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

Heather McBrien[*] Sebastian Rowland[†] Tarik Benmarhnia[‡] Sara Tartof[§]
Joan Casey[¶]

[*]Columbia Mailman School of Public Health
[†]Columbia Mailman School of Public Health
[‡]University of California San Diego
[§]Kaiser Permanente Southern California
[¶]Columbia Mailman School of Public Health, jac2250@cumc.columbia.edu

Abstract

Background: Climate change-induced wildfires cause trauma, stress, and injury in affected communities, while exposing 70% of the US population to smoke $PM_{2.5}$ annually and exacerbating cardiorespiratory disease. Few studies examine wildfire smoke exposure in vulnerable populations, and none evaluate residence near a fire or in an evacuation zone.

Methods: We identified 236,732 Kaiser Permanente Southern California members who used electricity-dependent durable medical equipment (DME). DME use is associated with respiratory illness and disability, indicating vulnerability to smoke exposure and difficulty evacuating disaster zones. Daily counts of outpatient, inpatient, and emergency healthcare visits made by DME users from 2016-2020 were linked with daily estimates of wildfire generated $PM_{2.5}$ by ZIP code. We used historical maps to identify evacuated ZIPs during the 2018 Getty and Woolsey fires. We performed negative binomial regression analyses using direct and lagged effects of wildfire $PM_{2.5}$ and difference-in-differences analyses to evaluate the association between wildfire evacuation exposure and health care visit frequency. We adjusted for temperature, temporal effects, non-wildfire $PM_{2.5}$, and spatial confounders.

Results: Woolsey fire evacuation exposure was associated with fewer outpatient and more inpatient visits (RR = 0.98, 95% CI: 0.78, 0.87, RR = 1.45, 95% CI: 1.01, 2.11), while Getty fire evacuation exposure was not associated with visit frequency. In contrast, increases in wildfire $PM_{2.5}$ were associated with small and constant decreases in outpatient visits for six days after a change. Wildfire $PM_{2.5}$ was not associated with frequency of inpatient or emergency visits at any lag.

Conclusions: DME users, presumed vulnerable to wildfire smoke exposure, may have sheltered in place on smoky days or took other precautions. However, the Woolsey fire (which was 10 times larger than the Getty) may have produced health concerns in those directly affected when evacuation was necessary and sheltering in place impossible.

1 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). The direct 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). Winds also move smoke plumes across continents, exposing major cities and 70% of the US population to wildfire smoke annually (Jia Coco Liu et al. 2016; O'Dell et al. 2021; Lassman et al. 2017).

Among other components harmful to health, wildfire smoke contains fine particulate matter ($PM_{2.5}$). Smoke $PM_{2.5}$ is likely more harmful to health than PM from other sources (Nakayama Wong et al. 2011; Aguilera, Corringham, Gershunov, and Benmarhnia 2021) and simultaneously constitutes most extreme $PM_{2.5}$ exposure in California, accounting for 71% of total fine particulate matter on days that exceed US Environmental Protection Agency standards (Jia Coco Liu et al. 2016). Exposure has been associated with respiratory and cardiovascular disease exacerbations (Colleen Reid 2019; Anjali Haikerwal and Dennekamp 2015; Yao et al. 2020), increases in health care and ED visits for respiratory and cardiovascular disease (Reid et al. 2019; Hutchinson et al. 2018), hospital admissions (Reid et al. 2016; Jia Coco Liu et al. 2017), and deaths from respiratory and cardiovascular disease (Kollanus et al. 2016; Doubleday et al. 2020; Jia C. Liu et al. 2015).

