GeoHealth

RESEARCH ARTICLE
10.1029/2023GH000884

Key Points:

- By not considering the differential health burden of wildfire PM2.5, we underestimate the number of hospitalizations attributable to PM2.5
- In California, between 2006 and 2019, the number of hospitalizations attributable to PM2.5 may have been underestimated by approximately 13%
- Underestimation of PM2.5-attributable hospitalizations was higher in vulnerable areas

Supporting Information:

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

Correspondence to:

N. Letellier,
nletellier@ucsd.edu

Citation:

Darling, R., Hansen, K., Aguilera, R., Basu, R., Benmarhnia, T., & Letellier, N. (2023). The burden of wildfire smoke on respiratory health in California at the zip code level: Uncovering the disproportionate impacts of differential fine particle composition. *GeoHealth*, 7, e2023GH000884. https://doi.org/10.1029/2023GH000884

Received 13 JUN 2023
Accepted 9 SEP 2023

Author Contributions:

Conceptualization: Tarik Benmarhnia, Noémie Letellier
Data curation: Rosana Aguilera
Formal analysis: Rachel Darling
Funding acquisition: Tarik Benmarhnia
Methodology: Kristen Hansen, Rosana Aguilera, Tarik Benmarhnia, Noémie Letellier
Resources: Tarik Benmarhnia

The Burden of Wildfire Smoke on Respiratory Health in California at the Zip Code Level: Uncovering the Disproportionate Impacts of Differential Fine Particle Composition

Rachel Darling[1], Kristen Hansen[1,2], Rosana Aguilera[1], Rupa Basu[3], Tarik Benmarhnia[1], and Noémie Letellier[1]

[1]Scripps Institution of Oceanography, UC San Diego, San Diego, CA, USA, [2]Herbert Wertheim School of Public Health and Human Longevity Science, UC San Diego, San Diego, CA, USA, [3]Air and Climate Epidemiology Section, California Office of Environmental Health Hazard Assessment, Oakland, CA, USA

Abstract Wildfires constitute a growing source of extremely high levels of particulate matter that is less than 2.5 microns in diameter (PM2.5). Recently, toxicologic and epidemiologic studies have shown that PM2.5 generated from wildfires may have a greater health burden than PM2.5 generated from other pollutant sources. This study examined the impact of PM2.5 on hospitalizations for respiratory diseases in California between 2006 and 2019 using a health impact assessment approach that considers differential concentration-response functions (CRF) for PM2.5 from wildfire and non-wildfire sources of emissions. We quantified the burden of respiratory hospitalizations related to PM2.5 exposure at the zip code level through two different approaches: (a) naïve (considering the same CRF for all PM2.5 emissions) and (b) nuanced (considering different CRFs for PM2.5 from wildfires and from other sources). We conducted a Geographically Weighted Regression to analyze spatially varying relationships between the delta (i.e., the difference between the naïve and nuanced approaches) and the Centers for Disease Control and Prevention's Social Vulnerability Index (SVI). A higher attributable number of respiratory hospitalizations was found when accounting for the larger health burden of wildfire PM2.5. We found that, between 2006 and 2019, the number of hospitalizations attributable to PM2.5 may have been underestimated by approximately 13% as a result of not accounting for the higher CRF of wildfire-related PM2.5 throughout California. This underestimation was higher in northern California and areas with higher SVI rankings. The relationship between delta and SVI varied spatially across California. These findings can be useful for updating future air pollution guideline recommendations.

Plain Language Summary Climate change is leading to an increase in the frequency and intensity of extreme weather events, including wildfires. Wildfire smoke is a large source of particulate matter (i.e., fine inhalable particles) that could have a greater health burden than particulate matter from other sources (e.g., vehicle or industrial emissions). We aimed to quantify the burden of respiratory hospitalizations related to all particulate matter exposure in California for the years 2006–2019 with and without considering the differential health burden of wildfire smoke. We then compared these two approaches to quantify the number of respiratory hospitalizations that may have been underestimated in the past by not taking into account the higher health burden of wildfire smoke. We found that throughout California, between 2006 and 2019, we may have underestimated the number of respiratory hospitalizations attributable to particulate matter exposure by approximately 410,000 (13%). This underestimation was higher in northern California and in vulnerable areas. These results may be helpful for updating recommendations in upcoming air pollution guidelines and for protecting communities at higher risk from wildfire smoke.

1. Introduction

As anthropogenically-caused climate change worsens, built and natural environments are expected to see increasingly detrimental consequences from natural disasters, including wildfires (IPCC, 2022). Climate change is creating conditions favorable to wildfires through increased temperatures and drier conditions, as well as a shift in the precipitation regime toward more rain falling on fewer days per year (Abatzoglou & Williams, 2016; Richardson et al., 2022). The last several consecutive fire seasons in the western United States (US), specifically in California, have been the worst in recorded history. The increased number and magnitude of wildfires due to climate change

Software: Kristen Hansen, Noémie Letellier
Supervision: Tarik Benmarhnia, Noémie Letellier
Validation: Rosana Aguilera, Tarik Benmarhnia, Noémie Letellier
Writing – original draft: Rachel Darling
Writing – review & editing: Kristen Hansen, Rosana Aguilera, Rupa Basu, Tarik Benmarhnia, Noémie Letellier

brings increased exposure to wildfire smoke (A. P. Williams et al., 2019). Within the western US, northern California is one of the regions likely to suffer the highest exposure to wildfire smoke in the future (Liu et al., 2016).

Wildfire smoke is a large source of particulate matter, including fine inhalable particles with a diameter of 2.5 μm or less, known as PM2.5. Wildfire smoke, by recent estimates, has accounted for up to 25% of PM2.5 across the US, and up to half in some western regions (Burke et al., 2021). Exposure to wildfire-related PM2.5 can lead to negative impacts on human health, and is known to cause and/or exacerbate respiratory illness in particular (Chen et al., 2021; Johnston et al., 2012). Wildfire smoke pollution is associated with both respiratory morbidity and mortality (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021; Aguilera, Corringham, Gershunov, Leibel, & Benmarhnia, 2021; Chen et al., 2021; Henderson & Johnston, 2012; Liu et al., 2015; O'Dell et al., 2021). Fine particles can induce respiratory issues through pulmonary inflammation and weakened pulmonary immune response (Hoek et al., 2013; Kurt et al., 2016). Repeated evidence supports the fact that smoke exposure can aggravate respiratory issues such as chronic obstructive pulmonary disorder (COPD) (Reid et al., 2016a, 2016b) and asthma (Arriagada et al., 2019; Malig et al., 2013; O'Dell et al., 2021; Ostro et al., 2016), and cause stress, especially oxidative, on the respiratory tract (Y. H. Kim et al., 2018; Wegesser et al., 2009).

