Wildfire exposure and health care use among people who use durable medical equipment in Southern California

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### Abstract

**Background:** Wildfires cause stress and injury in affected communities while exposing 70% of the US population to wildfire fine particulate matter (PM2.5) annually. Few studies examine wildfire smoke exposure in medically vulnerable populations, such as those using electricity-dependent durable medical equipment (DME), or evaluate residence near wildfires or in evacuation zones as risk factors for healthcare utilization.

**Methods:** We obtained daily counts of residential Zip Code Tabulation Area (ZCTA) level outpatient, inpatient, and emergency department healthcare visits, made from 2016-2020 by DME-using Kaiser Permanente Southern California members 45 or older. These visits were linked to daily estimates of ZCTA-level wildfire PM2.5 and wildfire boundary and evacuation data from the 2018 and 2019 Woolsey and Getty wildfires. We performed negative binomial regression to evaluate immediate and lagged effects of wildfire PM2.5 on healthcare visit frequency in an ecological time-series model, and effects of wildfire proximity and evacuation in a difference-in-differences model.

**Results:** Analyses consisted of 236,732 patients using DME in 274 ZCTA groupings. Increased wildfire PM2.5 concentrations (per 10 were associated with reduced risk (RR = 0.96, 95% CI: 0.94, 0.99) of all-cause outpatient visits one day after exposure and increases on four of the five subsequent days (RR range 1.03-1.12). Wildfire PM2.5 was not associated with inpatient or ED visits. Woolsey Fire proximity was associated with fewer all-cause outpatient visits (RR = 0.87, 95% CI: 0.78, 0.98), but more inpatient visits for cardiorespiratory concerns (RR = 1.45, 95% CI: 1.01, 2.11). Neither Getty Fire proximity nor evacuation from either fire was associated with any type of visit frequency.

**Conclusions:** DME users may have sheltered in place on or after smoky days, and during the Woolsey Fire. However, smoke and the Woolsey Fire may still have produced health concerns in this population particularly vulnerable to wildfire stress or smoke.

# Introduction

Wildfires are widespread, have increased in severity because of climate change, and will worsen in coming decades (Spracklen et al. 2009; Fried, Torn, and Mills 2004; Westerling et al. 2006; Abatzoglou and Williams 2016). Development in the wildland-urban interface has placed more communities in the path of these increasingly frequent disasters (Williams et al. 2019). The immediate impacts of wildfire, such as evacuations, power outages, and destruction of infrastructure cause trauma, stress, financial strain, and physical injury in affected communities (Belleville, Ouellet, and Morin 2019; McCaffrey Sarah 2014). Simultaneously, 70% of the US population is exposed to wildfire smoke annually as winds blow smoke over major cities (Jia Coco Liu et al. 2016; O’Dell et al. 2021; Lassman et al. 2017).

Among other hazardous components, wildfire smoke contains fine particulate matter (PM2.5). Of PM2.5 sources, wildfire PM2.5 may be particularly harmful because it consists of more organic and elemental carbon (Nakayama Wong et al. 2011; Aguilera, Corringham, Gershunov, and Benmarhnia 2021; Peng et al. 2021). It also constitutes most extreme PM2.5 exposure in California, accounting for 71% of total PM2.5 on days that exceed US Environmental Protection Agency (USEPA) daily standard of 12 (Jia Coco Liu et al. 2016).

Most studies examining wildfire PM2.5 exposure have focused on respiratory and cardiovascular disease. Exposure has been associated with asthma and chronic obstructive pulmonary disease symptom exacerbation (Colleen Reid 2019; Anjali Haikerwal and Dennekamp 2015; Yao et al. 2020), increases in ED and inpatient visits related to cardiorespiratory disease (Reid et al. 2019; Hutchinson et al. 2018, Reid et al. 2016; Jia Coco Liu et al. 2017), and increased mortality risk (Kollanus et al. 2016; Doubleday et al. 2020; Jia C. Liu et al. 2015).

Despite this robust understanding of wildfire smoke exposure, few studies (Jia Coco Liu et al. 2017; Ian P. Davies 2018; Rappold et al. 2017; Aguilera, Corringham, Gershunov, Leibel, et al. 2021) have examined smoke exposure in vulnerable populations, or wildfire-related exposures other than smoke. Only descriptive research has documented the effects of stress, evacuation, property destruction, or injury due to wildfire disasters (Belleville, Ouellet, and Morin 2019; McCaffrey Sarah 2014; Dodd et al. 2018). We hypothesize that residential proximity to wildfire, and evacuations due to wildfire, could influence health outcomes primarily through stress. Residents living near active wildfires are exposed to smoke, experience the disruption of usual activities in their communities, and face the threat of injury, evacuation, or longer-term displacement. Evacuation may cause more severe stress as these threats materialize.

People who use durable medical equipment may be particularly vulnerable to both wildfire PM2.5 exposure and stress from wildfire proximity or evacuation. DME use is common among older adults and is associated with respiratory illness and other disabilities (Jacobs and Lee 2014). A prior study among Kaiser Permanente Southern California (KPSC) members found increasing prevalence of DME rentals from 2008-2018 and the highest prevalence of use among older adults (Casey et al. 2021). DME types included bilevel positive airway pressure (BiPAP) machines, enteral feeding machines, infusion pumps, oxygen equipment, suction pumps, ventilators, and wheelchairs (Casey et al. 2021).

