

# Data Driven Analysis: Respiratory health impacts due to wildfire smoke in Alexandria, VA

Swarali Desai |

12.04.24

## 1. Introduction

Alexandria, Virginia, like many urban areas in the United States, faces increasing risks from wildfires and their associated impacts. While the city itself may not be at the epicenter of major wildfire events, it is not immune to the far-reaching effects of these natural disasters. Climate change has exacerbated wildfire risks, with warmer, drier conditions creating more favorable environments for fires to ignite and spread rapidly[18]. In Alexandria, approximately 79% of buildings are at risk of wildfire, although the risk level for these structures is relatively low[17]. However, the city's proximity to more fire-prone areas and its location within the Middle Potomac-Anacostia-Occoquan watershed makes it susceptible to indirect impacts, particularly from wildfire smoke[17][18].

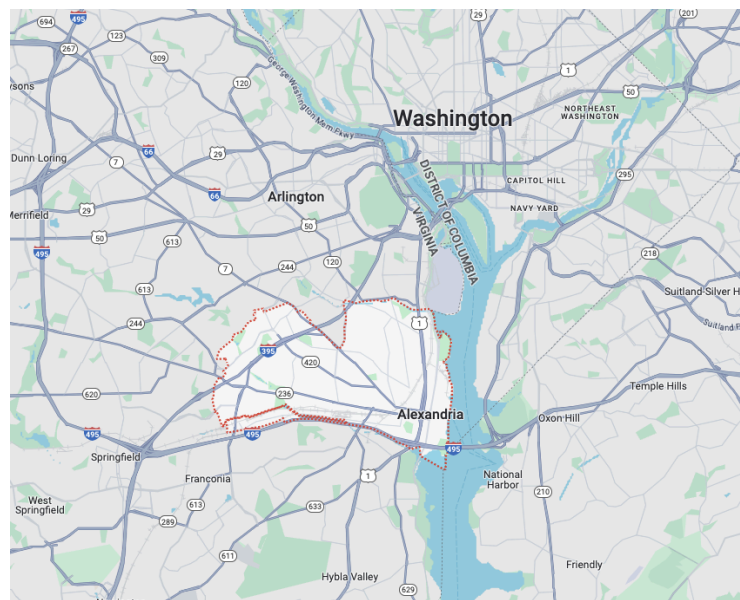


Fig 1: Map of Alexandria, VA (source: [Google maps](#))

The health implications of wildfire smoke exposure are a growing concern for Alexandria's residents. Fine particulate matter (PM<sub>2.5</sub>) from wildfire smoke can travel long distances, affecting air quality and public health even in urban areas far from the fire source[19]. This poses significant risks to vulnerable populations, including children, the elderly, pregnant women, and individuals with pre-existing respiratory conditions[18][19]. These pollutants can travel hundreds of miles, affecting respiratory health, increasing hospital admissions for asthma and chronic obstructive pulmonary disease (COPD), and contributing to long-term cardiovascular and mortality risks.

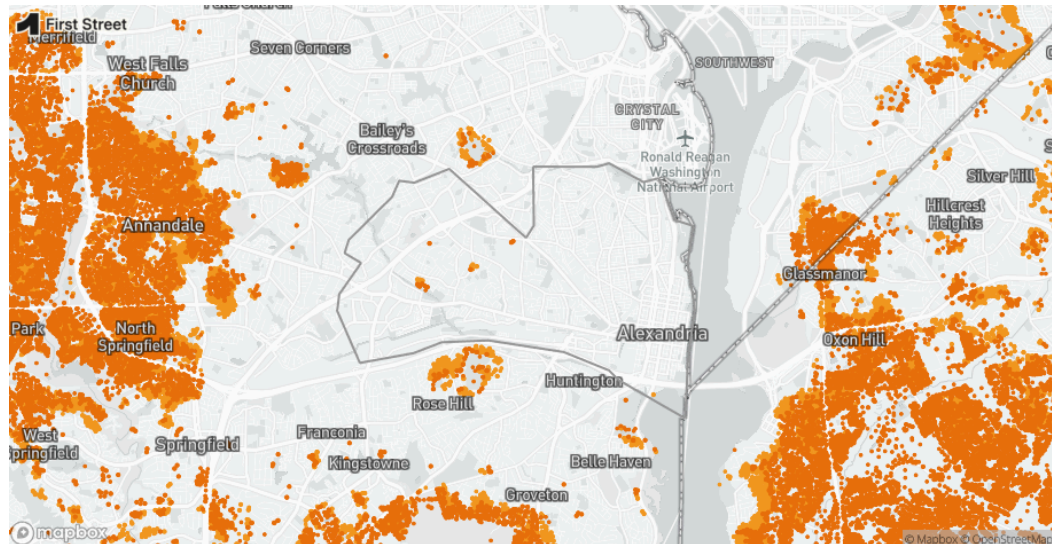


Fig 2: Wildfires around Alexandria (source: [https://firststreet.org/city/alexandria-va/5101000\\_fsid/fire](https://firststreet.org/city/alexandria-va/5101000_fsid/fire))

The recent Canadian wildfires have had a significant impact on air quality and public health in Alexandria, Virginia, as part of a broader effect on the Eastern United States. In early June 2023, smoke from wildfires in Quebec drifted south, causing unprecedented air quality issues in the region[20][21].

On June 7 and 8, 2023, the Metropolitan Washington Council of Governments issued a code red air quality alert for Alexandria and the surrounding area[21]. This level of alert indicates that air quality is unhealthy for all individuals, not just those with pre-existing respiratory conditions. The air quality deteriorated to such an extent that it reached a rare Code Purple status in some parts of the D.C. metro area, signifying very unhealthy air conditions[20].

