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The burden of fine particles on respiratory health: a Health Impact Assessment considering the differential toxicity of wildfire smoke PM2.5

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The burden of fine particles on respiratory health: a Health Impact Assessment considering the differential toxicity of wildfire smoke $PM_{2.5}$

A Thesis submitted in partial satisfaction of the requirements
for the degree Master of Science

in

Marine Biology

by

Rachel Darling

Committee in charge:

Professor Tarik Benmarhnia, Chair
Professor Lihini Aluwihare
Professor Fonna Forman

2022

The Thesis of Rachel Darling is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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LIST OF ABBREVIATIONS

$PM_{2.5}$	Particulate matter < 2.5 microns in diameter
EPA	U.S. Environmental Protection Agency
WHO	World Health Organization
CDC	The Centers for Disease Control and Prevention
SVI	Social Vulnerability Index
ERF	Exposure Response Function
RR	Relative Risk
PAF	Population Attributable Fraction
AN	Attributable Number (of hospitalizations due to exposure)

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ABSTRACT OF THE THESIS

The burden of fine particles on respiratory health: a Health Impact Assessment considering the differential toxicity of wildfire smoke $PM_{2.5}$

by

Rachel Darling

Master of Science in Marine Biology

University of California San Diego, 2022

Professor Tarik Benmarhnia, Chair

The last several consecutive fire seasons on the West coast, specifically in California, have been the worst in recorded history. These massive fires have been driven largely in part by the anthropogenically caused climate crisis. As the climate crisis worsens, the fire season will as well. This has massive implications for human health as air pollution from each fire can cause disease and hospitalizations. Wildfires are a large source of particulate matter that is less than 2.5 microns in diameter ($PM_{2.5}$). $PM_{2.5}$ has been known to cause extremely severe respiratory and cardiovascular issues. Recently, studies have shown that $PM_{2.5}$ generated by wildfires could have a different and more potent toxicity than $PM_{2.5}$ generated from other pollutant sources. This project studied the impact of $PM_{2.5}$ on hospitalizations for respiratory diseases in California between 2006-2013, through a health impact assessment (HIA). We quantified the burden of respiratory hospitalizations related to $PM_{2.5}$ exposure among California communities through two different approaches: (i) naïve (considering the same toxicity for all $PM_{2.5}$) and (ii) nuanced (considering the higher toxicity of $PM_{2.5}$ due to wildfires). The results of the HIA displayed higher attributable numbers of respiratory hospitalizations when accounting for the larger health burden wildfire $PM_{2.5}$ (i.e., nuanced approach). The delta between the naïve and nuanced approach was higher in northern California. By not considering the differential toxicity of wildfire $PM_{2.5}$, we underestimate the attributable number of respiratory hospitalizations in California related to $PM_{2.5}$ exposure. This study can be useful for future air pollution guideline recommendations.

INTRODUCTION

Climate change and wildfires

As anthropogenically induced climate change worsens, human and natural environments are expected to see increasingly detrimental consequences from natural disasters, including wildfires (IPCC, 2022). In the US, the annual wildfire-burned area (in millions of acres) has been increasing since the 1980s (Figure 1). Climate change will continue to extend the dry season and increase temperatures in locations such as California. The state has an infamous fire season that is compounded by the dry and powerful Santa Ana winds in Southern California. California is among the states with the largest area burned (Figure 2). In the last few years, especially in 2017, 2018, and 2020, California faced especially large, destructive fire seasons which are expected to increase in magnitude in the coming years, due to climate change (Williams et al., 2019). Exacerbated number and magnitude of wildfires brings increasing exposure to wildfire smoke. Wildfire smoke is a worldwide problem as smoke plumes can be transported across great distances by wind. Some studies are beginning to discover that although the United States west coast region contains the most wildfires, east coast states are also seeing health impacts of wildfire smoke that is transported across the country (O'Dell et al., 2021).

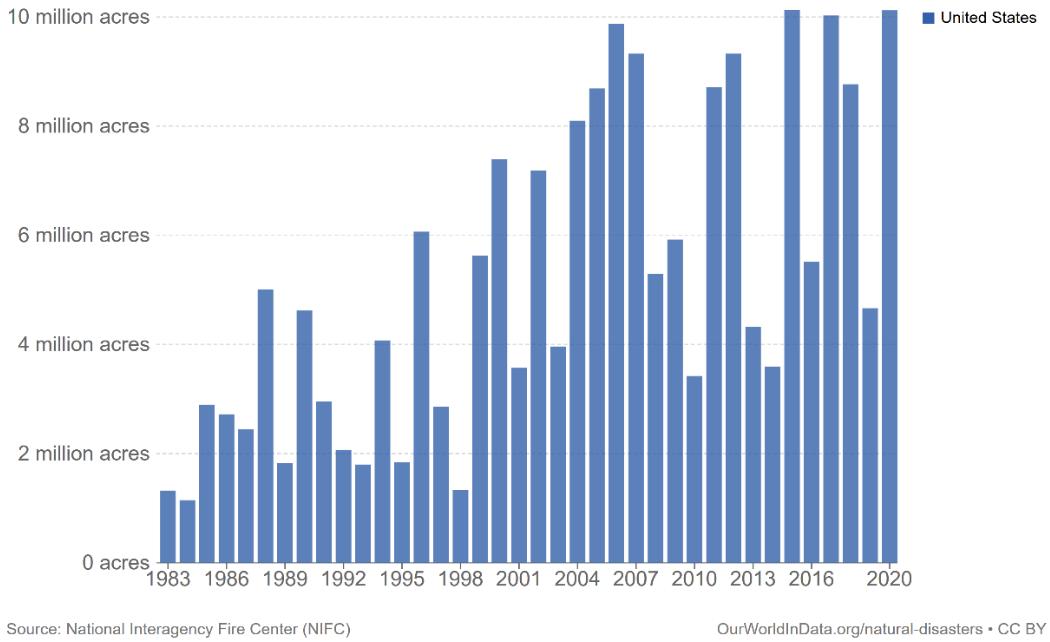


Figure 1. Wildfire acres burned in the United States, 1983 – 2020 (from OurWorldinData.org)

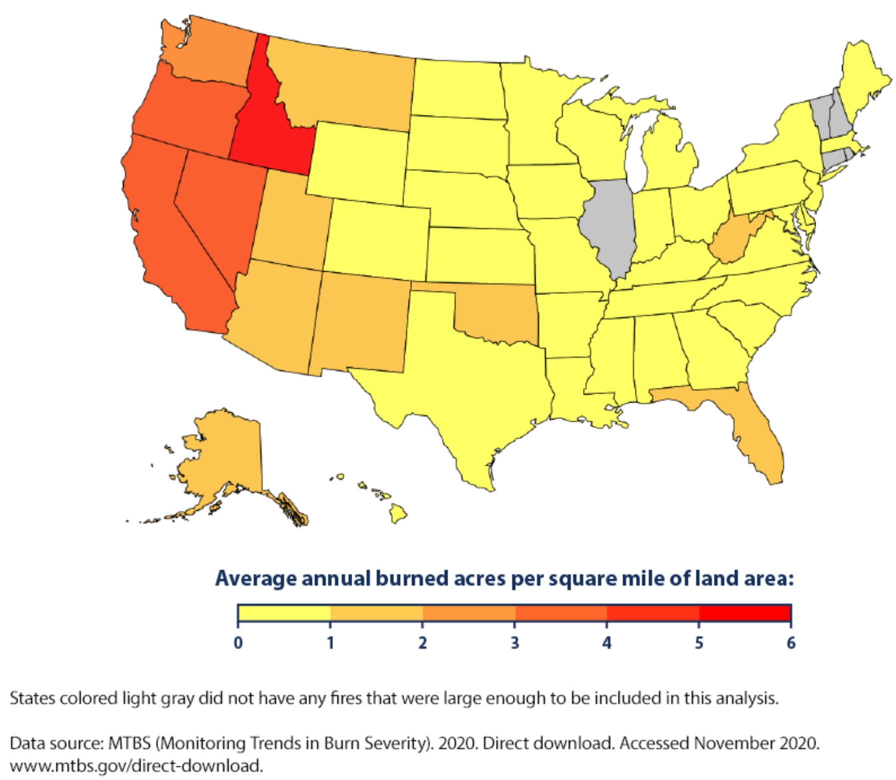


Figure 2. Average annual burned acreage by State, 1984-2018 (from Environmental Protection Agency).

Composition of wildfire smoke

Wildfire smoke contains a mixture of fine particulate matter and noxious gasses. Wildfire smoke involves mostly carbon or carbon compounds which brings a higher oxidative potential to cells when wildfire smoke is inhaled (Wegesser et al., 2009). Polycyclic Aromatic Hydrocarbons (PAHs) are found in both wildfire smoke and ambient air but have been found in higher concentrations in wildfire smoke. Other detrimental components of wildfire smoke include carbon monoxide, nitrogen dioxide, and volatile organic compounds. Additionally, due to the intense heat found in wildfire environments, heat-labile chemicals such as the volatile organic compound benzene, can become more unpredictable and more toxic (Kim et al., 2018; Naeher et al., 2007). In this study, we focus on the impacts of a specific component of wildfire smoke and its impacts on public health: $PM_{2.5}$. $PM_{2.5}$ is particulate matter that is less than 2.5 microns in diameter. $PM_{2.5}$ can originate from combustion (primary $PM_{2.5}$) or be formed via chemical reactions (secondary $PM_{2.5}$). Thus, $PM_{2.5}$ can have many different sources including vehicular combustion, wildfire combustion, and via chemical processes (Ebisu et al., 2019; Ostro et al., 2016).

Wildfire smoke health burdens

Exposure to the toxins in wildfire smoke - especially $PM_{2.5}$ - is associated with mortality. Globally, $PM_{2.5}$ exposure from wildfires was associated with ~340,000 deaths per year, and higher numbers of deaths in drier, wildfire prone, seasons from 1997 - 2006 (Johnston et al., 2012). A 2021 study, conducted in 43 countries and regions during 2000 - 2016, found that for each 10 $\mu g/m^3$ increase of wildfire-related $PM_{2.5}$ exposure was associated with an increased risk for all-cause mortality (relative risk 1.019, 95% CI 1.016–1.022) (Chen et al., 2021). Exposure to wildfire related $PM_{2.5}$ leads to negative impacts on human health through cardiovascular and respiratory illness (Chen et al., 2021, Johnston et al., 2012). Overall, $PM_{2.5}$ from all sources poses a strong health concern due its incredibly small size. $PM_{2.5}$ is small enough to be inhaled into the lung, cross the epithelial membrane in the alveoli of the lung, and thus enter the bloodstream. $PM_{2.5}$ can consequently enter organs and impair function, in addition to causing respiratory issues (Chen et al., 2021; Wang et al., 2015).

A growing body of literature suggests that wildfire smoke pollution is associated with respiratory outcomes, including respiratory morbidity and mortality (Aguilera et al., 2021a, Aguilera et al., 2021b; Chen et. al., 2021; Henderson and Johnston, 2012; Liu et al., 2015; O'Dell et al., 2021). Repeated evidence supports the fact that smoke exposure can aggravate respiratory issues such as chronic obstructive pulmonary disorder (COPD) (Reid et al., 2016), asthma in all age groups (Arriagada et al., 2019; Malig et al., 2012; O'Dell et al., 2021; Ostro et al., 2016), and stress, especially oxidative, on the respiratory tract (Kim et al., 2018; Wegesser et al., 2009). Additionally, evidence in the literature suggests that increased exposure to wildfire smoke can also lead to more respiratory infections such as pneumonia and bronchitis (Reid et al., 2016). Based on a 2019 meta-analysis, landscape fire smoke $PM_{2.5}$ levels were associated with asthma hospitalizations (RR = 1.06, 95% CI: 1.02–1.09) and emergency department visits (RR = 1.07, 95% CI: 1.04–1.09) (Arriagada et al., 2019).