This group may face unique challenges during wildfire events. Prior studies have found elevated effect estimates between wildfire smoke exposure and respiratory and cardiovascular disease outcomes among older adults compared to younger populations (Mahsin, Cabaj, and Saini 2021; Anjali Haikerwal and Dennekamp 2015). Further, people using DME may have co-occurring medical conditions such as cardiovascular disease that make them more vulnerable to both the effects of wildfire PM2.5 and wildfire-related stressors beyond wildfire smoke (e.g., threatened or actual evacuation). Limited mobility or need for electricity access may result in increased difficulty evacuating disaster zones (Casey et al. 2021; Kivimaki 2018).

we use 2016-2020 Kaiser Permanente Southern California (KPSC) electronic health records of older adults using DME from seven Southern California counties to examine the relationship between wildfire exposure and healthcare utilization. W (1), and by (2a) residential proximity to major active fires, and (2b) residence in an evacuated area.This time period includes two major wildfire events in populated areas: the Woolsey Fire, which burned around 400km2 from November 8th to 21st, 2018 in Los Angeles and Ventura counties, destroying 1643 structures, displacing 295,000 people, and killing three (Los Angeles Fire Department 2018; Matt Styles 2018; “Woolsey Fire Death Toll” 2019), and the Getty Fire, which necessitated evacuations in densely populated Los Angeles, and burned 3km2 from October 28th to November 5th, 2019 (Los Angeles Fire Department 2019).

# Methods

## Study population and outcome data

We used electronic health record data from KPSC to identify all individuals who were 45 or older as of October 28th, 2019 and had rented DME in the year prior. We obtained daily counts of healthcare visits by this population at the Zip Code Tabulation Area (ZCTA) level, in seven counties in Southern California from January 1st, 2016 to March 15th, 2020. 236,732 DME patients lived in the study area, which covered most of San Bernardino, Orange, Los Angeles, Riverside, San Diego, Ventura, and Kern counties (**Figure 1**). The area consisted of 582 ZCTAs, each containing 1-1773 patients. During 2018 and 2019, these seven counties experienced 23 wildfires that each burned over 3 km2 in California (Cal Fire Incident Archive 2018, 2019), contributing to wildfire smoke in the area.

The KPSC Institutional Review Board (IRB) approved this study, and the Columbia IRB did not consider it human subjects research.

## Exposure Definition

### Wildfire PM2.5

We measured wildfire smoke exposure by estimating daily wildfire and non-wildfire PM2.5 concentrations at the ZCTA level using a multistage approach described elsewhere (Aguilera et al. 2021). Briefly, we first estimated daily levels of PM2.5 (from any source) at the ZCTA level using a validated ensemble model combining multiple machine learning algorithms (e.g. random forest, gradient boosting) and multiple predictors (e.g. meteorological factors such as temperature, precipitation or wind patterns, satellite-derived aerosol optical depth or land-use variables). We identified smoke-plume exposed ZCTA codes/days with the National Oceanic and Atmospheric Administration’s (NOAA) Hazard Mapping System (HMS) using a smoke binary variable by intersecting ZCTA polygons with smoke polygons. We then estimated the counterfactual PM2.5 values in the absence of wildfire smoke using spatio-temporal imputation models. We finally estimated the difference between such counterfactual values to observed values during an exposure to wildfire smoke to estimate daily/ZCTA levels of wildfire smoke PM2.5. We also obtained daily/ZCTA levels of non-wildfire PM2.5.

We calculated daily wildfire and non-wildfire PM2.5 by averaging concentrations across the higher-level ZCTA groupings (hereafter ZCTA groupings) described in the outcome definition section.

### Proximity to wildfire and evacuation

To measure direct exposure to wildfire, we obtained data on the fire boundaries and evacuation zones of two significant Southern California wildfires – the Woolsey Fire and the Getty Fire. We chose these fires because they affected a significant number of people in our study area, during the study period. The Woolsey Fire, which burned from November 8th, 2018 until November 21st, 2018, required the evacuation of 295,000 people from Los Angeles and Ventura counties. It burned 1643 structures and almost 400 km2 of land, making it particularly destructive (Los Angeles Fire Department 2018; Matt Styles 2018; “Woolsey Fire Death Toll” 2019). The Getty Fire, which ignited on October 28th, 2019 and burned until November 5th, 2019, was notable because it necessitated evacuations during its 9-day duration in densely populated Los Angeles (Los Angeles Fire Department 2019).

Notably, The Thomas Fire also burned over 1100 km2 during our study period (National Interagency Fire Center 2018). However, most of the fire burned in the rural northern corner of Ventura County and outside the study area. Therefore, we did not include the Thomas Fire in the proximity analyses. Still, smoke from this fire contributed significantly to wildfire PM2.5 in Ventura County in December 2017 (**Figure 2**).

We obtained shapefiles of the total areas burned during the Getty and Woolsey fires from the CALFIRE Fire and Resource Assessment Program (FRAP 2018). Fire boundaries expanded while the fires were active, but fire perimeters recorded during the fires did not differ significantly from the total burned areas of either fire, since dynamic boundary data available did not include perimeters from very early in either fire[[1]](#footnote-1). We therefore used final fire perimeters to define exposure. We considered ZCTAs exposed if they were within 20km of a final fire perimeter on days that a fire was active. We hypothesized that living within 20km of a fire perimeter could elicit a stress response, similar to effects described in previous studies (Belleville et al. 2019; McCaffery 2014; Christanson 2019).

Next, we created an evacuation exposure metric. GIS data on evacuation zones were not available for either fire. Therefore, we reviewed webpages (described in the appendix) containing maps of the evacuation zones and digitized boundaries around all areas ever evacuated during either fire in QGIS (QGIS Software 2022) (**Figure 1**). Using these data, we considered ZCTAs exposed to evacuation stress if they were within 10 km of any evacuation zone boundary (**Figure 1**) on days where a fire was active. Like close residence to a wildfire burn area, evacuation and anticipating potential fire or evacuation can cause stress, which we aimed to capture with this exposure definition (Belleville, Ouellet, and Morin 2019; McCaffrey Sarah 2014; Dodd et al. 2018). We chose a 10km buffer rather than the previous 20km buffer because evacuation zones themselves can be large.

