HHS Public Access
Author manuscript
Epidemiology. Author manuscript; available in PMC 2018 January 01.

Published in final edited form as:
Epidemiology. 2017 January ; 28(1): 77–85. doi:10.1097/EDE.0000000000000556.

Wildfire-specific Fine Particulate Matter and Risk of Hospital Admissions in Urban and Rural Counties

Jia Coco Liu[a], **Ander Wilson**[b], **Loretta J Mickley**[c], **Francesca Dominici**[b], **Keita Ebisu**[a], **Yun Wang**[b], **Melissa P Sulprizio**[c], **Roger D Peng**[d], **Xu Yue**[c], **Ji-Young Son**, **G. Brooke Anderson**[e], and **Michelle L. Bell**[a]

[a]School of Forestry and Environmental Studies, Yale University, New Haven, CT

[b]Department of Biostatistics, T.H. Chan School of Public Health, Harvard University, Cambridge, MA, USA

[c]School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA

[d]Department of Biostatistics, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD

[e]Department of Environmental & Radiological Health Sciences, College of Veterinary Medicine & Biomedical Sciences, Colorado State University, Fort Collins, CO, USA

Abstract

Background—The health impacts of wildfire smoke, including fine particles ($PM_{2.5}$), are not well understood and may differ from those of $PM_{2.5}$ from other sources due to differences in concentrations and chemical composition.

Methods—First, for the entire Western US (561 counties) for 2004–2009, we estimated daily $PM_{2.5}$ concentrations directly attributable to wildfires (wildfires-specific $PM_{2.5}$), using a global chemical transport model. Second, we defined *smoke wave* as ≥2 consecutive days with daily wildfire-specific $PM_{2.5}$>20μg/m^3, with sensitivity analysis considering 23μg/m^3, 28μg/m^3, and 37μg/m^3. Third, we estimated the risk of cardiovascular and respiratory hospital admissions associated with smoke waves for Medicare enrollees. We used a generalized linear mixed model to estimate the relative risk of hospital admissions on smoke wave days compared to matched comparison days without wildfire smoke.

Results—We estimated that about 46 million people of all ages were exposed to at least one smoke wave during 2004 to 2009 in the Western US. Of these, 5 million are Medicare enrollees (≥65y). We found a 7.2% (95% confidence interval: 0.25%, 15%) increase in risk of respiratory admissions during smoke wave days with high wildfire-specific $PM_{2.5}$ (>37μg/m^3) compared to matched non-smoke-wave days. We did not observe an association between smoke wave days with wildfire-$PM_{2.5}$≤37μg/m^3 and respiratory or cardiovascular admissions. Respiratory effects of wildfire-specific $PM_{2.5}$ may be stronger than that of $PM_{2.5}$ from other sources.

Corresponding author: Jia Coco Liu, Full postal address: Room 8B, 205 Prospect St, New Haven, CT, USA, 06511, Telephone number: 203-432-9869, coco.liu@yale.edu.

Conflicts of interest: none to declare

Conclusion—Short-term exposure to wildfire-specific $PM_{2.5}$ was associated with risk of respiratory diseases in the elderly population in the Western US during severe smoke days.

Introduction

Wildfires are a growing concern, as climate change is anticipated to increase their frequency, intensity, and spreading speed[1]. Wildfires are known to cause substantial ecologic and economic burden, and the economic costs may be underestimated because they do not account for the potentially severe impact of air pollution from wildfires on human health[2]. Understanding the public health impact of wildfire smoke can inform intervention-focused policies to protect population health and promote more accurate estimates of the consequences of wildfires[3].

The Western US historically suffers from wildfires[4] due to large areas of forests, vegetation, and relatively arid weather. The burning of biomass can dramatically increase levels of toxic air pollutants, such as fine particles ($PM_{2.5}$)[5]. Numerous studies have demonstrated links between all-source particulate matter (PM) measured as total mass and health outcomes, especially for respiratory and cardiovascular diseases[3]. Many studies have indicated that $PM_{2.5}$ raises more human health concerns than coarse PM because the smaller particles penetrate the respiratory system more deeply[6].

The health effects of wildfire-emitted fine particles are not well understood. Wildfire smoke can increase ambient PM levels several times higher than that on days with no wildfire sources[3]. The size of fire-generated PM tends to be small, such as fine particles ($PM_{2.5}$)[7]. The composition of wildfire-generated $PM_{2.5}$ may be different from $PM_{2.5}$ from other sources, which in turn can affect toxicity[8,9]. Wildfires are episodic, making it especially challenging to link wildfire-specific air pollution with health.

We previously performed a literature review of the small number of studies on health impact of wildfire smoke on community populations. We found that the results on the effects of wildfires on hospital admissions were inconsistent, especially for cardiovascular diseases, in the Western US[3]. To date, most of the literature focused on a single fire episode and small population[e.g.10,11,12]. It is unknown whether the health impacts of wildfire-emitted $PM_{2.5}$ differ from those of $PM_{2.5}$ from other sources. As a result, research that investigates health impact from wildfires on a large geographical area and over a long time is needed.

