The Intersection of Total and Wildland Fire-Attributed PM2.5 Exposure Disparities in the United States

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# Abstract

              Wildland fire smoke exposure is an emerging public health threat, in part due to climate change. Previous research demonstrated disparities in fine particulate matter (PM2.5) exposure, with Black people, among others, exposed to higher concentrations. We investigate the additional PM2.5burden contributed by wildland fire smoke in the contiguous United States by race, ethnicity, urbanicity, per-capita income, and language spoken at home, using modeled total, non-fire, and fire PM2.5 from 2007 to 2018. Wildland fires contributed 7% to 14% of total PM2.5 annually, while non-fire PM2.5declined 24%. Wildland fires cause greater PM2.5 exposure for Black and Native American people, and those who live in non-urban and low-income areas. Disparities in 2007 to 2018 average non-fire PM2.5 concentrations where Black people live (9.1 μg/m3) were further exacerbated by the contributions of fires (1.0 μg/m3). These results support efforts by public health agencies and air quality managers to reduce smoke exposure.

# Keywords

Air pollution, wildland fires, wildfire, prescribed fire, PM2.5, exposure disparities, climate change

# Synopsis (~30 words)

This study investigates how wildland fire smoke contributes to total fine particulate matter exposure for different population groups, aiming to inform strategies to reduce exposure in the United States.

# Introduction

Due to the successful regulation of ambient sources of air pollution through the Clean Air Act, there has been a substantial improvement in United States (US) air quality over the last three decades, as reflected by declines in pollutants such as ambient fine particulate matter (PM2.5, particulate matter with an aerodynamic diameter less than or equal to 2.5 µm).1 However, in some areas of the US, recent increases in wildfire activity are contributing to flattening or reversing the decreasing trends in PM2.5.2, 3 Exposure to PM2.5 from wildland fire (i.e., prescribed fire and wildfire) smoke is an increasing threat to public health in the US, and it is expected to grow in the future as climate change contributes to favorable wildfire conditions,4-6 and as the use of prescribed fire increases to manage fuel loads with the goal of reducing wildfire risk following over 100 years of fire suppression.7, 8 Consequently, fire now comprises the largest percentage of estimated primary PM2.5 emissions in the US,9. However, less is known about the contribution of wildland fire PM2.5 to overall population PM2.5 exposure. Understanding the sociodemographic patterns of wildland fire smoke exposure in light of underlying patterns of exposure to ambient (non-fire) PM2.5 is increasingly important for understanding the public health burden of US air pollution.

Sociodemographic disparities in ambient PM2.5 exposure have been well documented, with people of color, including Black people in particular, experiencing a larger burden of pollution than other racial and ethnic groups nationally.10-13 Studies of wildland fire smoke exposure that examine disparities by sociodemographic characteristics in the US are more limited, but indicate that smoke exposure may be more prevalent among some sociodemographic groups. Fann et al. (2018)14 showed that a higher percentage of Black and Native American people live in areas with >75th percentile 2008-2012 wildfire PM2.5 compared to Asian and white people. A 2011 to 2021 national study assigning exposure using satellite detected smoke plumes reported that high density smoke disproportionately affected people of color and those with limited English.15 In contrast, Burke et al. (2021)2 reported higher wildfire-specific PM2.5 concentrations among non-hispanic white populations. PM2.5 attributed to wildland fire was estimated using a variety of methods across different overlapping time periods in these analyses. They each focus on fire attributed PM2.5 or an indicator of smoke without considering how smoke exposure disparities relate to disparities in PM2.5 exposure from non-fire sources. Furthermore, exposure by racial and ethnic groups captured in the US Census16 is not comprehensively analyzed in any of these studies.2, 14, 15 Some population groups disproportionately affected by non-fire PM2.5 may also be disproportionately affected by wildland fire smoke exposure, but existing studies provide inconsistent evidence.

Wildland fire smoke is a complex mixture consisting of water vapor, gases, and particles. Of these components, PM2.5 is the pollutant of primary health concern because it is a major component of smoke and extensive evidence has shown that PM2.5 exposure may lead to numerous health outcomes including respiratory- and cardiovascular-related effects as well as early death.10 The findings for ambient PM2.5 exposure (i.e., exposure during a typical day) have been supported by recent studies focusing on wildfire smoke that demonstrate similar health effects.17-19 The health impacts of wildfire smoke are widespread, and emissions from fires in western states cause increases in PM2.5 not only near the source fire, but also long distances downwind. National studies examining the public health burden of wildland fire smoke estimate thousands of attributable hospital admissions and deaths with dozens of billions of dollars of economic costs.14, 20

In this work, we address the following questions,

1. How do wildland fires contribute to US PM2.5 concentrations and how is this changing over time; and
2. How does wildland fire smoke contribute to disparities in total PM2.5 exposure among different sociodemographic groups?

We focus on PM2.5 exposure in the contiguous US (CONUS) from 2007 through 2018, using recent estimates of PM2.5 derived from wildland fire and non-fire sources, analyzing PM2.5 concentrations and trends. We aim to provide air quality managers and public health officials with information that will help prioritize areas to target actions to reduce regional and national-level exposure to PM2.5 in a changing climate with increasing wildland fire.

# Materials and methods

## PM2.5 concentrations and exposure

PM2.5 concentrations assigned to Census tracts were used as a surrogate for population-level PM2.5 exposure. Daily 24-hour average PM2.5 concentrations for 2007 to 2018 were obtained from the US Environmental Protection Agency (US EPA)’s Fused Air Quality Surface Using Downscaling (FAQSD) data product.21-24 This product statistically combines Community Multiscale Air Quality (CMAQ) 12 km resolution gridded model outputs with monitoring observations from US EPA National Air Monitoring Stations/State and Local Air Monitoring Stations using a Bayesian space-time downscaler approach to estimate PM2.5 concentrations at the centroid of each Census tract.

To estimate PM2.5 concentrations attributed to wildland fire within the total PM2.5 concentrations, we used previously published CMAQ simulations run with and without wildland fire emissions inputs, over years 2007 to 2018 at 12 km resolution.25, 26 Wildland fire emissions used as inputs to CMAQ were estimated using the BlueSky v3.5.1 modeling framework.25-27 Annual mean PM2.5 concentrations were calculated for the “total” and “non-fire” datasets, and “fire” PM2.5 is taken as the simple difference of total PM2.5 minus “non-fire” PM2.5. The resulting annual mean concentrations were assigned to 2010 US Census tract centers of population28 using cubic spline interpolation.29-31 The ratio of annual mean fire PM2.5 to total PM2.5 concentration was then multiplied by the annual mean PM2.5 concentration in the FAQSD dataset, in each census tract, to calculate the wildland-fire attributed annual average PM2.5 concentration. The resulting distributions of total, wildland fire, and non-fire PM2.5 concentrations are hereafter referred to as the “CMAQ” dataset. Separately, to characterize the high extreme of exposure for population subgroups, the population-weighted 98th percentiles of daily PM2.5 concentrations from FAQSD were calculated in each year.