## Outcome Definition

We obtained daily counts of all-cause outpatient visits, all-cause inpatient admissions, and all-cause emergency department (ED) visits, as well as inpatient admissions and ED visits specifically for circulatory or respiratory disease outcomes made by KPSC members 45 and older who rented DME. Causes were identified using *International Classification of Diseases* 10 codes I00-I99 and J00-J99, respectively. We included visits from January 1st, 2016 to March 15th, 2020.

Daily visit counts by ZCTA were low and often zero (median outpatient visits = 1 (IQR = 3), median ED and inpatient visits = 0, IQR = 0). For the wildfire PM2.5 analyses, to avoid zero-inflation in our models, we could have aggregated ZCTA counts to the weekly level. However, prior studies of wildfire smoke exposure have found associations between same-day air pollution and healthcare visits over the course of the following week (Reid et al. 2019; Hutchinson et al. 2018, Reid et al. 2016; Jia Coco Liu et al. 2017). To evaluate a lagged effect in our data, we required daily healthcare visit counts, therefore, we opted to aggregate our data into higher-level spatial groupings of several ZCTAs based on spatial proximity (hereafter ‘ZCTA groupings’; grouping method described in the appendix).

For proximity and evacuation analyses, we used ZCTA level daily visit counts aggregated to the weekly level. Because our exposure data was not as granular as that in the PM­­2.5 analyses­, as we used final fire boundaries and final evacuation zones rather than daily data, we evaluated relationships at the weekly level. This aggregation also removed weekend-weekday patterns in outpatient visits and prevented zero inflation. We considered a week exposed if the Woolsey or Getty fire burned any day that week.

## Analysis

### Wildfire PM2.5

To evaluate the relationship between daily wildfire PM2.5­ and daily ZCTA grouping-level healthcare visit counts, we used negative binomial regression. Many studies on lagged effects of air pollution use constrained distributed lag models to estimate stable coefficients in the presence of highly autocorrelated (and therefore highly co-linear) lagged exposures. We examined the autocorrelation of wildfire ­PM2.5 concentrations and found only weak autocorrelation (lags 1-7 days each had <0.25 correlation with lag 0). Unlike other sources of air pollution, wildfire PM2.5 concentrations increased dramatically on certain days, then decreased just as quickly (**Figure 2**). We therefore created unconstrained models, including separate terms for wildfire PM2.5 lags 0-7 days. We also performed an additional analysis examining weekly wildfire PM2.5 levels lagged up to two weeks. We created separate models for each healthcare visit type: all-cause outpatient, inpatient, and ED visits, and inpatient and ED visits for circulatory or respiratory disease endpoints.

We included offsets accounting for the number of KPSC members over 45 using DME in each ZCTA grouping. We controlled for temperature using a penalized spline term, as temperature can predict respiratory and cardiovascular healthcare utilization (Rochelle S. Green 2010) and wildfire (Vlassova et al. 2014), using daily temperature data from the PRISM Climate Group (PRISM Climate Group 2021). We also controlled for long-term seasonal trends not caused by exposure with a natural spline term, and used the number of years in the study period (four) to determine the natural spline flexibility (12 degrees of freedom).

We controlled for non-wildfire PM2.5, since non-wildfire PM 2.5 concentrations were high during the study period: mean daily non-wildfire PM2.5 by grouping was 11.00 (SD = 6.69), just under the annual USEPA exposure limit of 12 (**Figure 2a**). We also added a fixed effect for weekends to the outpatient visits model, accounting for fewer visits on weekend days.

We included fixed effects for a comprehensive set of socioeconomic variables to account for correlation between ZCTA groupings. We obtained values by ZCTA from the 5-year 2015-2019 ACS (U.S. Census Bureau 2016-2020) including median household income, home ownership (% homes occupied by owner), poverty (percent households below threshold income), age structure (percent of population under 5, 5-19, 20-64, and 65+ years), and racial/ethnic composition (percent Hispanic, percent non-Hispanic white, percent non-Hispanic Black). We took a simple mean within ZCTA groupings to obtain average covariate values by ZCTA grouping or summed within ZCTA groupings when appropriate (for example, we summed total population across groupings).

### Proximity to wildfire and evacuation

To evaluate proximity to and evacuation from wildfire, we used a difference-in-differences (DID) analysis with negative binomial regression to estimate the associations between wildfire proximity and evacuation and weekly ZCTA-level healthcare visit counts. We evaluated each relationship separately for each fire and each type of healthcare visit, performing 20 regression analyses. The DID estimators subtracted the change in visit frequency during a fire among control ZCTAs (difference 1) from the change in visit frequency during a fire among ZCTAs exposed to the fire or evacuation zone (difference 2). If all models were specified correctly and parallel trends conditions were met, the DID estimator corresponded to the difference in visit frequency attributable to direct wildfire exposure. We assessed the parallel trends assumption visually (plots are included in the appendix).

We chose control ZCTAs by excluding ZCTAs exposed to both the Getty and Woolsey Fires, and all ZCTAs exposed to other large, disastrous fires during the study period, to avoid bias in our analyses. However, we felt that ZCTAs exposed to other disastrous fires would serve as ideal comparison groups *prior* to their exposure to those fires. Therefore, we excluded observations from these ZCTAs made during and after fire exposures.

We identified control ZCTAs by creating a dataset of fire perimeters for all “disaster” fires in California from 2016-2020. This dataset included fires that burned over 1000 acres, were declared disasters by FEMA, caused a civilian fatality, or burned more than 10 structures of any size. We excluded data from ZCTAs within 20 km of any of these fire boundaries, from the date of fire ‘alarm date’ onward. (should add citation for what an alarm date is).

As in the wildfire PM2.5 models, we included offsets accounting for the population exposed and controlled for temperature with a penalized spline. We controlled for long-term seasonal trends not caused by exposure with a penalized spline term, as our data in these analyses were at the weekly level. We did not control for wildfire PM2.5 in these proximity and evacuation models, as we considered this a mediator rather than a confounder.