Although the evidence in literature varies, studies in recent years have brought increasing support to the idea that wildfire smoke also leads to cardiovascular and other non-respiratory health effects (Ostro et al., 2016; Reid et al., 2016). Wildfire smoke $PM_{2.5}$ has also been shown to pose a danger to pregnant women with high exposure events leading to birth complications such as preterm birth (Reid et al., 2016). A growing but important area of study is the negative mental health impacts of wildfires. Although more studies are needed on this topic, preliminary evidence discussed the negative implications of wildfire damage and forced evacuations on mental health, especially on minorities and women (Liu et al., 2015; Reid et al., 2016). Those who are most vulnerable to wildfire smoke are children, the elderly, and people with pre-existing health conditions. The elderly often fall in the last category as they can often have preexisting conditions that are worsened during wildfire conditions. Children's respiratory systems have proven to be especially vulnerable as well. Since children are still developing, they have faster metabolic rates, and faster breathing rates; their respiratory systems have proven to be especially vulnerable to wildfire smoke as well. They often show increases in asthma rates and respiratory issues during exposure events (Ebisu et al., 2019, Aguilera et al., 2021a).

Differential toxicity of wildfire smoke PM2.5

Notably, toxicology studies from recent years have found that wildfire $PM_{2.5}$ has a higher toxicity effect on the lung than the same mass of $PM_{2.5}$ from other sources. Studies have found that mice whose lungs were exposed to $PM_{2.5}$ from wildfires showed a stronger toxicity effect than those exposed to other ambient $PM_{2.5}$ (Kim et al., 2018; Wegesser et al., 2009). The mice exposed to wildfire $PM_{2.5}$ displayed more inflammation, oxidative stress, and a higher white blood cell count as compared to mice who were exposed to up to ten times more normal ambient air $PM_{2.5}$ (Wegesser et al., 2009). As mentioned previously, heat-labile compounds and the abundant amount of particulate matter derived from carbon compounds, such as wood and plant matter, in wildfire smoke could be a reason for the increased toxicity of wildfire smoke pollution (Naeher et al., 2007).

A 2021 epidemiological study found increases in respiratory hospitalizations ranging from 1.3 to up to 10% with a 10 μg/m^3 increase in wildfire specific $PM_{2.5}$, compared to 0.67 to 1.3% associated with non-wildfire $PM_{2.5}$ (Aguilera et al., 2021a). Wildfire specific $PM_{2.5}$, compared to ambient $PM_{2.5}$, was also found to be ~10x more harmful to children (especially ages 0-5) (Aguilera et al., 2021b). The potential differential toxicity of wildfire smoke $PM_{2.5}$ provides important avenues for study. Although recent years have led to more research in this topic, there is still a need to completely understand the differential toxicity of wildfire $PM_{2.5}$ on human health - and to support the need for policy change that takes the difference into account (Atkinson et al., 2014; Ebisu et al., 2019; Liu et al., 2015). Additionally, wildfires are episodic in nature which makes the problem inherently difficult to measure whether the health outcome was due to chronic or acute exposure (Johnston et al., 2012; O'Dell et al., 2021).

Current air quality regulations

Unsurprisingly, wildfire specific $PM_{2.5}$ has been increasing due to increasingly aggressive fire seasons, while ambient $PM_{2.5}$ has been decreasing due to progressing air quality standards. Many urban areas continue to see concentrations that are above the safe levels deemed by the National Ambient Air Quality Standards (NAAQS), however, stricter regulations have aided in the decrease of ambient $PM_{2.5}$ (McClure & Jaffe, 2018). Figure 3, from McClure & Jaffe, 2018, shows that the authors' statistical models of $PM_{2.5}$ concentration support the pattern of increasing wildfires in the west due to climate change, while $PM_{2.5}$ decreases elsewhere. Current air quality standards written by the World Health Organization (WHO) and US Environmental Protection Agency (EPA) do not take the differential toxicity of wildfire $PM_{2.5}$ into account. The most recent WHO air quality global guidelines, published in 2021, acknowledges that evidence has been presented to support the differential toxicity of wildfire $PM_{2.5}$ to health. However, the WHO claims that there are conflicting results on this topic and thus, they have not yet differentiated between $PM_{2.5}$ sources in air quality guidelines (WHO, 2021). The current WHO guidelines for yearly and daily $PM_{2.5}$ concentrations are 5 $\mu g/m^3$ annually with a short term 24-hour maximum limit at 15

$\mu g/m^3$ (WHO, 2021). The EPA guidelines for annual $PM_{2.5}$ are for 12 $\mu g/m^3$ primary $PM_{2.5}$ and 15 $\mu g/m^3$ for secondary $PM_{2.5}$. The EPA has a short term 24-hour limit for $PM_{2.5}$ at a value of 35 $\mu g/m^3$ (EPA, 2020).

The consideration of wildfire smoke in air quality regulations is especially important today, in a context where we know that: (i) wildfires contribute approximately ~25%, of total $PM_{2.5}$ concentration in the atmosphere (Burke et al., 2021), (ii) exposure to wildfire $PM_{2.5}$ will become more problematic as wildfire seasons worsen due to climate change, (iii) and the harmful health effects of $PM_{2.5}$ from wildfires, which has been shown to be more toxic than other sources of $PM_{2.5}$.

Vulnerable populations

In the discussion of climate change, natural disasters, and public health; environmental justice must be included. Marginalized people worldwide are bearing disproportionate consequences of climate change and its subsequent disasters. Environmental justice seeks to reduce that disproportionate burden (Bailey et al., 2019; IPCC, 2022; Ebisu et al., 2019). Minority communities in California are no different, as a clear pattern of low socioeconomic groups can be found in some zip codes in all major cities. The way a community reacts and adapts to hazards depends on many factors. The main factor is often socioeconomic status which can be a stark predictor of community success after a disaster. Thus, it is important to understand which communities bear the strongest consequences of wildfire smoke pollution exposure. Understanding which communities are most vulnerable can inform policy to help protect those communities from the effects of wildfire smoke $PM_{2.5}$ and the subsequent hospitalizations (Bailey et al., 2019; Spielman et al., 2020).

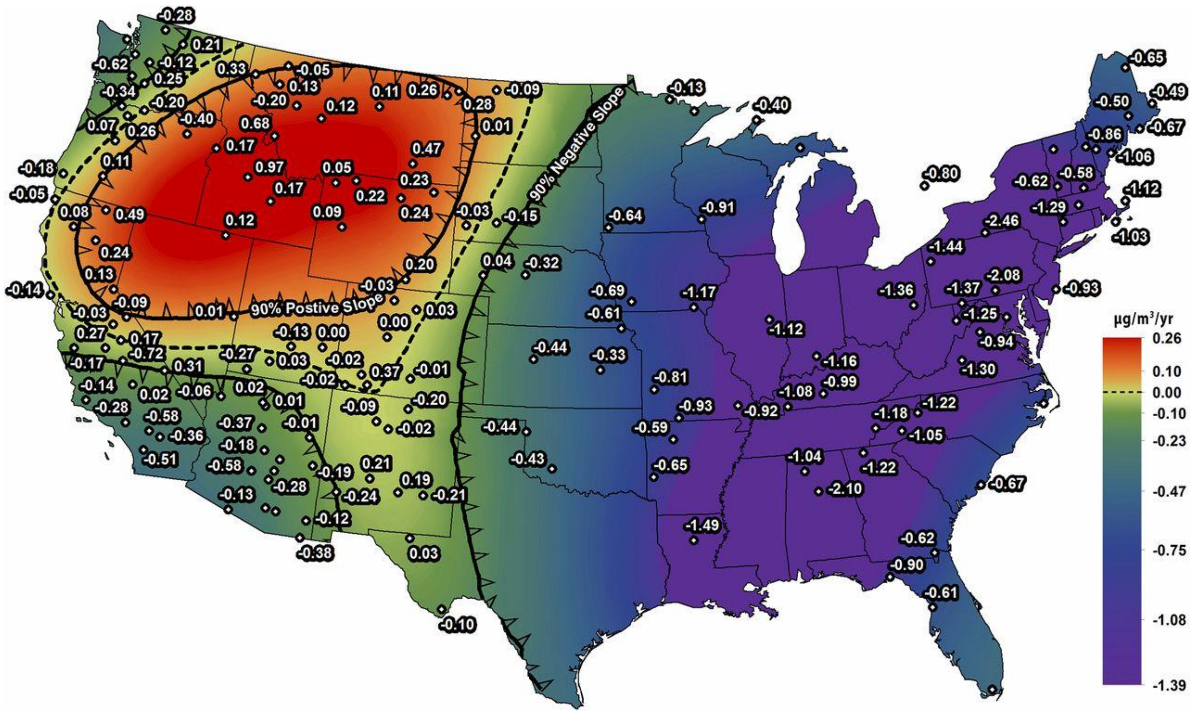


Figure 3. From McClure and Jaffe, 2018. This figure shows the 98th Quantile Regression of PM2.5 trends from 1988 – 2006. Krige-interpolated PM2.5 values are shown by the color ramp. Solid black lines with arrows show 90% of values within being positive or negative.

Aim

In response to the fact that wildfire specific $PM_{2.5}$ has been found to have a differential toxicity on health; a health impact assessment (HIA) was performed to determine the number of attributable hospitalizations for respiratory diseases due to $PM_{2.5}$ in California from 2006-2013. An HIA is used as a tool to assess the health risk of a specific issue, in this case $PM_{2.5}$ exposure. HIA's are used to provide quantitative evidence that can be used to guide policy or other community decisions that can help protect the health of affected populations and protect public health. The main aim of this study was to use both a "naive" and "nuanced" approach and quantify the delta between these two approaches. The naive approach assumes that the exposure to a concentration of $PM_{2.5}$ has the same impact on respiratory health, regardless of the source of the $PM_{2.5}$. The nuanced approach assumes that the exposure to wildfire $PM_{2.5}$ has a higher impact on respiratory health than other $PM_{2.5}$. Using the social vulnerability index (SVI), a Centers for

Disease Control and Prevention (CDC) derived metric, we used a geographically weighted regression to determine whether the SVI and the delta between the two approaches estimating the attributable hospitalizations were associated. In summary, this project aims to quantify the difference between two methods of estimating the number of respiratory hospitalizations attributed to $PM_{2.5}$ from all sources; one accounting for the higher toxicity of $PM_{2.5}$ from wildfire smoke (nuanced approach), the other not accounting for a difference (naïve approach), in California from 2006-2013.

METHODS

PM2.5 exposure

We built on the previous work done by Aguilera and colleagues (Aguilera et al., 2021a, b and c). Daily concentrations of $PM_{2.5}$ were estimated by zip code using 24-h daily means sampled and analyzed by the US EPA Air Quality System (https://www.epa.gov/aqs). These $PM_{2.5}$ values, coming from monitoring station data, represent fine particulate matter from all sources, including ambient levels and wildfire smoke. Aguilera and colleagues performed a multiple imputation approach using statistical methods and machine learning algorithms to estimate daily wildfire $PM_{2.5}$ concentrations at the zip code level in California (Aguilera et al., 2021c). Using aerosol optical depth (AOD) and other satellite imagery, they determined when smoke plumes intersected with certain zip codes. Through ground monitoring stations, satellite imagery, and the multiple imputation approach, the authors were able to estimate the specific amount of wildfire PM2.5 concentrations in each California zip code on an exposure day from 2006-2020. Further information and details can be found in Aguilera et al., 2021c.

