GeoHealth

RESEARCH ARTICLE

10.1029/2023GH000997

Spatial Heterogeneity of the Respiratory Health Impacts of Wildfire Smoke $PM_{2.5}$ in California

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Key Points:

- Statewide, exposure to wildfire $PM_{2.5}$ is associated with increased odds of respiratory acute care utilization in California
- The wildfire $PM_{2.5}$-health association varies spatially across air basins, counties, and ZIP Code Tabulation Areas
- Areas with higher proportions of Black and Pacific Islander populations and less affluence had worse wildfire $PM_{2.5}$-related outcomes

Supporting Information:

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

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Citation:

Do, V., Chen, C., Benmarhnia, T., & Casey, J. A. (2024). Spatial heterogeneity of the respiratory health impacts of wildfire smoke PM_{235} in California. *GeoHealth*, *8*, e2023GH000997. https://doi.org/10.1029/2023GH000997

Received 9 DEC 2023
Accepted 15 MAR 2024

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Abstract Wildfire smoke fine particles ($PM_{2.5}$) are a growing public health threat as wildfire events become more common and intense under climate change, especially in the Western United States. Studies assessing the association between wildfire $PM_{2.5}$ exposure and health typically summarize the effects over the study area. However, health responses to wildfire $PM_{2.5}$ may vary spatially. We evaluated spatially-varying respiratory acute care utilization risks associated with short-term exposure to wildfire $PM_{2.5}$ and explored community characteristics possibly driving spatial heterogeneity. Using ensemble-modeled daily wildfire $PM_{2.5}$, we defined a wildfire smoke day to have wildfire-specific $PM_{2.5}$ concentration ≥15 μg/m^3. We included daily respiratory emergency department visits and unplanned hospitalizations in 1,396 California ZIP Code Tabulation Areas (ZCTAs) and 15 census-derived community characteristics. Employing a case-crossover design and conditional logistic regression, we observed increased odds of respiratory acute care utilization on wildfire smoke days at the state level (odds ratio [OR] = 1.06, 95% confidence interval [CI]: 1.05, 1.07). Across air basins, ORs ranged from 0.88 to 1.57, with the highest effect estimate in San Diego. A within-community matching design and spatial Bayesian hierarchical model also revealed spatial heterogeneity in ZCTA-level rate differences. For example, communities with a higher percentage of Black or Pacific Islander residents had stronger wildfire $PM_{2.5}$-outcome relationships, while more air conditioning and tree canopy attenuated associations. We found an important heterogeneity in wildfire smoke-related health impacts across air basins, counties, and ZCTAs, and we identified characteristics of vulnerable communities, providing evidence to guide policy development and resource allocation.

Plain Language Summary Wildfire smoke is a growing public health threat, one becoming more pressing as climate change progresses. People are exposed to different levels of wildfire smoke. People also have different abilities to protect themselves from smoke exposure based on their job, housing quality, or other factors. In addition, people have different physiological responses to smoke. Therefore, the relationship between wildfire smoke and health could vary across the state of California. We conducted a study using modeled daily wildfire smoke fine particle concentrations and daily respiratory acute care utilizations 2006–2019 in California. We estimated area-specific wildfire smoke and acute care utilization associations at state, air basin, county, and ZIP Code Tabulation Areas levels. We found different associations across the state, with the strongest association in San Diego air basin. San Francisco Bay air basin had the highest number of acute care utilizations attributable to wildfire smoke due to their large population. We identified several community characteristics that may have explained the observed spatial differences, including higher proportions of Black and Pacific Islander populations and less community affluence. Our findings support the allocation of scarce resources to areas and communities more vulnerable to wildfire smoke to improve population health in a changing climate.

1. Introduction

Wildfire $PM_{2.5}$ is a growing threat to public health. Drier conditions and warmer temperatures in the Western United States (US) contribute to wildfire events that are more common, intense, and expansive in scope (Abatzoglou, 2013; Littell et al., 2009; Mueller et al., 2020; Westerling et al., 2006). The resulting wildfire $PM_{2.5}$ has increased overall trends in ambient air pollution, counteracting policy efforts to improve air quality (Burke et al., 2023; Ford et al., 2018). Wildfire $PM_{2.5}$ can infiltrate the lungs and precipitate respiratory events through inflammation and oxidative stress (Xing et al., 2016). In previous epidemiological studies, exposure to wildfire smoke has been linked to a variety of adverse health effects, particularly for respiratory conditions (Aguilera et al., 2020, 2021; Gould et al., 2024; Kondo et al., 2019; Reid & Maestas, 2019). Recent toxicologic and epidemiologic studies found that wildfire $PM_{2.5}$ can have a higher adverse health impact on the pulmonary system than $PM_{2.5}$ from other sources (Aguilera et al., 2021; Kim et al., 2018; Wegesser et al., 2009), and disregarding the differential dose-response of wildfire $PM_{2.5}$ led to an underestimation of $PM_{2.5}$ related health burden (Darling et al., 2023), which warrants independent studies of wildfire $PM_{2.5}$ health impacts.

Wildfire $PM_{2.5}$ concentrations vary across space and time, and so do the corresponding health effects. Proximity to wildfires, wind direction, and social factors determine levels of wildfire $PM_{2.5}$ exposure (Casey et al., 2024; Reid & Maestas, 2019). For example, in the past few years, several cities experienced the worst 24-hr average $PM_{2.5}$ levels recorded on Earth because of nearby wildfires (Masters, 2018; Osaka, 2022). Additional spatially-varying factors including meteorologic and topographic conditions such as the Santa Ana winds (Gershunov et al., 2021) may shape the spatial distribution of wildfire $PM_{2.5}$ and health outcomes (Leibel et al., 2020). Furthermore, the toxicity of wildfire $PM_{2.5}$ could change across space as the $PM_{2.5}$ ages when traveling (O'Dell et al., 2020). Few studies have accounted for the spatial dependence in wildfire $PM_{2.5}$ exposure on health and those that did focused on a single wildfire event affecting a small geographical area (i.e., San Diego air basin) (Aguilera et al., 2020) or only accounted for spatial autocorrelation among areas closely located (Reid et al., 2016). Evaluating how health effects related to wildfire $PM_{2.5}$ are distributed across larger geographical areas involving more wildfire events could inform future mitigation efforts to target specific areas and shape regulations to better prepare for wildfire $PM_{2.5}$-related health burden.