It has been shown that models estimating PM2.5 concentrations during wildfire smoke eventshave varying levels of agreement and particularly poor correlation with ground monitors at high concentrations.32 Furthermore, as air quality monitors cannot differentiate between PM2.5 from wildland fire and non-fire sources, models are relied upon to estimate wildland fire contributions to total PM2.5. To address these concerns, we compared the results of our approach with an entirely different method of calculating wildfire-specific PM2.5 concentrations as a sensitivity analysis.33 In Childs et al. (2022),33 wildfire PM2.5 concentrations were predicted at Census tracts using a machine learning model with satellite, Lagrangian modeling, and ground monitor inputs. This dataset notably focuses specifically on wildfire, neglecting prescribed fire, which differs from the CMAQ dataset used in the main analysis that includes both prescribed fire and wildfire (wildland fire = wildfire + prescribed fire). Results obtained using the Childs et al. (2022)33 wildfire-specific (“Childs fire”) PM2.5 were compared with results using the CMAQ method.

## Sociodemographic variables

All sociodemographic information was captured at the 2010 Census tract scale, to match the spatial resolution at which PM2.5 was estimated. Total residential population count and race and ethnicity are from the 2010 Census Summary File 1,16 and per-capita income and language spoken at home are 2006-2010 American Community Survey 5-year estimates.34 Although some studies of air pollution exposure disparities have used Census block groups (subsets of Census tracts), analyses of Census tract resolution data have been shown to be highly correlated with results from analyses using finer spatial resolutions.35 Regional analyses were performed using the regions of the CONUS defined by the US National Climate Assessment.36 Each dataset and the processing steps applied are described in detail below.

Population residing in each Census tract by race and ethnicity was categorized into the following groups: Hispanic, Non-Hispanic (NH) White (White), NH Black (Black), NH American Indian and Alaska Native (Native American), and NH Asian (Asian), including 97.8% of the total population. In addition, language spoken at home was examined to investigate exposure among non-English speakers. Language spoken at home was categorized into three groups as an indicator of English proficiency for people living in each tract: only English spoken at home; language other than English spoken at home, speaks English “very well”; and language other than English spoken at home, speaks English less than “very well”. These simplified groups were chosen to provide a high-level overview of Census data detailing many individual languages. To investigate potential socioeconomic factors that could be contributing to disparities in exposure, per-capita income for each Census tract was quintile-ranked into the following five categories: quintile 1: $150-$17,261, quintile 2: $17,261-$21,837, quintile 3: $21,837-$26,687, quintile 4: $26,687-$34,707, and quintile 5: $34,707-$293,610. To capture disparities in PM2.5 exposures by urbanicity with more detail than the urban/rural dichotomous classification provided by the Census, Rural-Urban Commuting Area (RUCA) classifications37 were used to describe urbanicity based on primary traffic flows between Census tracts. The ten primary RUCA codes were simplified into five categories defined by Messer et al. (2010),38 urban core (RUCA code 1), suburban (RUCA code 2), micropolitan (RUCA codes 3, 4, 5, and 6), small town (RUCA codes 7, 8, and 9), and rural (RUCA code 10). Each sociodemographic variable investigated was available for >99% of CONUS Census tracts.

## Comparative analyses

The distributions of PM2.5 across all Census tracts on each day were aggregated into annual average and overall average (2007 to 2018) measures of exposure. Correlation between census tract-level annual means of each of the datasets was examined using Pearson’s r. To examine exposure for each population subgroup, absolute PM2.5 burden was calculated overall and for demographic subgroups using the population-weighted mean (PWM) (equation 1),

where *P*i is the population residing in Census tract *i* and *C*i is the annual average PM2.5 concentration assigned to the Census tract. Relative PM2.5 burden is calculated as the simple ratio between the subgroup exposure over the overall exposure (equation 2).

A relative burden higher than one indicates an exposure higher than the general population and a relative burden less than one indicates a lower exposure. PWMoverall was set to the CONUS PWM for both CONUS and regional analyses. Additionally, to characterize the high extreme of daily PM2.5 exposure, population-weighted 98th percentiles were calculated using the open-source Statsmodels library stats.weightstats.DescrStatsW function.39 All analyses were performed using open-source Python 3.1140 software.