Hospitalization for respiratory diseases

We used the daily hospital admissions for respiratory diseases from the California Office of Statewide Health Planning and Development (OSHPD) database of patient discharge data from 2006 to 2013. Respiratory hospitalizations correspond to the ICD 9 codes 460:519 which include pulmonary diagnoses, such as asthma, COPD, pneumonia, and interstitial lung disease. In addition, data for flu diagnosis were also available. All data were previously aggregated at the daily level by zip code and converted to rates of admission by dividing the admission counts by the population (Aguilera et al., 2021a).

Evolution of $PM_{2.5}$ and wildfire specific $PM_{2.5}$ over time and by seasons

We conducted a descriptive analysis to evaluate whether our $PM_{2.5}$ concentration data displayed the increasing wildfire but decreasing ambient $PM_{2.5}$ pattern over the period of 2006-2020, as described in the literature and in Figure 1 (McClure & Jaffe, 2018). We calculated the average concentration per month, over the study period, of wildfire specific $PM_{2.5}$ and non-wildfire $PM_{2.5}$. Both sets of PM2.5 values were plotted per month using ggplot in R. Each season was color coded to determine whether there was seasonal variation in the data. The seasons were defined as follows: winter - December, January, and February; spring - March, April, and May; summer - June, July, and August; and fall - September, October, and November. A separate plot for ambient $PM_{2.5}$ and wildfire specific $PM_{2.5}$ were made using these methods (Figure 5 and Figure 6).

Additionally, average wildfire and ambient $PM_{2.5}$ concentrations over the study period of the HIA (2006-2013), were compared visually via a map made in ArcGIS Pro. The ESRI shapefile of the United States Postal Service (USPS) zip codes were uploaded to ArcGIS Pro. We calculated the average of both the wildfire $PM_{2.5}$ and non-wildfire $PM_{2.5}$ averages per zip code over the study period (2006 - 2013), then we performed a join in ArcGIS. The result was two maps that visually compare the range of concentrations of wildfire and ambient PM2.5 over the state of California

(Figure 7 and Figure 8). All days with a concentration of “0” for wildfire PM2.5 were removed because a value of zero meant there was no data for that given day.

Flu and respiratory hospitalizations

Next, we evaluated average hospitalizations over 2006-2013 to observe any immediate trends. There was some speculation in the literature (Ostro et al., 2016) regarding the swine flu epidemic in 2008 and how this may have skewed the number of observed respiratory hospitalizations. We conducted a linear regression to determine whether this occurred. The flu data were gathered from the California Department of Public Health (CDPH). The data was separated into months over the study period. A Z score transform was conducted on these data per month to normalize the data for both flu and respiratory hospitalizations. The Z score values for both respiratory and flu values were plotted in a time series to compare peaks and values (Figure 9). Flu hospitalizations were displayed as blue points, while respiratory hospitalizations are red. A simple linear regression model was used in R to predict the number of respiratory hospitalizations due to the flu.

Literature Review

A traditional, or narrative, literature review was conducted on bodies of work that researched the effects of ambient and wildfire specific PM2.5 exposure and/or the differential toxicity of wildfire smoke PM2.5. Sixteen of the most prominent papers in this subject were chosen and summarized. The literature review summarized: population, study region, study period, exposure, health outcomes measured, and main result. These results can be viewed in Table 2 in the Appendix. This review served as the informational basis for this project, in addition to displaying the need for more research on the differential toxicity of wildfire smoke specific PM2.5.

Health Impact Assessment

The main analysis was the Health Impact Assessment (HIA). An HIA includes a series of calculations to quantify the health burden of a given exposure, in this study we calculated the burden of $PM_{2.5}$ exposure. The calculation begins with finding the appropriate exposure response function(s) (ERFs). ERFs can also be described as risk ratios and are used to determine risk of exposure. If the risk or ERF is 1, this assumes that the health risk is the same for the exposed and unexposed populations. In this study, the health risk was respiratory hospitalizations due to an exposure of PM2.5. We found an exposure response function for the naïve approach and the nuanced approach conducted. As mentioned previously, the naive approach assumes that the health effect of all $PM_{2.5}$ is the same, regardless of their sources. Meanwhile, the nuanced approach assumes that the exposure to wildfire $PM_{2.5}$ is associated with a higher risk for respiratory health (Aguilera et al., 2021a). All the ERFs were chosen from literature. In the literature used in this analysis, ERFs were presented as percent change in hospitalizations (Aguilera et al., 2021a) due to a certain concentration of exposure. These values had to be converted to a relative risk number for a given exposure level for this HIA (see Equation 1). The naïve and nuanced approach ERFs were chosen from Aguilera et al., 2021a, from the multiple imputation approach analysis. After converting the values from percent change in exposure, the ERFs for the naïve and nuanced approach were 1.0072 (95% CI: 1.0036 – 1.011) and 1.10 (95% CI: 1.035 – 1.165) respectively, with a reference exposure concentration of 10 $\mu g/m^3$.

$$Converted\ ERF = \left(\frac{\%\ Change\ in\ Hosps}{100}\right) + 1 \quad \text{(Equation 1)}$$

These exposure response functions were used to calculate the new relative risk (RR), the population attributable fraction (PAF), and the attributable number (AN) of respiratory hospitalizations due to $PM_{2.5}$ exposure. The RR is a relative risk at a given exposure level, in this case, for an increase of every 10 $\mu g/m^3$. The PAF is the percent change in hospitalization rates due to an exposure to $PM_{2.5}$. The AN value measures the health burden of $PM_{2.5}$ exposure by displaying the number of preventable respiratory hospitalizations due to this pollutant. See below for the flow of calculations in the HIA.

Naïve approach

The naïve approach calculation of the HIA made use of the value for all $PM_{2.5}$ which was 1.0072 (95% CI: 1.0036 – 1.011). This is a value for an exposure concentration of 10 μg/m^3. The new RR is calculated by taking the natural logarithm of the ERF, which is then divided by the reference exposure concentration (in this case 10 μg/m^3). Then, this entire value is multiplied by the total $PM_{2.5}$ (the ambient and wildfire PM2.5 concentrations added together). The exponential of this value is then taken to get the final result (Equation 2). The PAF is found by subtracting the RR by 1, dividing by the RR, and then multiplying this value by 100 to make the value a percentage (Equation 3). Finally, the AN is found by multiplying the PAF by the number of respiratory hospitalizations (Equation 4). That AN value is used to find the Final AN value which is calculated by dividing by the population per zip code and then multiplied by 100,000 to standardize (Equation 5). Hospitalizations for the “all age” group category were used for this HIA.

$$RR = \exp x \left(\frac{\ln(RR)}{Ref.\ Exposure\ Conc.} x\ (WF\ PM2.5 + Ambient\ PM2.5)\right) \quad \text{Equation 2}$$

$$PAF = \frac{RR-1}{RR}\ x\ 100 \quad \text{Equation 3}$$

$$AN = \ PAF\ x\ Hosptalizations \quad \text{Equation 4}$$

$$Final\ AN = \frac{AN}{Pop.\ per\ zip\ code}\ x\ 100{,}000 \quad \text{Equation 5}$$

Nuanced approach

The nuanced approach follows almost the same sequence with a few minor differences. The main difference is that instead of considering the same ERF for all $PM_{2.5}$, we applied two distinct ERF in function to the source of the $PM_{2.5}$. For ambient $PM_{2.5}$, we used (as previously stated) an ERF of 1.0072. However, for wildfire specific $PM_{2.5}$ we used a different ERF of 1.10. Equation 6 was used to calculate the new RR specific to $PM_{2.5}$ from wildfires. Then, the PAF were separately calculated using equation 4. Finally, the AN for wildfire specific $PM_{2.5}$ and ambient $PM_{2.5}$ were added together at the end of the HIA (Equation 7). This value was then divided by the total population per zip code and multiplied by 100,000 to standardize the data (Equation 8). This calculation accounts for the differential toxicity of $PM_{2.5}$ from wildfires by including a specific and higher dose response only for this specific source of $PM_{2.5}$.

$$Nuanced\ RR = \exp x\ (\frac{\ln(RR)}{Ref.\ Exposure\ Conc.}\ x\ (WF\ PM2.5)) \quad \text{Equation 6}$$

$$Nuanced\ AN\ Combined\ = (WF\ PAF\ x\ Hosps) + (Ambient\ PAF\ x\ Hosps) \quad \text{Equation 7}$$

$$Nuanced\ AN\ Final\ = \frac{\text{Nuanced AN Combined}}{Pop.per\ zip\ code}\ x\ 100{,}000 \quad \text{Equation 8}$$

Lastly, the average number of attributable hospitalizations per year, over the study period (2006 -2013), for the naïve and nuanced analyses were estimated (Table 1). The average number of attributable hospitalizations over the study period were also mapped visually per zip code over the study period for the naïve and nuanced approach (Figure 10 & Figure 11). The delta between attributable hospitalizations between the naïve and nuanced approach was mapped as well to highlight just the number of attributable hospitalizations when the differential toxicity of wildfire smoke $PM_{2.5}$ was accounted for (Figure 11). These steps for the HIA are summarized in the Figure 4 below.

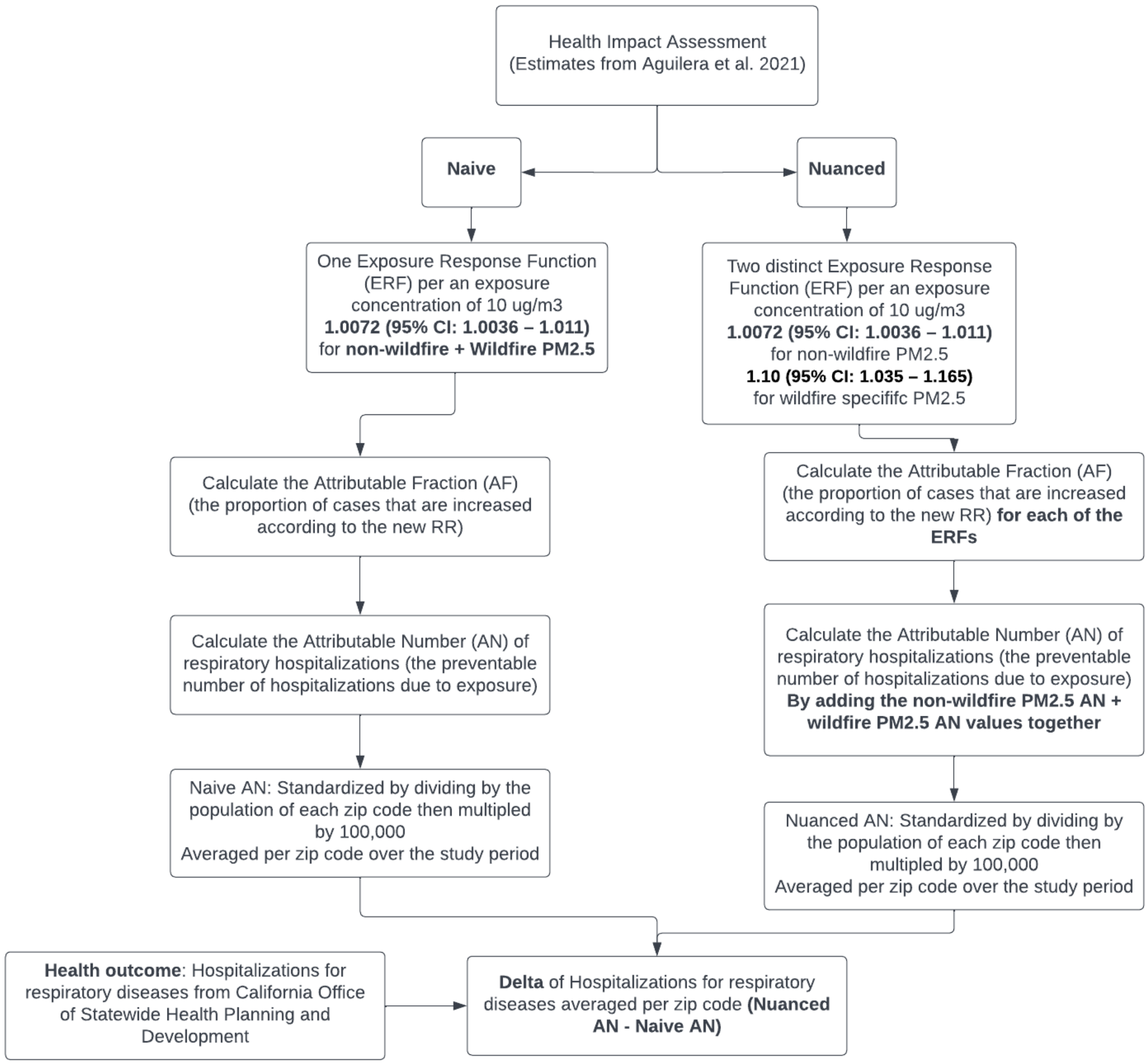


Figure 4. The methodology for the HIA calculation conducted in this study, including the differences between the naïve and nuanced approach in addition to how the final delta value between the two approaches was calculated.