Recent toxicologic studies have found that wildfire PM2.5 can have a higher toxicity effect on the lung than the same mass of PM2.5 from other sources (Y. H. Kim et al., 2018; Wegesser et al., 2009). Specifically, the lungs of mice exposed to wildfire PM2.5 showed significant damage when compared to the lungs of mice that were exposed to doses of normal ambient air PM2.5 that were 10 times greater (Wegesser et al., 2009). A 2021 epidemiologic study found increases in respiratory hospitalizations ranging from 1.3% to 10% with a 10 $\mu g/m^3$ increase in wildfire specific PM2.5, compared to a 0.67%–1.3% increase associated with the same amount of non-wildfire PM2.5 (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021). This difference may be explained by the differences in PM chemical composition. Wood smoke generated from wildfires contains a large number of harmful components including a high level of organic carbon, polycyclic aromatic hydrocarbons, and water-soluble trace metals (Adetona et al., 2016; Danielsen et al., 2011; Karthikeyan et al., 2006). It also has a smaller particle size in comparison to PM from ambient air (Danielsen et al., 2011). Wood smoke PM may have a greater potential to cause inflammation and oxidative stress in the lung than urban ambient PM (Black et al., 2017; Danielsen et al., 2011; K. M. Williams et al., 2013).

The increasing frequency, duration, and intensity of wildfires with climate change constitutes a growing source of PM2.5 emissions. Indeed, in the US, wildfire PM2.5 has been increasing due to increasingly aggressive fire seasons, while PM2.5 from other sources (e.g., vehicle emissions, coal-burning power plants, and industrial emissions) has been mostly decreasing due to progressing air quality standards (McClure & Jaffe, 2018). Statistical models of PM2.5 concentration support the pattern of increasing PM2.5 in the Northwest US due to wildfires, while PM2.5 decreases anywhere else in the US (McClure & Jaffe, 2018). Current air quality standards written by the World Health Organization (WHO) and US Environmental Protection Agency (EPA) do not differentiate between PM2.5 sources of emission (US EPA, 2021; WHO, 2021). Considering PM2.5 from wildfires and other sources to be equally harmful to human health may lead to significant underestimation of the burden of fine particles in areas that are increasingly exposed to wildfire smoke.

Some subgroups could face even higher risks of health effects from wildfire smoke (Kondo et al., 2019; Reid et al., 2016a, 2016b). Socioeconomic status (SES) or other demographics characteristics can be associated with exposure, adaptive capacity, and level of resilience. Recent work has found evidence that lower SES groups face a higher wildfire smoke-related health burden than high SES groups (Liu et al., 2017; Rappold et al., 2012; Reid et al., 2016b). Better identification of vulnerable communities that are most impacted by wildfire smoke, and communities most likely to need assistance before, during, and after a wildfire, can help inform the design of air quality policies and provide useful information for developing community resilience strategies.

The present study quantified the impact of PM2.5 on hospitalizations for respiratory diseases in California from 2006 to 2019, using a health impact assessment (HIA) that considered differential concentration-response functions (CRF) for PM2.5 from wildfire and non-wildfire sources of emissions. We quantified the burden of respiratory hospitalizations related to PM2.5 exposure at the zip code level through two different approaches: (a) naïve (considering the same CRF for all PM2.5) and (b) nuanced (using different CRFs for PM2.5 due to wildfires and PM2.5 from other sources). We analyzed the spatial variability of the difference (delta) between the naïve and nuanced approaches and whether such deltas were associated with the area's social vulnerability.

2. Materials and Methods

2.1. Wildfire and Non-Wildfire PM2.5 Exposure

We used wildfire and non-wildfire PM2.5 data over the period 2006–2019 previously estimated by Aguilera et al. (2023). These exposures were assessed from daily concentrations of PM2.5 estimated by zip code using 24-hr daily means sampled and analyzed by the US EPA Air Quality System (AQS) (https://www.epa.gov/aqs), which represent fine particulate matter concentrations from all sources (i.e., including both non-wildfire and wildfire sources). Aguilera et al. used an ensemble machine learning model with high model prediction capabilities (R^2 of 0.86) to estimate daily PM2.5 at each population-weighted zip code centroid in California (Aguilera et al., 2023). Briefly stated, the authors fit a series of machine learning models (including gradient boosting, random forest, and deep learning models) using PM2.5 concentrations from AQS monitors and a wide range of predictors for PM2.5, such as aerosol optical depth, land cover, and meteorological conditions, and used the ensemble of such models to improve PM2.5 prediction. Using a multiple imputation approach based on chained random forest models, the authors estimated the non-wildfire PM2.5 concentrations on zip code days covered by smoke plumes (identified using Hazard Mapping System's Smoke Product; Brey et al., 2018), which was then subtracted from the estimated PM2.5 from all sources to obtain wildfire-specific PM2.5 concentrations. This new ensemble-based statistical approach to estimate daily wildfire-specific PM2.5 at the zip code level has been previously described in detail (Aguilera et al., 2023). Such approach includes the following assumptions: (a) First, this approach assumes that HMS products are good proxy for ground-level exposure; this assumption is likely to be minor as we found a high correlation between HMS smoke density (for the period 2010–2020) and wildfire-specific PM2.5 (see Figure S5 in Aguilera et al., 2023). In addition, unless, another event generating increases in PM2.5 levels concomitant to the wildfire smoke event occurs on the same day and zip code, the proposed imputation approach would assign a value of 0 on a given day if the smoke levels on the ground are null and the estimated wildfire-specific PM2.5 value would be null as well. (b) Second, this approach assumes not intra-daily variability as the focus is on daily mean wildfire-specific PM2.5.

2.2. Hospitalization for Respiratory Diseases

We used daily hospital admission data for respiratory diseases provided by the California Department of Healthcare Access and Information (HCAI). We used patient discharge data from 2006 to 2019. The Patient Discharge Data set consists of a record for each inpatient discharge from a California-licensed hospital. Respiratory hospitalizations correspond to ICD 9 codes 460:519, which include pulmonary diagnoses such as asthma (493), COPD (490–496), and pneumonia (480–486). All data were aggregated at the daily level by zip code.

2.3. Health Impact Assessment

We conducted a HIA to quantify the burden of PM2.5 exposure on respiratory hospitalizations. The steps of the HIA calculation are described in Figure S1 in Supporting Information S1. We used differential CRFs for PM2.5 from wildfire and non-wildfire sources of emissions. First, we conducted a naïve approach that considered the same CRF for all PM2.5 (wildfire and non-wildfire). Second, we performed a nuanced approach that considered differential CRFs for PM2.5 from wildfire and from other non-wildfire sources. We used CRFs from Aguilera et al.'s multiple imputation approach, due to the flexibility of the imputation method to isolate wildfire PM2.5 from other sources compared to alternative methods (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021). After converting the values from percent change to relative risk (RR), the CRFs for all (wildfire and non-wildfire) PM2.5, non-smoke PM2.5, and wildfire-specific PM2.5 were 1.0076, 1.0072, and 1.10, respectively, with a reference exposure concentration of 10 μg/m^3. These CRFs were used to calculate the new RR exposure difference, the population attributable fraction (PAF), and the attributable number (AN) of respiratory hospitalizations due to PM2.5 exposure. The RR measures the increased response in relation to increased PM2.5 exposure. The PAF measures the proportion of hospitalizations associated with a given PM2.5 concentration. Finally, the AN value measures the health burden of PM2.5 exposure in terms of the number of preventable respiratory hospitalizations due to this pollutant. AN was estimated by multiplying the PAF by the number of respiratory hospitalizations. Hospitalizations for the whole population (i.e., all gender and age groups) were used for this HIA.

