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Key Points:

- We examine fire type-specific smoke $PM_{2.5}$ exposures across the Western U.S. from 2014 to 2020
- $PM_{2.5}$ from wildfire is greater than from prescribed and agricultural burns but smoke exposure from each has distinct spatiotemporal patterns
- We identify local areas where increased fire type-specific smoke exposure intersects with greater social vulnerability

Supporting Information:

Supporting Information may be found in the online version of this article.

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Exposure to Smoke From Wildfire, Prescribed, and Agricultural Burns Among At-Risk Populations Across Washington, Oregon, and California

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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 smoke exposure stemming from wildfire, prescribed, and agricultural burns across Washington, Oregon, and California from 2014 to 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, socioeconomic status, and in relation to the Center for Disease Control's Social Vulnerability Index. Overall, population-weighted $PM_{2.5}$ concentrations are greater from wildfires than from prescribed and from 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 $PM_{2.5}$ exposures among Native communities in all three states and, in California, higher agricultural burn-specific $PM_{2.5}$ exposures among lower socioeconomic groups. We also identified, for all three states, areas of significant spatial clustering of smoke exposures from all fire types and increased social vulnerability. 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, which can be used to inform more tailored exposure reduction strategies across sources.

Plain Language Summary Smoke from different types of fire impacts air quality across the Western U.S. While wildfire smoke is often thought to be of greatest concern, due to its known health impacts when inhaled, other types of fire used for management purposes, such as prescribed burns and agricultural burns, can also impact air quality in surrounding regions. In this study, we created a smoke emissions inventory that distinguishes between each of these fire types and used that inventory to estimate downwind smoke exposure for people in Washington, Oregon, and California. We found that smoke from wildfires is greater than that from both prescribed and agricultural burns, but both managed fire sources can also cause days with unhealthy air quality in some communities. We also identified some specific regions with more vulnerable populations that also experience higher smoke exposures relative to surrounding areas, which can be useful when targeting public health resources.

1. Introduction

Biomass burning is a significant source of fine particulate matter ($PM_{2.5}$) pollution across the United States. According to the U.S. Environmental Protection Agency's (EPA's) National Emissions Inventory for primary (i.e., directly emitted) $PM_{2.5}$ in the U.S., fire sources contributed 43.3% of total emissions in 2020 (43.7% in 2017) (US EPA, 2023). Most studies characterizing health impacts associated with smoke exposure from biomass burning have focused solely on wildfire smoke contributions, reporting, for example, associations with respiratory-related mortality and morbidities, including exacerbations of asthma and chronic obstructive pulmonary disease (COPD) (Cascio, 2018; Reid et al., 2016). Additional studies, while less consistent, have also documented evidence of 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; however, biomass burning for management purposes, such as prescribed burns and agricultural burns, may also be contributing to total smoke exposure (Cleland et al., 2021; Fann et al., 2018; Liu et al., 2017).

While wildfires are the dominant source of biomass burning smoke emissions across the Western U.S., prescribed and agricultural burns are also potential sources of smoke exposure. They differ from wildfires in that they are planned, and in some cases regulated, events that occur at different times of year (Jaffe et al., 2020; 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 suppression of wildfires toward fuel reduction efforts, including the use of prescribed burning, to help reduce excess fuel availability and to mitigate wildfire severity and smoke exposures in the long term (D'Evelyn et al., 2022; Kalies & 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 clear away biomass, reduce weeds or pests, prevent disease, and/or 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 emissions trends data from the EPA, total $PM_{2.5}$ emissions from agricultural burning in 2020 were 4.6, 4.9, and 3.9 times higher than those in 2010 in California (CA), Oregon (OR), and Washington (WA), respectively, highlighting a trend toward increasing agricultural burn smoke $PM_{2.5}$ across the West Coast states (EPA, 2023a).

Few studies have examined the health impacts of smoke from wildfires versus prescribed burns. One preliminary study that evaluated proximity to different fire types in Fresno, CA 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). Prunicki et al. (2019) did report higher pollutant concentrations from ground monitors closer to the wildfire relative to those closer to the prescribed burn, though the authors did not relate those concentrations directly to differences in immunosuppressive response. A national study about 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). This study did not examine actual prescribed burn contributions to smoke exposures but instead relied on proximity to fire locations as a proxy for exposure. In the Southeast U.S., where prescribed burns are more prevalent than in the Western U.S. (Kolden, 2019), health impact assessment studies have estimated 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). Unlike the study carried out by Prunicki et al. (2019), which is the only epidemiologic study to examine prescribed burn smoke and health effects, these two studies employ concentration-response functions from the existing epidemiological literature and do not link actual health outcome data with smoke concentrations. Similar to prescribed burns, there have been limited studies on the health effects of exposure to smoke from agricultural burns across the U.S.

Epidemiological 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 among various sources of smoke, which is in part the result of challenges in satellite detections of smaller burns and inconsistent administrative reporting.

Only a handful of studies have characterized how smoke exposures are distributed among 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 general and wildland fire smoke-specific air pollution exposures. The authors used their vulnerability index, in combination with wildfire smoke concentration estimates from the Community Multiscale Air Quality (CMAQ) model to map the spatial distribution of wildfire smoke exposure risk across the U.S. (Rappold et al., 2017). Similarly, Davies et al. generated and mapped a vulnerability index that combines socioeconomic attributes 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) and nationally (Vargo et al., 2023). While these studies help to identify specific locations where communities may be disproportionately impacted by fires and smoke emissions, they do not distinguish between sources of smoke.