While the health consequences of wildfire smoke exposure are well examined in general populations (see citations above), few studies have examined smoke exposure in vulnerable populations (Jia Coco Liu et al. 2017; Ian P. Davies 2018; Rappold et al. 2017; Aguilera, Corringham, Gershunov, Leibel, et al. 2021), or focused on non-smoke exposures. Only descriptive research has documented the effects of stress, evacuation, property destruction, or injury due to disaster (Belleville, Ouellet, and Morin 2019; McCaffrey Sarah 2014). We believe this second exposure pathway, operating primarily through stress and based on proximity to wildfire, produces significant health effects, especially in vulnerable populations. Here, we define a novel exposure measuring the effect of proximity to wildfire on health, and evaluate the effect of both wildfire smoke and proximity to wildfire on medical care usage in people who use durable medical equipment (DME). This population is particularly vulnerable to both smoke and local wildfire disasters.

DME use is common among seniors, and is associated with respiratory illness and other disabilities. Around 60% of Californian DME renters ensured by Medicaid use either Bilevel Positive Airway Pressure (BiPAP) machines, enteral feeding machines, hospital beds, infusion pumps, oxygen equipment, suction pumps, ventilators, or wheelchairs (Casey et al. 2021). Smoke exposure is particularly dangerous among seniors and exacerbates respiratory and cardiovascular disease (Mahsin, Cabaj, and Saini 2021; Colleen Reid 2019; Anjali Haikerwal and Dennekamp 2015; Yao et al. 2020), and those with DME-related disabilities are also more vulnerable to stress, while less able to evacuate disaster zones because of limited mobility or need for electricity (Casey et al. 2021; Kivimaki 2018).

Here, we use Kaiser Permanente electronic health record data from seven Southern California counties to examine health care usage in this population during two major wildfire events, and during smoke exposure throughout the three-year study period.

2 Methods

2.1 Study population and outcome data

We used electronic health record data from Kaiser Permanente to measure the association between health care use by DME users and two separate exposures: proximity to wildfire and wildfire smoke. We obtained daily counts of health care visits made by DME users at the ZCTA level, in seven counties in Southern California from January 1st, 2016 to March 15th, 2020. Specifically, we obtained counts of outpatient visits, ED visits, and inpatient admissions, as well as ED visits made only for cardiovascular or respiratory problems, and inpatient admissions only for cardiovascular or respiratory problems. 236,732 patients lived in the study area, which covered most of San Bernardino, Orange, Los Angeles, Riverside, San Diego, Ventura, and Kern counties (see Figure 1). The area was divided into 582 ZCTAs, each containing 1 - 1773 patients. In 2018 and 2019 respectively, these seven counties experienced 10 and 13 wildfires which burned over 1000 acres (Cal Fire Incident Archive 2018, 2019).

2.2 Exposure Definition

2.2.1 Proximity to wildfire

To measure proximity to wildfire, we obtained data on the fire boundaries and evacuation zones of two significant Southern California wildfires: the Getty fire and the Woolsey fire. The Getty fire is notable because it necessitated evacuations in the study area during its 9 day duration, in densely populated Los Angeles (Los Angeles Fire Department 2018). Similarly, the Woolsey fire required the evacuation of 295,000 people from Los Angeles and Ventura counties, also in the study area, and burned 1643 structures and almost 100,000 acres of land over 13 days, making it particularly destructive (Los Angeles Fire Department 2018; Matt Styles 2018; "Woolsey Fire Death Toll" 2019).

We identified ZCTAs proximal to either fire, marking them as exposed on days when they were within 20 km of the fire boundary, or within 10 km of the evacuation zone, and the fire was burning. We considered evacuated ZCTAs, those close to the evacuation zone, and those close to the fire all exposed, since both fire, evacuation, and anticipating potential fire or evacuation can cause stress. Figure 1 maps these areas, with data from ca.gov's GIS file archive (see the appendix for discussion of wildfire boundary and evacuation zone definition). Because the number of DME-using patients in each ZCTA ranged from 1 - 1773, and the number of daily health care visits by ZCTA was often low or zero. To avoid zero-inflation in our analysis, we aggregated daily visit counts to the weekly level, considering a ZCTA exposed if it was exposed any day in a week. This aggregation also removed weekend-weekday patterns in outpatient visits.