The understanding of the health impact of wildfire-related air pollution is hindered by the challenge of estimating exposure to air pollution that can be specifically attributable to wildfires. Ambient monitors measure $PM_{2.5}$ concentration but cannot distinguish the proportion directly attributable to fires versus other sources. The majority of current wildfire-health studies used air monitoring data, which are limited in spatial (no monitors available in rural areas) and temporal resolution (generally measure every 3–6 days) and cannot isolate wildfire-specific pollution[3].

Our study aimed to address many of these challenges described above. Using a chemical transport model, we could fill in the spatial and temporal gaps of monitoring data and make source attributions of the modeled $PM_{2.5}$. We estimated daily 2004–2009 $PM_{2.5}$

concentrations specifically from wildfires for 561 Western US counties and linked them to daily numbers of Medicare admissions for respiratory and cardiovascular diseases. We applied statistical methods that have not been previously used in wildfire-health studies and estimated health impacts of wildfire-specific $PM_{2.5,}$ incorporating rural populations into statistical analysis.

Methods

Study domain

The study domain is the Western US (lat: 31–49, lon: −101 to −125) (eFigure 1), where wildfires occur frequently[13]. The study region consists of 561 counties in 16 states.

Wildfire modeling

We employed wildfire simulations from the GEOS-Chem chemical transport model (v9-01-03) to generate daily wildfire-specific $PM_{2.5}$ levels for six years (2004–2009). GEOS-Chem is a global 3D atmospheric chemistry model driven by meteorology[14]. It has been used to understand the pollution impact of present-day fires[15,16] and to predict future wildfire-specific aerosols[1,17]. The modeling integrates meteorological data from Goddard Earth Observing System (GEOS-5) of the NASA Modeling and Assimilation Office and observed wildfire area burned based on the Global Fire Emissions Database (GFED3). GFED3 combines satellite observations of fire counts, area burned, and fuel load to produce gridded, daily maps of wildfire emissions[18,19].

The GEOS-Chem simulation model outputs used in this study are daily (24-hour-average), gridded surface $PM_{2.5}$ concentrations for fire seasons (May 1-Oct. 31) 2004–2009. The grid size is 0.5x0.67 degrees (approximately 50x75km) latitude-by-longitude. We generated estimates under two simulations: 1) the “all-source $PM_{2.5}$”: total $PM_{2.5}$ levels from all sources including wildfires; and 2) “no-fire $PM_{2.5}$”: $PM_{2.5}$ from all sources except the contribution from wildfires, by performing model simulations without wildfire emissions. Non-fire sources for $PM_{2.5}$ in the West include fossil fuel combustion from transportation, industry, and power plants[20,21]. The difference between outputs from these two simulations provides an estimate of the wildfire-specific $PM_{2.5}$ for each day and gridcell. We defined exposure based on daily wildfire-specific $PM_{2.5}$ estimates, which may differ from the actual locations of wildfires as smoke can travel large distances[22]. This model provided exposure estimates for all study subjects in the spatial domain, including those far from monitors. The results of GEOS-Chem simulations on particulate matter have been validated against observations[16,23]. We use ground-based or aircraft measurements, not satellite data, to validate the GEOS-Chem surface $PM_{2.5}$, including wildfire $PM_{2.5}$ (eAppendix Methods 2).

The modeled estimates of $PM_{2.5}$ from wildfires were spatially misaligned with health and weather data, with GEOS-Chem exposure data in a gridded form, health data at the county level, and weather data at the point level (i.e., monitor location). We converted daily grid-level wildfire-specific $PM_{2.5}$ and all-source $PM_{2.5}$ into daily county-level values using area-weighted averaging[24] (eAppendix Methods 3). We assumed that all persons residing in a given county have the same exposure to wildfire-specific $PM_{2.5}$ on a given day.

Hospital admissions data

The hospital admission data are based on billing records 2004–2009 from the Medicare Cohort Air Pollution Study (MCAPS)[25]. Ethical review was not required for this study. We included county-level data for all Medicare beneficiaries (US residents≥65y) enrolled in fee-for-service plan (70.0% of all Medicare beneficiaries) in 561 counties including rural and sparsely populated counties (eFigure 1). The Medicare data contain daily counts of cause-specific hospital admissions by county along with detailed information on date of admission, age category, sex, race, and daily total numbers of Medicare enrollees, representing the population at risk, in each combination of age category, sex and race. The hospital admissions counts can include repeated admissions.

We selected emergency hospital admissions for cardiovascular (CVD) and respiratory diseases as health outcomes. A visit coded as an emergency admission might not be admitted from an emergency room/department directly but the admission was emergency (admission type is emergency not elective). Previous studies connected these disease categories with total mass $PM_{2.5}$[e.g.25,26,27]. The ICD-9 codes of diagnoses are in eAppendix Methods 1.

Air monitoring data and weather data

Daily total $PM_{2.5}$ measurements from the monitoring data, reflecting real-world $PM_{2.5}$ from all sources, were used to calibrate the total GEOS-Chem $PM_{2.5}$ results ("all-source" $PM_{2.5}$). The air monitoring data were acquired from EPA AirData (http://aqsdr1.epa.gov/aqsweb/aqstmp/airdata/download_files.html#Daily). When a county had measurements from multiple monitoring sites on a given day, we averaged all monitor measurements to estimate the county's total $PM_{2.5}$ level on that day.

Weather information was used in statistical analysis since temperature may confound health impact of air pollution[28]. Daily county-level weather data, including temperature and dew point temperature, were obtained from the National Centers for Environmental Information of National Oceanic and Atmospheric Administration.