For the naïve approach, we used the CRF of 1.0076 for all (wildfire and non-wildfire) PM2.5. In contrast, for the nuanced approach, we applied two different CRFs specific to the source of PM2.5. We calculated two PAFs separately, one for non-wildfire PM2.5, which used the CRF of 1.0072, and another for wildfire-specific PM2.5, which used the CRF of 1.10. We then calculated the AN for each source and added them together. This nuanced approach calculation accounted for the differential health burden of PM2.5 from wildfires by including a specific and higher dose response only for this specific source of PM2.5.

For both the naïve and nuanced analyses, we estimated the sum of attributable hospitalizations for each year over the study period (2006–2019). In parallel, the AN values were summed per zip code, and then divided by the total population per zip code and multiplied by 100,000 to obtain standardized estimates across zip codes per 100,000 people. Zip code population values were obtained from the 5-year total population estimates (2009–2013) from the American Community Survey. We then calculated the delta between the two approaches by subtracting the AN of the naïve approach from the AN of the nuanced approach for each zip code. The delta value can be interpreted as the number of unaccounted for attributable respiratory hospitalizations due to PM2.5 exposure from all sources by not taking into account the differential CRF of wildfire-specific PM2.5.

Finally, in order to determine the total AN of respiratory hospitalizations (over the study period and across California) that are unaccounted for when not considering the differential impact of wildfire smoke PM2.5, we totaled the number of hospitalizations over the study period over the state of California both for the naïve and the nuanced approach and calculated the delta between the two values.

In supplementary analyses, we used the same steps of the HIA described above but with different CRFs for the nuanced approach. For this supplementary analysis, we used the CRFs obtained by Aguilera, Corringham, Gershunov, and Benmarhnia (2021) using the seasonal interpolation method to segregate wildfire smoke PM2.5 from other sources of PM2.5 (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021). The CRFs for non-smoke PM2.5 and wildfire-specific PM2.5 in this analysis were 1.013 and 1.030, respectively.

2.4. Social Vulnerability Index

To investigate relationships between the delta and population vulnerability, we used the Social Vulnerability Index (SVI), a metric developed by Centers for Disease Control and Prevention (CDC) and Agency for Toxic Substances and Disease Registry (CDC, 2021). The SVI determines the social vulnerability of each census tract based on 15 US census variables including SES, household composition, race/ethnicity/language, and housing/transportation characteristics. The SVI measures the ability of a community to adapt to natural or human-caused disasters. It is measured on a scale of 0–1, with 1 being the most socially vulnerable. As SVI was provided at the census tract level, census tracts were aggregated into zip codes using data from the U.S. Department of Housing and Urban Development crosswalk files (https://www.huduser.gov/portal/datasets/usps_crosswalk.html#data).

First, we fitted a univariate linear regression model to estimate the association between the delta between the naïve and nuanced approach (i.e., the difference in AN of hospitalizations between the two approaches) and the level of SVI, per interquartile range (IQR) increase in SVI level (IQR = 0.35). We used IQR for our main contrast of interest for simplifying the interpretability of our coefficient given the distribution of the SVI level. Indeed, by default, the contrast is set to a change of 1 which corresponds to a substantial and unrealistic change. Second, we used a bivariate map to display the delta and SVI on a single map to visualize the spatial distribution of these two variables and the geographical concentration of their relationship. Furthermore, we conducted a Geographically Weighted Regression (GWR), which allows us to explore spatially varying relationships. The GWR does not assume the relationships between the delta and SVI are constant across California. Instead, it allows the relationships to vary by geographical location (Fotheringham et al., 2002; Wheeler & Páez, 2010). By allowing local variations in rates of change, this method provides a set of coefficients specific to a location (in our case, the zip code). GWR generates a separate regression equation for each observation using a different weight in accordance with its proximity (i.e., higher weights for close observations and lower weights for distant ones). The GWR allows us to produce detailed maps of spatial variations in relationships. A spatially varying association suggests that one unit change in SVI induces different levels of change in the delta in different California zip codes (i.e., spatial non-stationarity) (Brunsdon et al., 1996). The GWR model was fitted with a Gaussian covariance structure using the spgwr package in R (Bivand et al., 2020), with the delta between the two approaches as the outcome and the median SVI as the independent variable.

The GWR model can be written as follows:

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_{ik} + \varepsilon_i$$

Table 1
Sum of the Attributable Number of Respiratory Hospitalizations Due To PM2.5 Per Year, Over the Study Period (2006–2019), For the Naïve Approach, Nuanced Approach, and the Delta of the Two Approaches

Year	Naïve approach	Nuanced approach	Delta (nuanced-Naïve)
2006	235,290	240,694	5,404
2007	240,182	273,860	33,678
2008	257,869	370,894	113,025
2009	236,822	243,778	6,956
2010	228,386	221,501	−6,885
2011	208,899	203,839	−5,060
2012	183,081	186,285	3,204
2013	192,101	211,966	19,865
2014	171,682	175,953	4,271
2015	135,190	145,485	10,295
2016	152,771	179,729	26,958
2017	168,394	229,472	61,078
2018	176,697	307,877	131,180
2019	128,280	134,420	6,140

Note. The naïve approach considers the same concentration-response functions (CRF) for all PM2.5 whereas the nuanced approach considers different CRFs for PM2.5 due to wildfires and PM2.5 from other sources. The delta values represent the number of attributable respiratory hospitalizations due to PM2.5 exposure from all sources (wildfire or non-wildfire) that go unaccounted for by not considering the different CRF of wildfire-specific PM2.5.

where y_i is the dependent variable (i.e., delta), $\beta_0(u_i, v_i)$ and $\beta_1(u_i, v_i)$ are the spatially varying coefficients associated with the intercept and independent variable (i.e., SVI), x_{ik} are the values of the independent variable, (u_i, v_i) represent the geographical coordinates, and ε_i is the error term.

A cross-validation procedure was employed to choose a bandwidth for the model. Our GWR model provided β estimates for every zip code across California, per IQR increase in SVI level. Outlier estimates due to very small population sizes (such as rural areas) are not displayed in the results but are still accounted for in the model fit. The GWR β estimates were truncated and plotted between the first and third quartiles of the regression to visualize variations in the coefficients. We used the median estimate value of the GWR model as the midpoint. Lastly, we calculated the prediction accuracy of the model, which describes the difference between the calculated AN of hospitalizations and the number of hospitalizations that the model predicts. This difference gives a visual representation of the goodness of fit of the model.

3. Results

Spatial distribution of PM2.5 from all sources and wildfire-specific PM2.5 in California, over the period 2006–2019, are shown in Figures S2 and S3 in Supporting Information S1, respectively.

