Exposure to Wildfire-specific Fine Particulate Matter and Risk of Hospital Admissions in 369 Urban and Rural Counties in the Western US 2004-2009

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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 chemical composition and high concentrations.

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* (SW) as $\geq$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 SWs for Medicare enrollees. We used a generalized linear mixed model to estimate the relative risk of hospital admissions on SW 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 SW during 2004 to 2009 in the Western US. Of these, 5 million are Medicare enrollees ($\geq$65y). We found a 7.2% (95% Confidence Interval: 0.25%, 14.63%) increase in risk of respiratory admissions during SW days with high wildfire-specific $PM_{2.5}$ (>37μg/m^3) compared to matched non-SW days. Significant association with respiratory admissions was not observed for SW days

with wildfire-$PM_{2.5}$ <37μg/m^3 or with cardiovascular admissions. Respiratory effects of wildfire-specific $PM_{2.5}$ may be stronger than that of $PM_{2.5}$ from other sources.

Conclusion: Short-term exposure to wildfire-specific $PM_{2.5}$ significantly increases 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 of wildfires[1]. Wildfires are known to cause substantial ecological and economic burden, with hundreds of millions of dollars spent annually on suppressing wildfires in the US[2], and these economic costs are likely to be underestimated because they do not account for the potentially severe impact of air pollution from wildfire smoke on human health[3]. 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[4].

The Western US historically suffers from wildfires due to its large area of forests and vegetation as well as relatively arid weather. During 2004-2009, over 1,800 large fires (defined as area burned >405 ha) occurred in the Western US[5]. The burning of biomass can dramatically increase levels of toxic air pollutants, such as fine particles ($PM_{2.5}$)[6]. Numerous studies have demonstrated links between airborne particles from other sources or particulate matter (PM) measured as total mass and health outcomes including mortality and hospital admissions, especially for respiratory and cardiovascular diseases[4]. 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[7]. As wildfires emit high concentrations of fine size PM[8], scientific understanding is needed on the health impact of wildfire-emitted $PM_{2.5}$.

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[4]. The size of fire-generated PM tends to be small, such as fine particles ($PM_{2.5}$)[8]. The composition of fire-generated $PM_{2.5}$ is likely to be different from $PM_{2.5}$ generated from other sources, which in turn can affect toxicity[9,10]. 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[4]. To date, most of the literature focused on a single fire episode and small population (e.g. [11,12,13]). It is unknown whether the health impacts of wildfire-emitted $PM_{2.5}$ differ from that 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 how much of this concentration is attributable directly to fires versus other sources. The majority of current studies estimating health effects from wildfires used air monitoring data, which are limited in spatial and temporal resolution and cannot isolate wildfire-specific pollution[4]. Another limitation of using the monitoring network to conduct population-based epidemiological studies is the lack of monitors in rural areas and the statistical issues that arise from low population density in rural areas.

We estimated the association between wildfire-specific $PM_{2.5}$ and risk of hospital admissions by addressing many of these challenges described above. Using a chemical transport model, we could fill in the spatial 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 counties in the Western US for the period 2004 to 2009. We linked daily levels of $PM_{2.5}$ concentrations specifically from wildfires to daily number of hospital admissions for respiratory and cardiovascular diseases from Medicare claims. We applied statistical methods that have not been previously used in wildfire-health studies and estimated health impact of wildfire-specific $PM_{2.5}$incorporating populations in rural counties to statistical analysis.

Methods

Study domain

The study domain is the Western US (lat: 31 to 49, lon: -101 to -125) (Supplementary Figure A.1), where wildfires occur frequently[14]. The study region has 561 counties in 16 states.

Wildfire modeling

We employed wildfire simulations from the GEOS-Chem chemical transport model (v9-01-03) to generate daily levels of wildfire-specific $PM_{2.5}$ for six years (2004-2009). GEOS-Chem is a global 3D atmospheric chemistry model driven by meteorology[15]. It has been used to understand the pollution impact of present-day fires [16,17] and to predict future wildfire-specific aerosols[1,18]. The modeling integrates meteorological data from Goddard Earth Observing System (GEOS-5) of the NASA Modeling and Assimilation Office (GMAO) 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[19,20]. More background information on GEOS-Chem and its validation can be found in the Supplementary Methods 1.