The smoke from Canadian wildfires brought high levels of fine particulate matter (PM2.5) to the region. These tiny particles can penetrate deep into the lungs and even enter the bloodstream, potentially causing or exacerbating respiratory and cardiovascular issues. This event highlighted the far-reaching consequences of wildfires and the need for improved air quality monitoring and public health responses in the face of such environmental challenges.

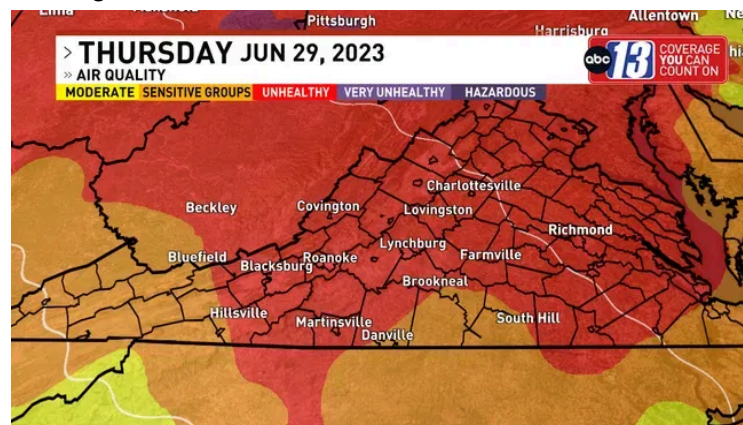


Fig 3: Impact of Canadian wildfire smoke on Virginia (source: [ABC news](https://abcnews.com))

This report investigates the historical and projected impact of wildfire smoke on Alexandria, aiming to provide actionable insights for policymakers to mitigate these effects and protect public well-being in the coming decades.

## **2. Background**

### **2.1. Background Research**

Wildfire smoke poses significant health risks, particularly due to its high concentration of fine particulate matter (PM2.5). Short-term exposure to wildfire smoke can cause respiratory irritation, leading to coughing, wheezing, and difficulty breathing[1][3]. It can exacerbate pre-existing conditions such as asthma, chronic obstructive pulmonary disease (COPD), and heart disease[1][6]. Children, women, older adults, and individuals with chronic health conditions are especially vulnerable to the effects of wildfire smoke[6][8]. Long-term exposure may contribute to reduced lung function, increased risk of respiratory infections, and cardiovascular problems[8]. Additionally, wildfire smoke contains other harmful components like carbon monoxide, which can cause headaches, dizziness, and in severe cases, premature death [5][7]

### **2.2. Research Questions**

This study seeks to address critical questions regarding the health implications of wildfire smoke in Alexandria, Virginia, focusing on mortality risks, healthcare infrastructure, and long-term public health preparedness. By analyzing these dimensions, we aim to provide actionable insights for local governance and healthcare planning. My key research questions include:

#### **1. Mortality Risk:**

- How does prolonged exposure to wildfire smoke influence mortality rates in Alexandria, particularly among vulnerable populations such as the elderly and individuals with preexisting respiratory or cardiovascular conditions?

#### **2. Healthcare Demand and Capacity:**

- Can current healthcare resources, including hospital beds, staff, and equipment, adequately meet the heightened demand for respiratory disease hospitalization during extended smoke events?

My initial hypothesis is that with an increase in smoke the hospitalization and mortality due to respiratory disease will increase over the years. By assessing potential increases in respiratory illnesses and healthcare strain, this analysis will help city officials and healthcare providers prepare for and manage medical demand during smoke events. Prioritizing health outcomes within a human-centered framework ensures that the community's well-being is at the forefront, supporting informed decisions on protective measures, resource allocation, and emergency responses.

### 2.3. Model

During my research I found that Distributed lag models are being employed to capture the multi-day effects of wildfire smoke exposure on health outcomes. These models account for the lingering impact of smoke exposure over time [16]. Research has shown that the health effects of wildfire smoke can persist for several days after exposure, making these models particularly useful for predicting longer-term impacts. Though the data I found was aggregated yearly so I decided to go forward with Statistical Time-Series models such as ARIMA and ARIMAX to predict the smoke impact on health.

### 2.4. Data

#### 1. Combined wildland fire datasets for the United States

The [Combined wildland fire datasets for the United States](#) and certain territories, 1800s-Present (combined wildland fire polygons) dataset has details about all wildfires that have happened over the years all over the US. This dataset is particularly significant as it provides a historical perspective on wildfire occurrences thus can be used to analyze long-term trends and patterns in wildfire activity. Specifically, I used the GeoJSON data format stored under the raw\_data folder. Most wildfires are bounded shapes, circles, squares, etc. This is represented by shapes called 'rings' in GeoJSON.

#### 2. Air Quality Index (AQI) Data from U.S. Environmental Protection Agency's (EPA)

The dataset is sourced from the [U.S. Environmental Protection Agency's \(EPA\) Air Quality System \(AQS\) API](#), which provides a database which standardizes monitoring with quality assurance procedures from 1980s, following the EPA's establishment in the early 1970s. The data collection typically initiated between 1983-1988 for most counties, though coverage varies geographically as some regions still lack monitoring stations. For this analysis, I utilized the US Environmental Protection Agency (EPA) Air Quality Service (AQS) API to retrieve historical air quality data, which is publicly available. Initially, I attempted to access data using the FIPS code for Alexandria City, through the county-based approach. The Federal Information Processing Series (FIPS) codes, required to identify the city, county, and state, were obtained from the US Census Bureau. However, this method returned data from only three monitoring stations, which was insufficient for robust analysis. To address this limitation, I opted for the bounding box approach, collecting data within a 50-mile radius around Alexandria City for both particulate and gaseous pollutants. These values were then averaged over the years to produce the final smoke estimate.

