Environment International 203 (2025) 109770

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Full length article

# Associations between $PM_{2.5}$ from prescribed burning and emergency department visits in 11 Southeastern US states

Jennifer D. Stowell [a,*], Kamal J. Maji [b], Zongrun Li [c], Yongtao Hu [c], Ambarish Vaidyanathan [c], Chad Milando [a], Armistead G. Russell [c], Patrick L. Kinney [a], M. Talat Odman [c], Gregory A. Wellenius [a]

[a] Department of Environmental Health, Boston University School of Public Health, 715 Albany Street, Boston, MA 02118, USA
[b] Department of Public Health, Environments, and Society, London School of Hygiene & Tropical Medicine (LSHTM), Keppel Street, WC1E 7HT London, UK
[c] School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Dr NW, Atlanta, GA 30332, USA

ARTICLE INFO

Handling Editor: Adrian Covaci

*Keywords:*
Prescribed fire
Smoke
Air pollution
Health impacts
Social vulnerability

ABSTRACT

Longer, more severe wildfire seasons are becoming the norm in fire-prone areas. Prescribed burning is a tool used to mitigate wildfire spread. However, prescribed burning also contributes to air pollution, including $PM_{2.5}$ (particulate matter with aerodynamic diameter <= 2.5 μm). While the health impacts of wildfire smoke (WFS) are well-studied, relatively less is known about the effects of prescribed fire smoke (PFS). Our study leverages healthcare claims available for residents of 11 Southeastern US states (2013–2021) to investigate the health impacts associated with PFS. We used a chemical transport model (CTM) and data fusion-based method to estimate county-level outdoor PFS-specific $PM_{2.5}$ concentrations and employed a time-stratified case-crossover design to quantify the relative risk of emergency department (ED) visits associated with $PM_{2.5}$ levels lagged 0–3 days. Models adjusted for non-prescribed fire $PM_{2.5}$ and $O_3$, temperature, humidity, and holidays. We also examined how relative risks varied across population subgroups. PFS-specific $PM_{2.5}$ was associated with a relative risk of ED visits for non-external causes (1.01, 95 % confidence interval (CI): 1.01, 1.02) comparing 4.3 $\mu g/m_3$ (95th percentile) versus 0 $\mu g/m^3$, upper respiratory infections (1.04, 95 % CI: 1.01, 1.07), and ischemic heart disease (1.06, 95 % CI: 1.01, 1.11). We did not observe an increased risk for overall respiratory outcomes, asthma, or COPD, which differs from published WFS findings. Relative risks varied across outcomes and modestly across population subgroups defined by age and markers of social vulnerability. However, after correcting for multiple comparisons, these differences were not significant. Some findings differed from associations previously reported elsewhere for WFS, highlighting the need for direct comparisons of the health impacts of WFS versus PFS for evaluating safety of prescribed burning as a fire management tool.

## 1. Introduction

Since the 1980s, the US has experienced a dramatic increase in wildfire activity, with record-breaking fire seasons becoming increasingly common (Westerling et al., 2006). In recent years, heightened wildfire activity has led to a doubling of the land area burned annually (Abatzoglou and Williams, 2016). This trend is closely linked to climate change, which has extended the fire weather season, characterized by high temperatures and low humidity (Abatzoglou and Williams, 2016). Wildland fires, including both wildfires and prescribed burns, have emerged as a major contributor to outdoor air pollution, accounting for over 30 % of the nation's primary emissions of fine particulate matter ($PM_{2.5}$) (Jaffe et al., 2020).

Prescribed burning is a strategic land management tool used to reduce the risk of wildfires by reducing hazardous fuel buildup. These controlled burns are carefully planned and executed under specific environmental conditions to minimize the risk of uncontrolled spread of fire and optimize smoke dispersion (Fernandes and Botelho, 2003). Typically, prescribed fires are conducted as low-intensity burns on days with lower temperatures and moderate winds. In the Southeastern US,

* Corresponding author.
*E-mail addresses:* stowellj@bu.edu (J.D. Stowell), kamal.maji@lshtm.ac.uk (K.J. Maji), zli867@gatech.edu (Z. Li), yongtao.hu@ce.gatech.edu (Y. Hu), av41@gatech.edu (A. Vaidyanathan), milando@bu.edu (C. Milando), ar7@gatech.edu (A.G. Russell), pkinney@bu.edu (P.L. Kinney), talat.odman@ce.gatech.edu (M.T. Odman), wellenius@bu.edu (G.A. Wellenius).

https://doi.org/10.1016/j.envint.2025.109770
Received 2 April 2025; Received in revised form 25 August 2025; Accepted 29 August 2025
Available online 1 September 2025

prescribed fires play a particularly significant role in land management practices. This region accounts for approximately 70 % of the nation's permits for prescribed fires, which can have substantial implications for downwind outdoor air quality (Kolden, 2019). In the Southeast, it has been estimated that prescribed fires are responsible for about 80 % of all fire-related emissions of $PM_{2.5}$ (Jaffe et al., 2020). During the peak burning season (January–April), prescribed burning can contribute more than 20 % of daily ambient $PM_{2.5}$ levels in affected areas (Maji et al., 2024). While prescribed burns offer numerous potential ecological benefits, including helping to mitigate the risk of catastrophic wildfires, their impact on air quality presents a complex challenge for environmental managers and public health officials (Schweizer and Cisneros, 2017).

Although the health impacts of wildfire smoke (WFS) exposure have been extensively investigated, the health effects of PFS remain comparatively understudied (Reid et al., 2016; Liu et al., 2015). While it has been suggested that PFS may be less impactful to health when compared to WFS, there is still likely to be some impact which is important to understand if prescribed burning is to be used more ubiquitously (Li et al., 2025; Schollaert et al., 2024; Navarro et al., 2018). This knowledge gap is particularly concerning given that prescribed burns often occur in closer proximity to populated areas than wildfires, potentially exposing more people to smoke on a recurring basis (Williamson et al., 2013). Current research on the health impacts of PFS is limited. Multiple U.S. land management agencies have adopted prescribed burning as a principal strategy to reduce wildfire activity, and the annual acreage burned is expected to increase substantially over the next decade (Sacks et al., 2023; U.S. Forest Service, 2022). Similar to WFS, the PFS research available generally relies on health impact assessments which estimate that prescribed burning could also lead to higher rates of death and emergency department (ED) visits for respiratory disease, albeit likely less than rates linked to WFS (Li et al., 2025; Fann et al., 2018). For example, in a previous study using an all-source $PM_{2.5}$ concentration response function, we estimated that PFS-related $PM_{2.5}$ was responsible for thousands of premature deaths in the United States (Maji et al., 2018). This illustrates the limitation of previous studies that have been restricted to using concentration–response functions derived from epidemiological research on ambient $PM_{2.5}$ (i.e., not source specific) or $PM_{2.5}$ specifically from WFS, which may or may not accurately reflect the health risks associated with PFS (Maji et al., 2024; Connolly et al., 2024).

Potential differences in the impacts of PFS versus WFS may stem from differences in the chemical composition and intensity of emissions (Urbanski et al., 2008). Indeed, the way that an area is burned can have a considerable influence on the resultant smoke (Clark et al., 2025). Prescribed burns tend to burn cooler and consume less fuels compared to wildfires and transition slowly from flaming to smoldering stages, allowing for more complete combustion of fuels (Kelp et al., 2023). As a result, PFS tends to have lower levels of carbon monoxide (CO), methane ($CH_4$), polycyclic aromatic hydrocarbons (PAHs), and $PM_{2.5}$ compared to WFS from an equal amount of fuel burned (Kiely et al., 2024; O'Dell et al., 2020). This is in part due to the types of fuel being burned with prescribed fire targeting finer fuels like grass and underbrush and wildfires burning deeper duff layers and coarse, woody debris. These potential differences may lead to differences in health impacts from these disparate types of smoke (US Environmental Protection Agency, 2021; Jaffe et al., 2020; Aguilera et al., 2021).

To effectively balance the potential benefits versus risks of prescribed burning as a land management tool, it is important to develop a more specific and comprehensive understanding of the potential health impacts of PFS, both in the population overall and within potentially susceptible subgroups. This requires new research on the potential adverse health impacts associated with PFS. In this study, we leverage a large healthcare claims dataset to evaluate the associations between short-term PFS-specific $PM_{2.5}$ outdoor concentrations and ED visits for non-external causes and cardiorespiratory diseases in the Southeast from 2013 to 2021 and explore how these associations vary across subgroups defined by individual and community-level characteristics.