Underestimated hospitalizations

In order to determine the attributable number of total hospitalizations that are being unaccounted for when not taking into account the differential toxicity of wildfire smoke PM2.5, we totaled the number of hospitalizations over the study period over the state of California. The total hospitalization values were totaled for the naive and nuanced approach. Once again, the delta between the two values was found. This value was then divided by the total number of attributable hospitalizations for the nuanced approach and then multiplied by 100. This gave us the percentage of hospitalizations that are unaccounted for when considering the true, differential toxicity of wildfire smoke PM2.5.

Social vulnerability index

We used the Social Vulnerability Index (SVI), a Centers for Disease Control and Prevention (CDC) derived metric, to analyze the relationship between social justice and health burden to wildfire smoke $PM_{2.5}$. The SVI measures the ability of a community to adapt to natural, or human caused, disasters; measured on a scale of 0 to 1, with 1 being the communities that are most socially vulnerable (CDC, 2014). This adaptation is measured in the community's ability to prevent suffering and excessive financial loss in the wake of a disaster. The SVI of every census tract is defined by 15 U.S. census variables including socioeconomic status, household composition and disability, minority status and language and housing type and transportation. In this analysis, we studied the association between the SVI values over California and the difference of attributable hospitalizations between the naïve and nuanced approach, to determine whether the highest hospitalizations also occurred where the highest SVI values were.

In order to do this, a geographically weighted regression was conducted. Census tracts were aggregated into zip codes using data from the U.S. Department of Housing and Urban Development crosswalk files for 2014 (https://www.huduser.gov/portal/datasets/usps_crosswalk.html#data). Additionally, the ESRI California zip code shapefile and the difference of the attributable number (of the naïve and nuanced approach) of hospitalizations mentioned in later sections, were used for this regression.

In this case, the calculations to determine the difference in attributable hospitalizations was summed instead of averaged, as compared to what was done in the rest of the analysis. The SVI data was merged with the zip code/census tract crosswalk. The SVI values that overlapped with multiple zip codes were aggregated by median, due to the fact that the data distribution was not normal. This data set was then merged with the ESRI California shapefile in order to run the regression using polygons.

The GWR model was fit using the *spgwr* package in R with the difference of the attributable number of hospitalizations as the outcome and the aggregated median SVI as the predictor variable. This allowed us to estimate the effects of SVI on the attributable number of hospitalizations across California, see Equation 1, where ε is the error. A cross-validation procedure was employed to choose a bandwidth for the model. A Gaussian correlation structure was employed as that is the default. This model results in a β estimate for every single zip code. The outlier estimates (due to very small population sizes) are not displayed in the results although it is worth noting that there were a few zip codes in Northeastern California with very high magnitude β estimates.

$$\text{Difference in Hospitalizations} = \beta_I(\text{MeanSVI}) + \varepsilon \qquad \text{Equation 9}$$

The GWR β estimates were truncated and plotted between the first and third quartiles of the regression in order to visualize variations in the coefficients (Figure 13). We used the median estimate value of the GWR model as the midpoint for this figure. Lastly, the predictions accuracy of the model was plotted in a figure which shows the difference between the attributable number of hospitalizations and the predicted number of hospitalizations that the model suggests giving a visual representation of the model fit (Figure 14).

RStudio Version 3.6.2 and ArcGIS Pro Version 2.9.1 were used for all analyses and figures.

RESULTS

Evolution of $PM_{2.5}$ during the period of 2006-2020

Through the comparative analysis, this study found that ambient $PM_{2.5}$ values are decreasing in the period of 2006-2020, while wildfire specific $PM_{2.5}$ values are increasing. The five largest peaks in non-wildfire $PM_{2.5}$ all occur during the summer and fall (Figure 5). These points occur in 2008, 2019, and 2020. The spring season consistently displayed the lowest ambient $PM_{2.5}$ values while winter consistently displayed some of the highest. Summer and fall values consistently fell in between spring and winter values barring occasionally exceptions. The average wildfire concentrations per month over the study period follow similar trends with peaks in 2008, 2018, and 2020 (Figure 6). However, the ambient $PM_{2.5}$ concentrations remained much steadier as opposed to the wildfire $PM_{2.5}$ concentrations which were more variable, with the highest concentrations occurring in the summer and fall. The two maps (Figure 7 and Figure 8) that displayed average concentration of wildfire and ambient $PM_{2.5}$ showed a hotspot in northern California for the wildfire specific $PM_{2.5}$, while the ambient $PM_{2.5}$ showed peaks in large cities and central California.

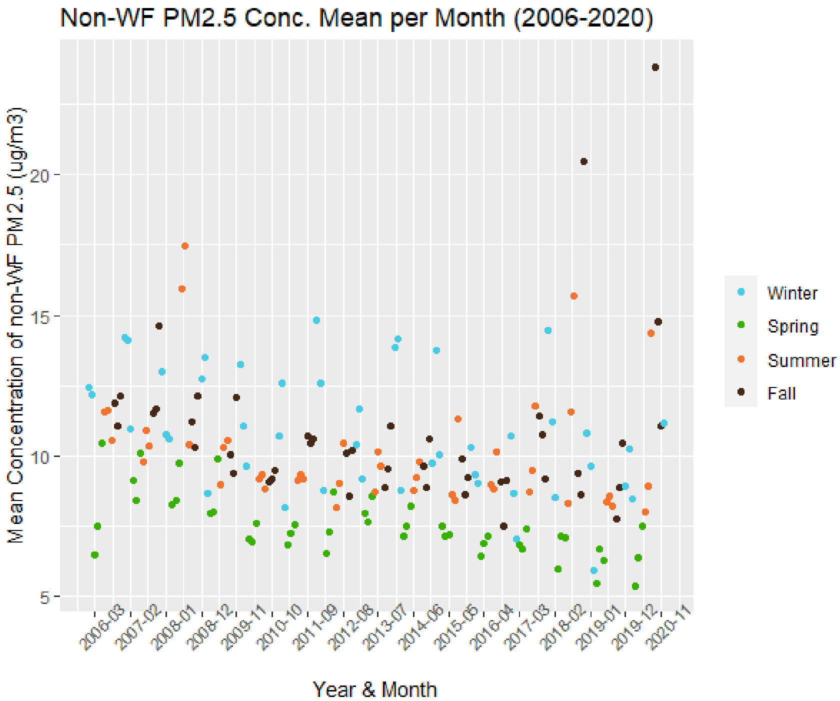


Figure 5. Plot of the average concentration per month of non-wildfire $PM_{2.5}$ over the study period (2006 - 2013), color coded by season.