3.1. Attributable Respiratory Hospitalizations: Naïve Versus Nuanced Approach

Table 1 displays the sum of the attributable hospitalizations per year over the study period for the naïve approach, nuanced approach, and the delta between the two. We found that considering a differential CRF of PM2.5 due to wildfires and from other sources leads to the AN of the rate of hospitalizations in the nuanced approach remaining consistently higher than in the naïve approach, except for the years 2010 and 2011, in which the opposite is the case (Table 1). Negative delta values were only observed in 2010 and 2011 due to the lower levels of PM2.5 from wildfire during these years. The year with the maximum number of attributable hospitalizations due to PM2.5 exposure in the study period was 2008. In 2008, across California, the sums of attributable respiratory hospitalizations due to PM2.5 for the naïve and nuanced approaches were 257,869 and 370,894, respectively. The delta of the two approaches yielded a value of 113,025 attributable hospitalizations. For the period of 2006–2019, the highest delta value was observed in 2018, with a difference between the two approaches of 131,180 respiratory hospitalizations.

The spatial distribution of the AN of respiratory hospitalizations per zip code for both nuanced and naïve approaches over the study period of 2006–2019 is shown in Figure 1. For the two approaches (and especially the nuanced approach), hotspots of the highest AN of respiratory hospitalizations are found in central and northern California. In Figure 2, we display the delta of the values between the nuanced and naïve approach. We found that the largest delta values occur most heavily in northern California, with some of the high and moderate values also seen in central California. Southern California mostly contains low delta values.

The delta of the sum of the AN of hospitalizations between the two approaches (during the period 2006–2019 and over the state of California) yielded a result of approximately 410,108. This number corresponds to the AN of respiratory hospitalizations due to all sources of PM2.5 that go unaccounted for when not considering a different CRF for wildfire smoke PM2.5. This value yields a percentage of total unaccounted for hospitalizations due to PM2.5 exposure of 13.1% when the differential CRF of wildfire smoke is not considered.

3.2. Burden of PM2.5 Exposure and Social Vulnerability

Figure 3 displays the spatial distribution of delta and SVI simultaneously and revealed that their relationship is not consistent across California, with particularly strong relationships in the central and northern part of the

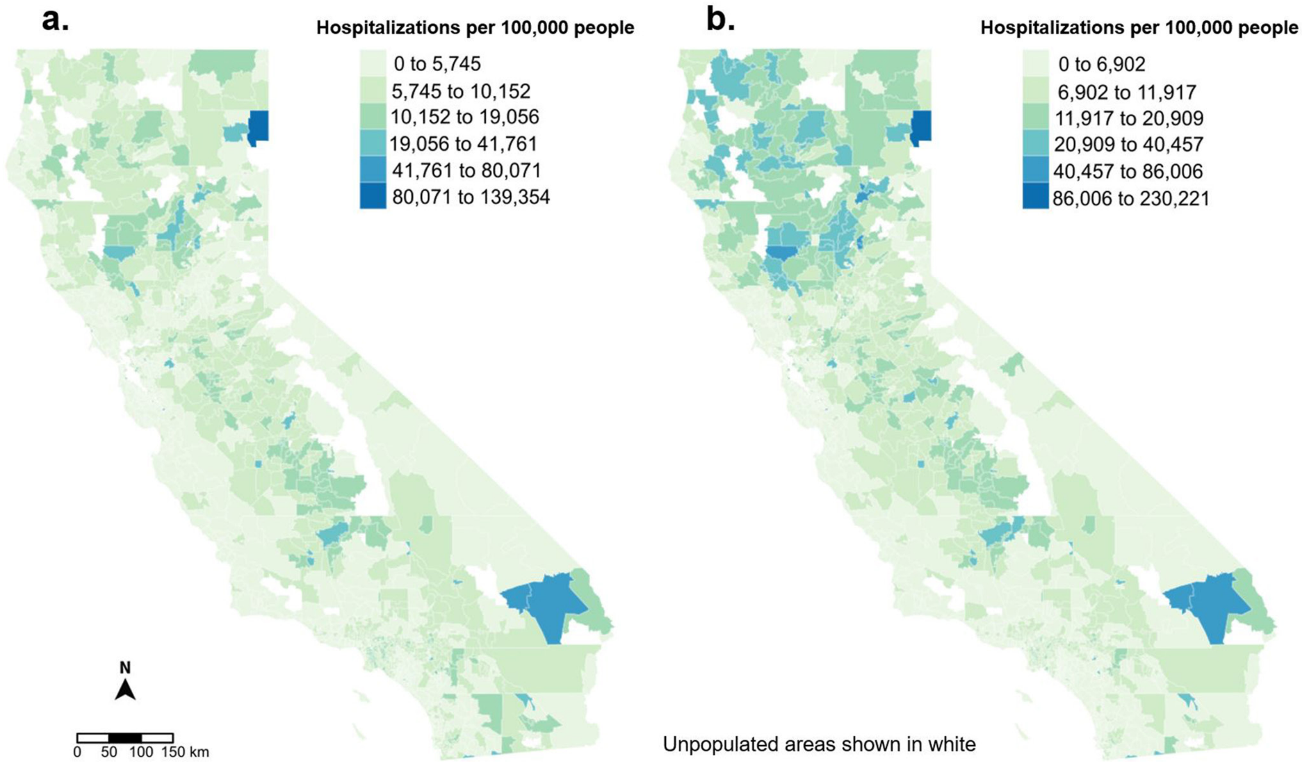

Figure 1. Spatial distribution of the total number of respiratory hospitalizations attributable to all PM2.5 in California (wildfire and non-wildfire), per 100,000 people, per zip code, for the period 2006–2019, using naïve (a) and nuanced approaches (b). The naïve approach considers the same concentration-response functions (CRF) for all PM2.5, whereas the nuanced approach considers different CRFs for PM2.5 from wildfires and from other sources.

state. This suggests that using a single model for the entire state might not adequately capture the complexity of this relationship. The number of PM2.5-attributable respiratory hospitalizations that go unaccounted for by not considering the differential CRF of wildfire-specific PM2.5 (i.e., the delta between the AN of the nuanced approach and the AN of the naïve approach) was significantly higher in zip codes with high SVI rankings (i.e., more vulnerable populations) (p-value = 0.013). Specifically, we observed an increase of 611 (CI 95% [132, 1,091]) unaccounted for respiratory hospitalizations per 100,000 people for an SVI increase of 0.35. First and third quartiles of the GWR analysis are equal to −11 and 869, respectively. Thus, 50% of the values of the relationship between SVI and respiratory hospitalizations fall between −11 and 869 unaccounted for hospitalizations per a 0.35 unit increase in SVI. To help visualize the variation in the coefficients over the state of California, Figure 4 depicts the truncated values from the first to the third quartile. Figure 4 reveals spatial differences at the zip code level, with some areas (in red) indicating major associations between delta values and SVI (e.g., areas around San Francisco and Sacramento, the northernmost region of California, and San Bernardino County). Figure S4 in Supporting Information S1 depicts a plot of the difference between the true and predicted values of respiratory hospitalizations. In Figure S4 in Supporting Information S1, we can see random scatter of the residuals, but there are higher magnitude errors in the north and center regions of the state. Coastal cities, which tend to have higher populations, tend to be more accurate (Figure S4 in Supporting Information S1).

Using CRFs from the seasonal interpolation method to segregate wildfire PM2.5 from other sources of PM2.5 produced results consistent with those obtained with the CRFs from the imputation method (Figures S4 and S5 in Supporting Information S1). Major associations were found in Bay Area and San Bernardino region using both methods. However, larger associations were found in the far northern part of the state using the imputation method, while larger associations were found in the southern part of the state using the seasonal interpolation method.