Community characteristics like socioeconomic status and racial/ethnic composition can drive spatial differences in the health impacts of wildfire $PM_{2.5}$ through both exposure disparities and differential response. For example, due to historical discriminatory practices, disparities in housing quality exist such that communities of color tend to have lower-quality, substandard housing (Hernández & Swope, 2019; Jacobs, 2011). Given wildfire $PM_{2.5}$'s ability to easily infiltrate the home (Mendoza et al., 2021), communities of color may be more exposed to wildfire $PM_{2.5}$. Differences in community characteristics could also lead to spatially varying physiological response and behavioral adaptations toward wildfire $PM_{2.5}$. Lower-income communities have more constraining choices to protect themselves from wildfire $PM_{2.5}$ (Burke et al., 2022). Minoritized groups with worse baseline health conditions due to social marginalization and systemic racism will likely have worse health responses to wildfire $PM_{2.5}$ (Berberian et al., 2022; Smith et al., 2022). Moreover, the effects of wildfire $PM_{2.5}$ may be worse in communities that already experience a disproportionately high burden of other environmental exposures due to the potential synergistic effects of compound exposures (C. Chen et al., 2024). Taken together, there is a need for further research on community characteristics as drivers of the spatially varying health effects of wildfire $PM_{2.5}$ (Marlier et al., 2023).

Here, we aimed to investigate the spatially-varying relationship between wildfire $PM_{2.5}$ exposure and respiratory acute care utilizations and to examine whether various community characteristics explained the observed spatial heterogeneity in impact of wildfire $PM_{2.5}$ on respiratory acute care utilization. We used ZIP Code Tabulation Area (ZCTA)-level ensemble-modeled daily wildfire $PM_{2.5}$ concentrations and daily respiratory acute care utilizations in California from 2006 to 2019 to estimate spatially-varying health effects across four spatial units: state, air basin, county, and ZCTA. We also examined community vulnerability factors of such health effects at the ZCTA level.

2. Materials and Methods

2.1. Data Sources and Study Population

We restricted all analyses to 1,396 ZCTAs in California satisfying two criteria: (a) having a population $\geq$1,000 in the 2010 US Decennial census for statistical power consideration (Bureau, 2021a); and (b) having at least one wildfire smoke day during the study period (2006–2019). The second criterion was a requirement for this study because unexposed ZCTAs do not contribute information to the case-crossover or within-community matched designs (Mittleman & Mostofsky, 2014; Schwarz et al., 2021). We chose ZCTA as the main spatial unit in our analyses because of the spatial resolution of health outcome.

2.1.1. Wildfire Smoke Day

We utilized a previously developed time-series data set for daily wildfire-specific $PM_{2.5}$ concentration at the ZCTA level (Aguilera et al., 2023) to identify smoke days. Briefly, Aguilera et al. (2023) first generated the ZCTA-specific daily $PM_{2.5}$ concentrations (all sources) from a stacked ensemble model using several dataadaptive algorithms and many predictors (e.g., air monitor data, satellite-derived aerosol properties, meteorological conditions, and land-use information). Then, they identified ZCTA-days exposed to smoke plumes using validated NOAA Hazard Mapping Systems products. Next, they applied a chained random forest algorithm to impute counterfactual non-wildfire $PM_{2.5}$ concentrations in ZCTA-days with wildfire smoke (expected $PM_{2.5}$ concentrations in the absence of the smoke) (Aguilera et al., 2023). The wildfire-specific $PM_{2.5}$ is the difference between the estimated daily $PM_{2.5}$ concentrations from the ensemble model and the imputed non-wildfire smoke $PM_{2.5}$ concentrations in each ZCTA. For each ZCTA, we defined a wildfire smoke day as a day with wildfire-specific $PM_{2.5}$ concentration $\geq 15\ \mu g/m^3$, a threshold based on the World Health Organization guideline for 24-hr $PM_{2.5}$ (Organization, 2021).

2.1.2. Health Outcomes

We used the Patient Discharge Data and Emergency Department Data collected by the California Department of Health Care Access and Information (CA.gov, 2023). This data set contains all acute care utilizations that are not prearranged in the general population of California, including unscheduled hospitalizations and emergency department visits. Emergency department visits that led to hospitalizations were recorded as unscheduled hospitalizations only. For each ZIP code, we identified daily respiratory acute care utilizations with primary diagnosis codes recorded as diseases of the respiratory system (see the list of included *International Classification of Diseases* codes in supplementary Text S1 in Supporting Information S1). The ZIP code was based on the patients' residential address at the time of the visit. Since the US Census Bureau created ZCTAs to represent populated areas of the ZIP code service area, with the latter being a sum of service routes by the United States Postal Service, we treated them as the same in analysis and used ZCTA in the remainder of this manuscript.

2.1.3. Community Characteristics

To explore whether the effects of wildfire smoke days varied by community characteristics, we used 15 ZCTA-level variables. Communities of color have a greater risk for wildfire-related health outcomes possibly due to disproportionate cumulative environmental burden and systemic discrimination (Berberian et al., 2022), so we obtained the proportions of self-reported race/ethnicity (separate proportions of white, Black, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, and Hispanic residents) from the 2010 US Decennial Census. We also collected population density from the same data source (2010 Census, 2023). Additional variables were obtained from the Public Health Alliance of Southern California Healthy Places Index report version 3.0 (Healthy Places Index, 2023; Maizlish et al., 2019), which are mostly based on averages of the American Community Survey data from 2015 to 2019. Included variables are the proportion of employment among those ages 20 to 64, the proportion of 25 and older with a bachelor's degree or higher, the proportion of insured among those aged 18–64, the proportion of the population with an income that is greater than 200% of the federal poverty level, per capita income in the US. dollars, the percentage of households with access to an automobile, and the population-weighted percentage of area with tree canopy. We also obtained the ZCTA-level percentage of households with access to central air conditioning (A/C) from the California Residential Appliance Saturation Study survey (KEMA Inc, 2010) because air conditioning access may buffer against air pollution exposure (Liang et al., 2021). Table S2 in Supporting Information S1 provided detailed descriptions and sources for each variable of community characteristics. All variables other than race/ethnicity and population density were coded such that a higher value corresponds to a higher proportion of economically advantaged subpopulations.