## 2. Data & methods

### 2.1. Health claims data

Information on ED visits was extracted for 2013–2021 from the Optum Labs Data Warehouse (OLDW) for eleven southeastern states: Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Kentucky (KY), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), and Virginia (VA). The OLDW is a longitudinal, real-world data asset with de-identified administrative claims and electronic health record (EHR) data and includes healthcare utilization claims for individuals with commercial or Medicare Advantage health insurance (OPTUMLabs, 2021). Available information includes individual-level data on county of residence, date of service, primary discharge diagnosis, age, and sex. Principal diagnosis codes based on the International Classification of Diseases (utilizing both ICD-9 and ICD-10) were used to identify cause-specific ED visits for all causes, all non-external causes, respiratory diseases, and cardiovascular diseases (Table 1). We also included subcategories of cardiorespiratory disease, including asthma, bronchitis, chronic obstructive pulmonary disease (COPD), upper respiratory infections, cardiac arrest, myocardial infarction, ischemic heart disease, and peripheral cerebrovascular disease (Maji et al., 2024; , Classification of Diseases, n.d.). The number of daily visits was calculated and aggregated by county, cause, age (0–17 years, 18–34 years, 35–64 years, 65 years and older), and sex (female, male).

**Table 1**
Emergency department visits in the Southeastern US for non-external, cardiovascular, and respiratory outcomes, 2013–2021.

| Health Outcome | ICD 9 & ICD 10* | ED Visits (N) | % Total Visits |
|---|---|---|---|
| Total visits | | 13,256,521 | – |
| Non-external causes | 001–799<br>A00–R99 | 10,441,323 | 78.76 |
| Cardiovascular | 390–459<br>I1–I99 | 1,391,411 | 10.50 |
| Acute myocardial infarction | 410<br>I21 | 64,770 | 0.49 |
| Congestive heart disease | 428<br>I50 | 151,314 | 1.14 |
| Dysrhythmia | 427<br>I46.9, I47–I49 | 222,706 | 1.68 |
| Ischemic heart disease | 410–414<br>I20–I25 | 194,477 | 1.47 |
| Peripheral cerebrovascular disease | 433–437, 440, 443:444, 451–453<br>I65–I68, I70, I73, I74, I77, I80–I82, G45, G46 | 213,774 | 1.61 |
| Stroke | 362.3, 430, 431, 433–436<br>G45, H34, I60, I61, I63-I65, I67 | 207,207 | 1.56 |
| Respiratory diseases | 460–519<br>J00-J99 | 1,660,929 | 12.53 |
| Asthma | 493<br>J45 | 144,525 | 1.09 |
| Bronchitis | 490<br>J20, J40 | 207,293 | 1.56 |
| COPD | 491, 492, 496<br>J41-J44 | 255,151 | 1.92 |
| Upper respiratory infections | 460–465, 466.0<br>J00-J06, J21 | 504,496 | 3.81 |

[*] Diagnosis codes defined by the 9th and 10th revisions of the International Classification of Diseases.

### 2.2. Prescribed fire smoke and meteorological data

We estimated daily average PFS-specific $PM_{2.5}$ outdoor concentrations, using 12-km grid resolution with the Weather Research & Forecasting (WRF) model coupled with the Community Multiscale Air Quality (CMAQ) chemical transport model, for 11 US states for all months of the year from 2013 to 2021, as described elsewhere (Maji et al., 2024). Briefly, we first identified prescribed burns from the Fire Inventory (FINN) version 2.5 dataset and then calibrated the burned area using burn permits records (Li et al., 2023; Wiedinmyer et al., 2023). The calibrated burned area from prescribed burns was an input to the BlueSky Modeling Framework to generate hourly PFS-related emissions. Anthropogenic emissions were obtained from the National Emission Inventory (NEI) and CMAQ simulations were conducted first for all emissions and then for emissions that exclude prescribed fire sources.

FINN data provides both fire emissions and burned areas regardless of type of fire (prescribed vs wildfire). FINN emissions estimates rely on generalized global descriptions of fuel types and burned areas from FINN can be different from the ground-based records. On the other hand, NEI provides emissions with a separation of wildfires and prescribed fires which are computed using SMARTFIRE version 2 and various publicly available datasets (Larkin, et al., 2010; Raffuse, et al., 2009; US Environmental Protection Agency, 2016, 2018–2020, 2022; Pouliot et al., 2008; Pouliot et al., 2017). However, since NEI uses a mixture of satellite and burn permit data emissions do not necessarily have uniform accuracy across space. Neither FINN nor NEI provide information on plume rise. To minimize these limitations, we used a fire-type differentiation algorithm to determine prescribed burns among FINN fires (Li et al., 2023). We modified the FINN burned areas with an adjustment factor derived from comparisons with burn permit records. Fuel types and fuel loads in Bluesky are based on the Fuel Characteristic Classification System which contains detailed information on fuels in the US and we utilized the latest emissions factors based on Prichard et al. (2020). Finally, we used the Briggs plume-rise scheme in Bluesky to generate three-dimensional PFS emissions inputs to CMAQ.

To improve data accuracy, the results of chemical transport modeling are fused with $PM_{2.5}$ observations (Friberg et al., 2016; Maji et al., 2024). This method adds greater accuracy to the modeling results by minimizing error across the entire simulation period. However, since we only have observations for total $PM_{2.5}$, we can only fuse them with the results of the simulation for all emissions. The accuracy improvement of the PFS-specific outdoor $PM_{2.5}$ is achieved through a scaling approach where simulated PFS-specific outdoor $PM_{2.5}$ (the difference between the simulation with all emissions and the one without prescribed fire emissions) is scaled by the effect of data fusion on total $PM_{2.5}$. This is accomplished by the following formula:

$$\Delta C_{Rx}^{DF}(\boldsymbol{x},\boldsymbol{t}) = \Delta C_{Rx}^{sim}(\boldsymbol{x},\boldsymbol{t}) \times [C_{all}^{DF}(\boldsymbol{x},\boldsymbol{t})/C_{all}^{sim}(\boldsymbol{x},\boldsymbol{t})]$$

where ($\Delta C_{Rx}^{DF}(\boldsymbol{x},\boldsymbol{t})$) represents the PFS-specific $PM_{2.5}$ (or other pollutant) concentration after scaling, $\Delta C_{Rx}^{sim}(\boldsymbol{x},\boldsymbol{t})$ represents simulated PFS-specific $PM_{2.5}$ concentration, $C_{all}^{DF}(\boldsymbol{x},\boldsymbol{t})$ represents the data-fused total $PM_{2.5}$ concentration, and $C_{all}^{sim}(\boldsymbol{x},\boldsymbol{t})$ reflects simulated total $PM_{2.5}$ concentration. Additional details on our data fusion methods can be found in Maji et al. (2024).

Mean daily temperature and relative humidity were obtained directly from WRF outputs, also at 12-km spatial resolution (Nasa, 2018). Gridded PFS-specific $PM_{2.5}$, non-prescribed fire $PM_{2.5}$, non-prescribed fire $O_3$, and meteorological data were aggregated for each county in the study domain. Exposure and meteorological values were extracted from the cells closest to the population center of each county and aggregated using population weighting to provide population-averaged exposures for each county and day.

### 2.3. Statistical analyses

We modeled the association between mean daily outdoor PFS-specific $PM_{2.5}$ and rates of ED visits using a 1-stage time-stratified case-crossover study design. Cases were aggregated by day and county and matched to referent days by county, calendar year, calendar month, and day of week. The case-crossover design effectively controls for confounding by characteristics that are time-invariant or vary slowly over time, whether such characteristics are observed or unobserved. Estimation was performed using conditional Poisson models and a distributed lag nonlinear framework (DLNM) using lagged values of outdoor PFS-specific $PM_{2.5}$ levels and other variables for up to three days prior to each case and referent day. Based on recent research regarding WFS-specific exposures, we assumed a nonlinear concentration–response relationship for PFS-specific $PM_{2.5}$ using cubic B-splines and internal knots at the 50th and 90th percentiles for lags up to 3 days (Heft-Neal et al., 2023). All models were adjusted for daily mean non-prescribed fire $PM_{2.5}$, non-prescribed fire $O_3$, temperature, relative humidity, and federal holidays. All modeled odds ratios were interpreted as risk ratios (RRs), and we report the RR and its 95 % confidence interval (CI) associated with the 95th percentile of daily PFS-specific outdoor $PM_{2.5}$ levels compared to 0 $\mu g/m^3$. In order to allow for more direct comparisons to other WFS and PFS literature, we also repeated our main analyses using linear terms for exposure and meteorological variables.