To date, no studies have examined how smoke exposures from prescribed fire and agricultural burns differ from those from wildfires across WA, OR, and CA. 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, they may provide 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 burns may become more widespread in the future (CA Forest Management Task Force, 2021; DNR, 2018; Infrastructure Investment and Jobs Act, 2021). If so, that trend makes it increasingly important to understand the impacts of smoke on communities, disaggregated by fire type. Here, we address this gap by characterizing smoke from wildfire, prescribed burns, and agricultural burns from 2014 to 2020 across WA, OR, and CA. We have a particular focus on differences in exposures among race/ethnicity groups and by socioeconomic status, to better understand how these multiple sources of smoke impact at-risk communities.

2. Materials and Methods

2.1. Overview

We estimate daily $PM_{2.5}$ exposure from wildfire, prescribed, and agricultural burns across WA, OR, and CA during 2014–2020, using biomass burning estimates from the Fire INventory from NCAR (FINN) and the GEOS-Chem chemical transport model. We calculate fire type-specific population-weighted $PM_{2.5}$ exposure estimates across the general population and by race/ethnicity, social vulnerability, and urban/rural areas. Finally, we generate bivariate Local Indicators of Spatial Association (LISA) maps to identify local high risk smoke exposure regions within the study area.

2.2. Biomass Burning Emissions

Biomass burning emissions were estimated using the Fire INventory from NCAR (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 such as GFED ($0.25 \times 0.25°$) (van der Werf et al., 2017) and QFED and GFAS (both $0.1 \times 0.1°$) (Koster, Darmenov, and da Silva, 2015; Kaiser et al., 2012). The greater spatial precision increases our ability to capture smaller prescribed and agricultural burns (Oliva & Schroeder, 2015; Wiedinmyer et al., 2023). That advantage (i.e., 1 km resolution includes smaller fires that may be omitted by coarser-resolution data sets) holds and is important for our analyses even though a 1-km-resolution inventory is much finer than the $0.25° \times 0.3125°$ resolution of the transport model (see Section 2.3).

FINN estimates total biomass burning emissions from all fire sources. To distinguish between wildfire, prescribed, and agricultural burns, we overlaid a compilation of data sets 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. Emissions locations that were unmatched to any wildfire or prescribed burns in each of the fire and fuel treatment inventories and that did not intersect with cropland were classified as wildfire. More information about the preparation of the fire type-specific biomass burning emission inventory can be found in Schollaert et al. (2024).

2.3. 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_2O_2 production and photolysis rates generated from a previously run full-chemistry simulation (GEOS-Chem, 2022). We first ran a global simulation at $4° \times 5°$

resolution with 72 vertical levels to generate boundary conditions, followed by a nested grid simulation for the 11 western states at 0.25° × 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 (GEOS-Chem, 2021). Given the uncertainties associated with secondary aerosol formation with wildfire smoke plumes, we focus here on total $PM_{2.5}$ mass concentrations (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: (a) no biomass burning emissions (background only), (b) background plus only wildfire emissions, (c) background plus only prescribed burning emissions, and (d) background plus only agricultural burning emissions. Background sources refer to non-fire emissions sources, which in the western U.S. are primarily industry, transportation, energy production, sea salt, and dust (Chmielewski, 2011; Chow & Watson, 2002; Hadley, 2017; Park et al., 2004; Prather, 2009). 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 corroborated GEOS-Chem-modeled total $PM_{2.5}$ from all sources against observations from the EPA's Air Quality System (AQS) networks in WA, OR, and CA (EPA, 2023b). For grid cells containing multiple monitors, we averaged observations across monitors. 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). From the validation analysis, we identified a small number of daily modeled wildfire-specific $PM_{2.5}$ concentrations (0.17% of all observations) were significantly higher than the maximum observed $PM_{2.5}$ concentration during the study period (max observed $PM_{2.5}$ = 824.1 μg/m^3). Because these outlier values significantly impacted validation metrics, all modeled values greater than the maximum observed concentration were reassigned to 824.1 μg/m^3.

2.4. Exposure Estimation

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

$$(\text{Population} - \text{weighted exposure level})_{\text{PM2.5}} = \frac{\sum(P_i \, x \, C_i)}{\sum P_i}$$

where P_i is the population of grid cell i, obtained from 2010 NASA Socioeconomic Data and Applications Center (SEDAC) 1 km gridded population data set (SEDAC, 2020a), aggregated to the 0.25° × 0.3125° nested grid resolution, and C_i is the concentration.