#### 3. IHME chronic respiratory disease mortality data: The IHME dataset provides age-standardized mortality estimates for chronic respiratory diseases by county, based on de-identified death records, population data, and disease classifications from the Global Burden of Disease Study. Covering 1980-2014, it includes mortality trends by disease type and sex across U.S. counties, highlighting the 10

counties with the highest and lowest rates in 2014. These results were published in JAMA in 2017([IHME respiratory mortality data for chronic respiratory diseases](#)). I have used this data to get the mortality rate for Asthma and Chronic Obstructive Pulmonary Disease in Alexandria City from the years 2010 to 2021.

Column Name	Description
measure_id	Identifier for the specific measure being recorded (e.g., 1 = Deaths).
measure_name	Name of the measure (e.g., Deaths).
location_id	Unique identifier for the location.
location_name	Name of the location (e.g., Alexandria City).
FIPS	Federal Information Processing Standards code for the location.
cause_id	Identifier for the cause being measured (e.g., 508 = Chronic respiratory diseases).
cause_name	Name of the cause (e.g., Chronic respiratory diseases).
sex_id	Identifier for sex (e.g., 1 = Male).
sex	Sex of the population (e.g., Male).
age_id	Identifier for age group (e.g., 27 = Age-standardized).
age_name	Name of the age group (e.g., Age-standardized).
year_id	Year of the data record (e.g., 1980, 1981).
metric	Type of metric being recorded (e.g., Rate).
mx	Recorded value for the metric (e.g., 71.639314).
lower	Lower confidence interval for the metric value.
upper	Upper confidence interval for the metric value.

Table 1: Schema for IHME mortality data

4. **Asthma and COPD hospitalization data:** The hospital admission data presented in this report is sourced from state and local public health departments and compiled by the [National Environmental Public Health Tracking Program](#). The data is based on the date of admission, using primary diagnosis codes to identify hospitalizations. Counts represent the number of admissions, not unique individuals, as repeated admissions for the same person are counted separately. Certain populations, such as those in Veterans Affairs or Indian Health Service facilities, and residents admitted to out-of-state hospitals in most states, are excluded, which may limit geographic comparability. To ensure confidentiality, data is suppressed for counties with populations under 100,000 and admission counts less than six. Admission rates are age-adjusted using the 2000 U.S. standard population. I have further divided the data based on gender for my analysis. The total data available was for 13 years from 2010 to 2022.



Column Name	Description
StateFIPS	Federal Information Processing Standards (FIPS) code for the state.
State	Name of the state (e.g., Virginia).
CountyFIPS	FIPS code for the county.
County	Name of the county (e.g., Alexandria).
Year	Year of the data record (e.g., 2010, 2011).
Value	Recorded value for the metric being analyzed (e.g., asthma hospitalization rate per 10,000 population).
Data Comment	Additional comments or notes about the data.
Unnamed: 7	Placeholder for missing or unused data; typically blank (e.g., NaN).
Gender	Gender associated with the recorded value (e.g., Male, Female).

Table 2: Schema for Asthma and COPD hospitalization data

5. **CO poisoning data:** The dataset on Carbon Monoxide (CO) poisoning hospitalizations is sourced from state and local public health departments through the [National Environmental Public Health Tracking Program](#). It includes hospital admission records based on primary and secondary diagnosis codes, representing admissions rather than individuals. The data are age-adjusted to the 2000 U.S. standard population and classified by cause (e.g., fire-related, non-fire-related, or unknown mechanisms). Federal institutions (e.g., VA hospitals) and out-of-state admissions are generally excluded, leading to potential underrepresentation in some areas. Variations in diagnostic and coding practices across jurisdictions may impact data comparability over time.

Column Name	Description
StateFIPS	Federal Information Processing Standards (FIPS) code for the state.
State	Name of the state (e.g., Virginia).
Year	Year of the data record (e.g., 2010, 2011).
Value	Recorded value for the metric being analyzed (e.g., percentage or rate of occurrences).
Data Comment	Additional comments or notes about the data (e.g., stability or reliability of the data).
Unnamed: 5	Placeholder for missing or unused data; typically blank (e.g., NaN).
Cause	Identifies the cause associated with the recorded value (e.g., Cause: Fire, Cause: Unknown Mechanism or Intent).

Table 3: Schema for CO poisoning data

6. **Census Data:** Demographic information from the U.S. Census Bureau will be used to identify demographic populations in Virginia, which is scaled to represent Alexandria based on its net population. It also provided me with the death rate based on gender for the population of Alexandria for the years 2010 - 2021.

Column Name	Description
Year	The year of the data record.
Alexandria_Population	Total population of Alexandria for the given year.
Alexandria_Deaths	Total deaths in Alexandria for the given year.
Virginia_Population	Total population of Virginia for the given year.
Virginia_Deaths	Total deaths in Virginia for the given year.

Table 4: Schema for Census data for virginia

### 3. Methodology

This analysis employs statistical modeling, predictive analytics, and human-centered approaches to examine the connections between wildfires, smoke levels, air quality, and respiratory health outcomes, with a particular focus on asthma, COPD hospitalizations, and mortality. The chosen methods are designed to uncover relationships between these variables and evaluate the temporal dynamics of their interactions.