The GEOS-Chem simulation model outputs used in this study are daily (24-hour average), gridded surface concentrations of $PM_{2.5}$ for the fire season (May 1- Oct. 31) over the period 2004 to 2009. The grid size is 0.5x0.67 degrees (approximately 50x75km) latitude-by-longitude. We generated estimates under two simulations: 1) the “all source $PM_{2.5}$”, which includes the total $PM_{2.5}$ levels from all sources including wildfires; and 2) “no-fire $PM_{2.5}$”, which includes $PM_{2.5}$ from all sources except the contribution from wildfires. The second set of estimates (no-fire $PM_{2.5}$) was generated by performing model simulations without emissions from wildfires. Non-fire sources for $PM_{2.5}$ in the West include fossil fuel combustion from transportation, industry, and power plants[21,22]. The difference between outputs from these two simulations provides an estimate of the $PM_{2.5}$ specifically from wildfires for each day and gridcell. We define exposure based on daily wildfire-specific $PM_{2.5}$ estimates. The wildfire-specific $PM_{2.5}$ is near zero on days when not affected by wildfire smoke and can reach high levels during or just after a fire event. This model provided exposure estimates for all study subjects in the spatial domain, including those far from ambient monitors. The results of GEOS-Chem simulations on particulate matter have been validated against observations[17,23]. We use ground-based or aircraft measurements, not satellite data, to validate the GEOS-Chem surface $PM_{2.5}$, including wildfire $PM_{2.5}$ (Supplementary Methods 1). It is worth noting that our exposure metric is designed to relate to wildfire smoke, which may differ from the actual location of a wildfire as smoke can travel large distances[24].

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 the daily grid-level wildfire-specific $PM_{2.5}$ and all-source $PM_{2.5}$ data into daily county-level values using area-weighted averaging[25]. We added a gridded layer (0.5x0.67 degree) on top of an equal-area projected map of the study domain (31-49N, 101-125W). There are 1332 grids in the study domain, 1188 of which overlapped with the Western US boundary. We calculated the areas of each county and each fragment the grids fall in the counties. Then we calculated the area ratio of each grid fragment within a county's boundary by dividing county area by fragment area. The county-level exposure was the sum of each area ratio in the county times the concentration in the grids that fall into the county. 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 from 2004 to 2009 from the Medicare Cohort Air Pollution Study (MCAPS)e.g.[26]. We included data for all Medicare enrollees (US residents $\geq$65y) with a place of residence in all the 561 counties in the Western US including rural and sparsely populated counties (Supplementary Figure A.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, and race. The hospital admissions counts can include repeated admissions. Daily total numbers of Medicare enrollees, representing the population at risk, in each combination of age category, sex and race are also included in the data.

We selected emergency hospital admissions for cardiovascular (CVD) and respiratory diseases as health outcomes. A patient with coding as an emergency admission might not be admitted from an emergency room/department directly but his/her admission was emergency (admission type is emergency not elective). Previous studies connected these disease categories with total mass $PM_{2.5}$ e.g.[26,27,28]. The diagnoses are classified using ICD-9 codes and are primary discharge causes of hospital admissions. Cardiovascular diseases are coded as the sum of admissions for ICD-9 390 to 459, including heart failure (ICD-9 428), heart rhythm disturbances (ICD-9 426–427), cerebrovascular events (ICD-9 430–438), ischemic heart disease (ICD-9 410–414 and 429), and peripheral vascular disease (ICD-9 440–449). Respiratory diseases are the aggregated admissions for chronic obstructive pulmonary disease (COPD) (ICD-9 490–492) and respiratory tract infections (ICD-9 464–466, 480–487).

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 Air Data (http://aqsdr1.epa.gov/aqsweb/aqstmp/airdata/download_files.html#Daily). These values were converted to daily county-level values. 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 to compare temperature and dew point temperature during Smoke Waves (defined later in this section) and non-Smoke-Waves since temperature may confound health impact of air pollution[29]. Daily weather data at county level, 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 GFED modeled total $PM_{2.5}$ estimates (”all-source” $PM_{2.5}$, including $PM_{2.5}$ from fires and other sources) in the entire study area (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[30]. 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 then proportion of total modeled $PM_{2.5}$ that were contributed by modeled wildfire-specific $PM_{2.5}$, and then multiplied the calibrated total modeled $PM_{2.5}$ with the proportion to obtain the calibrated modeled wildfire-specific $PM_{2.5}$. Results from the calibration process are shown in Supplementary Table A.1 and Supplementary Figure A.2.