# Results

## Fire and non-fire PM2.5 concentrations and trends

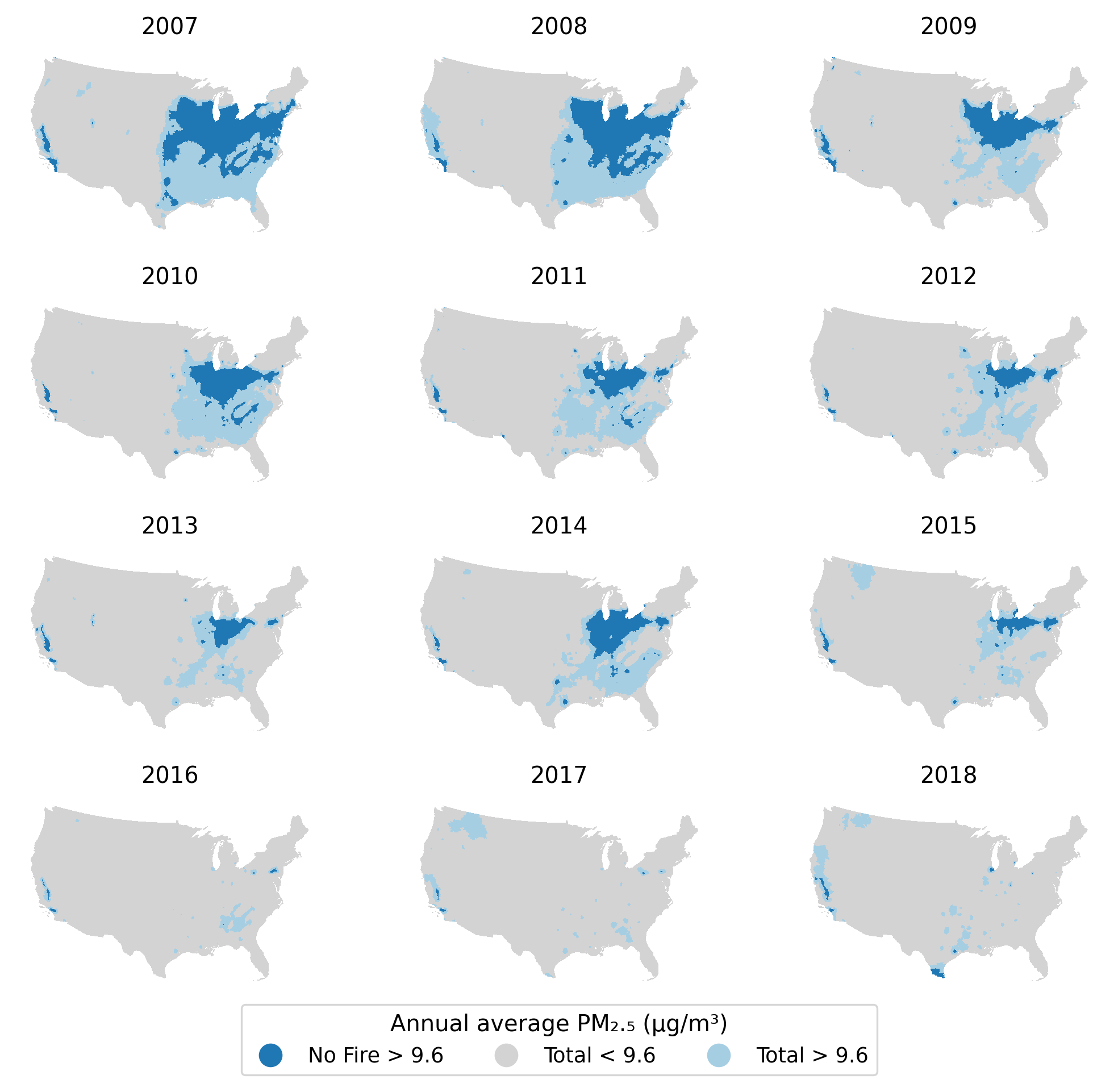
During the 2007 to 2018 study period, non-fire PM2.5 concentrations decreased consistently while fire PM2.5 concentrations varied between a minimum of 7% in 2009 and a maximum of 14% of total PM2.5 in 2017 (Figure 1; Figure S1). Decreases in total and non-fire PM2.5 were most prominent in the east and midwest (Figures S2 and S3), while regions with elevated fire PM2.5 were more variable year-to-year (Figure S4). Southeast fire PM2.5 concentrations were higher in 2007 and 2008 than in other years of the study period. The western US also experienced elevated fire PM2.5 in 2007 to 2008, then a notable increase again in 2015, 2017 and 2018 (Figure S4). Evaluating trends at the Census tract level, areas with above-median annual average concentrations for both fire and non-fire PM2.5 remained consistent throughout the study period despite decreasing total PM2.5 concentrations in most of the country, with areas of California and the midwest above the median for both in all years. In later years, more Census tracts in the inland northwest and southeast had above-median concentrations for each (Figure S5). The spatial distribution of fire PM2.5 ­is more variable than that of non-fire PM2.5 over the years studied.

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**Figure 1**. Yearly overall population-weighted annual mean non-fire and fire PM2.5 concentrations in the contiguous United States from 2007 to 2018. The X-axis of this plot ranges from 7 to 12 µg/m³.

In the primary analyses of this paper, we consider the full distribution of concentrations because disparities in PM2.5 exposure may exist even at low concentrations. However, to show where fires are contributing to relatively high PM2.5 concentrations within the CONUS, census tracts with annual concentrations exceeding the overall (2007 to 2018) national population weighted mean of 9.6 µg/m³ in individual years are mapped in Figure 2. The number of census tracts exceeding 9.6 µg/m³ decreased in each year from 2007 through 2018, although areas in the west, midwest, and south had many Census tracts greater than this threshold in 2018. As ambient concentrations of PM2.5 have decreased from regulatory actions under the Clean Air Act,9 the proportion of tracts above 9.6 µg/m³ where wildland fire contributions are necessary to exceed that threshold has increased (Figure 2; Figure S6).



**Figure 2.** Contiguous US Census tracts with population-weighted annual mean PM2.5 concentrations exceeding 9.6 μg/m3 , considering total PM2.5 and PM2.5 from non-fire sources from 2007 to 2018. Light blue denotes Census tracts that would not be above the 9.6 μg/m3 threshold if not for contributions from wildland fires.