#### 3.1 Wildfire Smoke Estimates

The methodology for generating smoke estimates involves several key steps. The analysis begins with acquiring the [USGS Wildland Fire Combined Dataset](#), a comprehensive dataset documenting fire occurrences from the 1800s to the present, which includes fire polygons in GeoJSON format. This dataset is pre-processed using a custom wildfire reader module to extract relevant features, such as the fire location, size, and date. The data is filtered to focus on wildfires that occurred within a 650-mile radius of Alexandria, Virginia, during the study period from 1964 to 2021.

For each wildfire, the geographic distance to Alexandria is calculated using geospatial methods, applying the **Haversine formula** to compute the shortest path over the Earth's surface. Fires within the 650-mile threshold are assigned a smoke estimate based on the following formula:

$$\text{Smoke Estimate} = \left( \frac{0.5 + \text{Circleness Scale}}{2} \right) \times \text{Fire Type Encoded} \times \text{Size} \times \left( \frac{1}{\text{Shortest Distance}} \right)$$

**Circleness Scale** accounts for the shape of the fire, with values closer to 1 indicating a circular shape (indicative of higher smoke density) and lower values representing irregular shapes.

**Fire Type Encoded** assigns a numerical value to the type of fire (e.g., wildfire, prescribed fire, etc.), allowing differentiation based on intensity or behavior.

**Size** represents the area of the fire in acres.

**Shortest Distance** is the proximity of the fire to Alexandria in miles, with closer fires contributing more heavily to the smoke estimate.

The processed data for all relevant wildfires is iterated upon, applying the smoke estimate formula for each entry. The results are aggregated (mean) per year to reduce variability in the data and stored in a CSV file for further analysis and visualization. This methodology provides a robust and reproducible framework for assessing the historical impact of wildfires on Alexandria, Virginia, enabling insights into how fire size and proximity influence air quality in the region.

### **3.2 Generating the AQI data**

The methodology for generating Air Quality Index (AQI) data involves several steps and utilizes the [EPA's Air Quality System \(AQS\)](#) API to retrieve historical air quality data for Alexandria, Virginia, from 1964 to 2021. Since Alexandria is an independent city without a designated county, a bounding box approach is used, covering a 50-mile radius around the city center. The analysis begins by acquiring an API key through the EPA's sign-up process. This key allows authenticated access to the API for subsequent requests.

The first step involves identifying relevant air quality monitoring stations and sensor types within the bounding box. These stations provide daily air quality measurements, including pollutant levels and other atmospheric data. The AQI values are then extracted from the monitoring data, focusing on relevant pollutants contributing to the AQI, such as particulate matter (PM<sub>2.5</sub>), ozone, and other harmful pollutants.

The gathered data is cleaned, processed, and aggregated to calculate annual mean AQI values for the city to reduce variability. This data is used to correlate with the smoke estimates generated and help develop a better estimate for forecasting.

### **3.3 Forecasting Smoke Estimates**

The methodology for forecasting smoke estimates involves using time-series analysis techniques to predict future smoke levels based on historical data. The process begins by aggregating the annual smoke estimates, which are calculated using the formula from the smoke estimation notebook, and comparing them to annual Air Quality Index (AQI) values derived from EPA monitoring data. This comparison helps evaluate the relationship between smoke estimates and observed air quality trends.

For forecasting, the ARIMA (AutoRegressive Integrated Moving Average) model is employed, as it is well-suited for capturing temporal trends and patterns in historical data. The model is trained on past smoke estimate values to generate forecasts with confidence intervals, providing insights into potential future impacts. This methodology ensures a robust analysis of temporal dynamics and facilitates the development of actionable strategies for mitigating the effects of wildfire smoke.

### **3.4 Exploratory Data Analysis**

The methodology for the exploratory data analysis involved integrating and visualizing wildfire smoke estimates, air quality indices, and health outcomes to identify trends and relationships. Spatial distribution of fires was analyzed through histograms, highlighting their proximity to Alexandria, while time-series visualizations captured annual trends in



burned areas and smoke estimates. Comparative graphs aligned smoke estimates with AQI values to evaluate their correlation. Health-related datasets, including asthma hospitalizations, COPD cases, and respiratory mortality, were filtered for Alexandria and Virginia and adjusted for population to analyze trends from 2010 to 2022. By combining environmental and health data, the analysis provides a comprehensive understanding of the long-term impacts of wildfire smoke on public health.

### 3.5 Health impact prediction

I have used a time-series modeling approach using historical data on smoke estimates and health records (hospitalization and mortality for Asthma and COPD) to predict future trends. Data preparation involved aggregating health outcomes by year, adjusting for gender differences, and integrating smoke estimate forecasts generated from prior analyses. Relationships between smoke exposure and health metrics were analyzed to identify significant correlations, informing the structure of predictive models. I chose to use an ARIMAX model for its ability to handle exogenous factors which were smoke estimates in my case, enabling robust forecasts of health impacts over a 30-year for Alexandria. I have built separate models to analyse the effect of smoke on hospitalization and mortality for men and women.

## 4. Findings

In the figure 4 below the histogram helps visualize the frequency of fires relative to their proximity to Alexandria. A red dashed line marks the 650-mile cut-off, which is the distance threshold for smoke impact modeling. Peaks in the histogram may indicate regions with higher wildfire activity. This visualization is useful for understanding the spatial distribution of wildfires around Alexandria and shows that most of the fires were beyond the 650 miles cutoff from Alexandria.