We calculate population-weighted smoke concentrations for the general population, by race-ethnicity, for vulnerable populations, and separately for urban/rural populations. The 2010 total population is 6.74, 3.34, and 37.3 million people, for WA, OR, and CA, respectively. The eight race/ethnicity subgroups employed are Non-Hispanic (NH) White (51.8%), Hispanic (26.7%), Asian (12.4%), Other (11.9%), Black (5.3%), two or more races, (2+ Races, 4.8%), American Indian/Alaska Native (AI/AN, 1.1%), and Native Hawaiian or Pacific Islander (NHOPI, 0.4%). We generated exposure estimates by socioeconomic status (SES), using the 2010 1-km U.S. socioeconomic status component of the Centers for Disease Control (CDC) Social Vulnerability Indicator (SVI), available from SEDAC. The full CDC SVI ranks each census tract on variables related to household composition, socioeconomic status, race/ethnicity, and housing/transportation. While we leverage the full SVI in a latter portion of the analysis, described below, we first calculate exposure by socioeconomic status to gain a better understanding of specific drivers of vulnerability. The CDC's SES indicator is based on measures of poverty, unemployment, housing cost, educational attainment, and health insurance, and ranges from 0 (highest SES) to 1 (lowest SES). We subsetted population-weighted exposure estimates across urban and rural areas. Specifically, using the 2010 Rural-Urban Commuting Area (RUCA) Codes for census tracts, we categorized metropolitan and micropolitan areas (codes 1–6) as "Urban" and small towns and rural areas (codes 7–10) as "Rural" (USDA, 2023). Based on these definitions, this three-state population is 97% urban, 3% rural. Additional details about the demographics by state are in Table S1 of the Supporting Information S1. To examine seasonal patterns, exposures were temporally disaggregated into wildfire season (June–October) and non-wildfire season (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).

2.5. Exploratory Spatial Analysis

To examine the spatial association between smoke exposure from each fire source and community vulnerability, we leverage the full SVI composite index, which ranges from 0 to 1, with values close to 1 indicating greater social vulnerability, which we refer to as "high SVI," and values close to 0 indicating lower social vulnerability, which we refer to as "low SVI" ("CDC/ATSDR Social Vulnerability Index," 2022). We assess spatial associations using a Local Indicator of Spatial Association (LISA) statistic, which has been used in previous studies 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 *univariate* LISA statistic measures the spatial correlation between values of a variable in one grid cell and the values of the same variable in neighboring grid cells, that is, spatial clustering of that variable. The *bivariate* LISA statistic measures spatial correlations between the value of one variable in a specific location and values of a second variable in neighboring cells (Anselin, 2010). Here, we assess spatial clustering of two variables—SVI and smoke concentrations—separately (univariate LISA) and together (bivariate LISA). Neighboring grid cells are those that share an edge or a corner. We also calculated global Pearson coefficients and global Moran's *i*. In the results section below, we focus on findings for multivariate LISA; a summary of results using the other metrics (Pearson; Moran; univariate LISA) is in Supporting Information S1 (Table S4).

From the bivariate LISA test, we determine the locations of four types of statistically significant overlapping clusters: (a) high SVI score, high smoke concentration, (b) low SVI score, high smoke concentration, (c) low SVI score, low smoke concentration, and (d) high SVI score, low smoke concentration. Within the fire type-specific $PM_{2.5}$ distributions during the wildfire and non-wildfire seasons, "high" and "low" values are those with z-scores greater or less than the z-score threshold at a $p \leq 0.001$ significance threshold (Anselin, 2010). We carried out all spatial correlation analyses in GeoDa (version 1.20.0.8).

3. Results

Average GEOS-Chem-modeled total $PM_{2.5}$ concentrations are 17 μg/m^3 during WF season and 7 μg/m^3 during non-WF season (Table 1), which is ~76% greater than observations during WF season (5% lower during non-WF season). Overall, correlations between modeled and measured $PM_{2.5}$ are higher during WF than during non-WF seasons (see additional information on spatial distributions of correlations in Figure S1 of the Supporting Information S1). RMSE and mean bias are noticeably larger during WF than during non-WF season (Table 1, Figure S2 in Supporting Information S1), likely driven by high concentrations during extreme fire events. Indeed, if we remove the highest predicted and observed concentrations (e.g., the top 5% of each data set; see Table S2 in Supporting Information S1), RMSE drops dramatically.

Correlations vary considerably across years, with high fire years (i.e., years with higher concentrations of fire smoke—for example, 2015, 2017, 2018, and 2020) generally having higher correlation coefficients (Table S3 in Supporting Information S1). That outcome may in part reflect the higher biomass burning emissions estimates from FINNv2, relative to other available emissions inventories (Wiedinmyer et al., 2023).

Average annual wildfire-specific $PM_{2.5}$ concentrations are higher than those from both prescribed and agricultural burns across the full three-state study area (WF: 8.82 μg/m^3, Rx: 0.23 μg/m^3, Ag: 0.15 μg/m^3). The spatial distribution of smoke from each fire type varies across each state. For example, in Oregon, average wildfire $PM_{2.5}$ is highest in the southwest corner of the state, whereas prescribed burn $PM_{2.5}$ concentrations are highest along the western edge of the state (Figure 1). Both wildfire and prescribed burn $PM_{2.5}$ concentrations are highest in central and northern CA and north central WA (Figure 1), whereas average agricultural burn $PM_{2.5}$ concentrations are highest in the agricultural regions of each state, namely CA's Central Valley, OR's Willamette Valley, and WA's Puget lowlands and southeastern region (Figure 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 the CA's Central and OR's Willamette Valleys (Oregon Department of Agriculture, n.d.; U.S. Geological Survey, n.d.; WSDA, 2023). While burning practices vary regionally and by producer, these crops are among those that are managed with fire across

Table 1
Summary of Comparison Between Total GEOS-Chem Modeled $PM_{2.5}$ and Ground Observations Across WA, OR, and CA Over the Full Study Period