2.2. Statistical Analyses

We estimated the health impacts of wildfire $PM_{2.5}$ concentrations on respiratory acute care utilizations at four geographical levels: state, air basin, county, and ZCTAs. The California Air Resources Board designates 15 air basins, geographies with distinct meteorological conditions to regionally distribute resources to address emissions. Each air basin contains between one and 11 counties (California Air Resources Board, 2023). We assigned ZCTAs to a county and an air basin based on the location of their population-weighted centroids. Counties and air basins with no ZCTAs that had a population $\geq$1,000 and experienced a wildfire smoke day were excluded from analyses (Figure 1). In meta-regression to investigate the influence of community characteristics on ZCTA-specific effect estimates, we further excluded 100 ZCTAs without complete community characteristics data. All analyses were conducted in R version 4.1.0 (R Core Team, 2021) and the analytic code is publicly available (C. Chen, 2024).

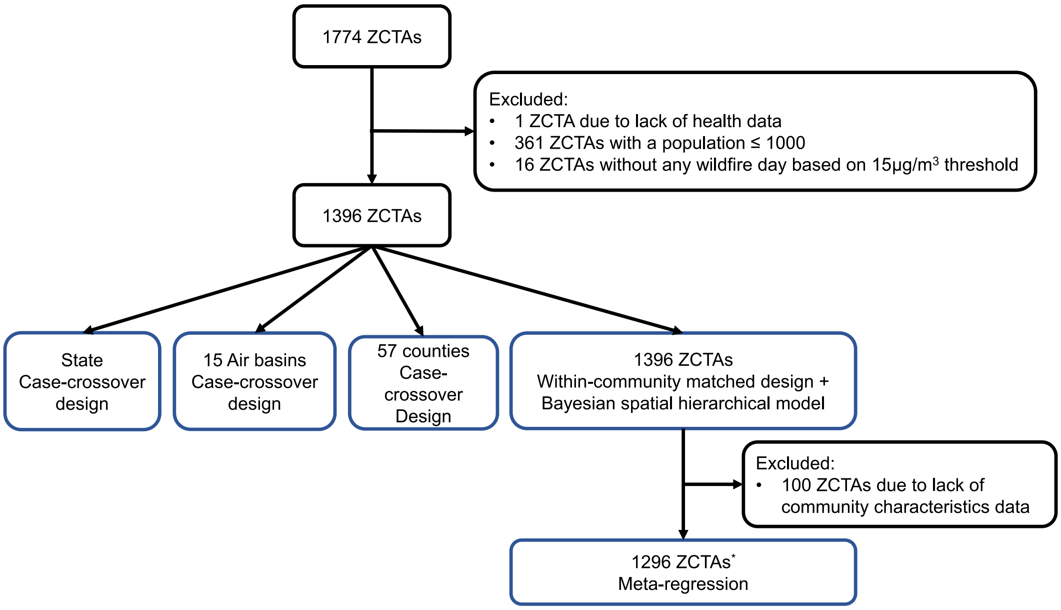

Figure 1. Flowchart of the California study population and exclusion criteria (black boxes) and method utilized in each set of analyses (blue boxes). *For analysis of air conditioning prevalence, we further excluded 274 ZIP Code Tabulation Areas (1122 in meta-regression) due to data missingness.

2.2.1. Case-Crossover Design for Health Analyses at State-, Air Basin-, and County-Level

We implemented the time-stratified case-crossover design to evaluate the effects of wildfire $PM_{2.5}$ on daily respiratory acute care utilization at the state level, air basin level, and county level (Maclure, 1991; Mittleman, 2005). In the time-stratified case-crossover design, we matched each day when an acute care utilization occurred (case) to other days of the same weekday during other weeks of the same month in the same ZCTA (controls). Prior work suggests this method of selecting control periods to result in an unbiased effect estimate (Janes et al., 2005; Sullivan et al., 2005). This study design compares exposures of a case to themselves at different times and accounts for individual-level confounders (e.g., age, race/ethnicity and sex) and temporal trends of the exposure (Maclure, 1991; Mostofsky et al., 2018). For state-level analysis, we ran a weighted conditional logistic regression to account for the matching procedure and included matched case and control sets from all 1,396 ZCTAs to estimate the odds ratio (OR) of exposure to wildfire smoke and respiratory acute care utilizations, with weight equal to the number of acute care utilizations in the case day. For air basin-level and county-level analyses, we ran the same conditional logistic regressions using only the matched sets in ZCTAs where population-weighted centroids fall within the corresponding air basin or county. These stratified analyses assume that wildfire smoke has the same effect across all ZCTAs within the same air basin or county. We used the "survival" package for conditional logistic regression (Therneau et al., 2023).

To incorporate the total acute care utilization counts during wildfire smoke days and provide estimates of the health burden, we calculated the population attributable number of acute care utilizations due to wildfire $PM_{2.5}$ during the study period at the county, air basin, and state levels. For each geographical area, we calculated the population attributable number as the product of area-specific attributable fraction (one minus the inverse of area-specific OR) (Lash et al., 2021) and the area-specific total number of acute care utilizations among all wildfire smoke days during the study period.

2.2.2. Within-Community Matched Design Coupled With Spatial Bayesian Hierarchical Model for ZCTA-Level Health Analyses

To explore finer scale spatially varying effects, we used a previously developed within-community matched design to estimate the ZCTA-specific effect of wildfire $PM_{2.5}$ on the risk of daily respiratory acute care utilization (C. Chen et al., 2024). Specifically, we identified matched controls for each day exposed to wildfire smoke as non-wildfire smoke days of the same year and ZCTA, and within the window of 30 calendar days before or after the wildfire smoke day. We excluded days in the 3 calendar days before or after any wildfire smoke day from the controls to avoid spillover effects from other wildfire days. To estimate rate differences, we calculated the difference between the acute care utilization rate on the exposed case day and the weighted averages of acute care utilization rates among non-exposed control days. Acute care utilization rates on exposed case days were the count of acute care utilizations divided by ZCTA population size from the 2010 US Decennial Census. Weighted averages for non-exposed control days were weighted acute care utilization rates based on inverse temporal distance to exposed day (i.e., one divided by number of days to the matched exposed day). We used the average rate difference of all exposed days within a ZCTA to represent the ZCTA-specific rate difference and scaled the rate difference to per 100,000 person-day.