2.2.2 Wildfire smoke

We measured wildfire smoke exposure by estimating both wildfire and non-wildfire $PM_{2.5}$ concentrations at the ZCTA level using a multistage approach allowing us to distinguish between wildfire and non-wildfire $PM_{2.5}$ exposure. Briefly, we first identified smoke-plume exposed ZCTA codes/days with the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS) and overall $PM_{2.5}$ concentration with USEPA monitoring data from the BLANK EDIT THIS stations and then used a spatiotemporal multiple imputation approach to estimate daily ZCTA-level wildfire and non-wildfire $PM_{2.5}$ concentrations. See 'Tarik's paper' and TARIK CITATION. for a more detailed description of our estimation methods.

Again, daily health care visit counts by ZCTA were low and often zero. Since there have been associations between same-day air pollution and hospital visits up to a week later, we planned to test for a lagged effect, necessitating daily health care visit counts rather than weekly ones. However, we still needed to prevent zero-inflation in our analysis. We therefore created higher-level spatial groupings of several ZCTAs based on spatial proximity, using ZCTA codes (see appendix for detailed description of this procedure). We calculated a daily higher-level grouping wildfire $PM_{2.5}$ measurement by averaging daily wildfire $PM_{2.5}$ across grouped ZCTAs.

2.3 Analysis

We used negative binomial regression to evaluate the relationship between wildfire proximity and each type of health care visit (outpatient visits, inpatient visits, emergency visits, inpatient visits for cardiorespiratory concerns, and emergency visits for cardiorespiratory concerns). We tested each relationship separately during both fires, performing ten regression analyses in R ("R Software" 2021) using the mgcv package (Wood 2017).

In each model, we controlled for weekly mean temperature with a penalized spline term, as temperature can be a predictor of respiratory and cardiovascular health care utilization (Rochelle S. Green 2010) and wildfire (Vlassova et al. 2014), using daily temperature data averaged over ZCTAs from the PRISM Climate Group website (PRISM Climate Group 2021). We also controlled for weekly temporal trends using a penalized spline, and we included an offset to account for each ZCTA population. We did not control for wildfire smoke exposure, or $PM_{2.5}$, as we considered this part of the exposure rather than a confounder.

We used negative binomial regression again to test the relationship between daily wildfire $PM_{2.5}$ and each type of daily health care visit. We performed these analyses with the higher-level spatial groupings described above in the exposure definition section. We were interested in lagged effects of wildfire $PM_{2.5}$ on health care visits, so we checked the autocorrelation of wildfire PM measurements to determine the appropriate modeling approach. We found wildfire $PM_{2.5}$ was only weakly autocorrelated, (lags 1-7 days had <0.25 correlation with lag 0) unlike other sources of air pollution, as it increased dramatically on certain days but then would just as sharply decrease (see Figure 2 for wildfire $PM_{2.5}$ levels throughout the study period). We attributed this variation to wind and weather. We therefore did not constrain our models, and instead included fixed effects for wildfire $PM_{2.5}$ lags 0-7.

We controlled for temperature with a natural spline, and controlled for temporal effects with a natural spline with 12 degrees of freedom, using the number of years of the study period (four) to determine the appropriate spline flexibility. We also controlled for non-wildfire pm with a natural spline, added an offset accounting for higher-level grouping population size, and added a fixed effect to the model of outpatient visits, accounting for fewer visits on weekend days.

We intended to include a random effect to account for variation between spatial groupings, but we were unable to do so because of limited computational power. Instead, we included fixed effects for a comprehensive set of socioeconomic variables, obtaining values by ZCTA from the 5-year 2015-2019 ACS (Bureau 2016-2020). We included variables describing income, poverty, population structure, racial structure, and home ownership. We took a simple mean over each ZCTA in a higher-level grouping to obtain average values of these covariates when appropriate, or summed across ZCTAs when appropriate. See the appendix for model equations and a list of specific variables used, and see https://github.com/heathermcb/kaiser_wildfires for all analysis code.