		Full area	WA	OR	CA
Observed Mean (μg/m^3)	*Full year*	8.18	6.80	7.95	9.14
	WF Season	9.55	8.01	9.57	10.49
	Non-WF Season	7.17	5.93	6.66	8.16
GEOS-Chem Mean (μg/m^3)	*Full year*	11.05	8.77	11.55	12.30
	WF Season	16.79	11.13	17.47	20.02
	Non-WF Season	6.82	7.09	6.85	6.65
Correlation	*Full year*	0.24	0.24	0.23	0.26
	WF Season	0.24	0.25	0.24	0.27
	Non-WF Season	0.19	0.17	0.10	0.27
RMSE (μg/m^3)	*Full year*	41.15	27.07	53.28	42.86
	WF Season	61.10	39.73	77.09	64.30
	Non-WF Season	13.76	11.46	19.31	12.46
MB (μg/m^3)	*Full year*	2.87	1.97	3.60	3.15
	WF Season	7.24	3.12	7.90	9.52
	Non-WF Season	−0.35	1.15	0.19	−1.51

the west coast (CARB, 2023; OR Department of Agriculture, n.d.; WA Department of Ecology, n.d.). Seasonal patterns also differ by fire type, with peak $PM_{2.5}$ concentrations during summer and fall for wildfires, fall for prescribed burns, and fall (in some locations, summer and winter) for agricultural burns (Figure S3 in Supporting Information S1).

Figure 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 to 2020 (maps of the "Good" category are provided in Figure S4 of the Supporting Information S1). As expected, the greatest number

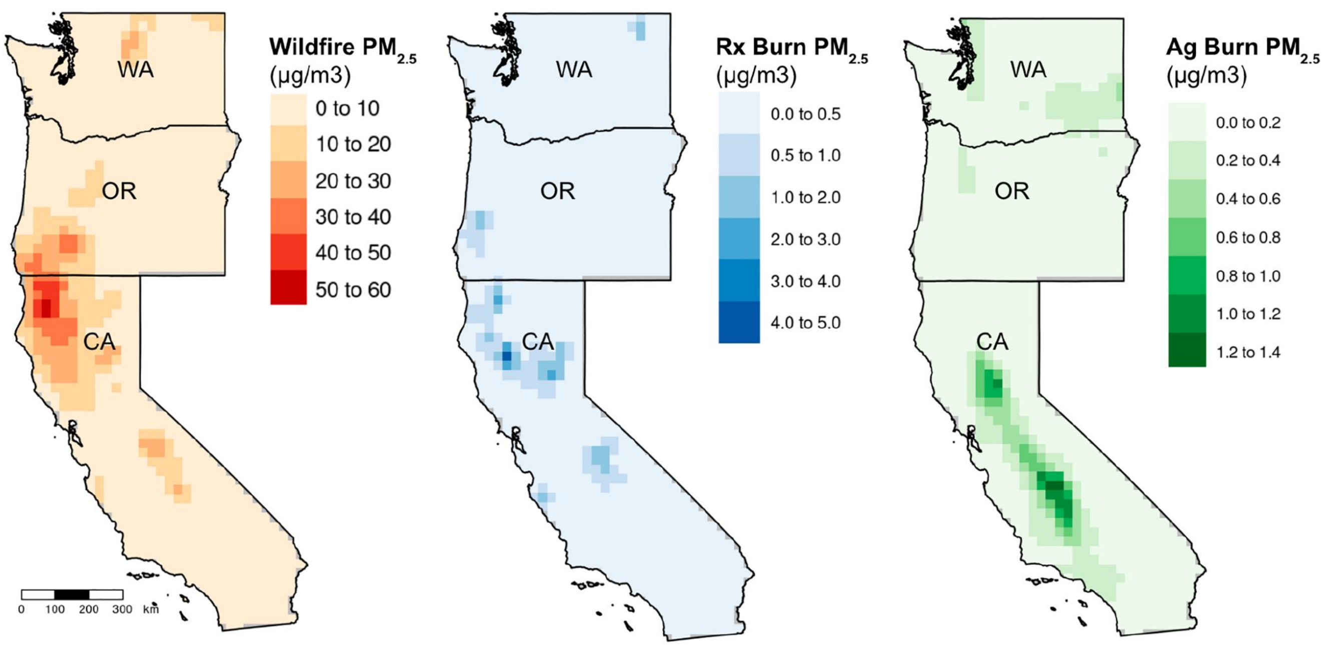

Figure 1. 2014–2020 average $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns. Note different concentrations scales across fire types.