We tested all models for sensitivity to parameterization of splines, by re-running all analyses with natural splines in place of penalized splines, described in the appendix. We conducted all analyses in R, (R Core Team 2021) using the mgcv package (Wood 2017). All analysis code and model equations are available on GitHub at https://github.com/heathermcb/wildfires\_DME.

# Results

## Health data description

The study population consisted of 236,732 KPSC DME users who between January 1, 2016 to March 15th, 2020 had a daily average of 2.5 (SD = 4.7) outpatient visits, 0.1 (SD = 0.4) inpatient visits, and 0.1 (SD = 0.5) ED visits per ZCTA grouping. There were on average 8 (SD = 8.9) outpatient visits per week per ZCTA, 0.2 (SD = 0.8) inpatient visits, and 0.5 (SD = 1.5) ED visits. The most common diagnoses were for circulatory or respiratory disease: of the 62,892 ED visits made over the study period, 49,364 (78%) were for circulatory or respiratory disease concerns, as were 30,325 (90%) of inpatient visits.

## PM2.5 exposure

Mean daily wildfire PM2.5 concentration by ZCTA grouping throughout the study period was 0.22 (SD = 2.67) (**Figure 2b**), since most groupings on most days (85% of days) had 0 wildfire PM2.5, while the maximum wildfire PM2.5 concentration was 551.53 . On the 366 days (23%) when study area wildfire PM­2.5 was non-zero, the mean concentration in groupings with non-zero measurements was 5.6(SD = 12.1). On days where wildfire PM2.5 exceeded USEPA limits, in ZCTA groupings over the limit, wildfire PM2.5 made up 91% of total PM2.5.

In adjusted negative binomial models, a daily 10 increase in wildfire PM2.5 was associated with a decrease in risk of outpatient visits one day later (RR = 0.96, 95% CI: 0.94, 0.99), but increases on four of the five subsequent days (**Table 1a**). Wildfire PM2.5 levels were not associated with the count of all-cause ED or inpatient visits or ED or inpatient visits for cardiorespiratory concerns.

In our additional analysis examining weekly wildfire PM2.5 levels lagged up to two weeks, a 10 increase in weekly PM2.5 concentration was associated with a same-week increase in outpatient visits (RR = 1.10, 95% CI: 1.04, 1.17), consistent with the daily outpatient visit model. Additionally, there were increases in weekly outpatient visits one and two weeks later (**Table 1b**). Weekly PM2.5 levels were not associated with the frequency of any other visits.

## Proximity to wildfire and evacuation

There were 54 ZCTAs (9%) within 20 km of the Woolsey Fire boundary, which we considered exposed to the fire. Despite the comparatively small size of the Getty Fire (~3 km2 vs ~400 km2), 98 ZCTAs (17%) were exposed, as the Getty Fire was closer to population centers. We estimated that 20 and 21 ZCTAs were evacuation exposed during the Woolsey and Getty fires, respectively. However, all evacuation exposed ZCTAs were also within 20km of the fire boundaries, meaning that the evacuation exposed ZCTAs were a subset of the wildfire proximate ZCTAs in both cases.

### Woolsey Fire proximity and evacuation exposure

During the Woolsey Fire, the frequency of all types of visits increased by 15 to 22% across the whole study area, except outpatient visits, which remained the same. Woolsey Fire proximity during the fire was associated with decreased outpatient visits, and increased inpatient admissions for cardiorespiratory disease (**Figure 3**, **Table 2a**). We observed similar associations between Woolsey Fire evacuation exposure and healthcare visits with elevated visit counts of all types of healthcare visits in ZCTAs evacuated during the fire, and during the fire, the frequency of all types of visits increased throughout the study area, except for outpatient visits (**Table 2a**).

### Getty Fire proximity and evacuation exposure

During the Getty Fire, outpatient visits, ED visits, and ED visits for cardiorespiratory problems increased across the entire study area. We observed reduced risks of all visits types among proximity exposed ZCTAs during the Getty Fire, but confidence intervals were very wide (**Figure 3**, **Table 2b**). We observed similar, if somewhat attenuated, associations among evacuation exposed ZCTAs.

None of our results were sensitive to spline flexibility.

# Discussion

Using electronic health data on 236,732 Kaiser Permanente DME patients from 2016-2020, we found that an increase in wildfire PM2.5 concentration was associated with next-day decreases in outpatient visits and increases in outpatient visits up to two weeks later. Increases in wildfire PM2.5 were not associated with the frequency of other visits. Residential proximity to the large Woolsey Fire was also associated with fewer all-cause outpatient visits, as well as more frequent cardiorespiratory inpatient visits. Our study was unique in that we evaluated healthcare utilization among DME users, a group hypothesized to be susceptible to disaster and wildfire smoke exposures, and we examined residence near a wildfire or an evacuation zone.

The literature describes a strong relationship between wildfire smoke exposure and cardiorespiratory health (Reid et al. 2016). Most studies measure this association through healthcare utilization and have found increased risk of hospital admissions and ED visits for cardiorespiratory outcomes following wildfire PM2.5, PM10, or general smoke exposure in the U.S., Canada, Australia, and Brazil (Henderson et al. 2011; Thelen et al. 2013; Delfino et al. 2009; Morgan et al. 2010; Ye et al. 2021; Johnston et al. 2014).

Fewer studies have examined wildfire PM2.5 exposure in vulnerable populations (Reid et al. 2019; Xi et al. 2020). Of studies examining older adults, all have reported associations between smoke exposure and increased inpatient and ED visit frequency (DeFlorio-Barker et al. 2019; Ignotti et al. 2010; Morgan et al. 2010; Henderson et al. 2011), and while some studies find older adults at elevated risk compared to younger adults (Ignotti et al. 2010; Delfino et al. 2009; Haikerwal et al. 2015), others found no difference (Rappold et al. 2011; Henderson et al. 2011). Surprisingly, we observed no association between wildfire PM2.5 and ED or inpatient visits. We hypothesized that older adult DME users would be particularly susceptible to wildfire PM­2.5 due to probable high prevalence of underlying cardiorespiratory disease (Jacobs and Lee 2014). The observed null association between wildfire PM2.5 and ED or inpatient visits may indicate that DME users, especially those vulnerable to smoke, may be sheltering in place during smoky periods or taking other precautions, or that study limitations may be obscuring associations between smoke and more urgent healthcare use.