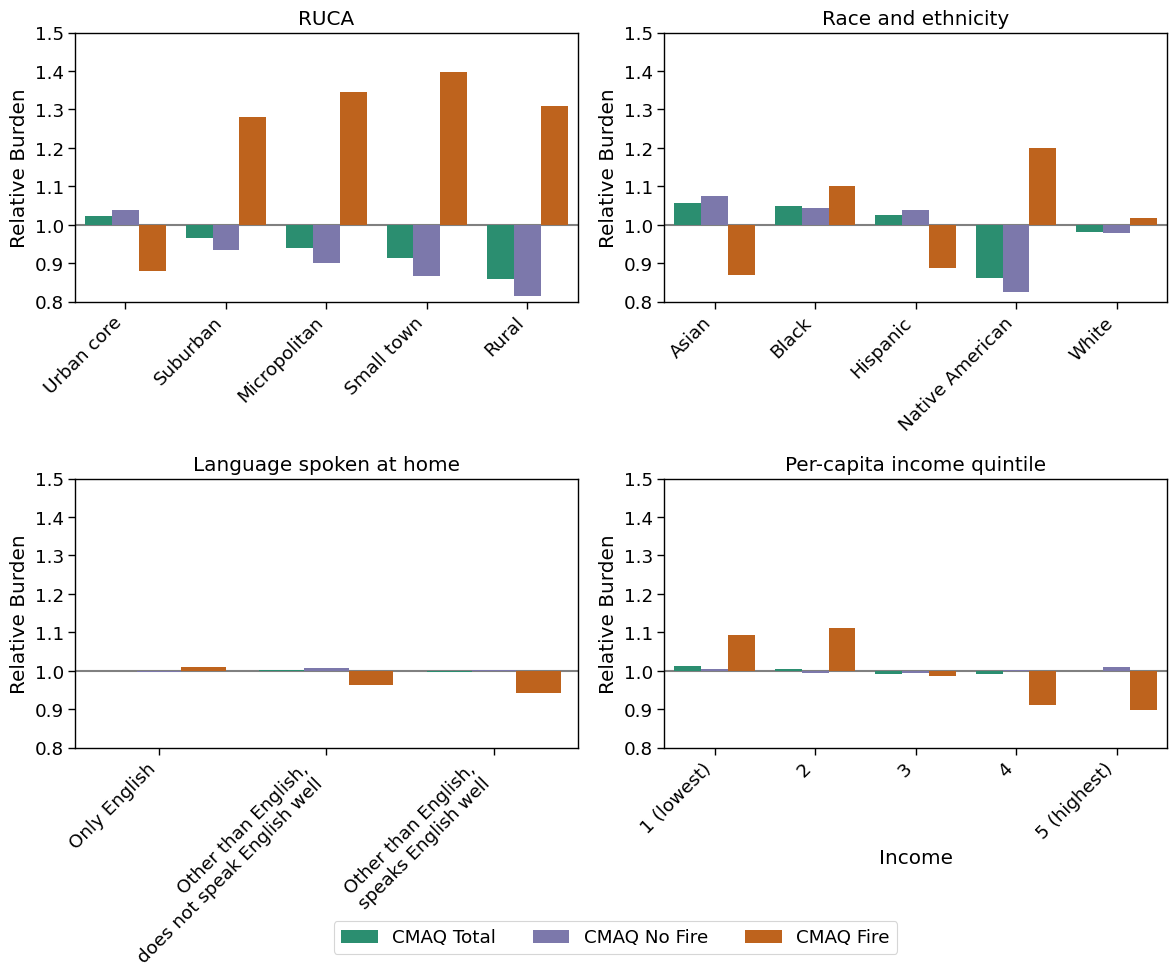
**Table 1.** Population-weighted annual mean PM2.5 concentrations (2007 to 2018) attributed to all sources (total), non-wildland fire (non-fire), wildland fire (fire), and the Childs33 dataset of wildfire PM2.5, by National Climate Assessment (NCA) regions, primary Rural Urban Commuting Area codes (RUCA), racial and ethnic groups, language spoken at home, and quintiles of per-capita income.[[1]](#footnote-2)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | CMAQ Total (µg/m³) | CMAQ Fire (µg/m³) | CMAQ Non-Fire (µg/m³) | CMAQ % Fire | Childs Fire (µg/m³) |
| Overall |  | 9.6 | 0.88 | 8.7 | 9.2 | 0.38 |
| NCA Region | Midwest | 10 | 0.63 | 9.8 | 6.1 | 0.47 |
| Northeast | 9.4 | 0.37 | 9.0 | 3.9 | 0.30 |
| Northern Great Plains | 7.4 | 1.1 | 6.3 | 15 | 0.71 |
| Northwest | 7.9 | 1.2 | 6.7 | 15 | 0.66 |
| Southeast | 9.4 | 1.4 | 8.0 | 15 | 0.32 |
| Southern Great Plains | 9.6 | 0.97 | 8.6 | 10 | 0.40 |
| Southwest | 9.7 | 0.92 | 8.8 | 9.5 | 0.35 |
| RUCA | Urban core | 9.8 | 0.77 | 9.0 | 7.9 | 0.37 |
| Suburban | 9.2 | 1.1 | 8.1 | 12 | 0.39 |
| Micropolitan | 9.0 | 1.2 | 7.8 | 13 | 0.42 |
| Small town | 8.8 | 1.2 | 7.5 | 14 | 0.43 |
| Rural | 8.2 | 1.1 | 7.1 | 14 | 0.46 |
| Race and ethnicity | Hispanic | 9.8 | 0.78 | 9.0 | 7.9 | 0.35 |
| Native American | 8.2 | 1.1 | 7.2 | 13 | 0.43 |
| Asian | 10 | 0.76 | 9.3 | 7.5 | 0.38 |
| Black | 10 | 0.97 | 9.1 | 9.6 | 0.36 |
| White | 9.4 | 0.89 | 8.5 | 9.5 | 0.39 |
| Language spoken at home | Only English | 9.6 | 0.89 | 8.7 | 9.3 | 0.38 |
| Other than English, does not speak English well | 9.6 | 0.85 | 8.8 | 8.8 | 0.37 |
| Other than English, speaks English well | 9.6 | 0.83 | 8.7 | 8.7 | 0.37 |
| Per-capita income quintile | 1 (lowest) | 9.7 | 0.96 | 8.7 | 9.9 | 0.37 |
| 2 | 9.6 | 0.98 | 8.6 | 10 | 0.39 |
| 3 | 9.5 | 0.87 | 8.6 | 9.1 | 0.39 |
| 4 | 9.5 | 0.80 | 8.7 | 8.4 | 0.38 |
| 5 (highest) | 9.6 | 0.79 | 8.8 | 8.3 | 0.36 |