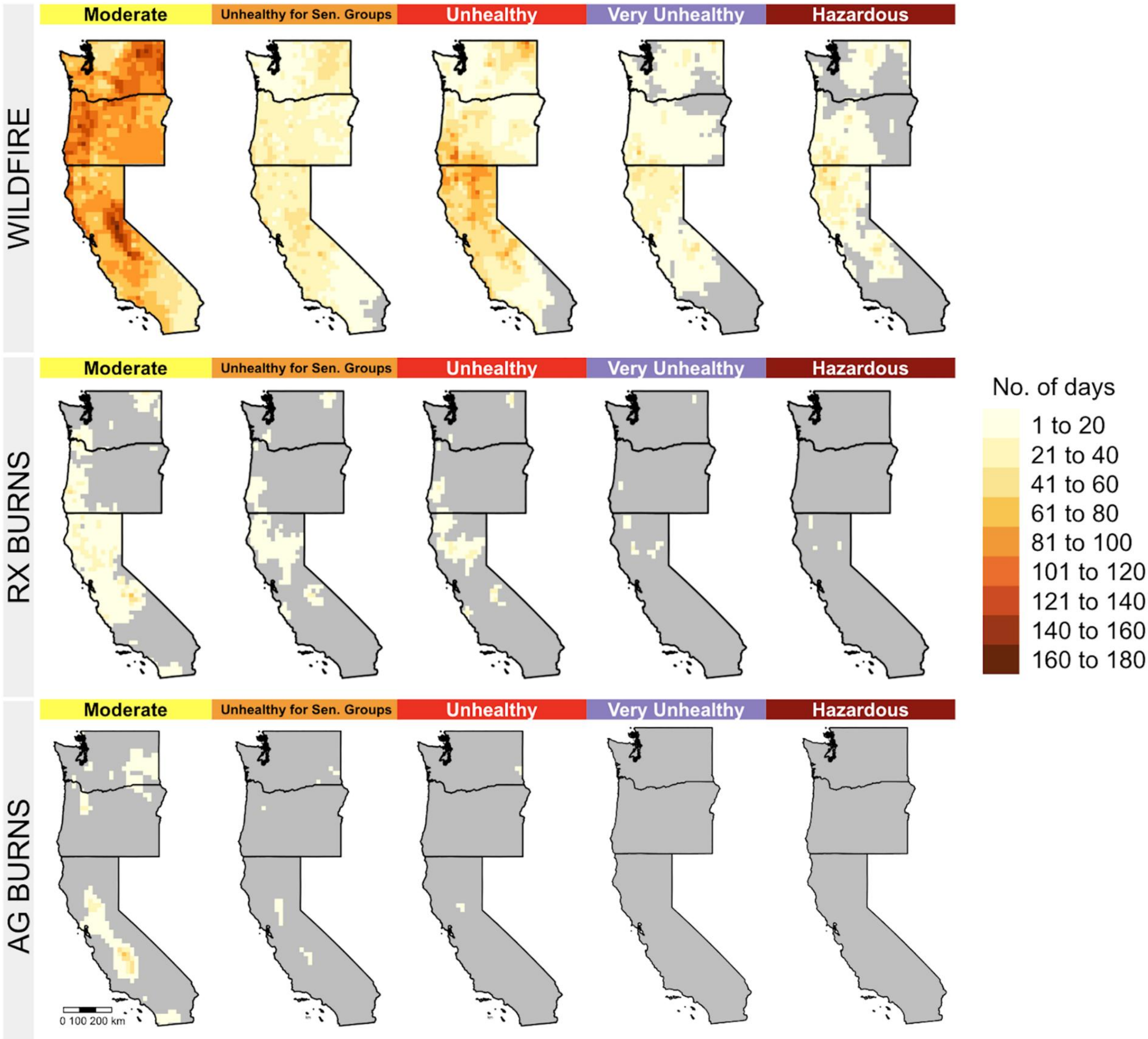

Figure 2. Number of days 2014–2020 that $PM_{2.5}$ concentrations from wildfires, prescribed, and agricultural burns reached the different EPA AQI categories. A version of this figure that includes backgrounds sources can be found in Supporting Information S1 (Figure S14).

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 μg/m^3), Unhealthy for Sensitive Groups (AQI 101–150 or 35.5–55.4 μg/m^3), and Unhealthy (AQI 151–200 or 55.5–150.4 μg/m^3) categories from prescribed burns as well. A few smaller regions in southwestern OR, northern CA, and northeastern WA also experienced prescribed burn $PM_{2.5}$ in the Very Unhealthy category (AQI 201–300 or 150.5–200.4 μg/m^3), and in northern CA, the Hazardous category (AQI 301–500 or 200.5–500.4 μg/m^3). While there are fewer days at elevated AQI categories from agricultural burn smoke, CA's Central Valley, OR's Willamette Valley, and southeastern WA 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 S5 and by year in Figures S6–S12 of the Supporting Information S1. A comparison with AQI estimates from ground monitors can be found in Figure S13 and Table S5 of the Supporting Information S1.

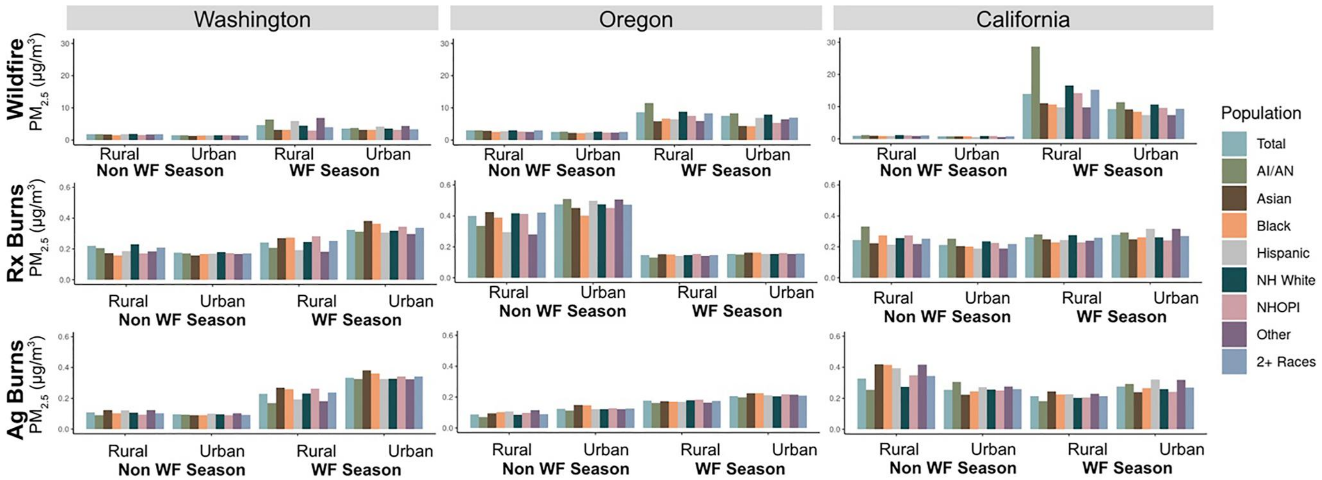

Figure 3. Population-weighted $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns for the total population and across race and ethnicity groups. Concentrations are broken down by season and urban/rural designations. Note the difference in *y*-axis scales.

