultural burn emissions are concentrated around the main agricultural regions of each state (i.e. southeastern Washington, the Willamette Valley in Oregon, and the Central Valley in California), with the majority of the burns happening before the growing season (February - May: 39%) and after the harvesting season (August - November: 44%).

Figure 2.5 compares the total monthly state-wide emissions across sources from 2012-2020. As anticipated, total monthly wildfire emissions are generally higher than monthly emissions totals from prescribed and agricultural burns across all three states, though total monthly emissions do increase across all sources throughout the study period (Figure 2.5, Figure 2.S1). While wildfire emissions consistently occur each year during the traditional wildfire “season” of June-September, emissions from prescribed and agricultural burns tend to peak multiple times per year.

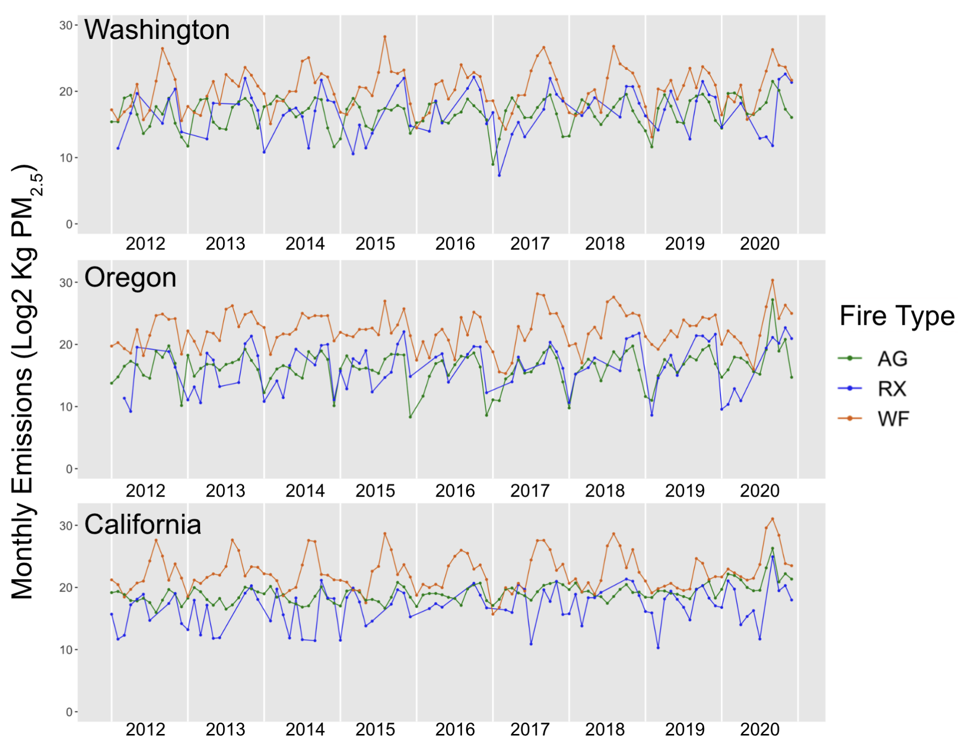

Figure 2.5. Monthly state-wide total $PM_{2.5}$ emissions for wildfire (WF), prescribed burns (RX), and agricultural burns (AG). Note the log base 2 y-axis scale. See Figure 2.S1 for the untransformed data.

When comparing the fire type-specific FINN $PM_{2.5}$ emissions estimates to county-level estimates from the 2014, 2017, and preliminary 2020 NEI, we found greater agreement among wildfire-specific estimates, relative to the other two fire types, and in more recent years of the NEI (Figures 2.S1-2.2). Lower agreement among prescribed and agricultural burns at the lower end of the wildfire emissions distribution may highlight the limitations of satellite detection of small fires and the challenges of using burner reports to characterize emissions from fuel treatments across a wide domain. The full comparison between the source-specific FINNv2.2 inventory and the NEI fire estimates can be found in figures 2.S1-2.2.

Discussion

We leveraged a series of national and state-level fire and fuel treatment inventories to reclassify FINNv2.2 to distinguish between wildfire, prescribed burns, and agricultural burn sources of daily 1 km $PM_{2.5}$ emissions. To our knowledge, this inventory is the first of its kind to characterize source-specific biomass burning emissions across the West Coast states over a several year period in a format that is compatible with global and regional air pollution transport models.

Uncertainties in these emissions estimates stem from uncertainties within FINN along with the limitations of each fire type input dataset used to classify the model estimates by source. Specifically, FINN is subject to missing fire detections due factors like cloud cover, smoke cover, and the timing of satellite flyovers. The timing of satellite flyovers may differentially impact detections of wildfires, which typically peak in the afternoon in forested ecosystems, relative to prescribed and agricultural burns, which are often applied in the morning and late evening (Mu et al., 2011; The National Wildfir Coordinating Group, 2019). Additionally, there are uncertainties associated with vegetation type, fuel loading, and fuel consumption estimates along with the emissions factors used in the model (Wiedinmyer et al., 2023). Similar to FINN, the MTBS database is also subject to missing fire detections due to cloud and smoke cover conditions and flyover timing. Because the FACTS database and state-level fuel treatment inventories rely on reports from management agencies and private burners on prescribed burn accomplishments, reporting errors in the location, burn area/quantity, and temporal information may contribute to the misclassification of fire type. In the case of Oregon and Washington, the locational attributes of these data come in the form of points (latitude and longitude) and total area burn estimates. To reflect the spatial area of the reported burns from these inventories, we generated circular buffers around the points using the burn area estimates, which is likely a mischaracterization of actual spatial burn area patterns. All of these sources of uncertainty likely contributed to the 28%, 22% and 19% of unmatched FINN emissions locations in Washington, Oregon, and California respectively (Table 2.1). Overall, differences in permitting and reporting requirements across federal and state agencies make it difficult to to track and compare fire emissions across geographies and likely contribute to uncertainties in this reclassified dataset. Standardization of tracking and reporting of both prescribed and agricultural burn achievements across management agencies would improve our understanding of how these different fire types impact air quality, relative to wildfire, in the future.

Despite these limitations, this reclassified FINN emissions inventory provides a useful data tool that can be used in future assessments of source-specific biomass burning across Washington, Oregon, and California. It can also be used in conjunction with regional and global air pollution dispersion models to better understand the differential impacts of each of these fire types on surface-level air pollution exposures and associated human health impacts, which could help to address a significant gap in the smoke-related epidemiological literature. As wildfires continue to worsen across the U.S. and more prescribed burns are applied to the landscape to mitigate them, while crop residue burning continues within the agricultural sector, it is crucial that we understand the differences these smoke sources have on communities to best optimize public health resources and tailor exposure reduction methods. While improvements in satellite technologies and standardized fuel treatment permitting and reporting protocols will likely improve the accuracy of future versions of the reclassified FINN emissions inventory, the present dataset can provide a first look into how these different fire sources contribute to air quality across the region.

Supplementary Material

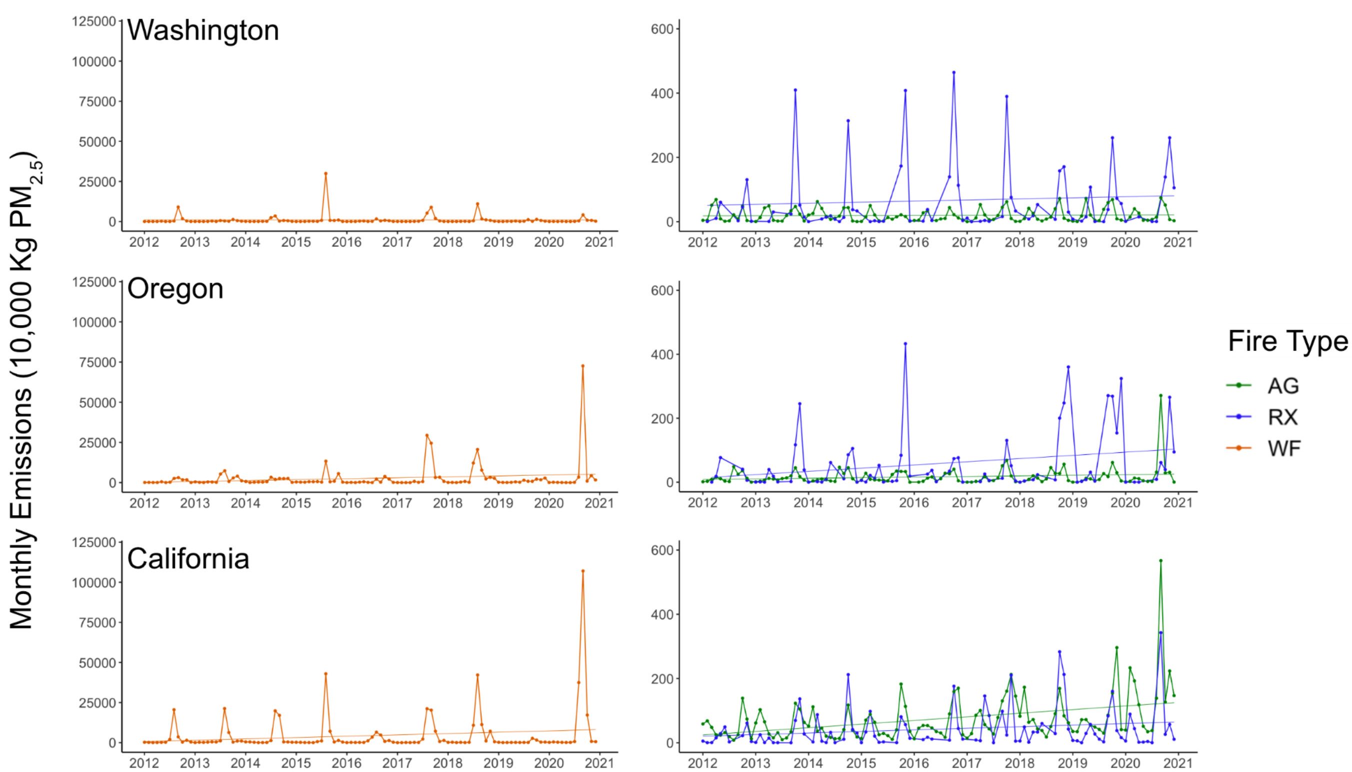

Figure 2.S1. Monthly state-wide total $PM_{2.5}$ emissions and linear trendlines for wildfire (left column), prescribed burns, and agricultural burns (right column). Note the difference in y-axis scales between the wildfire vs. the prescribed and agricultural burn plots.

Table 2.S1. Pearson's correlation coefficients for the reclassified FINNv2.2 $PM_{2.5}$ emissions estimates vs. monthly county-level NEI $PM_{2.5}$ estimates for wildfire, prescribed burns, and agricultural burns. *NEI estimates from 2020 are based on preliminary published data. *County-level monthly estimates of total wildfire, prescribed burn, and agricultural burn emissions for Washington, Oregon, and California were obtained from the 2014, 2017, and (preliminary) 2020 NEI. FINN emissions for each of these fire times were summed across each month and county and compared to NEI estimates using Pearson's correlation coefficients.*

		Wildfire	Prescribed Burns	Agricultural Burns
2014	**Washington**	0.67	0.73	0.95
	Oregon	0.59	0.12	0.43
	California	0.98	0.15	0.56
2017	**Washington**	0.95	0.61	0.91
	Oregon	0.87	0.3	0.6
	California	0.91	0.5	0.53
2020*	**Washington**	0.86	0.42	
	Oregon	0.94	0.24	
	California	0.65	0.38	

Table 2.S2. Pearson's correlation coefficients for the daily total state-wide reclassified FINNv2.2 wildfire-specific $PM_{2.5}$ emissions estimates vs. daily NEI wildfire-specific $PM_{2.5}$ estimates by quantile. *NEI estimates from 2020 are based on preliminary published data. *Daily wildfire event data were obtained from 2014, 2017, and (preliminary) 2020 NEI supporting data. Wildfire emissions were totaled across days for each state for both inventories and compared using Pearson's correlation coefficients.*

		Quantile of FINN $PM_{2.5}$ estimate			
		25th percentile	**50th percentile**	**75th percentile**	**100th percentile**
2014	**Washington**	0.004	0.04	-0.02	-0.02
	Oregon	0.09	0.06	-0.16	0.03
	California	0.09	0.06	-0.12	0.02
2017	**Washington**	-0.07	0.29	0.39	0.69
	Oregon	0.07	0.15	0.05	0.78
	California	0.24	0.02	0.16	0.57
2020*	**Washington**	0.02	-0.02	0.21	0.72
	Oregon	-0.16	0.15	0.48	0.90
	California	0.02	0.14	0.4	0.62

Chapter 3: EXPOSURE TO SMOKE FROM WILDFIRE, PRESCRIBED, AND AGRICULTURAL BURNS AMONG AT-RISK POPULATIONS ACROSS WASHINGTON, OREGON, AND CALIFORNIA[2]

Abstract

Wildfires, prescribed burns, and agricultural burns all impact ambient air quality across the western U.S; however, little is known about how communities across the region are differentially exposed to smoke from each of these fire types. To address this gap, we quantify

[2] To be submitted for publication as: Schollaert, C. Marlier, M. Marshall, J, Spector, J. Busch Isaksen, T. Exposure to smoke from wildfire, prescribed, and agricultural burns among at-risk populations across Washington, Oregon, and California

smoke exposure stemming from wildfire, prescribed, and agricultural burns across Washington, Oregon, and California from 2014-2020 using a fire type-specific biomass burning emissions inventory and the GEOS-Chem chemical transport model. We examine fire type-specific $PM_{2.5}$ concentration by race/ethnicity subgroups, socioeconomic status, and in relation to the Center for Disease Control's Social Vulnerability Index. Overall, $PM_{2.5}$ concentrations from wildfires are greater than those from both prescribed and agricultural burns. While we found limited evidence of exposure disparities among sub-groups across the full study area, we did observe disproportionately higher exposures to wildfire-specific $PM_{2.5}$ among Native communities and higher agricultural burn-specific $PM_{2.5}$ exposures among lower socioeconomic groups in California. We also identified areas of significant spatial clustering of smoke exposures from all fire types and increased social vulnerability across all three states. These results provide a first look at the differential contributions of smoke from wildfires, prescribed burns, and agricultural burns to $PM_{2.5}$ exposures among demographic subgroups across the West Coast states.

Introduction

Biomass burning is a significant source of fine particulate matter ($PM_{2.5}$) pollution across the U.S., contributing to over 40% of $PM_{2.5}$ concentrations across the U.S (Burke et al., 2021; EPA, 2017; Jaffe et al., 2020; McClure & Jaffe, 2018). Most studies characterizing health impacts associated with smoke exposure from biomass burning have focused solely on wildfire smoke contributions, reporting associations with respiratory-related mortality and morbidities, including exacerbations of asthma and chronic obstructive pulmonary disorder (COPD) (Cascio, 2018; Reid et al., 2016). Studies have also documented associations between wildfire smoke exposures and adverse cardiovascular outcomes, birth outcomes such as low birth weight, and mental health outcomes (Abdo et al., 2019; Cascio, 2018; Chen et al., 2021; Hadley et al., 2022;

Reid et al., 2016). Many of the existing studies on smoke exposure and health impacts assume that all biomass burning smoke stems from wildfires, while biomass burning for management purposes, such as prescribed burns and agricultural burns may also be contributing to total smoke exposure.

While wildfires are the dominant source of biomass burning smoke emissions across the western U.S., prescribed and agricultural burns are potentially unique sources of smoke exposure in that they are planned and in some cases, regulated events that occur at different times of year (Jaffe et al., 2020; Y. Li et al., 2021; McClure & Jaffe, 2018). There is growing consensus that in order to achieve long-term forest health, natural fire regimes should be restored (Ryan et al. 2013). As a result, forest and fire managers have shifted away from attempting total wildfire fire suppression towards fuel reduction efforts, including the use of prescribed burning, to help reduce excess fuel availability and mitigate wildfire severity and smoke exposures in the long term (D'Evelyn et al., 2022; Kalies & Yocom Kent, 2016; Kelp et al., 2023; Prichard et al., 2020; Tubbesing et al., 2019). Agricultural burning is the practice of burning crop residues before seeding or after harvest in order to reduce weeds, pests, prevent disease, and fertilize soil with ash (Kumar & Goh, 1999; McCarty et al., 2009). In the three West Coast states, cereals, grass seed, rice, and nuts are commonly managed with agricultural burning (CARB, 2023; Hart et al., 2012). According to the National Emissions Inventory, total $PM_{2.5}$ emissions from agricultural burns in 2020 were 4.6, 4.9, and 3.9 times higher than those in 2010 in California, Oregon, and Washington, respectively, highlighting a trend towards increasing agricultural burn contributions to smoke $PM_{2.5}$ across the West Coast states (EPA, 2023b).

Few studies have examined the health impacts of smoke from wildfires versus prescribed burns. One preliminary study on proximity to different fire types in Fresno, California found that children suspected to be exposed to wildfire smoke (based on proximity to the fire location), relative to those exposed to prescribed burn smoke, had a more severe immunosuppressive response (Prunicki et al., 2019). Another national study carried out on National Forest System land did not identify any differences in asthma, coronary heart disease, or COPD between those who lived within 10 km of a prescribed burn location versus those that did not (Kondo et al. 2022). Neither of these studies examined actual prescribed burn contributions to smoke exposures and instead relied on proximity to fire locations as a proxy for exposure. In the southeast U.S., where prescribed burns are much more prevalent (Kolden, 2019), health impact assessment studies, which rely on concentration response functions from the existing epidemiological literature, have documented increases in asthma-related hospitalizations and all-cause mortality as a result of $PM_{2.5}$ from prescribed burns (Afrin & Garcia-Menendez, 2021; Huang et al., 2019). These studies do not link actual health outcome data with prescribed burn smoke concentrations and therefore only reflect an estimate of potential health impacts. Similar to prescribed burns, there have been limited studies on the health effects of exposure to smoke from agricultural burns across the U.S. Studies in India and Brazil have found significant associations between agricultural burn smoke exposure and various respiratory conditions, including asthma and decreased lung function (Agarwal et al., 2013; Awasthi et al., 2010; Gupta, 2019). Exposure metrics varied across studies, including the use of measurements of total $PM_{2.5}$ and satellite-based fire activity data, but none utilized $PM_{2.5}$ estimates from agricultural burns alone. Limited epidemiological evidence of the health impacts of smoke from prescribed and agricultural burns may be due to the lack of $PM_{2.5}$ exposure data that differentiates between different sources of smoke.

Only a handful of studies have characterized how smoke exposures are distributed across at-risk groups. Rappold et al. (2017) developed a 'Community Health-Vulnerability Index' based on a combination of factors known to increase health risks associated with both anthropogenic and smoke-specific air pollution exposures. The authors used their vulnerability index, in combination with wildfire smoke concentration estimates from CMAQ to map the spatial distribution of wildfire smoke vulnerability across the U.S. (Rappold et al. 2017). Similarly, Davies et al. (2018) generated and mapped an index combining socioeconomic attributes that contribute to vulnerability along with ecological wildfire potential at the census tract level across the U.S. (Davies et al. 2018). Multiple studies have also used existing vulnerability indexes, such as the Center for Disease Control's (CDC) Social Vulnerability Index (SVI) along with smoke exposure models derived from Hazard Mapping System (HMS) plumes to identify disproportionately impacted communities in the southeastern region of the U.S. (Gaither et al., 2015; Vargo et al., 2023). While these studies help to identify specific locations where communities may be disproportionately impacted by wildfires and smoke emissions, they likely misclassify the smoke contributions from prescribed and agricultural burns under the umbrella of wildfire smoke.

To date, no studies have examined how smoke exposures from prescribed and agricultural burns differ from those from wildfires across Washington, Oregon, and California. While we know that smoke from total biomass burning is harmful to health, understanding the source of smoke may be important in targeting more effective exposure reduction interventions. For example, since prescribed and agricultural burns are human caused and planned events, there may be opportunities for more advanced and preventative exposure reduction strategies. Additionally, growing U.S. federal and state-level funding for forest management planning and increased fuel treatments, particularly in the western U.S., suggest that prescribed burning may become more widespread in the future (CA Forest Management Task Force, 2021; DNR, 2018, Infrastructure Investment and Jobs Act, 2021), making it increasingly important to understand the smoke impacts on communities. Here, we address this gap by characterizing smoke from wildfire, prescribed burns, and agricultural burns from 2014-2020 across Washington, Oregon, and California, with a particular focus on exposures among race/ethnicity groups and socioeconomic status, to better understand how these different sources of smoke impact at-risk communities.

Methods

Overview

We estimate daily $PM_{2.5}$ exposure from wildfire, prescribed, and agricultural burns across Washington, Oregon, and California from 2014-2020, using biomass burning estimates from the FINN and the GEOS-Chem chemical transport model. We calculate population-weighted $PM_{2.5}$ exposure estimates across the general population and individual race/ethnicity groups. Finally, we generate bivariate Local Indicators of Spatial Association (LISA) maps to identify local high risk smoke exposure regions within the study area.

Biomass burning emissions

Biomass burning emissions were estimated using the FINN version 2.2. We selected FINN over other available biomass burning emissions inventories because it provides daily aerosol (e.g. $PM_{2.5}$, PM_{10}, BC, OC) and gas-phase (e.g. CO, CO_2, NO_X, SO_2, NH_3) fire emissions estimates at a 1 km spatial resolution, which is more resolved than other available biomass burning emissions inventories that are available at 0.25 x 0.25 degree (GFED) and 0.1 x 0.1 degree (QFED and GFAS) resolutions, and thus maximizes our ability to capture smaller prescribed and agricultural burns (Oliva & Schroeder, 2015; Wiedinmyer et al., 2023). Even though this 1 km emissions inventory resolution is much finer scale than 0.25° x 0.3125° resolution of the transport model, detailed further in the next section, we opted for the fine scale emissions resolution to more accurately characterize emissions from smaller fires. FINN estimates total biomass burning emissions from all fire sources. To distinguish between emissions from wildfire, prescribed, and agricultural burns separately, we overlaid a compilation of datasets from the Monitoring Trends in Burn Severity (MTBS), the Forest Service Activity Tracking System (FACTS), and state-level administrative fuel treatment databases. We spatially joined each of these fire and fuel treatment inventories to the FINN emissions locations and confirmed matches by date. Unmatched emissions locations that intersected with crop cover, as determined by the National Land Cover Database (NLCD), were characterized as agricultural burns, as detailed in the previous chapter.

Smoke modeling

GEOS-Chem version 13.1 was used to model the transport of the emissions, using the aerosol-only simulation option. Unlike a full-chemistry simulation, the aerosol-only simulation utilizes archived monthly average concentrations of total nitrate, O_3, OH, and NO_3 as well as H_20_2 production and photolysis rates generated from a previously run full-chemistry simulation (GEOS-Chem, 2022). We first ran a global simulation at 4° x 5° resolution with 72 vertical levels to generate boundary conditions, followed by a nested grid simulation for the 11 western states at a 0.25° x 0.3125° resolution. Although our focus is only on the three West Coast states, our model domain spanned the full western U.S. to account for the 'buffer zone' near the nested grid boundaries within which pollutant concentration estimates may be uncertain (GEOS-Chem, 2020). We estimate $PM_{2.5}$ mass concentrations as the sum of the organic carbon, black carbon, nitrate, ammonium, and sulfate outputs. Given the limited capability of chemical transport models to adequately capture the complexities of secondary aerosol formation with smoke plumes, we assume that all aerosols in the model are primary (Garofalo et al., 2019; Palm et al., 2020; Tsigaridis et al., 2014; Wonaschütz et al., 2011).

To estimate wildfire, prescribed burn, and agricultural burn-specific $PM_{2.5}$ concentrations, we completed four model scenarios using different combinations of emissions inventories: 1) no biomass burning emissions (background), 2) background and wildfire emissions, 3) background and prescribed burning emissions, 4) background and agricultural burning emissions. We calculated wildfire-specific $PM_{2.5}$ concentrations as the difference between scenarios 1 and 2, prescribed burn-specific emissions as the difference between scenarios 1 and 3, and agricultural burn emissions as the difference between scenarios 1 and 4. We validated modeled $PM_{2.5}$ estimates from all sources against observations from the EPA's Air Quality System (AQS) networks in Washington, Oregon, and California (EPA, 2023a). Ground monitors were paired with the GEOS-Chem grid cell they fell within. If a grid cell contained multiple monitoring locations, we averaged the observations across monitors. To compare modeled and observed $PM_{2.5}$ estimates, we calculated Pearson's correlation coefficients, root mean square error, and mean bias during the wildfire season (June-October) and non-wildfire season (November-May).