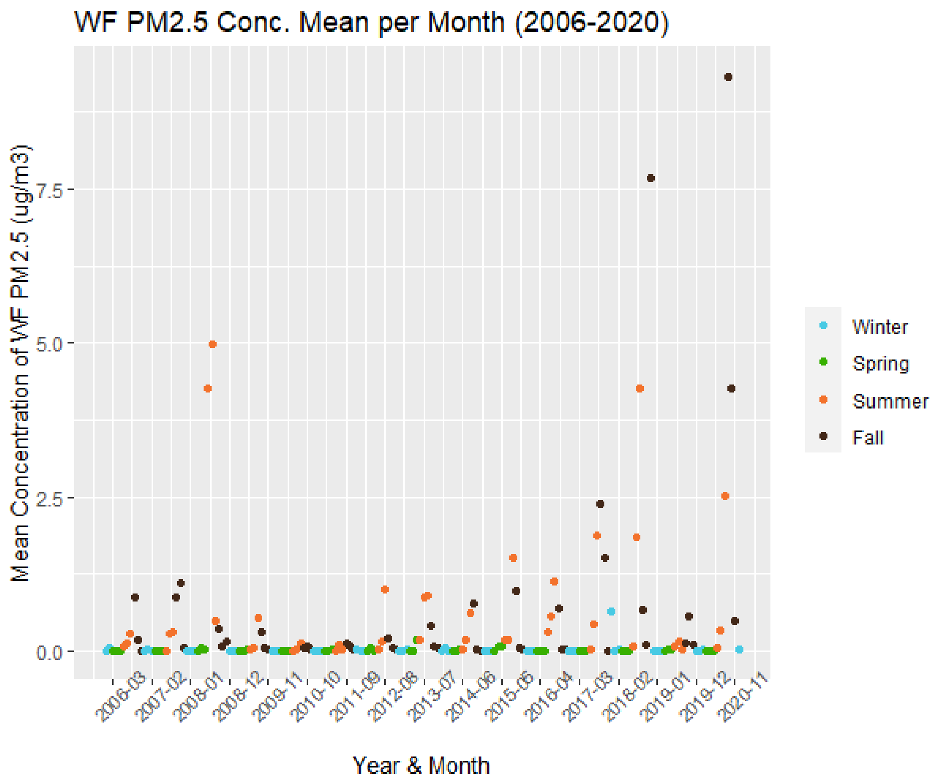
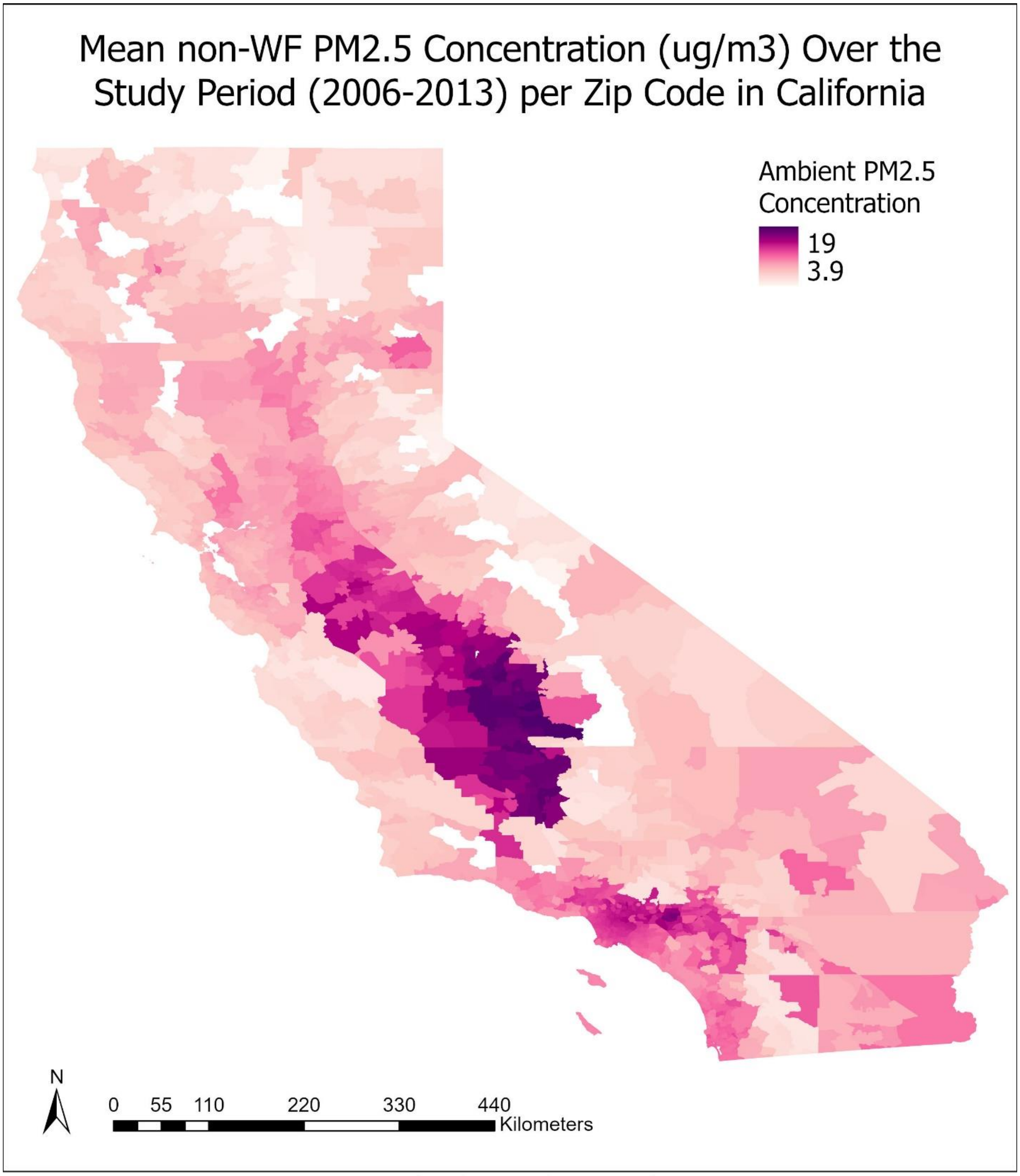
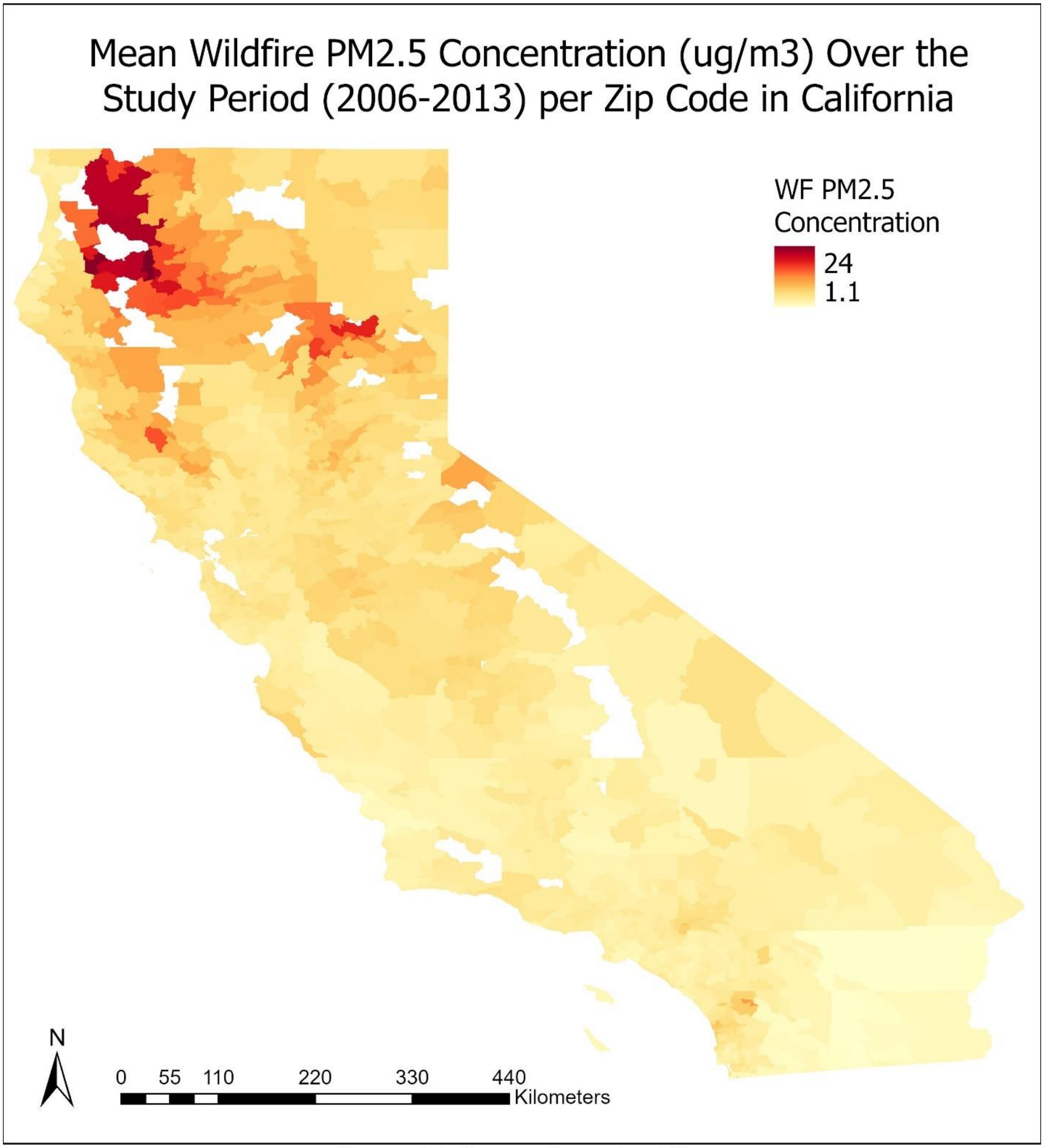


Figure 6. Plot of the average concentration per month of wildfire $PM_{2.5}$ over the study period (2006 - 2013), color coded by season.



Unpopulated areas shown in white

Figure 7. Map of the average non-wildfire $PM_{2.5}$ per zip code, in California over the study period (2006 – 2013).



Unpopulated areas shown in white

Figure 8. Map of the average wildfire specific $PM_{2.5}$ per zip code, in California over the study period (2006 – 2013).

Flu and respiratory hospitalizations

As mentioned previously, we conducted a linear regression analysis of respiratory and flu hospitalizations in California from 2006-2013. The linear regression estimate (95% confidence interval) was 0.50 (0.32, 0.68). Although there are outliers and years with higher cases, both the respiratory and flu hospitalizations show cyclical patterns (Figure 9). However, consistent with the literature and the timing of the swine flu outbreak in late 2008 as well as 2009, there is more variability and 2009 has the largest minimum respiratory hospitalization value (August 2009) of the study period and the second highest flu hospitalization maximum number (October 2009).

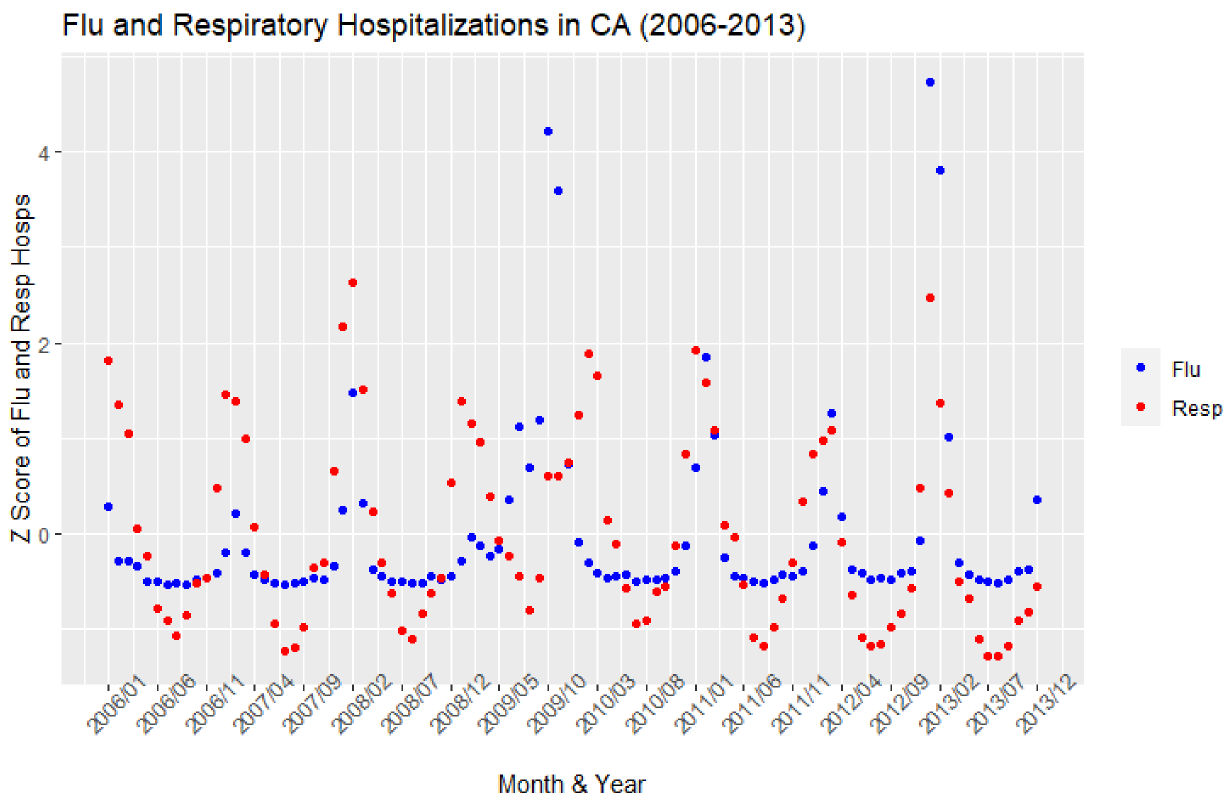


Figure 9. Plot of the Z score of respiratory and flu hospitalizations, per month in California, over the study period (2006 - 2013)

HIA results

As mentioned above, the main results of the HIA can be found in Table 1, Figure 10, Figure 11, and Figure 12. In Table 1, we display the average attributable hospitalizations per year over the study period for the naïve approach, nuanced approach, and the difference of the two. We found that considering the differential toxicity of wildfire smoke $PM_{2.5}$, and thus its more harmful impact than non-wildfire $PM_{2.5}$, leads to the attributable number of the rate of hospitalizations in the nuanced approach remaining consistently higher. The largest rate of respiratory hospitalizations per 100,000 people, occurred during 2006, 2007, 2008. The average number of respiratory hospitalizations for the naïve approach for these years were 1.851, 1.796, and 2.125, respectively. The nuanced approach yielded values of 2.104, 2.185, and 3.886, respectively. While the difference between the two approaches for these years yielded values of 0.254, 0.389, and 1.761, respectively. The year with the maximum number of attributable hospitalizations per 100,000 people in the study period was 2008 with the values mentioned above (naïve: 2.125, nuanced: 3.886, and the delta of the two approaches: 1.761).

