Modeling The Future Challenge Project 2020-21

An Analysis of the Impact of California Wildfires on Cardiovascular Disease

Team #7303

February 26, 2021

Executive Summary

Wildfires in California are an increasingly important problem for many people in fire-prone areas and are responsible for causing significant public health issues. The high levels of particulate matter, specifically $PM_{2.5}$, found in wildfire smoke can lead to cardiovascular complications, such as heart disease and respiratory infection.

In this report, we analyze how wildfire frequency and intensity affect the concentration of particulate matter in fire-prone areas, which we link to an increase in cardiovascular health complications. We use data on monthly particulate matter concentrations by county from California to find any outliers or peaks, which can be used to identify major fires.

We obtained data from a multitude of sources including institutions, government agencies, and credible authors to gain information on locations, dates, and intensities of wildfires along with methods to mitigate the risks. Government sources such as ones from CDC (Centers for Disease Control and Prevention), EPA (United States Environmental Protection Agency), and USFA (United States Fire Administration) provide crucial information in developing an analysis of the correlation of wildfires to cardiovascular disease and presenting evidence of possible solutions.

We found that months with a large spike in $PM_{2.5}$ were typically caused by a large wildfire. Then, we established a clear trend: the number of these large wildfires has increased at an exponential rate. Next, we connected the wildfires and increased levels of particulate matter to the increased levels of cardiovascular disease. We correlated the dates and areas of increased wildfire activity with the increasing increments of cardiovascular disease to conclude the positive correlation of wildfires causing increased cases of cardiovascular disease.

The results we gathered from the data and modeling displayed a clear causal relationship of increasing particulate matter concentrations leading to escalated cases of cardiovascular complications. The effects of particulate matter on human health is clearly detrimental as 36% of long-term exposure to particulate matter will lead to cardiovascular disease, and up to 90% of the smoke will have the malignant type of particulate matter. Consequently, the financial and demographic impacts are paramount as cardiovascular deaths is the primary cause of death in the US and the most expensive chronic condition to care for as it costs over $37 billion a year in California alone.

We propose three recommendations that should be implemented in wildfire-prone counties in California: filtration, education, and insurance. Our filtration plan offers a more protective filter against particulate matter in indoor spaces. We also suggest the introduction of an education program to raise awareness of wildfire prevention techniques. The insurance policy we recommend provides a cost-effective method to caring for those affected with cardiovascular disease. Filtration, education, and insurance will assist in mitigating all threats associated with wildfire-related cardiovascular complications.

Background Information

Wildfire History

In the past decades, wildfires have become a larger issue across the United States, with California as the state facing the greatest surge. Although there has been a decrease in the number of wildfires in the last 5 years, the amount of acres burned has increased from 5.4 million acres in 2016 to 10.3 million acres nationally in 2020 [31]. From 2014 to 2019, an average of 1.2 million acres burned annually, with $590.4 million dollars spent in fire suppression costs. While California was already fire-prone, increases in global warming is attributed to the extended fire season in California, with experts even suggesting year-round fires may become a regular occurrence [19]. Last year had been California's worst fire season, with fires becoming more intense and setting records in acreage burned [37].

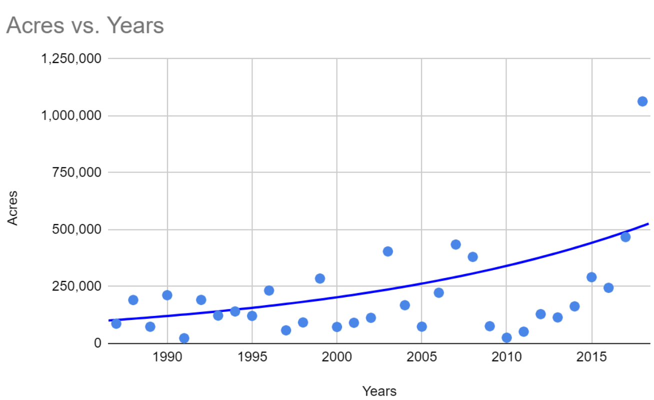

Figure 1.1 *Total acres burned for fires over 10,000 acres, from 1980 to 2016, showing a steady increase.*

One of the main reasons for this increase in the number of wildfires and damage is the increase in climate change. From 1984 to 2015, the total number of large wildfires had doubled on the west coast, and this time period also showed an increase in global temperature of 0.32 degrees Fahrenheit per year [37][21]. As climate change continues to escalate and global warming becomes a more significant threat, wildfires become more common due to an increase in dry forest brush susceptible to being set ablaze. The dry environment and warm climate makes it difficult for wildfires to be put out swiftly, and drought and fire seasons grow longer while wildfires threaten more landscapes as temperatures skyrocket [21].

The California state government has set preventative measures to attempt to deter wildfires. One such measure are the building codes set by the California Department of Forestry and Fire Protection so that the damage from fire can be mitigated. Preventing wildfires has been proven to be extremely difficult, especially since the contributing factors such as weather and human behavior are very unpredictable. Thus, California laws such as requiring external vents to be designed to stop ember intrusion were set in place [10]. This requirement is only one of many that aims to prevent buildings from catching on fire and harming residents, but clearly, it is inadequate in preventing cardiopulmonary diseases.

Wildfire Impact and Solutions

As a source of air pollution, wildfires and especially wildfire smoke can have many adverse public health effects. Among them, the principle concern is particulate matter [42]. Wildfires release particulate matter, also called $PM_{2.5}$, which has been shown to increase cardiovascular health complications. $PM_{2.5}$ exposure has been associated with cases of respiratory illnesses, asthma, and chronic obstructive pulmonary disease (COPD) [44]. Wildfires present a unique risk of cardiovascular health issues, endangering hundreds of thousands of people in fire-prone areas.

Among the most prominent public health issues, cardiopulmonary health risks, which includes problems in the heart and lungs, can refer to a range of diseases, the most common being cardiovascular disease and chronic obstructive pulmonary disease (COPD). In California alone, 8 million people suffer from a cardiovascular disease and 1.1 million suffer from COPD [19]. Cardiovascular disease includes a variety of heart-related health issues, such as coronary artery disease and heart defects. COPD is an inflammatory lung disease, which may result in coughing, respiratory problems, and wheezing. Compromised cardiopulmonary health can lead to many other complications, including (but not limited to) heart failure, heart attack, cardiac arrest, lung cancer, and respiratory infections. These health issues can be fatal, with heart disease being the leading cause of death in the United States [47].

Our paper analyzes the risks of cardiovascular health issues as a result of wildfires and particulate matter within wildfire smoke. Cardiovascular health risks pose a great threat to residents and building owners in fire-prone areas, especially those who are very old or even young with pre-existing health conditions, such as diabetes or increased blood cholesterol levels. We evaluate many risk mitigation strategies, including the installation of highly efficient HVAC filters to decrease the level of particulate matter that enters high-risk buildings. In addition, wildfire education programs aimed at the general public and students would promote awareness and prevention methods, and cost-effective insurance policies would reduce the cost of healthcare and make it more accessible.

Data Methodology

We draw data from the Federal Fire Occurrence database with wildfire data from the Bureau of Indian Affairs (BIA), Bureau of Land Management (BLM), U.S. Fish and Wildlife Service (FWS), National Park Service (NPS), Bureau of Reclamation (BOR), and U.S. Forest Service (USFS); the California Air Resources Board Air Quality and Meteorological Information (AQMIS2) showing monthly concentrations of $PM_{2.5}$ per county; the CDC Interactive Atlas of Heart Disease and Stroke; the Kidsdata database on annual average particulate matter concentration per county; and the CDC WONDER (Centers for Disease Control and Prevention Wide-ranging Online Data for Epidemiological Research) online database of particulate matter.

Federal Fire Occurrence Website

Scope and Parameters: National wildfire data collected from the BIA, BLM, FWS, and NPS, BOR, and USFS, from 1980 to 2016.