## Disparities in wildland fire and non-fire PM2.5 exposure

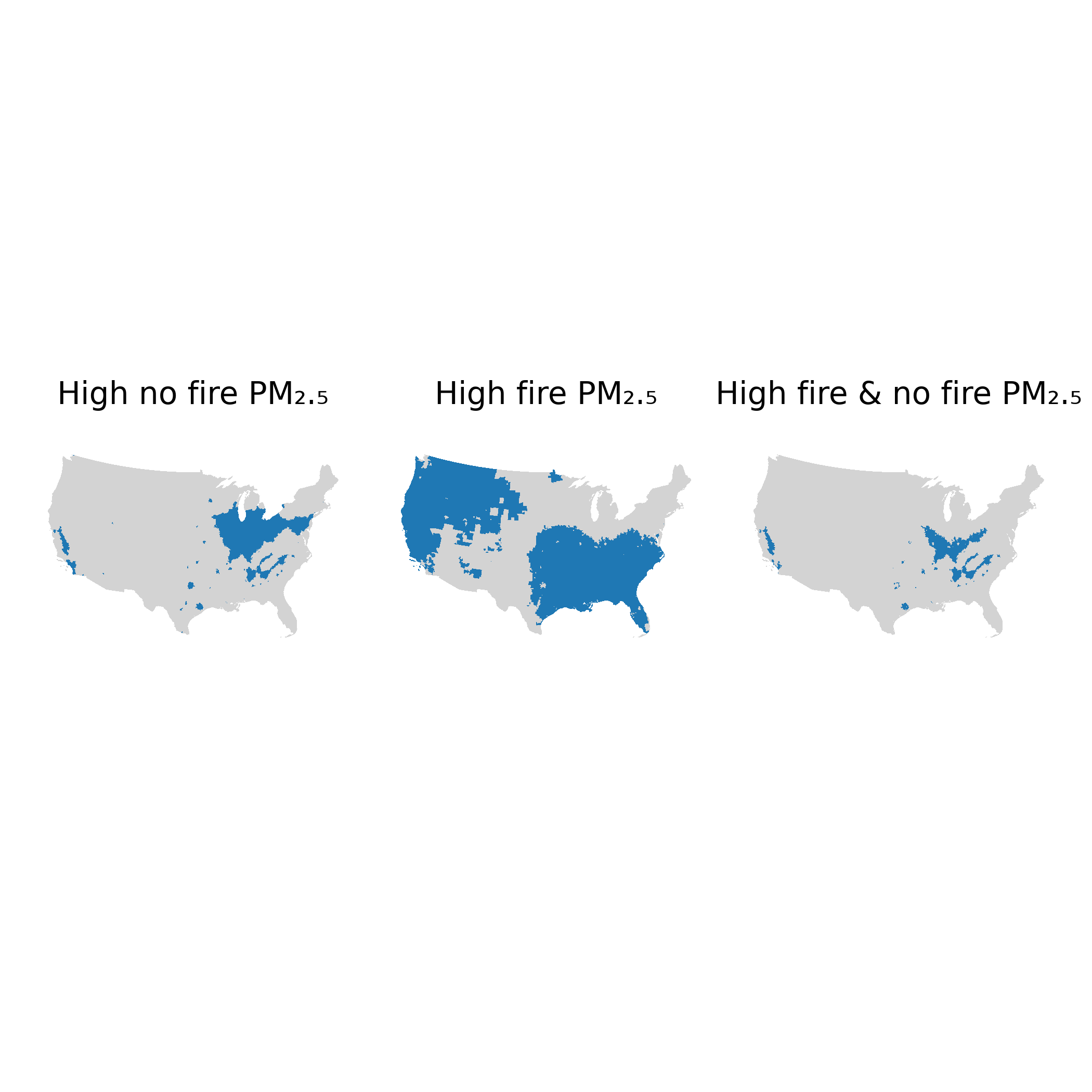
Averaged over 2007 to 2018, wildland fires contributed 0.88 µg/m³ (9.2%) to a total of 9.6 µg/m³ population weighted mean PM2.5 concentrations (Table 1). Fire and non-fire PM2.5 concentrations were weakly anticorrelated (Pearson’s r: -0.19; Table S1), suggesting that regions with high fire PM2.5 often do not coincide with regions with high non-fire PM2.5. Furthermore, the burden of fire PM2.5 was not distributed equally among the population (Table 1; Figure 3). Among racial and ethnic groups, concentrations were highest where Native American people live, receiving 1.1 µg/m³ (13%) of total PM2.5 concentrations from wildland fires. Asian people were exposed to the least wildland fire smoke, with 0.76 µg/m³ (7.5%) of total PM2.5 concentrations attributable to fires. By region, the northwest and southeast had the highest concentrations of fire PM2.5 (1.2 and 1.4 µg/m³; 15% of total PM2.5 for each), and the midwest and northeast experienced the least (0.63 and 0.37 µg/m³; 6.1 and 3.9% of total PM2.5). Those living in urban Census tracts experienced a smaller, though still substantial, fire PM2.5 burden (0.77 µg/m³; 7.9% of total PM2.5) than those living in less dense communities (1.1 to 1.2 µg/m³; 12 to 14% of total PM2.5). Census tracts with higher per-capita income (4th and 5th quintiles) were exposed to less fire PM2.5 (0.80 and 0.79 µg/m³; 8.4 and 8.3% of total PM2.5) than those with lower income (1st and 2nd quintiles: 0.96 and 0.98 µg/m³; 9.9 and 10% of total PM2.5). Larger differences in the relative burden of PM2.5 exposure were identified by race and ethnicity and urbanicity compared to language spoken at home and income (Table 1; Figure 3).

These results for fire PM2.5 contrast with the exposure for non-fire PM2.5 for some population groups, but not others. Among racial and ethnic groups, non-fire PM2.5 concentrations were highest where Asian people live (9.3 µg/m³) but fire PM2.5 concentrations were lowest (0.76 µg/m³; 7.5% of total PM2.5; Table 1). A similar pattern existed where Hispanic people live, and to a lesser extent, where white people live. For these groups, fire PM2.5 added to the total PM2.5 exposure but attenuated the relative burden of total PM2.5 compared to non-fire PM2.5 concentrations (Figure 3). Areas where Black people live were exposed to higher concentrations of both fire PM2.5 and non-fire PM2.5, and as a result, total PM2.5 relative burden was higher compared to that of non-fire PM2.5 (Figure 3).



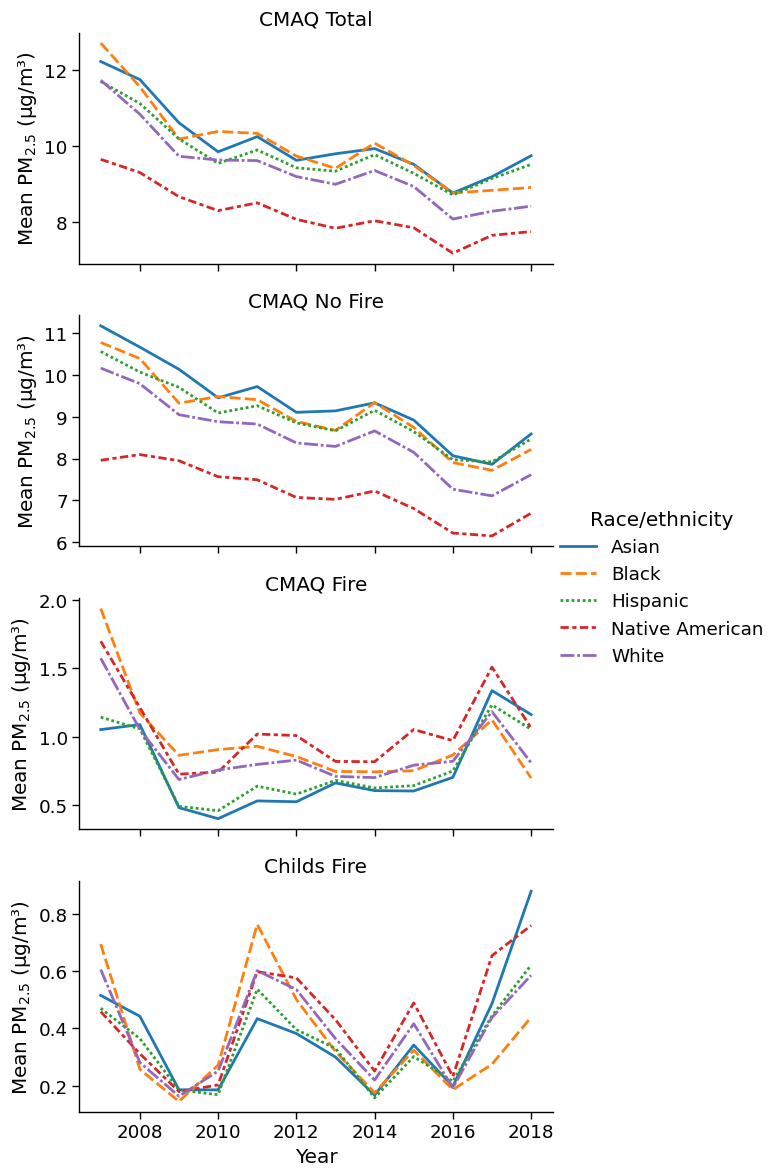
**Figure 3.** Relative burden of total (CMAQ Total), wildland fire (CMAQ Fire), non-fire (CMAQ No Fire) PM2.5 concentrations by Rural-Urban Commuting Area (RUCA) urbanicity classifications, race and ethnicity, language spoken at home, and per-capita income quintile.[[2]](#footnote-3)