Exposure estimation

Population-weighted source-specific smoke $PM_{2.5}$ concentrations were estimated using the following equation:

$$(Population - weighted\ exposure\ level)_{PM2.5} = \frac{\sum(Pi\ x\ Ci)}{\sum Pi}$$

Where P_i is the population of a given grid cell, obtained from 2010 NASA Socioeconomic Data and Applications Center (SEDAC) 1 km gridded population dataset (SEDAC, 2020a), aggregated to the 0.25° x 0.3125° nested grid resolution and C_i is the concentration. We calculate population-weighted smoke concentrations for the general population and race/ethnicity subgroups (Asian, Black, American Indian or Alaska Native (AI/AN), Native Hawaiian or Pacific Islander (NHOPI), Non-Hispanic (NH) White, Other, more than two races (2+ Races), and Hispanic). We also generated exposure estimates across socioeconomic status (SES), using the 2010 1 km regridded SES indicator from the CDC SVI, available from SEDAC. The SES indicator ranges from 0 to 1, with 1 being the highest level of SES vulnerability and 0 the lowest (CDC, 2021). We also subsetted the population-weighted exposure estimates across urban and rural areas. We identified urban and rural areas using 2010 Rural-Urban Commuting Area (RUCA) Codes for census tracts. Under that classification system, we categorized metropolitan and micropolitan areas (codes 1-6) as "Urban" and small towns and rural areas (codes 7-10) as "Rural" (USDA, 2023). To examine seasonal smoke patterns, exposures were broken down by wildfire and non-wildfire season. Wildfire season was defined as June-October and non-wildfire season as November-May. We tested for differences across groups using one-way Analysis of Variance (ANOVA). All analyses were carried out in RStudio (version 4.2.2).

Exploratory spatial analysis

To examine the spatial association between smoke exposure from each fire source and community vulnerability, we employ a bivariate Local Indicator of Spatial Association (LISA) statistic. Previous studies have used LISA statistics to examine spatial correlation between environmental exposures and social vulnerability, including wildfire smoke exposure (Gaither et al., 2015), flood risk (Tate et al., 2021), air pollution (Jephcote & Chen, 2012), and proximity to green space (Zhang, 2023). The LISA statistic is a measure of spatial correlation between the value of a variable at one grid cell location and the values of the neighboring grid cells. In the bivariate case, we examine the relationship between the value of one variable in a specific location and the neighboring values of a second variable (Anselin, 2010). Here, we assess the association between the CDC SVI and smoke concentrations of neighboring grid cells to determine if areas with higher than average SVI values spatially overlap with areas with higher than average smoke concentrations. The CDC's SVI ranks each census tract on variables related to household composition, socioeconomic status, race/ethnicity, and housing/transportation. The SVI is a composite index that ranges from 0 to 1, with values close to 1 indicating greater vulnerability (*CDC/ATSDR Social Vulnerability Index*, 2022). Neighbors are determined using distance-band spatial weights so that the neighbors of each grid cell are those that share an edge or a corner. From the LISA test, we determine the locations of four types of statistically significant associations: 1) high SVI score and high smoke concentration, 2) low SVI score and high smoke concentration, 3) low SVI score and low smoke concentration, and 4) high SVI score and low smoke concentration. We employ a lower significance threshold ($p<0.001$), using a Bonferonni correction, to account for multiple comparisons (Anselin, 2010). We carried out all spatial correlation analyses in GeoDa (version 1.20.0.8).

Results

Validation statistics of the modeled GEOS-Chem output are provided in Table 3.1. Overall, the correlation between the all-sources modeled data and observational data from ground monitors is higher during the wildfire relative to the non-wildfire season. Correlations vary considerably across years, with generally higher correlation coefficients during high fire years (e.g. 2015, 2017, 2018, and 2020) but also greater RMSE and mean bias relative to observed measurements, which may be attributable to higher biomass burning emissions estimates from FINNv2, relative to other available emissions inventories (Wiedinmyer et al., 2023). The spatial distribution of model performance, relative to ground observations, is provided in Figure 3.S1.

Table 3.1. Annual summary of comparison between total GEOS-Chem modeled $PM_{2.5}$ and ground observations across WA, OR, and CA from 2014-2020.

	Year	Observed Mean (μg/m3)		GEOS-Chem Mean (μg/m3)		Correlation		RMSE (μg/m3)		MB (μg/m3)	
		WF Season	*Non-WF Season*	*WF Season*	*Non-WF Season*	*WF Season*	*Non-WF Season*	*WF Season*	*Non-WF Season*	*WF Season*	*Non-WF Season*
WA	2014	5.96	6.26	7.21	6.73	0.42	0.20	6.03	6.90	1.19	0.39
	2015	7.09	6.63	10.26	5.74	0.18	0.30	32.10	5.41	2.84	-0.73
	2016	4.50	5.85	4.48	6.56	0.24	0.10	3.78	10.99	0.08	0.64
	2017	9.49	5.92	19.54	8.72	0.38	0.13	46.46	21.51	9.59	2.74
	2018	9.93	5.37	22.05	5.93	0.44	0.23	75.26	5.88	11.83	0.55
	2019	4.60	6.45	6.77	8.98	0.12	0.23	13.00	11.99	2.20	2.41
	2020	13.18	5.08	6.82	6.55	0.47	0.35	40.55	8.31	-6.54	1.39
	Total	6.83		8.77		0.25		27.04		1.94	
OR	2014	5.87	6.90	9.11	6.85	0.16	0.10	28.53	18.52	3.23	-0.08
	2015	7.29	6.85	13.91	3.85	0.48	0.08	59.44	7.53	6.55	-2.90
	2016	4.32	6.10	4.33	8.61	0.04	0.09	16.26	25.35	-0.01	2.50
	2017	12.61	6.65	50.06	9.90	0.42	0.08	145.21	31.66	37.46	3.23
	2018	10.56	6.70	27.24	4.73	0.43	0.17	107.87	8.15	16.66	-1.97
	2019	5.03	7.48	5.77	7.56	0.10	0.17	10.10	16.11	0.70	0.01
	2020	19.34	6.06	11.24	6.35	0.40	0.21	62.22	15.89	-8.78	0.23
	Total	8.01		11.58		0.23		53.52		3.57	
CA	2014	8.66	9.01	10.87	6.43	0.15	0.32	29.93	8.75	2.22	-2.43
	2015	8.44	8.96	10.68	5.01	0.21	0.50	38.17	7.72	2.20	-3.73
	2016	8.48	7.71	9.67	5.20	0.07	0.53	27.90	5.98	1.18	-2.44
	2017	10.47	8.44	28.02	8.39	0.25	0.22	70.34	17.17	17.36	0.04
	2018	11.29	9.93	27.10	7.56	0.39	0.37	76.70	15.68	15.61	-2.35
	2019	7.32	6.62	5.57	5.52	0.40	0.42	4.83	6.00	-1.70	-0.99
	2020	17.51	7.65	46.05	8.07	0.24	0.28	119.80	17.49	27.64	0.59
	Total	9.21		12.36		0.27		43.25		3.12	

Average annual wildfire-specific $PM_{2.5}$ concentrations are higher than those from both prescribed and agricultural burns across the full 3-state study area (WF: 8.82 $\mu g/m^3$, Rx: 0.23 $\mu g/m^3$, Ag: 0.15 $\mu g/m^3$), though the spatial distribution of smoke from each fire type varies across each state. Both wildfire and prescribed burn $PM_{2.5}$ concentrations are highest in central and northern California and north central Washington (Figure 3.1). In Oregon, average wildfire $PM_{2.5}$ is highest in the southwest corner of the state, while prescribed burn $PM_{2.5}$ concentrations are highest along the western edge of the state (Figure 3.1). As expected, average agricultural burn $PM_{2.5}$ concentrations are highest in the agricultural regions of each state, namely California's Central Valley, OR's Willamette Valley, and WA's Puget lowlands and southeastern region (Figure 3.1). Cereal grains and hay are commonly grown across all of these agricultural regions, with vegetables, tree fruits, nuts, and wine grapes also grown in California's Central and OR's Willamette Valleys (Oregon Department of Agriculture, n.d.; USGS, n.d.; WSDA, 2023). Seasonal patterns also differ across fire types, with peak wildfire $PM_{2.5}$ during wildfire season in summer and fall months and prescribed burn $PM_{2.5}$ highest during fall. While $PM_{2.5}$ from agricultural burns is also highest in the fall, burn activity and subsequent $PM_{2.5}$ exposure impacts are also present in the summer and winter, depending on the region (Figure 3.S2).

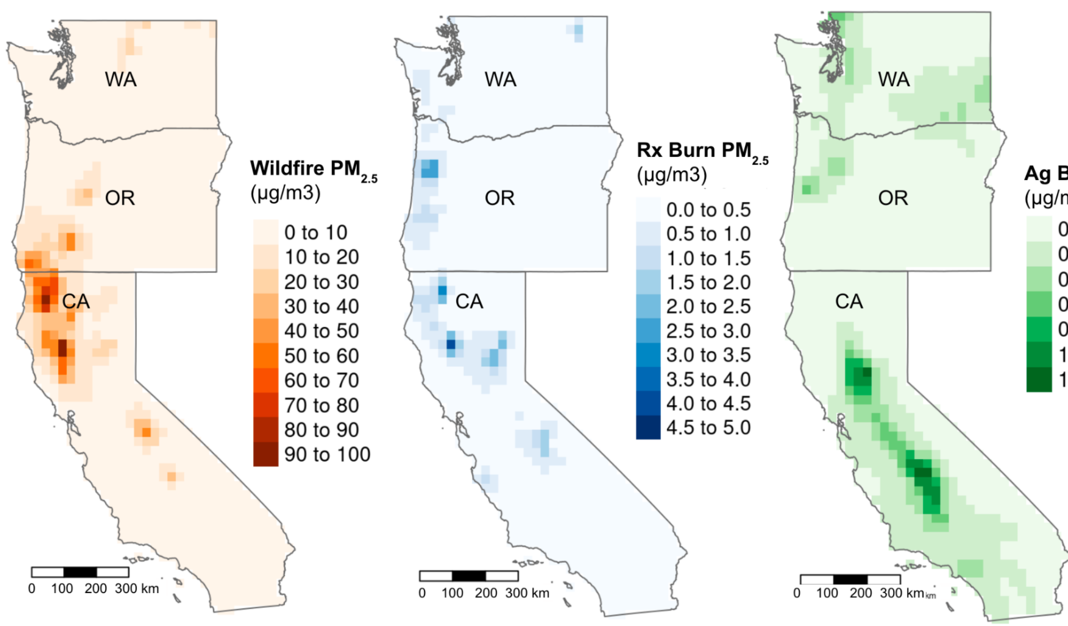

Figure 3.1. 2014-2020 average $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns. Note different concentrations scales across fire types.

Figure 3.2 depicts the number of days each grid cell experiences $PM_{2.5}$ concentrations within the five EPA Air Quality Index (AQI) categories above 'Good,' stemming from each fire type from 2014-2020. As expected, the greatest number of days at elevated AQI categories across each state stems from wildfire smoke; however, regions across all three states experienced daily $PM_{2.5}$ concentration that fell within the Moderate (AQI 51-100 or 12.1-35.4 $\mu g/m^3$), Unhealthy for Sensitive Groups (AQI 101-150 or 35.5-55.4 $\mu g/m^3$), and Unhealthy (AQI 151-200 or 55.5-150.4 $\mu g/m^3$) categories from prescribed burns as well. A few smaller regions in southwestern Oregon, northern California, and northeastern Washington also experienced prescribed burn $PM_{2.5}$ in the Very Unhealthy category (AQI 201-300 or 150.5-200.4 $\mu g/m^3$), and in northern California, the Hazardous category (AQI 301-500 or 200.5-500.4 $\mu g/m^3$). While there are fewer days at elevated AQI categories from agricultural burn smoke, California's Central Valley, OR's Willamette Valley, and southeastern Washington each experienced agricultural burn-specific $PM_{2.5}$ in the Moderate category, with a smaller number of grid cells in each of those regions experiencing a few days within the Unhealthy for Sensitive Groups and Unhealthy AQI categories from agricultural burn smoke. Maps of the number of days each grid cell experiences fire type-specific $PM_{2.5}$ concentration within each AQI category across the wildfire and non-wildfire season are presented in Figure 3.S3 and by year in Figures 3.S4-S10.

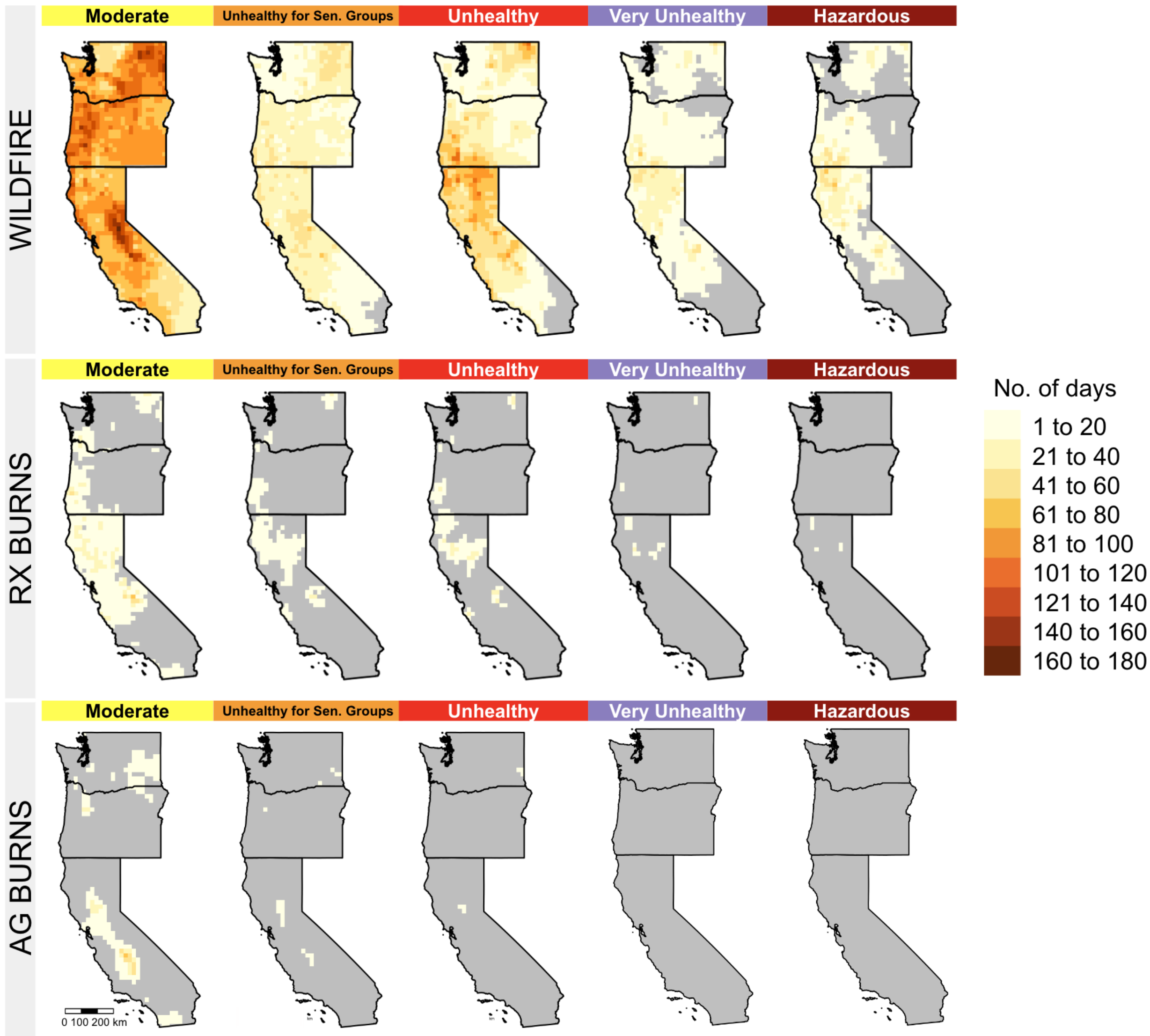

Figure 3.2. Number of days 2014-2020 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

On average, population-weighted wildfire $PM_{2.5}$ is highest across rural areas during wildfire season (Figure 3.3).When averaged across the 2014-2020 study period, population-weighted smoke concentrations do not significantly differ between most race/ethnicity groups across urban or rural regions in Washington, Oregon, California (Figure 3.3). However, wildfire $PM_{2.5}$ exposures among American Indian and Native Alaskans in rural California during the wildfire season are significantly higher than those among Asian, Black, Hispanic, and those that identify as Other ($F=3.362$, $p<0.001$) (Figure 3.3). Annual spatial differences in fire occurrence contribute to variability in population-weighted exposure levels across years throughout the study period (Figure 3.S11). Figure 3.4 depicts the relationship between fire type-specific $PM_{2.5}$ concentrations and the racial/ethnic makeup of counties across each state. Averaged across the full study area, counties most exposed to smoke from each source were predominantly Non-Hispanic White; however, Hispanic residents in California appear to be disproportionately represented among counties exposed to $PM_{2.5}$ from both prescribed and agricultural burns (Figure 3.4).

Figure 3.3. Population-weighted $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns for the total population and across race and ethnicity groups. Concentrations are broken down by season and urban/rural designations. Note the difference in y-axis scales.

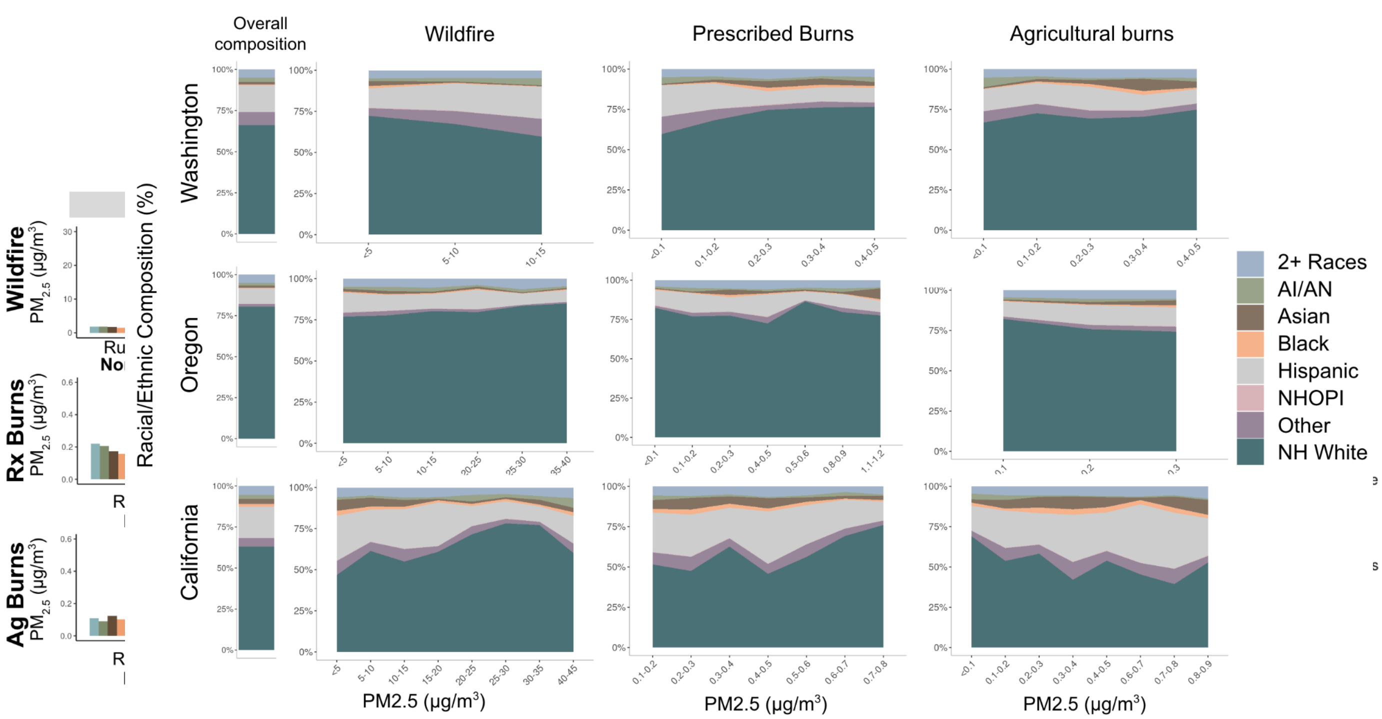

Figure 3.4. Average county racial/ethnic composition by population-weighted average $PM_{2.5}$ from wildfire, prescribed burns, and agricultural burns. State-wide racial/ethnic compositions are provided in the left column. Note the difference in x-axis scales.

When looking at exposure differences across socioeconomic groups, we see significant differences in exposure levels across all states stemming from each fire type (Figure 3.5). Focusing specifically on the most socioeconomically vulnerable (SVI SES score >0.8), grid cells with the lowest socioeconomic status experience significantly higher agricultural burn $PM_{2.5}$ exposure in rural and urban areas in California during both the wildfire (Rural: $F=5.931$, $p<0.001$; Urban: $F=9.081$, $p<0.001$) and the non-wildfire season (Rural: $F=27.62$, $p<0.001$; Urban: $F=6.48$, $p<0.001$). While exposure differences across SES groups vary year-to-year throughout the study period, lower SES grid cells in California were consistently exposed to higher agricultural burning $PM_{2.5}$ throughout the study period (Figure 3.S12).

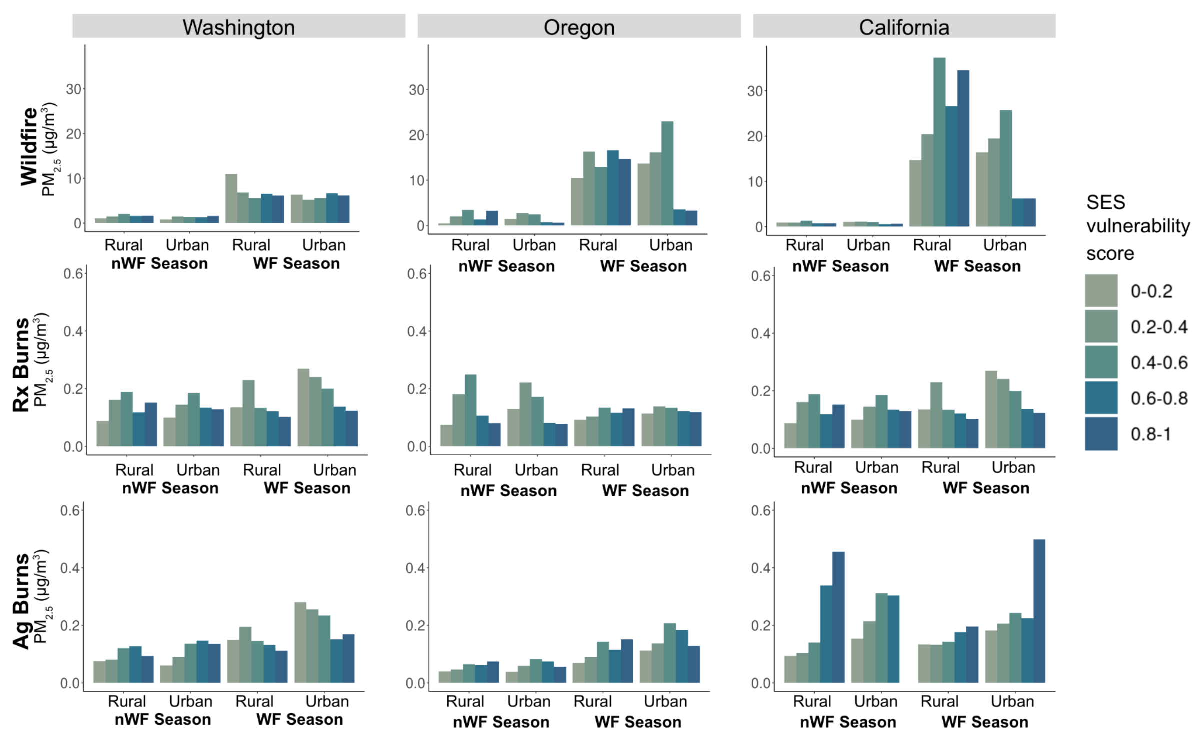

Figure 3.5. $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns for the total population and SVI SES score categories. Concentrations are broken down by season and urban/rural designations. Note the difference in y-axis scales.