Calibration

As in other chemical transport models, the GEOS-Chem $PM_{2.5}$ estimates were biased low during extreme events, reflecting the challenge in capturing smoke plumes on fine spatial scales[e.g.23]. To address this bias, we calibrated the daily, county-level 2004–2009 modeled total $PM_{2.5}$ estimates ("all-source" $PM_{2.5}$) in all 561 counties) with the county-level total $PM_{2.5}$ data from air monitors, by matching the quantile functions of the two datasets. This approach scales the distribution of modeled $PM_{2.5}$ data to more closely resemble the distribution of the monitored data[29]. This method maintains the ordering of $PM_{2.5}$ in the original (modeled) data (e.g., any day above the 98th percentile of $PM_{2.5}$ in the original modeled data is above the 98th percentile in the calibrated data). This calibration process results in empirical cumulative distribution functions for the simulated total $PM_{2.5}$ that matches that of the observed $PM_{2.5}$. Hence the overall proportion of $PM_{2.5}$ that comes from wildfire smoke is identical in the original and calibrated data. We calibrated the daily *total* modeled $PM_{2.5}$ using county-average monitoring data, calculated the proportions of total modeled $PM_{2.5}$ contributed by modeled wildfire-specific $PM_{2.5}$ on each day, and then multiplied the calibrated total modeled $PM_{2.5}$ with the proportions to obtain the calibrated wildfire-specific $PM_{2.5}$. Results from the calibration process are shown in eTable 1 and eFigure 2.

Definition of a Smoke Wave

Traditionally, the short-term effects of $PM_{2.5}$ have been investigated by estimating the association between day-to-day variations in pollutant levels with the day-to-day variation in health outcome rates. For example, some researchers applied time-series analysis to associate daily ambient air pollution exposures with daily hospital admission rates in large multi-city studies[25–27]. However, the frequency distribution of wildfire-specific $PM_{2.5}$ data differs from that of traditional ambient levels of total $PM_{2.5}$. Absent a wildfire smoke event, the wildfire-specific $PM_{2.5}$ level is near zero. Among all the days with an estimated wildfire-specific $PM_{2.5}$ levels, only 28.1% have values >1μg/m^3 but levels can reach >200μg/m^3 during the wildfire days. To estimate health effects associated with rare but extreme episodes of wildfire-specific $PM_{2.5}$ we introduced a new modeling approach that to our knowledge has not previously been used in the wildfire–health literature.

Specifically, we first introduce the concept of “smoke wave”. The concept of smoke wave allows us to capture periods with high concentration, sporadic, and short-lived characteristics of wildfire $PM_{2.5}$. We define a smoke wave as at least two consecutive days with daily calibrated wildfire-specific $PM_{2.5}$>20μg/m^3 (near the 98th percentile of all county-days across all 561 counties). This definition is based on daily wildfire-specific $PM_{2.5}$ levels above a designated threshold and the daily levels in all days in a smoke wave must exceed the threshold. We conducted sensitivity analyses that varied the definition of smoke wave with respect to duration and intensity; for example, we also defined smoke wave as at least *one* day with daily calibrated wildfire-specific $PM_{2.5}$>20μg/m^3 (“single-day smoke-waves”). Among all smoke-wave days, we investigated whether health impact differs on smoke wave days with different intensity and considered intensity thresholds of 23μg/m^3, 28μg/m^3, and 37μg/m^3 corresponding to the 98.5th, 99th, and 99.5th quantile of all county-days across all 561 counties, respectively. We investigated whether timing within smoke waves (during the first 2 days, 3rd to 7th day, and 8th or later day of a smoke wave) affects health risks, i.e. whether the health risks on an earlier day in a smoke wave differed from those for a later day in a smoke wave. We also conducted sensitivity analysis on counties with fee-for-service enrollment ≥75% among Medicare beneficiaries.

Statistical modeling

We conducted a matched analysis to compare the hospital admission rates (number of admissions/number of Medicare fee-for-service enrollees) on smoke-wave days (exposure) and matched non-smoke-wave days (no-exposure to high wildfire-specific $PM_{2.5}$). We chose to conduct matched analysis because the wildfire-specific $PM_{2.5}$ exposure is episodic and occurs infrequently (1.63% days were smoke wave days among all county-days). Each smoke-wave day was matched with up to three non-smoke-wave days in the same county. Smoke-wave days in counties with many smoke-wave days may be matched with fewer than three non-smoke-wave days when we were not able to find three suitable no-smoke-wave days. Among the total 10080 smoke-wave days in all counties in 6 years, 9184 were each matched with 3 non-smoke-wave days, 697 with 2 non-smoke-wave days, and 199 with 1 non-smoke-wave days. We considered non-smoke-wave days to be eligible match days if they are: 1) within the window of 7 calendar days before or 7 days after the smoke-wave day but primarily in a different year (before or after the year of the smoke-wave day) and 2) are separated from any other smoke-wave day by at least 2 days. Among all eligible days meeting the matching criteria for a non-smoke-wave day, we selected the matched non-smoke-wave days at random. By matching based on a 15-day period primarily in a different year, we accounted for larger seasonal trends such as the greater propensity for wildfires to occur during the hotter and drier months. We assessed the difference in daily temperature, daily dew point temperature, and non-fire $PM_{2.5}$ for exposure (smoke-wave) days and no-exposure (non-smoke-wave) days. All statistical analyses were conducted in R v2.15.0.