Adjustments: We adjusted the data to only include wildfires from California instead of all states and we only kept the data for fires that burned more than one acre. We organized the data by year and kept the start date, controlled date, longitude, latitude, and total acres while deleting the rest such as fire codes. We added in another column of data for counties, which we calculated by inputting the longitude and latitude into an API.

The use of the FCC ‘Area and Block’ Census API was pivotal to accessing key wildfire data [25]. Due to the sheer size of the data, we needed to automate the API to take the longitude and latitude of each row and output the county associated with the coordinates. We translated the API from a RAML file into an OpenAPI file. From here, we used a Google Sheets Add-On called RapidAPI and imported the converted OpenAPI file. We were able to call the API through a function within Google Sheets and apply it throughout all 18,000 entries.

Purpose: This data serves as a comparison to levels of particulate matter and cardiovascular hospitalizations. During periods of wildfire surges, we can see how levels of particulate matter and cardiopulmonary issues are affected. We also use this data to separate outcomes and show that increases in wildfires specifically cause increased particulate matter concentration. This helps form a link between wildfires and cardiopulmonary health issues. We also use this data to project future trends in wildfires in California to establish how the amount of particulate matter released due to wildfires is changing over time.

The largest drawback to this dataset is that it has not been updated since 2016 but it was the most all-encompassing data set available. We were also concerned about combining it with other data sets as every dataset calculates acreage differently so instead of adding more recent data we started all modeling from 2016 in order to keep everything consistent.

California Air Resources Board Air Quality and Meteorological Information (AQMIS2)

Scope and Parameters: Monthly averages of particulate matter ($PM_{2.5}$) in various counties in California in a Year-in-a-glance type report from 1980 to 2021.

Adjustments: We hand-compiled the data from five counties as the original data set only displayed one month of one year at a time. This time-consuming task meant we couldn’t get the data from all counties but we were able to take a representative sample of California’s counties by randomly selecting five counties: Los Angeles, Santa Clara, San Bernardino, Riverside, and San Diego.

Purpose: We used the monthly particulate matter data per year per county to identify and isolate outliers within the data. We looked for unusually high peaks in particulate matter and connected it back to notable fires within that month. When we made these connections, we were able to establish a causal relationship between wildfires and increased concentrations of $PM_{2.5}$, which helped establish a link chain to our risk of cardiopulmonary health issues as a result of increased particulate matter. This data separated outcomes as counties during months with significant fires had an increased likelihood of higher concentrations of $PM_{2.5}$. The monthly data also allowed us to analyze trends in particulate matter based on the time of year.

One drawback to this dataset is that it is very difficult to retrieve all of the data, as it must be done manually by inputting each desired year. However, the data program allowed us to specify the parameters of the data and has a large time range to analyze trends.

CDC Interactive Atlas of Heart Disease and Stroke

Scope and Parameters: Data about health indicators and diagnosis categories within states and/or counties with race, gender, and age parameters

Adjustments: We adjusted the data to cardiovascular disease hospitalization rate per 1,000 Medicare beneficiaries for people who are 65 years old or older, of all races/ethnicities, and both genders. We used data from 2005 to 2017 in 2-year increments.

Purpose: The cardiovascular data is compared to levels of particulate matter and the frequency and severity of wildfires so that we could connect wildfires to the risk that we are mitigating. We establish that as wildfires increased in frequency and severity, there were higher levels of particulate matter and more cardiovascular-related hospitalizations. This data separated outcomes by allowing us to identify the fire-prone counties where cardiovascular-related hospitalizations occurred at a higher rate, meaning that the people there are more likely to be at risk of cardiovascular health issues. We could use this data to predict future trends in cardiovascular disease hospitalizations.

One drawback to this data is that it is organized into 2 year increments, which limits our ability to isolate trends. However, this data does clearly identify the variables tested and is a reliable source.

KidsData Annual Average Particulate Matter Concentration

Scope and Parameters: Yearly $PM_{2.5}$ from 1999 to 2016 for most counties and statewide

Adjustments: Some parts of the data were filled in as N/A such as Alpine county in 2003. Thus, we looked towards CDC Wonder Fine Particulate Matter data and used the $PM_{2.5}$ concentrations in the dataset to fill in the N/A. We made sure that the county and year were matched up and filled in spots from 2003-2011 to create a more robust dataset.

Purpose: This data is for comparisons between $PM_{2.5}$ and hospitalizations rates as well as showing the general trend of $PM_{2.5}$ concentrations overtime statewide. It's very well suited for this task as it's organized by year so multiple years can be displayed at once. This allows us to make meaningful comparisons between these two major aspects of the report.

The yearly fine particulate matter data across the counties allowed us to compare the counties with higher levels of particulate matter with how fire-prone the area is and the number of cardiovascular-related deaths they experienced. This would allow us to establish a relationship between wildfires, the level of particulate matter, and cardiovascular risk.

We can accurately analyze how lowered levels of particulate matter would alleviate risks of cardiopulmonary issues, which would support our recommendations. This data separates the outcomes of wildfires by defining the counties that are more at risk of cardiovascular health issues through high levels of particulate matter. It also defines the severity of cardiopulmonary health issues as a result of high levels of particulate matter and can be used to project future trends in particulate matter.

One drawback to KidsData is that there are several N/A's in the data. In addition, at first glance it seems like an untrustworthy source. However, upon further inspection, KidsData is a subset organization of the Population Reference Bureau, a private nonprofit organization that specializes in collecting and supplying statistical data.

CDC Wonder Fine Particulate Matter ($PM_{2.5}$) Data 2003-2011

Scope and Parameters: Monthly Fine Particulate Matter ($PM_{2.5}$) (µg/m³) data across California from January 2003 to December 2011 AND Yearly Fine Particulate Matter ($PM_{2.5}$) (µg/m³) data across all counties from 2003 to 2011
Adjustments: We adjusted the monthly data to be specific to California instead of all the states across the U.S. We also retrieved the yearly data from all counties across California.
Purpose: The fine particulate matter data provides information on monthly levels of $PM_{2.5}$ in California so that we can compare the months with higher levels of particulate matter to cardiovascular-related hospitalizations. The main purpose of this data is to fill in the gaps left by the KIDS data.

One drawback to this dataset is that the time range is limited, therefore it is difficult to draw trends and compare to other datasets with larger time ranges. However, the CDC is a trustworthy source and uses reliable mechanisms to measure $PM_{2.5}$ concentrations.

Mathematics Methodology

Overview

The overall goal of our mathematical modeling is to predict the increase in cardiovascular hospitalizations due to particulate matter released from wildfires. However, the inherent nature of wildfires means that the data has extreme variation, so we focus on modeling trends instead of specific predictions. Modeling the variations in acres burned from year to year and the $PM_{2.5}$ concentrations per year would not be possible, so we broaden our scope to encompass general trends. We limited our modeling to 2026 and 2027 because the trends in the data aren't extremely strong so a model that forecasts decades into the future would not be accurate.

In this section, we explore $PM_{2.5}$ concentrations for California and specific counties, identifying significant outliers and peaks. Through data analysis, we link outliers to large wildfires in five of the counties. Next, we use equations to forecast the average acres burned per fire and total wildfires in California over time to establish a trend of increased severity and frequency of wildfires. Finally, we establish a relationship between $PM_{2.5}$ concentrations and hospitalizations due to cardiovascular disease in three counties, as well as project future risks. Through polynomial equations, scatter plots, line graphs, and bar graphs, we prove a causal link between wildfires, particulate matter, and cardiovascular health issues.

$PM_{2.5}$ Modeling Assumptions

1. *The total number of acres burned continues on its current trend.* We are incapable of accounting for any major events or changes to the Californian political, social, or geological landscape that would significantly increase or decrease the current projection of wildfires. Thus, we will assume that the total number of acres burned will continue on its current trajectory.