Since ZCTAs closer together might exhibit similar effects from a wildfire smoke day compared to ZCTAs farther away, we used a spatial Bayesian hierarchical model (BHM) to leverage this spatial autocorrelation and increase the precision of our rate difference estimates (Schwarz et al., 2021). We included a covariance structure to leverage this spatial autocorrelation across ZCTAs and used an empirical semivariogram to identify the shape and starting values of the covariance structure (spherical shape and 2, 16, and 8 for sill, nugget, and range parameters respectively) (Bivand et al., 2013). We also used flat priors to introduce minimal prior information into the Bayesian model: inverse gamma distribution with scale and shape equal to 0.001 for the sill and nugget parameters, and uniform distribution from 0.001 to 6 for the range parameter. We used 10,000 Monte Carlo Markov chain samples with 75% burn-in to estimate the ZCTA-specific rate differences after spatial pooling. Additionally, we calculated the signal-to-noise ratio to present the precision of the estimates, which is the ratio between the mean of the rate differences in the recovered samples and the corresponding standard deviation. The signal-to-noise ratio allows us to have a mappable measure of statistical precision and values higher than 2 are considered precise. We used the "spBayes" package in R for the spatial BMH (Finley et al., 2015).

2.2.3. Effect Modification by Community Characteristics at the ZCTA Level

We used meta-regression to evaluate potential effect modification by community characteristics on the effect of a wildfire smoke day on acute care utilization at the ZCTA level. For each community characteristic, which was selected a priori, we ran a meta-regression of the pooled ZCTA-specific rate difference on the community characteristic. To preserve statistical power, we excluded 100 ZCTAs without complete data for 14 community characteristics other than A/C prevalence, and we excluded 274 ZCTAs for meta-regression of the A/C prevalence. Our estimates are reported as rate difference per interquartile range increase of the community characteristic. We used the "meta" package for meta-regression (Balduzzi et al., 2019).

2.3. Sensitivity Analyses

Since atmospheric aridity might affect the probability of wildfire occurrence and ambient temperature is a known risk factor for respiratory acute care utilization, we conducted sensitivity analyses for the state-level case-crossover analyses by including two forms of daily ambient temperature as a linear term or a natural cubic function with six degrees of freedom. We calculated daily ambient temperature at the population-weighted centroid of each ZCTA based on an existing 4 km × 4 km temperature surface (Daly et al., 2008). We also evaluated lagged effect of wildfire smoke on acute care utilization for an individual lag of one day and over a predefined 7-day lag period in a case-crossover analysis. For the 7-day lag period analysis, we employed a distributed lag nonlinear model while constraining the effect of the exposure to follow a natural cubic spline function with two internal knots over the lag period as done in other studies (Doubleday et al., 2020).

To evaluate the robustness of the within-community matched design and spatial BHM, we conducted a sensitivity analysis using informative priors employed in previous studies for the sill and nugget in the spatial BHM, which are inverse gamma distributions (2 for shape and 1/starting value for scale) (C. Chen et al., 2024). This sensitivity analysis tested the robustness of the spatial BHM toward prior specification and the informative priors used here give more weight to our interpretation of the empirical semivariogram while the flat priors in main analysis were more data-driven. We also used community-level socioeconomic information from the Healthy Places Index report version 2.0 in the meta-regression, which is based on averages of 2011–2015, earlier than the averages of 2015–2019 in the main analysis (Delaney et al., 2018).

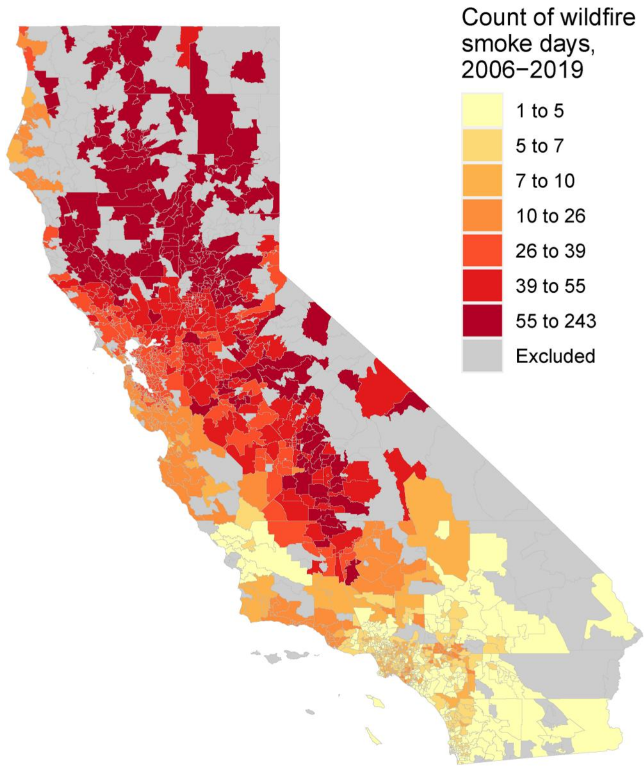

Figure 2. Spatial distribution of total ZCTA-level wildfire days in septiles between 2006 and 2019 among 1,396 ZIP Code Tabulation Areas included in the study. We considered wildfire days to be days with wildfire $PM_{2.5}$ concentrations $\geq$15 μg/m^3.

3. Results

3.1. Characteristics of ZCTAs, Wildfire Smoke Days, and Respiratory Acute Care Utilizations

Our study spanned 2006–2019 and included 1,396 California ZCTAs (99.1% of California population) that had a population $\geq$1,000 people and experienced at least one wildfire smoke day (wildfire $PM_{2.5}$ concentrations $\geq$15 μg/m^3). In total, we observed 40,065 wildfire smoke ZCTA-days in the 1,396 ZCTAs (0.6% of all ZCTA-days) during the study period. The median number of ZCTA wildfire smoke days was 17 (first and third quartiles: 6 and 43), with higher exposure in Central Valley and Northern California (Figure 2). Most of the wildfire smoke days occurred between June and November (96.7%), with more wildfire smoke days in 2007, 2008, 2017 and 2018 (Figure S1 in Supporting Information S1). We observed 18,049,797 non-scheduled respiratory acute care utilizations in the study area between 2006 and 2019, with 75,175 occurring on wildfire smoke days.