4. Discussion and Conclusions

In this study, we found a higher AN of respiratory hospitalizations due to PM2.5 exposure when accounting for differential CRF for PM2.5 from wildfire and non-wildfire sources of emissions. The number of PM2.5-attributable

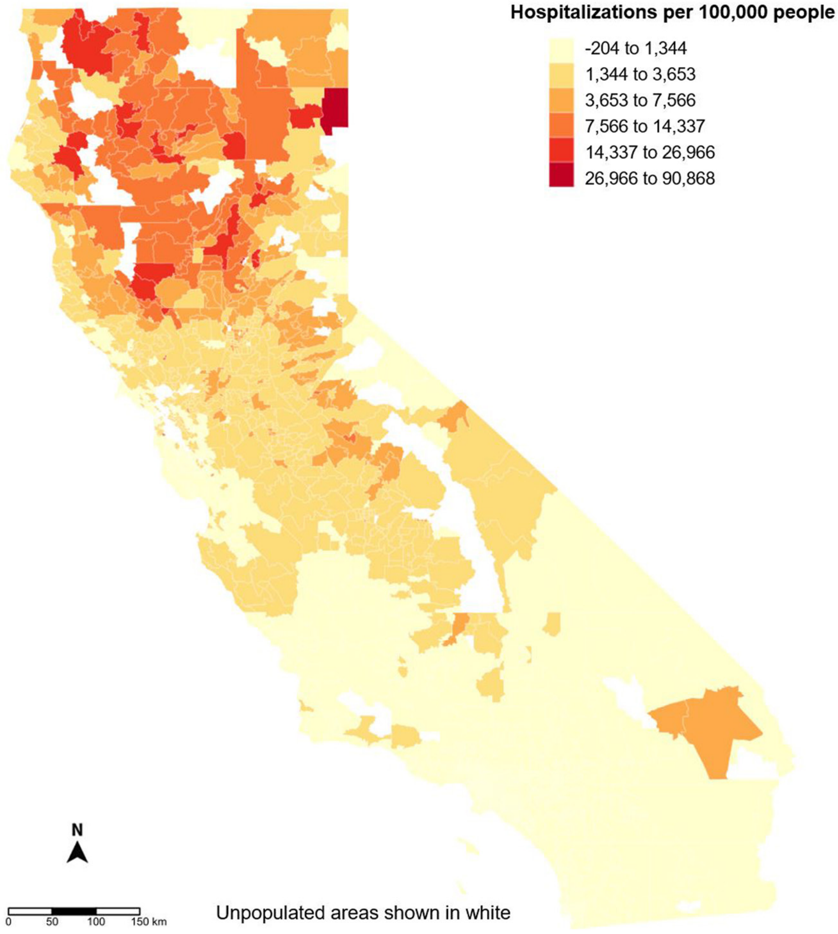

Figure 2. Spatial distribution of the delta of the two approaches (naïve and nuanced) in California, per 100,000 people, per zip code, for the period 2006–2019. The delta values can be interpreted as the number of respiratory hospitalizations due to PM2.5 exposure from all sources that go unaccounted for by not considering the different concentration-response functions of wildfire-specific PM2.5.

respiratory hospitalizations that go unaccounted for by not considering the differential CRF of wildfire-specific PM2.5 was higher in Northern California compared to the rest of the state. Throughout California, between 2006 and 2019, we found that previous analyses may have underestimated the number of respiratory hospitalizations attributable to PM2.5 exposure by approximately 13% by not accounting for the larger health burden of wildfire-specific PM2.5. This underestimation was higher in areas with high social vulnerability. These findings suggest that policies addressing PM pollution should consider emission sources in order to most effectively decrease any harmful health effects on the most vulnerable populations.

The nuanced approach of our HIA considered the fact that wildfire smoke PM2.5 can be more dangerous for respiratory diseases, in line with growing toxicologic and epidemiologic evidence (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021; Y. H. Kim et al., 2018; Wegesser et al., 2009). As expected, we found that the AN of hospitalizations due to PM2.5 exposure increased when we considered a specific CRF for this exposure. The highest AN of respiratory hospitalization values occurred in 2008, most likely due to the large fire season of that year. During the 2008 fire season, asthma hospital visits, asthma emergency department visits, and COPD flare ups were noted, especially in northern California, where most of the fires were located (Reid et al., 2016a, 2016b). The highest delta value was observed in 2018. This finding was expected, as the 2018 wildfire season was the most destructive wildfire season on record in California (CDFFP, 2018).

The most important finding of this study was the size and the spatial distribution of delta values, that is, the difference between the nuanced and naïve approaches. The highest delta values were observed in northern and

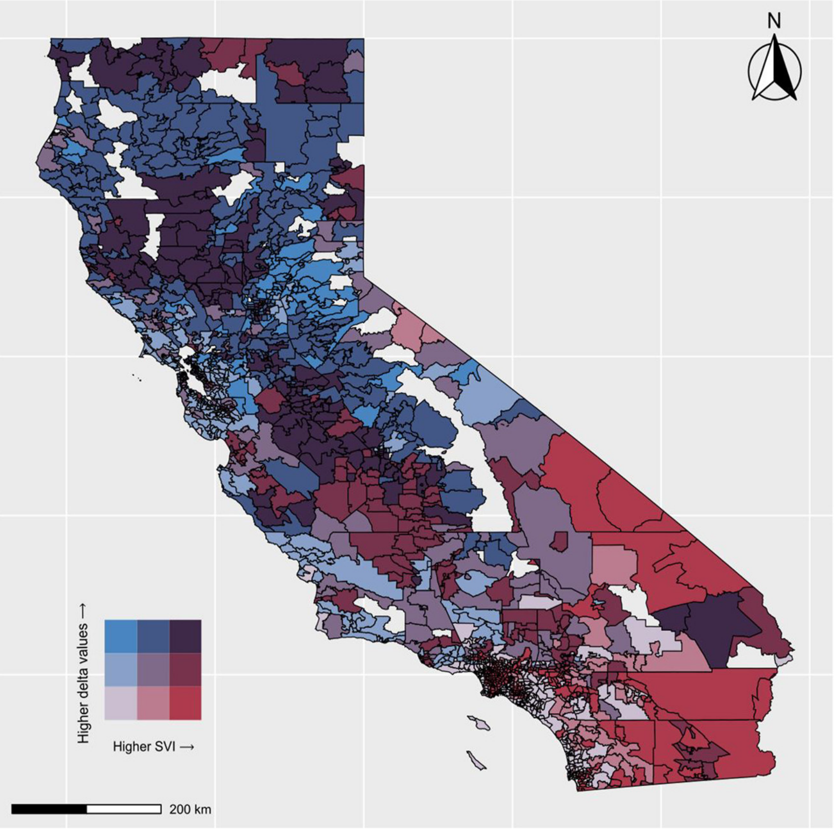

Figure 3. Bivariate map of Social Vulnerability Index and delta values (i.e., the number of respiratory hospitalizations due to PM2.5 exposure from all sources that go unaccounted for by not considering the different concentration-response functions of wildfire-specific PM2.5).