3 Results

3.1 Data description

During the 1561-day study period, there were an average of 8 outpatient visits per week per ZCTA. There were an average of 3 inpatient visits, 0.5 emergency visits, 0.2 inpatient visits for cardiorespiratory concerns, and 0.4 emergency visits for cardiorespiratory concerns per week per ZCTA. Of the 62,892 emergency visits made over the study period, most of them (49,364) were for cardiorespiratory concerns. Similarly, most of the inpatient admissions over the study period were for cardiorespiratory concerns (30,325 of 33,773). Therefore, the analyses conducted with emergency or inpatient visits may produce results similar to analyses of cardiorespiratory inpatient and emergency visits.

3.2 Proximity to wildfire

There were 98 ZCTAs exposed to the Getty fire, or within 20 km of the Getty fire boundary, in an evacuated area, or within 10 km of an evacuated area. Despite the comparatively large size of the Woolsey fire, only 54 ZCTAs were exposed, since the area burned was more rural. 33 ZCTAs were exposed to both fires. The average temperature in ZCTAs near the Getty fire was 20 degrees Celsius, while the mean temperature in the rest of the study area over the same time period was 19 degrees Celsius. During the Woolsey fire, exposed ZCTAs experienced an average temperature of 17 degrees Celsius, while unexposed ZCTAs averaged 16 degrees Celsius.

3.2.1 Getty fire exposure

Throughout the study period, (not specifically during the fire), outpatient visits in ZCTAS that were exposed were more frequent than in never-exposed ZCTAs (RR = 1.05, 95% CI: 1.03, 1.06), and emergency visits and emergency visits for cardiorespiratory concerns also more frequent (RR = 1.10, 95% CI: 1.07, 1.14 and RR = 1.18, 95% CI: 1.14, 1.22 respectively). The frequency of other visits did not differ between exposed ZCTAs and non-exposed ZCTAs. During the fire, outpatient visits, emergency visits, and emergency visits for cardiorespiratory problems increased in the whole study area (RR = 1.12, 95% CI: 1.07, 1.17, RR = 1.23, 95% CI: 1.10, 1.38, RR = 1.22, 95% CI: 1.08, 1.39 respectively), but there was no additional increase in ZCTAs exposed to the fire. There was no significant relationship between inpatient visits or inpatient visits for cardiorespiratory concerns exposure to Getty fire, either for ZCTAs close to the fire or those not in proximity.

3.2.2 Woolsey fire exposure

Similarly, all types of healthcare visits were more frequent in the ZCTAs exposed to the Woolsey fire overall (not during fire exposure) (RR = 1.15, 95% CI: 1.14, 1.17, RR = 1.10, 95% CI: 1.04, 1.17, RR = 1.13, 95% CI: 1.09, 1.18, RR = 1.12, 95% CI: 1.06, 1.19, RR = 1.17, 95% CI: 1.12, 1.22). During the Woolsey fire, the frequency of all types of visits increased in the whole study area, except outpatient visits, which remained the same (inpatient visits RR = 1.22, CI: 1.08, 1.39, emergency visits RR = 1.15, CI: 1.04, 1.27, inpatient cardiorespiratory visits RR = 1.19, CI: 1.04, 1.35, emergency cardiorespiratory visits RR = 1.17, CI: 1.06, 1.30). There were no additional changes in inpatient visits or emergency visits for all or cardiorespiratoy concerns in ZCTAs exposed to the fire. However, in the exposed area, outpatient visits decreased significantly, while inpatient admissions for cardiorespiratory concerns increased (RR = 0.98, CI: 0.78, 0.87, RR = 1.45, CI: 1.01, 2.11).

3.3 $PM_{2.5}$ exposure

During the study period, mean $PM_{2.5}$ levels over the entire study area exceeded the EPA recommended limit only 6 times. However, individually, 214 of the 274 geographical groupings experienced daily mean $PM_{2.5}$ concentrations greater that the EPA limit at some point. There were 156 days of the 1561 studied where at least one grouping experienced above-limit $PM_{2.5}$. Non-wildfire $PM_{2.5}$ measurements, which were calculated by taking total $PM_{2.5}$ and subtracting estimates of wildfire $PM_{2.5}$, followed a similar pattern - there were 156 days where at least one grouping was over the limit, and 214 groupings experienced above-limit levels.

