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# Measuring long-term exposure to wildfire $PM_{2.5}$ in California: Time-varying inequities in environmental burden

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**Wildfires have become more frequent and intense due to climate change and outdoor wildfire fine particulate matter ($PM_{2.5}$) concentrations differ from relatively smoothly varying total $PM_{2.5}$. Thus, we introduced a conceptual model for computing long-term wildfire $PM_{2.5}$ and assessed disproportionate exposures among marginalized communities. We used monitoring data and statistical techniques to characterize annual wildfire $PM_{2.5}$ exposure based on intermittent and extreme daily wildfire $PM_{2.5}$ concentrations in California census tracts (2006 to 2020). Metrics included: 1) weeks with wildfire $PM_{2.5} > 5$ μg/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 >15 μg/m$^3$ wildfire $PM_{2.5}$); and 5) mean annual wildfire $PM_{2.5}$ concentration. We classified tracts by their racial/ethnic composition and CalEnviroScreen (CES) score, an environmental and social vulnerability composite measure. We examined associations of CES and racial/ethnic composition with the wildfire $PM_{2.5}$ metrics using mixed-effects models. Averaged 2006 to 2020, we detected little difference in exposure by CES score or racial/ethnic composition, except for non-Hispanic American Indian and Alaska Native populations, where a 1-SD increase was associated with higher exposure for 4/5 metrics. CES or racial/ethnic × year interaction term models revealed exposure disparities in some years. Compared to their California-wide representation, the exposed populations of non-Hispanic American Indian and Alaska Native (1.68×, 95% CI: 1.01 to 2.81), white (1.13×, 95% CI: 0.99 to 1.32), and multiracial (1.06×, 95% CI: 0.97 to 1.23) people were over-represented from 2006 to 2020. In conclusion, during our study period in California, we detected disproportionate long-term wildfire $PM_{2.5}$ exposure for several racial/ethnic groups.**

wildfires | particulate matter | environmental justice | American Indian or Alaska Native | California

Wildfires—anticipated to lengthen, strengthen, and expand due to the changing climate across the globe, including California (CA) (1–6)—produce extreme short-term fine particulate matter ($PM_{2.5}$) concentrations and lead to elevated long-term average exposures. For example, Sacramento, CA, logged the planet's worst 24-h average $PM_{2.5}$ levels (263 μg/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 μg/m$^3$), exceeded the United States Environmental Protection Agency's (US EPA) annual standard of 12 μg/m$^3$. Moreover, while most of the United States has experienced steady declines in ambient $PM_{2.5}$ concentrations since 2000, wildfire smoke has reversed this trend in the Western United States (9). Wildfire-prone parts of the Western United States have seen average concentrations of wildfire $PM_{2.5}$ increase by >5 μg/m$^3$ between 2006 to 2010 and 2016 to 2020 (10).

Wildfires have substantial societal impacts. Studies report associations between elevated short-term wildfire $PM_{2.5}$ exposure and higher risk of adverse health outcomes, particularly respiratory disease (11–17). 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 (18–20). Yet, given the increasing frequency and intensity of such climate-sensitive exposures, assessing the possible health consequences of long-term intermittent and repeated wildfire exposure 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 and all-cause mortality as causal (21). Virtually all epidemiologic studies contributing to the US EPA conclusions on the health impacts of long-term $PM_{2.5}$ estimated exposure based on average long-term

## Significance

Fine particulate matter ($PM_{2.5}$), which disproportionately affects disadvantaged US communities, varies relatively smoothly over time. In contrast, wildfire $PM_{2.5}$ demonstrates short-term extreme concentrations. We proposed five metrics for assessing long-term outdoor wildfire $PM_{2.5}$ exposure for health and equity studies. Our California environmental justice analysis detected disparities in some years, but not study period-wide (2006 to 2020) for CalEnviroScreen (CES)-identified disadvantaged communities. Notably, CES scores do not explicitly include racial/ethnic identity. Analyses spanning 2006 to 2020 revealed that Native American and Alaska Native, multiracial, and non-Hispanic white populations had consistently disproportionate outdoor wildfire $PM_{2.5}$ exposure. Housing, occupational, behavioral, or economic constraints may result in larger actual disparities. Improved long-term wildfire $PM_{2.5}$ exposure measurement can support health-equity-focused interventions and climate resilience.

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$PM_{2.5}$ concentrations. This may miss spikes in $PM_{2.5}$ generated by episodic, short-lived events, like wildfires. Over the long term, wildfire $PM_{2.5}$ concentrations are zero-inflated with low exposure in most months and high peaks of concentrations on some days, resulting in an annual average that does not reflect people's experiences of sporadic wildfire $PM_{2.5}$ exposure. The nature of contemporary wildfire $PM_{2.5}$ concentrations requires novel metrics to accurately capture the exposure pattern.

Researchers lack an agreed-upon framework to measure long-term wildfire $PM_{2.5}$ exposure, hampering exposure and health studies of 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. Many studies have defined exposure as a binary yes/no based on whether a participant lived near a major fire (22–25). Some have estimated wildfire-related air pollution exposure for a single wildfire event or season (26–30). To our knowledge, only two studies evaluated the relationship between long-term (≥1 y), time-varying wildfire $PM_{2.5}$ concentrations and adverse health effects (31, 32). 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 mo prior, in utero, etc.), and observed no association between average 12-mo prior or life-long wildfire $PM_{2.5}$ concentrations and risk of infant or child mortality across multiple countries (31). Yu et al. reported associations between two-year average (lag0-1) wildfire $PM_{2.5}$ concentrations and risk of all-cause and site-specific cancer mortality in Brazil (32).

New models of daily wildfire $PM_{2.5}$ exposure make it possible to calculate alternative metrics that capture intermittent and variable wildfire $PM_{2.5}$ concentrations (10, 33–35). Between 2016 to 2020, an annual average of 16.4 million U.S. residents lived in places where ambient wildfire $PM_{2.5}$ exceeded 50 $\mu g/m^3$ on at least 1 d (10). Traditional exposure assessment focuses on three domains: frequency, duration, and concentration (36). 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. Deriving metrics that capture these distinct exposure domains is crucial. The health outcome of interest will dictate the most relevant metric. Cumulative exposure may be most appropriate for chronic disease outcomes 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" (37). A body of literature finds disproportionate exposure to total $PM_{2.5}$ (38, 39) in EJ communities. These disparities likely arose due to racial segregation and other forms of systemic racism (40). The impact of wildfire exposure on EJ communities, however, is mixed. Recent US nationwide studies of wildfire $PM_{2.5}$ have reported higher annual average wildfire $PM_{2.5}$ concentrations among higher-income and non-Hispanic (NH) white populations (9, 10), while some older studies using threshold-based exposure metrics (e.g., annual wildfire $PM_{2.5} > 1.5\ \mu g/m^3$) identified EJ concerns (41–43). Contradictory findings may be explained by year-to-year spatiotemporal variability in wildfire $PM_{2.5}$ and the lack of consensus on best exposure metrics. Communities of color may face elevated wildfire $PM_{2.5}$ concentrations as a result of