We generated bivariate LISA maps to identify areas across each state where clusters of high social vulnerability significantly overlapped with higher than average $PM_{2.5}$ concentrations from each fire type (i.e. local areas of high risk). We identified spatially distinct areas within each state as high risk across both the wildfire and the non-wildfire seasons. It is important to note that each test of local spatial associations is based on the $PM_{2.5}$ concentration distributions from each fire type, which greatly vary in magnitude as highlighted above (i.e. wildfire $PM_{2.5}$ concentrations are higher than those from prescribed and agricultural burns, on average). During the wildfire season, significant clusters of high wildfire $PM_{2.5}$ exposure and high social vulnerability exist in central and northwest California, southwest Oregon, and northcentral WA. Notably, 11.8% of grid cells across all three states have high wildfire $PM_{2.5}$ exposure and high social vulnerability, with only 6.8% of grid cells with high wildfire $PM_{2.5}$ exposure and low social vulnerability (Table 3.S2). Significant clusters of high prescribed burn $PM_{2.5}$ exposure and high social vulnerability exist in central and northern California, with a small coastal area of high risk in between the Los Angeles and Bay Area metropolitan areas. We identified significant clusters of high agriculture burn $PM_{2.5}$ exposure risk in the Los Angeles metropolitan area, California's Central Valley, areas of OR's Willamette Valley, and northern portions of WA's Puget lowlands, with 9.3% of grid cells experiencing high agricultural burn $PM_{2.5}$ exposure and high social vulnerability, relative to 6.1% of grid cells with high agricultural burn $PM_{2.5}$ exposure and low social vulnerability across all three states (Table 3.S2). We see a shift in local smoke exposure risk during the non-wildfire season, with a small area of significant clusters of high wildfire burn $PM_{2.5}$ exposure and high social vulnerability in north central California, with the largest areas of significant risk shifting to western OR and southwestern WA. Similar to during wildfire season, there are significant clusters of both high prescribed burn $PM_{2.5}$ and high social vulnerability in central and northern California, with expanded risk in western OR. Finally, during the non-wildfire season, we identified significant clusters of high agricultural burn $PM_{2.5}$ and high social vulnerability in California's Central Valley (Figure 3.6).

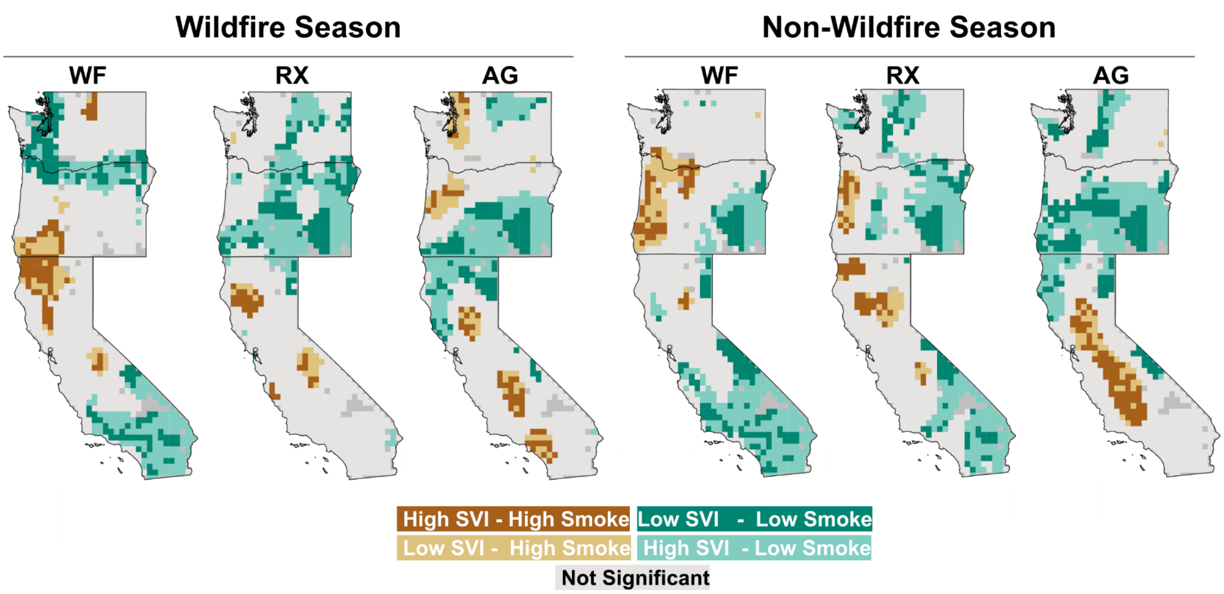

Figure 3.6. Bivariate LISA spatial clusters reflecting the local association between smoke $PM_{2.5}$ exposure from each fire type and SVI value.

Discussion

While wildfire smoke contributions to ambient $PM_{2.5}$ concentrations are much higher than those from prescribed and agricultural burns, smoke from the latter two sources do contribute to elevated AQI days in some regions across Washington, Oregon, and California. We did not observe significant $PM_{2.5}$ exposure differences from any fire type across race/ethnicity groups, except for American Indians and Alaskan Natives residing in rural California during wildfire season, who experienced significantly higher wildfire $PM_{2.5}$ exposures relative to other race/ethnicity groups. When examining exposure differences among socioeconomic groups, we identified that more socioeconomically vulnerable areas were more likely to experience higher agricultural burn $PM_{2.5}$ exposures across rural and urban areas of California.

While we did not find many persistent smoke exposure disparities at the state level beyond those noted above, local analysis of spatial correlations between fire type-specific $PM_{2.5}$ concentrations and overall social vulnerability allowed us to identify specific areas within each state where elevated exposures exist during the wildfire and non-wildfire seasons. Understanding specific areas where more socially vulnerable residents experience higher smoke exposures from any fire type can help state or local health agencies develop more targeted exposure reduction efforts, such as risk communication campaigns, establishment of clean air centers, or air filter distribution. In the case of fires on wildlands (i.e. wildfire and prescribed burns), this could also inform enforcement priorities for occupational smoke exposure rules for outdoor workers in all three states (CA DIR, 2021; OR OSHA, 2022; WA L&I, 2023).

The CDC's SVI is a composite representation of vulnerability that includes information on housing, transportation, and household characteristics, in addition to race/ethnicity and socioeconomic status. The SVI, and other composite vulnerability indicators, can be useful tools for state and federal health agencies looking to prioritize resource distribution. For example, the LISA maps presented here could be used by the California Department of Public Health to prioritize respirator distribution to local health districts in the northern part of the state, where increased social vulnerability overlaps with the highest wildfire and prescribed burn-related exposures. However, it is important to note that different factors may drive increased vulnerability in different communities and those different factors may warrant unique public health interventions. Within local health districts, exposure assessment by race/ethnicity subgroup, socioeconomic status, or other factors not examined here (e.g. educational status, English language proficiency, housing), could inform more tailored public health messaging and outreach to specific neighborhoods. For example, we know that after Non-Hispanic White, Hispanic residents in California are the most exposed to smoke from all fire types, so Spanish language public health guidance and tailored outreach in these specific communities may be effective exposure reduction strategies.

Despite the fact that smoke concentrations stemming for wildfires are much greater on average than smoke from prescribed and agricultural burns, the use of fire for management purposes - either forest or crop management - still results in days with air quality deemed ‘Unhealthy for Sensitive’ groups and beyond, per the EPA AQI definitions (Figure 3.2). Understanding where and to what extent these source-specific smoke events occur and who experiences the brunt of the impacts is important in improving public health preparedness and response efforts. Because prescribed and agricultural burns are both planned events, there can be advance communication with state and local health agencies regarding exposure reduction measures (D’Evelyn et al., 2022). Previous policy analyses of the barriers to prescribed burn implementation have called for improved communication pathways between local and regional public health and forest management agencies to better incorporate public health outreach into management processes (D’Evelyn et al., 2022; Miller et al., 2020; Schultz et al., 2019; Wood, 2021). In the case of prescribed burns, coordination with local health agencies could be integrated into the burn permitting process, managed by CAL FIRE, OR Department of Forestry, and Washington Department of Natural Resources in California, Oregon, and Washington, respectively. While prescribed and agricultural burns are both regulated by CAL FIRE in California, agricultural burns are regulated by different state-level agencies than prescribed burns in OR (Department of Environmental Quality) and Washington (Department of Ecology). While agricultural burns fall under the purview of state-level agencies in these three states, permitting decisions are largely handled by district offices, meaning local-level communication channels between health agencies and district management offices would likely be required in order to facilitate the incorporation of public health preparedness efforts into existing agricultural burn permitting systems. There is limited research on how communities surrounding agricultural areas experience and perceive risk related to agricultural burn smoke. Thus, more research is needed in order to inform how to best integrate exposure reduction strategies into existing regulatory processes. While state natural resource agencies aim to limit burning for management purposes to days when meteorological conditions for ideal dispersion patterns, conditions can change and burns are not always carried out according to plan, particularly as burns windows shrink in the face of climate change (Baijnath-Rodino et al., 2022; Kupfer et al., 2020). In these instances, establishing communication channels between burners and local health agencies in advance could prove crucial in reducing community exposures in ways that are not possible during unplanned wildfire events.

Limitations of this analysis stem from uncertainties in the biomass burning emissions inventory used. FINN is subject to missing observations due factors like cloud cover and the timing of satellite flyovers. This means that biomass burning events that do not appear in the emissions inventory were not included in the transport model, likely resulting in an underestimation of smoke exposures from all fire types. There is also the potential for fire type misclassification within the emissions inventory, stemming from errors in the federal and state-level administrative fuel treatment databases used to reclassify FINN. These factors likely contribute to uncertainty in the GEOS-Chem estimates of daily $PM_{2.5}$ from each fire type. Despite the fact that the 0.25° x 0.3125° GEOS-Chem output resolution allowed us to estimate exposure levels over a wide geographic area, over multiple years, and for multiple fire types, the coarse spatial resolution is unable to capture fine scale variability that exists within communities, particularly across the complex topography of many fire-prone landscapes across this region. Uncertainty in our analysis also stems from our use of a gridded population dataset, in which the accuracy of the population estimates, which are disaggregated from the census blocks, can vary depending on the size and shape of the block (SEDAC, 2020b). Despite this limitation, the use of gridded population data reduces spatial misalignment between the exposure and population data. Additionally, we rely on indexes created by the CDC to serve as proxies for income and general community vulnerability to smoke exposure; however, the CDC's SVI metric was designed to reflect overall social vulnerability to a wide range of stressors and not smoke specifically. Therefore, there may be factors missing from the SVI related to a community's ability to adapt to smoke exposure, making it an imperfect representation of how vulnerability to these different smoke types is distributed across the three states examined here.

Despite these limitations, we provide the first comprehensive exposure assessment of $PM_{2.5}$ from wildfire, prescribed burns, and agricultural burns across Washington, Oregon, and California. We leverage these data to examine exposure among race and ethnicity groups and socioeconomic status within the general population. Future studies should harness these data to look at exposures among other at-risk populations in this region, including outdoor agricultural workers, who may be disproportionately exposed and more susceptible to the health impacts of smoke from each of the fire types examined here (Méndez et al., 2020; Schenker et al., 2015).

These data can also be used in future epidemiological studies to distinguish the health impacts of exposure to smoke from different fire types and to explore potential exposure and health tradeoffs between the implementation of more prescribed burning in the face of worsening wildfire. While contributions of both prescribed and agricultural burns to ambient air quality are small relative to those from wildfire, they each warrant specific considerations in the development of exposure reduction interventions given the different timing, location, and planned or unplanned nature of the events. In the case of prescribed and agricultural burns in Washington, Oregon, and California, each is regulated and permitted by different state-level management agencies, further highlighting the need for understanding their distinct impacts on community-level exposures.

Conclusions

As the wildfire crisis continues to worsen across the western U.S, prescribed burning will likely increase over the next several years as a result of increased federal and state-level funding to support forest management as a wildfire mitigation tool (CA Forest Management Task Force, 2021; DNR, 2018, Infrastructure Investment and Jobs Act, 2021). Meanwhile, given the increases in emissions attributable to agricultural burns over the last decade, we may continue to see agricultural burning contribute to total smoke burdens moving forward (EPA, 2023b). While we know that smoke from all sources of biomass burning is harmful to health, understanding how each source of fire impacts communities presents a unique opportunity to design more catered public health strategies to reduce exposure among those most at-risk.

Supplementary material

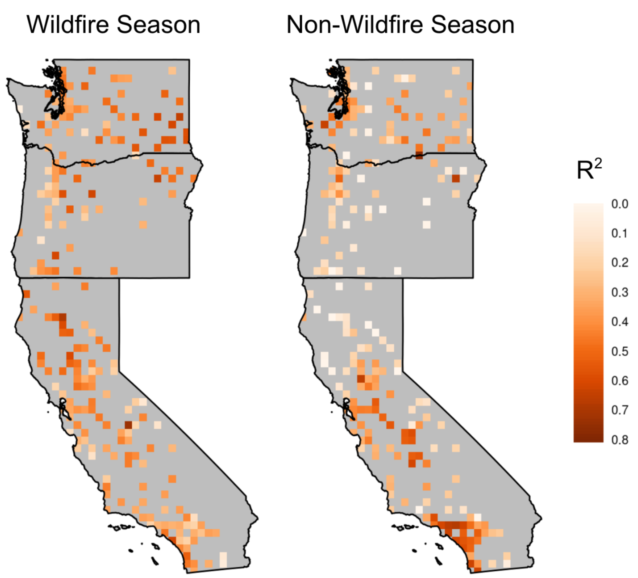

Figure 3.S1. Average R^2 values from comparison of total GEOS-Chem modeled $PM_{2.5}$ and ground observations at grid cells where ground monitoring stations are located during the wildfire and non-wildfire season.

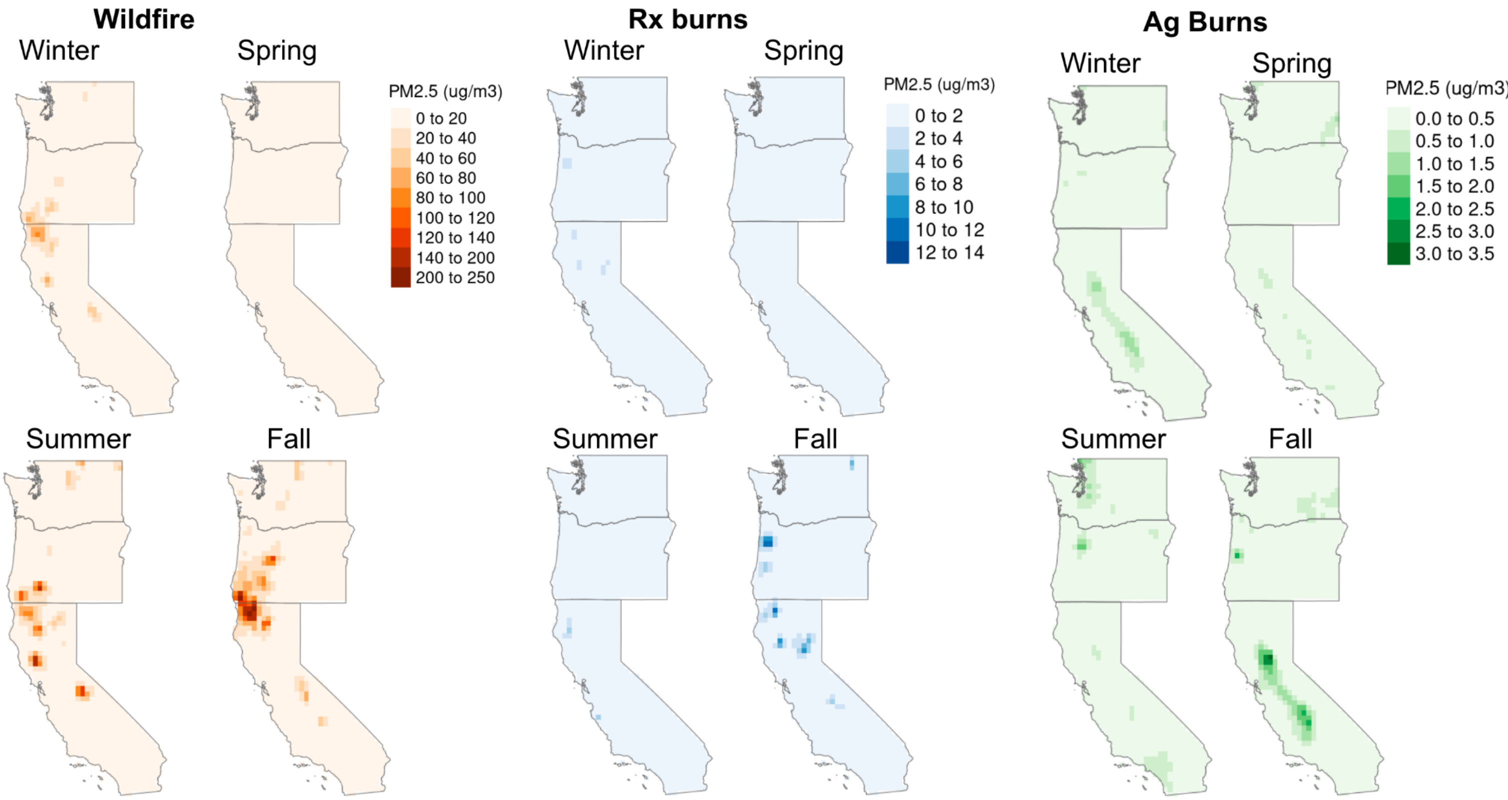

Figure 3.S2. Seasonal 2014-2020 average $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns. Note different concentrations scales across fire types.

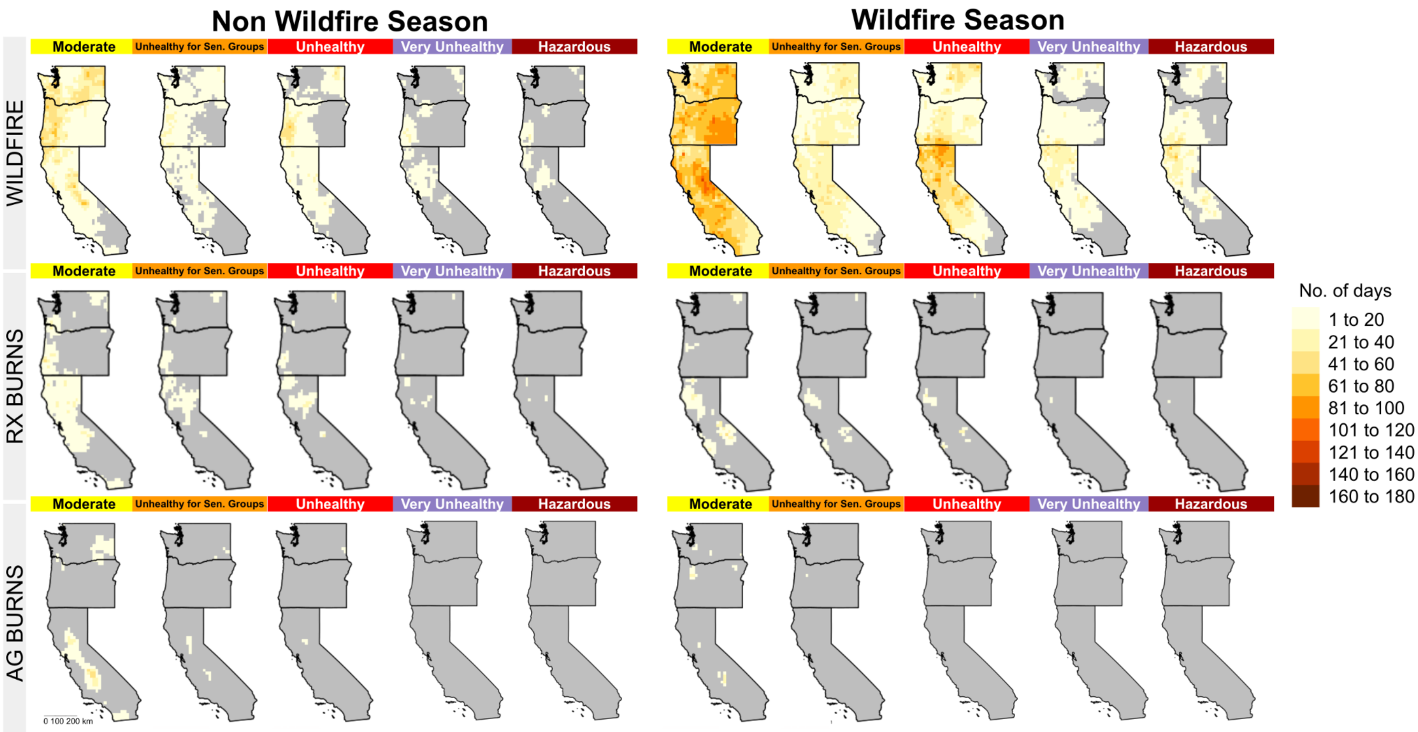

Figure 3.S3. Number of days 2014-2020 during the wildfire and non-wildfire season that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

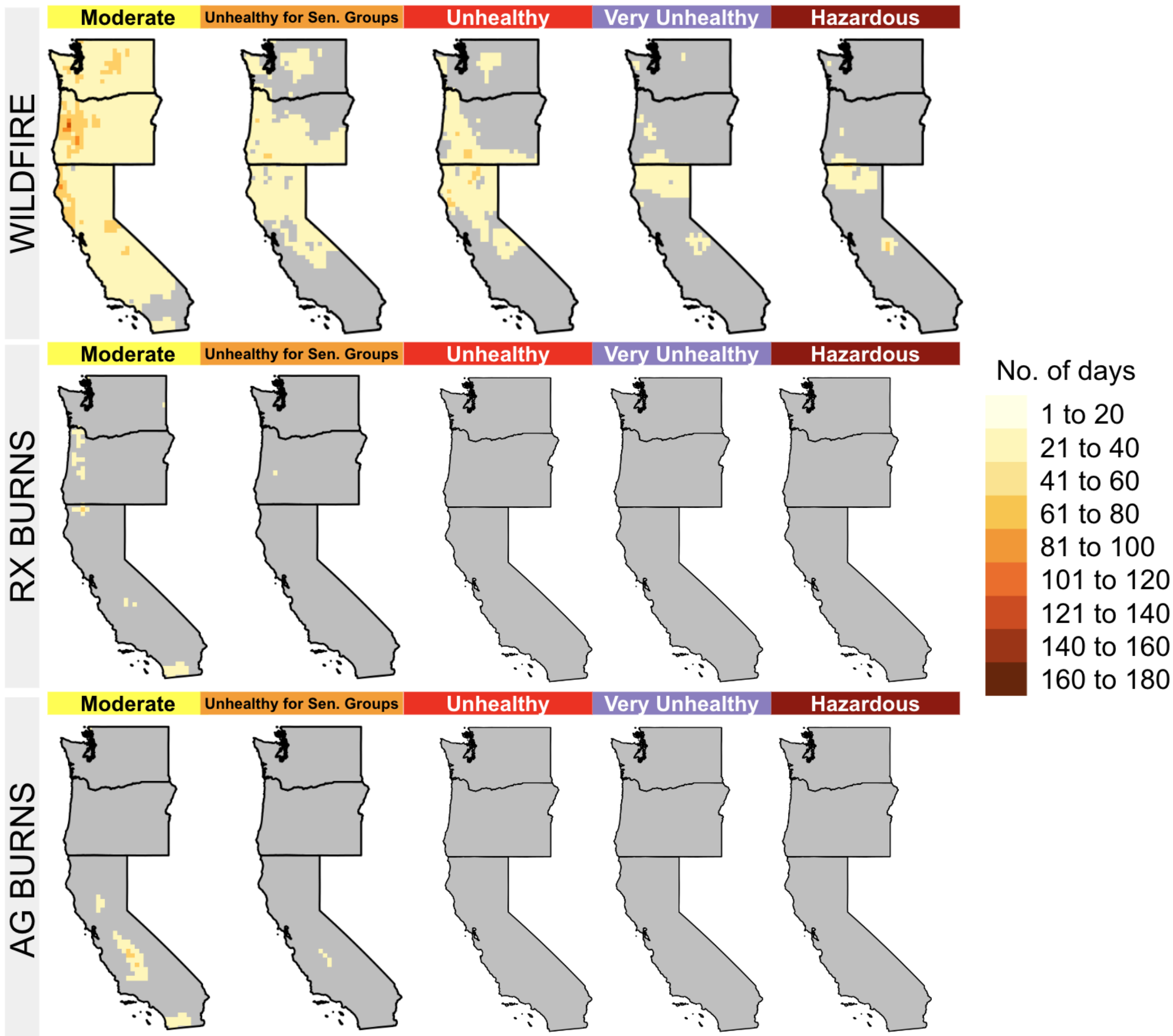

Figure 3.S4. Number of days in 2014 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