3.2. Spatial Heterogeneity of Wildfire Smoke Day Effects

We first conducted a state-level analysis that did not consider spatial heterogeneity and observed increased odds of respiratory acute care utilizations on wildfire smoke days (OR = 1.06, 95% confidence interval (CI): 1.05, 1.07), corresponding to 4,122 (95% CI: 3491, 4747) counts of acute care utilizations attributed to wildfire smoke between 2006 and 2019 (Table S1 in Supporting Information S1). We then conducted three analyses considering spatial heterogeneity for air basins, counties, and ZCTAs.

In our air basin-level analysis, the median OR point estimate was 1.09 (minimum and maximum: 0.88, 1.57) across the 15 air basins (Table S1 in Supporting Information S1). We observed higher point estimates in San Diego as well as Great Basin Valley, and lower point estimates in Salton Sea and North Central Coast (Figure 3). After incorporating total acute care utilization counts during wildfire smoke days, air basins with the highest acute

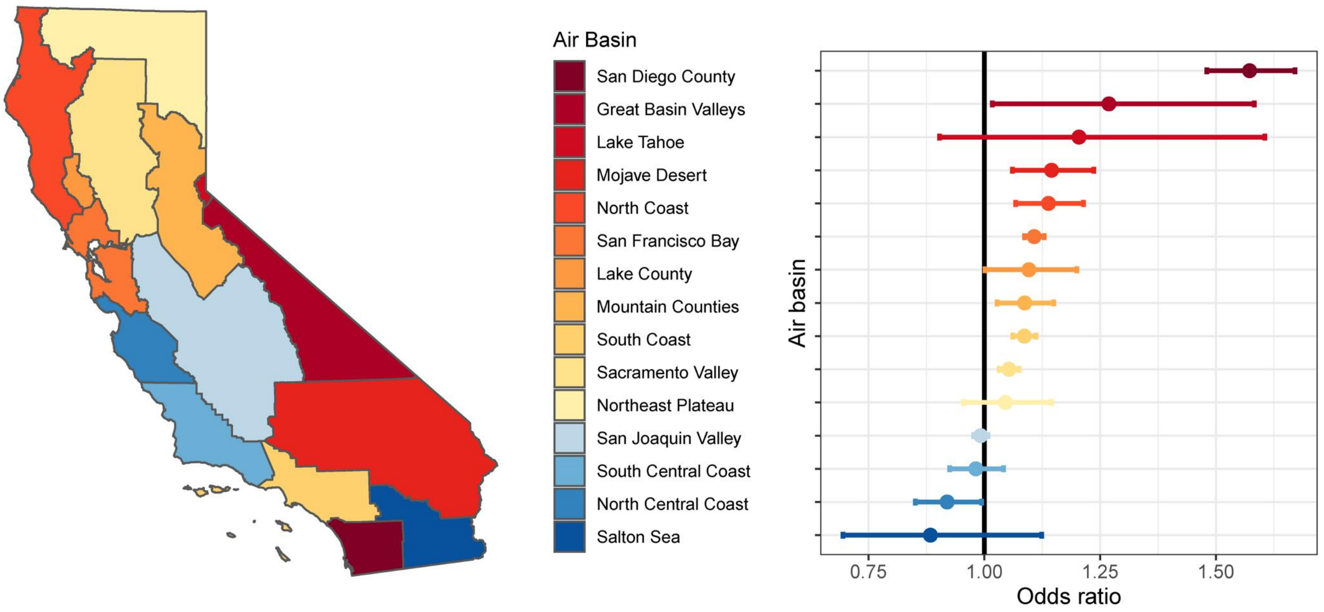

Figure 3. The air basin specific effect estimates (odds ratio) of wildfire smoke day on same-day respiratory acute care utilization, 2006–2019. Left: spatial distribution of the point estimates; Right: point estimates and 95% confidence intervals. We employed conditional logistic regressions in a time-stratified case-crossover design, matching on ZIP Code Tabulation Area, day of week, month, and year.

health burden were the San Francisco Bay and Sacramento Valley, with 1,616 (95% CI: 1,325, 1,901) and 798 (95% CI: 490, 1099) counts of acute care utilizations attributed to wildfire smoke between 2006 and 2019, respectively (Figure S2 and Table S1 in Supporting Information S1).

For our county-level analysis, the median point estimate for ORs was 1.06 (minimum and maximum: 0.45, 1.57) across 57 counties (Table S1 in Supporting Information S1). The direction of point estimates for air basins was similar to those in their respective counties with a few exceptions (Kings County in the San Joaquin air basin, Plumas County in Mountain Counties air basin) (Figure 4). San Diego County and Los Angeles County experienced the highest acute care utilizations attributed to wildfire smoke between 2006 and 2019 (Figure S3 in Supporting Information S1).

In the third analysis, we used a within-community matched design coupled with a spatial BHM to assess spatial heterogeneity at the ZCTA level. We observed the median point estimates for rate differences was −0.07 (minimum and maximum: −19.87, 29.61) across 1,396 ZCTAs after accounting for spatial autocorrelation. We observed more spatial heterogeneity in the ZCTA-level point estimates than across air basin or county. Precise, higher values were observed in coastal metropolitan areas of San Diego, Mojave Desert, and Great Basin Valleys, while precise, lower values observed in the Salton Sea, North Coast and Central Coast (Figure 5).

3.3. Effect Modification of Wildfire Smoke Day Effects by Community Characteristics

We evaluated effect modification by community characteristics as measured by 14 variables in 1,296 ZCTAs with rate difference and complete community characteristics (Figure 1). We included the spatial distribution of community characteristics among 1,296 California ZCTAs with complete data on these characteristics except for A/C prevalence, of which only 1,122 ZCTAs have data (Figure S4 in Supporting Information S1). We found that a higher proportion of Black residents and Pacific Islander residents was associated with higher rate differences for respiratory acute care utilizations between wildfire smoke days and non-wildfire smoke days. ZCTAs with a higher proportion of white residents and Asian residents were associated with lower rate differences (Figure 6). Communities with a higher proportion of economically advantaged subpopulations were associated with lower rate differences for respiratory acute care utilizations between wildfire and non-wildfire smoke days. Effect modification was more pronounced for proportions of automobile ownership, tree canopy, and A/C prevalence (Figure 6).