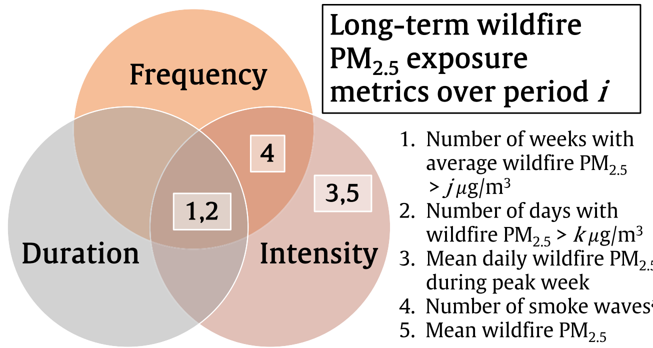


**Fig. 1.** Conceptual model for how to assess long-term exposure to wildfire $PM_{2.5}$. Our metrics capture aspects of three domains: frequency, duration, and intensity and we selected $i$ = 1 (annual). Other researchers can vary certain parameters, for example, $i$ could equal 1, 2, 3, etc. years; $j$, could equal 3, 5, 10, 25, etc. $\mu g/m^3$; $k$ could equal 0, 1, 3, 5, etc. $\mu g/m^3$. [a]We defined smoke waves as the number of instances of ≥ 2 consecutive days with > 15 $\mu g/m^3$ 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 by Liu et al. (41).

displacement driven by rising urban housing costs (44), leading to relocation into suburban wildland-urban interface (WUI) areas, or due to historical forced residence on federal Indian Reservations (45). In recent decades, population growth in the WUI has far outpaced that of other regions (3) and, in California, census tracts affected by wildfire burn zones had increasing percentages of people of color from 2010 to 2020 (46).

Studies focused on outdoor wildfire $PM_{2.5}$ concentrations likely underestimate actual exposure disparities. Socioeconomic disempowerment can constrain housing and personal protective, occupational, and relocation choices. This may result in increased wildfire $PM_{2.5}$ exposure via lower-quality housing with higher permeability to outdoor air pollution, inability to purchase and maintain air filtration systems, the need to continue work, even in unsafe conditions, and reduced ability to evacuate (47, 48). EJ communities face higher current total $PM_{2.5}$ and other pollutant exposures and worse projected climate exposures (49) and effects (50) due to a confluence of socioeconomic and racialized marginalization. Yet the lack of consensus on best metrics of long-term wildfire $PM_{2.5}$ exposure leaves a gap in our understanding of the degree to which wildfire $PM_{2.5}$ disproportionately affects these communities over time.

**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 (Fig. 1) for measuring long-term outdoor wildfire $PM_{2.5}$ exposure, summarize trends in exposure metrics, and apply these metrics in an EJ analysis in CA from 2006 to 2020. Our EJ analysis assessed whether certain racial/ethnic or socioeconomic groups experienced disproportionate wildfire $PM_{2.5}$ exposure during the study period.

## Results

In this study, we evaluated five metrics of long-term outdoor wildfire $PM_{2.5}$ exposure from 2006 to 2020 in 7,919 California census tracts. Across the study period, census tracts experienced medians of 7 wk (IQR: 5, 16; maximum: 76) with average weekly wildfire $PM_{2.5}$ concentrations >5 $\mu g/m^3$, 292 d (IQR: 276, 416; maximum: 1,696) with wildfire $PM_{2.5}$ concentrations >0 $\mu g/m^3$, and three smoke waves (IQR: 2, 8; maximum: 42). The median of mean annual peak week wildfire $PM_{2.5}$ concentration was 4.5 μg/m$^3$ (IQR: 3.9, 11; maximum: 31), and the median of mean annual wildfire $PM_{2.5}$ concentration was 0.21 μg/m$^3$ (IQR: 0.18, 0.54; maximum: 2.4). Rural tracts (n = 121) had higher wildfire $PM_{2.5}$ concentrations compared to urban tracts (n = 7,798) over the study period (*SI Appendix*, Table S1), for example, experiencing higher median peak week average concentrations (12 μg/m$^3$ vs. 4.5 μg/m$^3$) and higher median counts of smoke waves (7 vs. 1). Rural tracts that overlapped with federally recognized Tribal Lands (*SI Appendix*, Fig. S1) had the highest wildfire $PM_{2.5}$ concentrations (0.83 μg/m$^3$ vs. 0.21 μg/m$^3$ annual average in all tracts), while urban tracts that overlapped with federally recognized Tribal Lands had similar or lower wildfire $PM_{2.5}$ concentrations than their non-Tribal counterparts (*SI Appendix*, Table S1 and Fig. S2).

**Spatiotemporal Trends in Five Metrics of Outdoor 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 (Fig. 2 and *SI Appendix*, Figs. S3 and S4). Interestingly, distinct patterns emerged by metric. For example, annual average wildfire $PM_{2.5}$ exposure and mean concentration during the annual peak week were consistently higher in Northern California, while the number of days annually with non-zero wildfire $PM_{2.5}$ concentrations was more evenly distributed across the state. When summarized across the study period, the Spearman correlation between the five metrics ranged from 0.81 (total days with non-zero wildfire $PM_{2.5}$ concentration and mean peak-week wildfire $PM_{2.5}$ concentration) to 0.94 (mean annual wildfire $PM_{2.5}$ concentration and weeks with average wildfire $PM_{2.5} > 5$ μg/m$^3$) (*SI Appendix*, Fig. S5). When summarized annually, the Spearman correlation between metrics ranged from 0 (total weeks with average wildfire $PM_{2.5} > 5$ μg/m$^3$ and total smoke waves in 2010 and 2011) to 0.97 (mean annual wildfire $PM_{2.5}$ concentration and mean peak-week wildfire $PM_{2.5}$ concentration in 2008). In the years with the highest mean annual wildfire $PM_{2.5}$ exposures (2008, 2018, and 2020) vs. other years, Spearman correlations were higher, ranging from 0.74 to 0.97.

**Descriptive Differences in Outdoor 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 (*SI Appendix*, Fig. S6). When summarized over the whole study period, census tracts in the fourth quartile (disadvantaged communities) vs. the lower 3 quartiles of CES scores had similar long-term wildfire $PM_{2.5}$ exposure, as measured by the five metrics (Fig. 3 and *SI Appendix*, Fig. S7). However, heterogeneities were observed by year of the study period. For example, in 2020, disadvantaged vs. non-disadvantaged communities (quartile 4 vs. 1 to 3 of CES score) had nearly the same 90th percentile peak-week wildfire $PM_{2.5}$ concentration (56.7 vs. 56.4 μg/m$^3$) but a higher 90th percentile count of the number of weeks with average wildfire $PM_{2.5}$ >5 μg/m$^3$ (11 wk vs. 9 wk). Fig. 3*B* illustrates the spatiotemporal variability in exposure using the mean peak week metric. In 2020, many tracts in Northern California and the San Joaquin Valley experienced a dual burden of community disadvantage and high mean peak week wildfire $PM_{2.5}$ exposure, while in 2007 such doubly burdened tracts were primarily located in Southern California and the South San Francisco Bay Area (Fig. 3 and *SI Appendix*, Fig. S8).