Limited studies have assessed outpatient care utilization during smoke exposure and most have focused on outpatient visits for respiratory concerns, reporting increases during smoke exposure (Sheldon and Sankaran 2017; Lee et al. 2009; Moore et al. 2006; Mott et al. 2002, Henderson et al. 2011). None of those studies examined all-cause outpatient care use. Hutchinson et al. 2018 simultaneously reported decreases in all-cause outpatient visits during smoke exposure and increases in visits for respiratory concerns only. Similarly, Henderson et al. 2011 found increased physician visits for asthma and all-respiratory outcomes related to same-day wildfire smoke exposure but no increase in physician visits for cardiovascular disease. We observed an initial next-day decrease in all-cause outpatient visits, and then a positive association between wildfire PM2.5 and outpatient visits among DME users for the two weeks following exposure. These findings are consistent with much of the literature.

Few studies have evaluated proximity to wildfire boundaries or wildfire evacuation as risk factors for healthcare utilization or adverse health outcomes (Binet et al. 2021; Park et al. 2021; Tally et al. 2013). Proximity to wildfires can affect health through a stress pathway, on top of risks related to smoke exposure. Qualitative studies emphasize this point, and several have documented the immense stress experienced by those displaced by wildfire (Belleville et al. 2019; McCaffery 2014; Christanson 2019). After the 2014 Canadian Northwest Territory wildfires, one interviewee said: “Well, it took a toll on me because being stressed out from the fires and never knowing when we had to leave to be evacuated we didn’t know if we were going to come home to a community or to our houses” (Dodd et al. 2018). Agyapong et al. 2021 estimated the likely prevalence of post-traumatic stress disorder among Canadian Fort McMurray wildfire survivors at 12.8%, twice the baseline population prevalence. We attempted to assess this proximity/evacuation pathway for two major fires in our study area using a difference-in-differences analysis. We found no association between exposure and healthcare visits during the Getty Fire. However, during the Woolsey Fire, we observed an increase in cardiorespiratory inpatient visits and a decrease in all-cause outpatient visits. The 400 km2 Woolsey Fire, which caused $3 billion in damages (Holland 2018), was much larger than the 4 km2  Getty Fire, which destroyed 10 homes (LAFD 2018), that null associations between Getty proximity exposure and all visit types could be due to its smaller size; it may have not been large enough to produce a detectable effect in visit changes. A larger analysis examining several wildfires, rather than two, could be informative.

Study limitations could have influenced our results. First, we only had access to data on visits to Kaiser Permanente clinics and hospitals made by Kaiser members using DME. These patients would be highly motivated to seek care at Kaiser, given their insurance status, however they may have sought urgent care at other clinics or hospitals. Such alternate utilization would have produced artificially reduced visit counts, especially for inpatient and emergency visits. If patients sought care at other clinics only during wildfires (whether during evacuations or while a fire was burning nearby) this could have biased association estimates towards the null.

Second, all visits were infrequent over the study period. Inpatient and ED visits were much less frequent over the study period than outpatient visits. All models may have been underpowered to detect changes in these visits.

Third, we did not assess differences in healthcare use by type of DME or stratify by age group or sex beyond limiting our study population to those age 45 or older. Excluding younger people excluded most breast pump users, a generally healthy subpopulation who constitute 30% of DME users of all ages at KPSC (Casey et al. 2021). Subgroups such as those using ventilators or those using breast pumps likely have vastly different health needs and outcomes. We chose to focus on DME users aged 45 and older who were likely the most susceptible to wildfire. However, subgroups in our study may also have differing needs and outcomes, which we did not examine.

Lastly, as in any observational study, residual confounding could affect our results. We attempted to account for residual spatial confounding by including a set of ZCTA-level covariates that measured different facets of socioeconomic status.

**Conclusion**

This study found an association between elevated wildfire PM2.5 concentrations and increased acute all-cause outpatient visits among DME users. However, we found no relationship between elevated wildfire PM2.5 concentrations and inpatient or ED visits. One possible explanation, which has not been examined in any literature, is that DME users especially vulnerable to smoke may have sheltered in place during smoky periods or took other precautions. This could have prevented urgent visits.

Decreased outpatient healthcare utilization among DME users living close to wildfires suggests that wildfire disaster may interrupt routine care. While we saw a small increase in inpatient visits related to wildfire proximity, we saw no relation with elevated wildfire PM2.5­ and either ED or inpatient visits. Wildfire PM2.5­, while extreme on some days, may not be a disaster in the same way that living close to an active wildfire, and may therefore cause more disruption in routine care.

As wildfires become more frequent and severe with climate change, we must understand how they affect both local populations and those exposed to wildfire PM2.5. Protecting vulnerable populations that may be harmed by exposures which others can avoid or endure is essential. More work is needed to understand how DME users respond to wildfires, and how we can best support those affected by smoke, fire, and evacuation.