Definition of a Smoke Wave

Traditionally, the short-term effects of $PM_{2.5}$, or other pollutants, have been investigated by estimating the association between day-to-day variation in pollutant levels with the day-to-day variation in hospital admissions or mortality rates. For example, some researchers applied time-series analysis to explore the association between daily ambient air pollution exposures and daily hospital admission rates in large multi-city studies. Versions of these approaches have been used in previous research on air pollution for hospital admissions and mortality[26-28]. 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 level of 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 are greater than 1μg/m^3 but levels can reach over 200μg/m^3 during the wildfire days. To estimate health effects associated with rare but extreme episodes of wildfire-specific levels of $PM_{2.5}$ we introduced a new modeling approach that has not previously been used in the wildfire-health literature.

More specifically, first we introduce the concept of "Smoke Wave" (SW). The concept of SW allows us to capture periods with high concentration, sporadic, and short-lived characteristics of wildfire $PM_{2.5}$. We define a SW 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 SW must exceed the threshold. We conducted sensitivity analyses that varied the definition of SW with respect to duration and intensity, for example, we also defined SW as at least *one* days with daily calibrated wildfire-specific $PM_{2.5}$ >20μg/m^3. Hereon we refer to SW days using this alternative definition as "single-day SWs". Among all SW days, we investigated whether health impact differs on SW days with different intensity and considered intensity thresholds of 23μg/m^3, 28μg/m^3, and 37μg/m^3 corresponding to the 98.5th quantile, 99th quantile, and 99.5th quantile of all county-days across all 561 counties, respectively. We investigated whether timing within SWs affects health risks; we examined hospital admission impacts during the first 2 days of a SW, 3rd to 7th day of a SW, and 8th or later day of a SW. In other words, we investigated whether the health risks on an earlier day in a SW differed from those for a later day in a SW.

Statistical modeling

We conducted a matched analysis to compare the hospital admission rates on SW days (exposure) and matched non-SW 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 SW days among all county-days). By matching we can reduce the effects of confounding such as from seasonal trend[31]. Each SW day was matched with up to three non-SW days in the same county. SW days in counties with many SW days may be matched with fewer than three non-SW days when we were not able to find three suitable no-SW days. Among the total 10080 SW days in all counties in 6 years, 9184 were each matched with 3 non-SW days, 697 with 2 non-SW days, and 199 with 1 non-SW days. We considered non-SW days to be eligible match days if they are: 1) within the window of seven calendar days before or seven days after the SW day but in a different year (before or after the year of the SW day) and 2) are separated from any other SW day by at least two days. Among all eligible days meeting the matching criteria for a non-SW day, we selected the matched non-SW days at random. By matching based on a 15-day period in a different year, we accounted for larger seasonal trends such as the greater propensity for wild fires 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 (SW) days and no-exposure (non-SW) days. All statistical analyses were conducted in R version 2.15.0.

We investigated the risk of hospital admissions on the same day as a SW (lag 0). We fitted a log-linear (Poisson) mixed effects regression model separately for each disease group (cardiovascular or respiratory diseases) for SW days and matched non-SW days across all 561 counties (Supplementary Methods 2). A binary indicator variable for SW was specified as 1 on a SW day and 0 on matched non-SW days. The model included a county-specific random intercept and fixed effect for daily continuous measurement of temperature, modeled non-fire $PM_{2.5}$ levels, sex (male, female), age category (65-74, 75-84, $\geq$85 years), race (White, Black, other), type of day (weekend, weekday), and year. The analysis is weighted, which means SW days matched with less than three no-SW days are weighted less than SW days matched with three no-SW days. This model estimates the relative rate (RR) of hospital admissions on SW days compared with non-SW days. Similar statistical models have been applied in previous epidemiological studies[32]. 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 SW days and matched non-SW days. The matching approach guarantees that the SW and non-SW days have the same distribution across season (Supplementary Table A.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.