**Descriptive Differences in Outdoor Wildfire $PM_{2.5}$ Concentration by Racial/Ethnic Composition.** The relationship between census tract racial/ethnic composition and wildfire $PM_{2.5}$ exposure also differed over time (Fig. 4 and *SI Appendix*, Figs. S9 and S10). Fig. 4*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

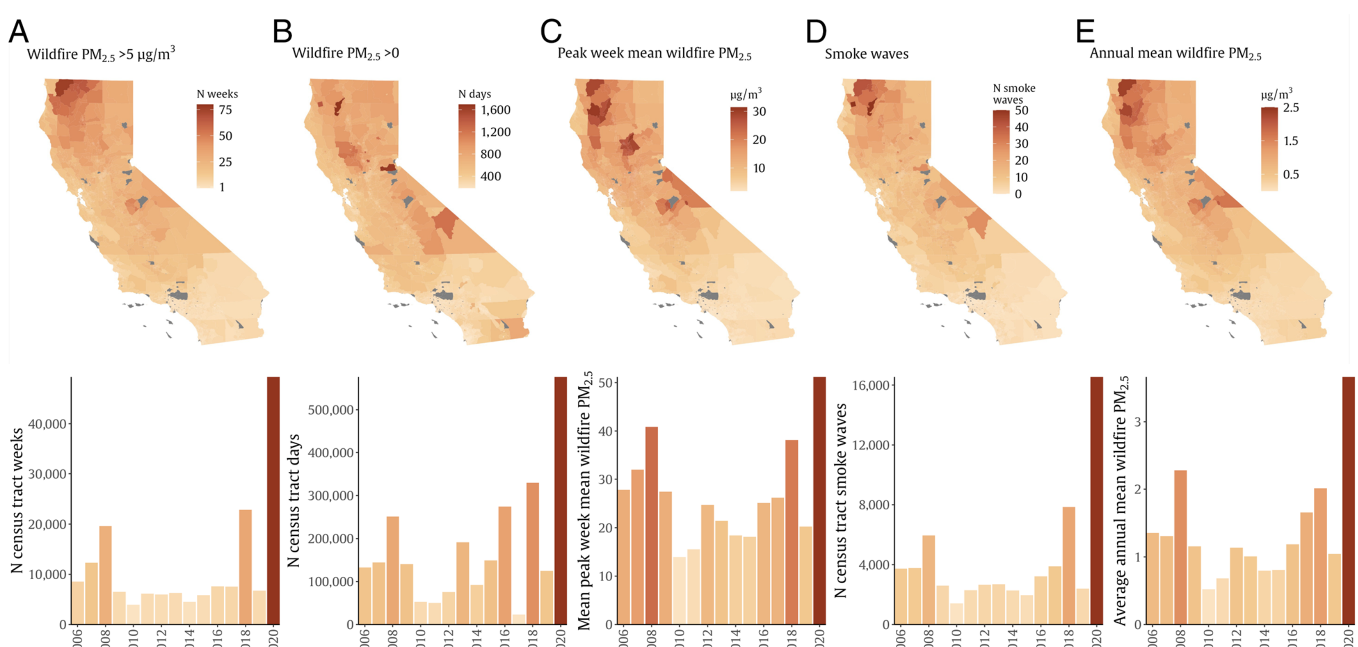


**Fig. 2.** Five metrics of census tract-level[a] outdoor wildfire $PM_{2.5}$ concentration summarized from 2006 to 2020. (*A*) Number of weeks with average wildfire $PM_{2.5} > 5$ μg/m$^3$; (*B*) Number of days with non-zero wildfire $PM_{2.5}$ concentrations; (*C*) Average of mean daily wildfire $PM_{2.5}$ 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; gray 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 > 15 μg/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. (41).

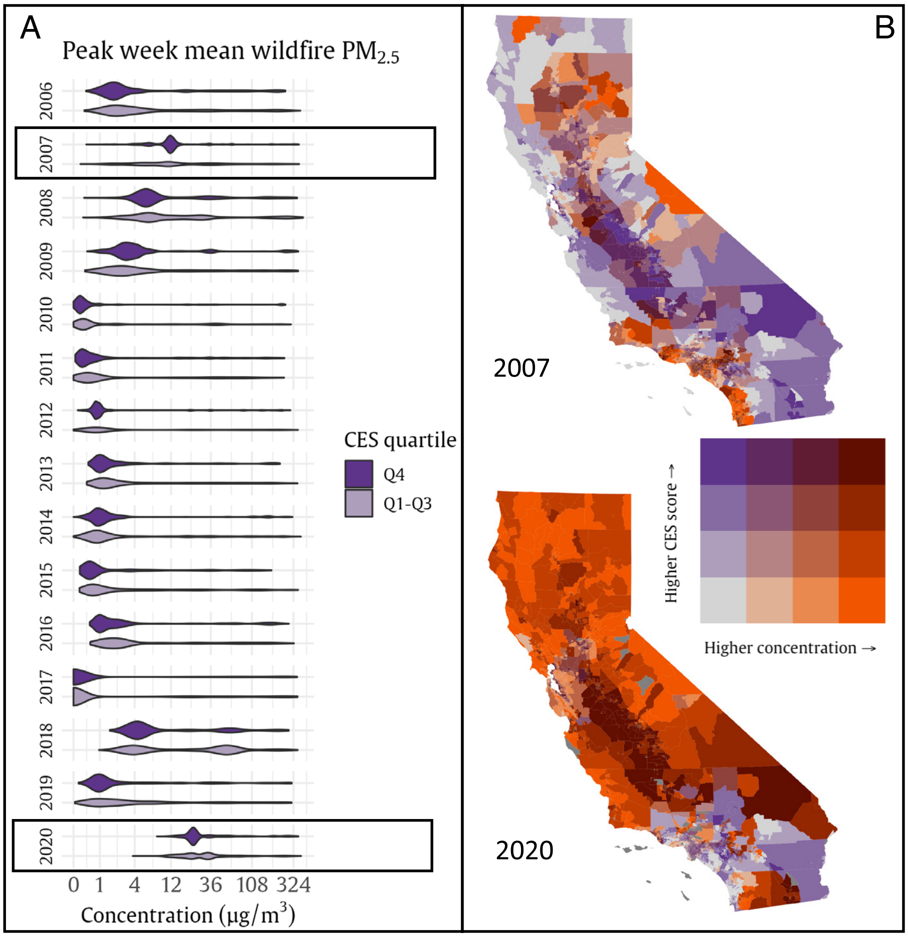


**Fig. 3.** Annual mean daily outdoor wildfire $PM_{2.5}$ concentration during the peak week by CalEnviroScreen score in California from 2006 to 2020. (*A*) Temporal distribution of mean daily wildfire $PM_{2.5}$ concentration during the peak week by CES quartile[a]; (*B*) Bivariate spatial distribution of mean peak week wildfire $PM_{2.5}$ concentration and CES quartile[a] in 2007 and 2020. Higher CES scores indicate greater cumulative environmental and socioeconomic disadvantage. [a]CalEnviroScreen (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.

races, 0.5% NH American Indian or Alaska Native, and 0.6% other residents. When averaging from 2006 to 2020, NH white and NH American Indian and Alaska Native populations were disproportionately exposed as measured by all five metrics (*SI Appendix*, Fig. S10). However, different patterns emerged on a year-to-year basis and when using absolute vs. relative scales. Consider smoke waves in 2018 and 2020. On an absolute scale, the most exposed census tracts were predominately NH white in 2018 and Hispanic and NH white in 2020 (Fig. 4 *D* and *E*). On the relative scale, NH American Indian and Alaska Native residents were more disproportionately exposed in 2018 and 2020 compared with other racial/ethnic groups (Fig. 4 *H* and *I*). In a secondary monthly level analysis restricted to 2020 (the year with the highest levels of wildfire $PM_{2.5}$ exposure in our dataset), we observed varying exposure patterns by race/ethnicity (*SI Appendix*, Fig. S11). For example, disproportionate peak week wildfire $PM_{2.5}$ exposure occurred for NH white populations in September and NH American Indian or Alaska Native populations in October.