Matching reduces the effects of confounding such as from seasonal trend[30]. We controlled for seasonal factors by 1) including a fixed effect of study year; 2) controlling for daily temperature; and 3) using a matched approach to ensure the same seasonality of smoke-wave days and matched non-smoke-wave days. The matching approach guarantees that the smoke wave and non-smoke-wave days have the same distribution across season (eTable 2), and hence controls by design for confounding by seasonal trends. We also conducted sensitivity analysis with the statistical model not adjusting for modeled non-fire $PM_{2.5}$ levels.

We investigated the Relative Risk (RR) of hospital admissions on the same day as a smoke wave (lag 0). We fitted a log-linear (Poisson) mixed effects regression model separately for each disease (cardiovascular or respiratory diseases) for smoke wave days and matched non-smoke-wave days across all 561 counties (details in eAppendix Methods 4). Similar statistical models have been applied in previous epidemiologic studies[31].

Results

Wildfire $PM_{2.5}$ characteristics

The frequency distribution of $PM_{2.5}$ levels from wildfire sources (calibrated) differs from that of $PM_{2.5}$ from non-fire sources. Levels of wildfire-specific $PM_{2.5}$ are highly skewed, with about 72% of daily county-level calibrated wildfire-specific $PM_{2.5}$<1μg/m^3. Wildfire-specific $PM_{2.5}$ has lower mean and median, but higher extremes, compared with $PM_{2.5}$ from non-fire sources (Table 1). The time-series pattern of wildfire-specific $PM_{2.5}$ is mostly zero with occasional high peaks for short periods.

Smoke wave characteristics

Based on our definition of a smoke wave (at least two consecutive days with wildfire-$PM_{2.5}$>20μg/m^3), about 66% of Western US counties (369 of 561) experienced at least one smoke wave during the 6-year period. Among the 369 counties with at least one smoke wave, on average a county had 4.6 smoke-wave days/year (Table 2). We found that the dates and locations of smoke wave days generally matched well with MODIS records of large wildfires (eFigure 4).

The number of smoke-wave days experienced by counties is spatially heterogeneous. Coastal California and central Idaho had the highest frequency of smoke-wave days (>10 smoke wave days/year) (Figure 1). The average wildfire-$PM_{2.5}$ concentration during each smoke wave day was lower during the first two days of smoke waves and gradually increased over time during a smoke wave (eFigure 3). The median length of a smoke wave was 3 days (ranged 2 to 58). Temperatures during smoke wave days did not differ largely based on the smoke wave day's intensity (eTable 3(a)) or smoke wave length (eTable 3(b)).

Hospital admission summary statistics

The study population for the 561 counties during the study timeframe (2004–2009) includes on average about 5 million Medicare enrollees per day. This population had a total of 832,244 cardiovascular admissions and 245,926 respiratory admissions during the study timeframe. Within the study timeframe, 369 counties had at least one smoke wave. For these counties, there were 648,789 cardiovascular admissions and 191,095 respiratory admissions. Counties that experienced a smoke wave had, on average, lower rates of hospital admissions than counties with no smoke wave (Table 3). There are 3,844,414 people exposed to at least one smoke wave, and 1,114,513 with no exposure to smoke waves.

Association between wildfire $PM_{2.5}$ and hospital admissions

Overall, smoke waves were not associated with increased rates of cardiovascular hospital admissions. The overall association with cardiovascular admissions on a smoke-wave day compared to a non-smoke-wave day was −0.74% (95% CI: −3.1%, 1.65%) (RR=0.99). The overall association with respiratory hospital admissions on a smoke wave day compared to a non-smoke-wave day was 2.3% (95% CI: −2.2%, 7.0%) (RR=1.0).

Smoke wave days with different intensity (level of wildfire $PM_{2.5}$) and the various days within the smoke waves exhibited indication of trends of different health effects. Central estimates for respiratory admissions showed an increasing trend as smoke wave day intensity increases (Figure 2 (b)). Smoke wave days with intensity >37μg/m^3 (99.5th quantile) were associated with a 7.2% increase in respiratory admissions by 7.2% (95% CI: 0.25%, 15%) compared to non-smoke-wave days. Therefore, more intense smoke wave days are estimated to have higher health impacts on respiratory diseases for the study population. This association is robust to no inclusion of a variable for non-fire $PM_{2.5}$ levels in the model (results not shown). Results on single-day smoke waves and counties with fee-for-service enrollment>75% are summarized in eAppendix Results 1 and 2.

Central estimates for CVD admissions tend to be highest during the first two days of a smoke wave, and decreasing over the later days within a smoke wave (Figure 3(a)). Respiratory admissions exhibit an opposite trend, with higher estimate estimate in later days of the smoke wave (Figure 3(b)). For each types of admission, effect estimates based on timing within a smoke wave were imprecise.

Discussion

Our systematic assessment indicates an association between respiratory admissions and intense smoke wave days, with daily wildfire-specific $PM_{2.5}$ levels >37μg/m^3. Single-day smoke waves have a potentially more certain positive association with respiratory admission rates, possibly due to larger sample sizes and the acute response of respiratory diseases.

