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Measuring Long-Term Exposure to Wildfire PM2.5 in California: Time-Varying Inequities in Environmental Burden

Casey JA (jacasey@uw.edu)
Kioumourtzoglou MA
Padula A
González DJX
Elser H
Aguilera R
Northrop AJ
Tartof SY
Mayeda ER
Braun D
Dominici F
Eisen EA
Morello-Frosch R
Benmarhnia T

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Abstract

Introduction: While considered extreme events, wildfires will lengthen and strengthen in a changing climate, becoming an omnipresent climate-sensitive exposure. However, few studies consider long-term exposure to wildfire fine particulate matter ($PM_{2.5}$). Here, we present a conceptual model to assess long-term wildfire $PM_{2.5}$ exposure and evaluate disproportionate exposures among marginalized communities.

Methods: We used 2006-2020 California census tract-level daily wildfire $PM_{2.5}$ concentrations generated from monitoring data and statistical techniques to derive five long-term wildfire $PM_{2.5}$ measures. We classified tracts based on their CalEnviroScreen (CES) score, a composite measure of environmental and social vulnerability burdens, and their racial/ethnic composition. We determined associations of (a) CES score and (b) racial/ethnic composition with the five wildfire $PM_{2.5}$ measures using separate mixed-effects models accounting for year and population density. To assess differences by year, models included CES or race/ethnicity year interaction terms.

Results: We conceptualized and compared five annual wildfire $PM_{2.5}$ exposure measures to characterize intermittent and extreme exposure over long-term periods: (1) weeks with wildfire $PM_{2.5}$ >5µg/m^3; (2) days with non-zero wildfire $PM_{2.5}$; (3) mean wildfire $PM_{2.5}$ during peak exposure week; (4) smoke-waves (2 consecutive days with 25µg/m^3 wildfire $PM_{2.5}$); (5) annual mean wildfire $PM_{2.5}$ concentration. Within individual years, we observed exposure disparities, but generally did not when averaging over the study period. Non-Hispanic American Indian and Alaska Native populations, however, were consistently over-represented among the exposed population compared to their California-wide representation.

Conclusion: We found that wildfire $PM_{2.5}$, measured via five metrics, disproportionately affected persistently marginalized California communities—with substantial year-to-year variability.

SIGNIFICANCE STATEMENT

Wildfires are a recurrent environmental exposure in a changing climate that produce extreme increases in short-term fine particulate matter ($PM_{2.5}$) concentrations and elevated long-term exposures in affected areas with important environmental justice implications. We proposed a conceptual model for assessing long-term wildfire $PM_{2.5}$ exposure using five metrics. Our California environmental justice analysis revealed exposure disparities for communities identified as disadvantaged by CalEnviroScreen, in some years. However, every year we found that Indigenous populations were disproportionately exposed to wildfire $PM_{2.5}$. Estimating average exposure, rather than more time-limited measures that capture short-term peaks, may obfuscate disparities and undermine opportunities to mitigate exposure burdens among marginalized communities. Improved understanding of wildfire smoke-related exposure disparities can inform interventions that advance health equity.

INTRODUCTION

Wildfires—anticipated to lengthen, strengthen, and expand in a changing climate in various parts of the globe, including California (CA) (1-6)— produce extreme short-term fine particulate matter ($PM_{2.5}$) concentrations and lead to elevations in long-term average exposures. For example, Sacramento, CA logged the planet's worst 24-hour average $PM_{2.5}$ levels (263 $\mu g/m^3$) during the 2018 Camp Fire (7, 8). Partially driven by wildfire smoke, the 2018 annual average $PM_{2.5}$ concentration in Sacramento, CA (12.7 $\mu g/m^3$) also exceeded the United States Environmental Protection Agency's (US EPA) annual standard of 12 $\mu g/m^3$. Moreover, while most of the United States (US) has experienced steadily declines in ambient $PM_{2.5}$ concentrations since 2000, wildfire smoke has reversed this trend in the Western US (9). Indeed, wildfire-prone parts of the Western US have seen concentrations of wildfire $PM_{2.5}$ increase by 5 $\mu g/m^3$ between 2006–2010 and 2016–2020 (10).

Wildfires have substantial societal impacts. Many studies report associations between elevated short-term wildfire $PM_{2.5}$ exposure and higher risk of adverse health outcomes, particularly respiratory disease (11-15). Further, 0.5% of all-cause deaths in 749 cities worldwide appear attributable to short-term wildfire $PM_{2.5}$ exposure (15). The epidemiological literature addressing the health impacts of wildfire smoke has focused on short-term exposures almost exclusively (16-18). Yet, given the increasing frequency and intensity of such climate-sensitive exposures, assessing the possible health consequences of repeated and intermittent exposures to wildfires has become a pressing issue.

The US EPA describes the relationships of long-term total $PM_{2.5}$ exposure (from all emission sources) with cancer, respiratory outcomes, and nervous system outcomes as *likely causal,* and the relationship with cardiovascular disease effects and all-cause mortality as *causal* (19). Virtually all epidemiologic studies contributing to the US EPA conclusions estimated $PM_{2.5}$ exposure based on average long-term concentrations. However, average long-term $PM_{2.5}$ concentrations may not capture $PM_{2.5}$ spikes generated by episodic, short-lived events, like wildfires. Over the long-term, wildfire $PM_{2.5}$ concentrations are zero-inflated with minor exposure in most months and severe concentration peaks on some days, resulting in an annual average that is not reflective of how people experience sporadic wildfire $PM_{2.5}$ exposure. Such specificities require novel metrics that consider these contemporary patterns of wildfire events.

Researchers lack an agreed-upon framework with which to measure long-term wildfire $PM_{2.5}$ exposure, stifling development of an evidence base for this increasingly important $PM_{2.5}$ source. To date, studies of long-term wildfire air pollution often ignore the unique spatiotemporal patterning of wildfire $PM_{2.5}$ concentrations. Previous studies tend to define exposure as a binary yes/no based on whether a participant lived near a major fire (20-23). Some studies have estimated wildfire-related air pollution exposure for a single wildfire event or season (24-28). To our knowledge, only one study evaluated the relationship between long-term time-varying wildfire $PM_{2.5}$ and adverse health effects (29). In their study on childhood exposure and mortality, Xue et al. estimated average wildfire $PM_{2.5}$ concentration over various time periods (e.g., month of health outcome, 12 prior months, *in utero*, etc.), and observed no association between average 12-month prior or life-long wildfire $PM_{2.5}$ concentrations and risk of infant or child mortality across multiple countries (29).

Although no long-term studies have characterized intermittent and variable $PM_{2.5}$ trends produced by wildfire in their exposure estimates, new models of daily wildfire $PM_{2.5}$ exposure make calculating alternative metrics possible (10, 30-32). Between 2016–2020, an annual average of 16.4 million Americans lived in places where wildfire $PM_{2.5}$ exceeded 50 μg/m^3 on at least one day (10). Traditional exposure assessment focuses on three domains: frequency, duration, and concentration (33). Similarly, the health effects of wildfire exposures depend on a combination of factors, including how often (frequency), how long (duration), and at which levels (concentration) these exposures occur. Advancing metrics that capture these distinct exposure domains is crucial as the most relevant metric will depend on the health outcome being examined. Indeed, cumulative exposure may be most appropriate for chronic effects like cancer, surpassed thresholds during sensitive developmental windows for birth outcomes, and spikes of exposure for acute respiratory effects.