Through Figures 10 and 11, we visualized the average attributable number of respiratory hospitalizations per zip code over the study period of 2006 - 2013. In Figures 10 and 11, the hotspots of the highest attributable number of respiratory hospitalizations generally matched the same regions; for example, central and Northern California have some of the highest rates. The zip code with the highest AN was zip code 96123 at the eastern edge of northern California and the second highest was zip code 92332, as the eastern edge of southern California. In Figure 12, we display the delta of the values between the nuanced and naïve approach. The largest values occur most heavily in northern California, with some hotspots in central California as well. Notably, the delta values seen in Table 1 and Figure 12 are all positive values, meaning the nuanced approach yielded larger values in all yearly averages and all average zip code values.

As mentioned previously, calculations were conducted to determine the number of hospitalizations that are unaccounted for when considering the true toxicity of wildfire smoke $PM_{2.5}$. The delta between the sum of all hospitalizations over the state of California yielded a result of approximately 263,580 unaccounted hospitalizations, when the differential toxicity of wildfire smoke is not considered. This yields a percentage of total hospitalizations that approximates to 13.5%.

Table 1. Table of the average attributable number of respiratory hospitalizations due to $PM_{2.5}$ per year over the study period for the naïve approach, nuanced approach, and the delta of the two approaches (per 100,000 people).

	Imputation Method - Aguilera et al		**Difference (Nuanced – Naïve)**
Year	Naïve Approach	Nuanced Approach	
2006	1.851	2.104	0.254
2007	1.796	2.185	0.389
2008	2.125	3.886	1.761
2009	1.744	1.927	0.184
2010	1.501	1.551	0.050
2011	1.529	1.606	0.077
2012	1.376	1.665	0.289
2013	1.429	1.825	0.396

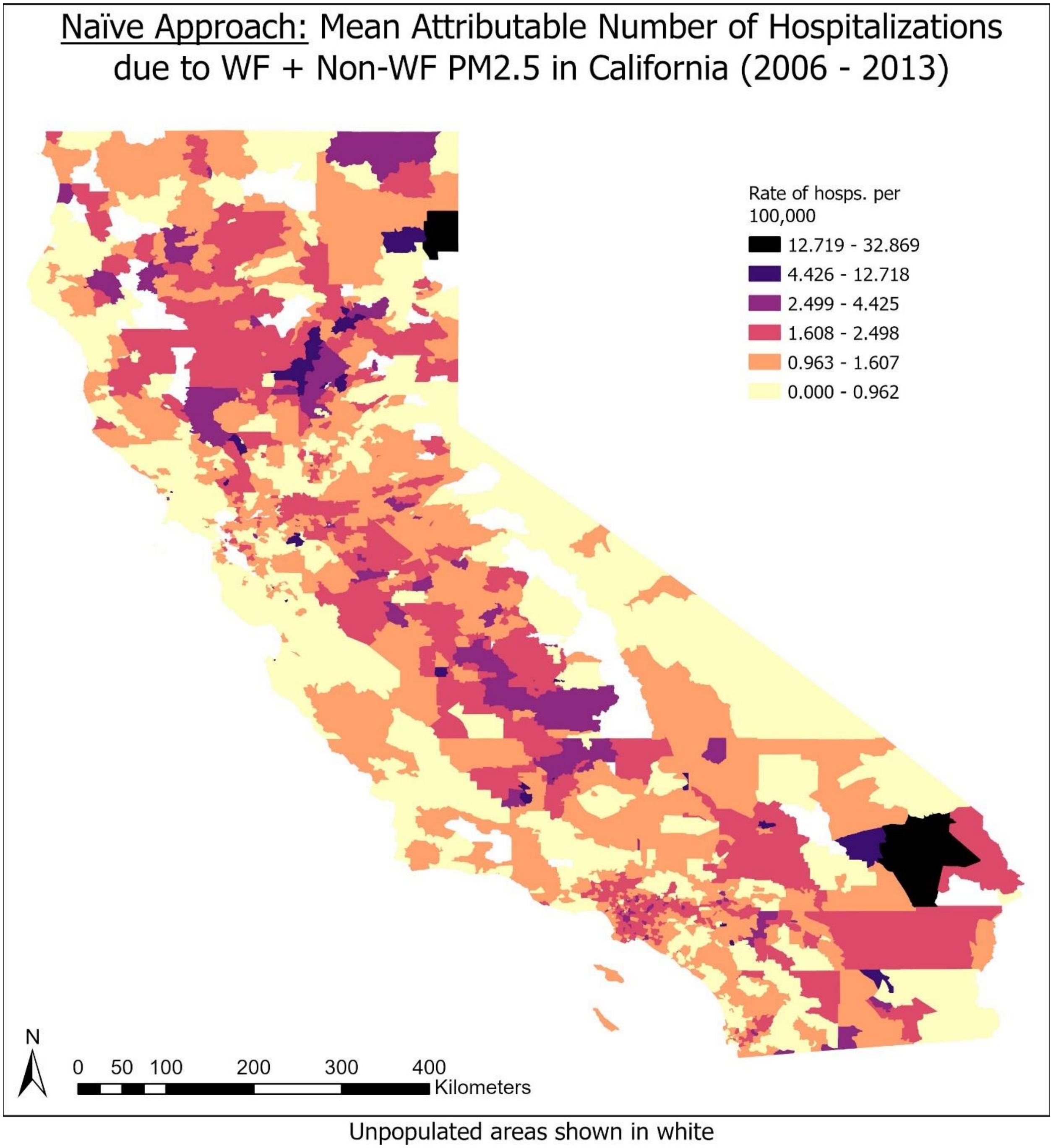


Figure 10. Average attributable number of respiratory hospitalizations, per zip code due to $PM_{2.5}$ (2006 - 2013): **the naïve approach**.

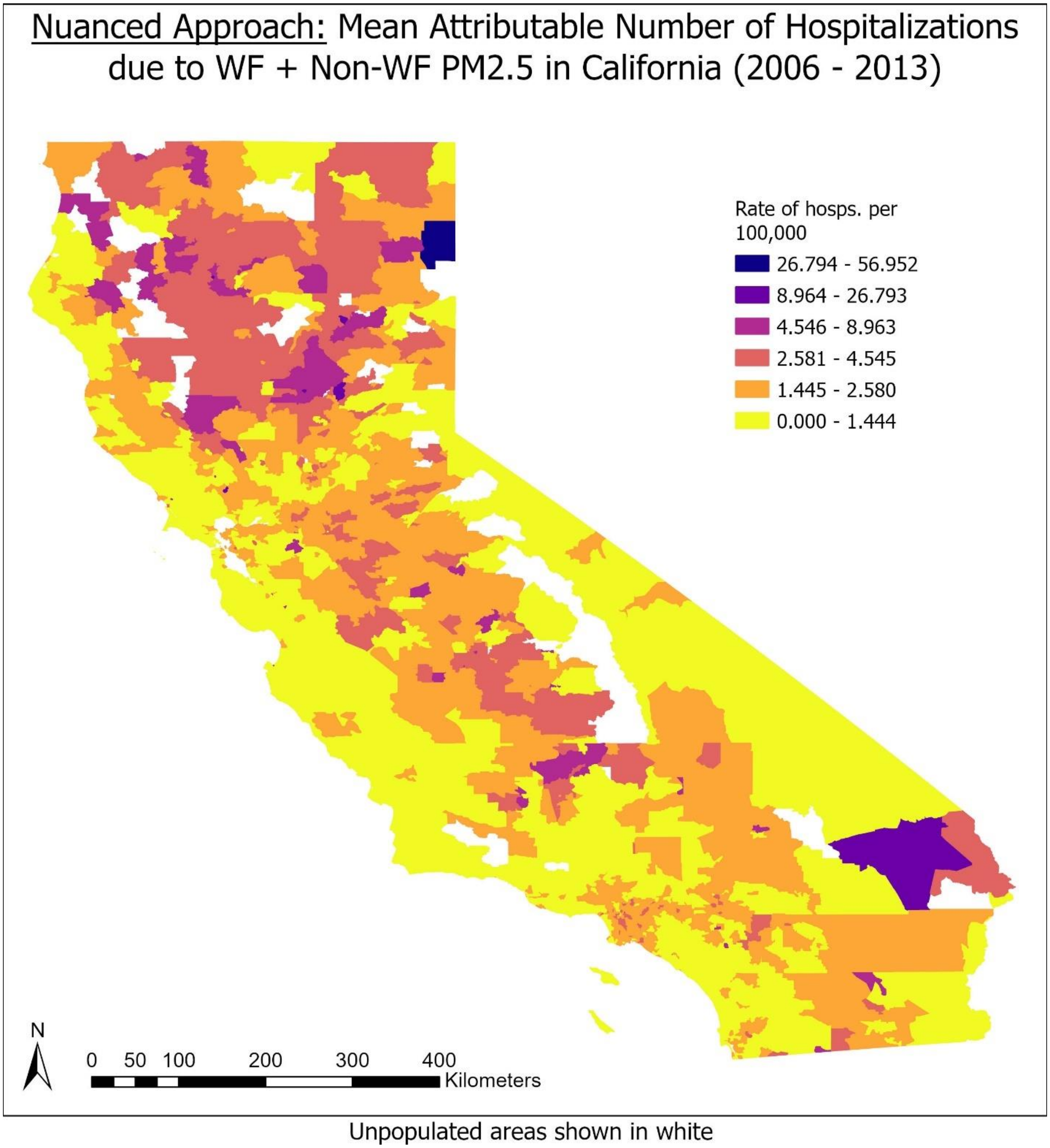


Figure 11. Average attributable number of respiratory hospitalizations, per zip code due to $PM_{2.5}$ (2006 - 2013): **the nuanced approach**.