Further, figure 5 illustrates fluctuations in wildfire intensity over time, as measured by the total acreage burned each year. The high peaks, such as those around 1980 and in the 2000s, suggest years with significant fire events close to Alexandria. According to this [article](#) the Allen fire in North Carolina which burned about 93000 Acres during 1985 this is why there appears to be a peak during that time period.

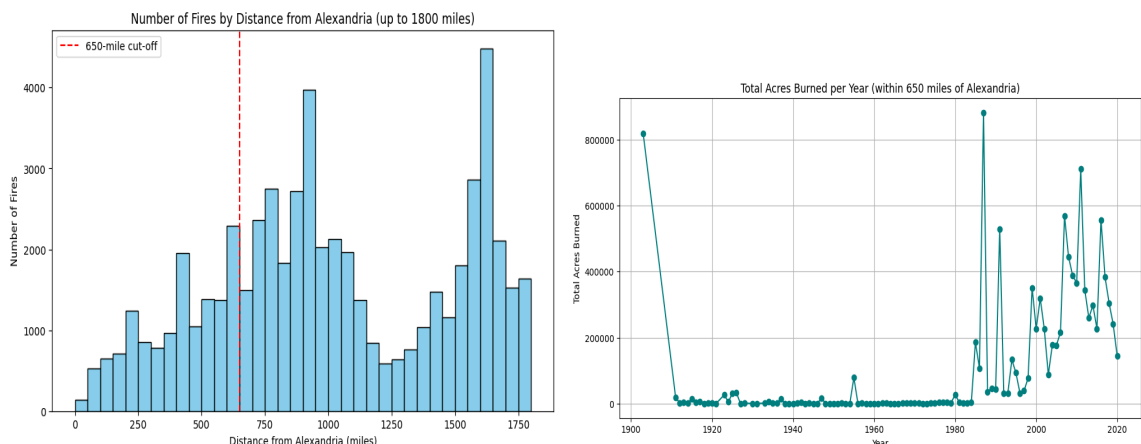


Fig 4: Number of fires with increasing distance

Fig 5: Acres burned per Year

The forecast of smoke estimates for Alexandria from 2020 to 2050 indicates a relatively stable trend with a slight decline in annual smoke estimates compared to historical data. The confidence interval suggests moderate uncertainty, but the general trend shows no significant increase in smoke exposure over the forecasted period. This could imply that future wildfire smoke impacts on Alexandria may remain similar to or slightly less than historical levels, assuming current patterns continue as shown in figure 6.

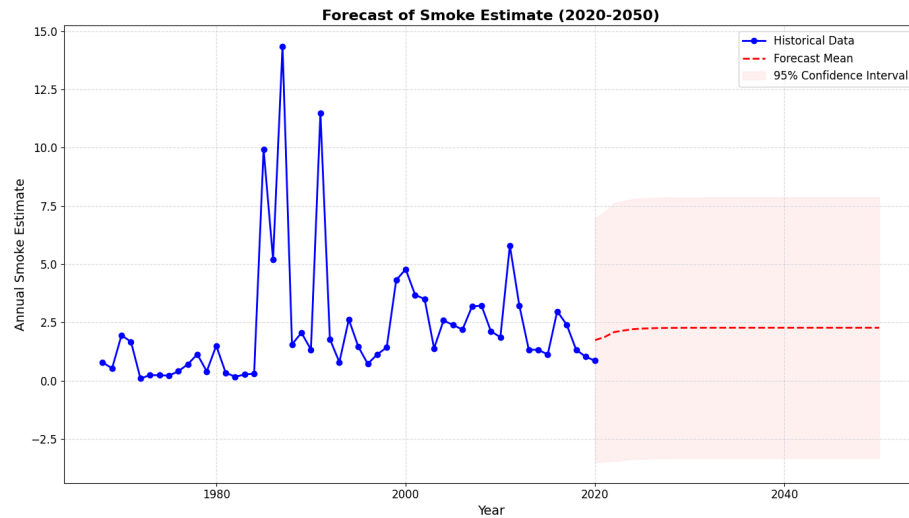


Fig 6: Smoke Estimate Forecast

Historical mortality has been declining over time, and the forecasted trend continues to show a decrease, albeit with significant uncertainty indicated by the wide confidence interval as seen in figure 6. The correlation between mortality due to Asthma and COPD and smoke estimates is weak thus we see a diverging trend for the forecast in figure 7. Whereas, the hospitalisation due to COPD in females is moderately highly correlated(0.59) with smoke estimates as seen in figure 8.