In addition to biologically relevant exposure assignment for health studies of long-term wildfire $PM_{2.5}$ exposure, exposure metrics matter for environmental justice (EJ) considerations. The White House Environmental Justice Advisory Council (WHEJAC) defines EJ communities as locations “with significant representation of persons of color, low-income persons, Indigenous persons, or members of Tribal nations, where such persons experience, or are at risk of experiencing, higher or more adverse human health or environmental outcomes” (34). A body of literature finds disproportionate exposure to total $PM_{2.5}$ (35, 36) in EJ communities, but recent US nationwide studies of wildfire $PM_{2.5}$ have found the opposite: higher annual average wildfire $PM_{2.5}$ concentrations among higher income and non-Hispanic white populations (9, 10). Nonetheless, some older studies using threshold-based exposure metrics (e.g., annual wildfire $PM_{2.5}$ > 1.5 mg/m^3) identified EJ concerns (37-39). Contradictory findings may be due to the fact that distributions of wildfire $PM_{2.5}$ can change dramatically from year-to-year and that different exposure metrics were used. Because EJ communities already face a higher burden of total $PM_{2.5}$ and other pollutants and are projected to be disproportionately burdened by climate exposures (40) and their effects (41), it is critical to determine whether disproportionate exposure extends to wildfire $PM_{2.5}$.

The present study

Increasing trends and more ubiquitous wildfire $PM_{2.5}$ exposures necessitate long-term exposure assessment to better understand implications for chronic health effects and EJ. Here, we introduce a conceptual model (**Figure 1**) for measuring long-term wildfire $PM_{2.5}$ exposure, summarize trends in exposure metrics, and apply these metrics in an EJ analysis in California from 2006-2020.

RESULTS

In this EJ study, we evaluated five metrics of long-term wildfire $PM_{2.5}$ exposure from 2006–2020 in 7,919 California census tracts. Across the study period, census tracts experienced a median of 13 weeks (IQR: 7, 28; maximum: 145) in which wildfire average weekly $PM_{2.5}$ concentrations exceeded 5 μg/m^3, 245 days (IQR: 229, 378; maximum: 1269) with detectable wildfire $PM_{2.5}$ concentrations, and 3 smoke waves (IQR: 1, 8; maximum: 59). The median of the mean weekly wildfire $PM_{2.5}$ (for the annual peak week) was 7.8 μg/m^3 (IQR: 3.6, 20.9; maximum: 281) and the median of the mean annual wildfire $PM_{2.5}$ concentration was 0.3 μg/m^3 (IQR: 0.2, 0.8; maximum: 21.4).

Spatiotemporal trends in five measures of wildfire $PM_{2.5}$ exposure

We observed geographic, seasonal, and year-to-year variability in exposure, with generally higher exposures in Northern California, summer and fall months, and 2008, 2018, and 2020 (**Figure 2, Supplementary Figure 1, Supplementary Figure 2**). Interestingly, distinct patterns emerged by metric. For example, annual average wildfire $PM_{2.5}$ exposure was consistently higher in Northern California, while the mean concentration during the annual peak week and number of days annually with non-zero wildfire $PM_{2.5}$ concentrations were more evenly distributed across the state (**Supplementary Figure 1**). When summarized across the study period, the Spearman correlation between the five metrics ranged from 0.7 (total days with non-zero wildfire $PM_{2.5}$ concentration and mean exposure during the peak week) to 1 (mean wildfire $PM_{2.5}$ concentration and peak-week mean wildfire $PM_{2.5}$ concentration) (**Supplementary Figure 3**). Summarized annually, the Spearman correlation between metrics ranged from 0.3 (total days with non-zero wildfire $PM_{2.5}$ concentration and total smoke waves in 2008) to 1 (mean wildfire $PM_{2.5}$ concentration and peak-week mean wildfire $PM_{2.5}$ concentration in several years).

Descriptive differences in wildfire $PM_{2.5}$ exposure by CES score

Higher CES scores predominated in the Central Valley, parts of Southeast California, Los Angeles, Riverside, and the East Bay in the San Francisco Bay Area (**Supplementary Figure 4**). When summarized over the whole study period, census tracts in the 4th quartile (disadvantaged communities) versus the lower 3 quartiles of CES scores had similar or lower long-term wildfire $PM_{2.5}$ exposure, as measured by the five metrics (**Figure 3; Supplementary Figure 5**). However, important heterogeneities were observed during specific years of the study period. For example, in 2020, disadvantaged versus not disadvantaged communities (quartile 4 versus 1-3 of CES score) had a lower median (1.2 versus 1.9 μg/m^3) and 90th percentile (8.4 versus 8.8 μg/m^3) annual mean wildfire $PM_{2.5}$ concentration. For the number of weeks with average wildfire $PM_{2.5}$ >5 μg/m^3 in 2020, disadvantaged versus not disadvantaged communities had a lower median exposure (5 versus 7 weeks) but a higher 90th percentile exposure (16 weeks versus 13 weeks). **Figure 3B** illustrates the spatiotemporal variability in which communities were most exposed. For example, in 2009 compared to 2020, a greater proportion of Southern California census tracts were disadvantaged and experienced high wildfire $PM_{2.5}$ exposure (**Supplementary Figures 5-6**).

Descriptive differences in wildfire $PM_{2.5}$ exposure by racial/ethnic composition

Descriptive differences in wildfire $PM_{2.5}$ exposure by racial/ethnic composition

The relationship between census tract racial/ethnic composition and annual wildfire $PM_{2.5}$ exposure also differed over time (**Figure 4, Supplementary Figures 7-8**). **Figure 4, Panel A** depicts the California-wide average census tract racial/ethnic composition, with 41.6% NH white, 36.4% Hispanic, 12.5% NH Asian, 5.9% NH Black, 2.6% NH two or more races, 0.5% NH American Indian or Alaska Native, and 0.6% other race/ethnicity residents. When averaging from 2006–2020, the most exposed census tracts were predominately NH white, but on a year-to-year basis different patterns emerged. For example, in 2019, the most exposed census tracts were predominately Hispanic, and in 2018, NH American Indian and Alaska Native residents were disproportionately represented among the most exposed census tracts.