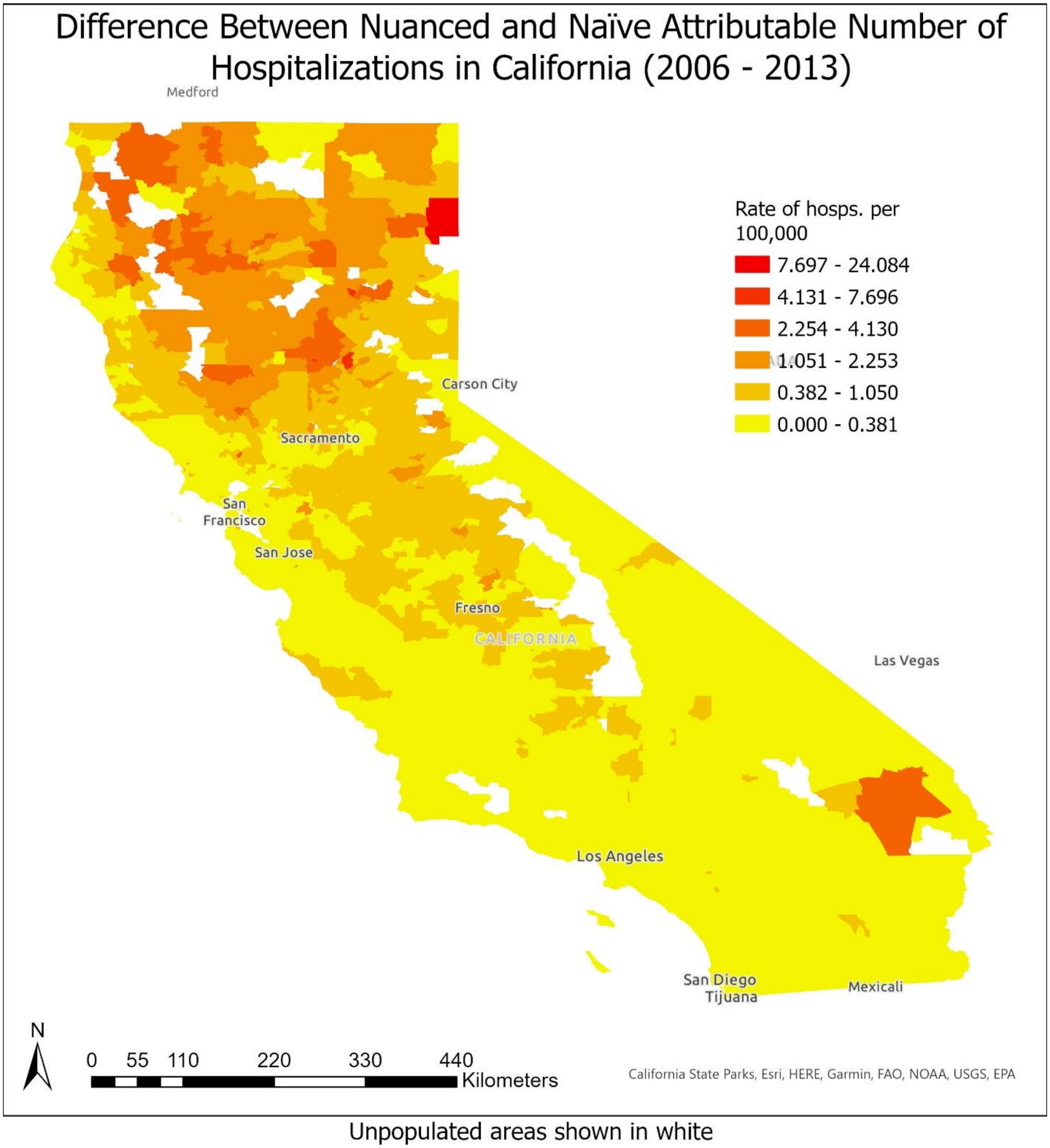


Figure 12. Attributable number of respiratory hospitalizations, per zip code due to $PM_{2.5}$ (2006 - 2013): **the delta of the two approaches**.

Geographically weighted regression

The results of the geographically weighted regression indicate that every 1 unit increase in the SVI resulting in an increase in the number of respiratory hospitalizations. In this analysis, the 1st quartile resulted in a value of 145.78 and the 3rd quartile resulted in a value of 941.17. Thus, 50% of the values of the relationship between increases in SVI and respiratory hospitalizations fall between 146 and 941 hospitalizations per a 1 unit increase in SVI. Additionally, abnormally high results were removed from the final plot because these values were inadequate predictors. Most likely, the zip codes with extremely small populations (such as rural areas) do not converge while fitting the GWR model and were thus removed from the results, but still used for fitting. Coastal cities have higher populations and can be more accurate, as can be seen in Figure 14. Figure 13 depicts the truncated values from the 1st to the 3rd quartile in order to visually determine the variation in the coefficients over the state of California while Figure 14 depicts a plot of the difference between the true and predicted values of respiratory hospitalizations. We see random scatter of the residuals in Figure 14, but there are higher magnitude errors in the northern portion of the state.

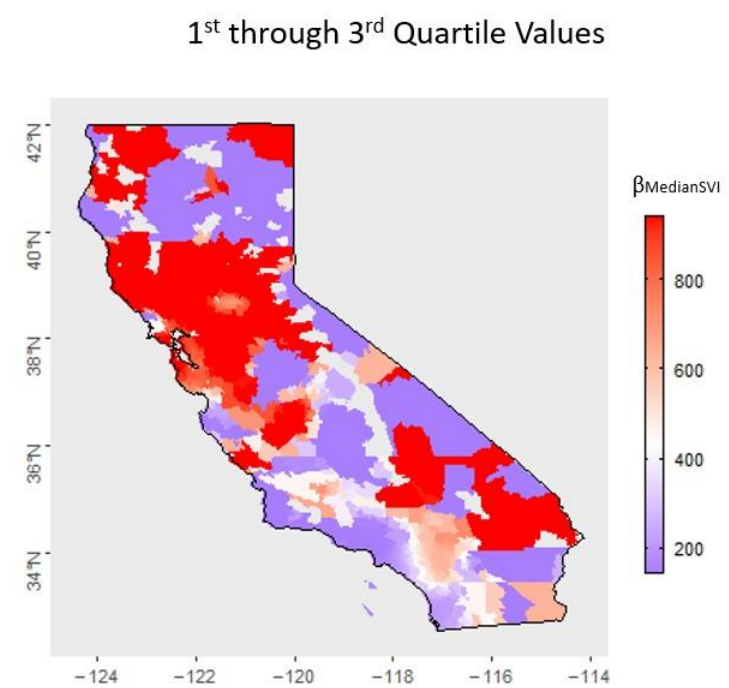


Figure 13. Plot depicting the values between the 1st and 3rd quartile of the GWR coefficients. Values are truncated to show the variation in the coefficients. These are the middle 50% of values in the analysis, which show an increase in hospitalizations due to a 1 unit increase in SVI.

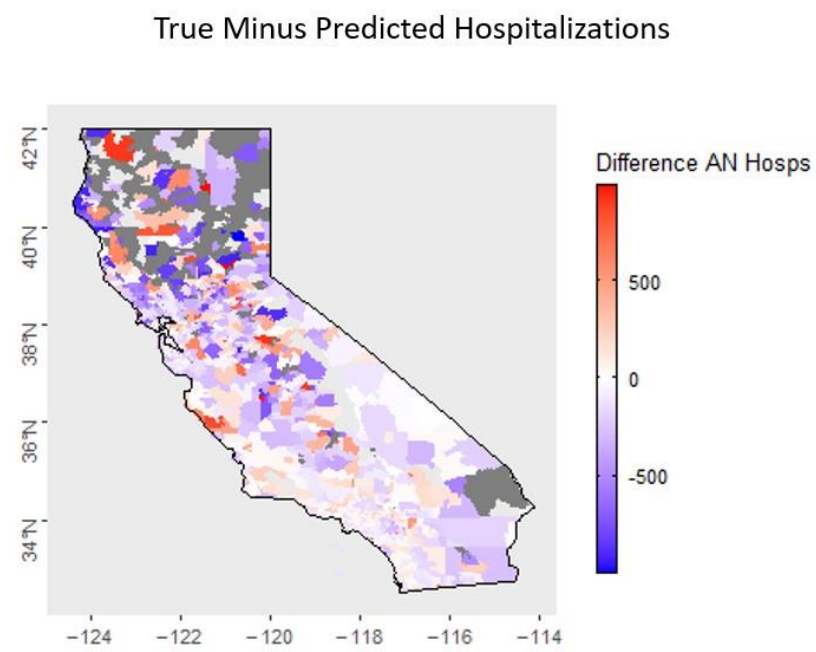


Figure 14. True hospitalizations (calculated) minus the predicted number of hospitalizations (calculated by model). Outlier values removed due to low population.

CONCLUSION

Evolution of $PM_{2.5}$, the exception of wildfire $PM_{2.5}$

Although air quality regulations are still not providing the utmost protection and better air quality protections are still needed; California has been seeing a marked decrease in ambient $PM_{2.5}$. However, when $PM_{2.5}$ is separated into its own category, independently considering wildfire smoke $PM_{2.5}$ it has been seen to increase, both from the information from this study and the literature. This is indicative of more wildfires due climate change as temperatures increase. This pattern is only projected to worsen as climate change mitigation is delayed (McClure & Jaffe, 2018). The peaks in ambient $PM_{2.5}$ that spike at the same time as the wildfire $PM_{2.5}$ in summer and fall in 2008, 2018, and 2020 coincide with extremely bad wildfire seasons (Aguilera et al., 2021a; Williams et al., 2019). Lastly, the peaks in winter are consistent with other studies in literature as well as EPA measurements. Winter $PM_{2.5}$ is often known to increase due to seasonal patterns such as dry air and stagnant weather in dry years especially (Chan et al., 2018).

Flu and respiratory hospitalizations

As mentioned above, the linear regression yielded a value of 0.50 (0.32, 0.68). This is the predictive value of how many respiratory hospitalizations can be attributed to flu cases. These results show a strong relationship between the amount of flu cases and respiratory hospitalizations in California. Thus, as Ostro et al. stated, the swine flu (and general flu illnesses) has a positive effect on the amount of respiratory hospital admissions each month in California. The general observable patterns of hospitalizations are relatively consistent with cold and flu season (fall and winter months) when many individuals often contract respiratory illnesses.

HIA conclusions

One of the approaches of the Health Impact Assessment (nuanced approach) considered the fact that wildfire smoke $PM_{2.5}$ can have differential toxicity in the lung and can be more dangerous for respiratory diseases. As expected, we found that when people are exposed to wildfire $PM_{2.5}$ and when we considered this specific $PM_{2.5}$ with its own toxicity the attributable number of hospitalizations due to $PM_{2.5}$ exposure, increases. This was seen in the fact that the attributable number of respiratory hospitalizations was constantly higher for the nuanced approach in all zip code averages and the yearly averages compared to the naïve approach. The most important finding of this study was the size and the spatial distribution of delta values, i.e., the difference between the nuanced and naïve approach. The delta values yielded all positive values supporting the conclusion that the burden of wildfire smoke $PM_{2.5}$ is higher due to the more harmful impact it brings on health. By not considering the differential toxicity of wildfire $PM_{2.5}$, we underestimate the attributable number of respiratory hospitalizations in California for the 2006-2013 related to $PM_{2.5}$ exposure.

As mentioned previously, the highest attributable number of respiratory hospitalization values occurred in 2008 (naïve: 2.125, nuanced: 3.886, and the delta of the two approaches: 1.761). There are two probable explanations for this peak according to the literature and the fire season patterns. Firstly, as mentioned above, the purpose of the linear regression between the flu and respiratory hospitalizations over the study period was conducted to investigate whether the swine flu had an impact on respiratory hospitalizations in 2008 (Ostro et al., 2016). As stated above, the regression did find a relationship between the flu and respiratory hospitalizations which allows us to conclude the swine flu also may have contributed to this peak. The second contributing factor is most likely due to the large fire season of 2008. During this fire season, asthma hospital visits, asthma emergency department visits, and COPD flare ups were noted, especially in northern California where most of the fires were (Reid et al., 2016).

The map of the delta values has the highest values in northern California and central California. Evidence from the literature and current observable trends suggests that increasing drought years are making northern California, and the Sierra Nevada Mountain region (which spans northern and central California) more susceptible to fires. A 2004 model study found that, with a double carbon dioxide atmosphere, wildfires that exceeded their containment limit were expected to increase by 51% in the southern San Francisco Bay area, and 114% in the Sierra Nevada region, as a best-case scenario (Fried et al., 2021). This trend has only continued to increase as large fires have burned these the past few years such as the Dixie fire (2021) and the August complex fire (2020) (NASA, 2021). The large number of forests in northern California also aid in producing tinder for fires when the conditions strike (NASA, 2021). These fire producing conditions are expected to get worse with increasing climate change (Fried et al., 2021, NASA, 2021).