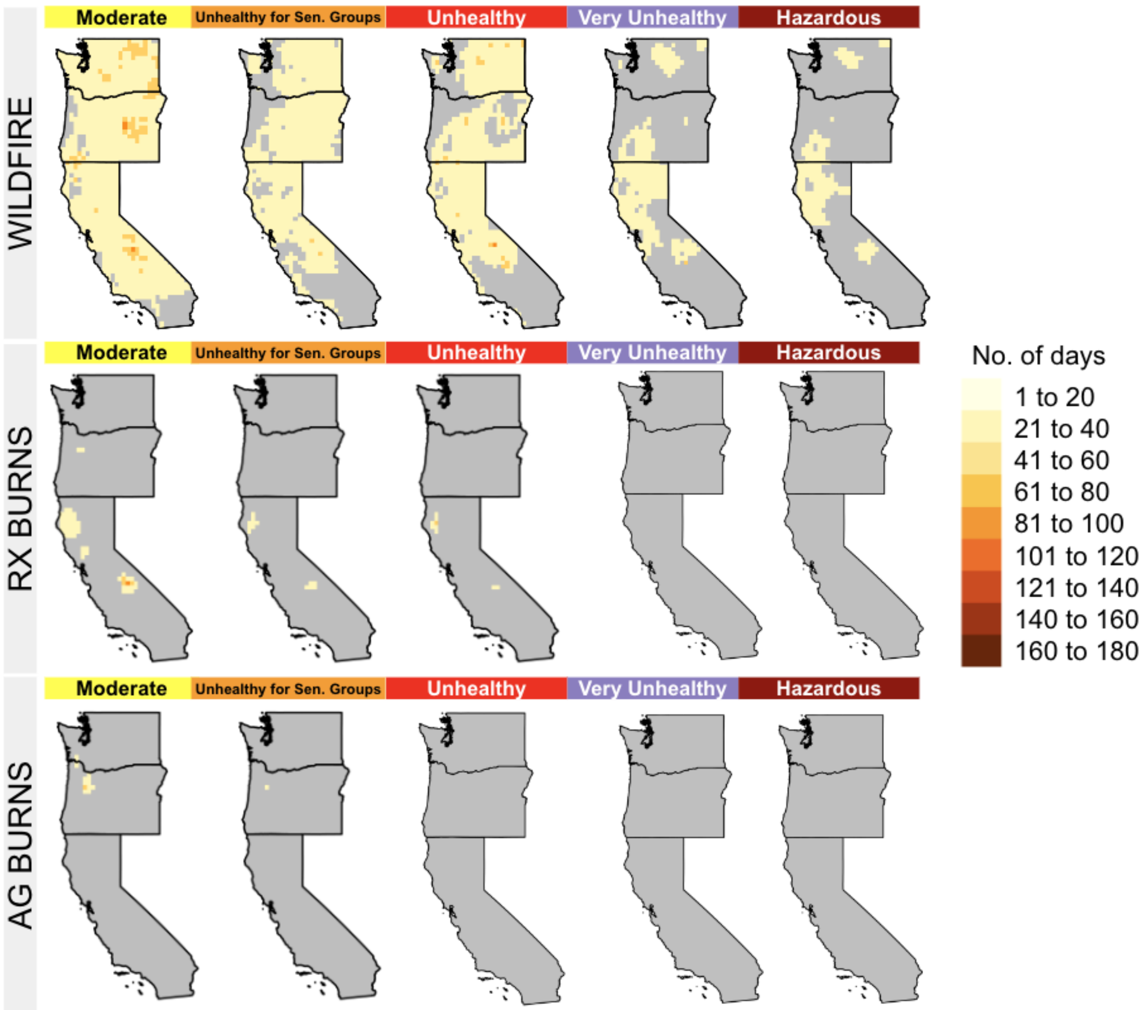

Figure 3.S5. Number of days in 2015 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

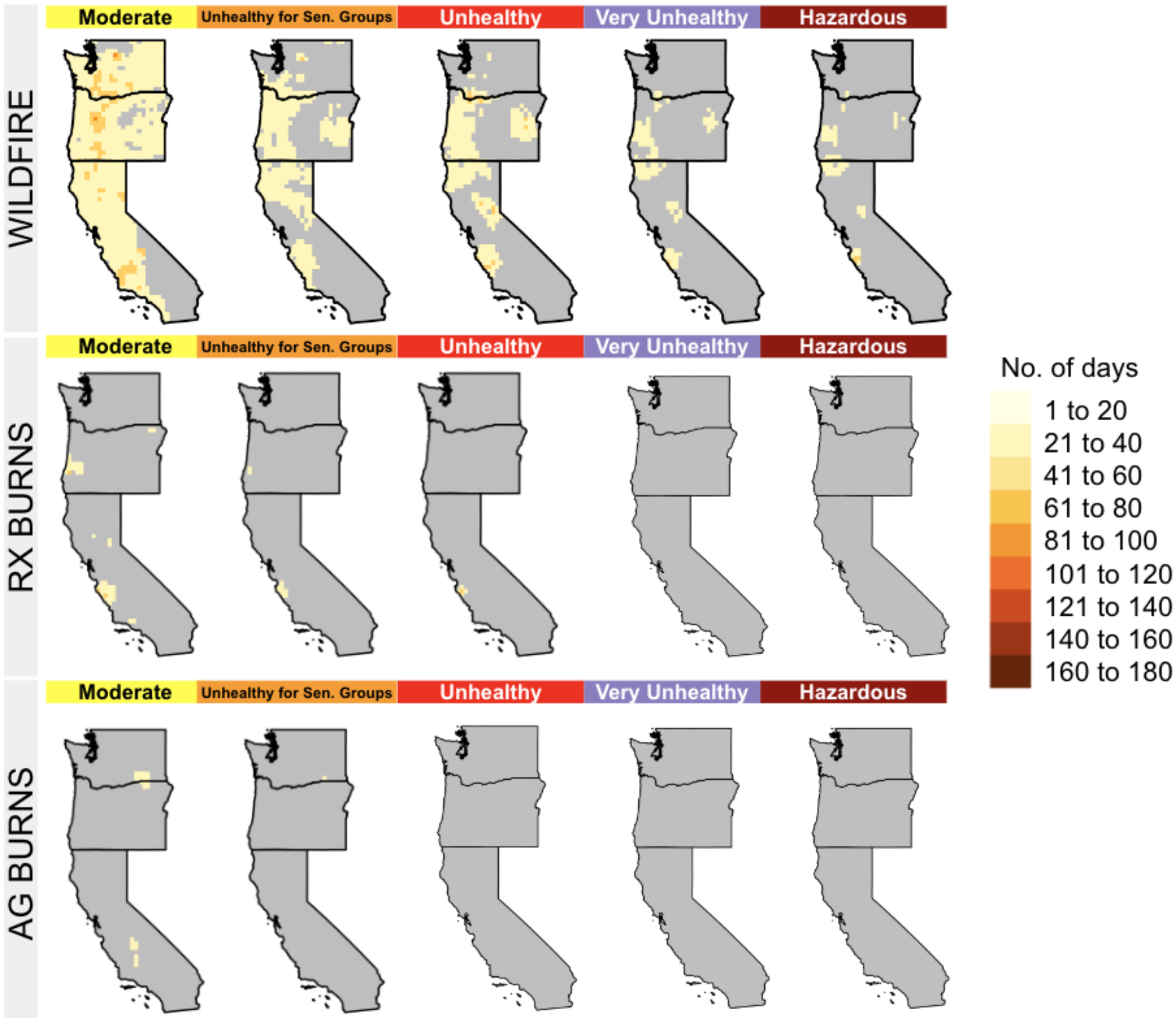

Figure 3.S6. Number of days in 2016 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

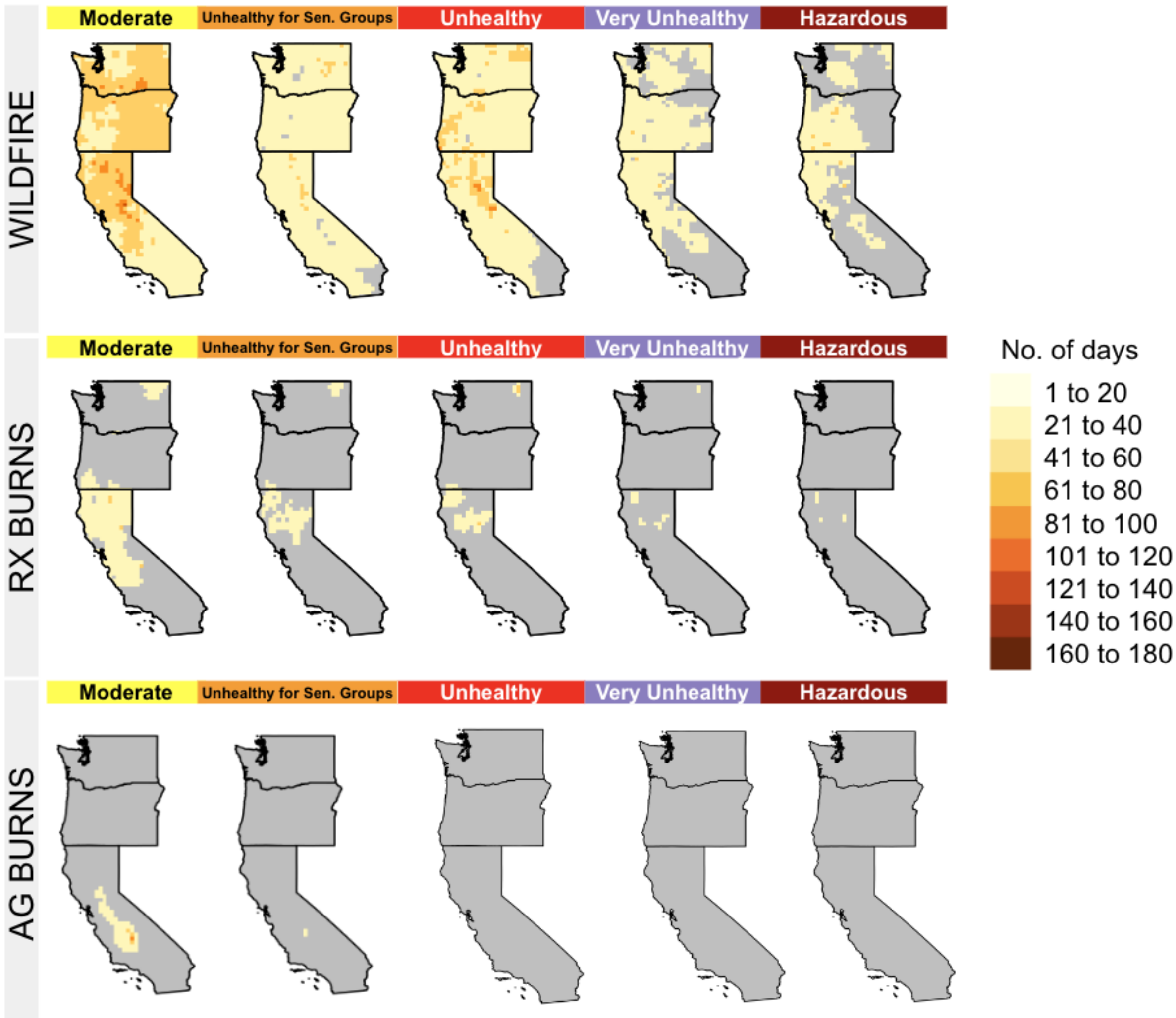

Figure 3.S7. Number of days in 2017 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

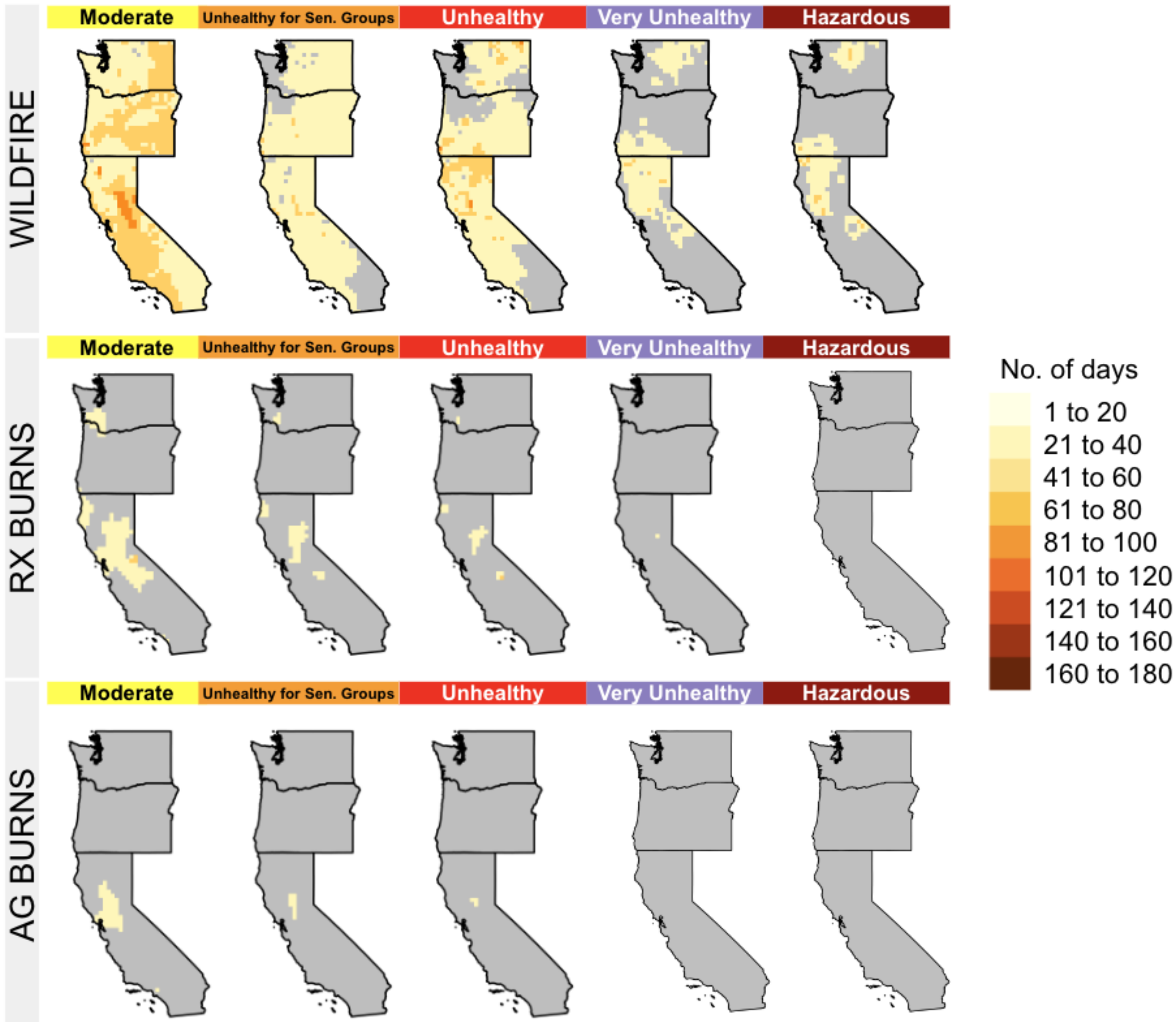

Figure 3.S8. Number of days in 2018 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

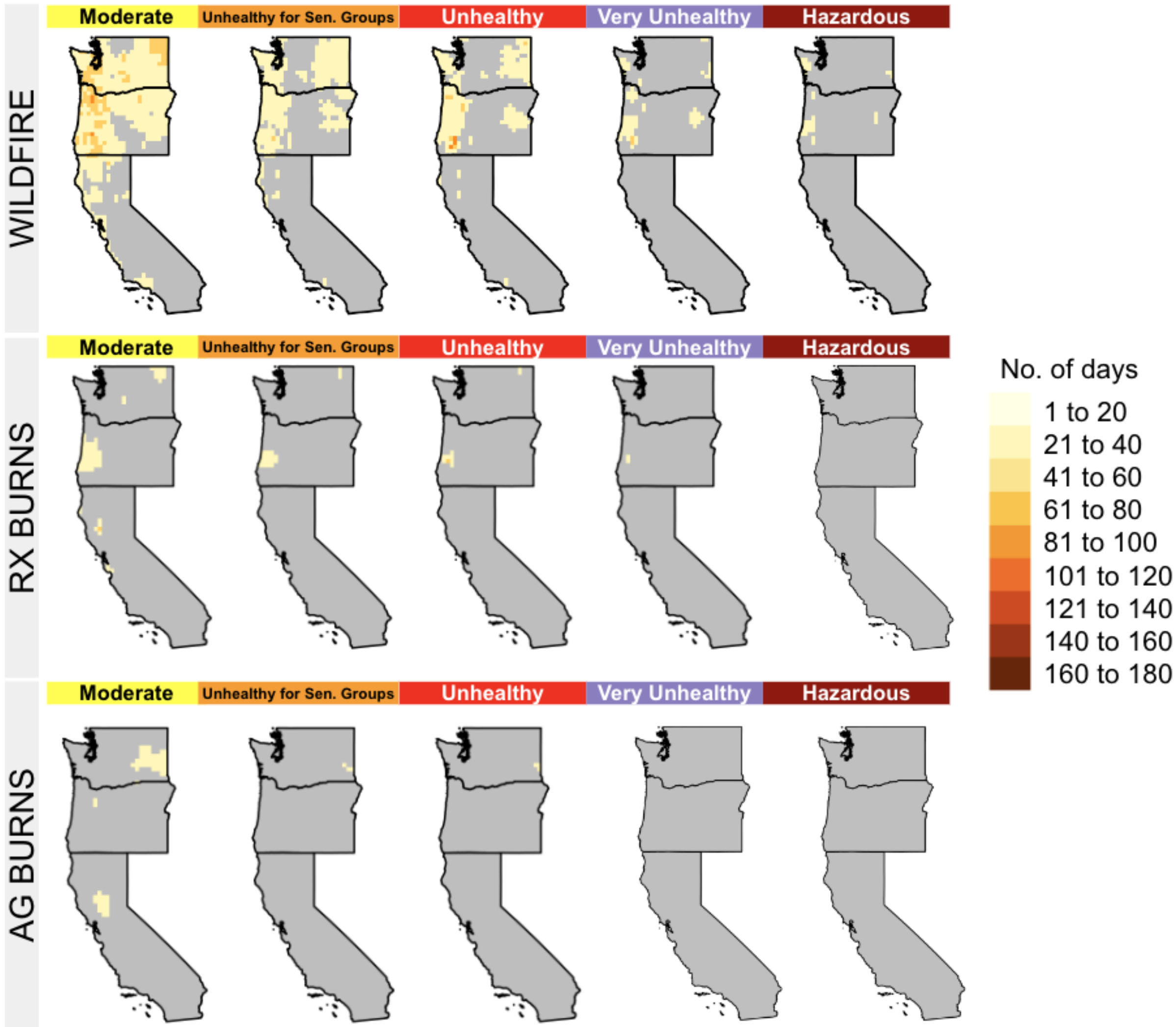

Figure 3.S9. Number of days in 2019 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

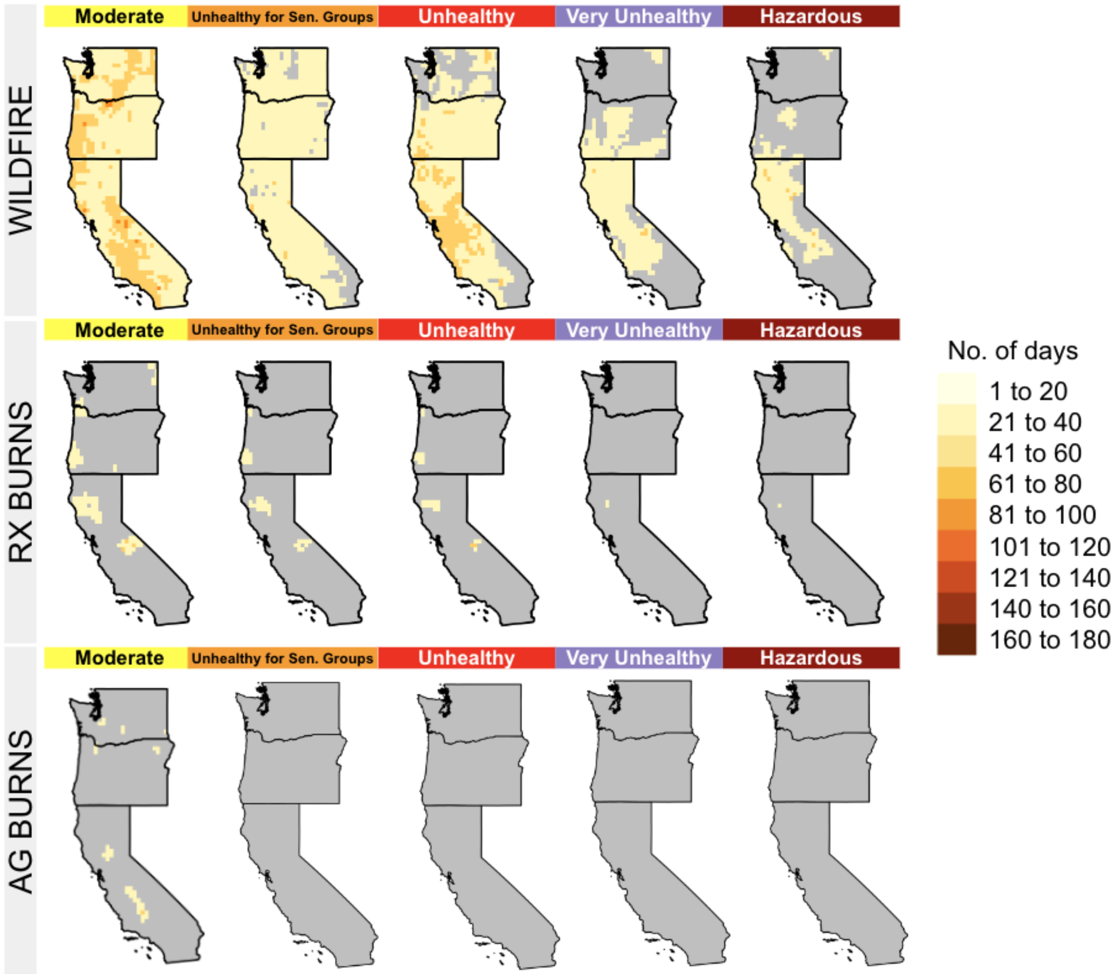

Figure 3.S10. Number of days in 2020 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories.

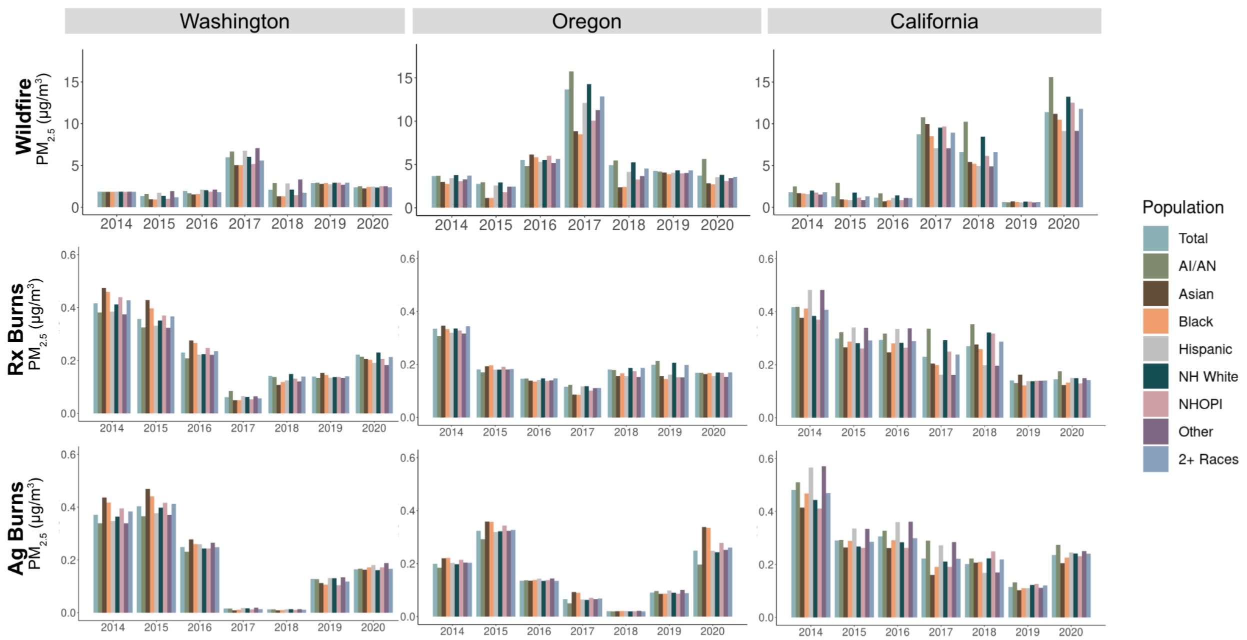

Figure 3.S11. Population-weighted $PM_{2.5}$ concentrations by year from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns for the total population and across race and ethnicity groups. Note the difference in y-axis scales.