In terms of relative risk (RR), non-Hispanic American Indian and Alaska Native populations faced disproportionately high exposure every year (RRs ranged from 2.18 in 2011 to 3.94 in 2014), and non-Hispanic white populations did in most years (RRs ranged from 1.15 in 2016 to 1.48 in 2012) (**Supplementary Table 1A**). Non-Hispanic Asian and non-Hispanic Black populations had consistent disproportionately low exposure (RRs ranged from 0.4 to 0.7), while Hispanic populations and non-Hispanic populations of 2+ races fluctuated between disproportionately high or low exposure, depending on the year. When we evaluated disproportionate exposure to high (>25 $\mu g/m^3$ annual average) exposure, the patterns remained somewhat consistent, but the size of the relative disparity grew for non-Hispanic American Indian and Alaska Native populations (e.g., RR in 2014 was 37; **Supplementary Table 1B**) and became more variable for other populations. For example, Hispanic individuals faced disproportionately high exposure in 2019 (RR = 1.6) but not in 2018 (RR = 0.3) or 2020 (RR = 0.4). Conversely, NH white people had disproportionately high exposure in 2018 and 2020 (both RR = 1.9) but not 2019 (RR = 0.8).

Association between CES score and wildfire $PM_{2.5}$ exposure, overall

Using linear and negative binomial regression models, we observed that averaged across 2006–2020 disadvantaged communities (census tracts that made up the highest quartile of CES score) had lower long-term wildfire $PM_{2.5}$ exposure across four of the five exposure measures, on average, from 2006–2020 compared to their more advantaged counterparts (**Figure 5,** orange estimates; Supplementary Table 2). The magnitudes of these differences were quite small. For example, quartile 4 versus 1-3 CES score tracts had 0.14 $\mu g/m^3$ lower (95% CI: -0.17, -0.10) annual mean wildfire $PM_{2.5}$ exposure (**Figure 5E**).

Association between CES score and wildfire $PM_{2.5}$ concentration, by year

The direction of the association between CES score and $PM_{2.5}$ concentration changed annually. For annual average wildfire $PM_{2.5}$ concentrations, quartile 4 versus quartile 1-3 CES scores were associated with higher concentrations during 5 of 15 years, lower concentrations during 8 of 15 years, and no difference during 2 of 15 years (**Figure 5E, Supplementary Table 2E**). The years 2018 and 2020 illustrate how census tracts with higher CES scores can have lower concentrations one year and higher the next. During 2018, census tracts with higher CES scores had lower exposure as quantified by all five measures, but during 2020, higher CES scores had higher exposure on three of five measures, for example experiencing 6.0 (95% CI: 4.6, 8.2) more days with non-zero wildfire $PM_{2.5}$ concentrations (**Figure 5B, Supplementary Table 2B**).

Association between racial/ethnic composition and wildfire $PM_{2.5}$ exposure, overall

In terms of racial/ethnic disparities in long-term wildfire $PM_{2.5}$ exposure, we saw relatively limited and small differences in average exposure throughout the study period (2006–2020) in models that controlled for population density (**Supplementary Figure 9**). A 1-SD increase (26.9% increase) in percent non-Hispanic white population was associated with additional average exposure, for example, 0.19 (95% CI: 0.12, 0.25) more days each year where with >0 μg/m^3 wildfire $PM_{2.5}$ and 0.71 μg/m^3 (95% CI: 0.41, 1.01) higher mean peak-week wildfire $PM_{2.5}$ exposure. Results from adjusted models were similar for non-Hispanic white populations. Conversely, census tracts composed of a higher proportion non-Hispanic Asian and Black individuals had lower average exposure over the study period. For example, a 1-SD increase (9.3% increase) in percent non-Hispanic Asian population was associated with 0.24 (95% CI: -0.30, -0.17) fewer days each year where wildfire $PM_{2.5}$ exceeded 0 μg/m^3 and -0.87 μg/m^3 (95% CI: -1.14, -0.60) lower mean peak-week wildfire $PM_{2.5}$ exposure.

Association between racial/ethnic composition and wildfire $PM_{2.5}$ concentration, by year

Associations between racial/ethnic composition and wildfire $PM_{2.5}$ did not remain consistent across individual study years. For example, in 2020, a 1-SD increase in percent non-Hispanic Black residents was associated with 1.42 (95% CI: 1.20, 1.63) more days with wildfire $PM_{2.5}$ exposure >5 μg/m^3, while in 2019, a 1-SD increase was associated with fewer days with wildfire $PM_{2.5}$ exposure >5 μg/m^3 (-0.33, 95% CI: -0.37, -0.28) (**Supplementary Figure 9**). The consistent relative exposure disparities observed for American Indian and Alaska Native populations (with the RR metric) persisted in many years of the adjusted analyses. Associations were most consistent for peak-week mean wildfire $PM_{2.5}$ and annual average wildfire $PM_{2.5}$ concentrations where in 7 of 15 years, a 1-SD increase with American Indian and Alaska Native population was associated with higher exposure. Associations were mostly null for other exposure measures.

DISCUSSION

In this study, we proposed distinct metrics to characterize repeated and intermittent exposure to wildfire $PM_{2.5}$ that can be adapted and modulated to study various health and EJ impacts, as wildfires, a climate-sensitive exposure, become more omnipresent. We applied these metrics to assess the EJ implications of exposure to long-term exposure to wildfire $PM_{2.5}$ in California by analyzing associations each year and across five measures of wildfire $PM_{2.5}$ exposure, rather than simply considering effects averaged over a study period with a single measure of exposure. We found that wildfire $PM_{2.5}$ disproportionately affected marginalized communities—in some years. Non-Hispanic American Indian and Alaska Native populations consistently experienced 2–3$\times$ the annual mean wildfire $PM_{2.5}$ concentration compared to the overall California population. Non-Hispanic white populations were also disproportionately exposed in many years, though generally not to the same extent as American Indian and Alaska Native populations. In addition, census tracts scoring in the 4th quartile of CES score ("disadvantaged") had distinctly higher concentrations of wildfire $PM_{2.5}$ in some years compared to other census tracts. These findings indicate that relying on averages may underestimate disparities in wildfire exposure burdens. As we observed, disaggregation of exposure metrics by time and space revealed disparities by community disadvantage and race/ethnicity. These disparities are relevant for future wildfire studies seeking to characterize health effects based on specific timeframes or for health endpoints with persistent disparities, particularly among communities facing disproportionate cumulative burdens from other environmental hazards and social stressors. Our results also highlight the importance of considering additional exposure metrics that incorporate elements of frequency, duration and concentration when characterizing intermittent and long-term wildfire-related $PM_{2.5}$ exposure.

Environmental exposures tend to follow a social gradient, wherein marginalized communities face disproportionately high exposures (42, 43). For example, long-term overall $PM_{2.5}$ concentrations in the US are higher in historically redlined communities, communities with lower income levels, and communities of color (35, 36, 44). Zoning, disproportionate siting, residential segregation, gentrification and other pathways contribute to these observed disparities (42). Wildfire-specific $PM_{2.5}$, while not randomly distributed, is generated by wildfires with somewhat unpredictable sizes and locations, and smoke transportation driven by various meteorological patterns, which may explain the less consistent evidence of disproportionate exposure to wildfire $PM_{2.5}$ among racially or socioeconomically marginalized groups. Indeed, our results differed quite dramatically by year, with disadvantaged census tracts, as defined by CalEnviroScreen, experiencing mean annual wildfire $PM_{2.5}$ that were 0.36 $\mu g/m^3$ higher in some years and 0.59 $\mu g/m^3$ lower in other years, compared to non-disadvantaged tracts.