Comparing the demographic characteristics of census tracts with greater than the overall population-weighted mean concentration of 9.6 µg/m³ to those with mean concentrations below that threshold, Native American people comprised a larger percent of the population in areas with high fire PM2.5 (0.9%) compared to areas with high non-fire PM2.5 (0.3%; Table S2). People living in areas with both high fire PM2.5 and non-fire PM2.5 are concentrated in the southeast, where 48.7% of the population lives in areas with both high non-fire PM2.5 and fire PM2.5, versus 22.3% or less of the population in other regions (Table S2; Figure 4). Areas with both high non-fire PM2.5 and fire PM2.5 had fewer white people (59% of the population, compared to 64% overall) and more Black, Hispanic, and Asian people than the overall population. These areas had lower per-capita income, as well (Table S2; Figure 4).



**Figure 4.** Locations of Census tracts with greater than the annual average population-weighted mean (2007 to 2018) non-fire PM2.5 (8.7 µg/m³), fire PM2.5 (0.88 µg/m³), and where both fire and non-fire PM2.5 exceed their respective mean concentrations.

The racial and ethnic groups most exposed to fire PM2.5 varied year-to-year, and their rank order changed between earlier and later years studied. Black people live in places with the highest fire PM2.5 concentrations in 2007 to 2008 and the least concentrations in 2016 to 2018 (Figure 5). This coincided with decreasing southeast concentrations and increasing western fire PM2.5 concentrations (Figure S7). Native American people live in locations that experience the least non-fire PM2.5 concentrations and often the highest annual mean fire PM2.5 concentrations. In contrast, Asian people live in areas with the highest non-fire PM2.5 and the least fire PM2.5 in most years, although concentrations where Asian people live notably increased in 2017 to 2018 (Figure 5). Figures S8 to S10 show trends in annual mean concentrations by urbanicity, language spoken at home, and quintile of per-capita income. The rank of urbanicity categories and income quintiles by fire PM2.5 concentrations largely did not change by year despite variability in concentrations; however, people who speak a language other than English at home were exposed to higher concentrations compared to English speakers in 2017 and 2018, whereas concentrations were approximately equal to or lower than English speakers in earlier years. Among sociodemographic characteristics analyzed, subgroup fire PM2.5 concentration rank order varied more year-to-year in 2007 to 2018 among racial and ethnic groups and by language spoken at home than by urbanicity and income.