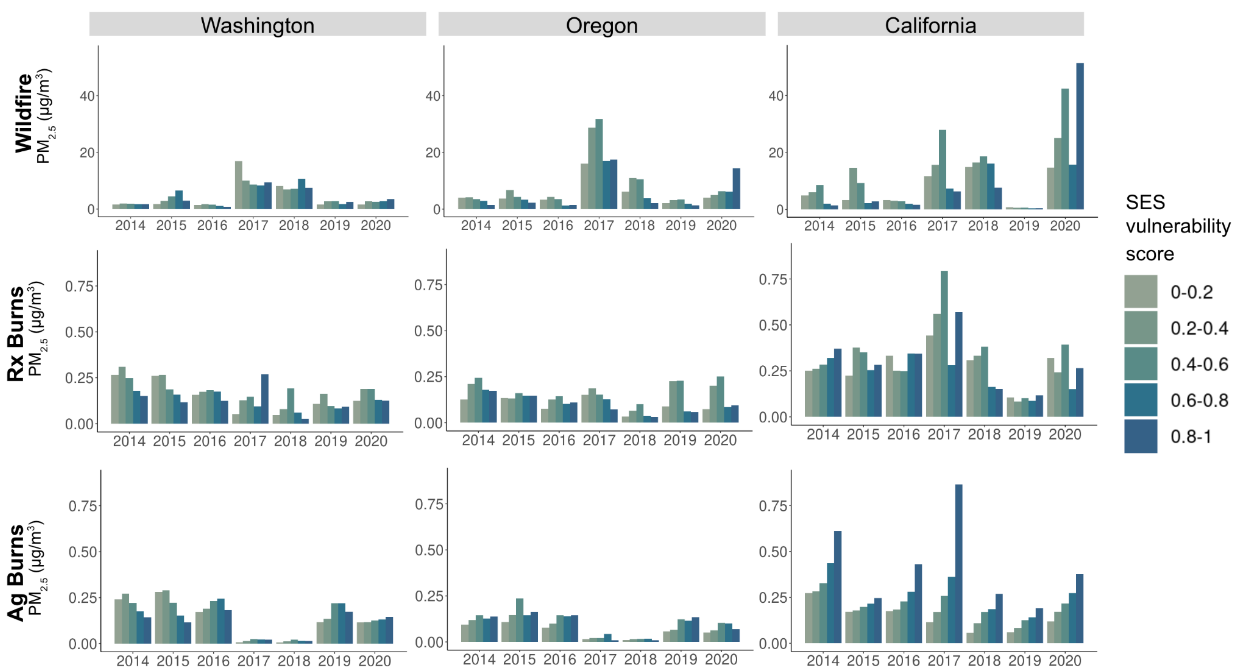

Figure 3.S12. $PM_{2.5}$ concentrations by year from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns for the total population and SVI SES score categories. Note the difference in y-axis scales.

Table 3.S2. Percent of grid cells (n_{total} = 2047) across all three states that experience each LISA category across the non-wildfire (NWF) and wildfire (WF) seasons.

	Wildfire		Prescribed Burns		Agricultural Burns	
	NWF	WF	NWF	WF	NWF	WF
High Expsoure - High SVI	7.7	11.8	7.9	5.4	9.3	10.0
High Expsoure - Low SVI	10.4	6.8	7.9	7.4	6.1	15.5
Low Expsoure - Low SVI	20.7	24.4	19.8	21.4	21.4	16.0
Low Expsoure - High SVI	28.6	27.0	29.2	26.0	27.1	24.3
Not significant	32.6	29.9	35.5	39.7	36.1	34.2

Chapter 4: CAN ECOLOGICAL FORESTRY IMPROVE PUBLIC HEALTH OUTCOMES? AN INTEGRATED FRAMEWORK AND CASE STUDY FROM CENTRAL SIERRA, CA[3]

Abstract

Prescribed burning can mitigate extreme wildfire risk and reduce total smoke emissions. Yet, prescribed burns' emissions may also contribute to smoke exposures in nearby communities. Incorporating public health considerations into forest management planning efforts may help reduce prescribed burn-related exposure impacts. We present a methodological framework linking landscape ecology, air quality modeling, and health impact assessment to quantify the air quality and health impacts of specific management strategies. We apply this framework to six forest management scenarios proposed for a landscape in the Central Sierra, California. We find that moderate amounts of prescribed burning can decrease wildfire-specific $PM_{2.5}$ exposures and reduce asthma-related health impacts in the surrounding region; however, the magnitude of that benefit levels off under scenarios with additional prescribed burning because of the added treatment-related smoke burdens. This framework can be applied to other fire-prone landscapes to incorporate public health considerations into forest management planning.

[3] Submitted for publication as: Schollaert, C. Jung, J. Wilkins, J. Alvarado, E. Baumgartner, J. Brun, J. Busch Isaksen, T. Lydersen, J. Marlier, M. Marshall, J. Masuda, Y. Maxwell, C. Tessum, C. Wilson, K. Wolff, N. Spector, J. Can ecological forestry improve public health outcomes? An integrated framework and case study from Central Sierra, California.

Introduction

Wildfires are becoming more frequent and severe due to climate change and post-colonial fire exclusion practices (Abatzoglou & Williams, 2016; Dennison et al., 2014; Hallegraeff et al., 2012; Halofsky et al., 2020; Littell et al., 2010; Ryan et al., 2013; A. L. Westerling, 2016; Williams, 2013). In addition to the direct economic damages and physical dangers to human life and property, wildfires produce significant quantities of smoke, which can degrade air quality and public health (Cascio, 2018; Reid et al., 2016). The punctuated and severe physical damages and increased air pollution caused by recent wildfire events, such as those in the western U.S., have garnered local and national attention. Forest management activities will likely play a significant role in efforts to mitigate future extreme wildfire risk, yet little is known about how those efforts may impact public health. We develop an approach for quantifying public health impacts of forest and fire management planning actively under consideration and demonstrate its utility via an analysis of real-world management scenarios.

Epidemiological studies have identified significant associations between smoke exposure and increases in all-cause and respiratory-related mortality and morbidities, including exacerbation of asthma (Cascio, 2018; Reid et al., 2016). Multiple studies indicate that short-term exposures to wildfire smoke are associated with cardiovascular outcomes, including mortality, hospitalization, and acute coronary syndrome (Cascio, 2018; Chen et al., 2021; Hadley et al., 2022; Reid et al., 2016). People with preexisting medical conditions, elderly individuals, and children may be more susceptible to the health impacts of wildfire smoke, while low-income communities and communities of color may be more vulnerable due to disproportionate exposure levels and limited adaptive capacity (J. C. Liu, Wilson, Mickley, Ebisu, et al., 2017; Rappold et al., 2017; Reid et al., 2016). Outdoor workers may also experience disproportionate exposure and health impacts from smoke (Davies et al., 2018; D'Evelyn et al., 2022; Reid et al., 2016). In response to our growing understanding of the population impacts associated with wildfire smoke exposures, there is widespread interest in strategies to decrease health-related damages from wildfire events (D'Evelyn et al., 2022; DNR, 2018; USFS, 2022). Current public health responses have largely focused on minimizing downstream risks primarily through risk communication and individual and community level interventions (e.g., at-home air filtration systems, clean air shelters, workplace regulations) (CA DIR, 2021; Cascio, 2018; Hadley et al., 2022; Laumbach, 2019; OR OSHA, 2022; Treves et al., 2022; WA L&I, 2021). Upstream actions—such as forest management, which may reduce emissions at the source—have the potential to decrease exposure and health risks for populations living near to and well beyond the jurisdiction where wildfires occur (Beatty, C.R., Stevenson, M., Pacheco, P., Terrana, A., Folse, M., and Cody, A., 2022; D'Evelyn et al., 2022).

There is growing consensus within the forest and fire management community that achieving long-term forest health requires restoring natural fire regimes, especially in the western U.S. (Hessburg et al., 2015; Ryan et al., 2013). Across the western U.S., forest management plans have shifted away from full-blown fire suppression towards fuel reduction, forest restoration, and maintenance efforts (Ryan et al., 2013; Stephens et al., 2020). The goals of these strategies are to re-introduce smaller and more frequent fires (e.g. via mechanical thinning and prescribed burning), to help reduce the occurrence of large and high-intensity fires (Kalies & Yocom Kent, 2016; Lydersen et al., 2017; Prichard et al., 2020; Tubbesing et al., 2019). The use of fire as an ecological management tool is not new: it has been used by Indigenous communities for millenia to accomplish a variety of land management goals (Kimmerer & Lake, 2001; Storm & Shebitz, 2006). In the U.S., federal and state-level funding and strategic plans targeting increased fuel treatments reflect this shift in management priorities (CA Forest Management Task Force, 2021; DNR, 2018, Infrastructure Investment and Jobs Act, 2021); however, barriers to prescribed burning still exist and have limited its application, particularly across the western U.S. (Kolden, 2019).

One barrier to prescribed burns is that they produce smoke, which can impact the health and wellbeing of surrounding communities (Jones & Berrens, 2021; Prunicki et al., 2019). For public health practitioners and decision-makers whose primary interests are in protecting the health of the communities they serve, any smoke exposure is often seen as counterproductive to these interests. However, previously contentious debates between public health, fire, and forest management communities have recently shifted towards collaboration and consensus due to the alarming trend of more frequent and intense wildfires and associated impacts on human and ecosystem health. There is now shared interest in understanding whether large scale forest restoration and climate resilience planning efforts could also advance public health interests (Altangerel & Kull, 2013; American Lung Association, 2022; D'Evelyn et al., 2022; Jones et al., 2022).

To date, few studies have examined whether forest management —in the form of prescribed burning and mechanical thinning—can reduce overall population exposure to wildfire smoke and whether such actions are associated with reduced adverse human health risks. This gap reflects that the two fields (i.e., fire and forest ecology vs. public health) have so far generally progressed independently of each other. Previous evaluations of the air quality and health impacts of increased forest management have relied on high-level representations of management increases (e.g., hypothetically increasing prescribed burns by a defined percentage uniformly across a geographic area), which are not designed around specific landscapes or real-world management scenarios (Burke et al., 2021; Ravi et al., 2018). To address this gap in the literature, an integrated framework is necessary to conceptually link disparate but related analyses from these disciplines. Such a framework will not only allow for the evaluation of ecological factors, but also of the human exposure and health implications of forest management scenarios that are actively under consideration for real-world landscapes (D'Evelyn et al., 2022; Hunter & Robles, 2020).

This paper presents a methodological framework that can be used to quantitatively integrate public health impacts into forest and fire management planning by reconciling data input requirements and spatiotemporal scales that differ across ecology, atmospheric science, and public health methodologies. We apply this framework in a case study that evaluates the smoke exposure and health impacts of six forest management scenarios under consideration for a 970,000 hectare landscape in the Tahoe-Central Sierra Initiative (TCSI) area in Central Sierra, California. The scenarios were developed by a consortium of land managers to investigate how increasing the area treated and the amount of prescribed burning would improve forest resilience to stressors such as wildfire, forest pests, and drought (C. J. Maxwell et al., 2022). Two management scenarios include mechanical and hand thinning treatments only in locations close to developed areas or on private lands: Minimal Management scenario (9,300 ha/year) and Business as Usual (BAU) scenario (16,600 ha/year). Four management scenarios include increasing amounts of prescribed burning and thinning, ranging from Fire^{Lite} (32,780 ha/year) to Fire++ (51,400 ha/year), in locations extending away from developed areas (Wilson, K. N. and Manley, Patricia N., personal communication, September 23, 2020) (Figure 4.1).

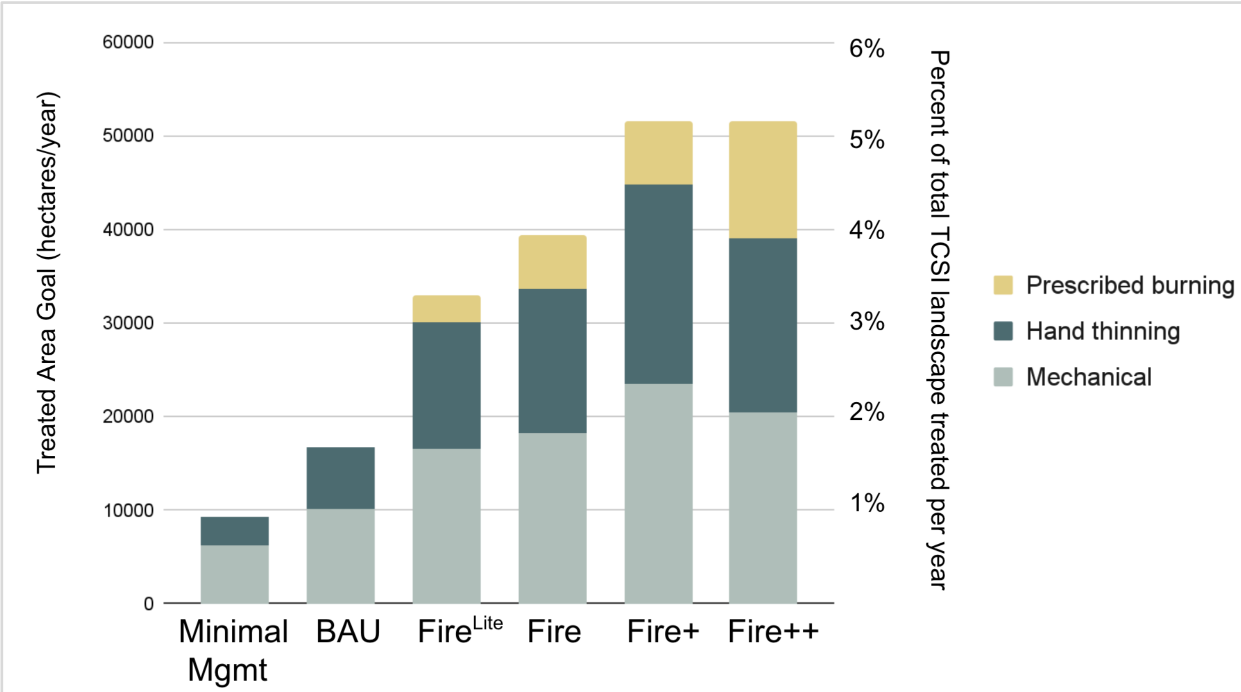

Figure 4.1. Treated area goals by treatment type across the six scenarios considered.

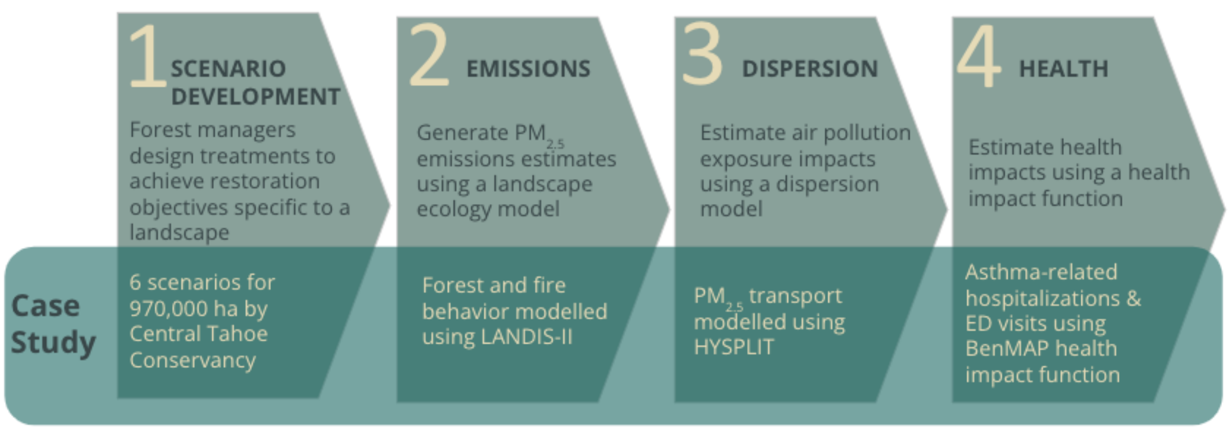

Figure 4.2. Methodological framework for linking forest and fire modeling, air quality modeling, and health impact estimation efforts.

We generate estimates of wildfire and prescribed burn-specific ambient smoke levels for the six proposed management scenarios (Figure 4.2). We then use population smoke exposure to estimate health impacts. Our results indicate that forest restoration practices can be associated with reduced health risks and adverse impacts; however, there are diminishing returns based on the intensity and scale of such practices as it relates to public health impacts. Our study advances these methods and evidence on whether sustainable forest management practices meant to return forests to natural fire regimes can result in broader societal benefits through reduced risks and impacts on human health.

Methods

Overview

We employ an interdisciplinary, multi-step modeling framework (Figure 4.2) that links forest management scenario development, emissions estimates generated by a landscape forecasting model, air pollution modeling, and health impact estimation to evaluate the exposure and health impacts of the proposed management strategies. We simulate the exposure and health impacts of each scenario from 1981-2020. We chose an historical time period instead of simulating scenario implementation into the future because of limitations and large uncertainties in future meteorological data availability, specifically future wind conditions required by both models used in this analysis.

Study area

Management scenarios were developed for 978,381 hectares in the Sierra Nevada ecoregion around Lake Tahoe called the TCSI. Forest types range from low elevation oak woodlands (Quercus spp.) to high elevation montane conifers (Abies spp. and Pinus spp.). The region was largely spared from the megafires from the 2020 and 2021 fire seasons and from the insect outbreaks and drought that contributed to the mass mortality event across the Sierras between 2012-2017. Most of the land area (~68%) is within the National Forest system, of which 41% is within 2.4 km of houses or other buildings (the wildland urban interface, or WUI).

Privately owned production forests cover about 14% of the land, of which 11% is within the WUI.

Management impacts on emissions were tracked within the TCSI; however, because emissions can be transported significant distances downwind, plumes were tracked across California and Nevada. Plume patterns primarily impacted regions to the west of the treatment landscape. Therefore, exposure levels were only calculated for western Nevada and California for the purposes of this case study.

Scenarios

A consortium of land managers from various agencies and researchers co-developed six forest management scenarios (C. Maxwell et al., 2022a). The TCSI is made up of seven management zones, including private industrial and non-industrial land, WUI defense zones (400 m from structures and evacuation routes), WUI threat zones (2000 m out from defense zone), general forest (forests within the National Forest system that are potentially treatable), roadless areas (forests within the National Forest system that can be treated but cannot do not have roads), and wilderness areas (reserve areas that are legislatively protected) (USFS, n.d.). Each management scenario varies in the extent and pace of thinning and prescribed burning applied to each zone. In the lowest-level management scenarios (Minimal Management and BAU), only private lands and WUI defense zones are treated using only mechanical thinning. In the BAU scenario, treatments include everything from the Minimal Management scenario plus mechanical treatments in the WUI threat zone. Prescribed burning is introduced in the middle-tier scenarios ($Fire^{Lite}$, Fire, Fire+), applied modestly in general forest zones (5% prescribed burning, 95% thinning) and roadless zones (20% prescribed burning, 80% thinning). In the Fire, Fire+, and Fire++ scenarios, prescribed burning is introduced in threat zones (20% prescribed burning, 80%

thinning), and is increased in the general forest and roadless zones under the Fire++ scenario (30% prescribed burning, and 70% thinning). Figure 4.1 provides an overview of the rate and amount of each treatment type applied to the landscape each year under each scenario.

Landscape forecast modeling

Forest change in the region was simulated using the LANDIS-II landscape change model (Scheller et al., 2007), which simulates forests as individual species-age cohorts within a grid of interacting cells, allowing spatial interactions among processes (e.g., management, growth and succession, and disturbance) through time over large areas. Individual species-age cohorts compete for resources within each cell. Forest succession and landscape carbon dynamics were simulated using the Net Ecosystem Carbon and Nitrogen (NECN) succession extension (v6.6) (Scheller et al., 2011). Model inputs and parameters were based on a combination of forest inventory, satellite data, and literature sources. Soil data were from a gridded Soil Survey Geographic Database (SSURGO) product of California (Soil Survey Staff, 2017), with duff, litter, and deadwood layers derived from interpolated Forest Inventory and Analysis National Program (FIA) data (B. T. Wilson et al., 2013). Initial communities were derived from FIA plots that were interpolated using an kNN algorithm and updated to the year 2019 using remote sensing. We simulated 36 tree species and three shrub functional groups that were derived from literature sources (Abrahamson, n.d.; Burns et al., 1990; Liang et al., 2017).

The climate data fed to the LANDIS-II model was a combination of gridMET 2 m temperature, precipitation, and relative humidity values and wind speed and direction values from the Weather Research and Forecasting (WRF) Advanced Research Weather and Forecasting (ARW) archived 27 km dataset that were resampled to the ecoregions used in the model (NOAA, n.d.). The model was run for 1981-2020, with 10 replicates of each management scenario to capture stochastic variation in disturbances and management. We divided the landscape into a 180-m (3.24 ha) grid. All model parameters, and the model and extension versions used, are available on github at: https://github.com/LANDIS-II-Foundation/Project-Tahoe-Central-Sierra-2019.

Dispersion modeling

We modeled dispersion patterns of the gridded emissions estimates using the Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT) (Stein et al., 2015a). We used 27 km meteorological data from the WRF-ARW archived dataset as the meteorological inputs for the model. Emissions estimates from LANDIS-II were inputted into HYSPLIT as 4 ha area sources, with total emissions estimates distributed equally across the area. Emission releases for both wildfires and prescribed burns began at 6:00AM, with wildfires burning for 11 hours and prescribed fires burning for 6 hours. Hourly emissions rates were calculated as the LANDIS-produced emissions rate divided by the total burn duration for each fire type. Plume rise was calculated within HYSPLIT based on estimates of fire heat release generated by LANDIS-II, using the Briggs equation (Stein et al., 2015b). The top of the HYSPLIT model domain (upper limit of meteorological grid) was set to the default height of 10,000 m. The concentration output grid was set to 27 km to match the WRF meteorological input grid. The total spatial extent spanned the 11 western states. Smoke concentrations were averaged at each grid point over 24 hours. The number of particles released per emissions cycle was set to 2500, with the maximum particle lifetime set to 15 days after release. Each management scenario was simulated in LANDIS-II 10 times, producing 10 replicates, which were all inputted into HYSPLIT. Ensemble mean dispersion distributions were generated for each scenario and used to calculate exposures.

Calculating particle dispersion across six management scenarios, each with 10 replicates over 40 years, requires numerous HYSPLIT simulations with different input and parameter setups. To reduce computation time and the need to re-parameterize the model by hand for each simulation, we developed a batch processing script, which allows the user to automate the generation of the HYSPLIT input files and run multiple simulations in parallel. More information on this can be found at https://github.com/Science-for-Nature-and-People/hysplit-batch.

Calculating exposure

Population-weighted smoke concentrations at the HYSPLIT grid cell level were calculated using the following equation:

$$(Population - weighted\ exposure\ level)_{PM2.5} = \frac{\sum(Pi\ x\ Ci)}{\sum Pi}$$

Where P_i is the population of a given grid cell, obtained from 2010 NASA Socioeconomic Data and Applications Center (SEDAC) 1 km gridded population dataset (SEDAC, 2020a), aggregated to our HYSPLIT output grid and C_i is the concentration. For the county-level health impact analysis, we generated an area average weighted concentration of $PM_{2.5}$ for each county by calculating the ratio of the total county area divided by the area of each grid cell that falls within the county. We then calculated the concentrations for each county by taking the sum of the concentration of each grid cell multiplied by the area ratio(J. C. Liu, Wilson, Mickley, Ebisu, et al., 2017).

Smoke wave definition

We define a smoke wave as at least two consecutive days of total smoke $PM_{2.5}$ (i.e., $PM_{2.5}$ from both wildfires and prescribed burns) greater than 15 μg/m^3, which is the threshold between

‘Good’ and ‘Moderate’ air quality under the Environmental Protection Agency’s (EPA) Air Quality Index (AQI). We chose this threshold because air pollution concentrations within the ‘Moderate’ range may pose a risk to those who are particularly susceptible to air pollution exposures, according to the EPA (U.S. EPA, Office of Air and Radiation, 2016). It is important to note that $PM_{2.5}$ concentrations reported in this study do not include contributions from sources outside of biomass burning within the TCSI such as anthropogenic sources and smoke from fires that may occur outside of the TCSI landscape. Therefore, these concentrations are likely underestimates of total $PM_{2.5}$ exposure.