In addition to estimating the overall impact of outdoor concentrations on the population, we investigated potential heterogeneity in the relative risk across subgroups of individuals defined by categories of age, sex, and values of the Social Vulnerability Index (SVI) from the US Centers for Disease Control and Prevention (CDC), SVI subthemes, and select population characteristics (Agency for Toxic Substances and Disease Registry, 2020). The SVI is a composite score that includes subthemes of socioeconomic status (Theme 1), household characteristics (Theme 2), racial and ethnic minority status (Theme 3), and housing type and transportation access (Theme 4). These themes were built using 16 variables from the 5-year American Community Survey (ACS) to identify at-risk communities. Additionally, we explored potential heterogeneity in relative risk by select ACS variables, including poverty, education, minority status, crowding, and unemployment. We assessed differences across all subgroups by calculating p-values using the Wald test and evaluated significance after correcting for multiple comparisons using a Bonferroni correction.

We performed multiple sensitivity analyses to test the robustness of the findings. First, we refit the main models with lag-response curves representing lag 0–7 days (rather than lag 0–3 days) to assess the sensitivity of results to this modeling assumption. Second, we refit the main model and treated the main exposure variable as linear rather than nonlinear. Third, we repeated the model using natural cubic splines rather than b-splines and evaluated the importance of knot placement and the number of knots by including one knot at the 50th percentile and three equally spaced knots. Fourth, to account for the potential influence of temperature on a longer time scale, we also repeated the main model using a term for 30-day moving average temperature. Fifth, we compared our main results to models excluding various combinations of covariates, including without non-prescribed fire $O_3$, without relative humidity, without temperature, and without both temperature and relative humidity. Finally, we ran our analyses excluding 2020 to see whether differences in health-seeking behavior during the COVID-19 pandemic affected overall health impacts. All analyses were performed using R version 4.2.1 and the "dlnm" (version 2.4.7) and "survival" (version 3.3–1) statistical packages (Gasparrini, 2011; Therneau, 2020). A 2-sided p-value of $< 0.05$ was used to determine statistical significance.

## 3. Results

### 3.1. Descriptive statistics

Over 13 million ED visits were identified from available records between 2013 and 2021. When comparing to the total population in each state, this cohort includes higher numbers of females, a higher number of adults, and fewer individuals under the age of 18.The number of county-level ED visits varied across the study area (Fig. 1A). Respiratory disease was identified as the primary discharge diagnosis in 12.5 % of ED visits followed by cardiovascular disease in 10.5 % of visits (Table 1). Patients tended to be adults aged 35–64 years (37.2 %) and were predominantly female (55.9 %, Table 2). When comparing age and sex distributions of our cohort to US Census data by state, the cohort

**Table 2**
Number and percent of Southeastern US emergency department visits by subgroup, 2013–2021.

| Description | Subgroup | # ED Visits | % Total Visits |
|---|---|---|---|
| Total | | 13,256,521 | – |
| Sex | Female | 7,404,545 | 55.9 |
| | Male | 5,849,476 | 44.1 |
| Age | 0–17 years | 1,235,977 | 9.0 |
| | 18–34 years | 2,189,090 | 16.5 |
| | 35–64 years | 4,927,077 | 37.2 |
| | 65+ years | 4,904,359 | 37.0 |

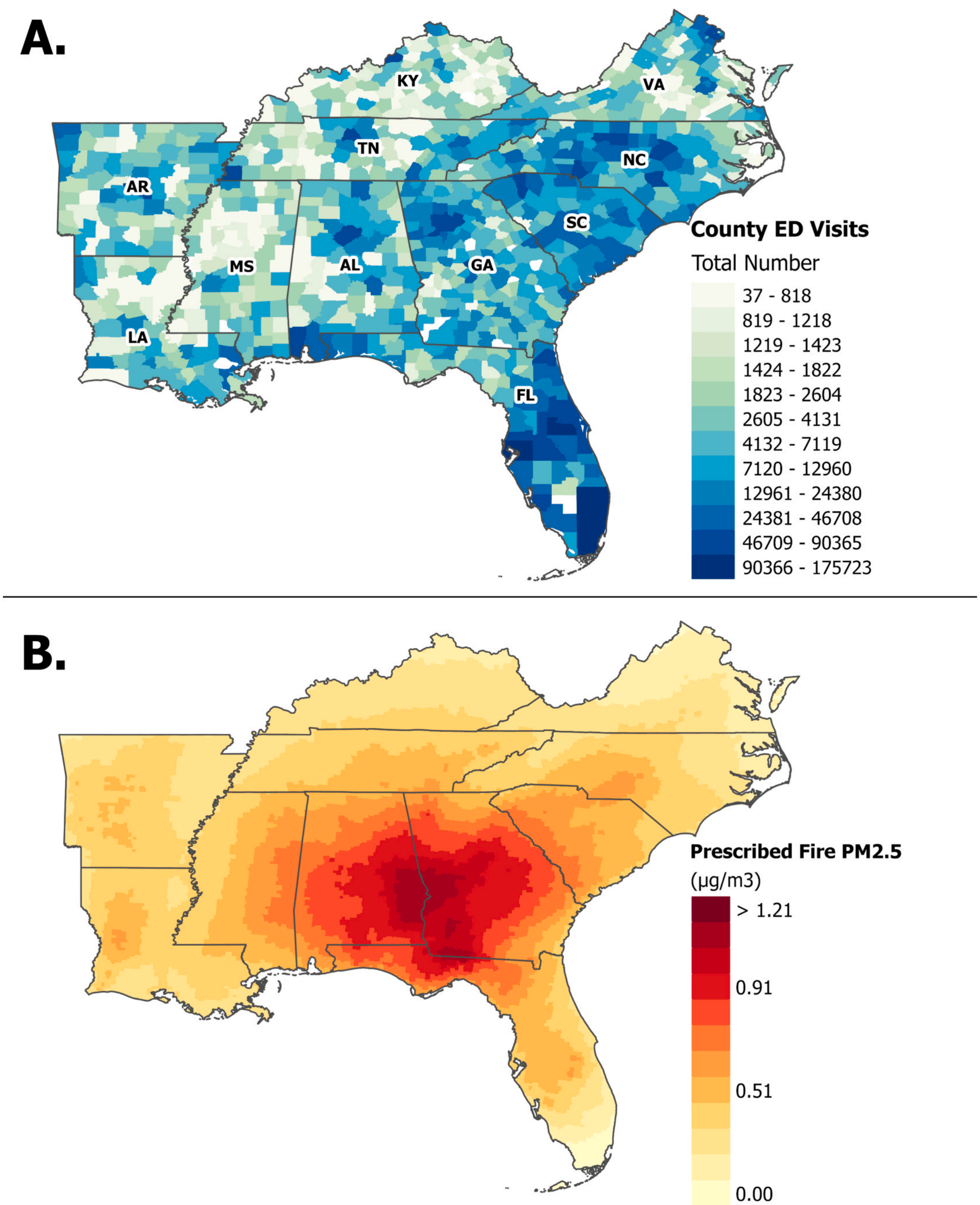


**Fig. 1.** Spatial distribution of emergency department visits and daily mean PFS $PM_{2.5}$, 2013–2021. Panel A: County-level spatial distribution of emergency department visits. Panel B: 12-km resolution spatial distribution of mean daily prescribed fire $PM_{2.5}$ concentrations.

tended to be slightly more female, with higher numbers in the adult age categories (Tables S2 and S3). Summary statistics for $PM_{2.5}$, $O_3$, and meteorological variables are shown in Table S1. After population-weighting, values for individual county-days ranged from 0 to 24.9 μg/$m^3$ (Fig. 2A), with 4.3 μg/$m^3$ representing the 95th percentile of exposure. Population-weighted daily PFS-specific $PM_{2.5}$ concentrations represented up to 22.9 % of the total daily $PM_{2.5}$ concentrations across the study domain, with the highest ratio of PFS-specific $PM_{2.5}$ occurring during February and March (Fig. 1B and Fig. 2B). We observed considerable heterogeneity in daily exposures (Fig. 2C) and in county median exposures (Fig. 2D) across the study domain. While some months had higher region-wide levels of PFS-specific $PM_{2.5}$, we observed continuous year-round PFS-related $PM_{2.5}$ concentrations in parts of the region. Within the study region, the highest daily PFS-specific $PM_{2.5}$ was observed in Kentucky (24.9 μg/$m^3$) on March 16, 2017. However, annual average PFS-specific $PM_{2.5}$ were highest in Georgia and Florida.

### 3.2. Modeled PFS $PM_{2.5}$ variation reflected in ground $PM_{2.5}$ observations

To provide more evidence that modeled PFS variation is reflected in the ground data, we selected 6 Georgia monitoring stations from Macon, Albany, Valdosta, Columbus and Augusta and analyzed their total $PM_{2.5}$ observations versus our predictions of PFS $PM_{2.5}$ during the months of March 2013–2021 (Figs. S1 and S2A–F). While all these sites are affected by PFS, Brunswick is located on the Atlantic Intercoastal Waterway and is mostly protected from PFS. In general, the total $PM_{2.5}$ observations increase in sync with the PFS impacts as predicted by our CMAQ model. However, not all observed $PM_{2.5}$ increases are accompanied by an increase in PFS $PM_{2.5}$. This is likely due to the $PM_{2.5}$ increase not being associated with PFS but another source altogether, or, it may also be due to PFS that our modeling cannot predict due to satellite invisibility or inaccurate predicted wind direction.