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 71.9% of daily county-level calibrated wildfire-specific $PM_{2.5}$ <$1\mu g/m^3$. 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 SW definition (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 SW during the six-year period. Among the 369 counties with at least one SW, on average a county had 4.6 SW days/year (Table 2). Since SW days are defined based on daily wildfire-specific $PM_{2.5}$ (rather than fire event days), their dates and locations do not necessarily reflect the exact dates and locations of wildfire events. We mapped the dates and locations of SW days in May-October 2004 and compared with these of MODIS satellite records of large wildfires (fire radiative power>500) in May-October 2004[33] (Supplementary Figure A.4). We found that the dates and locations of SW days generally matched well with MODIS records of large wildfires. The SW days in North Dakota, South Dakota and Montana are due to wildfires in Canada as wildfire smoke can travel across continent[24].

The number of SW days experienced by counties is spatially heterogeneous. Coastal California and central Idaho had the highest frequency of SW days (>10 SW days/year) (Figure 1). The average wildfire-$PM_{2.5}$ concentration during each SW day was lower during the first two days of SWs and gradually increased over time during a SW (Supplementary Figure A.3). The median length of a SW was 3 days (range 2 to 58). SWs occurred more often during 2006-2008 (Supplementary Table A.2). The temperature during SW days (69.9 ^oF) is higher than the temperature during non-SW days (68.5 ^oF). Temperatures during SW days did not differ largely based on the SW day's intensity (Supplementary Table A.3(a)) or SW length (Supplementary Table A.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 SW. For these counties, there were 648,789 cardiovascular admissions and 191,095 respiratory admissions. Counties that experienced a SW had, on average, lower rates of hospital admissions than counties with no SW (Table 3). There are 3,844,414 people exposed to $\geq$1 SW, and 1,114,513 with no exposure to SW.

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

Overall, SWs were not significantly associated with increased rates of cardiovascular hospital admissions. The overall association with cardiovascular admissions on a SW day compared to a non-SW day was -0.74% (95% CI: -3.08%, 1.65%) (Relative Risk=0.9926). The overall association with respiratory hospital admissions on a SW day compared to a non-SW day was 2.28% (95% CI: -2.21%, 6.97%) (Relative Risk=1.0228).

SW days with different intensity (level of wildfire $PM_{2.5}$) and the various days within the SWs exhibited indication of trends of different health effects. Central estimates for respiratory admissions showed an increasing trend as SW day intensity increases, ranging from 2.28% for SW days with the lowest minimum intensity (20μg/m^3) to 7.2% for SW days with the highest minimum intensity (37μg/m^3) (Figure 2 (b)). SW days with intensity higher than 37μg/m^3 (99.5th quantile) were significantly associated with increased respiratory admissions by 7.2% (95% CI: 0.25%, 14.63%) compared to non-SW days. Therefore, more intense SW 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).

The sensitivity analysis of the association between single-day SW and hospital admissions showed stronger effect that the effect of the SW days using main definition ($\geq$2 consecutive days with wildfire-specific $PM_{2.5}$>20 μg/m^3) (Table A.4). Compared to days with wildfire-specific $PM_{2.5}$$\leq$20μg/m^3, single-day SWs (daily wildfire-specific $PM_{2.5}$>20 μg/m^3) are associated with an increase of 5.65% (95% CI: 1.23%, 10/26%) in respiratory hospital admissions. The trend of effect by SW intensity is consistent with that of the main analysis, i.e. more intense SWs led to higher associations. No association was observed between single-day SWs and CVD admissions.

In terms of timing of SW days within a SW, central estimates for CVD exhibit a trend of the highest estimate during the first two days, and decreasing for later days within a SW (Figure 3(a)). Respiratory admissions exhibit the reverse trend with higher central estimates in later days of the SW (Figure 3(b)). For both causes of disease, effect estimates were not statistically different based on the timing within a SW.