In terms of relative exposure to annual mean wildfire $PM_{2.5}$, NH American Indian and Alaska Native populations faced disproportionately high exposure every year compared to their statewide representation [relative risk (RR) ranged from 1.02, 95% CI: 1.00, 1.04 in 2007 to 2.79, 95% CI: 2.70, 2.94 in 2012; 2006 to 2020 mean = 1.68, 95% CI: 1.02 to 2.79] (Fig. 5 and *SI Appendix*, Table S2). In most years, NH white populations were also disproportionately exposed (RR ranged from 0.99, 95% CI: 0.99, 1.00 in 2007 to 1.32, 95% CI: 1.31, 1.32 in 2012, 2006 to 2020 mean = 1.13, 95% CI: 0.99, 1.32) and multiracial (two or more races) populations (RR ranged from 0.97, 95% CI: 0.97, 0.97 in 2007 to 1.23, 95% CI: 1.23, 1.24 in 2018, 2006 to 2020 mean = 1.06, 95% CI: 0.97, 1.23). NH Asian, NH Black, and Hispanic populations generally had disproportionately low exposure (2006 to 2020 mean NH Asian RR = 0.87, 95% CI: 0.66, 1.10; NH Black RR = 0.91, 95% CI: 0.74, 1.01; Hispanic RR = 0.91, 95% CI: 0.76, 1.04).

**Association between CES Score and Outdoor Wildfire $PM_{2.5}$ Exposure, Overall.** Using linear and negative binomial regression models adjusted for year, population density, and census tract-centroid latitude and longitude, we observed that averaged across 2006 to 2020, no difference existed in long-term wildfire $PM_{2.5}$ exposure for 4 of 5 metrics comparing disadvantaged communities (census tracts that made up the highest quartile of CES score) to their non-disadvantaged counterparts (Fig. 6, orange estimates; *SI Appendix*, Table S2). Disadvantaged vs. non-disadvantaged communities had 0.3 (95% CI: 0.1, 0.4) more days with >0 $\mu g/m^3$ wildfire smoke annually, averaged from 2006 to 2020.

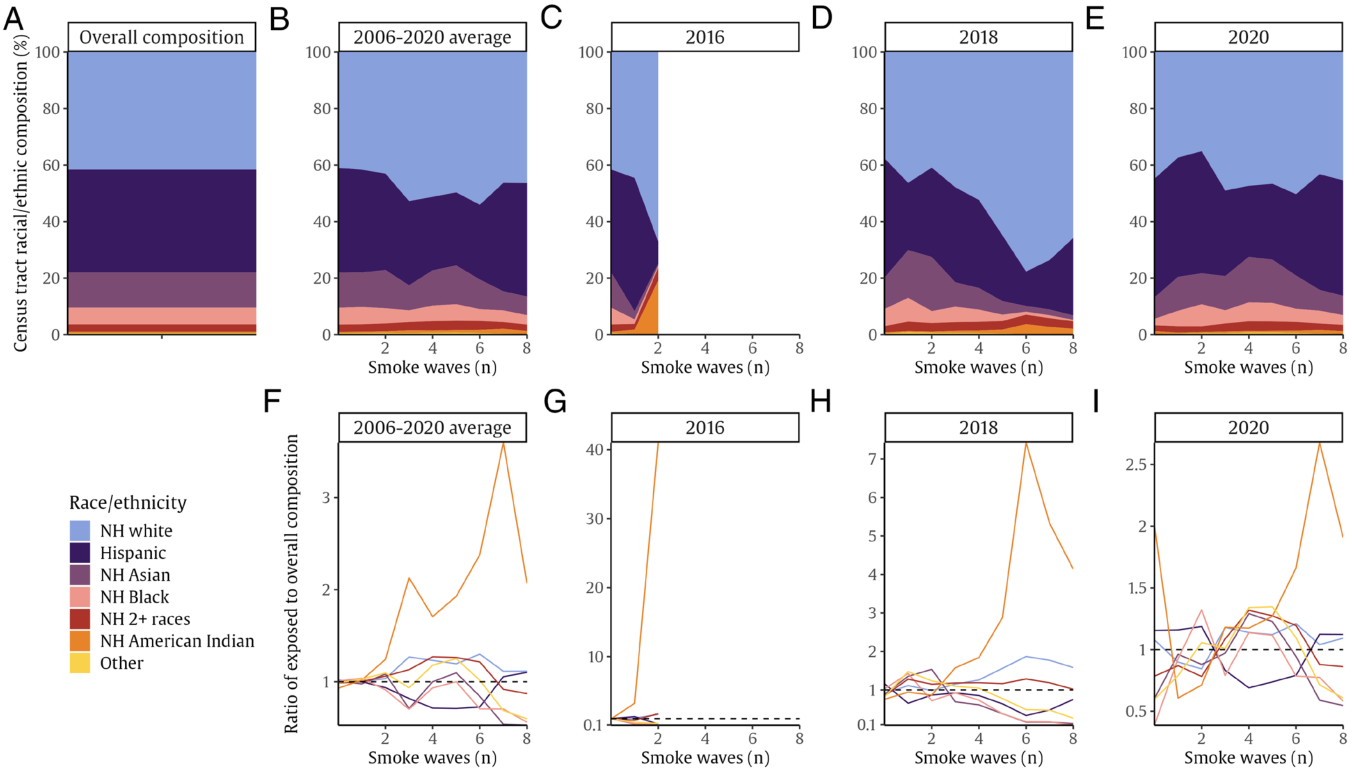


**Fig. 4.** Average absolute and relative census tract racial/ethnic composition by annual average count of smoke waves[a] in California. Absolute racial/ethnic composition (*A*) overall in California using 2010 census data; and by annual count of smokes waves (*B*) on average from 2006 to 2020, (*C*) in 2016, (*D*) in 2018, and (*E*) in 2020. Ratio of the average percent of a racial/ethnic group exposed by annual count of smoke waves to the percent of the group in the state overall (*F*) on average from 2006 to 2020, (*G*) in 2016, (*H*) in 2018, (*I*) in 2020. The x-axis breaks are consistent across years with results restricted to the 99.9th percentile of annual smoke wave exposure (n = 8). Not all years had census tracts exposed to eight smoke waves, resulting in white space. [a]We defined smoke waves as the number of instances of ≥ 2 consecutive days with > 15 μg/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 (41).

**Association between CES Score and Outdoor Wildfire $PM_{2.5}$ Concentration, by Year.** The direction of the association between CES score and $PM_{2.5}$ concentration varied annually. For annual average wildfire $PM_{2.5}$ concentrations, quartile 4 vs. quartile 1 to 3 CES scores were associated with higher concentrations during 9 of 15 y, lower concentrations during 3 of 15 y, with no difference during 3 of 15 y (Fig. 6*E* and *SI Appendix*, Table S3*E*). The magnitude of the differences was generally small (<0.1 μg/m$^3$). The years 2016 and 2018 illustrate how census tracts with higher CES scores can have lower concentrations 1 y and higher during another. During 2016, disadvantaged communities (measured via CES) had higher exposure as quantified by all five metrics. In 2018, the opposite was true, and disadvantaged communities had lower exposure on all five metrics. For example, during 2018, disadvantaged vs. non-disadvantaged census tracts had 11.6 μg/m$^3$ (95% CI: −12.1, −11.1) lower wildfire $PM_{2.5}$ concentrations during the peak week of exposure (Fig. 6*C* and *SI Appendix*, Table S3*C*).