In contrast, only 42 groupings experienced above-limit wildfire PM, on 21 days. Though wildfire PM contributed to above-limit mean PM measurements, the majority of above-limit levels were attributable to non-wildfire PM.

Increases in wildfire $PM_{2.5}$ were associated with slight decreases in outpatient visits lasting 6 days, with rate ratios ranging from 0.98 to 0.99 (see Table 1 for all RRs and CIs). The effects were almost constant over the period of 6 days. The frequency of inpatient visits, inpatient visits for cardiorespiratory concerns, emergency visits, and emergency visits for cardiorepsiratory concerns did not change with changes in wildfire $PM_{2.5}$. Increases in wildfire $PM_{2.5}$ resulted in a very small decrease in all inpatient admissions lagged by 3 days (RR = 0.98, 95% CI: 0.97, 0.99), however, lags 0-2 and 4-6 were not significant, and showed no sub-significant pattern of increase or decrease towards lag 3. Similarly, ER visits decreased slightly in frequency six days after increases in wildfire $PM_{2.5}$ (RR = 0.99, 95% CI: 0.98, 0.99), while all other lags were insignificant.

4 Discussion

In summary, we found an association between Woolsey fire exposure and reduced frequency of outpatient visits and increased frequency of inpatient visits. We found no association between Getty fire exposure and any kind of health care visit. Increases in wildfire $PM_{2.5}$ were associated with small decreases in outpatient visits for six days after a change, and no associations were found between PM and other kinds of health care visits.

Previous literature shows that higher wildfire $PM_{2.5}$ concentrations are associated with increased emergency visits, hospital admissions, and outpatient visits - outcomes identical to those we examined here. In particular, Hutchinson et al. examined outpatient care use during 2007 San Diego fires, and found $PM_{2.5}$ was associated with increases lasting five days in Medicaid outpatient presentations. Similarly, Sheldon et al. examined outpatient visits in a Singaporean sample during Indonesian wildfires, and again found increases in outpatient visits.

However, we found no association between wildfire $PM_{2.5}$ emergency visits or inpatient admissions by DME users. Instead, we found that increases in wildfire $PM_{2.5}$ were associated with less frequent outpatient visits. This is despite the vulnerability of DME users to wildfire – high rates of cardiorespiratory disease, inability to evacuate, and need for electricity to power DME in this population together with the literature would suggest an association.

Our findings would make sense if DME users were more prepared for disasters than other populations. However, Casey et al. found that DME users were *less* prepared for power outages than other groups, which may suggest they are similarly less or averagely prepared for wildfires. Even so, it is possible that DME users are sheltering in place on smoky days, perhaps because they are vulnerable. Patients may be choosing to stay home rather than make an outpatient visit, while reducing other activities, which may in turn protect them from the effects of smoke $PM_{2.5}$.

However, the associations found in our study may also be due to limitations. We only counted visits made to Kaiser clinics and hospitals, by Kaiser-insured DME users. These patients would be highly motivated to seek care at Kaiser, given their insurance status, however it is possible that they sought urgent care for PM~2.5-related needs at other clinics. This could influence our results. Additionally, the smoke $PM_{2.5}$ measurements made here are based on images of wildfire smoke plumes. This means that there are instances where there is smoke-generated PM not from wildfires which is correctly classified as non-wildfire PM in the data, but still may have a profound effect on health and health care use. For example, the highest daily ZCTA PM measurement in the study period was recorded in Kern county, and was the result of an agricultural burn (see Figure 3 of non-wildfire $PM_{2.5}$ – the tallest line in the figure shows mean PM levels on this day). This smoke PM, but not wildfire PM, and was classified as non-wildfire PM in the analysis, even though exposure to this smoke likely mimicked wildfire smoke exposure. Instances like these could confound the relationship examined here.