### 3.3. Associations between PFS and ED risks

All results are presented as RRs comparing days with extreme levels of PFS-specific $PM_{2.5}$ (95th percentile = 4.3 μg/$m^3$) versus days with no exposure. Fig. 3A illustrates the results from our main model and include 95 % confidence intervals reflecting the uncertainty in the epidemiological models. Outdoor PFS-specific $PM_{2.5}$ was most strongly associated with ischemic heart disease (1.06, 95 % CI: 1.01, 1.11), followed by upper respiratory infections (1.04, 95 % CI: 1.01, 1.07) and non-external causes (1.01, 95 % CI: 1.01, 1.02). We did not observe elevated relative risks for any of the remaining causes considered. Concentration-response functions (Figs. 3B and S4) suggest that the association between PFS-specific $PM_{2.5}$ and relative risk of ED visits for both non-external causes and cardiovascular diseases is monotonic and close to linear. When considering the lag-response function, we found an elevated relative risk of ED visits for non-external causes on lag day 0 (Fig. S5 and Table S4), for asthma, overall cardiovascular disease, and ischemic heart disease on lag day 1, and for upper respiratory infections on lag day 2. After adjusting our models to include only linear exposure and meteorological terms, we noted increased relative risk for non-external causes, overall cardiovascular disease, and ischemic heart disease (Table S5).

Results were mostly consistent across subgroups of the population defined by age and sex, apart from statistically significantly higher relative risk for ED visits for stroke among males ($p = 0.04$) and for dysrhythmias among females ($p = 0.03$, Fig. 4). We also observed only modest evidence of heterogeneity across subgroups of SVI, subthemes of SVI, and select neighborhood characteristics. When evaluating subgroups of SVI scores, we observed little variation across categories of SVI, save for higher relative risk for ischemic heart disease observed in the highest vulnerability category ($p = 0.02$, Fig. 5). We then examined differential relative risk by SVI subthemes 1–4 and select individual community-level characteristics (Fig. S7 A-D). Higher relative risk of ED visits for ischemic heart disease ED were associated with the very high category of Theme 2 (household characteristics, $p = 0.04$), and some variation was evident for ED visits for respiratory disease among those in the very high category of the percentage of individuals without a high school diploma ($p = 0.04$). We observed little meaningful differences across the remaining subgroups (Fig. S8A–E). However, after applying a Bonferroni post-hoc correction for multiple comparisons, the differences across groups did not remain significant.

The results of the sensitivity analyses were generally comparable to the main model for most outcomes (Fig. S9A and B). The largest divergences from the main model were found when removing temperature or both temperature and relative humidity for non-external causes and respiratory diseases. After regenerating the curves for lag 0–7 concentrations, we did not observe significant elevations in relative risk for longer lags (Fig. S6). Some outcomes also had slight changes in effect estimates when modeling using a linear exposure term, including upper respiratory infection, respiratory diseases, and COPD. While the interpretation of the results is the same, these differences tended to increase the RRs, confirming the need to include these variables in the model. Across most models, the exclusion of ozone and choice of knots had very little impact on the results. However, including a 30-day temperature covariate tended to slightly reduce the magnitude of associations for respiratory-related disease categories more than ED visits for cardiovascular-related outcomes. These changes were not significant and did not affect the interpretation of the results. Finally, excluding 2020 data from the analyses had minimal impacts across all outcomes.

## 4. Discussion

Prescribed burning is emerging as a potentially crucial strategy for mitigating wildfire impacts in the United States and worldwide (Pais et al., 2023; Wu et al., 2023). However, this practice contributes to ambient $PM_{2.5}$ levels, and the health risks associated with PFS pollutants remain largely unexplored. Given that prescribed burns are planned, understanding the epidemiology of PFS exposure is important to effectively prepare for and potentially mitigate exposures, thus reducing the overall health burden related to exposure. To address this knowledge gap and understand the implications of prescribed fire practices, we conducted a comprehensive study utilizing a large healthcare claims dataset from 11 Southeastern US states between 2013 and 2021. Employing chemical transport modeled and observation-fused PFS-specific $PM_{2.5}$ data, we assessed the association between prescribed burns and the relative risk of ED visits for various health outcomes and examined how these risks varied across different population subgroups defined by age and sex. The results revealed that PFS-specific $PM_{2.5}$ can account for over 20 % of the daily total $PM_{2.5}$ across the entire study area especially in the months of February and March. The ratio of PFS-specific $PM_{2.5}$ to total $PM_{2.5}$ is likely different in other areas of the county, where prescribed burning is not widely used. However, with continued increasing wildfire activity, the practice of prescribed burning is likely to increase elsewhere. For this analysis, we elected to compare the 95th percentile of exposure to no exposure in order to better understand how PFS impacts health in individuals experiencing more extreme exposures. To inform the wider use of prescribed burning, we estimated positive associations between PFS-specific $PM_{2.5}$ and the relative risks of ED visits for non-external causes, upper respiratory infections, and ischemic heart disease, with some variation in the association across subgroups defined by age, sex, and social vulnerability measures.

Several studies have estimated the potential health impacts of PFS-specific $PM_{2.5}$ based on concentration–response functions from the ambient pollution and/or wildfire literature (Huang et al., 2019; Kiely et al., 2024; Rosenberg et al., 2024; Maji et al., 2024; Maji et al., 2024; Afrin and Garcia-Menendez et al., 2021), but few studies to date have empirically evaluated the human health impacts of PFS. In one such