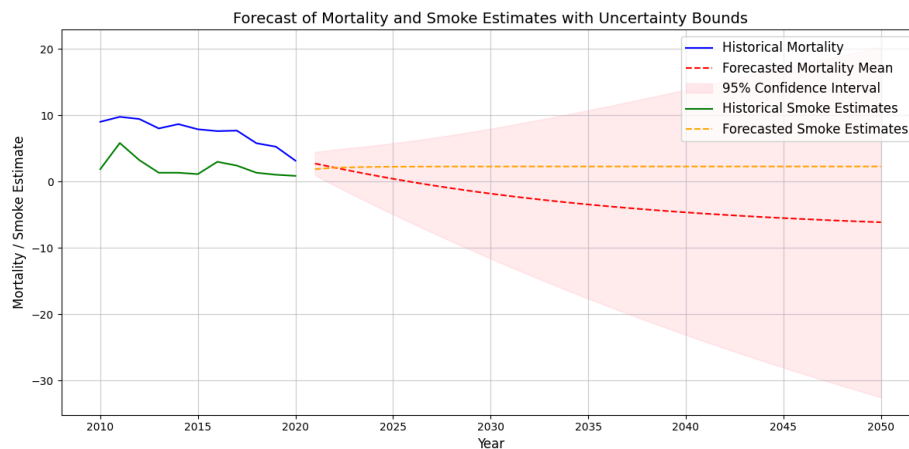


Fig 7 : Forecast of mortality with smoke estimates

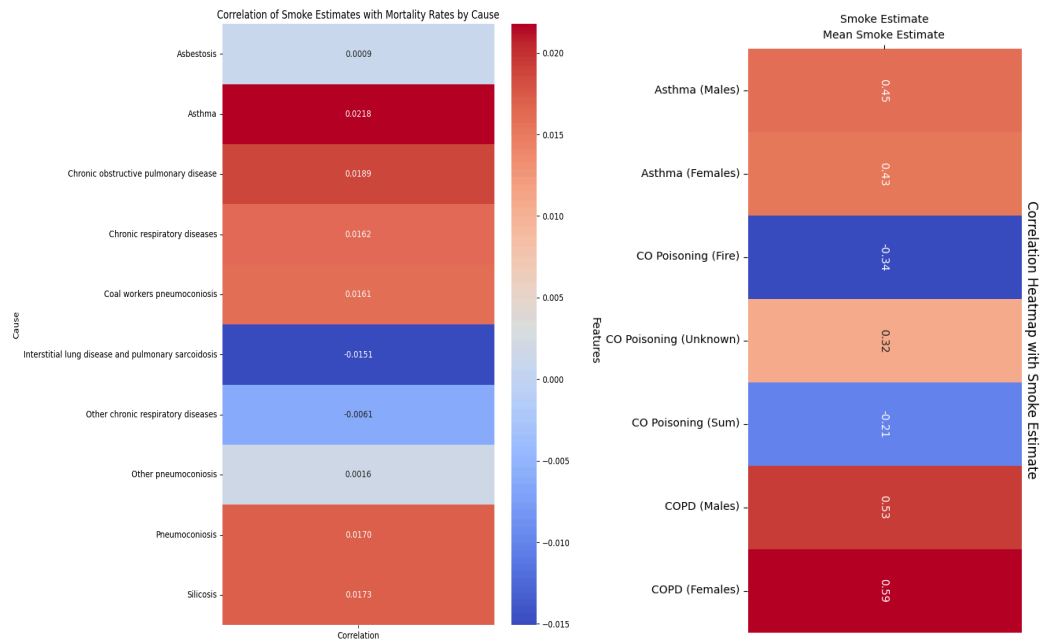


Fig 8 : Correlation for mortality and hospitalisation with smoke estimates for different cause

Further analysis shows that the hospitalisation due to COPD follows a similar trend to smoke estimates over time with female hospitalizations being consistently higher than male hospitalizations, indicating that females may experience greater vulnerability to COPD exacerbations related to smoke exposure. The confidence interval widens in later years, reflecting increasing uncertainty in the long-term forecast. Both male and female hospitalizations stabilize over time, with a steady trend observed from 2030 onwards. This suggests that future COPD hospitalizations may not significantly increase or decrease, assuming current trends and interventions remain consistent.