central California, presumably because of the higher proportion of PM2.5 coming from wildfires in those regions compared to others. Evidence from the literature and current observable trends suggest that the increasing frequency of drought conditions is making northern California, and the Sierra Nevada Mountain region (which spans northern and central California) more susceptible to fires (Kennedy et al., 2021). A 2004 model study projected that, with atmospheric carbon dioxide levels doubled, wildfires exceeding their containment limit could be expected to increase by 51% in the southern San Francisco Bay area and 114% in the Sierra Nevada region, as a best-case scenario (Fried et al., 2004). Large, damaging fires that have burned in the western US in the past few years, such as the Dixie fire in 2021 and the August complex fire of 2020, seem to provide evidence for this increasing trend in expansive wildfires (NASA, 2021). The large areas of forest present in northern California also contribute to the large areas burned by providing fuel for fires (NASA, 2021). Wind speed, relative humidity, and air temperature all influence the rate of spread (Sullivan, 2009). In southern California, Santa Ana conditions (i.e., low relative humidity and high wind speed) exacerbate the spread of wildfires, with one study finding a 3.5–4.5 times larger burned area on Santa Ana days compared to non-Santa Ana days (Billmire et al., 2014). These fire-producing conditions are expected to get worse with increasing climate change (Fried et al., 2004; NASA, 2021).

Considering the disproportionate burden that some communities may face during extreme events, including wildfires, is imperative to minimize health inequalities. In this study, we found that a higher level of social vulnerability at the zip code level was associated with a higher number of unaccounted for respiratory hospitalizations due to PM2.5 exposure. This result suggests that vulnerable communities experience higher PM2.5 exposure from wildfire. The inclusion of social vulnerability in planning efforts can help to identify at-risk groups that will be most burdened by wildfire. Although fine particulate emissions from wildfires are much more difficult to regulate than emissions from human sources, there is still room to improve the development of fire management strategies, disaster preparedness programs, and evacuation plans.

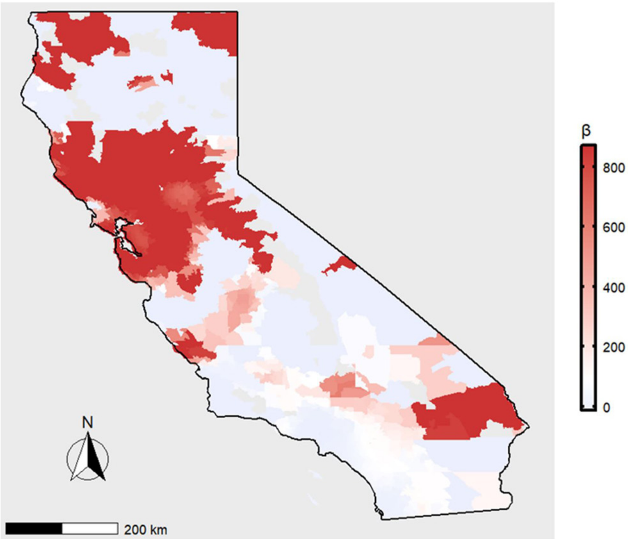

Figure 4. Spatial distribution of the associations between delta values and Social Vulnerability Index (SVI) across California (values between the first and third quartile of the Geographically Weighted Regression coefficients). The delta values can be interpreted as the number of unaccounted for respiratory hospitalizations due to PM2.5 exposure from all sources by not considering the differential concentration-response functions of wildfire-specific PM2.5. SVI measures the level of social vulnerability and the ability of a community to adapt to natural or human-caused disasters.

Our study has several limitations. First, we focused our analysis exclusively on the state of California. California is one of the regions of the US currently most impacted by wildfire smoke, and likely to suffer the most wildfire smoke under future climate change, but smoke produced by wildfires here can move long distances, including across state lines. Indeed, wildfire smoke can be transported across great distances by wind, with studies finding Western US wildfires impacting health on the East Coast (O'Dell et al., 2021). In California, Santa Ana and Diablo winds typically drive the largest wildfires and fan embers across great distances beyond California (Aguilera et al., 2020; Westerling et al., 2004). A second limitation is that the CRFs from the multiple imputation approach were based on non-summer wildfires in southern California and refer to the exposure being presence of fire upwind and strong Santa Ana winds (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021). Despite this, we used these CRFs for the entire state of California. Additionally, these CRFs did not include lagged effects when assessing the impact of PM2.5 exposure on respiratory health, but PM2.5 chemical constituents could have more delayed estimated effects on respiratory diseases (S. Y. Kim et al., 2012). Moreover, a wildfire episode is typically accompanied by an abrupt increase in particulate matter that can reach extremely high levels, which may increase the risk of acute respiratory reaction and hospitalization. The use of CRF assumes a linear relationship between PM2.5 and hospitalization, but this relationship may in reality not be linear, which could influence the calculation of attributable burden. Furthermore, although it has been established that the effects of PM2.5 exposure can vary by age group (Ebisu et al., 2019), we did not conduct age-specific analyses. Concerning the GWR model, smaller areas such as individual cities or counties, as opposed to entire zip codes, would have to be analyzed in order to see stronger or more detailed variation. Moreover, we focused our analysis on PM2.5, the main component of wildfire smoke that impacts public health, but wildfires produce elevated levels of other pollutants, including ozone (Bell et al., 2014; Jaffe et al., 2013). It would be interesting for future studies to quantify the health impacts of wildfire-specific ozone, as well as the impact of wildfire smoke on other health events. Finally, according the CDC, the SVI was created "to help public health officials and emergency response planners identify and map the communities that will most likely need support before, during, and after a hazardous event" (CDC, 2021). However, the use of such indices in policy making or risk-reduction efforts is the subject of some debate in the literature. For example, a recent publication reported some problems with the theoretical and internal consistency of SoVI, another SVI similar to SVI (Spielman et al., 2020).

The results of this study show that the burden of fine particles on respiratory health has been widely underestimated in California, and therefore support the conclusion that stronger air quality guidelines are needed to account for the differential health impact of wildfire PM2.5 and to prevent respiratory issues during wildfire episodes. The ~410,000 (or 13%) of unaccounted for respiratory hospitalizations between 2006 and 2019 in California suggest that, by not considering the different CRF of wildfire PM2.5 in air quality standards, the leading regulatory and health agencies such as the WHO and the EPA may leave people more at risk of the detrimental health impacts of wildfire smoke PM2.5, especially in northern California and in areas of high social vulnerability. In a changing climate, where wildfires are anticipated to be an increasingly important source of PM2.5, the results of this study can help policy makers to better prepare for, respond to, and protect communities at higher risk from wildfire smoke.

Conflict of Interest

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

Data Availability Statement

Daily PM2.5 and wildfire-specific PM2.5 concentrations for California Zip Codes (2006–2020) are available at: https://doi.org/10.5281/zenodo.8209822. This dataset was already published in a previous article (Aguilera et al., 2023).

Acknowledgments
We thank Maren Hale, University of California, San Diego, for her helpful feedback on this manuscript. This work was supported by the National Cancer Institute (R01CA228147) and the Office of Environmental Health Hazard Assessment (No.19-E0022).