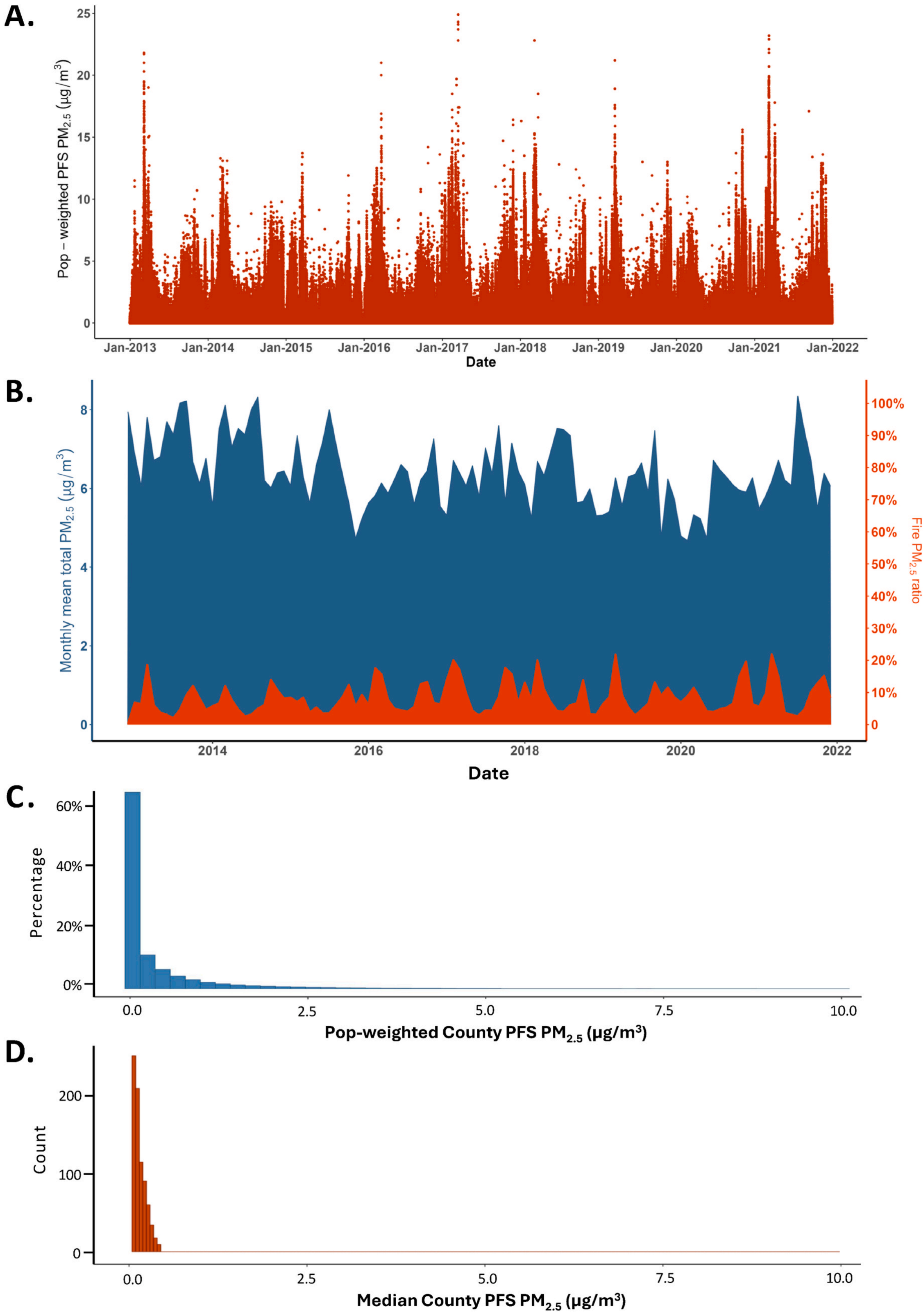


**Fig. 2.** Time series data for county-level prescribed fire-specific $PM_{2.5}$ from 2013 to 2021 in the Southeastern US. Panel A) population-weighted daily mean concentrations of prescribed fire $PM_{2.5}$ by county and day across the study period. Panel B) Population-weighted monthly mean prescribed fire $PM_{2.5}$ as a ratio of total $PM_{2.5}$ for the entire study domain and across the study period. Panel C: Density of modeled PFS $PM_{2.5}$ as a percentage of the total data points, truncated to 10 μg/m$^3$. Panel D) Median county PFS $PM_{2.5}$ concentrations for the entire study period truncated to 10 μg/m$^3$.

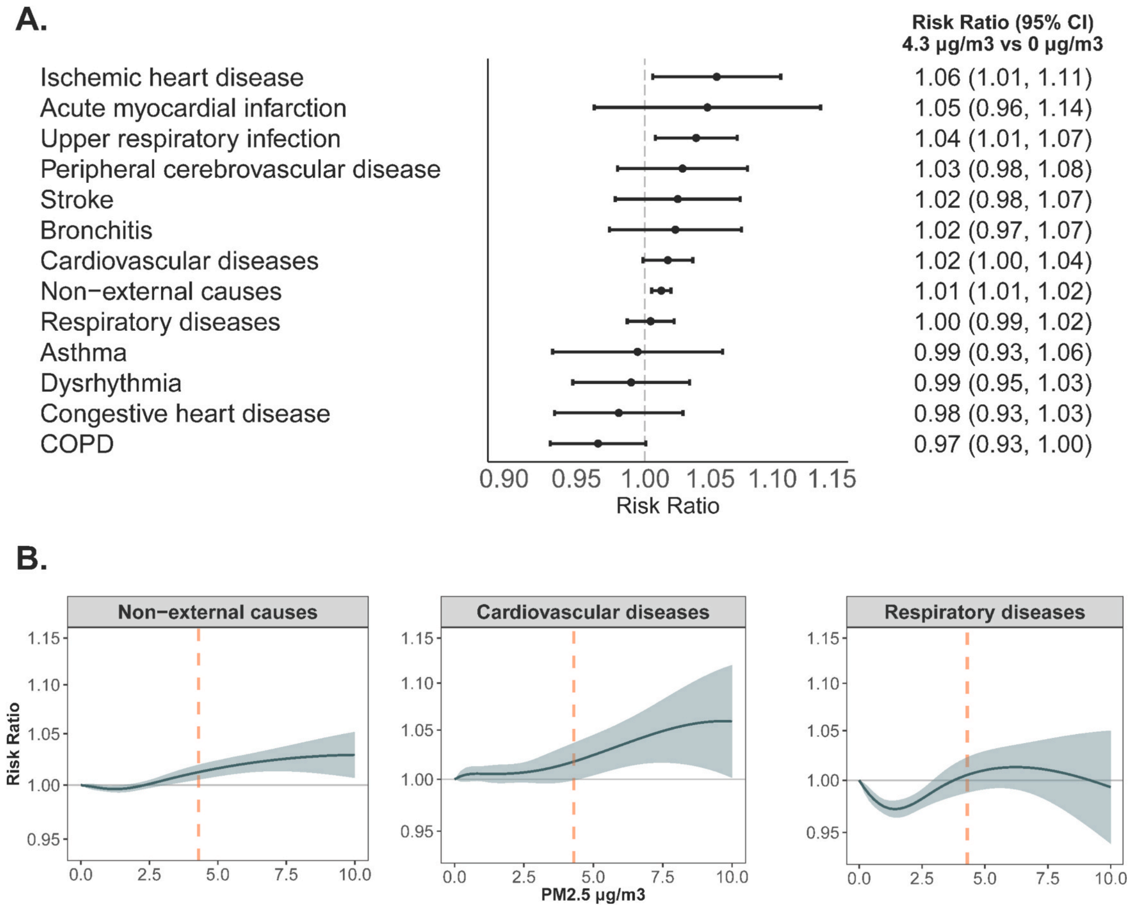


Fig. 3. Associations of outdoor prescribed fire-specific $PM_{2.5}$ concentrations with emergency department visits for specific causes in the Southeastern US from 2013 to 2021. Panel A: Changes in relative risk associated with 4.3 μg/m$^3$ (95th percentile) compared to 0 μg/m$^3$. Panel B: Exposure-response curves for main categories of disease and select outcomes with statistically significant higher relative risk at points along the spectrum of concentrations with 4.3 μg/m$^3$ (95th percentile) of PFS represented by the orange line.

study, Raab et al. (2023) leveraged data from the University of North Carolina Healthcare System to characterize the relationship between the number of PFS occurrences and ED visits and hospitalizations for heart failure (Raab et al., 2023). They found inverse associations with total hospital visits related to the number of prescribed burns within 1 km, 2 km, and 5 km of the patient's primary residence. However, the study focused on burn occurrences and not $PM_{2.5}$, only included adults, and results are based on a moderately-sized cohort. In a separate study, Prunicki et al. (2020) used a convenience sample of participants to estimate the impacts of PFS-specific $PM_{2.5}$ on children's immune systems (Prunicki et al., 2019). They found greater health impacts in those exposed to WFS compared to PFS. However, the sample size and selection methods limited the generalizability and interpretation of the results. Our study attempted to move the evidence beyond some of these limitations by leveraging a much larger population-level sample and utilizing novel measures of PFS-specific $PM_{2.5}$ (Sections 2.1 and 2.2).

Our data analysis uncovered only minimal differences in relative risks among various demographic and community subgroups exposed to PFS-specific $PM_{2.5}$. Notably, males displayed an elevated relative risk of ED visits for stroke and females demonstrated a statistically significant higher relative risk for dysrhythmia. Additionally, our investigation into the relationship between socioeconomic vulnerability and PFS-related relative risk revealed that housing conditions and education may contribute to excess relative risk related to ischemic heart disease and respiratory outcomes, respectively (Islam et al., 2021). While we could speculate about the mechanisms linking ED visit relative risk to the SVI and related characteristics, the lack of individual-level data on social vulnerability contribute to uncertainty in our findings and these differences did not remain significant after applying a post-hoc Bonferroni correction. Taken together, these results suggest that individuals are at similar risk of ED visits related to PFS $PM_{2.5}$, regardless of specific individual or community level characteristics.

While the scope of this study did not include direct comparisons between PFS and WFS impacts. Many of the results discussed in Section 3.2 diverge from prior findings from the wildfire literature, highlighting the need for further research into the potential health harms associated specifically with PFS exposure. For example, we did not observe a statistically significant link between PFS-specific $PM_{2.5}$ and overall respiratory outcomes, asthma, or COPD, while a number of prior studies link these outcomes to WFS $PM_{2.5}$ (Fann et al., 2018; Deflorio-Barker et al., 2019; Heaney et al., 2022; Liu et al., 2017; Mirabelli et al., 2009; Reid et al., 2016, 2019; Stowell et al., 2019). While some differences may be due to levels of population exposure, some differences might be explained by smoke pollutant composition. For example, prescribed burns have been shown to produce less than 50 % of $PM_{2.5}$ emissions compared to WFS for the same amount of fuel burned. Wildfires also often burn under hotter, and more oxygen starved conditions. These conditions may produce higher concentrations of hazardous pollutants such as PAHs, some of which are likely carcinogenic (Navarro et al., 2017; Eriksson et al., 2014). To better understand any potential differences between the health impacts of WFS and PFS studies are needed that can examine both exposures in the same health data set and employing consistent modeling approaches (Li et al., 2025).