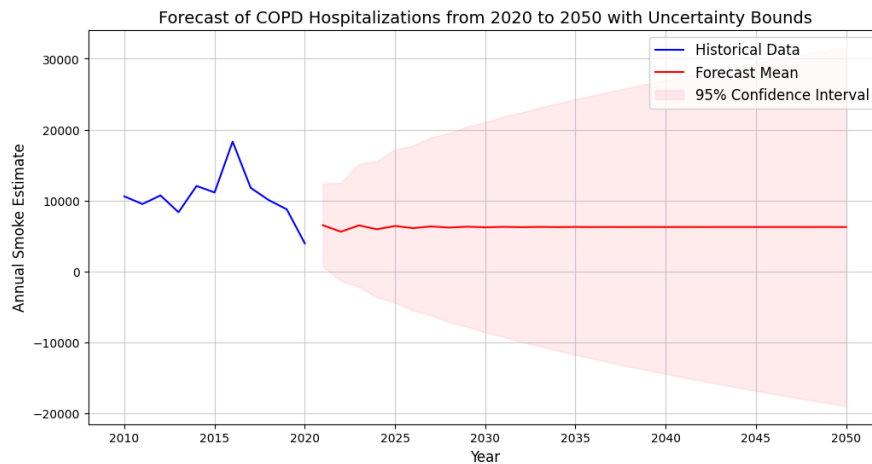


Fig 9.1 : Hospitalization trends for COPD - Overall

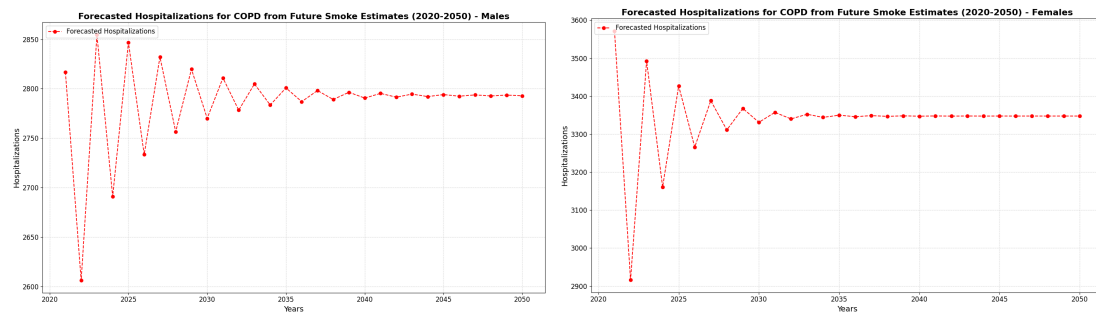


Fig 9.2 : Hospitalization trends for COPD - Males and Females

## 5. Discussion

The forecast for smoke estimates indicates a relatively stable trend over the next three decades, with slight variations and limited growth. This stability provides an opportunity for policymakers to focus on mitigation strategies without anticipating drastic changes in exposure levels. The analysis revealed a weak to moderate correlation between smoke estimates and health outcomes like asthma and COPD hospitalizations or mortality. This suggests that while wildfire smoke has an impact, other factors (e.g., underlying health conditions, socio-economic factors, or healthcare access) also play a significant role in determining health outcomes. Gender-based differences in health outcomes, particularly higher COPD hospitalizations in females, highlight the importance of tailoring public health interventions. Addressing these disparities can ensure more equitable healthcare access and outcomes. The widening confidence intervals in forecasted trends (both for smoke estimates and health outcomes) reflect inherent uncertainties in long-term modeling. These uncertainties arise from factors like climate variability, future wildfire management policies, and advancements in healthcare. This highlights the need for adaptive policies and continuous monitoring. The analysis underscores the importance of continued investment in wildfire mitigation, air quality improvement, and healthcare access. Proactive strategies, including community awareness and infrastructure support, can help manage smoke-related health risks especially for women.

### 5.1. Ethical considerations

In designing my study, I was mindful that I was working with protected health records and took care not to identify individuals or seek information beyond what was publicly available from curated, legally consented sources. To ensure ethical compliance, all data used in this analysis was obtained from reputable US government sources, such as the Centers for Disease Control and the US Census Bureau, both of which uphold strict privacy and ethical standards. I adhered to all license agreements governing data usage, with my work remaining non-profit and open-source.

## 6. Limitations

### 6.1 Data Availability and Accessibility:

The analysis was constrained by incomplete data for certain years and metrics, such as mortality data prior to 2010, highlighting the need for improved data collection and integration processes. Better data quality would significantly enhance the reliability of future analyses.

Access to [Virginia Respiratory Diseases Data](#), which could provide crucial insights into baseline respiratory health and its correlation with wildfire smoke exposure, was not granted despite efforts to obtain it. The absence of this dataset limited the scope of the study in assessing the full impact of smoke on respiratory conditions in Alexandria.

## **6.2 Dependence on Historical Data:**

The reliance on historical data introduces potential inconsistencies due to variations in reporting practices, data collection methodologies, and technological advancements over time. These factors may limit the depth and reliability of the findings, adding complexity to drawing accurate conclusions.

## **6.3 Simplifications in the Smoke Model:**

The smoke model used in this analysis is inherently limited by the available data, which includes only fire area, distance, and type. Critical factors such as wind patterns, fire intensity, duration, and cross-border wildfire contributions (e.g., from Canada) were not accounted for, leading to a less comprehensive estimation of smoke exposure.

The initial smoke estimate was generated without refinement against a well-established target variable, further limiting its accuracy and robustness.

## **6.4 Scope of Wildfire Data:**

The dataset used for this study focused exclusively on US national wildfires. However, evidence suggests that wildfires in neighboring regions, such as Canada, significantly contribute to Alexandria's smoke levels. The exclusion of such data reduces the comprehensiveness of the analysis.

## **6.5 Observational Study Design:**

As an observational study, this analysis is limited to identifying potential associations between predictor and outcome variables. It does not establish causation. Although some association was observed between the annual smoke index and health indicators, the effect size cannot be fully validated without addressing the uncertainties inherent in estimating these metrics.

These limitations underscore the need for more comprehensive data, refined models, and further research to provide deeper insights into the complex relationship between wildfire smoke and public health.



## **7. Conclusion**

This study investigated the impact of wildfire smoke on respiratory health outcomes in Alexandria, Virginia, with a focus on hospitalizations and mortality rates associated with asthma and COPD. The analysis revealed a weak correlation between smoke exposure and mortality, but a moderate correlation was found between smoke estimates and COPD hospitalizations, particularly among females, highlighting a significant gender disparity in health outcomes. While the forecasted smoke estimates showed a relatively stable trend over the next three decades, the projections for COPD hospitalizations indicated a stabilization as well, with no significant increase or decrease expected under current conditions.

These findings emphasize the importance of tailored public health interventions, particularly for vulnerable populations such as women, to address disparities in respiratory health outcomes. Moreover, the limitations of the smoke model, data availability, and reliance on historical records underscore the need for more comprehensive and integrated data collection efforts. Including cross-border wildfire contributions and refining predictive models would enhance the accuracy and scope of future studies.

This research highlights the value of human-centered data science in addressing environmental health challenges and underscores the need for proactive strategies, such as improving air quality monitoring, raising public awareness, and bolstering healthcare infrastructure. By prioritizing these measures, policymakers and healthcare providers can better prepare for and mitigate the health impacts of wildfire smoke, ultimately improving the quality of life for Alexandria's residents.

## **8. Future Work**

Future work should address several key challenges to improve the accuracy and applicability of predictive models. Enhancing smoke exposure estimates in areas with limited air quality monitoring and accounting for individual-level factors that influence susceptibility to smoke-related health effects are critical priorities. Integrating real-time data streams can enable more localized and timely predictions, while developing models that differentiate between the impacts of wildfire smoke and other air pollution sources will provide greater precision. Refining these models will allow public health officials and healthcare providers to implement more targeted interventions during wildfire smoke events, reducing strain on healthcare systems and improving outcomes for vulnerable populations.