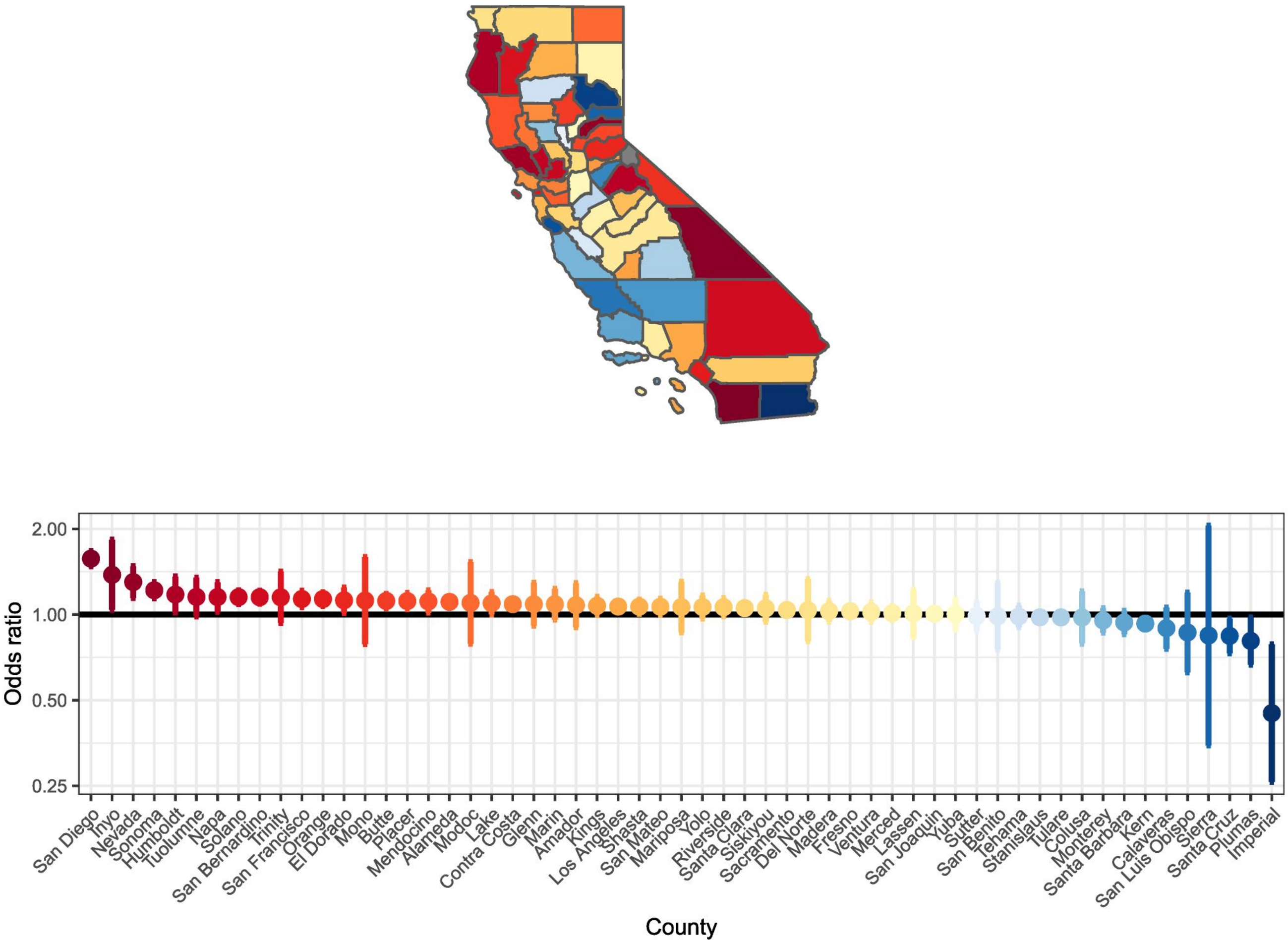

Figure 4. The county specific effect estimates (odds ratio) of wildfire smoke day on same-day respiratory acute care utilization. Top: spatial distribution of the effect estimates; Bottom: point estimates and 95% confidence intervals. We employed conditional logistic regressions in a time-stratified case-crossover design, matching on ZIP Code Tabulation Area (ZCTA), day of week, month and year. Note: the Alpine county (gray) was excluded from analysis because the ZCTAs within this county have a population <1,000).

3.4. Sensitivity Analyses

At the state level, adding daily ambient temperature as a potential confounder in the evaluation of wildfire smoke day effect did not meaningfully change effect estimates, regardless of the form of temperature in the model (linear or nonlinear) (Figure S5 in Supporting Information S1). Effect estimates were similar for the same-day wildfire smoke and previous day wildfire smoke when included in separate models (Figure S5 in Supporting Information S1). When considering lagged exposures up to 7 days, we observed that effect estimates of individual exposure on lags 0–1 were stronger compared to effect estimates of exposure on lags 2–6 (Figure S6 in Supporting Information S1). A priori, we focused on the average of same-day and previous-two-day exposures on respiratory health, and this period appears to be most salient for respiratory related acute care utilization. Our ZCTA-specific effect estimates were also robust to the choice of priors in spatial BHM (Figure S7 in Supporting Information S1). The effect modification results did not change meaningfully when utilizing ZCTA-level sociodemographic information from earlier years (2011–2015) among 1,235 ZCTAs (Figure S7 in Supporting Information S1).

4. Discussion

It is imperative to determine areas that experience the worse health outcomes after wildfire $PM_{2.5}$ exposure to reduce their associated burden. In our study, we found that wildfire smoke days (i.e., days with wildfire $PM_{2.5} \geq 15$ μg/m^3) were associated with increased same-day respiratory acute care utilizations in a statewide California model. However, the amplitude of this relationship differed spatially across air basins, counties, and