2. *Each acre of land burned by wildfire produces a similar amount of $PM_{2.5}$.* Due to the vast unpredictable nature of the natural landscape and the incalculable factors of both density of wildfire fuel and the decomposition of it into $PM_{2.5}$, we are incapable of calculating the exact $PM_{2.5}$ created per acre burned. Thus, we will assume that roughly 0.195 metric tonnes of $PM_{2.5}$ is produced per hectare or 19,540,000 ($\mu g/m^2$) burned [18].

3. *We only consider the effects of wildfire on particulate matter concentrations*. We assume that particulate matter concentrations illustrated within the report are derived specifically from wildfire sources. Due to the immense number of causes for the formation of particulate matter and the various events that can subsequently change it (emissions from combustion of gasoline, oil, or diesel fuel), we are incapable of accounting for every variable within our data [8]. Thus, it is pertinent to view changes to particulate matter concentrations solely in accordance with changes in wildfire occurrence.

4. *$PM_{2.5}$ concentrations are consistent throughout counties.* When we reference wildfire data and particulate matter concentrations in counties, we assume that the entire county experiences a uniform amount of $PM_{2.5}$. While this is not realistic, as different regions and communities in a county may have different $PM_{2.5}$ levels, our study only specifies to the county level. This paper cannot account for all of the communities within all counties across California, and we focus only on county data and statewide data. We assume that data about one county is applicable throughout the entire area of the county for the purpose of our research.

5. *Large fires/outliers follow a normal distribution.* The main causes of wildfires, such as weather events, industry, camping, and human error, do not occur at significantly different rates across California. Therefore we can assume that the number of large wildfires that occur in counties across California is only augmented by the environmental differences but the number of stimuli that cause these fires are essentially random.

Modeling of $PM_{2.5}$ Concentrations

Our first step was to project the trend of $PM_{2.5}$ concentration in the atmosphere. This was done with a simple linear regression model on a scatter plot as seen in Figure 2.1. The issue with this measurement is that $PM_{2.5}$ concentration has a lot of confounding variables, such as air pollution.

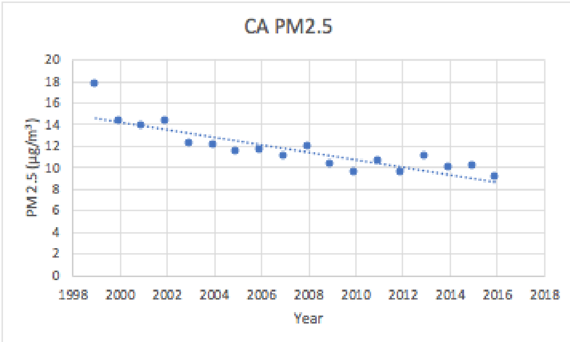

Figure 2.1 *California $PM_{2.5}$ concentration, from 1999 to 2016, showing an overall decrease.*

As seen in Figure 2.3, the total number of acres burned in California has increased at an exponential rate meaning that more $PM_{2.5}$ has been released into the atmosphere than ever. This, however, is not reflected in the overall $PM_{2.5}$ concentration. In order to isolate $PM_{2.5}$ concentrations that are released due to wildfires from other factors, we first had to consider Figure 2.2.

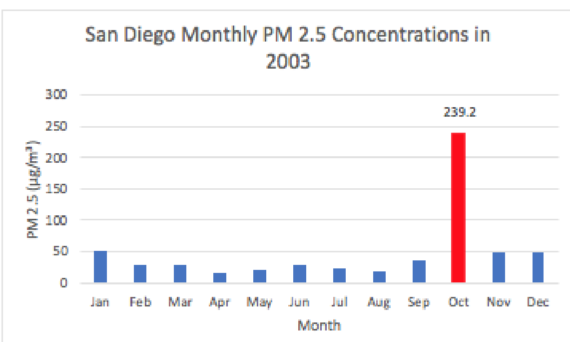

Figure 2.2 *San Diego $PM_{2.5}$ concentration, monthly from the year 2003, showing the Cedar fire in October.*

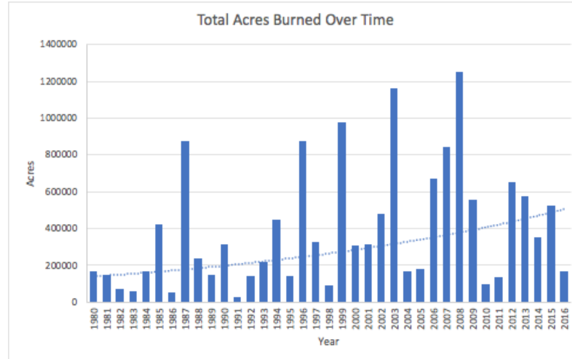

Figure 2.3 *Total acres burned over time in California, from 1980 to 2016, showing a steady exponential increase.*

In October of 2003, a massive wildfire burned a total of 273,246 acres, destroyed 2,820 structures, and killed 15 people [40]. The result of this blaze is a massive outlier in our data as $PM_{2.5}$ concentrations skyrocketed to over 239 . An analysis of other outliers as seen in Figure 2.4 showed that many outliers in our data were caused by large wildfires.

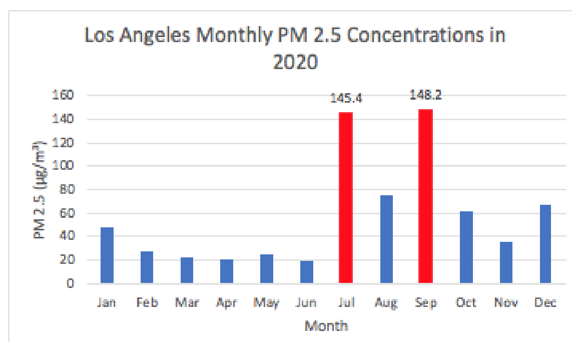

Figure 2.4 *Los Angeles $PM_{2.5}$ concentration, monthly from the year 2020, showing the Soledad and Bobcat fire in July and September respectively.*

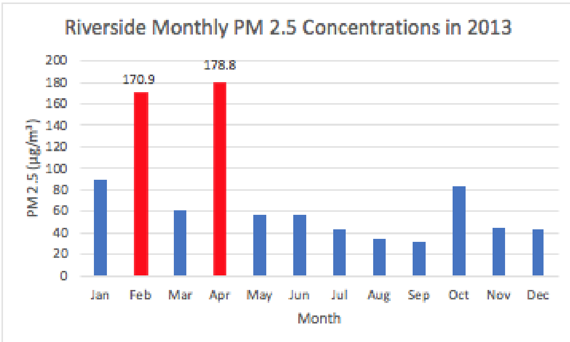

Figure 2.5 *Riverside $PM_{2.5}$ concentration, monthly from the year 2013, showing the Jurupa and Summit fire in February and April.*

$$x > Q3 + 1.5(Q3 - Q1)$$

$$Q3 = \frac{3}{4}(n + 1)^{th}\ term$$

$$Q1 = \frac{1}{4}(n + 1)^{th}\ term$$

We used the standard 1.5 interquartile range formula seen above to identify all the outliers. *n* is the total number of values for the data and it shows what term in the data represents the corresponding quartile. Since we focus on unusually high outliers, if an x-value is greater than the formula, it is considered an outlier. In order to prevent the amount of data from being overwhelming, we randomly selected 5 counties from around California and applied our formula to all the values, the results of which are in Table 2.6.

County	Number of Outliers	Percentage caused by Wildfire
Los Angeles	10	70%
San Bernardino	11	54%
San Diego	11	63%
Santa Clara	3	67%
Riverside	7	57%

Table 2.6 *Number of outliers of $PM_{2.5}$ concentration, from the year 2000 to 2021, showing the percentage of major spikes being caused by wildfires.*

Assuming that the distribution of outliers follows a normal distribution, we can calculate with 95% confidence that the percentage of outliers caused by wildfires is between 56% and 68%. With this knowledge we can model $PM_{2.5}$ concentrations by basing it off forecasts of acres burned.