To our knowledge this is the first study to use wildfire-specific data to analyze the health impact of wildfire-specific $PM_{2.5}$ over multiple years at a large geographical scale. Key contributions of this study include: 1) estimation of exposure to $PM_{2.5}$ specifically from wildfires; 2) ability to estimate exposure to wildfire $PM_{2.5}$ every county with and without air monitors, therefore expanding the study populations to include persons that live far from $PM_{2.5}$ monitoring stations; and 3) application of statistical models that estimate percent increases in hospital admission by matching smoke wave days to non-smoke-wave days.

Although previous literature on the association between wildfire smoke and health is limited, several studies have made important contributions. The majority of such studies used air monitor measurements, which cannot identify pollution specifically from wildfires with current technology, and studied a single wildfire episode and one or a small number of communities[3]. A few studies compared air pollution exposure (from all sources) during wildfires to the periods or locations with no fire[e.g.11,32,33]. Our study results for respiratory diseases are consistent with those found in most of the previous literature[e.g.34,35], in that wildfire smoke was found to be associated with respiratory diseases. Association between wildfire smoke and cardiovascular morbidities was found in five US studies that each examined a single local wildfire episode[3], but our multi-state, multi-year study did not provide evidence for such association.

Previous studies have demonstrated that the chemical composition of $PM_{2.5}$, which is related to source, can result in different effect estimates for human health[9,36,37]. Thus, estimates from wildfire $PM_{2.5}$ may differ from those from $PM_{2.5}$ from other sources, such as transportation or industry. Earlier studies examined the association between risk of hospital admission and levels of $PM_{2.5}$ from all sources (i.e., $PM_{2.5}$ total mass) (e.g., change of risk of hospital admission for Medicare enrollees per 10μg/m^3 increase in $PM_{2.5}$ in the Western US[25,26,38]). As we compared the health risk among smoke wave days with that of non-smoke-wave days, rather than by a specific increment of $PM_{2.5}$, direct comparisons of results is challenging. Further, these studies focused on urban counties with high populations, whereas our study included rural populations in the analysis as well. Still, a general comparison can give some indication of whether $PM_{2.5}$ from wildfire smoke is more or less harmful than $PM_{2.5}$ total mass.

For Medicare cardiovascular admissions, one study estimated an increased risk of 0.53% (95% posterior interval: 0.00%, 1.05%) per 10μg/m^3 $PM_{2.5}$ total mass (from all sources) for 25 urban counties in the Southwest US , and 0.74% (-1.74, 3.29%) for 9 urban counties in the Northwest[26]. Our results did not indicate an association between wildfire $PM_{2.5}$ and risk of cardiovascular admissions.

For respiratory hospital admissions, we estimated an increase of 7.2% (0.25%, 15%) comparing smoke-wave days with wildfire-$PM_{2.5}$>37μg/m^3 to non-smoke-wave days with wildfire-specific $PM_{2.5}$<20μg/m^3, which corresponds to an average difference of 29.6μg/m^3 in those two groups of days. The earlier study identified associations between $PM_{2.5}$ total mass and respiratory admissions for the Medicare population in the Southwest at lag 2 days at 0.94% (0.22%, 1.67%) per 10 μg/m^3 [26], which corresponds to an increased risk of 2.8% (0.64, 5.0%) per 29.6μg/m^3. Therefore, our estimates of respiratory admissions risks indicate that wildfire-specific $PM_{2.5}$ from intense smoke waves are associated with more harm than $PM_{2.5}$ from other sources for the elderly in the Western US. Further research is needed to investigate the relative toxicity of $PM_{2.5}$ from wildfire smoke with that of other sources.

Our approaches for assessing pollutant exposure and estimating health risks address key challenges in studying the health impact of wildfire-specific pollutant. The GEOS-Chem model provided a new approach to distinguish wildfire-specific $PM_{2.5}$ from $PM_{2.5}$ from other sources. The fire scheme in the simulation can explain up to 60% of the observed variance of area burned in the Western US, and is ecosystem dependent[17]. This method also improves the spatial and temporal resolution of exposure estimates for air pollution. Unlike air monitoring data that generally measure $PM_{2.5}$ concentrations every 3–6 days in urban areas, GEOS-Chem estimates concentrations for every day and covers the entire study area. Our smoke-wave methods provide an approach suitable for the study of highly-skewed air pollution data and enable identification and investigation of pollution episodes with high source-specific pollutant concentrations. Matched analysis can reduce the confounding effect of seasonality and county-specific effects. These methods can be applied to future studies investigating other pollution events and populations.