# Appendix

## Notes on wildfire evacuation zones, boundaries, and exposure definition

We reviewed the following webpages containing maps of the evacuation zones, and traced what we believed to be an accurate boundary around all areas evacuated in each fire in QGIS (QGIS Software 2022). The evacuation zone boundaries we defined are plotted in Figure 1, along with the fire boundaries. Our code is available at <https://github.com/heathermcb/kaiser_wildfires>.

| Getty Fire: |
| --- |
| 1. <https://www.newsweek.com/getty-fire-evacuation-map-update-california-los-angeles-1468222> |
| 1. <https://www.newsweek.com/getty-center-fire-map-evacuation-los-angeles-california-1468100> |
| 1. <https://www.express.co.uk/news/world/1196943/getty-fire-evacuation-map-405-fire-update-los-angeles-fire-evacuation-road-school-closures> |
| 1. <https://www.flyertalk.com/forum/los-angeles/1993097-getty-fire-405-closed-sepulveda-pass-now-open.html> |
| 1. <https://heavy.com/news/2019/10/getty-fire-los-angeles/> |

| Woolsey Fire: |
| --- |
| 1. <https://www.kclu.org/local-news/2018-11-10/map-shows-boundaries-of-woolsey-hill-brush-fires-and-evacuation-areas> |
| 1. <https://wildfiretoday.com/tag/woolsey-fire/> |
| 1. <https://www.dailynews.com/2018/11/08/this-map-shows-where-the-hill-fire-and-woolsey-fire-are-burning/> |
| 1. <https://www.mercurynews.com/2018/11/09/map-of-woolsey-and-hill-fires-highway-101-closed-malibu-evacuated/> |
| 1. <https://woolseylawyers.com/woolsey-fire-map/> |

## Higher-level groupings of ZCTAs

We created higher-level groupings of ZCTAs using the numerical ZCTA codes. We used a bespoke method, and then tested the resulting spatial groupings to make sure that ZCTAs grouped together had similar exposure measurements, to guard against exposure misclassification. We grouped ZCTAs together if all their numerical codes differed by 1 in sequence. For example, codes 90001-90008 and 90011-90014 were in the study area. We grouped codes 90001 - 90008 together, as they are all sequentially 1 digit apart, while 90011-90014 formed a second grouping. This method resulted in groupings of ZCTAs that were all adjacent, since similar codes tend to be geographically close.

Using this method, we created 274 groups containing 1-19 ZCTAs each, with a mean and mode group size of 2. We assessed the correlation between wildfire PM2.5 within each group and between all ZCTAs regardless of group, concluding that wildfire PM2.5 measurements within groups were highly correlated (mean within-group correlation was r = 0.96), while mean correlation of PM2.5 between any two ZCTAs was 0.48. We also mapped the groups to confirm that all ZCTAs grouped together were adjacent. The code that creates these groupings and assesses them is available at <https://github.com/heathermcb/kaiser_wildfires>.

# References

Abatzoglou, John T, and A Park Williams. 2016. “Impact of Anthropogenic Climate Change on Wildfire Across Western US Forests.” *Proc Natl Acad Sci U S A* 113 (42): 11770–75.

Aguilera, R., Luo, N., Basu, R., Wu, J., Gershunov, A., & Benmarhnia, T. (2021). Using machine learning to estimate wildfire PM2. 5 at California ZIP codes (2006-2020). https://chemrxiv.org/engage/chemrxiv/article-details/6169e9597d3da5ff02f96022

Aguilera, Rosana, Thomas Corringham, Alexander Gershunov, and Tarik Benmarhnia. 2021. “Wildfire Smoke Impacts Respiratory Health More Than Fine Particles from Other Sources: Observational Evidence from Southern California.” *Nature Communications* 12 (1): 1493.

Aguilera, Rosana, Thomas Corringham, Alexander Gershunov, Sydney Leibel, and Tarik Benmarhnia. 2021. “Fine Particles in Wildfire Smoke and Pediatric Respiratory Health in California.” *Pediatrics* 147 (4).

Agyapong, Vincent IO, et al. "Prevalence rates and correlates of likely post-traumatic stress disorder in residents of fort mcmurray 6 months after a wildfire." *International Journal of Mental Health and Addiction* 19.3 (2021): 632-650.

Anjali Haikerwal, Anthony Del Monaco, Muhammad Akram, and Martine Dennekamp. 2015. “Impact of Fine Particulate Matter (PM 2.5) Exposure During Wildfires on Cardiovascular Health Outcomes.” *JAHA*.

Belleville, Genevieve, Marie-Christine Ouellet, and Charles M. Morin. 2019. “Post-Traumatic Stress Among Evacuees from the 2016 Fort McMurray Wildfires: Exploration of Psychological and Sleep Symptoms Three Months After the Evacuation.” *International Journal of Environmental Research and Public Health* 16 (9).

Binet, Émilie, et al. "A portrait of mental health services utilization and perceived barriers to care in men and women evacuated during the 2016 Fort McMurray Wildfires." *Administration and Policy in Mental Health and Mental Health Services Research* (2021): 1-13.

US Census Bureau. 2016-2020. “American Community Survey 5-Year Public Use Samples,” 2016-2020.

California Department of Forestry and Fire Protection Fire and Resource Assessment Program (FRAP). <https://frap.fire.ca.gov/>. 2018.

Cal Fire Incident Archive. 2018. “Getty Fire Incident.” 2018.

———. 2019. “Woolsey Fire Incident.” 2019.

Casey, Joan A, Marriele Mango, Seth Mullendore, Mathew V Kiang, Diana Hernández, Bonnie H Li, Kris Li, Theresa M Im, and Sara Y Tartof. 2021. “Trends from 2008 to 2018 in Electricity-Dependent Durable Medical Equipment Rentals and Sociodemographic Disparities.” *Epidemiology* 32 (3): 327–35.

Christianson, Amy Cardinal, and Tara K. McGee. "Wildfire evacuation experiences of band members of Whitefish Lake First Nation 459, Alberta, Canada." *Natural Hazards* 98.1 (2019): 9-29.

Colleen Reid, Melissa May Maestas. 2019. “Wildfire Smoke Exposure Under Climate Change.” *Pulmonary Medicine*.

DeFlorio-Barker, Stephanie, et al. "Cardiopulmonary effects of fine particulate matter exposure among older adults, during wildfire and non-wildfire periods, in the United States 2008–2010." *Environmental health perspectives* 127.3 (2019): 037006.