$PM_{2.5}$ Forecasts

Both the average number of acres burned per year and total number of acres burned per year fit an exponential curve the best as seen in Figures 2.7 and 2.8.

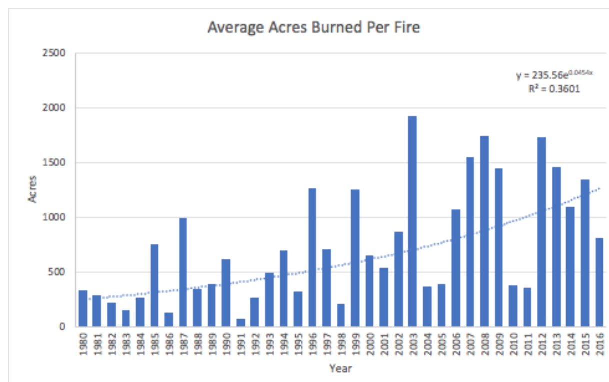

Figure 2.7 *Average acres burned per fire in California, annually from the year 1980 to 2016, used to project average acres burned per fire over time.*

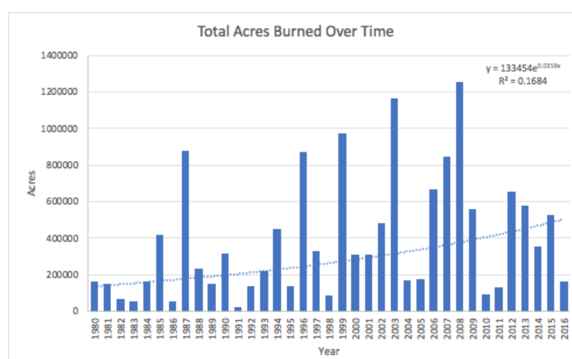

Figure 2.8 *Total acres burned over time in California, from the year 1980 to 2016, showing a steady exponential increase to predict future acres lost.*

The exponential fit was found by using the equation below which uses least squares regression to find the best values for *a* and *b* in the exponential formula.

$$y = Ae^{Bx}$$
$$\ln y = \ln A + B \ln x$$
$$a = \frac{\Sigma \ln y \, \Sigma x^2 - \Sigma x \, \Sigma x \ln y}{n \Sigma x^2 - (\Sigma x)^2}$$
$$b = \frac{n \Sigma x \ln y - \Sigma x \Sigma \ln y}{n \Sigma x^2 - (\Sigma x)^2}$$

The line of best fit found for total acres is $y=133454e^{0.0359x}$ and $y=235.56e^{0.0454x}$ for average number of acres burned per year. The forecasts are shown in Figures 2.9, 2.10, and Table 2.11.

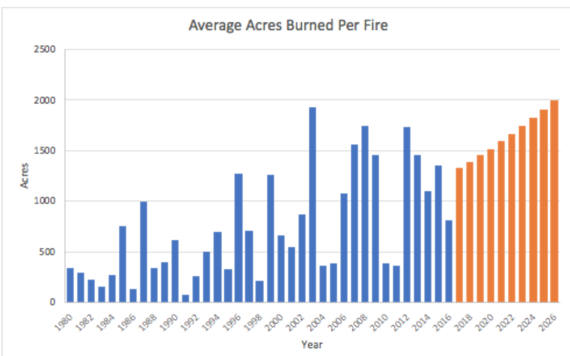

Figure 2.9 *Projected average acres burned per fire in California, from the year 1980 to 2026, the years 2017 to 2026 are projected to increase.*

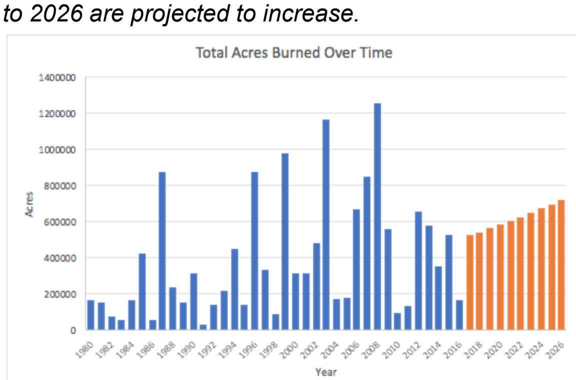

Figure 2.10 *Projected total acres burned over time in California, from the year 1980 to 2026, the years 2017 to 2026 are projected to increase.*

Year	Total Acres	Average Acres per Fire
2017	5,221,512	1,322
2018	5,412,368	1,383
2019	5,610,206	1,448
2020	5,815,268	1,515
2021	6,027,825	1,585
2022	6,248,158	1,659
2023	6,476,546	1,736
2024	6,713,273	1,817
2025	6,958,652	1,901
2026	7,213,013	1,989
Year	$PM_{2.5}$ Released Statewide (μg/m^2)	$PM_{2.5}$ Per Fire (μg/m^2)
2017	1.02×10^{14}	2.58×10^{10}
2018	1.05×10^{14}	2.70×10^{10}
2019	1.09×10^{14}	2.83×10^{10}
2020	1.13×10^{14}	2.96×10^{10}
2021	1.17×10^{14}	3.10×10^{10}
2022	1.22×10^{14}	3.24×10^{10}
2023	1.26×10^{14}	3.39×10^{10}
2024	1.31×10^{14}	3.55×10^{10}
2025	1.35×10^{14}	3.72×10^{10}
2026	1.40×10^{14}	3.89×10^{10}

Table 2.11 *Table of values that shows the total acres, average acres per fire, $PM_{2.5}$ released statewide, and $PM_{2.5}$ per fire. It is organized by year and projects the future increase in $PM_{2.5}$ concentrations.*

Our models make it clear that California is on a trend towards disaster. Wildfires have been growing bigger and bigger since the 1980s and releasing more $PM_{2.5}$ than ever, putting millions of Californians at risk of cardiovascular complications.

Hospitalizations Forecasts Assumptions

1. *$PM_{2.5}$ concentrations continue on a polynomial trend*. The polynomial trendline of $PM_{2.5}$ is measured using 3 fire-vulnerable California counties. Trends show that $PM_{2.5}$ concentrations dip around 2013, and increase afterwards. We assume that this upwards trend would continue for the next several years, as there is an increasing number of wildfires due to climate change.

2. *Hospitalizations will increase in the future, following the polynomial trend of the graph and mirroring the polynomial graph of $PM_{2.5}$*. The data for hospitalizations comes from the CDC, and covers 2005-2017. The equation decreases steadily from 2005 to 2013, however after the interval of 2013-2015 the graph begins to increase. The dataset stops at 2017, but we see a strong statistical relationship between $PM_{2.5}$ concentrations and hospitalizations. Therefore, the trendline and statistical relationship allow us to assume hospitalizations will continue to increase.

3. *Hospitalizations per 1,000 Medicare beneficiaries predict the rate of hospitalizations in all California counties.* Although the counties we specifically represented are Los Angeles, Santa Clara, and San Bernardino, these 3 counties have large populations of at least 100,000 people. They also are representative of the major regions in California. Thus, the rate of hospitalions will be generalized to all California counties.

4. *We only consider the effects of $PM_{2.5}$ concentration on the rate of cardiovascular hospitalizations.* We see that $PM_{2.5}$ concentrations are the most accurate predictor of the impact of wildfires on cardiovascular disease concentrations. Thus, we consider only particulate matter's impact on cardiovascular hospitalizations, excluding other factors such as personal behaviors and genetics.

5. *Hospitalizations for cardiovascular disease is the most accurate measure of the cardiovascular impact of particulate matter concentrations.* Other measures, such as deaths due to cardiovascular disease, are less representative of the cardiovascular impact for disease because they don't isolate and eliminate the impact of scientific advances in medicine that improve the health prospects of cardiovascular patients. Hospitalizations are less likely to be influenced by medical advancements over time and other unrelated factors.