Calculating health impacts

Changes in county-level asthma-related hospitalization and ED visits resulting from each of the scenarios were calculated using EPA’s Environmental Benefits Mapping and Analysis Program (BenMAP) health impact equation:

$$\Delta Y = Y_0 * (1 - e^{-\beta \Delta PM}) * Pop$$

Where Y_0 is the baseline incidence, β is the effect estimate derived from the existing literature, ΔPM is the change in $PM_{2.5}$ concentration, and Pop is the total exposed population. Effect estimates were derived from the Borchers-Arriagada et al. meta-analysis of wildfire smoke-specific asthma-related health outcomes (Borchers Arriagada et al., 2019). Asthma-related outcomes were chosen because the effect estimates are most robust across the wildfire smoke epidemiological literature (including across geographies) relative to other outcomes (Borchers Arriagada et al., 2019; Kondo et al., 2019). Health outcomes are only calculated for California and not surrounding states due to lack of data availability for the specific outcomes of interest. Baseline asthma-related hospitalization and ED visit rates for California counties from 2015-2019 were acquired from the California Department of Health and Human Services. County-level rates were averaged across the five years of available data. 2020 county-level population data were acquired from the U.S. Census Bureau. Although our simulated smoke-specific $PM_{2.5}$ data go back to 1981, population data from 2020 was used because these scenarios are under consideration on the current landscape, potentially impacting the current population now and into the future. In order to capture uncertainties in the meta-analysis effect estimates, we also calculated the change in health outcomes using the confidence intervals of the effective estimates derived from Borchers-Arriagada et al. (Borchers Arriagada et al., 2019).

Results

Forest management impacts on $PM_{2.5}$ exposure

We find the magnitude and spatial distribution of total smoke $PM_{2.5}$ concentrations (from wildfire and prescribed burns) are greatest under the Minimal Management and BAU scenarios, which involve no prescribed burning (Figure 4.3A). Population-weighted 40-year average total smoke concentrations under those two scenarios are 2.2 $\mu g/m^3$ and 1.8 $\mu g/m^3$, respectively. Population-weighted total smoke under scenarios that include prescribed burning were lower: 0.71 to 0.96 $\mu g/m^3$. Of that, the portion from wildfires ranges from 0.28 $\mu g/m^3$ (Fire++) to 0.41 $\mu g/m^3$ ($Fire^{Lite}$), while the portion from prescribed burns ranges from 0.30 $\mu g/m^3$ ($Fire^{Lite}$) to 0.68 $\mu g/m^3$ (Fire++). Differences in the magnitude and spatial distribution of wildfire and prescribed burn-specific average dispersion patterns can be found in Figure 4.S1. We also see seasonal wildfire smoke concentration differences across scenarios, with the wildfire smoke season ending earlier in the year, tapering off in October on average, under all scenarios that include prescribed burning, relative to the longer wildfire season that extends into November under the Minimal Management and BAU scenarios (Figure 4.3B).

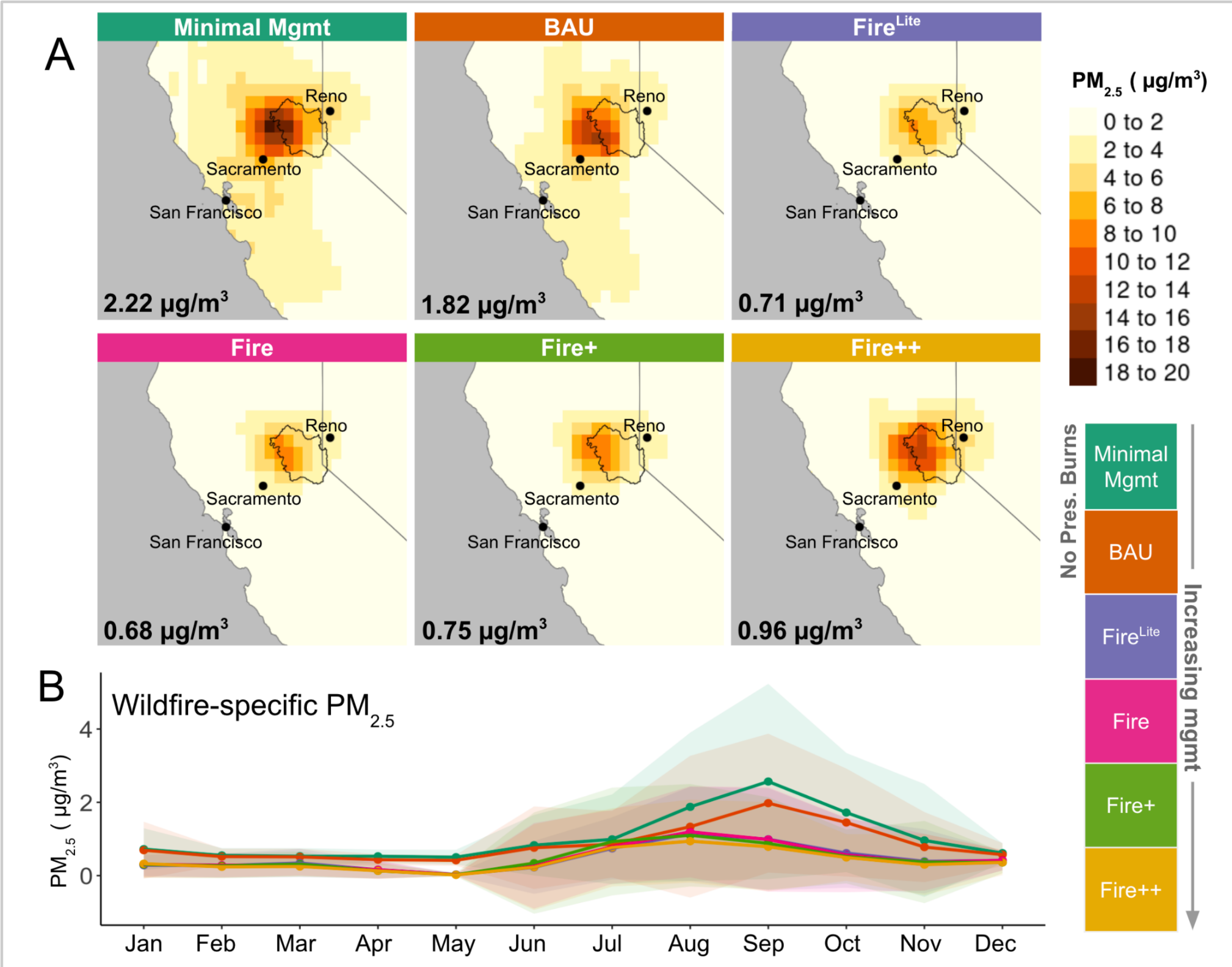

Figure 4.3. A) 40-year average total smoke $PM_{2.5}$ dispersion patterns for each scenario. Population-weighted 40-year average total smoke $PM_{2.5}$ concentrations are at the bottom left of each map panel. The TCSI is outlined in black, B) Monthly wildfire smoke-specific $PM_{2.5}$ concentrations. Shading represents the standard deviation of the monthly estimates.

Whether they stem from wildfire or prescribed burns, smoke events are often episodic and last on the order of hours to weeks. We examine how management scenarios impact the magnitude and frequency of these "smoke waves" (i.e., short-term smoke events; see Figure 4.4). The highest smoke-wave frequency (0.3 smoke waves per grid cell per year) occurs under the Fire++ scenario with the greatest amount of prescribed burning (12,408 hectares per year); however, the average magnitude of those smoke events (48.2 $\mu g/m^3$), stemming primarily from prescribed burning, is lower than smoke waves experienced under the Minimal Management

(66.3 μg/m^3) and BAU scenario (66.5 μg/m^3), where smoke waves stem entirely from wildfire smoke events (Table 4.S1). We find an inflection point of the lowest frequency (0.15 and 0.16 days) of smoke waves events under Fire^{Lite} and Fire scenarios, under which 2,883 and 5,655 hectares per year are treated with prescribed burns, respectively. This suggests that the rate and extent of prescribed burns under these scenarios may be optimal (among scenarios considered here) in terms of mitigating wildfire smoke exposure risk, while also minimizing smoke impacts stemming from prescribed burns. This finding is consistent with our finding for average concentration (Figure 4.3A) that the Fire scenario is optimal among scenarios considered.

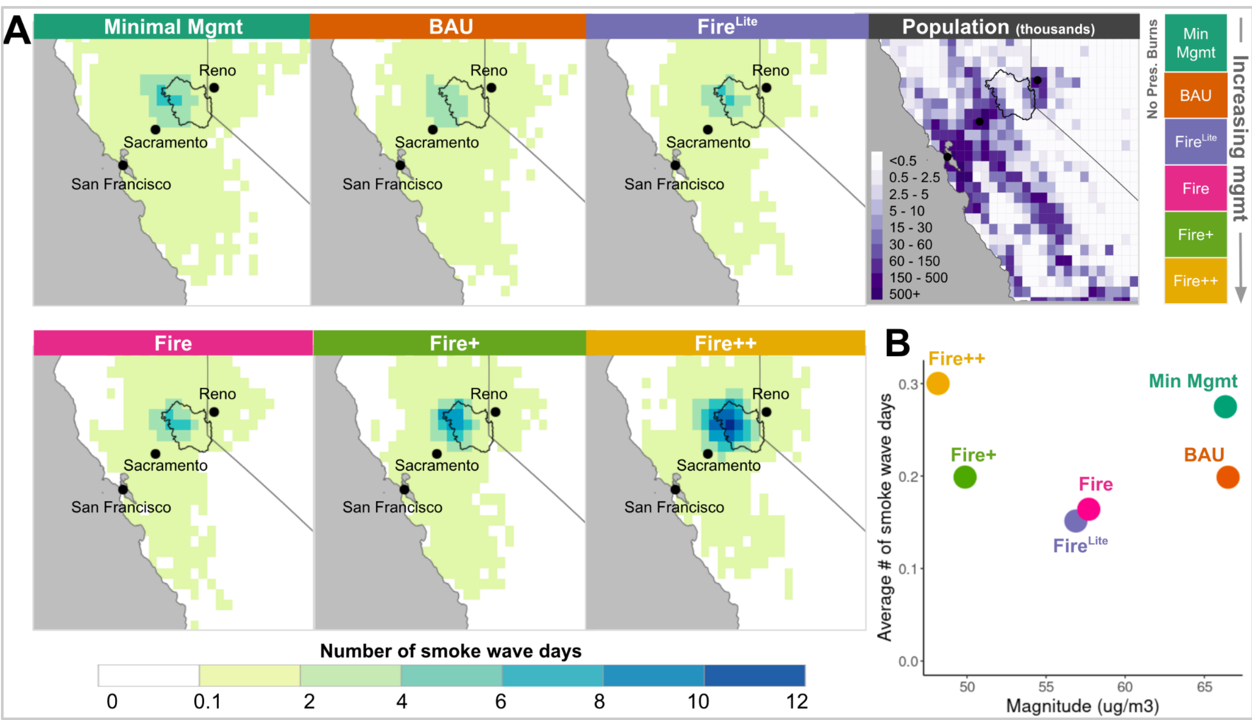

Figure 4.4. A) Average number of smoke wave days stemming from total smoke per year per grid cell in California and Nevada. Grid cell-level population count estimates in thousands of people are provided in the top right map panel. The TCSI is outlined in black, B) Average number and magnitude of smoke wave days per year per grid cell stemming from total fire smoke (smoke from wildfire and prescribed burns).

Figure 4.4A shows the spatial distribution of average number of smoke wave days per year. The highest frequency of smoke wave days under the scenarios that utilize prescribed burning occur in areas within or directly surrounding the TCSI. However, as noted above, the average magnitude of smoke waves is less for prescribed burn scenarios than for the Minimal Management and BAU scenarios.

Forest management associations with public health benefits

Compared with the BAU scenario, estimated asthma-related hospitalizations and emergency department (ED) visits were lower under all scenarios with increased management (Figure 4.5). Relative to BAU, the greatest health impact reduction for both outcomes occurs under the Fire^{Lite} and Fire scenarios in which modest levels of prescribed burning are applied to the landscape. For both asthma-related hospitalizations and ED visits, the magnitude of the health benefits levels off as more smoke is emitted through prescribed burning. This trend is similar to that observed in our analysis of smoke wave days, indicating a favorable scenario in regard to health co-benefits where enough prescribed burning is applied to the landscape to mitigate wildfire smoke exposure risk, but not enough to substantially increase prescribed burn-specific smoke exposures risk and subsequent asthma-related health impacts.

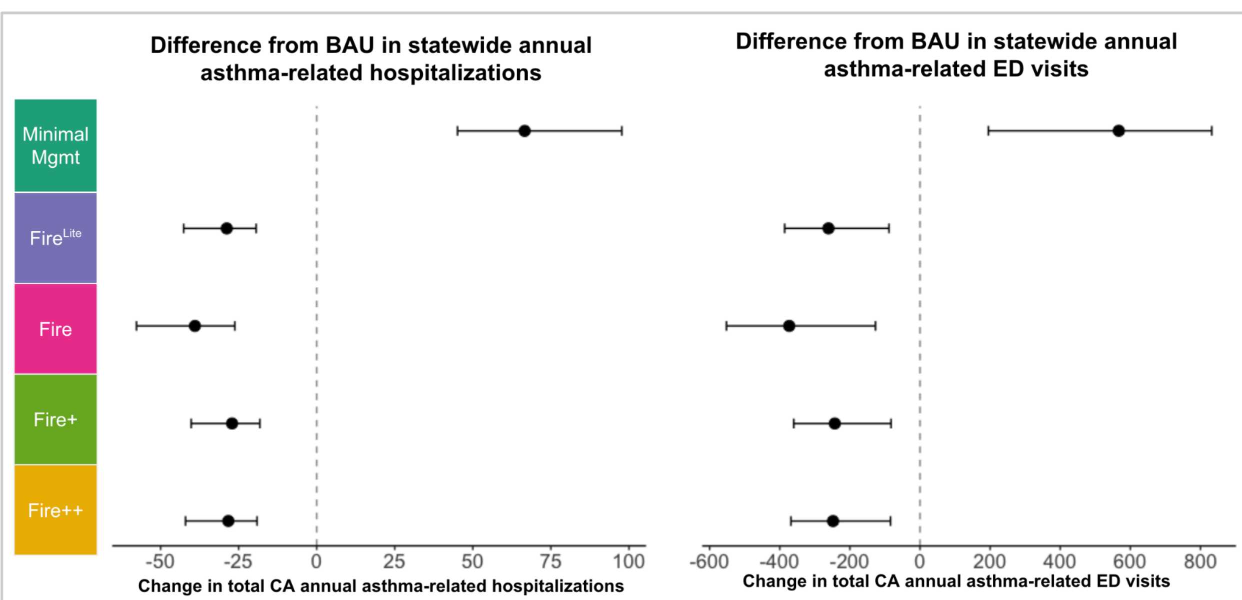

Figure 4.5. Change in annual state-wide asthma-related hospitalizations and asthma-related ED visits relative to BAU. The error bars represent the change in annual asthma-related hospitalizations and ED visits relative to BAU calculated using the 95% confidence interval of the relative risk reported in Borchers-Arriagada et al. 2019.

Figure 4.6 shows the spatial distribution of the relative difference from BAU in health impacts under each management scenario at the county level, normalized by population. While reductions in asthma-related health outcomes are minimal in most counties under scenarios with increased management, we find notable benefits in counties closer to the TCSI and with higher pre-existing rates of these asthma-related outcomes. For example, we estimate that in Sacramento County, which sees an average baseline rate of 64.5 asthma-related ED visits and 6.4 asthma-related hospitalizations per 10,000 residents per year, we would expect a reduction of 0.6 hospitalizations and 0.05 ED visits per 10,000 residents per year, under the Fire scenario versus BAU. It is also important to note that fuel treatment increases also result in increases in both outcomes (0.02 hospitalizations and 0.18 ED visits per 10,000) in Butte County, which lies directly northwest of the TCSI boundary under the Fire++ scenario (Figure 4.6).

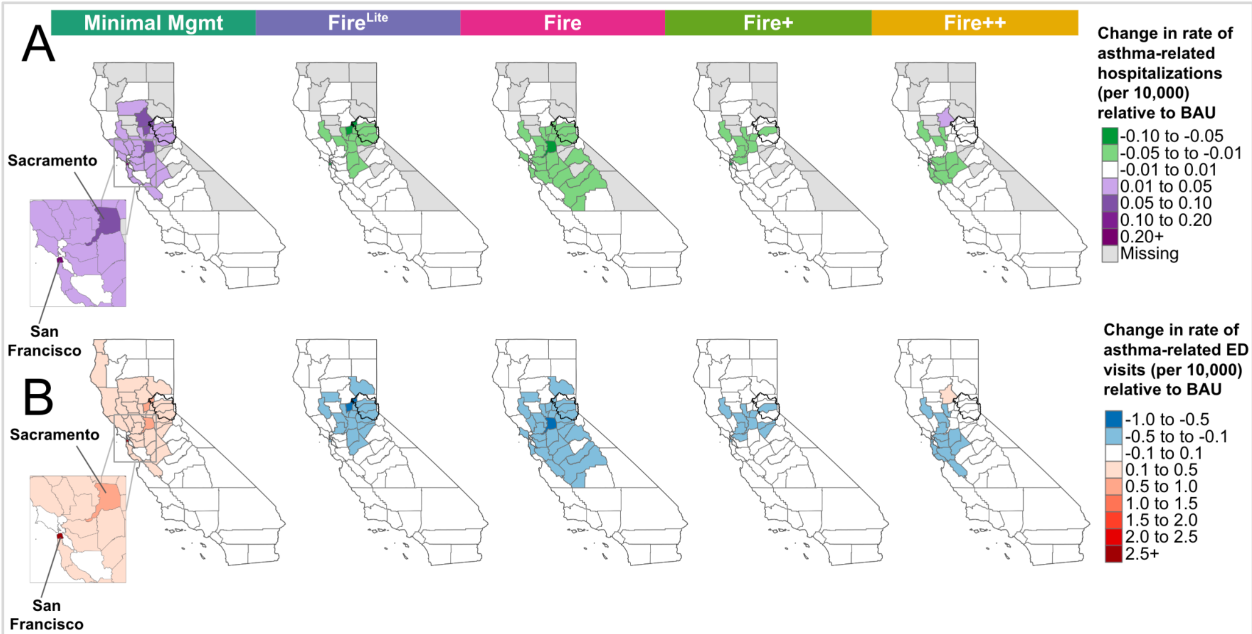

Figure 4.6. A) Change in county-level asthma-related hospitalizations per 10,000 residents relative to BAU. Missing values indicate suppressed baseline incidence data in accordance with California Health and Human Services Data De-identification Guidelines, B) Change in county-level asthma-related ED visits per 10,000 residents relative to BAU.

Discussion

There is growing interest in addressing the human health and well-being impacts from wildfire smoke. The public health sector has traditionally relied on risk communication and individual-level exposure reduction interventions to mitigate adverse health impacts from wildfire smoke. Those interventions focus on downstream behavior change instead of addressing the source of exposure. Discussions regarding the merits and risks of forest restoration practices, such as prescribed burning and mechanical thinning, have emerged in recent years (Hessburg et al., 2015; Ryan et al., 2013). Yet little work has quantified to what extent such practices could benefit public health goals. We provide an integrated framework for evaluating how forest restoration practices can impact emissions, air pollution exposures, and human health outcomes, such as asthma, using a case study from Central Sierra, California. We find that forest management activities can reduce overall exposure to smoke-related air pollution and associated health impacts in nearby communities. We chose to focus on the Central Sierra, California because it is an area that is under active management where stakeholders are interested in managing the landscape for improving forest and fire ecology and human health and well-being goals. The scenarios themselves were previously developed with stakeholder input and represent actual management options under consideration rather than hypothetical scenarios with no basis in existing policy or practice.

Our results indicate that out of the six scenarios under consideration, the $\text{Fire}^{\text{Lite}}$ and Fire scenarios, which introduce moderate amounts of prescribed burn treatments, provide the largest benefit of mitigating future wildfire smoke exposure (i.e., 0.41 $\mu g/m^3$ population-weighted 40-year average under $\text{Fire}^{\text{Lite}}$ compared to 1.8 $\mu g/m^3$ under BAU), while minimizing the contributions of prescribed burns to ambient smoke exposures (i.e., 0.31 $\mu g/m^3$ population-weighted 40-year average under $\text{Fire}^{\text{Lite}}$ compared to 0.68 $\mu g/m^3$ under Fire++). We found that increasing management above BAU results in approximately a month shorter wildfire smoke season, which could help combat rising resource demands within the forest management sector linked to lengthening wildfire seasons in California (S. Li & Banerjee, 2021). Differences in the total magnitude and duration of smoke exposures may be particularly important in California's Central Valley, the state's most productive agricultural region in which harvest of many crops intersects with peak wildfire season. Not only could lower wildfire smoke levels reduce the dose of $PM_{2.5}$ experienced by workers, which is often already higher than the general population due to time spent outside and higher respiration rates due to exertion, but the shortened wildfire smoke season could also reduce the duration of worker exposures, particularly for those who work later into the Fall (Figure 4.3A). We found that as the amount of prescribed burning increases to the amounts called for under the Fire+ (6,681 ha/year) and Fire++ scenarios (12,408 ha/year), smoke from the fuel treatments may have diminishing returns on the assessed health outcomes relative to the BAU scenario (Figure 4.5-6). Importantly, under all metrics evaluated, the Minimal Management scenario, which calls for less management than is currently implemented, resulted in worse smoke exposure levels and associated health impacts (i.e., 70 additional asthma-related hospitalizations and 582 additional asthma-related ED visits per year) (Figure 4.5-6). This highlights the importance of some degree of baseline fuels treatment in mitigating wildfire and smoke impacts. While we found the middle tier scenarios (Fire$^{\text{Lite}}$ and Fire) can reduce exposure and provide health co-benefits (i.e., 261-371 fewer asthma-related hospitalizations and 29-38 ED visits across California per year), decision-makers must also evaluate which scenarios can also achieve forest management objectives, climate mitigation goals, conservation objectives, and other priority considerations. Multiobjective evaluation is a clear next step in evaluating forest management scenarios, as other scenarios may look more favorable when examining these other outcomes (Dobre et al., 2022; Evans et al., 2022; Maxwell et al., 2022; C. Maxwell et al., 2022b; White et al., 2022).

Our integrated framework provides a roadmap that could be applied to other fire-prone landscapes where efforts to revive natural fire regimes are under consideration. While other management planning efforts have primarily relied on metrics related to wildfire risk, wildlife management, wildland urban interface (WUI) protections, water quality management, and other considerations to evaluate the efficacy of proposed management strategies, our framework presents an opportunity to add an additional metric of evaluation: the public health impacts of proposed forest and fire management activities (CA Forest Management Task Force, 2021; DNR, 2018). To achieve this, we developed methods to link outputs from ecological and air quality models along with population and epidemiological data, which all rely on different sets of assumptions and are presented at varying spatiotemporal scales. Not only does this approach allow for the examination of prescribed burn impacts on air quality and health, but also the impacts of those fuel treatments on future wildfire occurrence, behavior, and downwind smoke impacts. This holistic incorporation of public health considerations into planning efforts opens the door to the development of more equitable and effective forest management interventions that restore natural fire regimes while simultaneously improving the air quality and health of surrounding communities.

Like all model-based studies, our methodological framework and analysis are constrained by existing data and models, including the assumptions and associated uncertainties of those models. For example, our approach only considers primary $PM_{2.5}$ and does not consider other pollutants, nor atmospheric chemistry or atmospheric formation of $PM_{2.5}$. Acknowledging the weaknesses of each individual model component, we present a framework that integrates methods from multiple disciplines and establishes a blueprint for future applications that could incorporate improvements to the specific models used here or the use of more complex models, which may provide, e.g. more accurate representations of chemistry and transport.