## 9. References

- [1] <https://www.epa.gov/wildfire-smoke-course/health-effects-attributed-wildfire-smoke>
- [2] <https://www.oregon.gov/oha/ph/Preparedness/Prepare/Documents/OHA%208626%20Wildfire%20FAQs-v6c.pdf>
- [3] <https://ecology.wa.gov/air-climate/air-quality/smoke-fire/health-effects>
- [4] <https://www.airnow.gov/sites/default/files/2021-09/wildfire-smoke-guide-chapters-1-3.pdf>
- [5] <https://oehha.ca.gov/media/wildfiresmoke2016.pdf>
- [6] <https://www.epa.gov/wildfire-smoke-course/why-wildfire-smoke-health-concern>
- [7] <https://www.lung.org/blog/how-wildfires-affect-health>
- [8] D'Evelyn SM, Jung J, Alvarado E, Baumgartner J, Caligiuri P, Hagmann RK, Henderson SB, Hessburg PF, Hopkins S, Kasner EJ, Krawchuk MA, Krenz JE, Lydersen JM, Marlier ME, Masuda YJ, Metlen K, Mittelstaedt G, Prichard SJ, Schollaert CL, Smith EB, Stevens JT, Tessum CW, Reeb-Whitaker C, Wilkins JL, Wolff NH, Wood LM, Haugo RD, Spector JT. Wildfire, Smoke Exposure, Human Health, and Environmental Justice Need to be Integrated into Forest Restoration and Management. *Curr Environ Health Rep.* 2022 Sep;9(3):366-385. doi: 10.1007/s40572-022-00355-7. Epub 2022 May 7. PMID: 35524066; PMCID: PMC9076366.
- [9] <https://www.cdc.gov/wildfires/risk-factors/index.html>
- [10] <https://ceh.unicef.org/spotlight-risk/wildfire-smoke>
- [11] <https://www.alexandriava.gov/health-department/ahd-publications-reports>
- [12] <https://usafacts.org/data/topics/people-society/population-and-demographics/our-changing-population/state/virginia/county/alexandria-city/>
- [13] Alexandria climate data to study confounding factors:  
<https://climatecheck.com/virginia/alexandria>
- [14] Alexandria wildfire risk data:  
[https://firststreet.org/city/alexandria-va/5101000\\_fsid/fire?utm\\_source=redfin](https://firststreet.org/city/alexandria-va/5101000_fsid/fire?utm_source=redfin)
- [15] canadian wildfires June 7 2023 impact of Alexandria:  
<https://www.cnn.com/us/live-news/us-air-quality-canadian-wildfires-06-07-23/index.html>  
<https://www.alexandriava.gov/news-tes/2023-06-07/air-quality-action-day-notice>

[16] Doubleday, A., Schulte, J., Sheppard, L. *et al.* Mortality associated with wildfire smoke exposure in Washington state, 2006–2017: a case-crossover study. *Environ Health* **19**, 4 (2020). <https://doi.org/10.1186/s12940-020-0559-2>

[17] <https://climatecheck.com/virginia/alexandria>

[18] <https://pmc.ncbi.nlm.nih.gov/articles/PMC9076366/>

[19] <https://www.epa.gov/wildfire-smoke-course/health-effects-attributed-wildfire-smoke>

[20]

<https://wtop.com/local/2023/06/code-purple-very-unhealthy-air-sweeps-through-dc-area-as-impact-of-canadian-wildfires-continues/>

[21] <https://www.alexandriava.gov/news-tes/2023-06-07/air-quality-action-day-notice>

[https://firststreet.org/city/alexandria-va/5101000\\_fsid/fire](https://firststreet.org/city/alexandria-va/5101000_fsid/fire)

### 9.1. Data Sources links

**Combined data:** <https://www.sciencebase.gov/catalog/item/61aa537dd34eb622f699df81>

**AQI data:** [https://aqs.epa.gov/aqsweb/documents/data\\_api.html](https://aqs.epa.gov/aqsweb/documents/data_api.html)

**IHME respiratory mortality data for chronic respiratory diseases:**

<https://ghdx.healthdata.org/record/ihme-data/united-states-chronic-respiratory-disease-mortality-rates-county-1980-2014>

License and terms and conditions: Data made available for download on IHME Websites can be used, shared, modified or built upon by non-commercial users in accordance with the [IHME FREE-OF-CHARGE NON-COMMERCIAL USER AGREEMENT](#). For more information (and inquiries about commercial use), visit IHME [Terms and Conditions](#).

**Asthma and COPD hospitalization data:** Centers for Disease Control and Prevention. Environmental Public Health Tracking Network. Hospitalizations for Asthma and COPD Accessed From: <https://ephtracking.cdc.gov/DataExplorer>. Accessed on 11/22/2024

**Census data:**

[https://data.census.gov/table/ACSST1Y2023.S1301?g=050XX00US51510\\$1400000\\_160XX00US5101000](https://data.census.gov/table/ACSST1Y2023.S1301?g=050XX00US51510$1400000_160XX00US5101000)

**CO poisoning data:** Centers for Disease Control and Prevention. Environmental Public Health Tracking Network. Carbon Monoxide Poisoning Hospitalizations. Accessed From: <https://ephtracking.cdc.gov/DataExplorer>. Accessed on 11/22/2024