Modeling of $PM_{2.5}$ Trends and Hospitalizations

To find a relationship between $PM_{2.5}$ concentration and hospitalizations for cardiovascular disease, we studied 3 counties in California that were vulnerable to wildfires and had populations over 100,000. The counties we used are San Bernardino, Los Angeles, and Santa Clara. For $PM_{2.5}$ concentration, as seen in Figure 2.12, we graphed the average concentration per year and used polynomial equations to match the parabola shape of the graph. The individual polynomial equations for each county are as follows:

San Bernardino

$$y = 0.1161x^2 - 3.4507x + 62.345$$

Los Ángeles

$$y = 0.1552x^2 - 3.9847x + 69.268$$

Santa Clara

$$y = 0.0616x^2 - 1.5589x + 33.519$$

In order to have a general polynomial equation for all 3 counties, we found the average $PM_{2.5}$ concentration of all 3 counties (San Bernardino, Los Angeles, and Santa Clara) annually and graphed them in Figure 2.13. The equation for the polynomial graph is as follows:

$$y = .1109x^2 - 2.9981x + 55.044$$

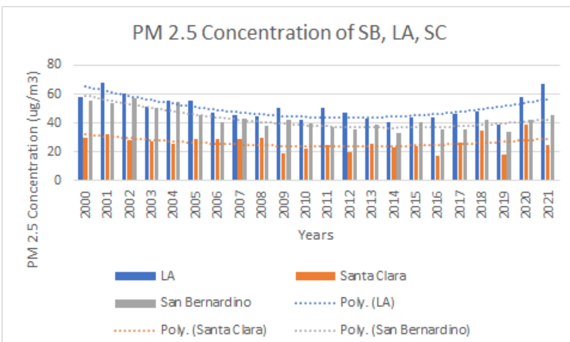

***Figure 2.12** Yearly $PM_{2.5}$ Concentration in Los Angeles, San Bernardino, and Santa Clara, from years 2000 to 2021. $PM_{2.5}$ concentrations for each county forms a 2nd degree polynomial line.*

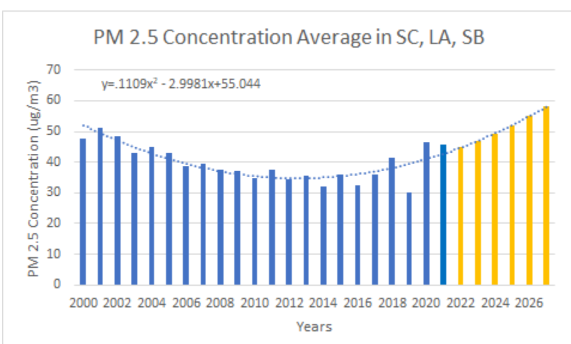

***Figure 2.13** Yearly $PM_{2.5}$ concentration, from years 2000 to 2026. $PM_{2.5}$ concentrations between Los Angeles, San Bernardino, and Santa Clara are averaged out and plotted on the graph. A 2nd order polynomial equation is used to project the years 2021 to 2026.*

Then in Figure 2.16, we graphed the Total Cardiovascular Disease Hospitalization Rate per 1,000 Medicare Beneficiaries for the same 3 counties as before. Lastly, in Figure 2.17, we took the average of the hospitalization rates for the 3 counties and graphed them as a single trend line. The equation for the average hospitalizations in Santa Clara, San Bernardino, and Los Angeles are as follows:

$$y = 0.3435x^3 - 2.9183x^2 + 1.6287x + 72.233$$

In order to create a relationship between $PM_{2.5}$ concentrations and cardiovascular hospitalizations, we compared Figures 2.13 and 2.17 as they summed up the trends of each of the 2 counties. The first thing we noticed was that, when looking at the same time periods, the graphs had a similar parabola shape. We then decided to locate the vertex of each graph, to determine how similar the lowest $PM_{2.5}$ concentration was to the lowest hospitalization rate. The vertex of Figure 2.13 was found to be at (13.517, 34.781). The 13.517 x-value represents 2014. If you plug in the equation, an x-value of 1 represents the year 2000, thus 13.517 would represent a $PM_{2.5}$ concentration of 34.781 ug/m3 in the year 2014.517. The vertex of Figure 2.17 was at (5.37, 50.017). The x-value of 5.37 has to be converted in a series of steps to represent the year it is in. The value x=1 represents the years 2005-2007, which could be simplified into 2006. Thus, an x-value of 5 would represent 2013-2015, or 2014 averaged out. The 0.37 fraction of 5.37 would be divided by 2, as an increase in x by 1 represents a jump of 2 years. Thus, the vertex of hospitalizations would be a rate of 50.017 per 1,000 Medicare beneficiaries in the year 2014.185. If we were to compare the vertices of the 2 graphs, the difference between the 2 would be approximately 0.332 of a year, or a little less than 4 months. Therefore, we can conclude that the 2 graphs have a strong statistical relationship.

PM$_{2.5}$ and Hospitalizations Forecasts

Using the equations generated by Figures 2.13 and 2.17, we forecasted future concentrations of PM$_{2.5}$ and hospitalizations into 2027. The forecast of PM$_{2.5}$ is shown in Figure 2.14. We then forecasted future hospitalization rates, shown in 2.15. Below, we calculated how much PM $_{2.5}$ concentrations change over a 10 year period in both projections as well as how similar our projections are:

PM$_{2.5}$ concentrations 2027:2017 = 1.568.
PM$_{2.5}$ per fire prediction 2027:2017 = 1.504.
The similarity ratio can be represented by the following equation:
Similarity ratio: (PM$_{2.5}$/fire ratio)/(PM$_{2.5}$ concentration ratio) * 100 = 95.95%

Year	PM$_{2.5}$ Concentrations (μg/m^3)
2017	37.01
2018	38.115
2019	39.442
2020	40.991
2021	42.761
2022	44.754
2023	46.968
2024	49.404
2025	52.062
2026	54.941
2027	58.043

Table 2.14 *Table showing the projected values of PM$_{2.5}$ concentrations yearly from 2017 to 2027. The table shows a steady increase in PM$_{2.5}$ levels.*

Year	Hospitalization Rate per 1,000 Medicare Beneficiaries
2017-2019	58.458
2019-2021	74.363
2021-2023	100.921
2023-2025	140.19
2025-2027	194.233

Table 2.15 *Table showing the projected values of hospitalization rates per 1,000 Medicare beneficiaries. The dates are in 2 year increments and hospitalization rates are quickly increasing.*

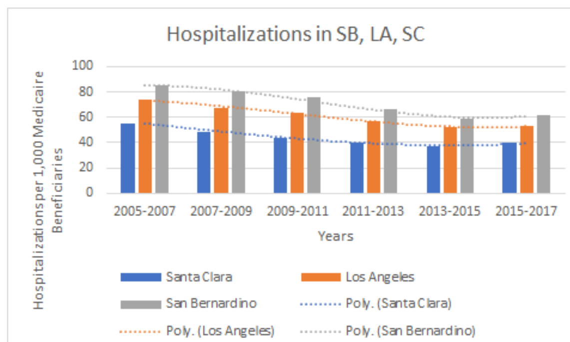

Figure ***2.16*** *The hospitalization rates in San Bernardino, Los Angeles, and Santa Clara per 1,000 Medicare beneficiaries. Measured in 2 year increments from 2005 to 2017. It includes a 3rd order polynomial line that fits the values.*

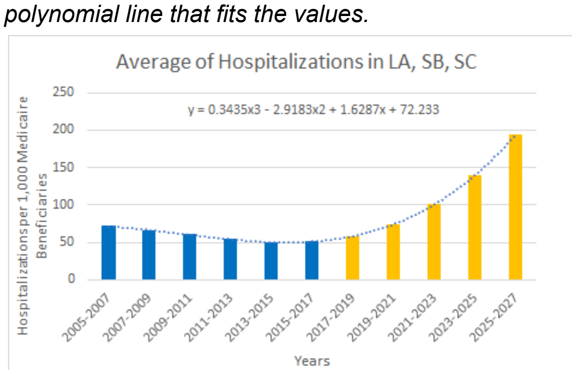

Figure 2.17 *Hospitalization rate in Los Angeles, San Bernardino, and Santa Clara are averaged and graphed above. It spans 2005 to 2027, and the years*

2017 to 2027 are projected using a 3rd order polynomial equation. The years are also in 2 year increments.