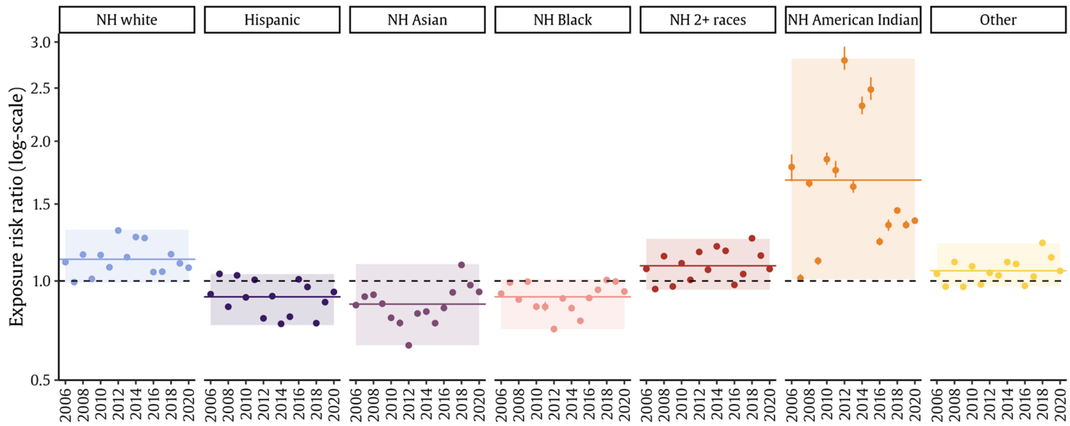


**Fig. 5.** Risk ratios and 95% CI for each racial/ethnic group for mean annual wildfire $PM_{2.5}$ exposure by year, 2006 to 2020. A risk ratio greater than 1 (dashed line) indicates that racial/ethnic group *j* was over-represented among the exposed population, compared to their statewide representation, during year *y* and 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*. Solid colored horizontal lines and boxes represent the 2006 to 2020 mean risk ratio with 95% CI for each racial/ethnic group *j*. 95% CIs were calculated with bootstrapping. NH, non-Hispanic.

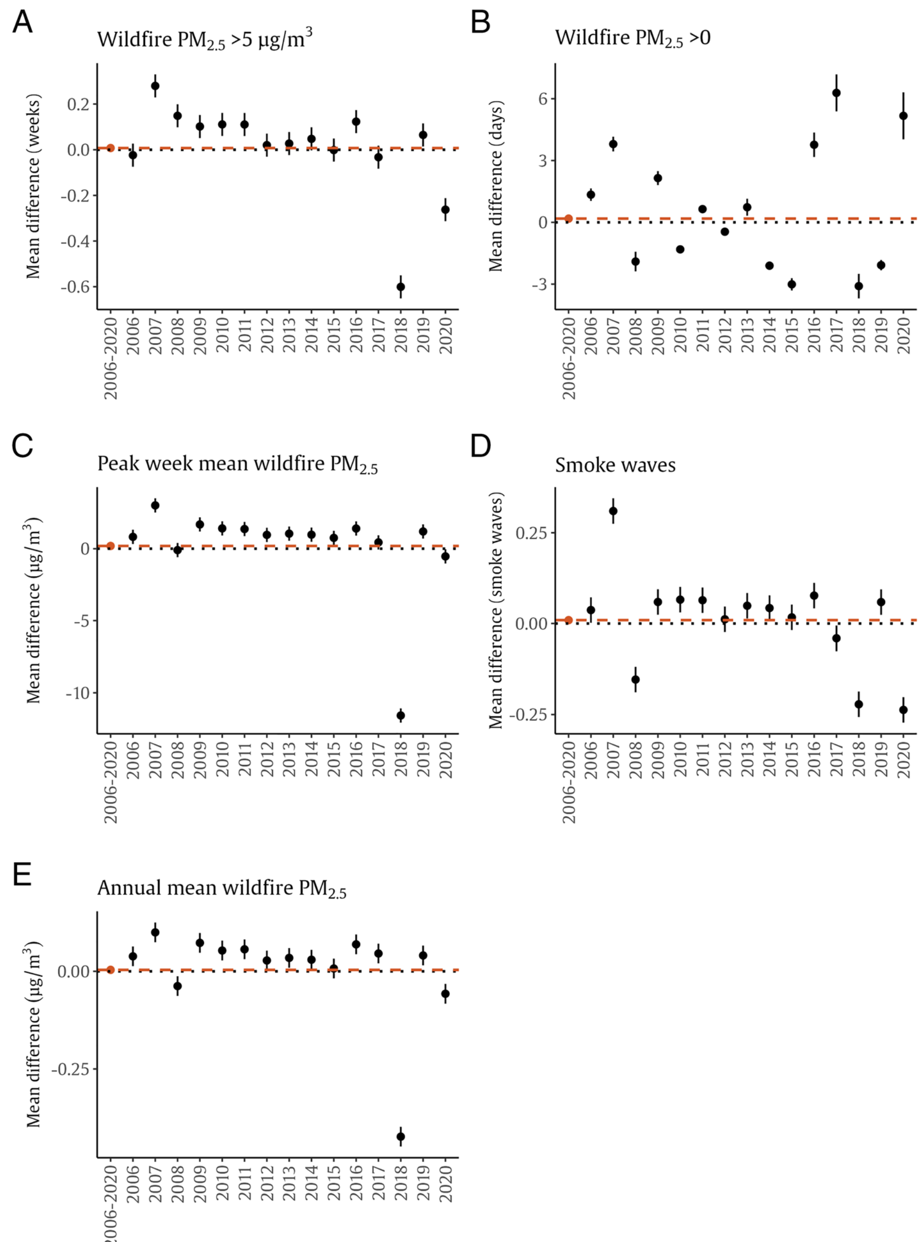


**Fig. 6.** Mean difference in long-term outdoor wildfire $PM_{2.5}$ concentration in CES score quartile 4 (disadvantaged communities) vs. quartiles 1 to 3 averaged across 2006 to 2020 (orange) and during each year (black). (*A*) Number of weeks with average wildfire $PM_{2.5} > 5$ μg/m$^3$; (*B*) Number 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 the difference in long-term wildfire PM2.5 exposure between census tracts in quartile 4 vs. quartiles 1 to 3 of CES score with lines (95% CI). The black horizontal dotted line at zero represents no difference in long-term wildfire PM2.5 exposure between high and low CES score census tracts. The orange horizontal dashed line represents the 2006 to 2020 mean difference in long-term wildfire PM2.5 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 (tensor product with 20 degrees of freedom). [a]We defined smoke waves as the number of instances of ≥ 2 consecutive days with > 15 μg/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. (41). CES score, CalEnviroScreen score.