References

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *PNAS*, *113*(42), 11770–11775. https://doi.org/10.1073/pnas.1607171113

Adetona, O., Reinhardt, T. E., Domitrovich, J., Broyles, G., Adetona, A. M., Kleinman, M. T., et al. (2016). Review of the health effects of wildland fire smoke on wildland firefighters and the public. *Inhalation Toxicology*, *28*(3), 95–139. https://doi.org/10.3109/08958378.2016.1145771

Aguilera, R., Corringham, T., Gershunov, A., & Benmarhnia, T. (2021). Wildfire smoke impacts respiratory health more than fine particles from other sources: Observational evidence from Southern California. *Nature Communications*, *12*(1), 1–8. https://doi.org/10.1038/s41467-021-21708-0

Aguilera, R., Corringham, T., Gershunov, A., Leibel, S., & Benmarhnia, T. (2021). Fine particles in wildfire smoke and pediatric respiratory health in California. *Pediatrics*, *147*(4), e2020027128. https://doi.org/10.1542/peds.2020-027128

Aguilera, R., Gershunov, A., Ilango, S. D., Guzman-Morales, J., & Benmarhnia, T. (2020). Santa Ana winds of Southern California impact PM2.5 with and without smoke from wildfires. *GeoHealth*, *4*(1), e2019GH000225. https://doi.org/10.1029/2019gh000225

Aguilera, R., Luo, N., Basu, R., Wu, J., Gershunov, A., & Benmarhnia, T. (2023). A novel ensemble-based statistical approach to estimate daily wildfire-specific PM2.5 in California (2006–2020) [Dataset]. Environment International, *171*, 107719. https://doi.org/10.1016/j.envint.2022.107719

Arriagada, N. B., Horsley, J. A., Palmer, A. J., Morgan, G. G., Tham, R., & Johnston, F. H. (2019). Association between fire smoke fine particulate matter and asthma-related outcomes: Systematic review and meta-analysis. *Environmental Research*, *179*, 108777. https://doi.org/10.1016/j.envres.2019.108777

Bell, M. L., Zanobetti, A., & Dominici, F. (2014). Who is more affected by ozone pollution? A systematic review and meta-analysis. *American Journal of Epidemiology*, *1*, 15–28. https://doi.org/10.1093/aje/kwu115

Billmire, M., French, N. H., Loboda, T., Chris Owen, R., & Tyner, M. (2014). Santa Ana winds and predictors of wildfire progression in southern California. *International Journal of Wildland Fire*, *23*(8), 1119–1129. https://doi.org/10.1071/wf13046

Bivand, R., Yu, D., Nakaya, T., & Garcia-Lopez, M. A. (2020). spgwr: Geographically weighted regression [Software]. R package version 0.6-33. Retrieved from https://CRAN.R-project.org/package=spgwr

Black, C., Tesfaigzi, Y., Bassein, J. A., & Miller, L. A. (2017). Wildfire smoke exposure and human health: Significant gaps in research for a growing public health issue. *Environmental Toxicology and Pharmacology*, *55*, 186–195. https://doi.org/10.1016/j.etap.2017.08.022

Brey, S. J., Ruminski, M., Atwood, S. A., & Fischer, E. V. (2018). Connecting smoke plumes to sources using Hazard Mapping System (HMS) smoke and fire location data over North America. *Atmospheric Chemistry and Physics*, *18*(3), 1745–1761. https://doi.org/10.5194/acp-18-1745-2018

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis*, *28*(4), 281–298. https://doi.org/10.1111/j.1538-4632.1996.tb00936.x

Burke, M., Driscoll, A., Heft-Neal, S., Xue, J., Burney, J., & Wara, M. (2021). The changing risk and burden of wildfire in the United States. *Proceedings of the National Academy of Sciences*, *118*(2), e2011048118. https://doi.org/10.1073/pnas.2011048118

California Department of Forestry and Fire Protection (CDFFP). (2018). Incident archive. Retrieved from https://www.fire.ca.gov/incidents/2018/

Centers for Disease Control and Prevention. (2021). CDC SVI documentation 2014. Centers for disease Control and prevention. Retrieved from https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2014.html

Chen, G., Guo, Y., Yue, X., Tong, S., Gasparrini, A., Bell, M. L., et al. (2021). Mortality risk attributable to wildfire-related PM2.5 pollution: A global time series study in 749 locations. *The Lancet Planetary Health*, *5*(9), e579–e587. https://doi.org/10.1016/s2542-5196(21)00200-x

Danielsen, P. H., Møller, P., Jensen, K. A., Sharma, A. K., Wallin, H. K., Bossi, R., et al. (2011). Oxidative stress, DNA damage, and inflammation induced by ambient air and wood smoke particulate matter in human A549 and THP-1 cell lines. *Chemical Research in Toxicology*, *24*(2), 168–184. https://doi.org/10.1021/tx100407m

Ebisu, K., Malig, B., Hasheminassab, S., & Sioutas, C. (2019). Age-specific seasonal associations between acute exposure to PM2.5 sources and cardiorespiratory hospital admissions in California. *Atmospheric Environment*, *218*, 117029. https://doi.org/10.1016/j.atmosenv.2019.117029

Fotheringham, A. S., Brundson, C., & Charlton, M. (2002). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley and Sons, Ltd.

Fried, J. S., Torn, M. S., & Mills, E. (2004). The impact of climate change on wildfire severity: A regional forecast for northern California. *Climatic Change*, *64*(1), 169–191. https://doi.org/10.1023/b:clim.0000024667.89579.ed

Henderson, S. B., & Johnston, F. H. (2012). Measures of forest fire smoke exposure and their associations with respiratory health outcomes. *Current Opinion in Allergy and Clinical Immunology*, *12*(3), 221–227. https://doi.org/10.1097/aci.0b013e328353351f

Hoek, G., Krishnan, R. M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., & Kaufman, J. D. (2013). Long-term air pollution exposure and cardio-respiratory mortality: A review. *Environmental Health*, *12*(1), 43. https://doi.org/10.1186/1476-069x-12-43

IPCC. (2022). Summary for policymakers. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, et al. (Eds.), *Climate change 2022: Impacts, adaptation, and vulnerability. Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change*. Cambridge University Press.