This study represents a novel investigation of the potential health impacts of outdoor PFS-specific $PM_{2.5}$ concentrations. However, the results should be considered in light of the following limitations. First,

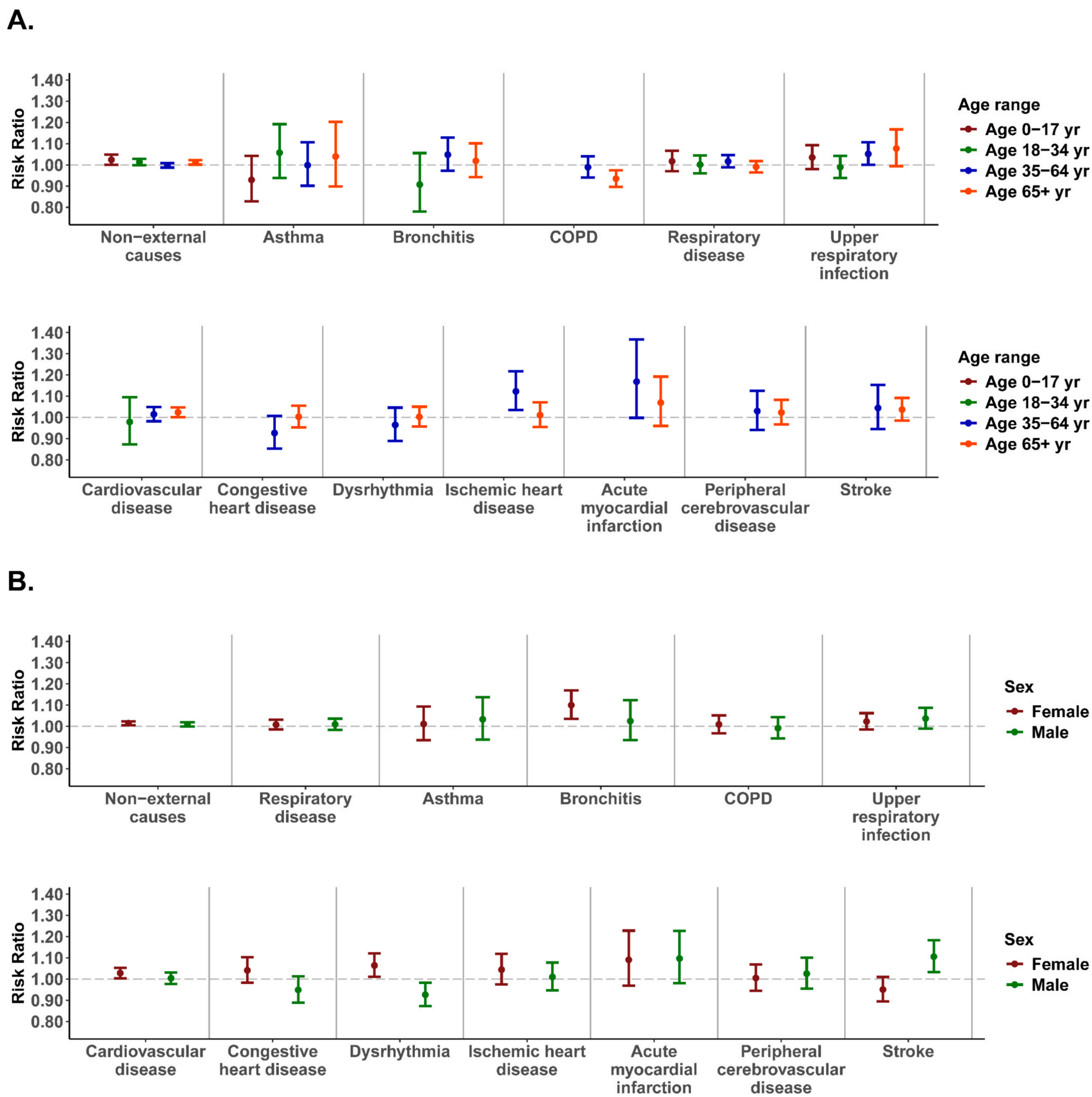


**Fig. 4.** Stratified impacts of outdoor prescribed fire-specific $PM_{2.5}$ levels on ED visits. Risk ratios and 95 % confidence intervals comparing 4.3 μg/m$^3$ (95th percentile) to 0 μg/m$^3$ stratified by subgroups of age (Panel A) and sex (Panel B).

the methods used for PFS exposure assessment utilize satellite data, which often miss smaller burns, burns outside overpass times, and burns masked by cloud cover. Despite using version 2.5 of FINN, small fires may still be missing from the analysis, potentially underestimating actual exposures. Second, the study population includes only individuals with commercial or Medicare Advantage health insurance, precluding the study of these exposures in some of the most marginalized populations. This systematic exclusion may have led us to underestimate the true health impacts of PFS in the broader population. Third, despite important strengths of our exposure modeling strategy, some degree of exposure error is unavoidable as the health data were only available at the county level and we lacked data on individual-level time activity patterns. While the current literature is unclear regarding differences in effects by spatial resolution, the use of county-level data may mask higher spikes in exposures at more granular resolutions, suggesting that these results may underestimate actual impacts of exposure. In addition, our selection of12-km resolution PFS exposure aggregated to the county level was chosen as a compromise between extreme computational costs and the size of exposure fields used for health assessments, However, this may bias our results either toward or away from the null. While we are unable to evaluate this bias in our current paper, we do not expect the bias to be differential. Fourth, the lack of access to individual-level data limited our ability to fully characterize factors that may affect vulnerability beyond age, sex, and community-level markers such as SVI. Finally, this study was only conducted in the Southeastern region of the US, and results may not be generalizable to other regions. Future

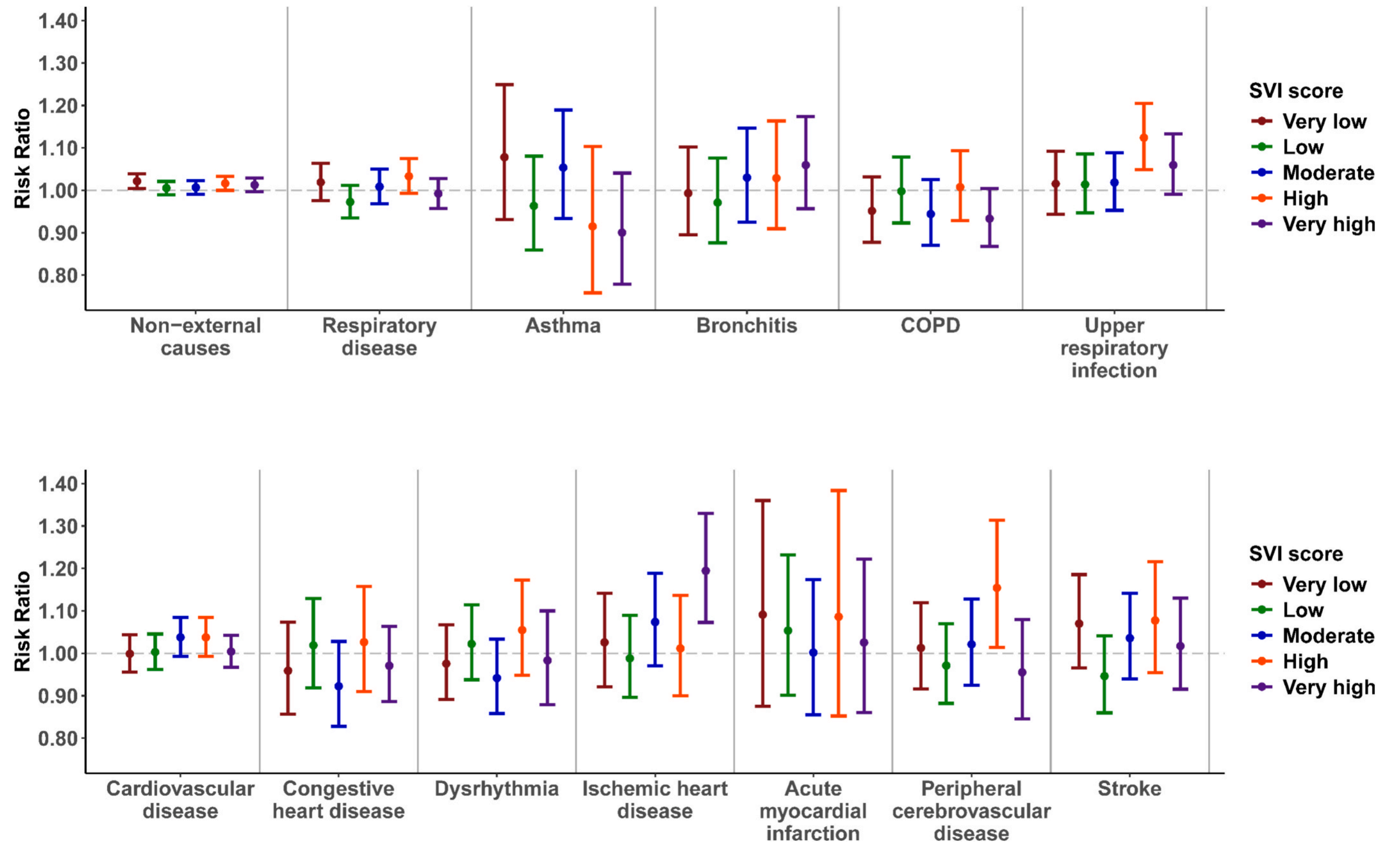


**Fig. 5.** Impacts of outdoor prescribed fire-specific $PM_{2.5}$ concentrations on ED visits by categories of SVI. Risk ratios and 95 % confidence intervals comparing 4.3 μg/$m^3$ (95th percentile) to 0 μg/$m^3$ stratified by categories of social vulnerability index (SVI) score.

studies would benefit from more granular data on individual characteristics to minimize errors in exposure assessment and more fully understand vulnerability.