At first glance the forecasted hospitalizations seem unreasonably high, but when we cross apply the particulate matter projections in Table 2.11, it parodies the exponential growth rate modeled there. With every passing year wildfires have a larger impact on the $PM_{2.5}$ concentrations as the number of acres burned continues to reach record numbers. This expected increase in $PM_{2.5}$ concentrations results in the exponential increase of hospitalizations as we predict.

Results and Risk Analysis

Wildfires can have a devastating impact on ecosystems and climate change by emitting carbon dioxide and other greenhouse gases. From 1998 to 2018, wildfires released 8 billion tons of CO_2 annually, contributing to global warming. Decomposing dead wood in the aftermath of a fire also contributes to greenhouse gas emissions, and global warming prevents forest regrowth. Windblown soot and black carbon, a type of climate pollutant, harms the environment and exacerbate problems of climate change, which in turn continues to increase the number and severity of wildfires [36]. Since 1950, the acreage burned by California wildfires each year has been increasing, and summer temperatures have increased as well. Recent unusually warm temperatures have created conditions for extreme, high-severity wildfires that spread rapidly. Of the 20 largest fires in California's history, eight have occurred after 2017 [48].

In addition to climate change effects, wildfires can worsen public health through wildfire smoke, which is made up of a mixture of gases and fine particles [23]. Particulate matter within the smoke consists of solid particles and liquid droplets in the air, and is the primary public health threat of short and long-term exposure to wildfire smoke. $PM_{2.5}$ refers to particulate matter that is smaller than 2.5 micrometers in diameter. Particulate matter exists in larger forms (PM_{10}), but $PM_{2.5}$ is the most dangerous because it can go deep into the lungs and bloodstream [42]. They can aggravate chronic heart and lung diseases [23]. 90% of the particles released from wildfire smoke are $PM_{2.5}$. When scientists look to quantify the impact of wildfire smoke, they tend to focus on $PM_{2.5}$ [42]. Long-term exposure to air pollution from $PM_{2.5}$ has been shown to increase the number of deaths from cardiovascular disease. A study in Seoul, South Korea showed that every 1-$\mu g/m^3$ (Microgram per Cubic Meter of Air) increase of long-term exposure to $PM_{2.5}$ was associated with a 36% increased risk of cardiovascular events among healthy participants with no history of cardiovascular diseases [36].

The current trend of acres burned by wildfires in California is disastrous. By 2026, we predict nearly 141 trillion micrograms of $PM_{2.5}$ will be released into the the atmosphere causing the average $PM_{2.5}$ concentration to catapult to 55 $\mu g/m^3$ which is much higher than EPA recommended 12 $\mu g/m^3$ for long term exposure and also higher than the amount considered safe for 24 hours (35 $\mu g/m^3$) [43]. The impacts that this will have on cardiovascular health if we do not take action cannot be understated. Annual health care costs for cardiovascular disease (CVD) in California have been estimated at $37 billion — far greater than any other chronic condition. In 2014, 1 in 3 deaths in California (78,000 deaths) was due to cardiovascular disease. In addition, 1 in 3 adults in California (8 million people) lives with at least 1 of the most common forms of CVD; this includes heart disease, heart failure, stroke, or hypertension [19]. Cardiovascular disease is the leading cause of death in California, and took 62,797 lives in 2017 [16].

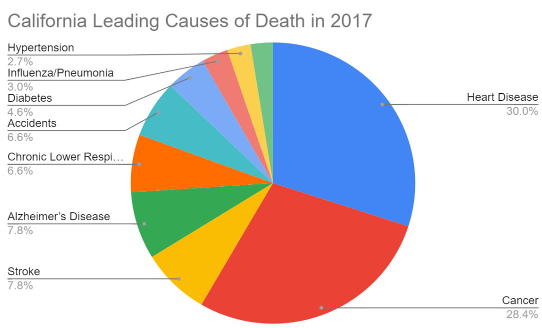

***Figure 3.1** Percentages of leading causes of death in California in 2017. Heart disease causes 30% of deaths and is the largest [16].*

Short-term and long-term exposure to $PM_{2.5}$ increases premature deaths and hospital admissions. The estimated economic value of short-term wildfire-attributable $PM_{2.5}$-related premature deaths and respiratory hospital admissions from 2008 to 2012 is between $11 billion and $20 billion per year. If we look at the impacts of long-term exposure to $PM_{2.5}$, the economic cost increases. The estimated value of the long-term $PM_{2.5}$ related premature deaths and hospital admissions falls between $76 billion and $130 billion per year. As time goes on, these long-term impacts continue to increase in cost. The value of long-term deaths and admissions from 2012-2016 is estimated to be $450 billion [9]. In addition, the cost of healthcare to treat heart related diseases have increased and are expected to reach up to a trillion dollars in 2035 [14]. From 2011 to 2018, heart disease expenses increased from $316.6 billion to $400 billion [14][20].

CVD is most common in people over 50 and your risk of developing it increases as you get older. Excessive alcohol consumption can lead to high cholesterol and increase your chances of getting cardiovascular disease [14]. People with preexisting health conditions are at most risk for cardiopulmonary health issues due to particulate matter. People with high levels of cholesterol, high blood pressure, and people who are diagnosed with diabetes are more prone to cardiopulmonary problems. In addition, those who smoke, are physically inactive, are obese, and maintain unhealthy diets can be more vulnerable to the harmful impacts of particulate matter in wildfire smoke [15]. In 2020, 42.4% of US adults were obese [17]. The risk of cardiovascular disease is thus high among adults. In addition, many children are also at risk for cardiovascular disease if they have unhealthy diets that consist of high amounts of saturated fat. This increases their blood cholesterol levels and can lead to hardening of the arteries (atherosclerosis). 7% of children ages 10 to 15 years old saw early signs of atherosclerosis. This rate is doubled in those aged 15 to 20 [16]. Thus, younger people with high cholesterol are also vulnerable to cardiovascular disease.

Overall the environmental, ecological, and economic damage caused by the current trend of wildfire damage is all-encompassing and severe. Without immediate action by insurers and politicians, the cardiovascular troubles caused by $PM_{2.5}$ will only continue to grow, costing billions of dollars every year and damaging the livelihoods of millions.

Recommendation

Filtration

Wildfire-prone areas show increased levels of particulate matter, and California law requires buildings to implement a MERV 13 filter to oppose this threat. Currently, state law under the 2019 California Energy Code Title 24 part 6, subchapters 3 and 7 state that Air Filters of MERV 13 is required for nonresidential, high-rise residential hotel/motel occupancies, and low-rise residential buildings [33][32]. However, these preventative actions are not mitigating enough of the health risks people experience within the fire and smoke-prone areas of California, which is why we recommend the installation of MERV 16 filters in counties with a $PM_{2.5}$ concentration of 12 μg/m^3 as according to the EPA standard updated on 2012 [23].

$PM_{2.5}$ describes a range of particles that have a size from 0.1 to 3 microns with the majority of them falling in the 1-3 micron range. Therefore, $PM_{2.5}$ is extremely difficult to filter due to its small size. MERV 13 filters are capable of trapping a minimum of 85% of $PM_{2.5}$ particles, while MERV 16 filters trap a minimum of 95% of $PM_{2.5}$ particles [45]. MERV 13 filters only trap 50% of particles in the 0.1 to 0.3 micron range while MERV 16 filters 95% of these molecules.