Some prior wildfire $PM_{2.5}$ EJ analyses corroborate our results. Nationwide county-level studies using different exposure models and conducted during different time periods have reported a higher percentage of Black residents in areas exposed to > 1.1 $\mu g/m^3$ annual mean wildfire $PM_{2.5}$ (2008–2012) (39), poorer counties experiencing more smoke waves (2004–2009) (37), and more vulnerable counties having higher annual mean wildfire $PM_{2.5}$ exposure but fewer extremely high (> 35 $\mu g/m^3$) wildfire $PM_{2.5}$ days (2008–2012) (38). Two other nationwide studies from Burke et al. found that counties with a higher proportion of non-Hispanic white residents had higher wildfire $PM_{2.5}$ concentrations (2006–2018)(9) and no correlation between wildfire $PM_{2.5}$ and income (45). In the only other census tract-level study, Childs et al. compared two time periods and found limited socioeconomic or racial disparities in annual mean wildfire

$PM_{2.5}$ exposure from 2006–2010; however, from 2016–2020, this relationship shifted, and results showed an association between higher percentages of Hispanic and non-Hispanic white residents and higher per capita income with higher exposure (10).

Prior wildfire $PM_{2.5}$ studies have not assessed disparities for American Indian and Alaska Native populations or individuals of 2 + racial/ethnic groups. Our analyses revealed considerable wildfire $PM_{2.5}$ exposure disparities for American Indian and Alaska Native residents, especially on the relative scale, where each year this group was overrepresented among the exposed population relative to their statewide representation. Our results are consistent with Masri et al., who observed that higher proportions of American Indian and Alaska Native populations in California census tracts had the most wildfires and burned acres from 2000–2020 (46). In the US, American Indian and Alaska Native populations tend to live in more rural communities, which may result in higher wildfire risk and related $PM_{2.5}$ exposures. Notably, in our analysis, results for this group often persisted in models where we adjusted for population density. Further work could improve understanding of how historical policies have resulted in the observed disparities for American Indian and Alaska Native people. Farrell et al. found that, during the processes of illegal land dispossession and forced migration, Indigenous peoples were forcibly moved to areas that are now more susceptible to climate extremes, including higher temperatures and wildfire risks (47). Furthermore, the suppression of Indigenous land management practices in California, in addition to climate change, has resulted in increased wildfire risks (48).

Our California study builds on prior work, centering EJ questions, using newly developed daily estimates of wildfire $PM_{2.5}$ concentration, and evaluating EJ associations across the study period and by year. We presented a coherent conceptual model for estimating long-term exposure to wildfire $PM_{2.5}$, though other measures of exposure exist and may yield different results in terms of temporal and demographic patterns of exposure burden. We used CES score, which consists of approximately 20 indicators, and wildfires contribute to elevated levels of two of the environmental exposure indicators (49, 50): average total $PM_{2.5}$ concentrations and summer average daily maximum 8-hour ozone concentrations. This could increase the association between exposure and outcome. Notably, our observed EJ findings could also underestimate true exposure disparities because lower SES individuals are more likely to reside in lower-quality housing with higher permeability to outdoor air pollution, reduced ability to purchase and maintain air filtration systems, and constrained options to mitigate work-related exposures, particularly for outdoor occupations in, for example agriculture and construction. We did not estimate wildfire impacts on air quality indoors, where people spend most of their time (51). Low-cost air quality sensors (e.g., PurpleAir sensors) could help provide part of this information, though they are differentially located in wealthier communities (45, 52, 53). Evidence suggests that populations in wealthier counties more often Google "air filter" and stay fully indoors at home on heavy wildfire smoke days compared to populations in lower income counties (45). These differences, as well as other factors like pre-existing health conditions, may explain stronger relationships observed between wildfire smoke exposure and adverse health effects among older adults and persistently marginalized racial/ethnic groups (37, 54, 55). We did not assess differences in associations by region of California, including air basins or metropolitan areas with different air quality and meteorological characteristics, though preliminary research suggests EJ-related disparities may be more pronounced in some regions (52). Finally, while we assessed associations across our study period and by each year, we did not consider trends over time (e.g., whether disparities are worsening). We observed year-to-year fluctuations in associations and given expected increases in population exposures to wildfire smoke, future research can help identify spatio-temporal trends and communities where interventions to mitigate wildfire smoke-related exposures are most needed, for example, due to higher rates of underlying chronic health conditions, and co-exposures to other environmental hazards and social stressors that may enhance vulnerability to the adverse health effects of wildfire-related $PM_{2.5}$ (56).

While, to date, the vast majority of climate and health studies have focused on quantifying the short-term impacts of climate-sensitive exposures (CSE) including wildfires, extreme heat, or floods on acute outcomes such as emergency departments visits or premature mortality, little evidence exists regarding the potential impact of long-term health impacts of CSE which mostly focused on mental health outcomes (57, 58). Existing studies linking long-term exposures such as floods or droughts to mental health have limitations related to exposure assessment (59). As CSE become omnipresent, it is essential to better characterize and understand the long-term impacts and design robust epidemiological studies that consider the unprecedented nature of such exposures. In this paper, we propose a framework for quantifying various dimensions of wildfires smoke exposure that can easily be extended to other extreme and episodic CSE, which we can no longer consider exceptional or rare. These exposure metrics can be integrated into a time-to-event framework, that has been used extensively for traditional long-term exposure to air pollution for example (60, 61), to analyze the long-term effects of time-varying exposure to wildfires or other CSE on various chronic diseases such as dementia, cardiovascular diseases, or cancer incidence.

In this study, we provided a conceptual framework for measuring long-term exposure to wildfire $PM_{2.5}$, a key contribution to public health research because wildfire-related $PM_{2.5}$ continues to make up a larger portion of total $PM_{2.5}$ exposure in the Western US (9) and is becoming more common elsewhere (38, 62). Such exposure metrics can support a new generation of epidemiology studies to evaluate unique challenges posed by climate change on human health. Our results indicate that rather than relying on estimates of average exposure, deriving more time-limited measures can reveal exposure disparities and elucidate opportunities to inform public health interventions with benefits to health equity.

MATERIALS AND METHODS

Study design and conceptual model

We conducted analyses within 2010 California census tract boundaries, excluding 33 (0.4%) tracts with no recorded population. We identified EJ communities using CalEnviroScreen (CES) 3.0 and 4.0. These tools do not include data on census tract-level racial/ethnic composition, so we supplemented with race/ethnicity data from the 2010 Decennial US Census (63, 64). We derived daily census tract-level wildfire $PM_{2.5}$ concentrations for 2006–2020 (see details below) using satellite imagery, monitored concentrations, and machine-learning based multiple imputation (32).

Building upon principles from exposure science to include measures of frequency, duration, and concentration (33, 65), we developed a conceptual model of long-term wildfire $PM_{2.5}$ exposure (**Figure 1**). Domains included frequency (number of exposures within a time period), duration (how long exposed), and intensity (level of exposure). We summarized exposure metrics at the annual level, but other researchers could use alternative time frames (e.g., month, 5-year period) depending on the research question.