Our results describing the effects of proximity to wildfire on health care use are more easily explained. We found that outpatient visits during the Woolsey fire decreased in frequency, while inpatient admissions increased. If hospitals and clinics close to the fire closed during the emergency, and patients were forced to evacuate, a decline in outpatient visits would be expected. Regarding inpatient visits, evacuation could cause an increase in serious health problems in this population, in turn causing an increase in inpatient admissions to other, open hospitals. However, like in the $PM_{2.5}$ analyses, during both the Woolsey and Getty fires, patients may have been seeking care at other, non-Kaiser clinics.

Because the Woolsey fire was so much larger than the Getty fire – the Woolsey fire burned almost 100,000 acres of land, while the Getty burned approximately 800 – null results in the Getty fire analysis make sense. The magnitude of the Getty exposure may not have been large enough to produce significant results. A larger analysis examining several wildfires, rather than two, could shed light on this issue.

5 Conclusion

As wildfires become more frequent and severe with climate change, it is critical we understand how they affect both populations directly affected by wildfire and those exposed to smoke, especially vulnerable populations that could be harmed by exposures which others can avoid or endure, without as many lasting effects. More work is needed to understand how DME using patients are responding to wildfires, and how we can best support those affected by smoke, fire, or evacuation.

6 Appendix

6.1 Notes on wildfire evacuation zones, boundaries, and exposure definition:

We obtained shapefiles of the Woolsey and Getty fire boundaries from https://frap.fire.ca.gov/mapping/gis-data/. These files describe boundaries around all areas burned by the fires. In reality, the fire boundaries were smaller at the beginning of the fires, and expanded as they burned. We used these static boundaries to identify exposed ZCTAs.

The Woolsey fire, in particular, burned for 13 days. Therefore, ZCTAs that were close to the fire boundary and defined as 'exposed' in our study may not have been proximal to the fire at first, and may not have been truly exposed until later. Unfortunately, dynamic fire boundary data isn't available.

Just as the fire boundaries changed, evacuation zones also changed throughout each fire. Additionally, machine-readable data on evacuation zones for either fire was not available, though there were several maps available of evacuation zones at different points during each fire. 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" 2009). The evacuation zone boundaries we defined are plotted in Figure 1, along with the fire boundaries. As always, 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
2. https://www.newsweek.com/getty-center-fire-map-evacuation-los-angeles-california-1468100
3. https://www.express.co.uk/news/world/1196943/getty-fire-evacuation-map-405-fire-update-los-angeles-fire-evacuation-road-school-closures
4. https://www.flyertalk.com/forum/los-angeles/1993097-getty-fire-405-closed-sepulveda-pass-now-open.html
5. 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
2. https://wildfiretoday.com/tag/woolsey-fire/
3. https://www.dailynews.com/2018/11/08/this-map-shows-where-the-hill-fire-and-woolsey-fire-are-burning/
4. https://www.mercurynews.com/2018/11/09/map-of-woolsey-and-hill-fires-highway-101-closed-malibu-evacuated/
5. https://woolseylawyers.com/woolsey-fire-map/

6.2 Higher-level groupings of ZCTAs

We created higher-level groupings of ZCTAs using the numerical ZCTA codes. We used an ad-hoc method for convenience, 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 $PM_{2.5}$ within each group and between all ZCTAs regardless of group, concluding that wildfire $PM_{2.5}$ measurements within groups were highly correlated (x coeff), while mean correlation of $PM_{2.5}$ between any two ZCTAs was XXXXXX. We also mapped the groups to confirm that all ZCTAs grouped together were adjacent. The code that creates these groupings and assesses them available at https://github.com/heathermcb/kaiser_wildfires.

Model equations and ACS variables used

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, 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).

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).

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

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.

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

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.

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*.

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.

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.

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.

PRISM Climate Group. 2021. "PRISM Climate Group Daily Temperature Data." 2021.

"QGIS Software." 2009. http://qgis.org.

"R Software." 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.

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.

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).

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.

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/.

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.