Discussion

This analysis is the most comprehensive assessment to date of the association between wildfires and human health, covering 6 years and the Western US. Our systematic assessment indicate an association between wildfire-specific $PM_{2.5}$ episodes and hospital admissions for respiratory diseases during the intense Smoke Wave days, with daily wildfire-specific $PM_{2.5}$ levels >37μg/m^3. Single-day SWs have potentially stronger association with respiratory admissions rate, possibly due to a larger sample size 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. In addition to the large spatial scale and timeframe, 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 estimates percent increases in hospital admission by matching SW days to no-SW 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[4]. A few studies compared air pollution exposure (from all sources) during wildfires to the periods or locations with no fire (e.g.[12,34,35]). Our study results for respiratory diseases are consistent with those found in most of the previous literature (e.g.[36,37]), in that wildfire smoke was found to have significant impact on respiratory diseases in most prior investigations. Association between wildfire smoke and cardiovascular morbidities was found in five US studies that each examined a single local wildfire episode[4], but our multi-state, multi-year study did not provide evidence for an association with cardiovascular admissions.

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[10,38,39]. Thus, effects from wildfire $PM_{2.5}$ may differ from that from $PM_{2.5}$ from other sources, such as transportation or industry. Earlier studies examined the association between risk of hospital admissions and levels of $PM_{2.5}$ from all sources (i.e., $PM_{2.5}$ total mass) (e.g., change of risk of hospital admissions for Medicare enrollees per 10μg/m^3 increase in $PM_{2.5}$ in the Western US[26,27,40]). As we compared the health risk among SW days with that of non-SW 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 (i.e., from all sources).

For Medicare cardiovascular admissions, one study estimated an increased risk of 0.53% (95% posterior interval: 0.00%, 1.05%) per 10 μg/m^3 $PM_{2.5}$ total mass (from all sources) for the Southwest US based on 25 urban counties, and 0.74% (-1.74, 3.29%) for the Northwest region based on 9 urban counties[27]. 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%, 14.63%) comparing SW days with wildfire-$PM_{2.5}$ >37μg/m^3 to non-SW days with wildfire-specific $PM_{2.5}$ ≤20μg/m^3, which corresponds to an average difference of 29.6 μg/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 [27], which corresponds to an increased risk of 2.81% (0.64, 5.02%) per 29.6μg/m^3. Therefore, our estimates of respiratory admissions risks indicate that wildfire-specific $PM_{2.5}$ from intense SWs may be more harmful that $PM_{2.5}$ 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 risk 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[18]. This method also improves the spatial and temporal resolution of exposure estimates for air pollution. Unlike air monitoring data that measure $PM_{2.5}$ concentrations every three to six days in urban areas, GEOS-Chem estimates concentrations for every day and covers the entire study area, including counties with no air monitors. Our Smoke Wave methods provide an approach suitable for the study of highly-skewed air pollution data and enables 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 spatial misalignment between the exposure estimates (gridded estimates) and health data (county). Our SW approach does not fully capture the dose-response relationship, cause-specific health outcomes, etc. which could be investigated in future studies. The GFED emissions applied to GEOS-Chem contribute uncertainty to the modeled estimates of fires-specific $PM_{2.5}$. The GFED3 data may underestimate fire contributions to background $PM_{2.5}$ because of the omission of small fires[41] 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[42]. Another limitation arises as EPA monitors generally measure $PM_{2.5}$ values every three days and are located in more 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 $PM_{2.5}$ over the six years. 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. Further, it is largely unknown whether wildfire smoke from different tree species, soil types, or ecosystems generates different PM chemical compositions and hence leads to different health impacts. 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 current wildfire-health literature investigated effect of lag 0 or short lags (<5 days)[4]. Future studies can explore the lagged effect of wildfire-specific air pollutant.

Our findings indicate that wildfires can significantly increase the risk of admissions for respiratory diseases for the elderly population during severe wildfire episodes. Findings from this study can aid decision makers in protecting population health under exposure to wildfire smoke. For example, public health preparedness programs involving increased capacity of hospitals can be established in response to potentially higher respiratory admissions during the fire season. As climate change is anticipated to increase in 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, 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.

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Figure legends

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. CVD (a) and respiratory (b) associations on SW days compared with non-SW days, by different intensity (level of wildfire-specific $PM_{2.5}$) definitions for a SW.

Figure 3. CVD (a) and respiratory (b) associations comparing SW days to non-SW days, by timing of the days within a SW

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 (μg/m^3) during the wildfire season (May 1- Oct. 31), 2004-2009.