On average, population-weighted wildfire $PM_{2.5}$ is highest across rural areas during wildfire season (Figure 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 WA, OR, CA (Figure 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). Annual spatial differences in fire occurrence contribute to variability in population-weighted exposure levels across years throughout the study period (Figure S15 in Supporting Information S1). Figure 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 countries exposed to $PM_{2.5}$ from both prescribed and agricultural burns (Figure 4).

When looking at exposure differences across socioeconomic groups, we see significant differences in exposure levels across all states stemming from each fire type (Figure 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 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: $F = 6.48$, $p < 0.001$) in California. While exposure differences across SES groups vary year-to-year throughout the study period, lower SES grid cells were consistently exposed to higher agricultural burning $PM_{2.5}$ throughout the study period (Figure S16 in Supporting Information S1).

After identifying significant univariate spatial clustering of SVI values and smoke concentrations for each fire type (Table S4 in Supporting Information S1), 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 CA, southwest OR, 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 as high wildfire $PM_{2.5}$ exposure and low social vulnerability (Table S6 in Supporting Information S1). Significant clusters of high prescribed burn $PM_{2.5}$ exposure and high social vulnerability exist in central and northern CA, with a small coastal area of high risk in between Los Angeles and Bay Area metropolitan areas. We identified significant clusters of high agriculture burn $PM_{2.5}$ exposure risk in the Los Angeles

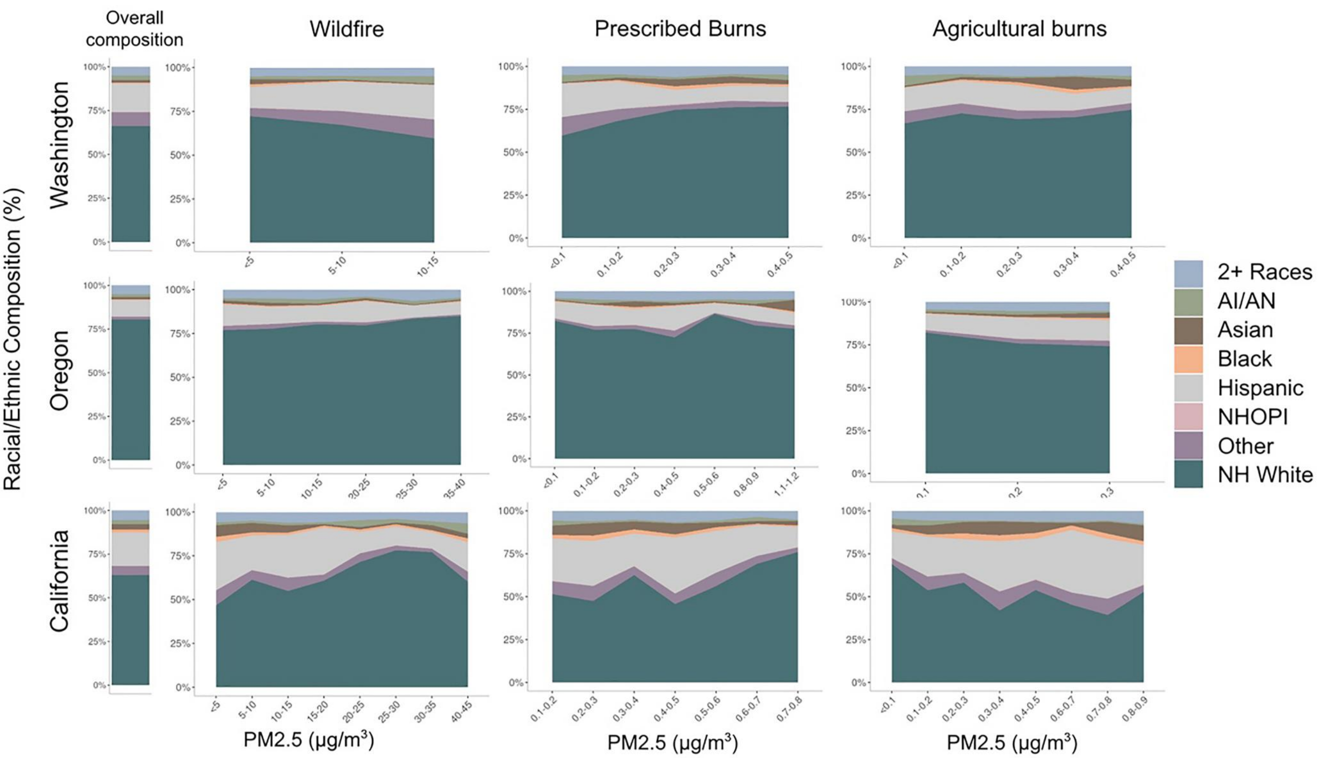

Figure 4. Average county racial/ethnic composition by population-weighted average $PM_{2.5}$ from wildfire, prescribed burns, and agricultural burns. State-wide racial/ethnic compositions are provided in the left column. Note the difference in *x*-axis scales.

metropolitan area, CA'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 S6 in Supporting Information S1). 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 CA, 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 CA, 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 CA's Central Valley (Figure 6).