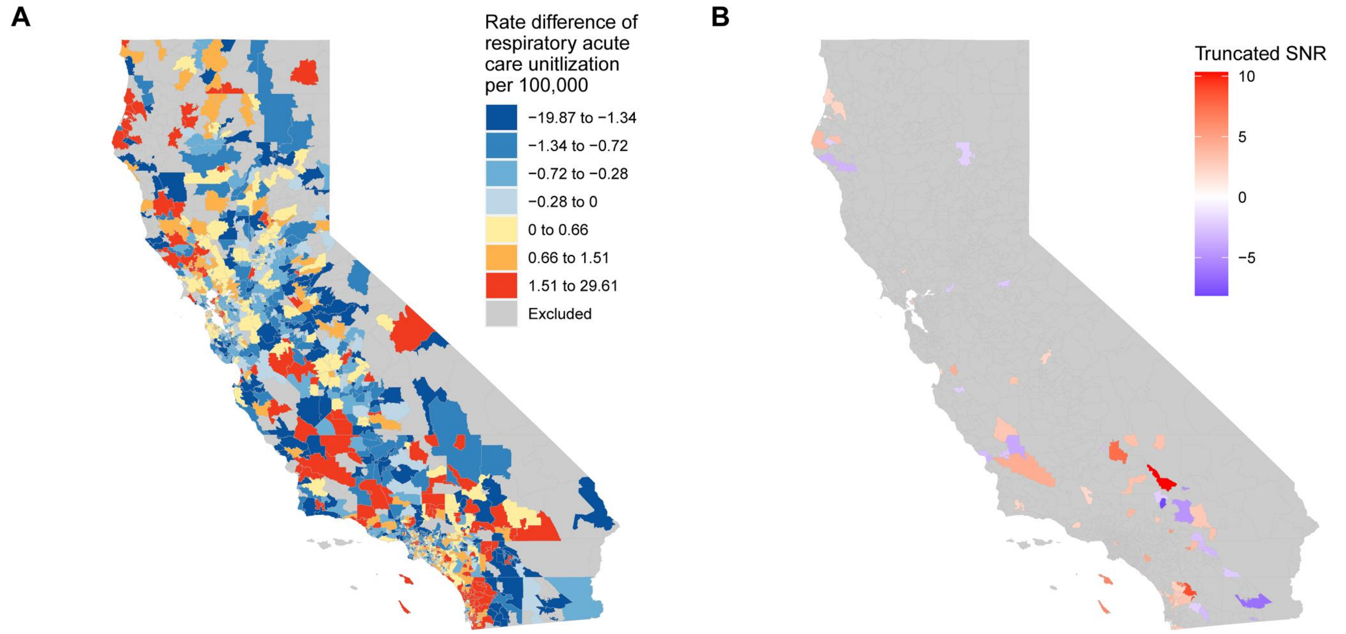

Figure 5. The ZIP Code Tabulation Area specific effect estimates (rate difference) of wildfire smoke day on same-day respiratory acute care utilization: (a) spatial distribution of the effect estimates and (b) signal-to-noise ratio with absolute value larger than two, representing higher precision of estimates.

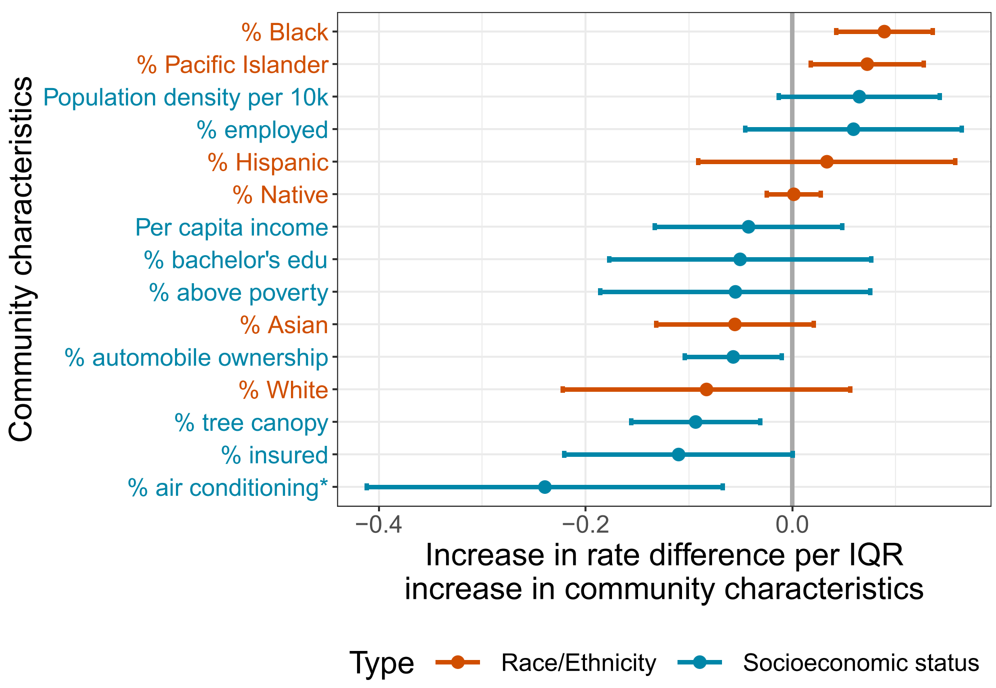

Figure 6. Effect modification of community characteristics on the effect of wildfire smoke (i.e., days with wildfire $PM_{2.5} \geq 15$ μg/m^3) on same-day respiratory acute care utilization rate among 1,296 CA ZIP Code Tabulation Areas (ZCTAs). Race/ethnicity data was obtained from the 2010 US Decennial Census and socioeconomic information was obtained from the Healthy Place Index 3.0, and air conditioning was obtained from the California Residential Appliance Saturation Study survey. *We included 1,122 ZCTAs for % air conditioning meta-regression because of data missingness.

ZCTAs. Additionally, we found that the impact of wildfire smoke days was worse for ZCTAs with higher proportions of Black and Pacific Islander residents and less pronounced in more affluent areas with buffering resources like tree canopy and A/C. Taken together, our study found that the health consequences of wildfire $PM_{2.5}$ exposure vary across space and community characteristics, providing valuable evidence to guide the development of effective policies and the allocation of resources.

Identifying areas experiencing the worse health effects is crucial for resource allocation, public health response, and preparedness directives. In California, we observed higher health impacts from wildfire $PM_{2.5}$ in certain air basins including San Diego, Great Basin Valleys, and Lake Tahoe. As air basins were created to originally manage and control non-wildfire pollution emissions, wildfire $PM_{2.5}$ and its health impacts may still differ within these air basins. As climate change progresses, an estimated 82 million individuals in the Western US are predicted to experience some wildfire smoke waves (at least two consecutive days with >98th quantile of wildfire-specific $PM_{2.5}$) by the middle of the 21st century (Liu et al., 2016), making wildfire an increasingly important source of total $PM_{2.5}$. Prior work found that $PM_{2.5}$-related health burdens are under-estimated when wildfire $PM_{2.5}$ is not explicitly considered in health impact assessments (Darling et al., 2023). Thus, it is critical to revisit air pollution problems with an eye to wildfire $PM_{2.5}$ and to consider spatial differences in these exposures and effects.