**Association between CES Score and Wildfire $PM_{2.5}$ Concentration, by Urban/Rural Status.** In our secondary urban/rural stratified analysis, on average from 2006 to 2020, the CES score was associated with one metric in rural census tracts (weeks with average wildfire $PM_{2.5} > 5$ μg/m$^3$) and one metric in urban census tracts (days with any wildfire $PM_{2.5}$) (*SI Appendix*, Figs. S12 and S13). From 2006 to 2020 in rural tracts, disadvantaged tracts had 0.9 (95% CI: −1.4, −0.4) fewer weeks per year during which average wildfire $PM_{2.5}$ exceeded 5 μg/m$^3$ compared to their non-disadvantaged counterparts. Year by year, we continued to see variability in associations with urban tracts closely mirroring the main combined analysis and rural tracts following similar patterns but exhibiting higher-magnitude differences. For example, in 2020, urban disadvantaged vs. non-disadvantaged census tracts (CES quartile 4 vs. 1 to 3) experienced an average of 4.7 (95% CI: 3.7, 5.7) more days with wildfire $PM_{2.5} > 0$ μg/m$^3$; in rural areas, disadvantaged tracts had an average of 30.9 (95% CI: 15.9, 45.8) more days.

**Association between Racial/Ethnic Composition and Outdoor 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 to 2020) in models that controlled for year, population density, and census tract centroid latitude and longitude (*SI Appendix*, Fig. S14). A 1-SD increase (1.4 percentage point increase) in the percent NH American Indian or Alaska Native population was associated with additional average exposure, for example, 0.60 (95% CI: 0.55, 0.64) more days each year where with >0 μg/m$^3$ wildfire $PM_{2.5}$ and 0.20 μg/m$^3$ (95% CI: 0.13, 0.26) higher mean peak-week wildfire $PM_{2.5}$ exposure. Higher proportions of other racial and ethnic groups were not associated with any wildfire $PM_{2.5}$ exposure metric.

**Association between Racial/Ethnic Composition and Outdoor Wildfire $PM_{2.5}$ Concentration, by Year.** Associations between racial/ethnic composition and wildfire $PM_{2.5}$ were inconsistent across individual study years. For example, in 2020, a 1-SD increase in percent NH multiracial residents was associated with 0.53 (95% CI: 0.51, 0.55) more weeks with wildfire $PM_{2.5}$ exposure > 5 μg/m$^3$, while in 2019, a 1-SD increase was associated with fewer weeks with wildfire $PM_{2.5}$ exposure > 5 μg/m$^3$ (−0.07, 95% CI: −0.09, −0.05) (*SI Appendix*, Fig. S14). 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 weeks with wildfire $PM_{2.5}$ exposure >5 μg/m$^3$, non-zero wildfire $PM_{2.5}$ days, and smoke waves for which in 7 to 9 of 15 y, a 1-SD increase with American Indian and Alaska Native populations were associated with higher exposure.

**Association between Racial/Ethnic Composition and Outdoor Wildfire $PM_{2.5}$ Concentration, by Urban/Rural Status.** Averaged across the study period, we observed null or small-in-magnitude associations between census tract-level racial/ethnic composition and the five wildfire $PM_{2.5}$ metrics in urban areas (*SI Appendix*, Fig. S15). For example, the urban NH white population had null exposure differences based on 3 metrics (weeks with wildfire $PM_{2.5}$ > 5 μg/m$^3$, peak week exposure, and annual average wildfire $PM_{2.5}$) and lower exposure via non-zero days of wildfire $PM_{2.5}$ and smoke waves. A 1-SD increase in urban NH white population was associated with 0.18 fewer days annually (95% CI: −0.24, −0.11) with non-zero wildfire $PM_{2.5}$. In rural areas period-wide (2006 to 2020), wildfire $PM_{2.5}$ exposure was elevated for NH American Indian or Alaska Native (weeks with wildfire $PM_{2.5}$ > 5 μg/m$^3$, days with non-zero wildfire $PM_{2.5}$, and smoke waves), Black (days with non-zero wildfire $PM_{2.5}$), and multiracial (weeks with wildfire $PM_{2.5}$ > 5 μg/m$^3$ and annual average wildfire $PM_{2.5}$) populations (*SI Appendix*, Fig. S16). For example, a 1-SD increase in the NH multiracial population was associated with 0.05 μg/m$^3$ (95% CI: 0, 0.11) higher annual average wildfire $PM_{2.5}$ exposure. NH white populations were not disproportionately exposed on average in rural tracts. For two of the five metrics (weeks with wildfire $PM_{2.5}$ > 5 μg/m$^3$, days with non-zero wildfire $PM_{2.5}$), an increase in the proportion Hispanic individuals was associated with lower 2006 to 2020 wildfire $PM_{2.5}$ in rural areas. For example, a 1-SD increase in the Hispanic population was associated with 1.1 (95% CI: −2.3, 0.1) fewer days annually with any wildfire $PM_{2.5}$. Like our overall findings, we observed year-to-year variability in estimated associations in both urban and rural areas, with higher racial composition of every group being associated with more exposure in at least 1 y, and larger-in-magnitude differences in rural areas. For example, in 2020, a 1-SD increase in NH American Indian or Alaska Native population was associated with 2.4 μg/m$^3$ (95% CI: 2.2, 2.7) higher peak-week wildfire $PM_{2.5}$ concentration in urban areas and 4.4 μg/m$^3$ (95% CI: 2.3, 6.5) higher concentrations in rural areas.

**Sensitivity Analyses.** We completed a sensitivity analysis using Childs et al. wildfire $PM_{2.5}$ estimates (10) to compare with our model and to repeat analyses underlying Figs. 2–5. From 2006 to 2020, we found a high correlation between the two products (0.87), with higher correlations in urban areas and the San Joaquin Valley (*SI Appendix*, Fig. S17). Overall, we observed similar patterns in analyses repeated with the Childs et al. dataset, with year-to-year variability in which socioeconomic, racial, and ethnic groups were most exposed (*SI Appendix*, Figs. S18–S21). This illustrated our conclusions were robust to the use of two distinct wildfire $PM_{2.5}$ products.

## Discussion

In this study, we proposed distinct metrics to characterize repeated and intermittent exposure to outdoor wildfire $PM_{2.5}$ that can be adapted and modulated to study various health and EJ impacts, as wildfires—a climate-sensitive exposure—become omnipresent in some locations. We applied these metrics to assess the EJ implications of long-term exposure to wildfire $PM_{2.5}$ in California by analyzing associations across the 15-y study period and during each year using five metrics of wildfire $PM_{2.5}$ exposure rather than relying on a single measure of exposure. We observed no difference in exposure averaged over the study period between disadvantaged and non-disadvantaged communities (as defined by CES) but, within individual years, disadvantaged or non-disadvantaged communities were often more exposed. Our analysis based on race/ethnicity revealed that NH American Indian and Alaska Native populations were consistently 1.0 to 2.8× more likely and NH white and NH multiracial populations were 1.0 to 1.3× more likely to experience higher annual mean wildfire $PM_{2.5}$ concentrations compared to their statewide representation. Stratifying by urban/rural status in regression modeling also showed higher exposures for NH American Indian and Alaska Native, multiracial, and—for non-zero wildfire $PM_{2.5}$—Black populations in rural areas. Every group faced disproportionate exposure in at least one year, exhibiting the spatiotemporal variability of wildfire $PM_{2.5}$. 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 (51) or that lack agency or resources to protect themselves from wildfire $PM_{2.5}$ exposure (10, 44). It remains unknown which elements of wildfire $PM_{2.5}$ exposure (i.e., frequency, duration, or concentration) most substantially impact health. Our results highlight the importance of considering multiple exposure elements when characterizing intermittent and long-term wildfire-related $PM_{2.5}$ exposure for health and equity studies.