4. 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 WA, OR, and CA. 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 CA 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 CA.

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 $PM_{2.5}$ concentration and overall social vulnerability allowed us to identify specific areas within each state where elevated exposures exist during the wildfire and non-wildfire seasons. Notably, we identified these specific areas using definitions of "high" smoke concentrations within the $PM_{2.5}$ distribution from each individual fire type. While "high" concentrations within the distributions

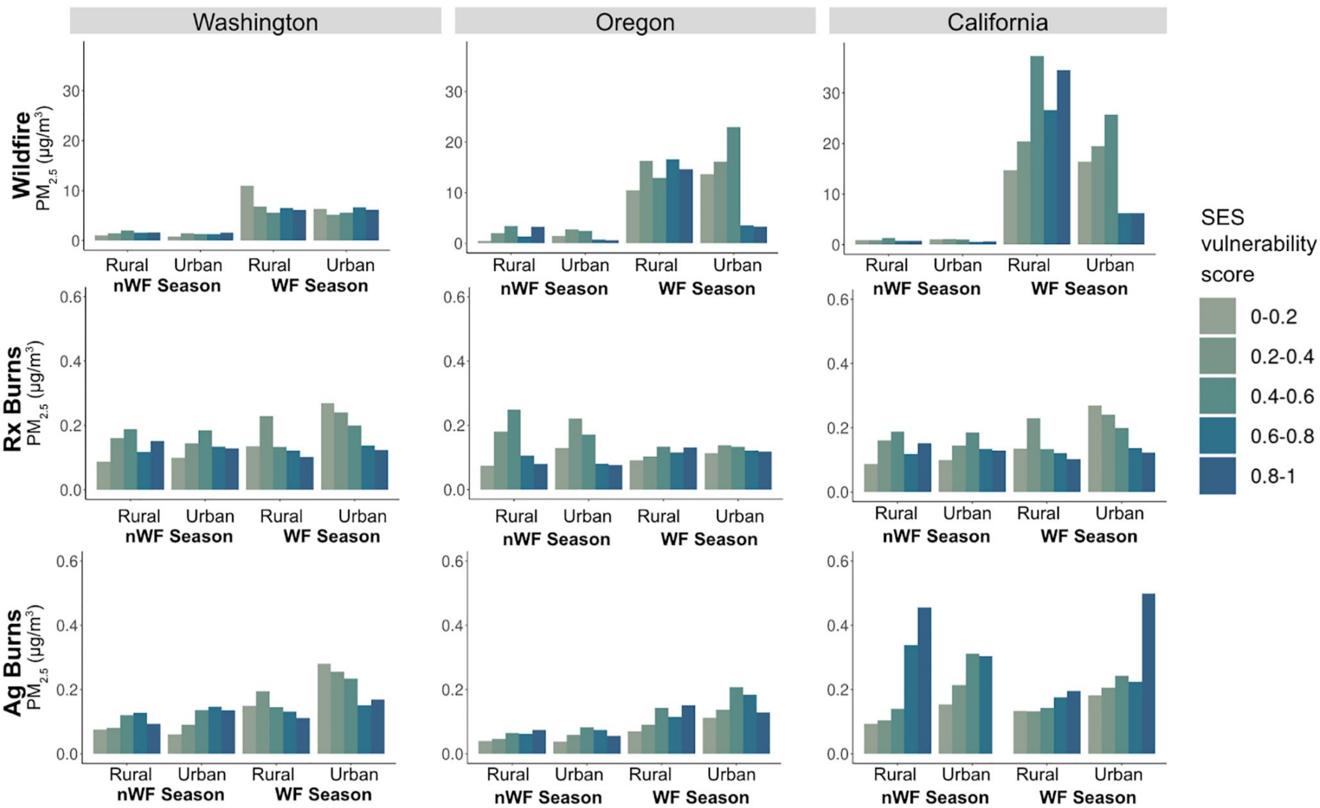

Figure 5. $PM_{2.5}$ concentrations from wildfire, prescribed (Rx) burns, and agricultural (Ag) burns for the total population and SVI SES score categories. Concentrations are broken down by season and urban/rural designations. Note the difference in *y*-axis scales.