We evaluated the impacts of these scenarios under historical conditions; however, recent studies have shown that extensive management alone will not be sufficient to achieve sustainable forest management objectives given the projected impact of climate change on future forest and fire conditions (C. Maxwell et al., 2022a). Future work should examine the combined effects of future climate and forest management activities to holistically evaluate potential impacts on air quality and public health. Use of effect estimates from the current epidemiological literature, in this case relative risk estimates from a meta-analysis by Borchers-Arriagada et al., applies the assumption that the characteristics of the exposed population and landscape are the same as those from the studies from which the effect estimates were derived (Borchers Arriagada et al., 2019). Our analysis focused on asthma-related health outcomes because the wildfire smoke impact on these outcomes has been relatively consistent across geographies (Borchers Arriagada et al., 2020; Kondo et al., 2019). Our results may be sensitive to our selection of health outcomes and future health impact assessments of forest management plans may consider evaluating additional outcomes. Finally, our analysis does not consider the impacts of co-exposures, such as anthropogenic sources of air pollution, smoke from fires outside the TCSI, and extreme heat exposure, on the health of impacted populations. These co-exposures may contribute to uncertainties in our total exposure estimates and/or modify the concentration-response relationships used to estimate health impacts in this study.

Conclusion

Given recent policy shifts, it is likely that more attention and resources will be allocated towards ramping up fuel treatments across the western U.S. (D'Evelyn et al., 2022; DNR, 2018; USFS, 2022). As forest managers start to develop more aggressive and longer-term management strategies at the local, state, and regional levels, it will be critical to integrate public health considerations into planning efforts. D'Evelyn et al. initiated an important communication channel between researchers and practitioners across the public health and forest and fire management sectors to begin to establish common goals and collaboration strategies (D'Evelyn et al., 2022). Following that effort, our methodological framework and case study provides a grounded approach to further bridge the public health and forest management sectors within actual management planning discussions. Through its application in the Central Sierra, we found the greatest smoke exposure reduction and health co-benefits under management scenarios with moderate amounts of prescribed burning. For the specific scenarios evaluated, the exposure and health benefits tapered off as more prescribed burning was applied to landscape. Our modeling framework is flexible and agnostic to the needed advances in models outlined above and can be adapted to other landscapes and other existing models to estimate smoke emissions and dispersion patterns. Accelerating our understanding of whether and how ecological and public health objectives can be achieved through active forest management is urgently needed to realize a resilient and sustainable future in fire-prone landscapes.

Supplementary material

Figure 4.S1. 40-year mean wildfire and prescribed burn-specific $PM_{2.5}$ dispersion patterns for scenarios Fire^{Lite} - Fire++. Minimal Management and BAU are not included because they do not include the use of prescribed burning; therefore, the mean smoke dispersion patterns estimated under those scenarios are reflected in Figure 3A.

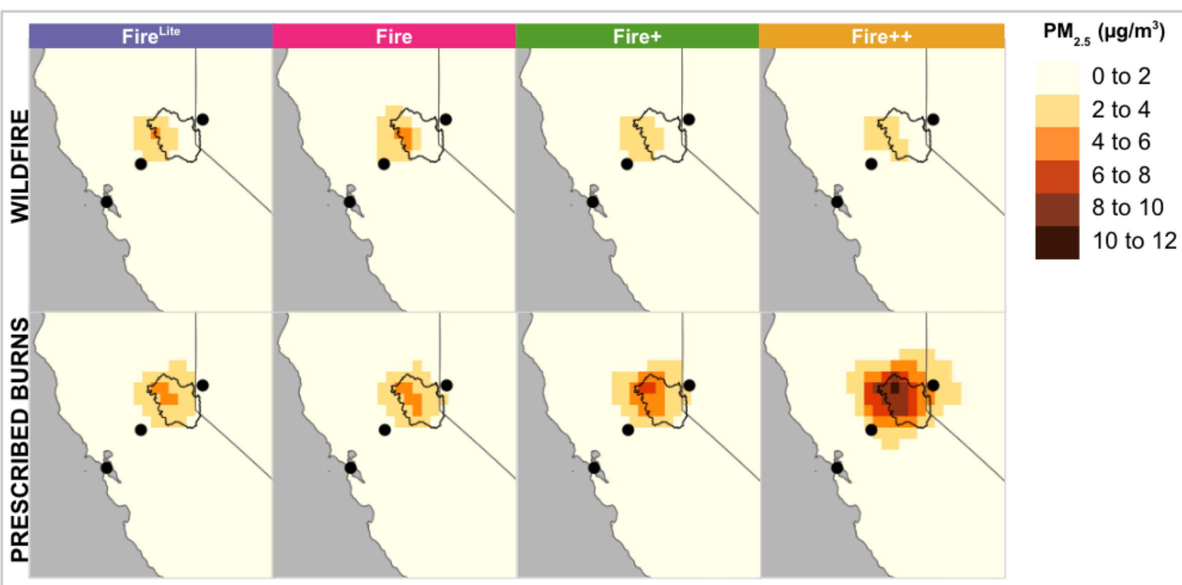

Table 4.S1. Average number and magnitude of smoke wave (SW) days per year per grid cell stemming from wildfire and prescribed burn-specific smoke.

	Source: Wildfire		Source: Prescribed Burns	
	# SW days/year	Magnitude (µg/m³)	# SW days/year	Magnitude (µg/m³)
Minimal Mgmt	0.28	66.33	–	–
BAU	0.20	66.50	–	–
FireLite	0.12	53.62	0.02	23.18
Fire	0.13	54.45	0.02	22.70
Fire+	0.13	42.69	0.06	24.24
Fire++	0.14	30.44	0.15	34.16

* BAU = Business as Usual

Chapter 5: ESTIMATED IMPACTS OF FOREST RESTORATION SCENARIOS ON SMOKE EXPOSURES AMONG OUTDOOR AGRICULTURAL WORKERS IN CALIFORNIA[4]

Abstract

As wildfires continue to worsen across western U.S.,forest managers are increasingly utilizing prescribed burns as a way to reduce excess fuels and future wildfire risk. While the ecological benefits of these fuel treatments are clear, little is known about the smoke exposure tradeoffs of using prescribed burns to mitigate wildfires, particularly among at-risk populations. Outdoor agricultural workers are a population at increased risk of smoke exposure due to their time spent outside and the physical demands of their work. Here, we assess the smoke exposure impacts among outdoor agricultural workers resulting from the implementation of six forest management scenarios proposed for a landscape in the Central Sierra, California. We leverage emissions estimates from LANDIS-II to model daily PM2.5 concentrations with HYSPLIT and link those to agricultural employment data from the Bureau of Labor Statistics. We find that moderate amounts of prescribed burning result in the greatest reduction in total smoke exposure among outdoor agricultural workers, particularly during months of peak agricultural activity. The reduction in total smoke exposure, relative to scenarios with the least amount of management, decreases as more prescribed burning is applied to the landscape due to the contributions of the fuel treatments themselves to overall smoke burden. The results of this analysis can not only inform forest management planning for this specific landscape, but may also contribute to

[4] To be submitted for publication as: Schollaert, C. Alvarado, E. Baumgartner, J. Busch Isaksen, T. Jung, J. Marlier, M. Marshall, J. Masuda, Y. Tessum, C. Wilkins, J. N. Spector, J. Estimated impacts of forest restoration scenarios on smoke exposures among outdoor agricultural workers in California.

preparedness efforts aimed at reducing future smoke exposures among outdoor agricultural workers in the wake of the developing wildfire crisis.

Introduction

As wildfires continue to worsen across the western U.S., outdoor agricultural workers are a population that may be increasingly vulnerable to smoke impacts. California's agricultural industry provides over three-quarters of the fruits and nuts and over one third of the vegetables consumed across the U.S., bringing in approximately $22.5 billion in 2021 and employing over 400,000 workers annually (CDFA 2023; CA EDD 2023). The growing and harvesting seasons, when workers spend most of their shifts outdoors, also overlaps with peak wildfire smoke season. A study of wildfire smoke exposure among outdoor agricultural workers in California estimated that between 2004-2009, there were 646,000 worker smoke exposure days over the 'Unhealthy for Sensitive Groups' Air Quality Index (AQI) threshold per county (Marlier et al. 2022). Established by the U.S. Environmental Protection Agency as a tool to communicate air pollution risk exposure to the public, the AQI is a set of six categories based on corresponding ranges of PM2.5 concentrations (EPA 2023). The PM2.5 concentration threshold for the 'Unhealthy for Sensitive Groups' AQI category is 35.5 $\mu g/m^3$. The authors also projected that number to increase by over 190 percent by 2046 as a result of climate change (Marlier et al. 2022). Another study in Washington state found that counties with the highest agricultural worker populations experienced the greatest number of days with both elevated heat and air pollution exposures during wildfire season, indicating the potential for hazardous co-exposures during peak crop production periods (Austin et al. 2020). Recent surveys of agricultural workers and employers in California have document varied awareness of air quality issues pertaining to wildfire smoke in the workplace along with limited knowledge of exposure reduction measures, such as the use of masks or respirators, which highlights the need for an increased understanding of smoke exposures in agricultural settings and more targeted exposure reduction efforts (Riden et al. 2020; Wadsworth, Riden, and Pinkerton 2022).

Few studies have examined the health impacts of wildfire smoke exposure among outdoor agricultural workers, but a rich literature has documented the negative links between wildfire smoke exposure and human health outcomes in the general population and subpopulations. Studies of wildland firefighters have documented an increased risk of short term declines in lung function and long term elevated risk of hypertension following occupational exposure to wildfire smoke (Groot et al. 2019; Navarro 2020). Among the general population, wildfire smoke exposure is known to be associated with respiratory-related mortality and morbidities, such as asthma and chronic obstructive pulmonary disease (COPD) exacerbations and adverse cardiovascular outcomes, mental health outcomes, and birth outcomes, such as low birth weight (Cascio 2018). Relative to the general population, outdoor agricultural workers are likely more vulnerable to the health impacts of wildfire smoke exposure due to more time spent outside during work shifts inhaling ambient air and heavier physical labor demands, which drive increased inhalation rates and higher smoke doses per unit smoke inhaled. Many outdoor agricultural workers are also of lower socioeconomic status, have reduced access to healthcare, and higher rates of preexisting conditions, which are all factors that may increase vulnerability to wildfire smoke exposure impacts (Schenker et al. 2015; Méndez, Flores-Haro, and Zucker 2020).

To address occupational exposures to wildfire smoke among outdoor workers, the California Division of Occupational Safety and Health (Cal/OSHA) introduced a wildfire smoke emergency standard in 2019 (CA Section 5141.1). Made permanent in 2021, CA Section 5141.1 requires that employers implement various exposure reduction measures at two AQI thresholds, as determined by the nearest regulatory PM2.5 monitor or an approved on-site direct monitoring device (CalOSHA 2021). When ambient air pollution levels meet or exceed the lower of the two thresholds – AQI 151 (PM2.5 ≥ 55.5 μg/m3) – employers are required to implement engineering controls when possible, such as providing an enclosed space with filtered air, administrative controls, such as work schedule changes, and provide NIOSH-approved particulate respirators for voluntary use (CalOSHA 2021). At the upper threshold – AQI 500 (PM2.5 500.5 μg/m3) – employers must provide particulate respirators for mandatory use by workers (CalOSHA 2021). Marlier et al. (2022) estimated that 244,000 worker-days per county were impacted by the lower AQI 151 CA Section 5141.1 threshold between 2004-2009, with these impacts more than doubling in the next few decades. This was the first study to assess wildfire smoke exposures among outdoor agricultural workers in relation to the CA Section 5141.1 thresholds.

Resilience-focused fuel treatment strategies, such as the use of prescribed burning, are being increasingly implemented to restore more natural fire regimes and reduce extreme wildfire risk across the western U.S. (Ryan, Knapp, and Varner 2013; Stephens et al. 2020; Hessburg et al. 2015). These fuel treatments have the potential to reduce smoke exposures from wildfires, but also contribute to hazardous air pollution themselves (Burke et al. 2021; Ravi et al. 2018; D'Evelyn et al. 2022). Spatiotemporal differences in smoke exposures from wildfires and prescribed burns may have implications for outdoor agricultural workers, approximately 25% of whom are seasonally employed during the growing and harvesting seasons, which often overlap with peak wildfire smoke season (Figure 5.4). Resilience-focused fuel treatments may also reduce smoke exposures among outdoor workers—therefore addressing occupational health goals in addition to ecological goals—but this has not previously been studied.

While Marlier et al. (2022) explored past and future wildfire smoke exposures under climate change among agricultural workers, no previous studies have examined the impacts of management tradeoffs in this population. To address this gap, we compare the smoke exposure impacts of six forest management scenarios, which vary in the scale and pace of management efforts, proposed for a 970,000 hectare landscape in the Central Sierra among outdoor agricultural workers, with the goal of identifying optimal scenarios for reducing workplace exposures (Figure 5.1). The Central Sierras are a fire-prone mountainous region, just east of California's Central Valley, the state's most productive agricultural region (USGS 2023). We leverage modeled estimates of PM2.5 concentrations from wildfires and prescribed burns to estimate county-level agricultural worker exposure levels and use those to evaluate the scenarios in the context of CA Section 5141.1.

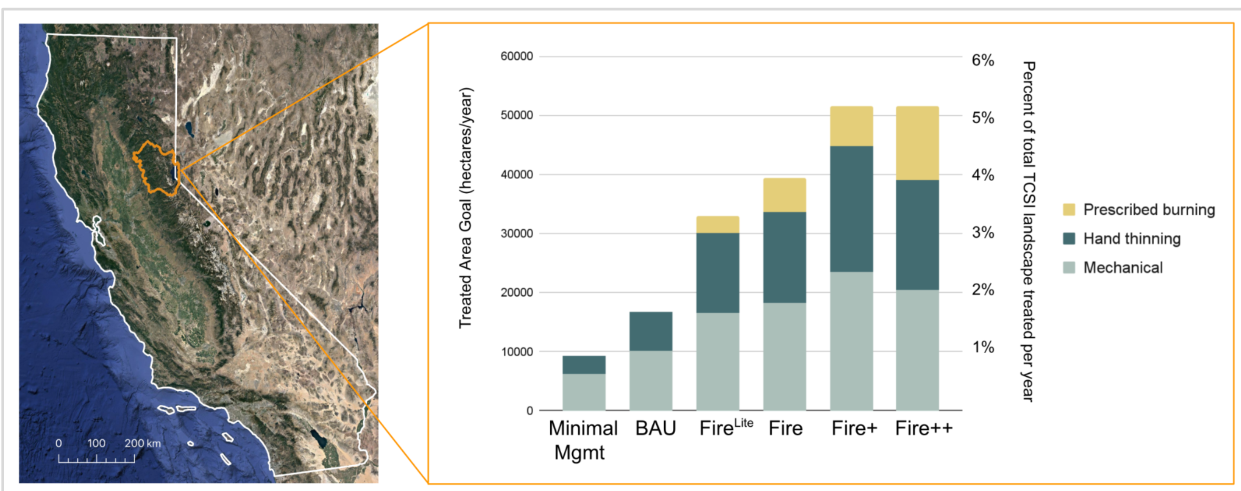

Figure 5.1. Location of 970,000 hectare Tahoe Central Sierra Initiative landscape (orange) and the distribution of annual treated area goals by treatment type across scenarios.

Methods

Scenarios

Six forest management scenarios were co-developed by management agencies and researchers for a 970,000 hectare landscape called the Tahoe Central Sierra Initiative (TCSI). Each management scenario varies in the amount and rate of hand thinning, mechanical thinning, and prescribed burning applied to the landscape each year (Figure 5.1). The Business as Usual (BAU) Scenario most closely resembles what management currently looks like on the landscape. Prescribed burning is introduced in the middle tier scenarios ($Fire^{Lite}$ and Fire) and increases in the amount applied per year under the upper tier scenarios (Fire+ and Fire++). Additional information about the scenarios can be found in Chapter 4 and in(C. Maxwell et al., 2022a)).

Emissions and dispersion modeling

Emissions from wildfires and prescribed burns were estimated from 1981-2020 using the LANDIS-II landscape change model with the SCRPPLE fire extension (Scheller et al., 2007). Subsequent downwind wildfires and prescribed burn-specific daily $PM_{2.5}$ concentrations were generated using the Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT), with emissions estimates from LANDIS-II represented as 4 ha area sources and a 27 km meteorological data from the WRF-ARW archived dataset (NOAA, n.d.; Stein et al., 2015a). The HYSPLIT gridded $PM_{2.5}$ output consists of 24-hour averaged concentrations at a 27 km resolution, with the model domain spanning the 11 western states.

Employment data

Monthly employment data were obtained from the United States Bureau of Labor Statistics Quarterly Census of Employment and Wage (BLS QCEW) (Figure 5.2). We combined monthly employment counts for 'Crop Production' jobs (NAICS 111 Sector Code) and 'Support Activities for Crop Production' jobs (NAICS 1115 Sector Code) from 2018-2022. Monthly employment counts were averaged across this five year period to represent the most contemporary agricultural worker population. These employment counts reflect the number of jobs in a county and therefore do not directly reflect the actual number of workers or where those workers reside.

Figure 5.2. Average annual crop production employment 2018-2022 per California county. Data from the United States Bureau of Labor Statistics Quarterly Census of Employment and Wage.

Linking employment and smoke concentrations

Daily area average weighted wildfire and prescribed burn $PM_{2.5}$ concentrations were calculated for each county to match the spatial resolution of the BLS QCEW data. Employment-weighted smoke concentrations were calculated using the following equation:

$$E_{PM2.5} = \frac{\sum(Pi \; x \; Ci)}{\sum Pi}$$

Where $E_{PM2.5}$ is the employment-weighted $PM_{2.5}$ concentration, P_i is the employment of a given county, and C_i is the $PM_{2.5}$ concentration. To evaluate the impact of each of the management scenarios under Section California 5141.1, worker-days were calculated by multiplying the employment counts for each county by the number of days where total smoke $PM_{2.5}$ (i.e. the sum of wildlife and prescribed burn $PM_{2.5}$) met or exceeded 151 and 500 AQI rule thresholds (DIR, 2021). State-wide impacts were calculated by summing worker-days for each rule threshold across California counties.

Results

The distributions of annual average employment-weighted source-specific $PM_{2.5}$ concentrations are shown in Figure 5.3. We estimate that employment-weighted annual average total smoke (i.e. smoke from wildfire and prescribed burns) $PM_{2.5}$ concentrations are greatest under the Minimal Management (1.66 $\mu g/m^3$), BAU (1.30 $\mu g/m^3$), and the Fire++ scenarios (1.30 $\mu g/m^3$). Employment-weighted annual average total smoke $PM_{2.5}$ concentrations were lowest under the $Fire^{Lite}$ scenario (0.98 $\mu g/m^3$) and increased as more management is introduced under the Fire (1.07 $\mu g/m^3$) and Fire+ (1.17 $\mu g/m^3$) scenarios. Under all management scenarios, the annual employment-weighted average $PM_{2.5}$ for prescribed burns are less than those from wildfires.

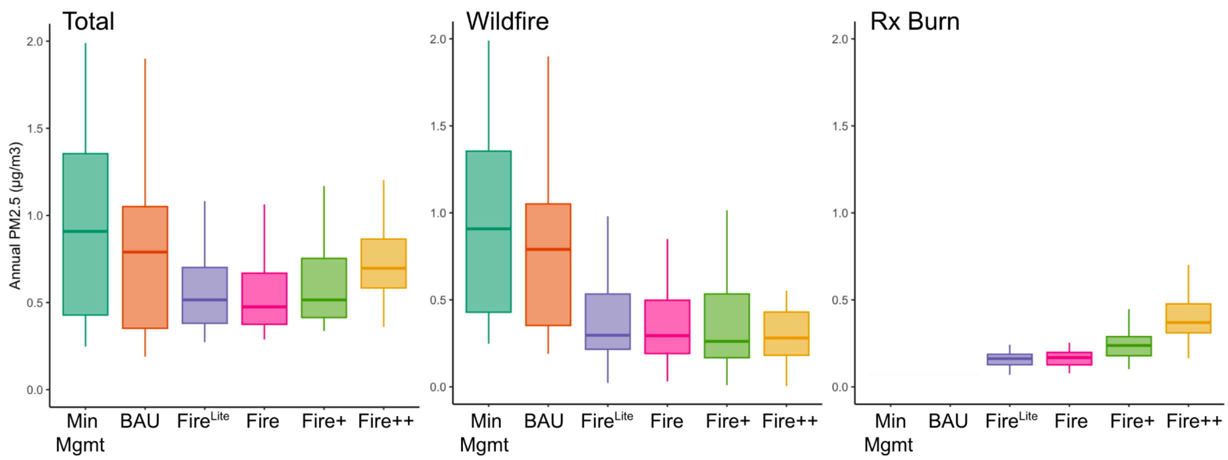

Figure 5.3. Boxplots of annual employment-weighted average $PM_{2.5}$ concentrations from total smoke, wildfire, and prescribed burns across each scenario.

Wildfires drive peak monthly employment-weighted total smoke $PM_{2.5}$ concentrations in August through November under the Minimal Management and BAU scenarios (Figure 5.4). Total smoke concentrations for the year are also highest during these months under the scenarios that include prescribed burn use, but the magnitude of those concentrations is lower than the lowest management scenarios (Figure 5.4). Importantly, these months of elevated total smoke $PM_{2.5}$ across all scenarios overlaps with peak monthly crop production employment during the growing and harvesting seasons (Figure 5.4). During the first six months of the year, prescribed burn contributions under the Fire++ scenario drive higher employment-weighted average monthly exposure levels relative to all other scenarios.

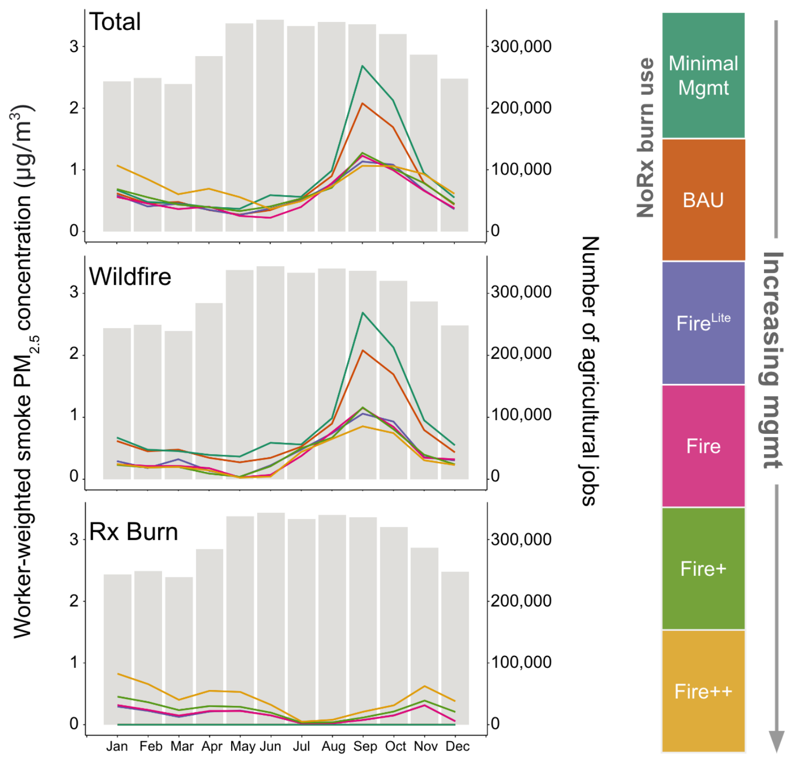

Figure 5.4. Monthly employment distribution (gray bar) and average monthly employment-weighted total smoke (top), wildfire (middle), and prescribed burn smoke (bottom) concentrations across scenarios.

When assessing the impacts of each management scenario under CA Section 5414.1, the number of state-wide worker-days that reach or exceed the lower AQI 151 threshold are lowest under the Fire^{Lite} (29,106 days), Fire (26,624 days), and Fire+ (30,908 days) scenarios. As more prescribed burning is applied to the landscape under the Fire++ scenario, the number of worker-days that reach or exceed the AQI 151 threshold starts to increase in counties directly west of the TCSI landscape, such as in Butte and Sutter counties (Figure 5.5). We see a similar trend for the higher AQI 500 CA Section 5141.1 threshold, but the number of worker-days does not increase as more prescribed burning is applied to the landscaped under the upper tier scenarios, likely because the magnitude of smoke exposures stemming from prescribed burns are lower relative to those from wildfire (Figure 5.3, Figure 4.5). The annual number of worker-days impacted by the two CA Section 5414.1 thresholds for each individual county are provided in Table 5.S1.