Jaffe, D. A., Wigder, N., Downey, N., Pfister, G., Boynard, A., & Reid, S. B. (2013). Impact of wildfires on ozone exceptional events in the western US. *Environmental Science & Technology*, *47*(19), 11065–11072. https://doi.org/10.1021/es402164f

Johnston, F. H., Henderson, S. B., Chen, Y., Randerson, J. T., Marlier, M., DeFries, R. S., et al. (2012). Estimated global mortality attributable to smoke from landscape fires. *Environmental Health Perspectives*, *120*(5), 695–701. https://doi.org/10.1289/ehp.1104422

Karthikeyan, S., Balasubramanian, R., & Iouri, K. (2006). Particulate air pollution from bushfires: Human exposure and possible health effects. *Journal of Toxicology and Environmental Health, Part A*, *69*(21), 1895–1908. https://doi.org/10.1080/15287390600751264

Kennedy, M. C., Bart, R. R., Tague, C. L., & Choate, J. S. (2021). Does hot and dry equal more wildfire? Contrasting short- and long-term climate effects on fire in the Sierra Nevada, CA. *Ecosphere*, *12*(7), e03657. https://doi.org/10.1002/ecs2.3657

Kim, S. Y., Peel, J. L., Hannigan, M. P., Dutton, S. J., Sheppard, L., Clark, M. L., & Vedal, S. (2012). The temporal lag structure of short-term associations of fine particulate matter chemical constituents and cardiovascular and respiratory hospitalizations. *Environmental Health Perspectives*, *120*(8), 1094–1099. https://doi.org/10.1289/ehp.1104721

Kim, Y. H., Warren, S. H., Krantz, Q. T., King, C., Jaskot, R., Preston, W. T., et al. (2018). Mutagenicity and lung toxicity of smoldering vs. flaming emissions from various biomass fuels: Implications for health effects from wildland fires. *Environmental Health Perspectives*, *126*(1), 017011. https://doi.org/10.1289/ehp2200

Kondo, M. C., De Roos, A. J., White, L. S., Heilman, W. E., Mockrin, M. H., Gross-Davis, C. A., & Burstyn, I. (2019). Meta-analysis of heterogeneity in the effects of wildfire smoke exposure on respiratory health in north America. *International Journal of Environmental Research and Public Health*, *16*(6), 960. https://doi.org/10.3390/ijerph16060960

Kurt, O. K., Zhang, J., & Pinkerton, K. E. (2016). Pulmonary health effects of air pollution. *Current Opinion in Pulmonary Medicine*, *22*(2), 138–143. https://doi.org/10.1097/mcp.0000000000000248

Liu, J. C., Mickley, L. J., Sulprizio, M. P., Dominici, F., Yue, X., Ebisu, K., et al. (2016). Particulate air pollution from wildfires in the Western US under climate change. *Climatic Change*, *138*(3–4), 655–666. https://doi.org/10.1007/s10584-016-1762-6

Liu, J. C., Pereira, G., Uhl, S. A., Bravo, M. A., & Bell, M. L. (2015). A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research*, *136*, 120–132. https://doi.org/10.1016/j.envres.2014.10.015

Liu, J. C., Wilson, A., Mickley, L. J., Ebisu, K., Sulprizio, M. P., Wang, Y., et al. (2017). Who among the elderly is most vulnerable to exposure to and health risks of fine particulate matter from wildfire smoke? *American Journal of Epidemiology*, *186*(6), 730–735. https://doi.org/10.1093/aje/kwx141

Malig, B. J., Green, S., Basu, R., & Broadwin, R. (2013). Coarse particles and respiratory emergency department visits in California. *American Journal of Epidemiology*, *178*(1), 58–69. https://doi.org/10.1093/aje/kws451

McClure, C. D., & Jaffe, D. A. (2018). US particulate matter air quality improves except in wildfire-prone areas. *Proceedings of the National Academy of Sciences*, *115*(31), 7901–7906. https://doi.org/10.1073/pnas.1804353115

NASA Earth Observatory. (2021). What's behind California's surge of large fires? Retrieved from https://earthobservatory.nasa.gov/images/148908/whats-behind-californias-surge-of-large-fires

O'Dell, K., Bilsback, K., Ford, B., Martenies, S. E., Magzamen, S., Fischer, E. V., & Pierce, J. R. (2021). Estimated mortality and morbidity attributable to smoke plumes in the United States: Not just a western US problem. *GeoHealth*, *5*(9), e2021GH000457. https://doi.org/10.1029/2021gh000457

Ostro, B., Malig, B., Hasheminassab, S., Berger, K., Chang, E., & Sioutas, C. (2016). Associations of source-specific fine particulate matter with emergency department visits in California. *American Journal of Epidemiology*, *184*(6), 450–459. https://doi.org/10.1093/aje/kwv343

Rappold, A. G., Cascio, W. E., Kilaru, V. J., Stone, S. L., Neas, L. M., Devlin, R. B., & Diaz-Sanchez, D. (2012). Cardio-respiratory outcomes associated with exposure to wildfire smoke are modified by measures of community health. *Environmental Health*, *11*(1), 71. https://doi.org/10.1186/1476-069x-11-71

Reid, C. E., Brauer, M., Johnston, F. H., Jerrett, M., Balmes, J. R., & Elliott, C. T. (2016a). Critical review of health impacts of wildfire smoke exposure. *Environmental Health Perspectives*, *124*(9), 1334–1343. https://doi.org/10.1289/ehp.1409277

Reid, C. E., Jerrett, M., Tager, I. B., Petersen, M. L., Mann, J. K., & Balmes, J. R. (2016b). Differential respiratory health effects from the 2008 northern California wildfires: A spatiotemporal approach. *Environmental Research*, *50*, 227–235. https://doi.org/10.1016/j.envres.2016.06.012

Richardson, D., Black, A. S., Irving, D., Matear, R. J., Monselesan, D. P., Risbey, J. S., et al. (2022). Global increase in wildfire potential from compound fire weather and drought. *npj Climate and Atmospheric Science*, *5*(1), 23. https://doi.org/10.1038/s41612-022-00248-4

Spielman, S. E., Tuccillo, J., Folch, D. C., Schweikert, A., Davies, R., Wood, N., & Tate, E. (2020). Evaluating social vulnerability indicators: Criteria and their application to the social vulnerability index. *Natural Hazards*, *100*(1), 417–436. https://doi.org/10.1007/s11069-019-03820-z

Sullivan, A. L. (2009). Wildland surface fire spread modeling, 1990–2007. *International Journal of Wildland Fire*, *18*(4), 369–386. https://doi.org/10.1071/wf06142

US EPA. (2021). National ambient air quality standards (NAAQS) for PM. Retrieved from https://www.epa.gov/pm-pollution/national-ambient-air-quality-standards-naaqs-pm

Wegesser, T. C., Pinkerton, K. E., & Last, J. A. (2009). California wildfires of 2008: Coarse and fine particulate matter toxicity. *Environmental Health Perspectives*, *117*(6), 893–897. https://doi.org/10.1289/ehp.0800166

Westerling, A. L., Cayan, D. R., Brown, T. J., Hall, B. L., & Riddle, L. G. (2004). Climate, Santa Ana winds and autumn wildfires in southern California. *Eos*, *85*(31), 289–296. https://doi.org/10.1029/2004eo310001

Wheeler, D. C., & Páez, A. (2010). Geographically weighted regression. In M. M. Fischer & A. Getis (Eds.), *Handbook of applied spatial analysis: Software tools, method, and application* (pp. 461–486). Springer. https://doi.org/10.1007/978-3-642-03647-7_22

Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P. (2019). Observed impacts of anthropogenic climate change on wildfire in California. *Earth's Future*, *7*(8), 892–910. https://doi.org/10.1029/2019ef001210

Williams, K. M., Franzi, L. M., & Last, J. A. (2013). Cell-specific oxidative stress and cytotoxicity after wildfire coarse particulate matter instillation into mouse lung. *Toxicology and Applied Pharmacology*, *266*(1), 48–55. https://doi.org/10.1016/j.taap.2012.10.017

World Health Organization. (2021). *WHO global air quality guidelines: Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. World Health Organization. Retrieved from https://apps.who.int/iris/handle/10665/345329