We also compared the MERV 16 to another common filter, High-Efficiency Particulate Air (HEPA) Filters. HEPA filters are equally as strong as MERV 16 and offer the highest available particle removal efficiency of air filters, but cost significantly more. In addition, even though MERV 16 filters have the same strength as HEPA filters, studies have shown that MERV 16 filters provide greater airflow, cost less, and require less-frequent replacement than HEPA filters. Because MERV 16 filters do not need to be changed as often, the cost of maintenance labor decreases and allows building owners to save money in the long run [46]. Another advantage of MERV 16 filters is they have the same thickness as medium capacity filters (MERV 5-13). In addition, MERV 16 filters have been proven in studies to be the most effective at reducing particles that could lead to adverse health effects like $PM_{2.5}$, while minimizing undesirable effects [42].

The current standard, MERV 13 filters, can vary in price depending on the manufacturer, but are mostly found in packs that cost under $100. On Amazon, the Filtrete (20 x 20 x 1 inches) 2-pack of MERV 13 filters costs $49.98, which was one of the air filter manufacturers that the New York Times recommended [29]. The Aerostar 6-pack of MERV 13 filters (11 ¾ x 11 ¾ x ¾ inches) costs $32.52 with 13,540 ratings. FilterBuy, another manufacturer, sells a 4-pack of MERV 13 filters (20 x 20 x 2 inches) at $55.08. In comparison, MERV 16 filters are a little more expensive. On Amazon, the Lennox carbon coated 2-pack of MERV 16 filters (25 x 5 x 16 inches) costs $149.99. Another MERV 16 filter (20 x 20 x 5 inches) from Lennox corporation sells at $118.99 for a single filter. Lastly, Lennox sells a MERV 16 filter (20 x 25-⅜ x 4-⅜ inches) for $119.95. Using these 3 product examples, we calculated the average cost of 1 cubic inch of each filter type. To our surprise, we found that MERV 16 filters tended to cost less.

In order to calculate the cost for each cubic inch, we used the following formula.

$$C_M=(D_{c1}+D_{c2}+D_{c3})$$

C_M=average cost of MERV filter type

$$D_c=LWH*N_p/C_f$$

D_c=cost of 1 cubic centimeter of a filter product

N_p=number of packs

C_f=cost of the filter product

The average cost of MERV 13 filters is about $0.0956 per cubic inch. The average cost for MERV 16 filters is about $0.0503 per cubic inch. This contradicts the common idea that higher quality filters would be more expensive. Although these calculations are based on products from Amazon, it shows that a switch to MERV 16 filters would be inexpensive and that these higher quality filters do not necessarily mean higher net prices. This also does not take into account the money saved as these filters decrease risk of cardiovascular disease and do not need to be replaced as frequently as other high quality filters (HEPA for example).

The installation of a higher efficiency filter (MERV 16) requires ensuring that the filter is compatible with the existing HVAC system. This must be taken into account to ensure airflow won't be severely cut off with a stronger filter. Trained professionals can modify the HVAC system if necessary to accommodate the new filter [42]. Our recommendation includes the diagnosis and distinguishment of fire-prone areas, from where we will send professionals to inspect HVAC systems and potentially modify systems to accommodate for the installation of MERV 16 filters.

With the implementation of better filtration we can reduce the exposure to high levels of $PM_{2.5}$ in indoor spaces across California. This is a small step that would go a long way to mitigate the impacts of increasing $PM_{2.5}$ levels.

	MERV 13	MERV 16	Difference in Cost (M_{13}-M_{16})
Cost of each cubic inch	$0.0956	$0.0503	$0.0453
Cost of a 20 x 20 x 5 inch filter	$191.2	$100.6	$90.6
Cost of replacing 506,226 homes* (1 filter per home) 14.18 million x .357 = 506,226	$96,790,411	$50,926,335	$45,864,075

**This number of homes is an estimate based on looking at the total percent of cities in California that meet the WHO's (World Health Organization) target for annual exposure to PM2.5. This target is 10ug/m3 and the percent of cities that meet it in California are 35.7% [8]. The total number of homes in California is 14.18 million.*

Table 4.1 *Three MERV 13 filters and 3 MERV 16 filters on the market were analyzed. The cost of 1 cubic inch of MERV 13 and 16 filters were determined. In addition, the average size of 1 filter was 20 by 20 by 5 inches, and this cost is also illustrated. Lastly, the estimated cost of replacing filters in fire-prone areas to MERV 13 or MERV 16 are estimated in the last row.*

Education

In order to reduce the risk of wildfires and cardiopulmonary effects, we recommend that the California state government implements the Five-Step Process in Public Fire Education Planning as stated by the U.S. Fire Administration [46]. The five steps consist of conducting a community risk analysis, developing community partnerships, creating an intervention strategy, implementing the strategy, and evaluating the results. In the past, there were a multitude of fire prevention programs to assist in city fire prevention that mainly consisted of public education and programs citizens could partake in. Although they were not specific for wildfire prevention, we found that the Five-Step Process in Public Fire Education Planning could assist in implementing Public Service Announcements (PSA) and education tactics in the classroom setting to effectively reduce the consequences of wildfires.

The first step of the Five-Step Process proposal is to conduct a risk analysis of the community, which consists of California communities in fire-prone areas for our study. When analyzing the risk of particulate matter due to wildfires, we find that the people most at risk would be senior citizens and those who are consistently exposed to $PM_{2.5}$. To prevent these risks from exacerbating, the next step of the proposal must take place, which is to develop community partnerships. We recommend that county governments affiliate with local schools, media sources, and fire departments to share the risks of wildfires and particulate matter with the public. This coalition will then commence step 3 of the proposal, which is to create an intervention strategy. In relation to wildfires, the intervention strategy would consist of PSAs, education of children, and other methods to diffuse information within a community. Local media sources can spread awareness through radios, billboards, and public posters while schools can provide specific curriculums to vulnerable students. After completing step 4 of implementing the strategy, the results should show a decrease in wildfire-related cardiopulmonary consequences. Step 5 is to improve the methods used to decrease the drawbacks that were seen in the first run of the Five-Step Process. In order to find drawbacks, local communities could provide surveys to analyze how aware citizens are of the dangers of wildfires and ways to change their behavior to make it less likely they cause a wildfire. These surveys could help identify which demographics the Five-Step Process is currently struggling to reach, and new methods could be developed to attract these demographics.

Public education about wildfires has significant implications for mitigating risks in fire-prone areas. A Poisson model of preventable Florida wildfires from 2002 to 2007 measured the effectiveness of wildfire prevention education (WPE) efforts [41]. The study shows that the WPE program reduced costs by preventing expenditures on suppression and expected economic damage from wildfires. The WPE efforts measured were media public service announcements, presentations, brochures and flyers, and community wildfire hazard assessments. When the authors conducted a cost-benefit analysis, they found that for every dollar invested in WPE programs, the state saved $35 in wildfire damages.

The wildfire education strategies would cover a wide variety of topics, such as the importance of changing filters regularly, how to prevent wildfires, how to act during wildfires, and how to help the community recover from wildfires. Broad wildfire prevention efforts addressed towards the general public can have significant implications for mitigating the risks of wildfires, such as cardiovascular disease due to particulate matter concentrations.

Apart from community education through PSAs, another important intervention strategy for mitigating wildfires is to spread awareness in public school systems, especially for grades k-12. By partnering up with local schools, county governments can create curriculums that support wildfire education and teach students from a young age the importance of wildfire prevention and safety.

The Minnesota Firewise in the Classroom Community Assessment Process (MN Firewise in the Classroom) was one method of fire education [34]. It proved to be effective by increasing wildfire awareness in both teachers and students. When students were educated about fires in school, they brought back their knowledge to their parents, family, and communities. Students also were able to identify high-risk areas and write a detailed report based on their consultation with the local fire department. West Virginia reported similar benefits through their own Firewise program as well [11]. Students had increased wildfire awareness, interest in emergency management, and a broader sense of community and how to help their communities. Other residents in the community also reported increased awareness of wildfires.