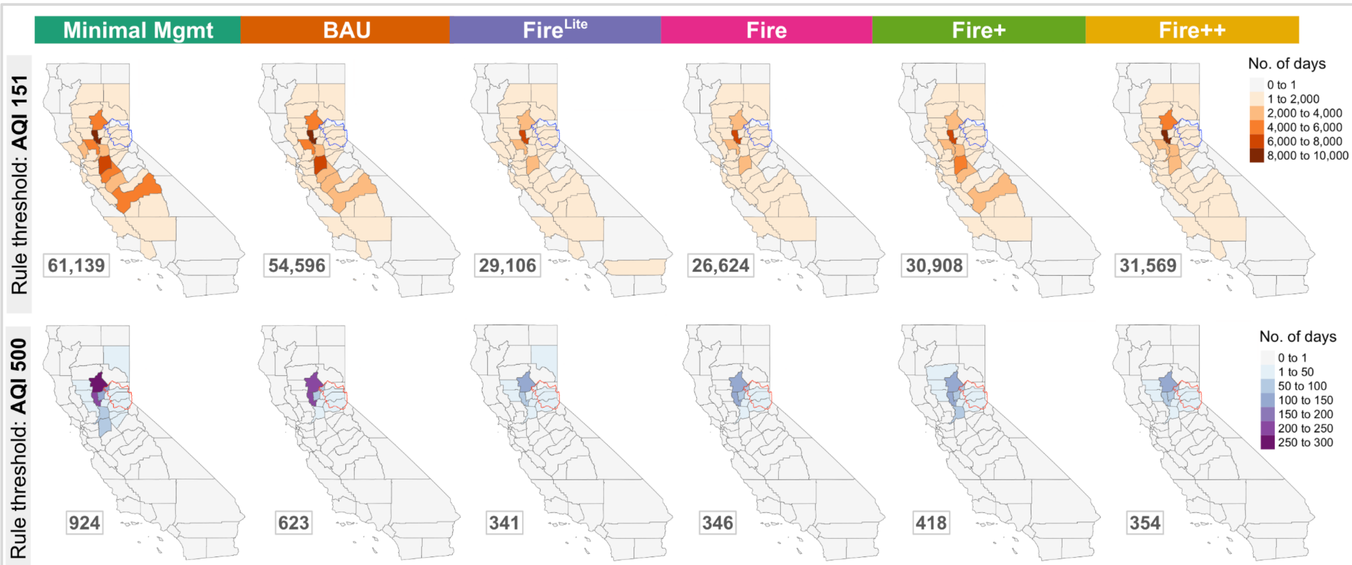

Figure 5.5. Average number of worker-days per year per county that exceed the AQI 151 (top) and AQI 500 (bottom) thresholds of CA Section 5141.1. The numbers at the bottom left of each map represent the total state-wide number of worker-days per year.

While the number of worker-days impacted by the lower AQI 151 threshold outnumber those impacted by the upper AQI 500 threshold, the most exceedances for both thresholds under all scenarios occur during the July through November wildfire smoke season (Figure 5.5). The greatest number of exceedances of both rule thresholds occur during the wildfire season in August through October under the Minimal Management scenario. While exceedances of the lower threshold follow a similar pattern under the BAU scenario, exceedances of the upper threshold under this scenario peak earlier in the season in July and August. While temporal patterns of lower threshold exceedances look similar among the scenarios that include the use of prescribed burning, the timing is more variable at the upper AQI 500 threshold, with a more delayed peak under the Fire^Lite scenario in October, relative to the earlier September timing of maximum exceedances under the Fire, Fire+, and Fire++ scenarios (Figure 5.5).

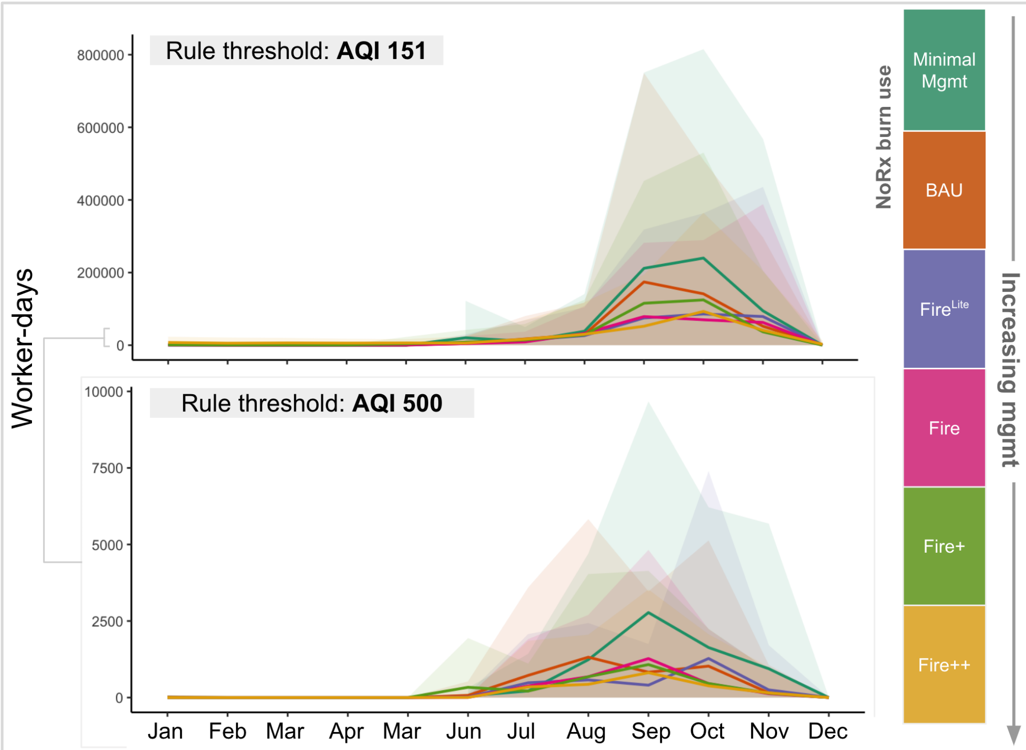

Figure 5.6. Average monthly state-wide worker-days that exceed the AQI 151 (top) and AQI 500 (bottom) thresholds of CA Section 5141.1. Note the difference in y-axis scale between the top and bottom panels. Shading represents the standard deviation of the monthly estimates

Discussion

Summary of results

Outdoor agricultural workers are a population that are at increased risk of wildfire smoke exposures, given the overlap of peak crop production and wildfire seasons, proximity to fire-prone landscapes, and the physically demanding work, which contribute to higher respiratory rates and subsequent air pollution doses per unit of exposure. Forest management activities, intended to reduce extreme wildfire risk, may be a useful tool to reduce smoke exposure among this population. Here we demonstrate the utility of a scenario-based approach to evaluate the ability of proposed forest management activities planned for the Central Sierra region to reduce smoke exposures among outdoor agricultural workers in California.

We find that implementation of relatively moderate amounts of prescribed burning (i.e. the FireLite and Fire scenarios), results in the lowest annual employment-weighted exposure to total smoke (Figure 5.3). This pattern highlights that the pace and magnitude of fuel treatments applied under these middle tier scenarios are most favorable due to their ability to reduce smoke from wildfires while simultaneously limiting prescribed burn-specific smoke impact among workers. Sub-annually, we see the greatest reduction in smoke exposures among workers in scenarios that use prescribed burning, relative to those that do not, in the months of August through November, when agricultural activity is at its peak across the state (Figure 5.4, Figure 5.6).

We also examined the impacts of these proposed scenarios relative to CA Section 5141.1 and found that the Minimal Management scenario would result in the greatest number of impacted worker-days across the state under the AQI 151 (61,139 worker-days) and AQI 500 thresholds (924 worker-days). The fewest number of worker-days affected under each of the rule thresholds occurred under the two middle tier scenarios, with 29,106 and 26,624 worker-days exceeding the lower threshold and 341 and 346 worker-days exceeding the upper threshold under the FireLite and Fire scenarios, respectively. In addition to the potential worker health burdens associated with these exposures, these smoke impacts may have economic implications for employers in terms of respirator costs, work hours lost, etc. (Borgschulte et al., 2022). While the prescribed burns themselves also contribute to total smoke exposures, particularly under Fire+ and Fire++ scenarios, these fuel treatments are planned events and thus present the opportunity to activate preventive measures and leverage a wider range of the hierarchy of exposure controls to protect workers. For example, employers could proactively establish engineering controls like clean air centers, make administrative work schedule adjustments, or purchase respirators in advance, all which may be less feasible during an unplanned wildfire.

Strengths and Limitations

The primary strength of our analysis stems from our evaluation of spatially and temporally explicit forest management prescriptions designed for a specific landscape, unlike previous studies which have relied on hypothetical high-level representations of prescribed burn increases uniformly applied across large geographic areas (Burke et al., 2021; Ravi et al., 2018). We also generate worker exposure estimates that may directly inform future work-place preparedness efforts, such as anticipating respirator requirements for impacted regions. Some limitations come from the BLS QCEW, which provides estimates of the number of jobs within a county but is limited in its representativeness of the true working population in agriculture. The QCEW is estimated to represent about 80% of documented agricultural employment, not accounting for unpaid family workers, self-employed workers, or workers that hold multiple jobs (Jobe, 2022). The QCEW also does not account for undocumented workers, and given that the U.S. Department of Labor estimates that approximately half of farm workers do not hold legal immigration status, these employment counts are likely an underestimate of the actual agricultural workforce (M. Castillo & Simnitt, 2020). Further, subpopulations, such as undocumented workers, may have elevated risk profiles compared to their counterparts (F. Castillo et al., 2021). It is also important to note that other job sectors beyond NAICS 111 and 1115 are likely to also be impacted by elevated smoke exposures, including those who work in construction, outdoor recreation, and transportation.

Uncertainties in our analyses also stem from aggregating smoke concentrations across county boundaries, which masks spatial variability in $PM_{2.5}$ exposures that may exist within the county, particularly in larger rural counties. Our estimates of worker-day impacts at each of CA Section 5141.1 thresholds do not account for anthropogenic sources of $PM_{2.5}$ or smoke from fires outside of the TCSI landscape. We also do not account for exposure misclassification as a result of actions that outdoor workers or employers might take during wildfire smoke events, such as staying home from work, relocation, or altering work schedules; however, studies of risk perception to environmental hazards in agricultural workplaces in California have found limited concern or response pertaining to poor air quality among employers, relative to other environmental hazards (Wadsworth et al., 2022). Additionally, interviews and focus groups of California agricultural workers have documented limited knowledge of wildfire smoke exposure risk along with a sense of pressure among workers to continue working despite the presence of environmental hazards (Courville et al., 2016; Riden et al., 2020). Finally, while we do not characterize the actual dose of $PM_{2.5}$ absorbed and how that may vary relative to the general population due the physical exertion and the elevated respiratory rates of outdoor agricultural workers, we assume constant levels of exertion and respiratory demands among workers across scenarios.

Conclusions

This study provides an evaluation of the potential wildfire smoke reduction and prescribed burn smoke impacts that future forest management activities could have on outdoor agricultural worker populations in California. While this study is specific to a particular region in California, our modeling framework could be applied in other geographies and to other at-risk populations to assess the potential exposure impacts of prescribed fire use. For example, our framework could be used to examine exposure impacts among outdoor agricultural workers resulting from resilience-focused prescribed burning in different regions of the U.S, such as Washington state where agricultural regions are in close proximity to fire-prone forested lands. Outside of the U.S., our framework can be applied to better understand the downwind exposure impacts resulting from other human-driven biomass burning practices, such as agricultural burning in India or land clearing burns by the palm oil industry in Indonesia. As climate change continues to drive worsening wildfire smoke impacts across the western U.S. and forest management activities ramp to counteract those impacts, we must better understand the exposure burdens among at-risk populations. Outdoor agricultural workers are a population who are particularly at-risk to wildfire smoke exposures. As forest management planning continues to ramp up across the western U.S., it is crucial that we continue to research and prioritize mitigation strategies that maximize exposure reduction benefits for this at-risk population.

Supplementary Material

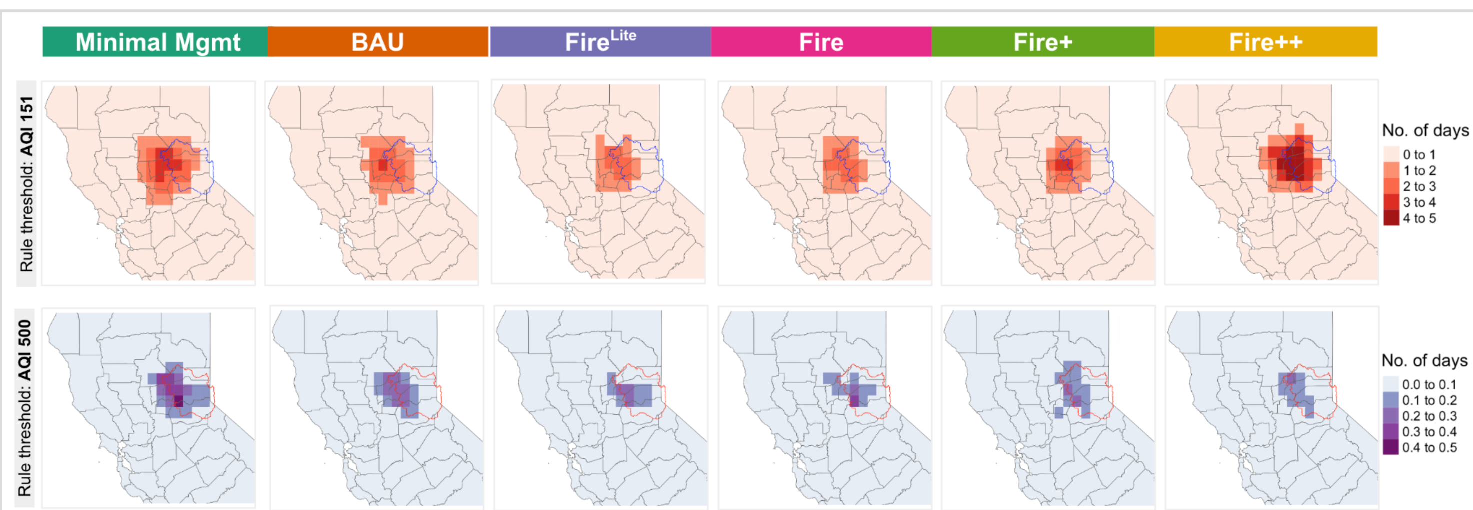

Figure 5.S1. Average number of days per year that grid cell meets or exceeds the AQI 151 (top) and AQI 500 (bottom) thresholds of CA Section 5141.1 (based only on concentrations, not worker-days)

Table 5.S1. Average number of worker-days per year for each county at the AQI 151 and AQI 500 thresholds of CA Section 5141.1. Counties with no worker impacted days are not included.

	Minimal Management		BAU		FireLite		Fire		Fire+		Fire++	
	AQI 151	AQI 500	AQI 151	AQI 500	AQI 151	AQI 500	AQI 151	AQI 500	AQI 151	AQI 500	AQI 151	AQI 500
Alameda	92	0	65	0	59	0	45	0	42	0	36	0
Amador	31	1	31	1	14	0	14	0	22	0	28	0
Butte	5,669	260	4,125	208	3,357	132	3,817	115	3,613	124	5,432	146
Calaveras	62	1	70	0	25	0	21	0	36	0	39	0
Colusa	936	24	483	0	363	9	352	0	394	3	449	3
Contra Costa	123	0	133	0	71	0	54	0	66	0	46	0
El Dorado	363	32	343	24	246	18	280	13	263	17	506	13
Fresno	5,504	0	3,144	0	1,533	0	1,029	0	2,229	0	987	0
Glenn	646	12	350	0	276	4	272	0	265	4	370	4
Inyo	0	0	0	0	0	0	0	0	0	0	0	0
Kern	1,446	0	1,073	0	975	0	536	0	829	0	98	0
Kings	560	0	388	0	217	0	156	0	342	0	140	0
Lake	12	0	6	0	4	0	2	0	4	0	3	0
Lassen	72	2	32	1	35	1	32	1	32	0	33	1
Madera	1,769	0	641	0	260	0	71	0	285	0	307	0
Marin	16	0	8	0	9	0	2	0	6	0	5	0
Mariposa	0	0	0	0	0	0	0	0	0	0	0	0
Merced	3,416	0	2,128	0	1,053	0	653	0	1,175	0	670	0
Mono	0	0	0	0	0	0	0	0	0	0	0	0
Napa	2,145	0	915	0	821	0	657	0	446	0	798	0
Nevada	142	12	101	8	90	6	91	5	96	5	174	5
Placer	523	41	417	25	344	22	364	22	355	22	633	16
Plumas	17	1	12	0	10	0	12	0	11	0	19	0
Riverside	0	0	0	0	9	0	0	0	0	0	0	0
Sacramento	2,970	98	2,924	28	1,865	7	1,775	7	2,026	56	2,089	14
San Benito	450	0	270	0	174	0	117	0	155	0	44	0
San Bernardino	0	0	0	0	0	0	0	0	0	0	0	0
San Joaquin	7,466	88	7,117	0	3,503	0	3,294	0	4,204	0	3,061	0
San Luis Obispo	238	0	224	0	137	0	180	0	238	0	52	0
San Mateo	86	0	36	0	42	0	26	0	32	0	22	0
Santa Clara	529	0	456	0	249	0	257	0	283	0	110	0

Santa Cruz	--	--	492	0	214	0	257	0	--	--	--	--
Shasta	12	0	6	0	5	0	9	0	6	0	8	0
Solano	603	0	521	0	308	0	261	0	254	0	245	0
Sonoma	703	0	--	--	175	0	--	--	--	--	301	0
Stanislaus	4,523	0	3,900	0	1,837	0	1,411	0	2,016	0	1,122	0
Sutter	10,694	229	8,789	242	6,349	93	6,438	130	6,964	130	8,733	93
Tehama	677	0	451	0	328	0	406	0	349	2	399	0
Tulare	1,480	0	434	0	260	0	87	0	87	0	130	0
Ventura	216	0	201	0	121	0	0	0	0	0	40	0
Yolo	5,387	21	4,069	0	2,724	0	2,519	0	2,626	0	2,594	0
Yuba	1,559	102	1,239	85	1,045	48	1,128	53	1,159	54	1,849	59

Chapter 6: CONCLUSIONS

The western U.S. experiences smoke from multiple sources of fire, including wildfire, prescribed burns, and agricultural burns. As climate change continues to drive increasing extreme wildfire risk across the western U.S., wildfire smoke exposures and related human health impacts will likely worsen (Abatzoglou & Williams, 2016; J. C. Liu et al., 2016). This worsening wildfire trend also threatens the health of dry western forests, which have historically relied on low severity wildfires to maintain ecosystem function, but are now unable to withstand the uncharacteristic, high severity wildfires we see today (Williams, 2013). The reintroduction of more frequent, low severity fire through the use of prescribed burning is one intervention that can reduce wildfire risk and improve the climate resilience of dry western forests (Hessburg et al., 2015; Ryan et al., 2013). Despite this benefit, there are still barriers to prescribed burn applications related to the contributions of those fuel treatments to hazardous air pollution exposures (Miller et al., 2020). Meanwhile, outside of our forested landscapes, agricultural burning is implemented at different times throughout the year as a crop management tool, further contributing to the smoke landscape of the western U.S. This dissertation sought to develop a more holistic understanding of these various sources of smoke exposure by evaluating the impacts of wildfires and forest and natural resource management activities through both a historical and scenarios-based lens, with a particular focus on groups most at-risk of the health impacts associated with exposure.

First, we developed a fire type-specific biomass burning emissions inventory that could be used to model downstream source-specific smoke exposures. This 1 km emissions inventory distinguishes between emissions from wildfires, prescribed burns, and agricultural burns in order to get a holistic characterization of biomass burning emissions sources across the western U.S. Using those emissions estimates, we modeled daily downwind $PM_{2.5}$ concentrations from each fire source and examined exposure levels across the general population, socioeconomic status, and race/ethnicity subgroups. As expected, we found that wildfire-specific $PM_{2.5}$ exposures were much greater than those from both prescribed and agricultural burns; however, each fire type had a distinct spatiotemporal distribution and different exposure patterns across subgroups that varied across states and study years. While we found limited evidence of systematic exposure disparities across the full region, we identified local areas where higher exposure levels overlap with areas of greater social vulnerability, as determined by the CDC SVI.

Next, we took a scenarios-based approach to quantify the exposure and health impacts of a set of forest management scenarios designed specifically for a fire-prone landscape in the Central Sierra, California. We developed an interdisciplinary modeling framework that generated emissions and $PM_{2.5}$ exposure estimates from both wildfires and prescribed burns on this landscape. Using those source-specific $PM_{2.5}$ exposure estimates, we calculated potential asthma-related health impacts across California, estimating that increases in fuel treatment application, relative to what is currently carried out the landscape, could result in health co-benefits, but exposure and health returns plateaued or diminished under scenarios that call for the greatest amounts of prescribed burning. We also examined the exposure impacts of each scenario on outdoor agricultural workers and saw a similar exposure profile. This highlights the need to continue to consider tradeoffs and leverage modeling approaches, such as those presented here, to understand the impacts of wildfire and prescribed burn-related smoke impacts and proactively protect those communities as forest management ramps up. It also must be noted that these results are landscape specific, which is a primary reason why they are useful. While state-level agencies can establish management goals for a state or region, those goals are turned into very specific management plans that are carried out at the forest-level, where fuels, topography, meteorology, and the distribution of anthropogenic features are unique. Thus, the results of our scenarios-based study are not necessarily generalizable but can be used as a model for how to assess specific forest management plans developed for other geographies and incorporate public health considerations into those specific contexts.

Taken as a whole, the historical (Chapter 2-3) and forward looking (Chapters 4-5) portions of this dissertation can be considered together to holistically understand the impacts of each of these fire types moving forward. For example, in our assessment of the different forest management scenarios proposed for the Central Sierra, we saw the greatest exposure and health impacts in the region directly west of the treatment landscape, i.e. California's Central Valley, which we know from our historical exposure assessment, already experiences the brunt of the state's smoke exposure impacts from multiple sources of fire. While we did not consider previous exposure impacts in our scenarios-based study, that information could be included in decision-making efforts to take into account the existing exposure burdens in addition to exposures projected for the future. In doing this, forest management plans could potentially be designed to maximize exposure reduction benefits for areas hit hardest historically, particularly areas with higher concentrations of at-risk populations.

The incorporation of these types of public health considerations will require continued collaboration between the public health and forest management sectors. This dissertation is the product of those types of collaborations and benefitted from contributions across the fields of environmental and occupational health, fire ecology, forest management, environmental engineering, atmospheric sciences, and public policy. While often challenging, transdisciplinary consensus and collaboration are necessary and require knowledge sharing across disciplines and a willingness to incorporate interdisciplinary analytical methods into existing and evolving decision making processes. In order to achieve equitable forest and natural resource management planning, these cross-sector relationships must continue to evolve so that we can improve upon methodological linkages and leverage them to understand the downstream health impacts. This will only become more pressing as wildfires continue to worsen across the western U.S. and more federal and state funding goes towards management planning to mitigate risk (CA Forest Management Task Force, 2021; DNR, 2018, Infrastructure Investment and Jobs Act, 2021).

Future directions of this work could include the use of the reclassified biomass burning emissions inventory and historical exposure data in epidemiological studies to better understand the distinct contributions of each fire source on health impacts across the region. Additionally, those data could be used to assess occupational exposure to smoke from wildfires, prescribed burns, and agricultural burns among outdoor workers in Washington, Oregon, and California. Information on baseline exposure levels to smoke from these different sources could be used in conjunction with our evaluation of the potential impacts of management scenarios proposed for the TCSI or other managed landscapes to better understand the impacts that additional exposure burdens may have in relation to what outdoor workers have already experienced. As previously mentioned, similar scenario-based modeling methods should be implemented in management planning efforts for other fire-prone geographies. Similar methods could also be used in agricultural settings when planning burns for crop management purposes. While collaboration across the public health and agricultural sectors around the topic of agricultural burn-related smoke exposure has been limited in the past, future cross-sector relationships, similar to those ramping up with the forest management sector, could be useful in supporting the management needs of growers while protecting workers and nearby communities from the health impacts of smoke.

There is no doubt that wildfires pose the greatest threat to air quality across the western U.S.; however, the smoke exposure landscape across the region is complex and composed of multiple sources with unique drivers and possible interventions. Prescribed and agricultural burns are smaller, lower severity fire events, yet still contribute to unhealthy smoke levels for the general population and at-risk communities. The planned and regulated nature of these fire types presents an opportunity for increased collaboration with public and occupational health agencies to proactively implement exposure reduction inventions for impacted communities and outdoor workers. To that end, this dissertation provides a baseline understanding of the differential impacts of wildfires, prescribed, and agricultural burns on the western U.S. smoke exposure landscape and what role forest management can play to improve that landscape in the future.

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