Data and metrics

Wildfire $PM_{2.5}$ exposure metrics

Our team previously developed methods to estimate daily wildfire $PM_{2.5}$ (32) and applied the same methodology for census tract level concentrations.Briefly, we fit an ensemble of machine learning models using monitored $PM_{2.5}$ concentrations and a wide range of predictors for $PM_{2.5}$, such as aerosol optical depth, land cover and meteorological conditions, to estimate daily concentrations of $PM_{2.5}$. We then isolated daily wildfire smoke $PM_{2.5}$ from total $PM_{2.5}$ by using different smoke products and spatio-temporal imputation techniques. We used these daily wildfire smoke $PM_{2.5}$ predictions to compute the five metrics of long-term wildfire $PM_{2.5}$ exposure across California census tracts from 2006-2020. First, the number of weeks each year for which mean wildfire $PM_{2.5}$ concentrations exceeded 5 $\mu g/m^3$. Second, the number of days each year for which wildfire $PM_{2.5}$ concentrations were >0 $\mu g/m^3$. Third, the mean daily wildfire $PM_{2.5}$ concentration during the peak weak of exposure for each year. Fourth, the number of smoke waves each year, and fifth, the annual mean wildfire $PM_{2.5}$ concentration. We defined smoke waves as the number of instances of 2 consecutive days with 25$\mu g/m^3$ wildfire $PM_{2.5}$, which was close to the study area and period 90th percentile of wildfire $PM_{2.5}$ concentration on days with any wildfire $PM_{2.5}$, similar to prior work (66).

Environmental burden and population vulnerability

The California Office of Environmental Health Hazard Assessment originally developed CES in 2010 to measure the cumulative impact of environmental exposures and social vulnerability factors to “support the incorporation of equity and environmental justice goals into policymaking” (67). Our study relied on census tract-level scores from versions 3.0 and 4.0 of CES. CES 3.0 included 20 indicators based on data from 2006-2015 in two components: Pollution Burden (environmental exposures [n=7 metrics] and effects [n=5 metrics]) and Population Characteristics (sensitive populations [n=3 metrics] and socioeconomic factors [n=5 metrics]) (68) (**Supplementary Methods**). CES 4.0 added children’s lead risk from housing as an additional environmental exposure and otherwise updated indicators from CES 3.0

using data from 2009-2020 (63). We linked CES 3.0 data to 2006-2012 wildfire $PM_{2.5}$ estimates and CES 4.0 data to 2013-2020 estimates. The final relative CES ranging from 0 to 100 is calculated as follows:

$$\left(\frac{\sum exposures_{percentile}}{n_{exposures\ indicators} \times 10} + \left(\frac{\sum environmental\ effects_{percentile}}{2}\right) \Big/ n_{environmental\ effects\ indicators} \times 10\right)$$

$$\times \frac{\sum sensitive\ populations_{percentile}}{n_{sensitive\ populations\ indicators} \times 10} + \frac{\sum socioeconomic\ factors_{percentile}}{n_{socioeconomic\ factors\ indicators} \times 10}$$

The CES datasets included information on 8,035 California census tracts (99.7% of 8,057 total tracts). Our final dataset included the 7,919 census tracts (98.3%) with non-missing CES 3.0 and 4.0 scores (we excluded the 93 tracts missing in both datasets, the 13 missing in CES 3.0 only and the 10 missing in CES 4.0 only) (63, 68).

The California Environmental Protection Agency (CalEPA) uses CES to allocate proceeds from the state's cap-and-trade program; other state agencies also target funding with this tool (69). We used CES to identify disadvantaged California communities disproportionately burdened by multiple sources of pollution and social vulnerability (i.e., both environmentally and socially disadvantaged). California state agencies often designate communities with the highest 25% of CES scores as disadvantaged. We adopted this threshold in our analyses, and compared disadvantaged census tracts in the highest CES quartile to those in quartiles 1-3. Notably, CES does not include a measure of census tract level racial/ethnic composition. Studies have, however, shown a correlation between worse CES score and a higher percent people of color in California census tracts (70), which might be expected given underlying structural causes of environmental racism (43, 71).

We additionally considered census tract racial/ethnic composition related to wildfire $PM_{2.5}$ exposure, following prior studies (9, 10, 39). For these analyses, we used 2010 decennial census tract-level data on race/ethnicity (64), as these estimates have smaller margins of error compared to American Community Survey data (72). We calculated the percent of individuals in each California census tract self-identifying in the following categories: Hispanic, non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, non-Hispanic American Indian or Alaska Native, and non-Hispanic of two or more races. For analyses, we used continuous percentages of each racial/ethnic group within a census tract.

Statistical analysis

We first computed Spearman correlations between the five measures of long-term wildfire $PM_{2.5}$ exposure overall and for each year and generated univariate maps of the wildfire $PM_{2.5}$ concentrations, CES scores, and racial/ethnic composition of census tracts. Second, we constructed summary maps to highlight census tracts with (1) high CES scores, (2) high proportions of people of color, and (3) high long-term wildfire $PM_{2.5}$ exposures. Third, we visualized changes in measures of long-term wildfire exposure by the sociodemographic variables of interest over time. Fourth, we estimated summary statistics of exposure to high annual average wildfire $PM_{2.5}$ concentrations by racial/ethnic group for each year in the study period. We estimated exposure risk ratios to evaluate whether specific racial/ethnic groups had disproportionately high exposure to wildfire $PM_{2.5}$ using the following equation:

$$RR_{jy} = \frac{\frac{\sum_{i=1}^{n} \omega_{iy} p_{ij}}{\sum_{i=1}^{n} p_{ij}}}{\frac{\sum_{i=1}^{n} \omega_{iy} t_{i}}{\sum_{i=1}^{n} t_{i}}},$$

where w_{iy} is either (a) the annual average wildfire $PM_{2.5}$ in census tract *i* during year *y* or (b) an indicator of wildfire $PM_{2.5}$ in census tract *i* exceeding 25 μg/m^3 during year *y*; p_{ij} is the population of racial/ethnic group *j* in census tract *i*; *t* is the total population in census tract *i*; and *n* is the total number of census tracts. A risk ratio greater than 1 indicates that racial/ethnic group *j* was over-represented among the exposed population, compared to their statewide representation, during year *y.* A risk ratio less than 1 indicates that racial/ethnic group *j* was under-represented among the exposed population, compared to their statewide representation, during year *y*.

We estimated the associations between the binary CES score (with 0 representing quartiles 1-3, and 1 representing quartile 4 [disadvantaged community]) as the explanatory variable and the five measures of long-term wildfire $PM_{2.5}$ as the dependent variable over the study period. We fit linear mixed models for the continuous metrics mean peak-week and annual wildfire $PM_{2.5}$ and negative binomial models for the discrete metrics number of weeks with mean wildfire $PM_{2.5}$ >5 μg/m^3, number of non-zero wildfire $PM_{2.5}$ days, and number smoke waves. We conducted a similar analysis replacing the CES score with each binary racial/ethnic composition variable (e.g., 1 = quartile 4 [high percentage of non-Hispanic Black individuals]; 0 = quartiles 1-3). Models included a categorical variable for year to account for time trends, census tract level population density in 2010 (natural spline with 8 degrees of freedom), and for each census tract centroid's latitude/longitude (natural spline with 20 degrees of freedom) to account for spatial dependence of observations (**Supplemental Figure 10**). We ran comparable models for racial/ethnic composition using six separate models with a term for each racial or ethnic group as the explanatory variable.