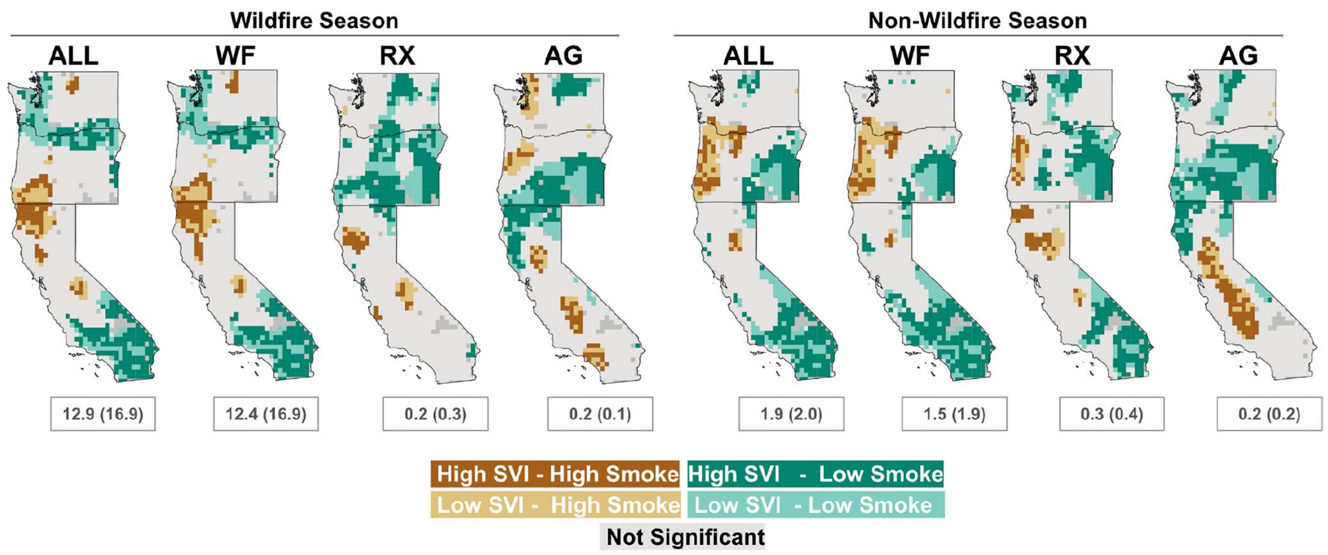

Figure 6. Bivariate LISA spatial clusters reflecting the local association between smoke $PM_{2.5}$ exposure from all fire sources, wildfire, prescribed, and agricultural burns and SVI value across the wildfire and non-wildfire seasons. "High" and "low" smoke designations are based on average concentrations that are higher or lower than the mean smoke concentration for each fire type across each season. The mean and standard deviation $PM_{2.5}$ concentrations for each fire type are provided in the boxes at the bottom of each map. The SVI distribution is constant across fire types and seasons.

of prescribed and agricultural burn-specific $PM_{2.5}$ are considerably lower than those from the wildfire $PM_{2.5}$ distribution (Figures 1 and 6), we determined that these managed fires can still contribute to short-term elevated $PM_{2.5}$ levels (Figure 2), making it important to understand their individual spatial distributions relative to population vulnerability. 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 CA 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 CA 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 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 CalFIRE, OR Department of Forestry, and WA Department of Natural Resources in CA, OR, and WA, respectively. While prescribed and agricultural burns are both regulated by CalFIRE in CA, agricultural burns are regulated by different state-level agencies than prescribed burns in OR (Department of Environmental Quality) and WA (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 permitted 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. 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. Model overestimation relative ground measurements could be due in part to our use of emissions estimates from FINNv2, which are on the higher end of the available global biomass burning emissions inventories (Wiedinmyer et al., 2023). However, because factors contributing to positive bias in our estimates are likely consistent across fire types, there is likely limited impact on our characterization of relative differences across sources. Despite FINN estimates being on the higher end of those from other available products, FINN's fine-scale spatial resolution allowed us to capture smaller fire events, which would not be possible with the use of a coarser inventory (Wiedinmyer et al., 2023). While it is challenging to validate source-specific ambient concentrations, particularly in areas where ground monitoring locations are very sparsely distributed, we previously compared emissions totals under each fire type to those reported by the 2014, 2017, and 2020 EPA National Emissions Inventory, which uses similar fuel treatment input data sources but different emissions estimate methodologies, to gain a sense of how our reclassified FINN inventory compares to other existing fire type-specific inventories. We found greater agreement among wildfire-specific estimates, relative to the other two fire types, and in more recent years of the NEI. Though among prescribed and agricultural burn emissions estimates, we found greater agreement at the higher end of the $PM_{2.5}$ emissions distributions, relative to lower emissions managed fire events. The full comparison between the source-specific FINNv2.2 inventory and the NEI fire estimates can be found in Schollaert et al. (2024). We also verified a subset of the highest prescribed-burn specific concentrations we estimated (i.e., >99.9th percentile of daily Rx $PM_{2.5}$), by comparing the spatiotemporal distribution of those estimates to burn area reports from the USFS FACTS database from a few localities in Northern CA in November 2017 (Figure S17 in Supporting Information S1). Despite the fact that the 0.25° × 0.3125° GEOS-Chem output resolution allowed us to estimate exposure levels over a wide geographic areas, 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 data set, 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 provided the first comprehensive exposure assessment of $PM_{2.5}$ from wildfire, prescribed burns, and agricultural burns across WA, OR, and CA. We leveraged these data to examine exposure among race and ethnicity groups and socioeconomic status within the general population. Future studies should harness these exposure 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 WA, OR, and CA, each is regulated and permitted by different state-level management agencies, further highlighting the need for understanding their distinct impacts on community-level exposures.

5. Conclusions

As the number and severity of wildfires continues to increase 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, increases in emissions attributable to agricultural burns over the last decade highlight the notable role that the agricultural sector places in total smoke burden (EPA, 2023a).

Understanding how each source of fire differentially impacts communities will present opportunities to design more tailored public health strategies and ultimately to reduce exposures, especially among those most at-risk.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

GEOS-Chem $PM_{2.5}$ output data is available via Dryad (Schollaert, 2024). Census data is available in Center for International Earth Science Information Network—CIESIN—Columbia University (2017).

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