Environmental exposures often follow a social gradient, wherein marginalized communities face disproportionately high exposures (52, 53). For example, long-term overall $PM_{2.5}$ concentrations in the United States are higher in historically redlined communities, communities with lower income levels, and communities of color (38, 39, 54). Zoning, disproportionate siting, residential segregation, gentrification, and other pathways contribute to these observed disparities (52). Wildfire-specific $PM_{2.5}$, while not randomly distributed, is generated by wildfires with somewhat unpredictable sizes and locations, and smoke transport driven by various meteorological patterns. These characteristics 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 $PM_{2.5}$ concentrations that were 0.10 μg/m$^3$ higher in some years and 0.42 μg/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 μg/m$^3$ mean annual wildfire $PM_{2.5}$ (2008 to 2012) (43), poorer counties experiencing more smoke waves (2004 to 2009) (41), and more vulnerable counties having higher mean annual wildfire $PM_{2.5}$ exposure but fewer extremely high (>35 μg/m$^3$) wildfire $PM_{2.5}$ days (2008 to 2012) (42). In a nationwide study, Burke et al. found that counties with a higher proportion of NH white residents had higher wildfire $PM_{2.5}$ concentrations (2006 to 2018) (9). Although this is consistent with our RR estimates, when using a regression framework, we did not observe period-wide disparities in wildfire $PM_{2.5}$ concentrations for NH white populations in California. In a second nationwide study, Burke et al. observed no correlation between county-level wildfire $PM_{2.5}$ and income (47). In the only other census tract-level study, Childs et al. compared two time periods and found limited socioeconomic or racial disparities in mean annual wildfire $PM_{2.5}$ exposure from 2006 to 2010; however, from 2016 to 2020, this relationship shifted, and results showed an association between higher percentages of Hispanic and NH white residents and higher per capita income with higher exposure (10).

Prior US-based wildfire $PM_{2.5}$ studies have not assessed disparities for American Indian and Alaska Native populations or multiracial (2+ races) people. In the Amazon, Indigenous territories experienced 0.64 ± 0.21 μg/m$^3$ greater smoke $PM_{2.5}$ than the whole of South America from 2014 to 2019 (55). The Black Summer fires in Australia from 2019 to 2020 disproportionately affected areas with large Indigenous and socially disadvantaged populations (56). Our analyses also 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 California census tracts with higher proportions of American Indian and Alaska Native populations had more wildfires and burned acres from 2000 to 2020 (57) and with Davies et al., who found Native American populations overrepresented in communities high wildfire risk and low adaptative capacity (45). In the United States, 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. Indigenous peoples may also participate in prescribed or cultural burning that could increase wildfire $PM_{2.5}$ exposure in the short-term (58). However, until recently, cultural burning activities carried significant liability, potentially limiting such activities until a new California law went into effect in 2022, removing liability risk for private citizens and Indigenous peoples who set controlled burns (59). Previous suppression of Indigenous land management practices in California likely also resulted in increased wildfire risks during our study period (60). 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 (61).

Data from the Interagency Monitoring of PROtected Visual Environments (IMPROVE) network and other deployed monitors, generally, but not always (62), suggest that rural areas experience a greater burden of wildfire-generated $PM_{2.5}$ (63). Likewise, we found that rural California census tracts often had 2× higher wildfire $PM_{2.5}$ exposure measured across the five metrics. Our study did not find that disadvantaged rural tracts, as defined by CES, were more exposed on average but did identify some exposure disparities, particularly for American Indian/Alaska Native and multiracial people, in rural California tracts. Such analysis is important because fewer wildfire studies focused on rural areas or the wildland-urban interface have evaluated environmental injustice (44). Evidence also suggests that environmental justice considerations are rarely accounted for in decisions related to wildfire hazard reduction strategies and activities in federal forest lands (64). In addition to higher exposure, rural communities—given their economic reliance on tourism, agriculture, and construction, immersion in natural environments, and reduced healthcare access—may additionally face heightened risk of adverse health outcomes from wildfire smoke exposure (65).

Our California study builds upon the prior wildfire studies by centering EJ questions, using daily estimates of wildfire $PM_{2.5}$ concentration, and evaluating patterns of long-term exposure inequities 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 metrics of exposure exist and may yield different results in terms of temporal and demographic patterns of exposure burden. We used CES, which consists of approximately 20 indicators, and wildfires contribute to elevated levels of two of the environmental exposure indicators (66, 67): average total $PM_{2.5}$ concentrations and summer average daily maximum 8-h ozone concentrations. This could increase the association between exposure and outcome. Our observed EJ findings could also underestimate true exposure disparities as persistently marginalized individuals face constraints to health-protective behaviors (47), including lower income and housing quality, less access to health messaging, and ability to mitigate work-related exposures, particularly for outdoor workers, for example in construction (68). In Northern California, members of the Hoopa Valley Tribe, who did not evacuate when a large fire affected their land, cited occupational (45%) and economic (12%) reasons (69). We estimated outdoor wildfire $PM_{2.5}$ concentrations, not wildfire impacts on air quality indoors, where people spend most of their time (70). Low-cost air quality sensors (e.g., PurpleAir sensors) could help provide part of this information, though they are disproportionately located in wealthier communities (47, 71, 72). 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 (47). 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 (41, 73, 74). We did not assess differences in associations by, for example, air basins with different air quality and meteorological characteristics, though preliminary research suggests EJ-related disparities may be more pronounced in some regions (71) and we did observe differences in patterns of exposure by urban/rural tract status. 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 spatiotemporal 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 $PM_{2.5}$ (16, 41, 45). Finally, our study was restricted to California. Different exposure patterns likely exist elsewhere, which future research could investigate.

While, to date, the vast majority of climate and health studies have focused on quantifying the short-term impacts of climate-sensitive exposures, including wildfires, extreme heat, or floods, on acute outcomes such as emergency department visits or premature mortality, little evidence exists regarding the potential impact of long-term health impacts of climate-sensitive exposures, which mostly focused on mental health outcomes (75, 76). Existing studies linking long-term exposures such as floods or droughts to mental health have limitations related to exposure assessment (77). As climate-sensitive exposures become omnipresent, it is essential to better characterize and understand the long-term impacts and design robust epidemiological studies considering the unprecedented and ever-changing nature of such exposures. In this study, we provided a conceptual framework for measuring multiple elements of 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 United States (9) and is becoming more common elsewhere (42, 78). Our framework for quantifying various dimensions of wildfire smoke exposure can easily be adapted to other extreme and episodic climate-sensitive exposures, which are no longer 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 (79, 80), to analyze the long-term effects of time-varying exposure to wildfires or other climate-sensitive exposures on various chronic diseases such as dementia, cardiovascular diseases, or cancer incidence. Such exposure metrics can support a new generation of epidemiology studies to evaluate unique challenges posed by climate change on human health 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 (81, 82). We derived daily census tract-level outdoor wildfire $PM_{2.5}$ concentrations for 2006 to 2020 (see details below) using satellite imagery, monitored concentrations, and machine learning–based multiple imputation (35).

Building upon principles from exposure science to include measures of frequency, duration, and concentration (36, 83), we developed a conceptual model of long-term outdoor wildfire $PM_{2.5}$ exposure (Fig. 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 adopt alternative time frames (e.g., month, 5-y period) depending on the research question.