## 5. Conclusions

In summary, this study provides novel insights into the potential adverse health impacts of outdoor PFS-specific $PM_{2.5}$ concentrations in the Southeastern US. The results revealed statistically significant elevations in the relative risk of ED visits for non-external causes, ischemic heart disease, and upper respiratory infections associated with PFS-specific $PM_{2.5}$, with only modest variation across subgroups defined by age, sex, and contextual markers of social vulnerability. While these results indicate little variation in relative risk across subgroups, additional data at the individual level is needed to refine subgroup definitions and provide more detailed insights. Interestingly, our main findings diverge from the broader literature on WFS exposure, which typically reports strong associations with respiratory disease (including asthma and COPD) and variation by susceptibility and vulnerability. These results underscore the value of a more comprehensive understanding of the potential adverse health impacts associated with PFS exposure, as it is increasingly used as a land and fire management tool. To inform effective decision-making regarding land management practices and public health protection, additional research directly comparing the health effects of WFS and PFS-related exposures is needed.

## CRediT authorship contribution statement

**Jennifer D. Stowell:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kamal J. Maji:** Writing – review & editing, Data curation. **Zongrun Li:** Writing – review & editing, Data curation. **Yongtao Hu:** Writing – review & editing, Data curation. **Ambarish Vaidyanathan:** Writing – review & editing, Conceptualization. **Chad Milando:** Writing – review & editing, Data curation. **Armistead G. Russell:** Writing – review & editing, Funding acquisition, Conceptualization. **Patrick L. Kinney:** Writing – review & editing, Funding acquisition, Conceptualization. **M. Talat Odman:** Writing – review & editing, Funding acquisition, Conceptualization. **Gregory A. Wellenius:** Writing – review & editing, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Wellenius has recently served as a consultant for Google, LLC (Mountain View, CA) and currently serves as a consultant for the Health Effects Institute (Boston, MA). The authors declare that they have no other known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

Research described in this article was conducted under Research Agreement No. 4988-RFA20-1A/21-11 between Georgia Institute of Technology, Boston University, and the Health Effects Institute (HEI).

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2025.109770.

## Data availability

All exposure data, including prescribed fire smoke concentrations and meteorology, will be publicly available at time of publication (https://zenodo.org/records/13380570). The health data is used through a proprietary agreement with Optum Labs and interested parties should contact them directly through their website at https://labs.optum.com/. For General information about Optum Labs data please visit: https://business.optum.com/en/data-analytics/life-sciences/real-world-data/claims-data.html.

## References


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

Afrin, S., Garcia-Menendez, F., 2021. Potential impacts of prescribed fire smoke on public health and socially vulnerable populations in a Southeastern U.S. state. Sci. Total Environ. 794, 148712. https://doi.org/10.1016/j.scitotenv.2021.148712.

Agency for Toxic Substances and Disease Registry, 2020. CDC/ATSDR Social Vulnerability Index, <https://www.atsdr.cdc.gov/placeandhealth/svi/index.html>.

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. Nat. Commun. 12, 1493. https://doi.org/10.1038/s41467-021-21708-0.

Clark, N., Urbanski, S., Goodrich, S., 2025. Smoke and difference between wildfire and prescribed fire smoke in the western United States. US Forest Service Res. Develop.

Classification of Diseases, Functioning, and Disability. <https://www.cdc.gov/nchs/icd/index.html>.

Connolly, R., et al., 2024. Mortality attributable to PM<sub>2.5</sub> from wildland fires in California from 2008 to 2018. Sci. Adv. 10, eadl1252. https://doi.org/10.1126/sciadv.adl1252.

Deflorio-Barker, S., Crooks, J., Reyes, J., Rappold, A.G., 2019. Cardiopulmonary effects of fine particulate matter exposure among older adults, during wildfire and non-wildfire periods, in the United States 2008-2010. Environ. Health Perspect. 127. https://doi.org/10.1289/ehp3860.

Eriksson, A.C., et al., 2014. Particulate PAH emissions from residential biomass combustion: time-resolved analysis with aerosol mass spectrometry. Environ. Sci. Technol. 48, 7143–7150. https://doi.org/10.1021/es500486j.

Fann, N., et al., 2018. The health impacts and economic value of wildland fire episodes in the US: 2008-2012. Sci. Total Environ. 610, 802–809. https://doi.org/10.1016/j.scitotenv.2017.08.024.

Fernandes, P.M., Botelho, H.S., 2003. A review of prescribed burning effectiveness in fire hazard reduction. Int. J. Wildland Fire 12, 117–128. https://doi.org/10.1071/WF02042.

Friberg, M.D., et al., 2016. Method for fusing observational data and chemical transport model simulations to estimate spatiotemporally resolved ambient air pollution. Environ. Sci. Technol. 50, 3695–3705. https://doi.org/10.1021/acs.est.5b05134.

Gasparrini, A., 2011. Distributed lag linear and non-linear models in R: the package dlnm. J. Stat. Softw. 43, 1–20. https://doi.org/10.18637/jss.v043.i08.

Heaney, A., et al., 2022. Impacts of fine particulate matter from wildfire smoke on respiratory and cardiovascular health in California. Geohealth 6. https://doi.org/10.1029/2021GH000578.

Heft-Neal, S., et al., 2023. Emergency department visits respond nonlinearly to wildfire smoke. Proc. Natl. Acad. Sci. 120, e2302409120. https://doi.org/10.1073/pnas.2302409120.

Huang, R., Hu, Y.T., Russell, A.G., Mulholland, J.A., Odman, M.T., 2019. The impacts of prescribed fire on PM<sub>2.5</sub> air quality and human health: application to asthma-related emergency room visits in Georgia, USA. Int. J. Environ. Res. Public Health 16. https://doi.org/10.3390/ijerph16132312.

Islam, M., Sultana, Z.Z., Iqbal, A., Ali, M., Hossain, A., 2021. Effect of in-house crowding on childhood hospital admissions for acute respiratory infection: a matched case–control study in Bangladesh. Int. J. Infect. Dis. 105, 639–645. https://doi.org/10.1016/j.ijid.2021.03.002.

Jaffe, D.A., et al., 2020. Wildfire and prescribed burning impacts on air quality in the United States. J. Air Waste Manag. Assoc. 70, 583–615. https://doi.org/10.1080/10962247.2020.1749731.

Kelp, M.M., et al., 2023. Prescribed burns as a tool to mitigate future wildfire smoke exposure: lessons for states and rural environmental justice communities. Earth's Future 11, e2022EF003468. https://doi.org/10.1029/2022EF003468.

Kiely, L., et al., 2024. California case study of wildfires and prescribed burns: PM2.5 emissions, concentrations, and implications for human health. Environ. Sci. Technol. 58, 5210–5219. https://doi.org/10.1021/acs.est.3c06421.

Kiely, L., et al., 2024. California case study of wildfires and prescribed burns: PM<sub>2.5</sub> emissions, concentrations, and implications for human health. Environ. Sci. Technol. 58, 5210–5219. https://doi.org/10.1021/acs.est.3c06421.

Kolden, C.A., 2019. We're not doing enough prescribed fire in the western United States to mitigate wildfire risk. Fire 2, 30.

Larkin, N., et al., 2010. Developing an Improved Wildland Fire Emissions Inventory.

Li, Z., et al., 2023. An analysis of prescribed fire activities and emissions in the Southeastern United States from 2013 to 2020. Remote Sens. (Basel) 15, 2725.

Li, Z., et al., 2025. The trade-offs between wildfires and prescribed fires: a case study for 2016 Gatlinburg wildfires. ACS ES&T Air 2, 236–248. https://doi.org/10.1021/acsestair.4c00233.