According to a study by the NFPA Firewise Communities Program, engaging the youth in fire preparedness is very important and valuable within communities [49]. There are currently no nationwide wildland fire education programs exclusively focused on the youth, but the youth may play a critical role in reducing loss and long-term recovery impacts from wildfires by instilling knowledge to land and homeowners. The report recommended a program available in both English and Spanish in a stand-alone format without a teacher or outside presenter. The diverse, no-cost, easy-to-use, and on-demand program would increase effectiveness in engaging the youth in how to reduce wildfire risk in the community.

As an extension of step 2, developing community partnerships, we recommend that California school districts implement a more robust wildfire education program, such as Firewise and Learn Not to Burn, in the classroom to teach students about the health risks of wildfires and how to prevent wildfires in their communities. The county government working with local schools and educational facilities can help educate students about the dangers of wildfires and lower the associated risks. The program would be part of school curriculums at no cost and available in multiple languages. Some program tools that the districts could use are Sesame Street and Smokey the Bear for younger children, which would help make wildfire-related information accessible to residents of all ages in fire-prone areas. Wildfire prevention education efforts would target students in elementary school to middle school, while in high school students can take part in voluntary wildfire training and community programs. The educational program would address the potential risk of cardiopulmonary and other public health issues that result from wildfires and wildfire smoke. Schools would encourage healthier diets and physical activity to combat cardiopulmonary health risks, as well as protective face masks and information about filters to address the dangers of wildfire smoke and particulate matter.

Insurance

In addition to combating cardiovascular risks of wildfires, another method to diminish wildfire impact is to reduce current and future healthcare costs by implementing cardiovascular related insurance in wildfire-prone areas. We recommend a cost-effective insurance plan that calls for an individualized prevention program which would include risk factor assessments, early detection, primary prevention, secondary prevention, and tertiary treatment. Primary prevention would consist of diagnosis and treatment for mild symptoms - those considered are hypertension, hyperlipidemia, and diabetes mellitus [6]. Secondary prevention is defined as the pharmacological treatment after the occurence of a myocardial infarction or stroke. Tertiary treatment is classified as treatment for acute myocardial infarction or stroke, specifically, hospital level treatment. This would allow greater health benefits for a lower price to all as the prevention program would allow individuals to recognize their risks, leading to earlier treatment. Studies done in India and Germany under similar insurance plans such as “KardioPro” show that early detection and prevention allow cost-effective solutions to cardiovascular health risks every year [33][15]. By offering this insurance plan in the wildfire-prone communities of California, people can obtain the treatment they need at a lower cost, reaching a greater demographic and reducing future complications.
There is a clear indication that an insurance plan specifically targeted towards cardiovascular diseases (CVD) would be an incredibly powerful tool for those exposed to wildfires and the subsequent particulate matter released. A plan that provides greater access and full coverage towards prevention and treatments creates an immense contribution towards lowering the ICER (Incremental cost-effectiveness ratio). A study conducted in India about national coverage of cardiovascular disease shows that primary prevention, secondary prevention, and tertiary treatment for CVD would have a large impact on the population. Specifically, the policy would have the largest impact on morbidity, mortality, and cost-effectiveness [15]. The study also found that primary prevention for CVD should be the main point of any policy targeted towards CVD within a population. In terms of value, assuming a 50% adherence rate and access to healthcare was constant and unchanging. The India study concluded that 3.6 million DALYs (Disability-adjusted life year) would be saved adhering to a policy of primary prevention alone. This policy would be the most beneficial to adopt due to the large improvement in care, as well as its cost effectiveness in the status quo.

There were also significant developments in the mortality and lethality of CVD, in which the rates decreased by approximately 10% when conferred with tertiary care provided under the India National Coverage plan [15].

Specifically, the use of screening is estimated to be one of the leading solutions for stopping further mortality in CVD [28]. The policy was also pivotal in increasing life expectancy, in which primary prevention methods were accountable for saving 3.6 million DALYs per year, or 2544 per year per million [15]. The inclusion of all three methods - primary, secondary, and tertiary - also witnessed major aversion in DALYs. The data showed that there were 4699.02 DALYs averted per million per year under this plan. The inclusion of multiple screening methods and care was pivotal in decreasing both the cost and mortality of contracting and screening for CHD.

Our policy to provide a cost-effective plan could also reduce healthcare costs for the patients at risk by decreasing hospital and pharmaceutical costs. When early detection and prevention plans were implemented in Germany through KardioPro, there was a 1.63 million euro decrease in hospital costs for all groups [2]. For the CHD(coronary heart disease) group and high-risk group, the difference in hospital costs were 0.33 million euros and 0.74 million euros respectively. There was also a decrease in pharmaceutical costs for all groups of 0.86 million euros. However, there was an overall increase for physician costs, which shows an increased amount of visits to cardiologists to access more screenings and preventive measures. The case study in India found that primary, secondary, and tertiary methods only averted 2544.47, 147.87, and 2076.77 DALYs respectively. It presented the greatest aversion of DALYs when primary and secondary prevention as well as tertiary treatment methods were all used, measuring at approximately 4699.02 [15]. In addition, the study presented evidence that the incremental cost of each DALY averted for coverage surrounding all three treatments was $2,432. These preventative measures combined with certain features of KardioPro will offer an overall reduction in healthcare costs, which is why we recommend the formation of a policy where an insurance plan, which will include CHD screening, risk factor assessment, early detection, primary prevention, secondary prevention, and tertiary treatment, is offered to wildfire prone communities.

Conclusion

The risk wildfires pose to California is truly unparalleled. Year over year, the number of acres destroyed from wildfires increases with no end in sight. Air quality is rapidly getting worse and will reach extremely unhealthy levels in certain counties within the next five years. In the status quo, California is in no shape to stop the looming threat of comorbidities caused by poor air quality. Unchecked heart related diseases will cost the insurance industry over a trillion dollars per year by 2035 and inflict pain and suffering onto the lives of hundreds of thousands of people. We strongly urge the State of California and insurance providers to consider our proposals recommended today to help control this slow-forming disaster because we cannot stand-by and watch the problem get irreversibly worse.

Appendix

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API Tools - AREACENSUS.json


```
{
  "openapi": "3.0.0",
  "info": {
    "title": "Area and Census Block",
    "version": "v1"
  },
  "servers": [
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      "url": "https://geo.fcc.gov/api/census"
    }
  ],
  "paths": {
    "/area": {
      "get": {
        "responses": {
          "200": {
            "description": "",
            "content": {
              "application/xml": {
                "schema": {
                  "example": {
                    "status": "OK"
                  }
                }
              }
            }
          },
          "500": {
            "description": "",
            "content": {
              "application/xml": {
                "schema": {
                  "example": {
                    "status": "Internal Server Error"
                  }
                }
              }
            }
          }
        },
        "description": "Get census block, county, state, and market area information based on latitude/longitude input.\n",
        "operationId": "GET_area",
        "parameters": [
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            name": "lat",
            "in": "query",
            "required": true,
            "description": "Latitude [-90 90] in decimal or DMS (degrees:minutes:seconds) Examples:- [38.26 or 38:15:36N]",
            "schema": {
              "type": "number"
            }
          },
          {
            "name": "lon",
            "in": "query",
            "required": true,
```

```
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77:30:36W]",
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          }
        },
        {
          "name": "format",
          "in": "query",
          "description": "Format for the returned results. <br>Valid value - XML (default), JSON, JSONP",
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              "json",
              "jsonp",
              "xml"
            ],
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          }
        }
      ]
    }
  },
  "/block/find": {
    "get": {
      "responses": {
        "200": {
          "description": "",
          "content": {
            "application/xml": {
              "schema": {
                "example": {
                  "status": "OK"
                }
              }
            }
          }
        },
        "500": {
          "description": "",
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            "application/xml": {
              "schema": {
                "example": {
                  "status": "Internal Server Error"
                }
              }
            }
          }
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```

```
38:15:36N]",
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77:30:36W]",
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                "xml",
                "json",
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    "headers": {},
```

```
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    "links": {},
    "callbacks": {}
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}
```