Finally, to test for changes in the association between CES score or racial/ethnic composition and the five measures of long-term wildfire $PM_{2.5}$ from 2006-2020, we added an interaction term between the categorical year variable and the binary CES score variable or the racial/ethnic composition variable. Analyses were conducted using R Statistical Software, version 4.1.2 (73). Code to run analyses is available at: https://github.com/joanacasey/longterm-wildfire-pm.git.

Declarations

Competing interests: The authors declare no competing interests.

CLASSIFICATIONS: Major: Social Sciences; Minor: Physical Sciences

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75. Supplementary Methods 1: Domains of CalEnviroScreen 4.0. Please see the CalEnviroScreen 4.0 Report for additional details (1).

Figures

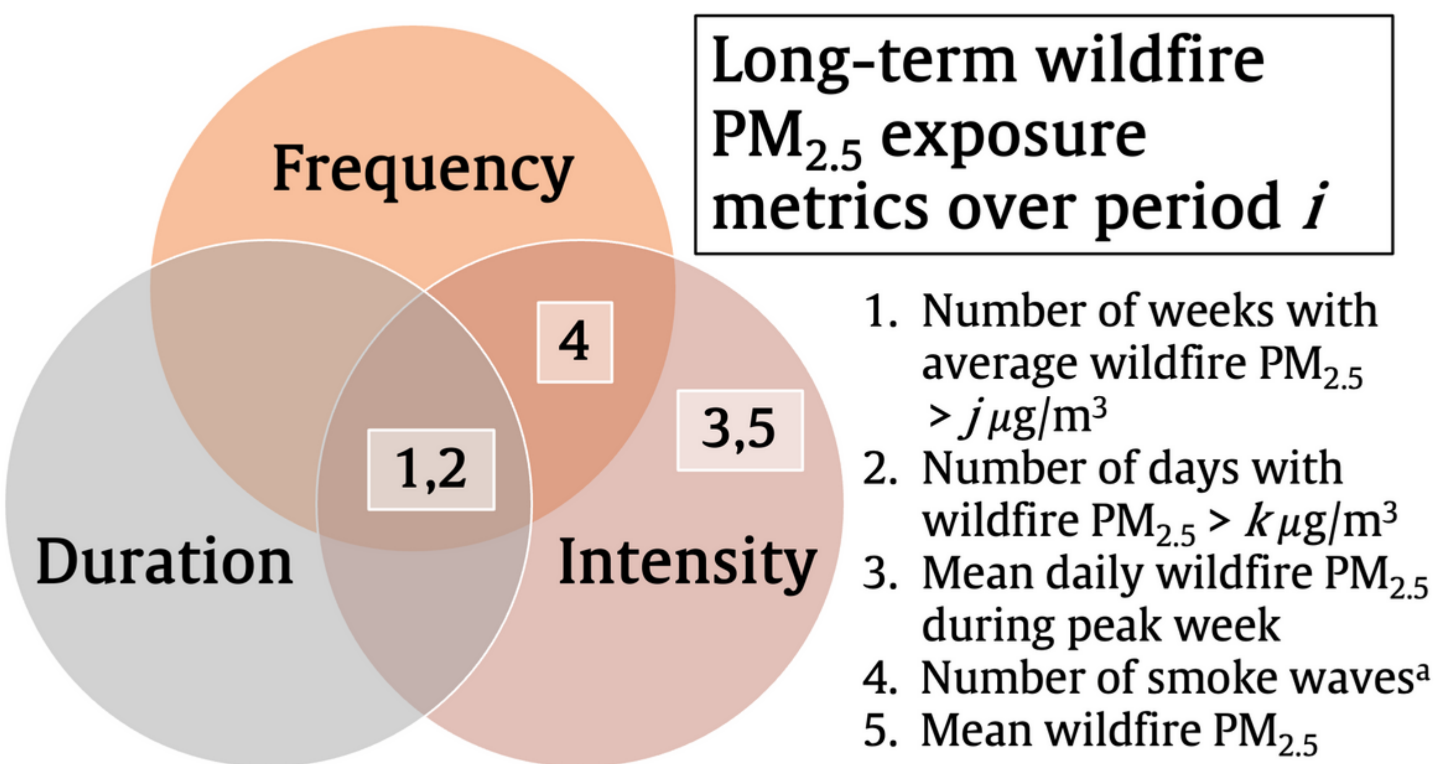

Figure 1

Conceptual model for how to assess long-term exposure to wildfire $PM_{2.5}$. Our metrics capture aspects of three domains: frequency, duration, and intensity. Other researchers can vary certain parameters, for example, *i* could equal 1, 2, 3 etc. years; *j*, could equal 3, 5, 10, 25, etc. µg/m^3; *k* could equal 0, 1, 3, 5, etc. µg/m^3.

[a] We defined smoke waves as the number of instances of ≥2 consecutive days with ≥ 25µg/m^3 wildfire $PM_{2.5}$, which was close to the study area and period 90th percentile of wildfire $PM_{2.5}$ concentration on days with any wildfire $PM_{2.5}$, similar to prior work by Liu et al. (2017).