	Minimum	**25th Percentile**	**Median**	**Mean**	**75th 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 SWs during 2004-2009.

SW characteristics	Average (Standard Deviation)	Median	Minimum	Maximum
# SW days /year [a]	4.6 (4.9)	2.5	0.33	26.5
# 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

Table 3. County-level hospital admission per 100,000 Medicare enrollees per day (2004-2009)

		Minimum	**25^{th} percentile**	**Median**	**Mean**	**75^{th} percentile**	**Maximum**
561 counties	CVD	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 SW	CVD	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 SW	CVD	4.88	9.03	13.5	14.1	17.4	43.7
	Respiratory	0	2.43	3.91	4.25	5.74	17.8

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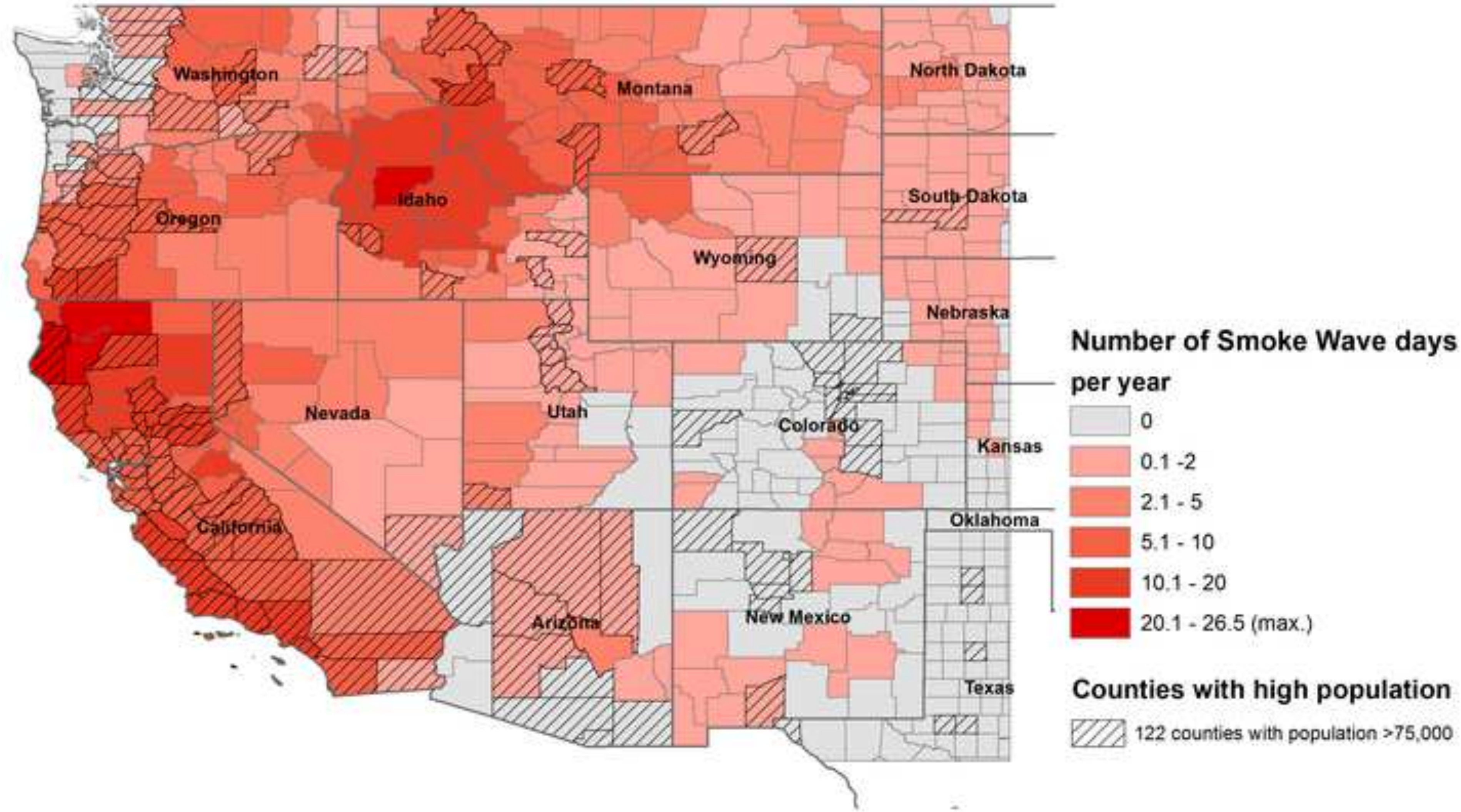