**Data and Metrics.**

***Outdoor wildfire $PM_{2.5}$ exposure metrics.*** Our team previously developed methods to estimate daily outdoor wildfire $PM_{2.5}$ (35) 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 the National Oceanic and Atmospheric Administration Hazard Mapping System, fire perimeter data from CalFIRE, and spatiotemporal imputation techniques to predict plausible values of $PM_{2.5}$ that would have been observed in the absence of wildfire smoke in a given day in a given census tract (64). This model had an $R^2$ of 0.78 using hold-out test validation overall (35) and when restricted to lower levels of wildfire $PM_{2.5}$ (below 50 μg/m$^3$, *SI Appendix*, Fig. S22). 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 to 2020:

- The number of weeks each year for which mean wildfire $PM_{2.5}$ concentrations exceeded 5 μg/m$^3$.
- The number of days each year for which wildfire $PM_{2.5}$ concentrations were >0 μg/m$^3$.
- The mean daily wildfire $PM_{2.5}$ concentration during the peak week of exposure for each year.
- The number of smoke waves each year.
- The mean annual wildfire $PM_{2.5}$ concentration.

We defined smoke waves as the number of instances of ≥2 consecutive days with >15 μg/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 (84).

***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" (85). 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 to 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)] (86) (*SI Appendix*, *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 to 2020 (81). We linked CES 3.0 data to 2006 to 2012 wildfire $PM_{2.5}$ estimates and CES 4.0 data to 2013 to 2020 estimates. The final relative CES ranging from 0 to 100 is calculated as follows:

$$\left(\frac{\frac{\sum \text{exposures}_{\text{percentile}}}{n_{\text{exposures indicators}}\times 10}+\left(\frac{\sum \text{environmental effects}_{\text{percentile}}}{2}\right)}{n_{\text{environmental effects indicators}}\times 10}\right)\times\frac{\sum \text{sensitive populations}_{\text{percentile}}}{n_{\text{sensitive populations indicators}}\times 10}+\frac{\sum \text{socioeconomic factors}_{\text{percentile}}}{n_{\text{socioeconomic factors indicators}}\times 10}.$$

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) (81, 86).

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 (87). 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 to 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 percentage of people of color in California census tracts (88), which might be expected given underlying structural causes of environmental racism (51, 53).

We additionally considered census tract racial/ethnic composition related to wildfire $PM_{2.5}$ exposure, following prior studies (9, 10, 43). We treat race/ethnicity not as a biological but as a social construct and hypothesize that certain racial/ethnic groups might experience disproportionate wildfire $PM_{2.5}$ exposure due to systemic racism, which might constrain choices about where individuals could live. Communities of color may face higher wildfire $PM_{2.5}$ concentrations due to displacement into suburban wildland-urban interface (WUI) areas related to rising urban housing costs (44) or historical forced residence on federal Indian Reservations (45). For these analyses, we used the 2010 decennial census tract-level data on race/ethnicity (82), as these estimates have smaller margins of error compared to the American Community Survey data (89). We calculated the percent of individuals in each California census tract self-identifying in the following categories: Hispanic, NH white, NH Black, NH Asian, NH American Indian or Alaska Native, and NH 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 metrics 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 metrics of long-term wildfire exposure by the sociodemographic variables of interest over time. Fourth, we generated bivariate maps of annual mean wildfire $PM_{2.5}$ (quartiles) and CES scores (quartiles) to identify locations with a dual burden of wildfire $PM_{2.5}$ and community disadvantage. Fifth, we plotted census tract racial/ethnic composition by levels of the five wildfire metrics we proposed. In absolute plots, we showed the average racial/ethnic composition in percents at different levels of wildfire $PM_{2.5}$ exposure. In relative plots, we showed the ratio of the average census tract level composition for a specific racial/ethnic group at a specific wildfire $PM_{2.5}$ exposure level during a specific time period (average across 2006 to 2020 or annual) to the average statewide census tract level composition for a specific racial/ethnic group. Sixth, 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 $\omega_{iy}$ is the annual average wildfire $PM_{2.5}$ in census tract $i$ 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 CIs for these RRs using 100 bootstrap samples, randomly resampling with replacement days and census tracts from the full dataset. In each bootstrap sample, we estimated annual wildfire $PM_{2.5}$ and recalculated the RRs. We used the 2.5th and 97.5th percentiles of the bootstrap sample race/ethnic and annual distributions for the 95% CIs.

We estimated the associations between the binary CES score [with 0 representing quartiles 1 to 3 and 1 representing quartile 4 (disadvantaged community)] as the explanatory variable and the five metrics of long-term wildfire $PM_{2.5}$ as the dependent variable over the study period. We fit linear mixed models for number of weeks with mean wildfire $PM_{2.5} > 5\ \mu g/m^3$, mean peak-week wildfire $PM_{2.5}$, number of smoke waves, and mean annual wildfire $PM_{2.5}$ and negative binomial models number of non-zero wildfire $PM_{2.5}$ days. We conducted a similar analysis, replacing the CES score with each binary racial/ethnic composition variable [e.g., 1 = quartile 4 (high percentage of NH Black individuals); 0 = quartiles 1 to 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 each census tract centroid's latitude/longitude (tensor product with 20 degrees of freedom) to account for spatial dependence of observations (*SI Appendix*, Fig. S23). 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. To test for changes in the association between CES score or racial/ethnic composition and the five metrics of long-term wildfire $PM_{2.5}$ from 2006 to 2020, we added an interaction term between the categorical year variable and the binary CES score variable or the racial/ethnic composition variable.

We completed three secondary analyses. First, we categorized census tracts as urban or rural based on the US Department of Agriculture Rural-Urban Commuting Area Codes [urban = levels 1 to 9 (metropolitan, micropolitan, and small town); rural = level 10] (90) and repeated our main analyses. Second, we identified tracts that overlapped with federally recognized Tribal Lands using US Census data (91) and compared the distribution of our five annual exposure metrics across urban, rural, and Tribal (any overlap with Tribal Land) tracts. Third, we evaluated within-year racial and ethnic differences in exposure during 2020, the year with the highest wildfire $PM_{2.5}$ concentrations. For this analysis, we replicated Fig. 4 at the monthly level. In a sensitivity analysis, we also tested the robustness of our results to the use of alternative daily wildfire $PM_{2.5}$ estimates (10), since no wildfire $PM_{2.5}$ gold standard exists. While the two products aim to isolate the amount of daily $PM_{2.5}$ attributable to wildfire smoke in a given location, they rely on distinct methods. We interpolated the Childs et al. product at the census tract population-weighted centroids as done in Aguilera et al. 2023 (10). Then, we compared our model to that of Childs et al. and repeated our main analysis using their estimates. Analyses were conducted using R Statistical Software, version 4.1.2 (92). Code to run analyses is available at https://github.com/joanacasey/longterm-wildfire-pm.git.

**Data, Materials, and Software Availability.** Wildfire PM25 data have been deposited in Harvard Dataverse (TBD). Previously published data were used for this work [CalEnviroScreen: California Office of Environmental Health Hazard Assessment. Uses of CalEnviroScreen. https://oehha.ca.gov/calenviroscreen/how-use. Published 2022. Accessed 8 November 2022. Census data: (82). https://doi.org/10.18128/D050.V12.0. Published 2018. Accessed 10 October 2020].

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