Limitations of our study include potential spatial misalignment between the exposure estimates (gridded estimates) and health data (county). Our study population was restricted to Medicare fee-for-service enrollees, a sample of elderly persons. Our smoke wave approach does not fully capture the dose–response relationship, cause-specific health outcomes, etc. that could be investigated in future studies. The GFED emissions applied to GEOS-Chem contribute uncertainty to the modeled estimates of wildfires-specific $PM_{2.5}$. The GFED3 data may underestimate fire contributions to background $PM_{2.5}$ because of the omission of small fires[39] and the biases in the modeled fuel consumption. GFED3 relies on satellite observations of active fire counts and area burned, and may have difficulty discerning such phenomena, especially on cloudy days[40]. Another limitation arises as EPA monitors generally measure $PM_{2.5}$ values every 3–6 days and are located in populated areas. Given a large number of days with monitoring measurements for calibration, we assumed that the systematic sampling of EPA monitors generate measurements with mean and standard deviation representing the full time-series of real-world $PM_{2.5}$. While it would be ideal to have the full continuous measure we believe that calibration using this discrete sample of the continuous measure is the best possible alternative in using the available data. While our exposure estimates are advances over methods that do not isolate the air pollution from wildfires specifically, additional work could address these limitations. We choose not to a priori identify lags in this study as little is known about how wildfire-specific $PM_{2.5}$ affects human health. Most of the wildfire-health literature to date has investigated effects of lag 0 or short lags (<5 days)[3]. Future studies can explore the lagged effect of wildfire-specific air pollution.

Our findings indicate that wildfires are associated with increased risk of admissions for respiratory diseases for the elderly population during severe wildfire episodes. As climate change is anticipated to increase the frequency and intensity of wildfires[1], the health burden from wildfire-specific pollutants may increase in the future. With improvement of atmospheric modeling, future studies can estimate daily wildfire-specific $PM_{2.5}$ at a finer spatial resolution. Future studies can also investigate vulnerability to wildfire smoke, health impact of different species of wildfire-specific $PM_{2.5}$, the economic consequence of the health burden from wildfire smoke, combined effect of wildfire smoke and other air pollutants, and estimated health burden in the future under climate change.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

Sources of financial support:

NIH/NIEHS R21 ES022585-01

NIH R01 ES019560

NIH R01 ES024332

EPA RD 83479801

NIH R21 ES021427

NIEHS R21 ES020152

Yale Institute of Biospheric Studies Doctoral Dissertation Improvement Grant

This publication was developed under Assistance Agreement No. 83587101, awarded by the U.S. Environmental Protection Agency to Yale University. It has not been formally reviewed by EPA. The views expressed in this document are solely those of the authors and do not necessarily reflect those of the Agency. EPA does not endorse any products or commercial services mentioned in this publication.

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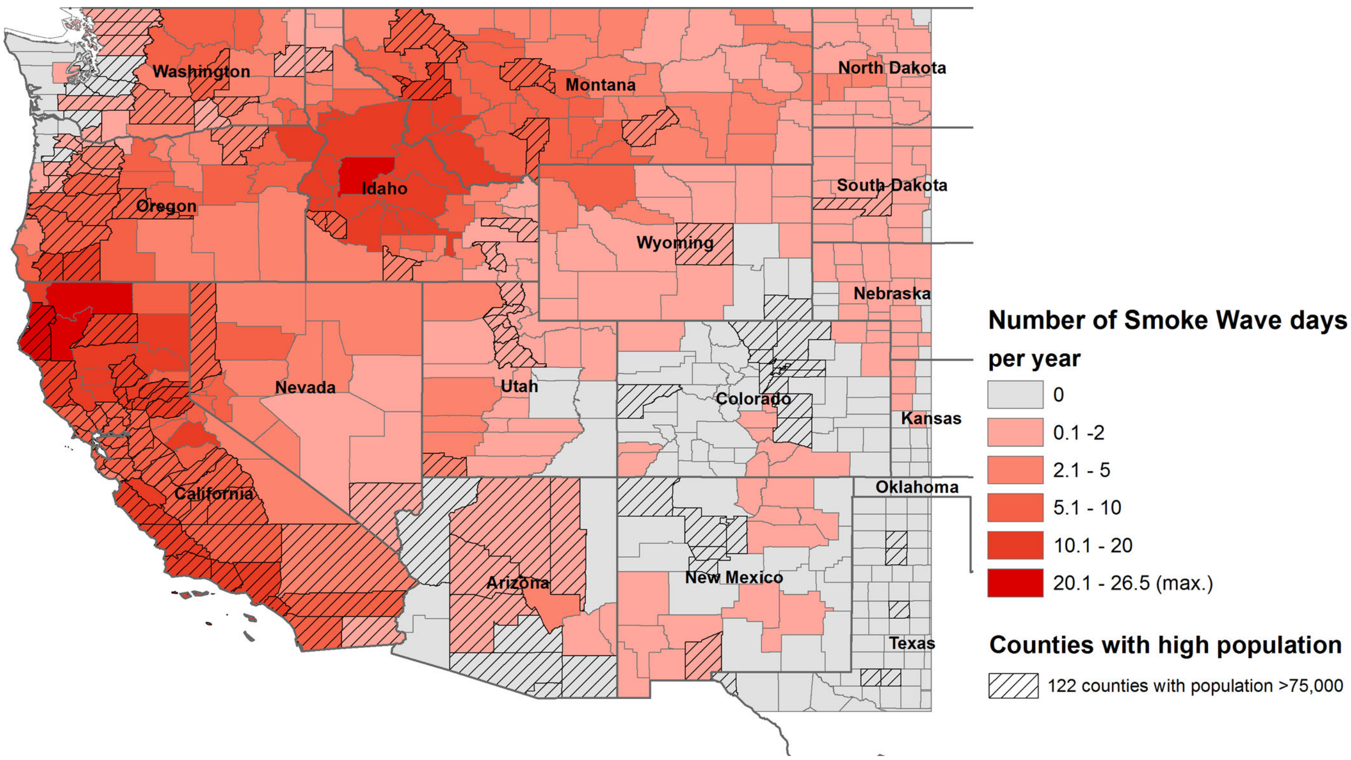

Figure 1.
Average number of Smoke Wave days/year for 561 Western US counties during 2004–2009. Hashed counties have population >75,000 in the 2010 Census.