When considering community characteristics, we found that the effects of wildfire $PM_{2.5}$ were worse for historically marginalized racial groups and less-resourced communities. These community characteristics may also be key drivers of the observed spatial heterogeneity of health effects. Prior work evaluating health disparities in the context of wildfire smoke observed that socially and economically disadvantaged subgroups faced worse health effects (H. Chen et al., 2021; Reid et al., 2016, 2023). In our study, we identified Black and Pacific Islander residents as minoritized racial groups experiencing worse consequences at the same level of exposure. Structural racism has given rise to disparities in environmental exposures, quality of housing stock, access to economic and material resources, and baseline health (Bailey et al., 2017). Such racially patterned disparities may worsen the health effects of exposure to wildfire $PM_{2.5}$. We also found that ZCTAs with greater material resources had a dampened health response to wildfire $PM_{2.5}$ exposure. Access to resources such as A/C, automobiles, and healthcare services may indicate greater wealth, which has been linked to improved capacity to mitigate and cope with wildfire $PM_{2.5}$ exposure (Burke et al., 2022; deSouza & Kinney, 2021). However, uncertainties remain in the mechanisms behind such vulnerability due to the ecological nature of this study. Other factors such as population behavior adaptation toward wildfire smoke and the intersectionality of social characteristics, such as educational attainment and disability status, at the individual level could also contribute to the observed spatial heterogeneity (Bowleg, 2012; Burke et al., 2022; Jackson, 2017; Josey et al., 2023). Our findings contribute to prior research focused on examining vulnerability to wildfire $PM_{2.5}$ across subgroups (Vargo et al., 2023). Additionally, current air quality management plans can make an effort to protect the most vulnerable. For example, clean air centers in California may be expanded to serve additional communities of color and economically disadvantaged areas (Bay Area Air Quality Management District, 2021; US EPA, 2021).

This study had a few limitations. First, the modeled wildfire-specific $PM_{2.5}$ (Aguilera et al., 2023) may underestimate extreme exposure values given the training sample. However, our use of a binary exposure definition dichotomized at $\geq 15\ \mu g/m^3$ would correctly classify extreme values as wildfire smoke days. The binary definition meant that we assumed health risks were the same for any exposure level exceeding the threshold, and thus we could not capture any exposure-response relationships that may occur particularly at the higher wildfire $PM_{2.5}$ values (Heft-Neal et al., 2023). Second, we utilized spatial units based on administrative borders, which may not be the most relevant unit to assess spatial heterogeneity in the effect of wildfire $PM_{2.5}$ exposure. In addition, these units are of irregular shapes and sizes, with uneven population densities across them. However, we centered our exposure estimates to the population-weighted centroids of ZCTAs to improve the spatial alignment of health outcome and exposure. Another limitation is that we assigned wildfire $PM_{2.5}$ exposure at individuals' residential ZCTAs but people may move across ZCTAs, which can result in exposure misclassification. However, for days with high wildfire $PM_{2.5}$, individuals who can stay home would likely remain at indoors and reduce the possibility of exposure misclassification.

With the increasing severity of wildfires, it is crucial to improve our understanding of wildfire $PM_{2.5}$-related health impacts. We have a few recommendations for future research endeavors in the area. First, we only evaluated spatial variation in the health impacts of wildfire $PM_{2.5}$ in California, and future studies should extend to other US states and countries. Such consideration could facilitate early identification of vulnerable areas and populations, and it can guide subsequent targeted intervention efforts. Second, given the heterogeneity that we and others have observed by community characteristics, future studies should identify the most salient characteristics that modify the relationship between wildfire $PM_{2.5}$ and health. We tested how community characteristics in isolation modified the effect of wildfire $PM_{2.5}$ on health but these characteristics likely act synergistically, and future studies should endeavor to identify the combination of characteristics that leads to the highest vulnerability. Third, we evaluated short-term exposure and acute outcomes, but climate change will likely lead to increases in repeated wildfire $PM_{2.5}$ exposure. Thus, it is crucial to improve our understanding of the health impacts of cumulative and long-term wildfire $PM_{2.5}$ exposure. Fourth, research may benefit from incorporating human mobility patterns (e.g., cell phone location data), which may reduce wildfire smoke exposure misclassification. Last, we summarized ZCTA community characteristics using a combination of Decennial Census Survey data and American Community Survey-based Healthy Places Index data, which may miss important sub-populations. For example, although the 2010 Census enumerated people in emergency and transitional shelters (Bureau, 2021b), those experiencing homelessness—likely a highly vulnerable group (Ramin & Svoboda, 2009)—may still be missed. We encourage an inclusive future research agenda that prioritizes potentially vulnerable and understudied populations.

Most previous wildfire epidemiological studies assume that the effect of wildfire $PM_{2.5}$ is consistent across geographies and populations. Our results suggest that instead, spatial heterogeneity exists in the relationship between short-term wildfire $PM_{2.5}$ exposure and respiratory acute care utilizations in California. We identified several community characteristics that may have explained the differences observed; these included higher proportions of Black and Pacific Islander populations and more affluent community. Allocating scarce resources based on differential response to wildfire $PM_{2.5}$ could help reduce health disparities.

Conflict of Interest

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

Data Availability Statement

The ZCTA-level wildfire-specific $PM_{2.5}$ data used to identify wildfire smoke days in the study are publicly available (raguilbeck, 2023). The ZCTA-level community characteristics are available from the Public Health Alliance of Southern California Healthy Places Index report version 3.0 (Healthy Places Index, 2023) and the 2010 Census (2010 Census, 2023). The Healthy Places Index 3.0 data can be accessed by using an application programming interface (API) key (Public Health Alliance of Southern California, 2023). The respiratory acute care utilization data is not publicly available to protect patients' privacy but access of the health outcome data could be requested directly at the California Department of Health Care Access and Information website (California Department of Health Care Access and Information, 2024). The analytic code is publicly available (C. Chen, 2024).

Acknowledgments

We want to express our gratitude to Dr. Rosana Aguilera for her support and expertise in the wildfire smoke-related fine particulate matter data set. *Funding:* This project is supported by the National Institute on Aging RF1AG071024 (JAC, TB, and VD) and RF1AG080948 (TB and CC), and the National Heart, Lung, and Blood Institute F31 HL172608 (VD).

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