The results of this study support the conclusions that: wildfire $PM_{2.5}$ has a differential, more negative toxicity on the lung and, the fact that stronger air quality guidelines are needed to prevent illness, especially respiratory issues, during wildfire episodes. The ~263,580 (or 13.5%) of unaccounted hospitalizations suggests that by not considering the differential toxicity of wildfire $PM_{2.5}$, the leading regulatory and health agencies such as the WHO and the EPA leave people more vulnerable to the detrimental health impacts of wildfire smoke $PM_{2.5}$, especially in northern California.

Geographically weighted regression

The model's success at determining the respiratory hospitalizations can be determined by the amount of random scatter on the plot (Figure 14). In this analysis, the vast size and diversity of zip code populations of California left a wide range of data. As mentioned previously, this data had to be truncated to the 1^{st} and 3^{rd} quartile (Figure 13) and also for outlier values when finding the difference in predictor versus true values (Figure 14). Through these plots, there is evidence of a relationship between SVI and respiratory hospitalizations, but in order to see stronger or more detailed variation, smaller areas such as individual cities or counties would have to be analyzed.

This thesis is currently being prepared for submission for publication of the material. Darling, Rachel; Aguilera; Rosana; Hansen, Kristen; Benmarhnia, Tarik; Letellier, Noemie. The thesis author was the primary investigator and author of this material.

APPENDIX

Table 2. Literature review containing 16 formative papers on the subject of how particulate matter affects respiratory health.

Study	Population Sample	Study Region & Study Period	Exposure (modeled, reference PM 2.5 conc.)	Health Outcomes Measured	Main Results
Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California - **Aguilera et al 2021**	Patients needing respiratory hospitalizations	Southern California (1999-2012)	Multiple Imputation Approach: Multiple machine learning algorithms and predictors variables Estimated daily PM2.5 levels per zip code in California Reference Concentration: 10 ug/m^3 PM2.5	Respiratory hospitalizations due to wildfire PM2.5 concentrations (per 100,000 individuals)	Particulate matter may be more toxic than equal doses of ambient PM2.5, however, air quality regulations assume the same toxicity Increases in respiratory hospitalizations ranging from 1.3 to up to 10% with a 10 μg/m^3 increase in wildfire specific PM2.5, compared to 0.67 to 1.3% associated with non-wildfire PM2.5
The changing risk and burden of wildfire in the United States - **Burke et al 2021**	Those facing societal burdens of wildfire; affected houses in the Wildland Urban Interface (WUI)	The United States (~1985-2018)	Statistical model that relates satellite derived fire/smoke data to data from monitoring stations	——	Wildfires have accounted for up to 25% of PM2.5; 54% of the wildfire smoke experienced by the country comes from the western US; marginalized communities are most affected, the Clean Air Act exempts wildfire pollution, climate change is responsible for ~1/2 the increase in burned area in the US
Estimated mortality and morbidity attributable to smoke plumes in the United States: Not just a Western US problem - **O'Dell et al 2021**	Cases of mortality & asthma hospitalizations	The United States (2006 -2018)	Health Impact Assessment (HIA) with PM2.5 values from observational evidence, using metanalysis to determine hospital and emergency dept. admissions due to PM2.5 Reference Conc.: 10 ug/m^3 PM2.5	Asthma hospitalizations and emergency department visits Mortality Disability Adjusted Life Years (DALYs) (per 100,000 individuals) (All due to wildfire PM2.5 exposure)	Majority of landscape fires occur in the West, but 74% of deaths and ~75% of asthma hospitalizations and emergency dept. visits attributable to wildfire smoke occur outside the West Disability Adjusted Life Years (DALYs) for PM2.5 wildfire smoke are 3x higher than for Hazardous Air Pollutants (HAPs) Relative Risk (RR): Asthma Hospitalizations: 1.08 Emergency Dept. Visits: 1.07

Table 2. Literature review containing 16 formative papers on the subject of how particulate matter affects respiratory health, Continued.

Mortality risk attributable to wildfire-related PM2.5 pollution: a global time series study in 749 locations - **Chen et al 2021**	Patients worldwide who suffered all cause, respiratory, or cardiovascular mortality	Worldwide: 749 cities, 43 countries (2000-2016)	PM2.5 conc. determined by 3D GEOS-Chem chemical transport model Relationship between wildfire exposure and mortality was determined by a quasi-Poisson time series model & pooled random effects metanalysis Reference Conc.: 10 ug/m³ PM2.5	Mortality: All cause, respiratory, and cardiovascular due to wildfire pM2.5 exposure	65.6 million all-cause deaths, 15.1 million cardiovascular deaths, & 6.8 million respiratory deaths Mortality RRs: All cause – 1.019, 1.017 – cardiovascular, 1.019 – respiratory 0.62% all cause, 0.55% cardiovascular, and 0.64% respiratory deaths attributable to wildfire PM2.5 exposure Wildfire PM2.5 had stronger effects on mortality
Fine Particles in Wildfire Smoke and Pediatric Respiratory Health in California - **Aguilera et al 2021**	Children under 19 years of age	San Diego County, California (~2011-2017)	Multiple Imputation Approach (mentioned previously in first row) Reference Conc.: 10 ug/m³ PM2.5	Respiratory disease pediatric visits due to wildfire smoke PM2.5 exposure (per 100,000 individuals)	Wildfire specific PM2.5, compared to ambient PM2.5, was found to be ~10x more harmful to children (especially ages 0-5) – even modest fires proved to be especially impactful for children
Association between fire smoke fine particulate matter and asthma-related outcomes: Systematic review and meta-analysis - **Arriagada et al 2019**	Asthma patients: all ages	United States, Canada, Australia (studies ranged from 1994 to 2012)	Used multiple statistical models; data derived from a literature review (less weight given to studies with high variance) Reference Conc.: 10 ug/m³ PM2.5	Asthma hospitalizations and emergency dept. visits due to landscape fire smoke (LFS) PM2.5	LFS PM2.5 levels positively associated with asthma hospitalizations (RR = 1.06) & emergency dept. visits (RR = 1.07) All adults aged over 65 years & women, seem to be the groups most sensitive to asthma-related outcomes when exposed to LFS PM2.5
Age-specific seasonal associations between PM 2.5 and cardiorespiratory hospital admissions in California - **Ebisu et al 2019**	All ages separated into category (children, adults, the elderly)	Eight sites in California (2002-2009)	2-stage time series model to estimate PM2.5 sources & relationship to hospitalizations Measured conc. in % increase in IQR of chemical PM2.5: PM2.5 total mass (11.6) & burning biomass (2.71) among other chemical constituents	Cardiovascular and respiratory hospitalizations due to PM2.5 from multiple sources	Excess risk used to determine the health effects of the IQR increase in admissions: 1.32% for cardiovascular hospitalizations (lag 0) and 3.58% for respiratory hospitalizations for children (0-18 yrs) Short term exposures to PM2.5 from different sources is more harmful than other pollutants (especially for children in summer)

Table 2. Literature review containing 16 formative papers on the subject of how particulate matter affects respiratory health, Continued.

US particulate matter air quality improves except in wildfire-prone areas - **McClure & Jaffe 2018**	——	The United States (1988-2016) – comparing Northwest to the rest of the US	Measured 98th quantile PM2.5 trends using Kriging, Quantile regression, Gaussian Geostatistical Simulation, & satellite imagery Data from IMPROVE network	——	Found a positively increasing trend in PM2.5 in the Northwest and a negative trend in most areas – the increase is attributed to wildfires Satellite imagery and Aerosol Optical Depth (AOD) measurements support this conclusion
Critical Review of Health Impacts of Wildfire Smoke Exposure **- Reid et al 2016**	Patients worldwide suffering from respiratory, cardiovascular, or mental health problems due to wildfire smoke	Worldwide (literature review on relevant studies up until 2015)	Methods from the review included: self-reported, air pollution monitors, comparison of fire periods to non-fire periods, satellite imagery, & air quality models Studied PM2.5 to PM10	Respiratory, cardiovascular, mental health Mortality	Evidence for association between wildfire smoke exposure & respiratory health effects (asthma and COPD); increased risk of respiratory infections and mortality; mixed evidence for cardiovascular end points; more research needed on whether certain populations are more susceptible
Associations of Source-Specific Fine Particulate Matter with Emergency Department Visits in California **- Ostro et al 2015**	All patients admitted for cardio or respiratory ED visits	8 metro. areas in California (2005-2009)	EPA Positive Matrix Factorization (PMF) model, population weighted centroids for patient location to assign exposure Modeled multiple sourced of PM2.5	Emergency dept. visits for cardiovascular & respiratory diseases	Vehicle, biomass, and soil sources of PM2.5 were associated with ED visits for respiratory problems and asthma Soil sourced had highest risk estimate for asthma (Excess Risk: 4.5%) Conclude some sources of PM2.5 have more risk than others
A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke **- Liu et al 2015**	All ages (varied by study)	Review of 61 studies worldwide (1986-2014)	Stationary ground monitors, satellite remote sensing, & air sample measurements	Respiratory illness and mortality; cardiovascular disease	Wildfire smoke is associated with increased risk of respiratory and cardiovascular diseases Children, elderly, & those with underlying disease are most susceptible to WF smoke
Epidemiological time series studies of PM 2.5 & daily mortality & hospital admissions: a systematic review & meta-analysis **- Atkinson et al 2014**	All ages (varied by study)	Review of 110 studies worldwide (until May 2011)	Single pollutant models, random effects models (for two stage metanalysis when necessary) Reference Conc.: 10 ug/m³ PM2.5	All cause, respiratory, cardiovascular morbidity & mortality	10 ug/m³ PM2.5 associated with a 1.04% increased risk of death Associations for respiratory death higher than those for cardiovascular (1.51% & 0.84%) + associations with all health problems

Table 2. Literature review containing 16 formative papers on the subject of how particulate matter affects respiratory health, Continued.

Measures of forest fire exposure and their associations with respiratory outcomes - **Henderson and Johnston 2012**	All ages (varied by study)	8 smoke exposure studies (1994-2008)	Simple methods: PM measurements (using known fires); # of known fires as proxy for smoke; burned area as proxy; satellite images and PM10 Complex methods: Pollution dispersion model using satellite imagery; 24-hour PM value using multiple sources (gov't data, remote sensing)	Respiratory morbidity & mortality	Studies were consistent with previous work Growing body of literature suggests that smoke exposure is associated with acute respiratory outcomes
Estimated global mortality attributable to smoke from landscape fires - **Johnston et al 2012**	All age	Global exposure to fire smoke measured globally (1997-2006)	Chemical transport model with satellite derived aerosol optical depth, looked at WHO subregions	Daily burden of mortality	Average annual mortalities attributable to landscape fire smoke: 339,000 Most affected regions: sub-Saharan Africa & Southeast Asia (157,000 & 110,000) El Niño years had higher mortality estimates than La Niña years
Coarse particles and respiratory emergency department visits in California - **Malig et al 2012**	All ages separated into category (children, adults, the elderly)	35 California Counties (2005-2008)	Time stratified case crossover design Reference Conc.: 10 ug/m^3 PM2.5	Respiratory emergency department visits	Significant association between respiratory ED visits and coarse particle exposure Asthma visits: 2-day lag, excess risk = 3.3% at 10 ug/m^3 PM2.5 Coarse particle exposure may trigger asthma & EDVs
The Temporal Lag Structure of Short-term Associations of Fine Particulate Matter Chemical Constituents and Cardiovascular and Respiratory Hospitalizations - **Kim et al 2012**	All age	Denver, Colorado (2003-2007)	Ground PM2.5 collection & monitoring; used a lag model	Respiratory & cardiovascular hospitalizations	Relative risks were larger for: longer lags for respiratory admissions & smaller lags for cardiovascular admissions (shown to depend on the constituent of PM2.5)

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