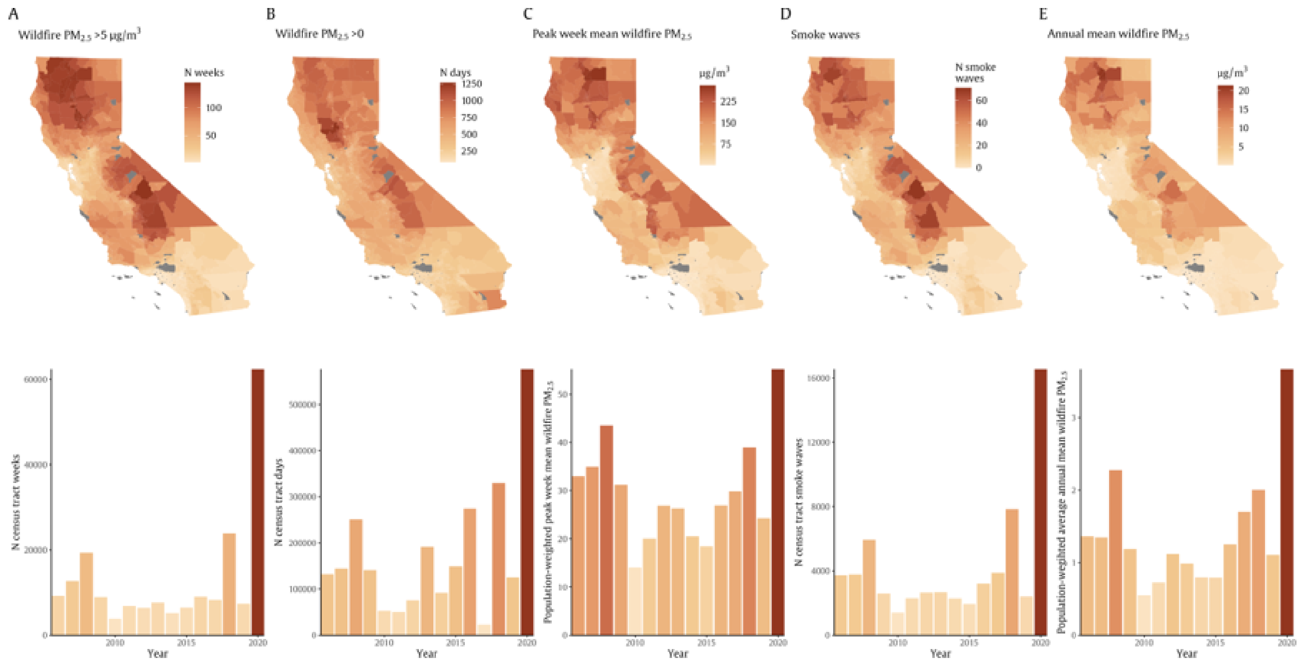

Figure 2

Five measures of census tract-level[a] wildfire $PM_{2.5}$ concentration summarized from 2006–2020. (A) Number of weeks with average wildfire $PM_{2.5}$ > 5 µg/m^3; (B) Number of days with non-zero wildfire $PM_{2.5}$ concentrations; (C) Average of mean daily wildfire $PM_{2.5}$ concentration during the peak week; (D) Number of smoke waves[b]; (E) Average of mean annual wildfire $PM_{2.5}$ concentration.

[a] Maps include 7919 census tracts; grey census tracts indicate missing sociodemographic data; these tracts were not included in analyses.

[b] We defined smoke waves as the number of instances of 2 consecutive days with 25µg/m^3 wildfire $PM_{2.5}$, which was close to the study area and period 90th percentile of wildfire $PM_{2.5}$ concentration on days with any wildfire $PM_{2.5}$, similar to prior work by Liu et al. (2017).

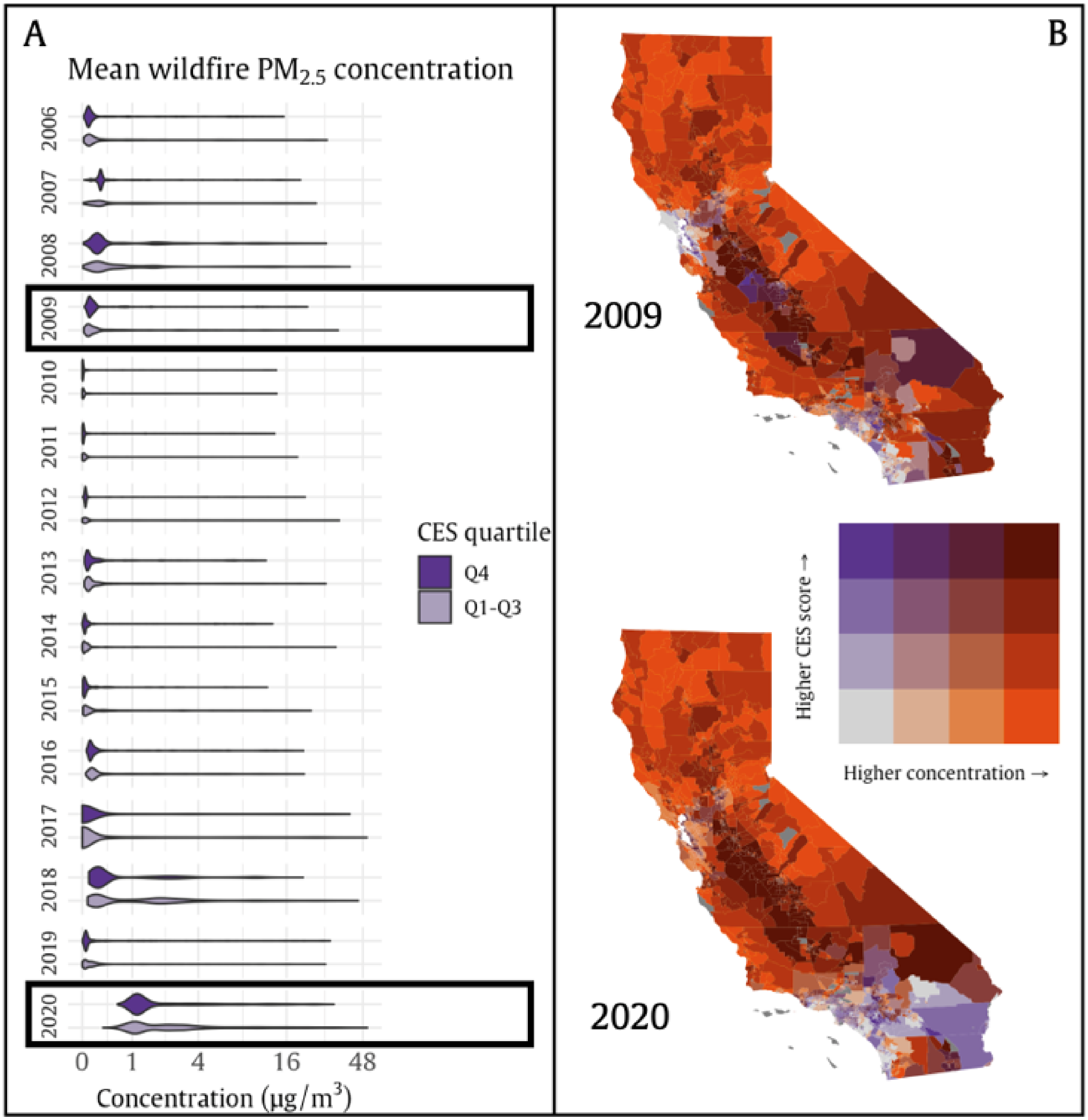

Figure 3

Annual mean wildfire $PM_{2.5}$ concentration by CalEnviroScreen score in California from 2006–2020. (A) Temporal distribution of mean wildfire $PM_{2.5}$ concentration by CES quartile[a]; (B) Bivariate spatial distribution of mean wildfire $PM_{2.5}$ concentration and CES quartile[a] in 2009 and 2020. Higher CES scores indicate greater cumulative environmental and socioeconomic disadvantage.

[a] CalEnvironScreen (CES) score data available from the California Office of Environmental Health Hazard Assessment: https://oehha.ca.gov/calenviroscreen was used to compute CES quartiles where quartile 4

indicates a disadvantaged community.