Delfino, Ralph J., et al. "The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003." *Occupational and environmental medicine* 66.3 (2009): 189-197.

Dodd, Warren, et al. "Lived experience of a record wildfire season in the Northwest Territories, Canada." *Canadian Journal of Public Health* 109.3 (2018): 327-337.

Doubleday, Annie, Jill Schulte, Lianne Sheppard, Matt Kadlec, Ranil Dhammapala, Julie Fox, and Tania Busch Isaksen. 2020. “Mortality Associated with Wildfire Smoke Exposure in Washington State, 2006-2017: A Case-Crossover Study.” *Environ Health* 19 (1): 4.

Fried, Jeremy S., Margaret S. Torn, and Evan Mills. 2004. “The Impact of Climate Change on Wildfire Severity: A Regional Forecast for Northern California.” *Climatic Change* 64 (1): 169–91.

Henderson, Sarah B., et al. "Three measures of forest fire smoke exposure and their associations with respiratory and cardiovascular health outcomes in a population-based cohort." *Environmental health perspectives* 119.9 (2011): 1266-1271.

Emily Holland (November 28, 2018). ["$6 Billion In Real Estate Destroyed In Woolsey Fire: Report"](https://patch.com/california/malibu/6-billion-real-estate-destroyed-woolsey-fire-report). *patch.com*. Patch Media.

Hutchinson, Justine A, Jason Vargo, Meredith Milet, Nancy H F French, Michael Billmire, Jeffrey Johnson, and Sumi Hoshiko. 2018. “The San Diego 2007 Wildfires and Medi-Cal Emergency Department Presentations, Inpatient Hospitalizations, and Outpatient Visits: An Observational Study of Smoke Exposure Periods and a Bidirectional Case-Crossover Analysis.” *PLoS Med* 15 (7): e1002601.

Ian P. Davies, James C. Robertson, Ryan D. Haugo. 2018. “The Unequal Vulnerability of Communities of Color to Wildfire.” *PLOS ONE*.

Ignotti, Eliane, et al. "Impact on human health of particulate matter emitted from burnings in the Brazilian Amazon region." *Revista de saude publica* 44 (2010): 121-130.

Jacobs, Bret C., and Justin A. Lee. "Durable medical equipment: Types and indications." *Medical Clinics* 98.4 (2014): 881-893.

Johnston FH, Purdie S, Jalaludin B, Martin KL, Henderson SB, Morgan GG. 2014. Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996–2007: a case-crossover analysis.Environ Health13:105, doi:10.1186/1476-069X-13-10525491235.

Kivimaki, Steptoe, M. 2018. “Effects of Stress on the Development and Progression of Cardiovascular Disease.” *Nat Rev Cardiol*.

Kollanus, Virpi, Pekka Tiittanen, Jarkko V Niemi, and Timo Lanki. 2016. “Effects of Long-Range Transported Air Pollution from Vegetation Fires on Daily Mortality and Hospital Admissions in the Helsinki Metropolitan Area, Finland.” *Environ Res* 151 (November): 351–58.

Lassman, William, Bonne Ford, Ryan W. Gan, Gabriele Pfister, Sheryl Magzamen, Emily V. Fischer, and Jeffrey R. Pierce. 2017. “Spatial and Temporal Estimates of Population Exposure to Wildfire Smoke During the Washington State 2012 Wildfire Season Using Blended Model, Satellite, and in Situ Data.” *GeoHealth* 1 (3): 106–21.

Lee TS, Falter K, Meyer P, Mott J, Gwynn C. 2009. Risk factors associated with clinic visits during the 1999 forest fires near the Hoopa Valley Indian Reservation, California, USA.Int J Environ Health Res19:315-32719629821.

Liu, Jia Coco, Loretta J Mickley, Melissa P Sulprizio, Francesca Dominici, Xu Yue, Keita Ebisu, Georgiana Brooke Anderson, Rafi F A Khan, Mercedes A Bravo, and Michelle L Bell. 2016. “Particulate Air Pollution from Wildfires in the Western US Under Climate Change.” *Clim Change* 138 (3): 655–66.

Liu, Jia Coco, Ander Wilson, Loretta J. Mickley, Keita Ebisu, Melissa P. Sulprizio, Yun Wang, Roger D. Peng, Xu Yue, Francesca Dominici, and Michelle L. Bell. 2017. “Who Among the Elderly Is Most Vulnerable to Exposure to and Health Risks of Fine Particulate Matter From Wildfire Smoke?” *American Journal of Epidemiology* 186 (6): 730–35.

Liu, Jia C, Gavin Pereira, Sarah A Uhl, Mercedes A Bravo, and Michelle L Bell. 2015. “A Systematic Review of the Physical Health Impacts from Non-Occupational Exposure to Wildfire Smoke.” *Environ Res* 136 (January): 120–32.

Los Angeles Fire Department. 2018. “LAFD News: Getty Fire.” 2018.

Mahsin, M D, Jason Cabaj, and Vineet Saini. 2021. “Respiratory and cardiovascular condition-related physician visits associated with wildfire smoke exposure in Calgary, Canada, in 2015: a population-based study.” *International Journal of Epidemiology*, September.

Matt Styles, Joseph Sterna. 2018. “Woolsey Fire Response Hurt by Poor Disaster Preparation, Lack of Firefighters, Report Says.” 2018.

McCaffrey Sarah, Stidham Melanie, Rhodes Alan. 2014. “Wildfire Evacuation and Its Alternatives: Perspectives from Four United States’ Communities.” *International Journal of Wildland Fire* 24: 170–78.

Moore D, Copes R, Fisk R, Joy R, Chan K, Brauer M. 2006. Population health effects of air quality changes due to forest fires in British Columbia in 2003: estimates from physician-visit billing data.Can J Public Health97:105-10816619995.