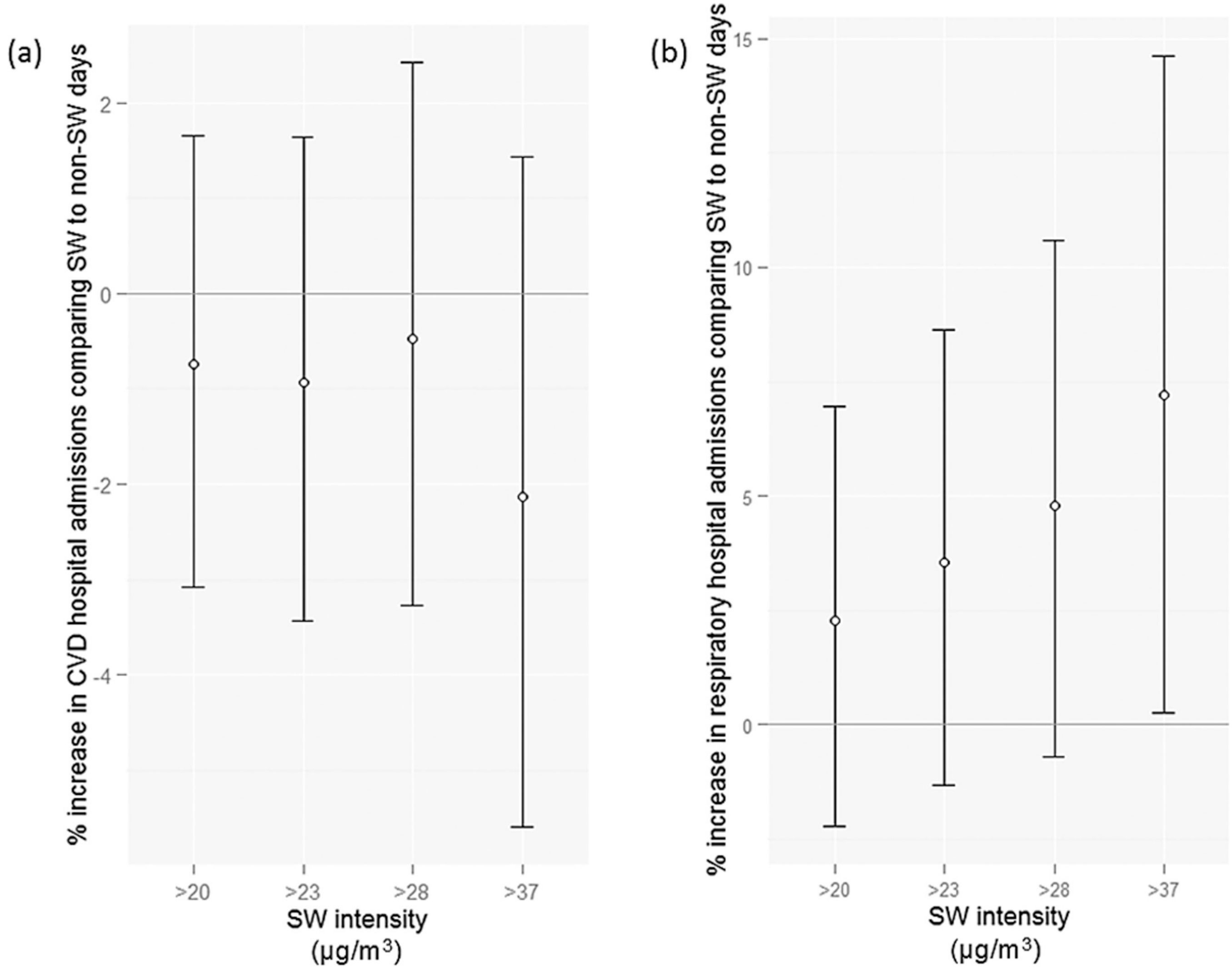

Figure 2.

Associations between hospital admissions and exposure to smoke-wave (SW) days (compared to non-smoke-wave days) for (a) cardiovascular disease and (b) respiratory disease, by different intensity (level of wildfire-specific $PM_{2.5}$) definitions of a smoke wave.