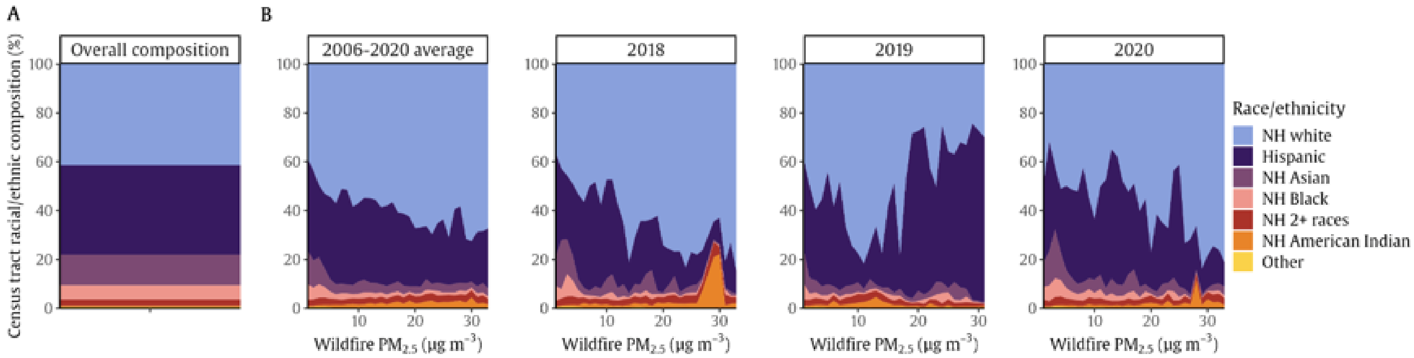

Figure 4

Average census tract racial/ethnic composition by annual average wildfire $PM_{2.5}$ concentration in California. (A) Overall California racial/ethnic composition using 2010 census data; (B) Racial/ethnic composition by annual average wildfire $PM_{2.5}$ concentration on average from 2006-2020, in 2018, 2019, and 2020.

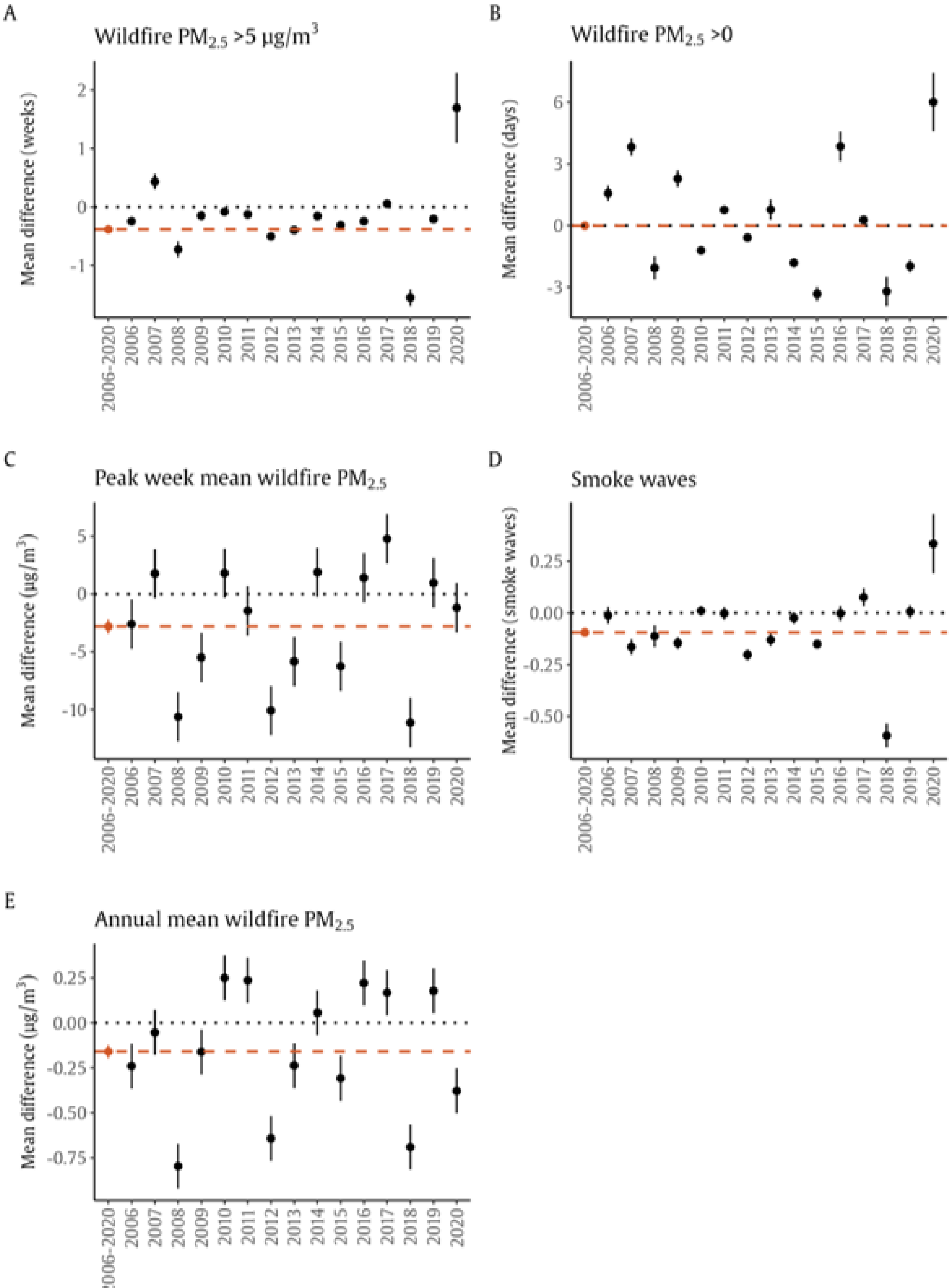

Figure 5

Mean difference in long-term wildfire $PM_{2.5}$ concentration in CES score quartile 4 (disadvantaged communities) versus quartiles 1-3 averaged across 2006−2020 (orange) and during each year (black). (A) Number of weeks with average wildfire $PM_{2.5}$ > 5 µg/m^3; (B) Number of days with non-zero wildfire $PM_{2.5}$ concentrations; (C) Average of mean daily wildfire $PM_{2.5}$ exposure during the peak week; (D)

Number of smoke waves[a]; (E) Average of mean annual wildfire $PM_{2.5}$ concentration. Points represent the average marginal estimate of difference in long-term wildfire $PM_{2.5}$ exposure between census tracts in quartile 4 versus quartiles 1-3 of CES score with lines (95% CI). The black horizontal dotted line at zero represents no difference in long-term wildfire $PM_{2.5}$ exposure between high and low CES score census tracts. The orange horizontal dashed line represents the 2006–2020 mean difference in long-term wildfire $PM_{2.5}$ exposure measure. Models were controlled for census tract level population density in 2010 (natural spline with 8 degrees of freedom) and census tract centroid latitude/longitude (natural spline with 20 degrees of freedom).

[a] We defined smoke waves as the number of instances of 2 consecutive days with 25μg/m^3 wildfire $PM_{2.5}$, which was close to the study area and period 90th percentile of wildfire $PM_{2.5}$ concentration on days with any wildfire $PM_{2.5}$, similar to prior work by Liu et al. (2017).

CES score, CalEnviroScreen score

Supplementary Files

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