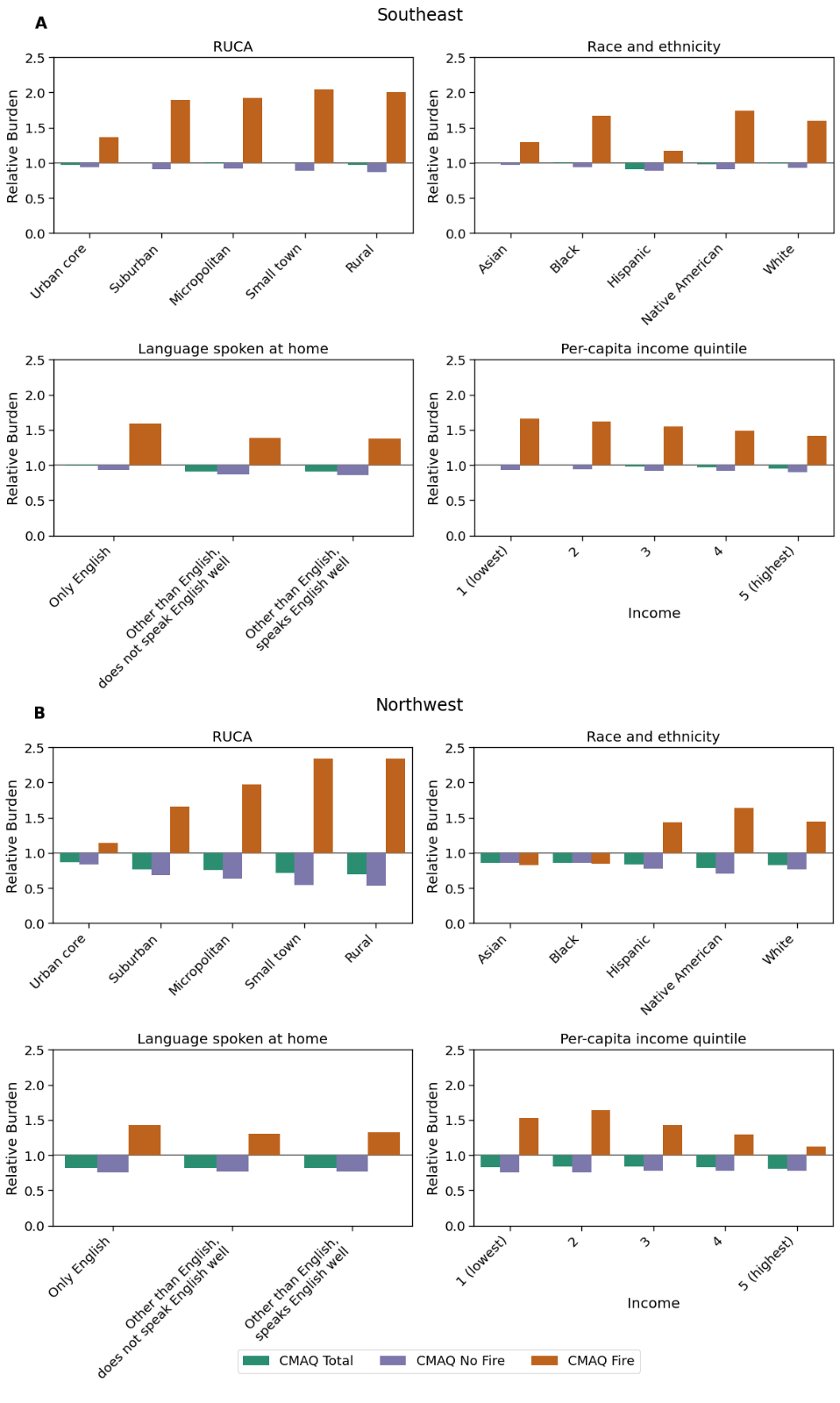


**Figure 5.** Annual average population-weighted PM2.5 concentrations in 2007 to 2018 by race and ethnicity for total PM2.5 (CMAQ Total),non-fire PM2.5 (CMAQ No Fire), wildland fire-specific PM2.5 (CMAQ Fire), and wildfire PM2.5 estimated by Childs et al. (2022)33 (Childs Fire).

The 98th percentile of daily total PM2.5 concentrations, investigated as a metric of peak concentrations likely due to wildfire, declined from 31 µg/m³ in 2007 to a minimum of 18 µg/m³ in 2016, with higher concentrations in 2017 and 2018 (20 and 22 µg/m³; Figure S11). Among racial and ethnic groups, Asian people live in places with higher 98th percentile concentrations than each of the other racial and ethnic groups considered for each year in 2007 to 2018 (Figure S12). This is consistent with the results for Asian non-fire PM2.5 population-weighted mean concentrations (Figure 5). The 98th percentile of concentrations in 2017 and 2018 increased steeply in the western US, among Asian and Hispanic people, those who primarily speak a language other than English at home, and those living in urban areas (Figure S12). This increase coincided with the increase in California burned area in those years41 and a large increase in Childs fire PM2.5 was simultaneously observed. In combination with the trends in annual mean fire PM2.5 (Figure 5), these results indicate a shift in the demographics of the burden of PM2.5 in 2017 and 2018 compared to earlier years studied.

## Disparities in exposure within regions of the CONUS

Relative burden of total, fire, and non-fire PM2.5 within regions was investigated with a focus on the southeast and northwest (Figure 6) because those regions had the highest fire PM2.5 concentrations (Table 1). Relative burden in other regions is shown in Figures S13 to S17. Disparities by urbanicity are largely consistent across regions, with lower fire PM2.5 and higher non-fire PM2.5 concentrations in urban areas. Higher fire PM2.5 concentrations were observed in lower income areas in the northeast and southeast but were less consistent in regions with lower fire PM2.5 concentrations. Considering racial and ethnic groups, the burden of fire PM2.5 varied more by region than that of non-fire PM2.5. Fire PM2.5 concentrations were higher where Native American people live compared to other groups in all regions except those with the lowest fire PM2.5 concentrations (i.e., the midwest, northeast and southwest). Patterns of fire PM2.5 burden among other racial and ethnic groups vary across the regions of the CONUS, with Black people, for example, among the most burdened in the southeast but among the least burdened in the northwest. Black and Asian people are among the groups living in areas with the highest non-fire PM2.5 burden across all regions. Relative burden of fire PM2.5 by language spoken at home is similarly varied by region. In general, characteristics such as urbanicity and income vary more consistently with the relative burden of fire PM2.5 across regions of the CONUS than racial and ethnic groups and by language spoken at home.



**Figure 6.** Relative burden of total (CMAQ Total), wildland fire (CMAQ Fire), non-fire (CMAQ No Fire) PM2.5 concentrations by Rural-Urban Commuting Area (RUCA) urbanicity classifications, race and ethnicity, language spoken at home, and per-capita income quintile in the southeast (A) and the northwest (B). Regional subgroup concentrations are compared to overall CONUS concentrations.

## Sensitivity analysis

Census-tract level annual mean fire PM2.5 modeled using our CMAQ approach is moderately correlated with predictions from Childs et al. (2022)33 (Pearson’s r: 0.49; Table S1). The Childs overall population-weighted mean is 0.38 µg/m³, which is considerably lower than the 0.88 µg/m³ predicted using CMAQ (Table 1). Comparing the main analysis results with those produced using the Childs et al. (2022)33 data, some results are robust regardless of the choice of fire PM2.5 modeling method, including higher fire PM2.5 burden among Native American people compared to the overall population (relative burden of 1.2 and 1.1 using CMAQ and Childs fire PM2.5, respectively). However, results are less consistent for other groups. Black people are predicted to have less exposure than the overall population using the Childs fire PM2.5 predictions (Childs relative burden: 0.96; CMAQ fire relative burden: 1.1; Figure S18). Regionally, Childs fire PM2.5 is highest in the northern great plains (relative burden: 1.9), whereas CMAQ fire PM2.5 is highest in the southeast (relative burden: 1.6). Trends also vary in specific years between the two approaches; Childs fire PM2.5 predicts much higher relative increases in population-weighted mean concentrations across all racial and ethnic groups in 2011 and 2018 in particular (Figure 5). The results using the two models of fire PM2.5 diverge in 2018, where the Childs fire PM2.5 increased for all racial and ethnic groups relative to 2017 and CMAQ fire PM2.5 decreased. Western US burned area increased between 2017 and 201842 and the two models of fire PM2.5 disagree on whether this led to increased population-weighted fire PM2.5 concentrations.