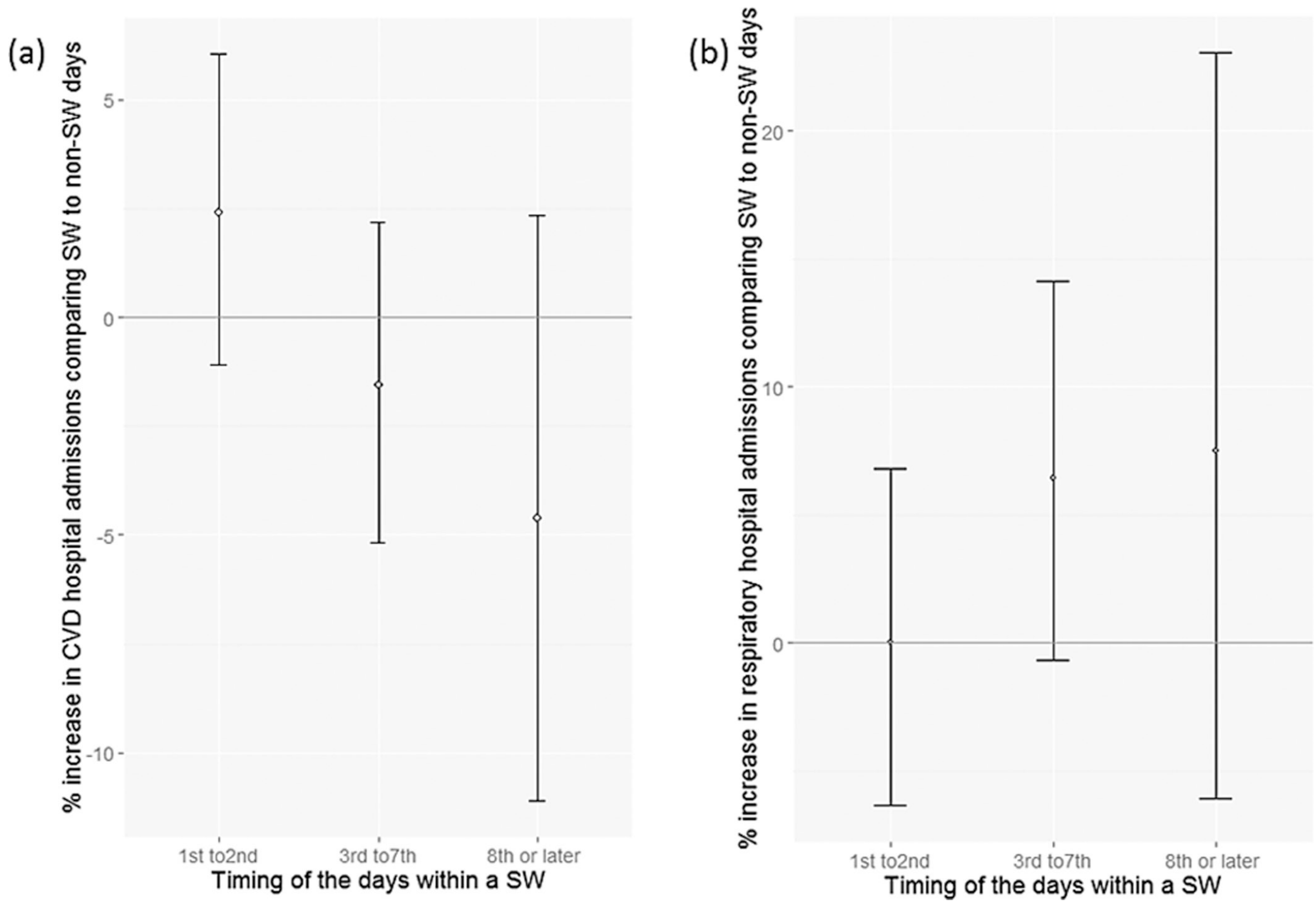

Figure 3.
Associations between hospital admissions and exposure to smoke-wave (SW) days (compared to non-smoke-wave days) for (a) cardiovascular disease and (b) respiratory disease, by timing of the days within a smoke wave.

Table 1

Summary statistics for daily GEOS-Chem $PM_{2.5}$ concentrations (calibrated) from wildfire sources and non-fire sources in 561 western US counties ($\mu g/m^3$) during the wildfire season (May 1– Oct. 31), 2004–2009.

	Minimum	25^{th} Percentile	Median	Mean	75^{th} Percentile	Maximum
$PM_{2.5}$ from wildfires	0	0.09	0.3	2.0	1.2	242
$PM_{2.5}$ from non-fire sources	0	4.4	6.2	7.0	8.7	45.1

Table 2

Summary statistics for smoke waves (SW, defined as at least two consecutive days with wildfire-specific $PM_{2.5}$ >20μg/m^3) for the 369 Western US counties that experienced smoke waves during 2004–2009.

SW characteristics	Average (Standard Deviation)	Median	Minimum	Maximum
No. SW days /year [a]	4.6 (4.9)	2.5	0.33	26.5
No. SW events / year [a]	1.0 (0.8)	0.83	0.17	3.8
SW intensity (μg/m^3) [b]	29.3 (6.4)	28.1	20.1	70.0
SW length (days) [b]	4.4 (4.7)	3	2	58

[a]Statistics based on the 369 county-average values.

[b]Statistics based on all SW-level values across all SWs in the 369 counties.

Table 3

County-level hospital admission per 100,000 Medicare enrollees per day (2004–2009)

		Minimum	25th percentile	Median	Mean	75th percentile	Maximum
561 counties	Cardiovascular disease	1.59	8.18	11.5	12.2	15.0	43.7
	Respiratory	0	1.81	3.33	3.59	4.87	17.1
369 counties with smoke waves	Cardiovascular disease	1.59	7.87	10.7	11.2	13.7	39.7
	Respiratory	0	1.63	3.07	3.25	4.52	11.7
192 counties with no smoke waves	Cardiovascular disease	4.88	9.03	13.5	14.1	17.4	43.7
	Respiratory	0	2.43	3.91	4.25	5.74	17.8