Figure 2

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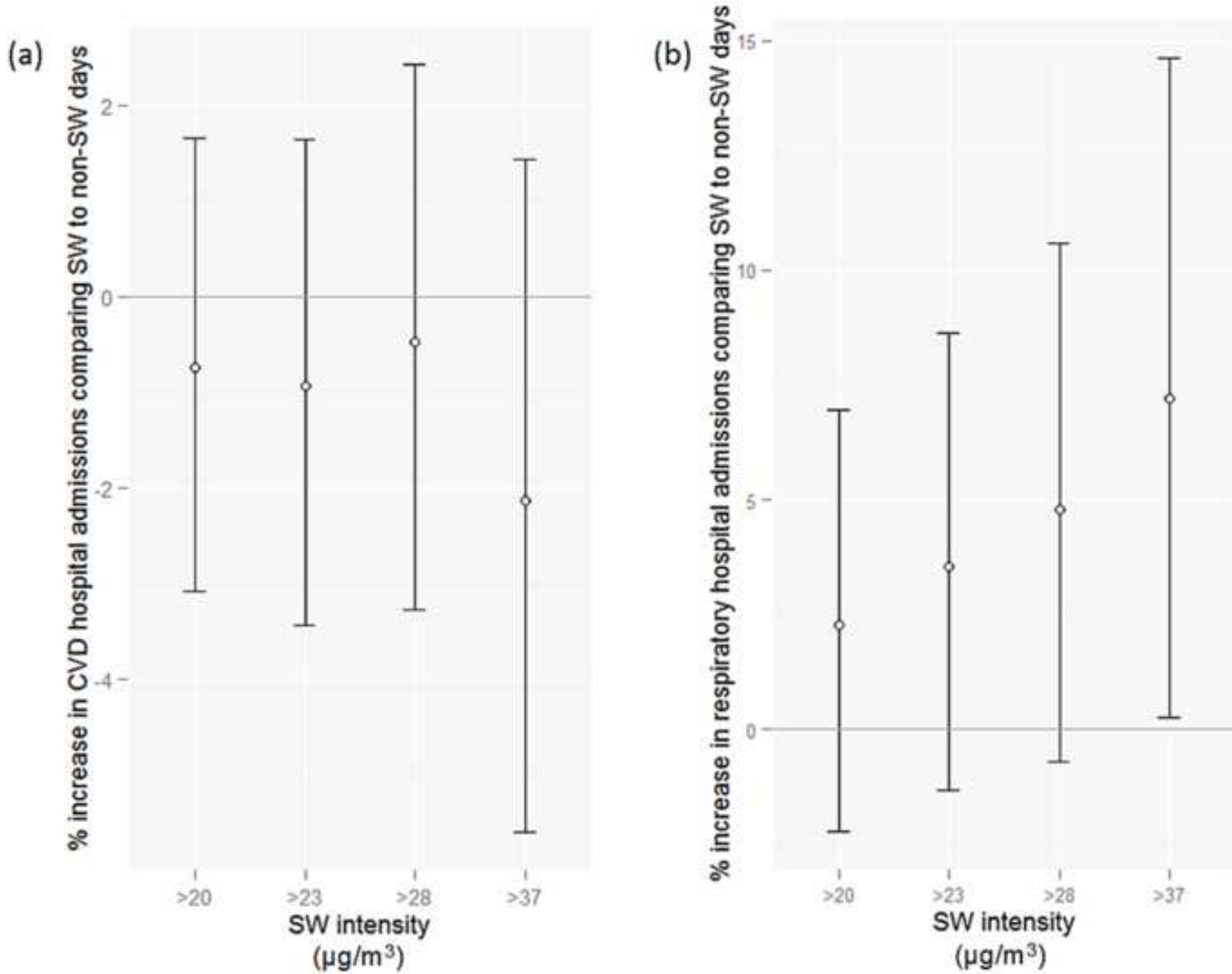

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