# Discussion

At the national scale, we found that disproportionate non-fire PM2.5 concentrations where Black people live are compounded by disparities in fire PM2.5, and more people of color live where both fire PM2.5 and non-fire PM2.5 concentrations are high. Some previous studies have investigated racial and ethnic disparities in wildland fire smoke exposure at the national level, although none of them comprehensively included the major racial and ethnic groups classified by the US Census investigated in this work. Fann et al. (2018)14 reported that Black and Native American people were overrepresented and that white people were underrepresented in areas with >75th percentile wildland fire PM2.5 estimated using CMAQ in the CONUS in 2008 to 2012. These results are consistent with this study, although Asian and Hispanic groups were not investigated by Fann et al. (2018).14 Burke et al. (2021)2 only reported a positive association between wildfire PM2.5 and percent white, which is directionally consistent with our results, but did not consider any other racial and ethnic groups. Vargo et al. (2023)15 identified a higher number of days with intense smoke in areas with a higher proportion of minority populations but did not characterize exposure for racial and ethnic groups at a more detailed level. Studies of wildfire PM2.5 in California have identified higher exposure among Native Americans relative to the overall population,43, 44 and another identified elevated Black and Hispanic PM2.5 exposure in Los Angeles and San Francisco Bay during wildfire events in 2020.45 In summary, a higher burden of fire PM2.5 was consistently identified where Native American people live in the limited number of studies14, 43 considering their exposure, but results for other groups were not consistent. We identified higher fire PM2.5 concentrations where Black people live, consistent with Fann et al. (2018)14 for the CONUS and Johnson Gaither et al. (2019)46 in Georgia, but these results were not reproduced in the sensitivity analysis using the Childs fire PM2.5. This may be in part attributable to the lack of focus on prescribed fire in Childs (2022).33 In the CMAQ approach, wildland fire PM2.5 is modeled, including wildfire and prescribed fire. Childs fire PM2.5 focuses on predicting wildfire PM2.5, although it’s unclear how much prescribed fire is captured by the remotely sensed model inputs. Historically, the western US has had more wildfires and the southeastern US has had relatively more prescribed fire;47 and different sociodemographic patterns of exposure because of this regional PM2.5 difference are expected. Our results indicating higher relative burden of non-fire PM2.5 among people of color are generally consistent with those previously reported for white, Black, Hispanic, and Asian people.11-13

Because wildfire smoke cannot be controlled through emission control technologies like stationary or mobile sources of air pollution, and the one approach used to curtail the risk of catastrophic wildfire, prescribed fire, also emits smoke, public health actions focus on interventions that individuals and communities can employ to reduce smoke exposure.18 Examples of these measures include clean air shelters, which are buildings with adequate heating, ventilation, and air conditioning systems where those without access to filtered air can shelter during extreme smoke events; personal protection equipment such as high-efficiency respirators (e.g., N95 masks) that can be used outdoors during smoke events; and low-cost air cleaning methods that can be implemented to improve indoor air quality during smoke events.48 It’s likely that the use of these interventions varies among sociodemographic groups, due to inequality in understanding of the health risks of smoke and a variety of factors that may affect individuals’ ability to take action to reduce their exposure, such as access to resources and occupation.48 For example, those living in the central valley of California experience high concentrations of fire PM2.5 (Figure 4). Many of the people residing in this location are Hispanic and employed as outdoor workers,49, 50 which could contribute to challenges around communicating the health risks of smoke and actions to reduce exposure if bilingual materials are not presented, and they may also have challenges in reducing exposure due to their occupation. Therefore, while the regional and national scale results of this study can help inform where disparities in exposure to both fire and non-fire PM2.5 occur, more detailed analyses may be necessary at individual locations to help support local and more targeted interventions as the vulnerable populations in each location may comprise different characteristics. The results of this study may inform public health officials and air quality managers of areas and groups that may benefit most from those interventions.

Using available PM2.5 monitoring and modeling methods presents challenges for understanding the spatiotemporal distribution of fire PM2.5. Because the current regulatory air quality monitoring network focuses primarily on large population centers and was not designed with wildland fire smoke in mind, exposures to both non-fire PM2.5 and fire PM2.5 are less understood in rural areas.18, 51 Although we rely on models to predict PM2.5 concentrations continuously throughout US Census tracts, those located farther from monitoring sites have larger uncertainties associated with the predictions.21-24 Additionally, because the fraction of PM2.5 attributed to fires is modeled and cannot be validated with measurements, it is unclear if the estimates of fire PM2.5 analyzed in this study may underestimate or overestimate true fire PM2.5 concentrations. Model predictions of PM2.5 have been shown to be less reliable during intense wildfire smoke events.32 A study using CMAQ to investigate fire PM2.5 showed that the model underpredicts concentrations when monitors observe high concentrations and overpredicts concentrations when monitors observe low concentrations during wildland fire smoke events.52 In a sensitivity analysis, we compare the results obtained using the CMAQ approach with those obtained using a recently published daily fire PM2.5 dataset,33 although their approach is also subject to limitations. Childs et al. (2022)33 relies heavily on the NOAA Hazard Mapping System to predict wildfire PM2.5, which tends to miss small fires and best characterizes smoke events with regional impact on air quality.53 Further evaluation and improvement of models of fire PM2.5 may increase understanding of patterns of exposure and improve research of the short and long-term health effects of smoke exposure. Regarding limitations of the population data studied, we do not consider demographic estimates for years other than 2010. It is possible that demographic changes within the study period may cause the reported PM2.5 concentration estimates for subgroups to either underestimate or overestimate true concentrations. Furthermore, the race and ethnicity categories tracked by the Census are coarse, and some people (e.g., people of Middle Eastern or North African descent) may not identify as part of any of the officially listed groups.54 Our approach using residential Census tract concentrations as a surrogate for exposure does not consider how behavioral patterns may vary by sociodemographic group and affect exposure to PM2.5 from fires and other sources.

We found that fires comprise 9.2% of total annual average PM2.5 concentrations in the United States from 2007 to 2018, and fire PM2.5 is distributed among the population differently than non-fire PM2.5. Among racial and ethnic groups, disparities in non-fire PM2.5 concentrations where Black people live are exacerbated by the contributions of fires. Native American people live in areas with the lowest non-fire PM2.5 but the highest fire PM2.5, and Asian people live in areas with the highest non-fire PM2.5 but lowest fire PM2.5. Those living outside of urban areas experience a higher proportion of their total PM2.5 burden from wildfire than those living in urban areas. Furthermore, there is no apparent relationship between income and non-fire PM2.5, but people living in lower-income areas experience higher fire PM2.5 concentrations than those living in higher income areas. As concentrations of non-fire PM2.5 are reduced through the successful implementation of the Clean Air Act1 and the burden of wildfires is increasing,2-6 investigating the distribution of fire PM2.5 is increasingly important to identify communities disproportionately burdened so that targeted interventions to reduce exposures can occur.

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2. Per-capita income quintiles: quintile 1: $150-$17,261, quintile 2: $17,261-$21,837, quintile 3: $21,837-$26,687, quintile 4: $26,687-$34,707, and quintile 5: $34,707-$293,610. RUCA categories: urban core (RUCA code 1), suburban (RUCA code 2), micropolitan (RUCA codes 3, 4, 5, and 6), small town (RUCA codes 7, 8, and 9), and rural (RUCA code 10). [↑](#footnote-ref-3)