Liu, J.C., et al., 2017. Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties. Epidemiology 28, 77–85. https://doi.org/10.1097/ede.0000000000000556.

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. Environ. Res. 136, 120–132. https://doi.org/10.1016/j.envres.2014.10.015.

Maji, K.J., et al., 2024. Estimated impacts of prescribed fires on air quality and premature deaths in Georgia and surrounding areas in the US, 2015-2020. Environ. Sci. Technol. 58, 12343–12355. https://doi.org/10.1021/acs.est.4c00890.

Maji, K.J., et al., 2024. Estimated impacts of prescribed fires on air quality and premature deaths in Georgia and surrounding areas in the US, 2015–2020. Environ. Sci. Technol. 58, 12343–12355. https://doi.org/10.1021/acs.est.4c00890.

Maji, K.J., et al., 2024. Prescribed burn related increases of population exposure to PM2.5 and O3 pollution in the Southeastern US over 2013–2020. Environ. Int. 193, 109101. https://doi.org/10.1016/j.envint.2024.109101.

Maji, K.J., et al., 2024. Prescribed burn related increases of population exposure to $PM_{2.5}$ and $O_3$ pollution in the southeastern US over 2013–2020. Environ. Int. 193, 5. https://doi.org/10.1016/j.envint.2024.109101.

Maji, K.J., Dikshit, A.K., Arora, M., Deshpande, A., 2018. Estimating premature mortality attributable to PM2.5 exposure and benefit of air pollution control policies in China for 2020. Sci. Total Environ. 612, 683–693. https://doi.org/10.1016/j.scitotenv.2017.08.254.

Mirabelli, M.C., et al., 2009. Respiratory symptoms following wildfire smoke exposure airway size as a susceptibility factor. Epidemiology 20, 451–459. https://doi.org/10.1097/EDE.0b013e31819d128d.

Nasa, 2018.

Navarro, K.M., Cisneros, R., Noth, E.M., Balmes, J.R., Hammond, S.K., 2017. Occupational exposure to polycyclic aromatic hydrocarbon of wildland firefighters at prescribed and wildland fires. Environ. Sci. Technol. 51, 6461–6469. https://doi.org/10.1021/acs.est.7b00950.

Navarro, K.M., Schweizer, D., Balmes, J.R., Cisneros, R., 2018. A review of community smoke exposure from wildfire compared to prescribed fire in the United States. Atmosphere 9, 185.

O'Dell, K., et al., 2020. Hazardous air pollutants in fresh and aged western US wildfire smoke and implications for long-term exposure. Environ. Sci. Technol. 54, 11838–11847. https://doi.org/10.1021/acs.est.0c04497.

OPTUMLabs, 2021. OLDW, <https://www.optumlabs.com/>.

Pais, S., Aquilué, N., Honrado, J.P., Fernandes, P.M., Regos, A., 2023. Optimizing wildfire prevention through the integration of prescribed burning into 'fire-smart' land-use policies. Fire 6, 457.

Pouliot, G., Pace, T., Biswadev, R., Pierce, T., Mobley, D., 2008. Development of a biomass burning emissions inventory by combining satellite and ground-based information. J. Appl. Remote Sens. 2, 021501.

Pouliot, G., Rao, V., McCarty, J.L., Soja, A., 2017. Development of the crop residue and rangeland burning in the 2014 National Emissions Inventory using information from multiple sources. J. Air Waste Manage. Assoc. 67, 613–622. https://doi.org/10.1080/10962247.2016.1268982.

Prichard, S.J., et al., 2020. Wildland fire emission factors in North America: synthesis of existing data, measurement needs and management applications. Int. J. Wildland Fire 29, 132–147. https://doi.org/10.1071/WF19066.

Prunicki, M., et al., 2019. The impact of prescribed fire versus wildfire on the immune and cardiovascular systems of children. Allergy 74, 1989–1991. https://doi.org/10.1111/all.13825.

Raab, H., Moyer, J., Afrin, S., Garcia-Menendez, F., Ward-Caviness, C.K., 2023. Prescribed fires, smoke exposure, and hospital utilization among heart failure patients. Environ. Health 22, 86. https://doi.org/10.1186/s12940-023-01032-4.

Raffuse, S., et al., 2009. SMARTFIRE Algorithm Description Report No. STI-905517-3719.

Reid, C.E., et al., 2016. Differential respiratory health effects from the 2008 northern California wildfires: a spatiotemporal approach. Environ. Res. 150, 227–235. https://doi.org/10.1016/j.envres.2016.06.012.

Reid, C.E., et al., 2016. Critical review of health impacts of wildfire smoke exposure. Environ. Health Perspect. 124, 1334–1343. https://doi.org/10.1289/ehp.1409277.

Reid, C.E., et al., 2019. Associations between respiratory health and ozone and fine particulate matter during a wildfire event. Environ. Int. 129, 291–298. https://doi.org/10.1016/j.envint.2019.04.033.

Rosenberg, A., et al., 2024. Health impacts of future prescribed fire smoke: considerations from an exposure scenario in California. Earths Future 12. https://doi.org/10.1029/2023ef003778.

Sacks, J.D., Holder, A.L., Rappold, A.G., Vaidyanathan, A., 2023. At the intersection: protecting public health from smoke while addressing the U.S. wildfire crisis. Am. J. Respir. Crit. Care Med. 208, 755–757. https://doi.org/10.1164/rccm.202304-0744VP.

Schollaert, C.L., Marlier, M.E., Marshall, J.D., Spector, J.T., Busch Isaksen, T., 2024. Exposure to smoke from wildfire, prescribed, and agricultural burns among at-risk populations across Washington, Oregon, and California. Geohealth 8, e2023GH000961. https://doi.org/10.1029/2023GH000961.

Schweizer, D.W., Cisneros, R., 2017. Forest fire policy: change conventional thinking of smoke management to prioritize long-term air quality and public health. Air Qual. Atmosphere Health 10, 33–36. https://doi.org/10.1007/s11869-016-0405-4.

Stowell, J.D., et al., 2019. Associations of wildfire smoke PM2.5 exposure with cardiorespiratory events in Colorado 2011–2014. Environ. Int. 133, 105151. https://doi.org/10.1016/j.envint.2019.105151.

Therneau, T.M., 2020. A Package for Survival Analysis in R. <https://CRAN.R-project.org/package=survival>.
U.S. Forest Service. Confronting the Wildfire Crisis. (U.S. Department of Agriculture, 2022).
Urbanski, S.P., Hao, W.M., Baker, S., 2008. In: Bytnerowicz, Andrzej, Arbaugh, Michael J., Riebau, Allen R., Andersen, Christian (Eds.), Developments in Environmental Science. Elsevier, pp. 79–107.
US Environmental Protection Agency (EPA), 2016. Technical Support Document (TSD): Preparation of Emissions Inventories for the 2016v3 North American Emissions Modeling Platform.
US Environmental Protection Agency (EPA), 2018. Technical Support Document: Preparation of Emissions Inventories for the Version 7.1 2014 Emissions Modeling Platform for the 2014 National Air Toxics Assessment..
US Environmental Protection Agency (EPA), 2019. Technical Support Document (TSD): Preparation of Emissions Inventories for the 2019 North American Emissions Modeling Platform.
US Environmental Protection Agency (EPA), 2020. Technical Support Document (TSD): Preparation of Emissions Inventories for the 2020 North American Emissions Modeling Platform.
US Environmental Protection Agency (EPA), 2021. Comparative Assessment of the Impacts of Prescribed Fire Versus Wildfire (CAIF): A Case Study in the Western U.S.
US Environmental Protection Agency (EPA), 2022. Technical Support Document (TSD): Preparation of Emissions Inventories for the 2017 North American Emissions Modeling Platform.
Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western US forest wildfire activity. Science 313, 940–943. https://doi.org/10.1126/science.1128834.
Wiedinmyer, C., et al., 2023. The Fire Inventory from NCAR version 2.5: an updated global fire emissions model for climate and chemistry applications. Geosci. Model Dev. 16, 3873–3891. https://doi.org/10.5194/gmd-16-3873-2023.
Williamson, G.J., Price, O.F., Henderson, S.B., Bowman, D.M.J.S., 2013. Satellite-based comparison of fire intensity and smoke plumes from prescribed fires and wildfires in south-eastern Australia. Int. J. Wildland Fire 22, 121–129. https://doi.org/10.1071/WF11165.
Wu, X., Sverdrup, E., Mastrandrea, M.D., Wara, M.W., Wager, S., 2023. Low-intensity fires mitigate the risk of high-intensity wildfires in California's forests. Sci. Adv. 9, eadi4123. https://doi.org/10.1126/sciadv.adi4123.