Morgan G, Sheppeard V, Khalaj B, Ayyar A, Lincoln D, Jalaludin Bet al.. 2010. Effects of bushfire smoke on daily mortality and hospital admissions in Sydney, Australia.Epidemiology21:47-5519907335.

Mott JA, Mannino DM, Alverson CJ, Kiyu A, Hashim J, Lee Tet al.. 2005. Cardiorespiratory hospitalizations associated with smoke exposure during the 1997 Southeast Asian Forest Fires.Int J Hyg Environ Health208:75-8515881981.

Nakayama Wong, L. S., H. H. Aung, M. W. Lamé, T. C. Wegesser, and D. W. Wilson. 2011. “Fine Particulate Matter from Urban Ambient and Wildfire Sources from California’s San Joaquin Valley Initiate Differential Inflammatory, Oxidative Stress, and Xenobiotic Responses in Human Bronchial Epithelial Cells.” *Toxicology in Vitro* 25 (8): 1895–905.

O’Dell, Katelyn, Kelsey Bilsback, Bonne Ford, Sheena E. Martenies, Sheryl Magzamen, Emily V. Fischer, and Jeffrey R. Pierce. 2021. “Estimated Mortality and Morbidity Attributable to Smoke Plumes in the United States: Not Just a Western US Problem.” *GeoHealth* 5 (9): e2021GH000457.

Park, Bo Young, et al. "The association between wildfire exposure in pregnancy and foetal gastroschisis: A population‐based cohort study." *Paediatric and perinatal epidemiology* 36.1 (2022): 45-53.

PRISM Climate Group. 2021. “PRISM Climate Group Daily Temperature Data.” 2021.

“QGIS Software.” 2022. <http://qgis.org>.

R Core Team, 2021. <https://www.R-project.org/>.

Rappold, Ana G., Jeanette Reyes, George Pouliot, Wayne E. Cascio, and David Diaz-Sanchez. 2017. “Community Vulnerability to Health Impacts of Wildland Fire Smoke Exposure.” *Environmental Science & Technology* 51 (12): 6674–82.

Rappold, Ana G., et al. "Peat bog wildfire smoke exposure in rural North Carolina is associated with cardiopulmonary emergency department visits assessed through syndromic surveillance." *Environmental health perspectives* 119.10 (2011): 1415-1420.

Reid, Colleen E, Michael Brauer, Fay H Johnston, Michael Jerrett, John R Balmes, and Catherine T Elliott. 2016. “Critical Review of Health Impacts of Wildfire Smoke Exposure.” *Environ Health Perspect* 124 (9): 1334–43.

Reid, Colleen E, Ellen M Considine, Gregory L Watson, Donatello Telesca, Gabriele G Pfister, and Michael Jerrett. 2019. “Associations Between Respiratory Health and Ozone and Fine Particulate Matter During a Wildfire Event.” *Environ Int* 129 (August): 291–98.

Rochelle S. Green, Brian Malig, Rupa Basu. 2010. “The Effect of Temperature on Hospital Admissions in Nine California Counties.” *International Journal of Public Health* 55: 113–21.

Sheldon, Tamara L., and Chandini Sankaran. "The impact of Indonesian forest fires on Singaporean pollution and health." *American Economic Review* 107.5 (2017): 526-29.

Spracklen, D. V., L. J. Mickley, J. A. Logan, R. C. Hudman, R. Yevich, M. D. Flannigan, and A. L. Westerling. 2009. “Impacts of Climate Change from 2000 to 2050 on Wildfire Activity and Carbonaceous Aerosol Concentrations in the Western United States.” *Journal of Geophysical Research: Atmospheres* 114 (D20).

Tally, Steven, et al. "The impact of the San Diego wildfires on a general mental health population residing in evacuation areas." *Administration and Policy in Mental Health and Mental Health Services Research* 40.5 (2013): 348-354.

Thelen, Brian, et al. "Modeling acute respiratory illness during the 2007 San Diego wildland fires using a coupled emissions-transport system and generalized additive modeling." *Environmental Health* 12.1 (2013): 1-22.

Vlassova, Lidia, Fernando Perez-Cabello, Marcos Rodrigues Mimbrero, Raquel Montorio Lloveria, and Alberto Garcia-Martin. 2014. “Analysis of the Relationship Between Land Surface Temperature and Wildfire Severity in a Series of Landsat Images.” *Remote Sensing* 6 (7): 6136–62.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam. 2006. “Warming and Earlier Spring Increase Western u.s. Forest Wildfire Activity.” *Science* 313 (5789): 940–43.

Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., ... & Stewart, S. I. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences*, *115*(13), 3314-3319.

Wood, Simon. 2017. *Generalized Additive Models: An Introduction with r*. 2nd ed. Chapman; Hall/CRC.

“Woolsey Fire Death Toll.” 2019. <https://www.mercurynews.com/2018/11/14/woolsey-fire-death-toll-increases-to-3-lasd-investigating/>.

Xi, Yuzhi, et al. "Mortality in US hemodialysis patients following exposure to Wildfire smoke." *Journal of the American Society of Nephrology* 31.8 (2020): 1824-1835.

Yao, Jiayun, Michael Brauer, Julie Wei, Kimberlyn M McGrail, Fay H Johnston, and Sarah B Henderson. 2020. “Sub-Daily Exposure to Fine Particulate Matter and Ambulance Dispatches During Wildfire Seasons: A Case-Crossover Study in British Columbia, Canada.” *Environ Health Perspect* 128 (6): 67006.

Ye, Tingting, et al. "Risk and burden of hospital admissions associated with wildfire-related PM2· 5 in Brazil, 2000–15: a nationwide time-series study." *The Lancet Planetary Health* 5.9 (2021): e599-e607.

1. https://data-nifc.opendata.arcgis.com/search?tags=Category%2Chistoric\_wildlandfire\_opendata [↑](#footnote-ref-1)