

Analysis of Wildfire Smoke and Its Impact on Respiratory Health of Madison, WI

DATA 512 AU 2024 – Course Project



Table of Contents

1. Introduction	2
2. Background	3
3. Methodology	4
4. Findings	8
5. Discussion	13
6. Limitations	14
7. Conclusion	15
8. References	16
9. Data Sources	17

1. Introduction

Madison, Wisconsin, the state's capital and second-largest city, is a hub of cultural, economic, and academic activity and home to over 270,000 residents. Nestled between lakes Mendota and Monona, Madison is renowned for its picturesque landscapes, vibrant community, and a commitment to sustainability. It is home to the University of Wisconsin-Madison, a prominent institution contributing to innovation and research, and a thriving arts scene, with museums, theaters, and festivals enhancing the city's cultural identity.

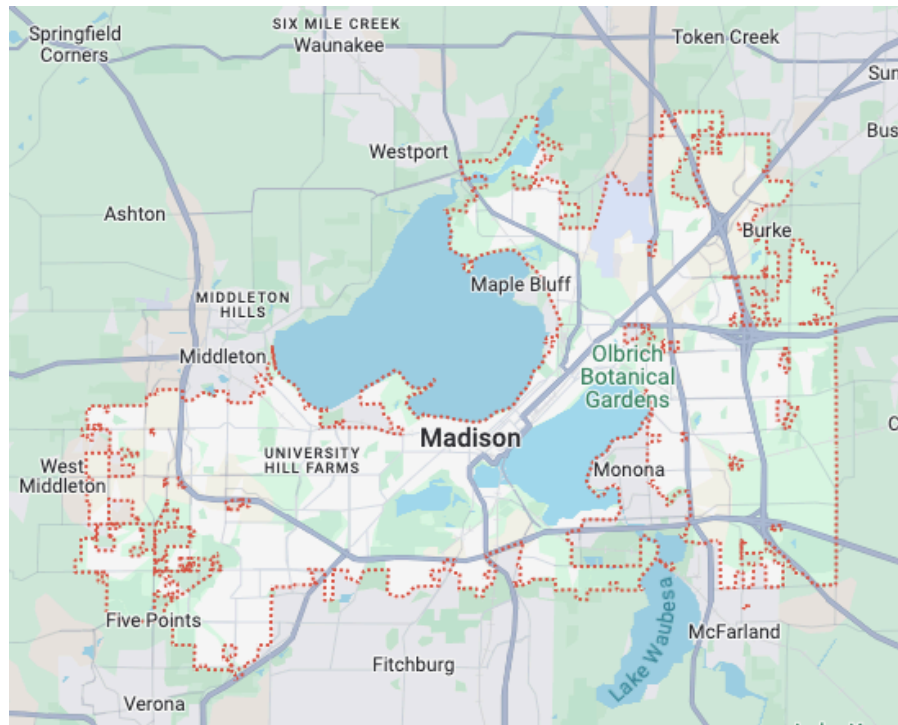


Figure 1.1: Madison's Location on Google Maps

Madison, with its humid continental climate and significant seasonal variations, is increasingly impacted by regional wildfire smoke events despite not being directly in wildfire-prone areas. These smoke intrusions, intensified by climate change, pose growing public health risks, particularly for chronic respiratory conditions like COPD, asthma, and tuberculosis. Understanding the link between wildfire smoke and respiratory illnesses is crucial as these events become more frequent and severe, raising healthcare demands, costs, and threats to residents' quality of life. This analysis is motivated by the need to address these escalating health risks, provide evidence for informed policy-making, and predict future impacts to better safeguard Madison's population against a pressing and unresolved environmental health challenge.

From a scientific perspective, understanding the health consequences of wildfire-induced smoke provides crucial insights into the direct impact of climate-related events on respiratory health. Practically, these findings can guide public health interventions, informing policies that protect vulnerable populations, especially during peak wildfire seasons. Based on the insights uncovered and the severity of any effects observed, we can then advise the Madison city council, city manager/mayor, and city residents on potential impacts to design solutions to mitigate these health impacts.

2. Background

Environmental factors, particularly smoke, have long been associated with respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and tuberculosis (TB). Numerous studies have explored the direct and indirect effects of pollutants, including wildfire smoke, on the incidence and severity of these conditions.

Exposure to fine particulate matter (PM_{2.5}), a significant component of wildfire smoke, is known to exacerbate respiratory symptoms, increase hospital admissions, and contribute to long-term health issues. For instance, a study by Reid et al. (2016) reviewed the impact of wildfire smoke exposure on respiratory health and found a consistent association with increased emergency department visits and hospitalizations for asthma and COPD during wildfire events. Similarly, Liu et al. (2017) demonstrated that exposure to PM_{2.5} from wildfires in the western United States, including regions near Wisconsin, significantly increased the risk of respiratory distress. Many studies have highlighted how regional variations in air quality influence respiratory health, emphasizing the need for localized research to inform public health interventions.

Building on this foundational research, the current study aims to provide a more detailed analysis of the respiratory health impacts of wildfire smoke in Madison, Wisconsin. By integrating localized air quality data and health records, this research aims to identify whether increased smoke exposure correlates with adverse health effects. The specific research questions include:

1. Does wildfire smoke significantly affect respiratory health (COPD, asthma, and tuberculosis) outcomes in Madison?
2. Is there a relationship between wildfire smoke exposure and increased death rates from respiratory illnesses, particularly those linked to COPD, asthma, and tuberculosis?
3. What is the demand for hospitalization and emergency visits for asthma, COPD, TB in the upcoming years and how can healthcare providers prepare for this demand?

The study hypothesizes that the increasing levels of smoke exposure correlate with a rise in respiratory illnesses, hospitalizations, and potentially mortality rates. If confirmed, it is expected for these trends to continue upward if smoke levels persist or increase in coming years. Drawing from the findings, we can provide recommendations to the Madison city council, city leadership, and local residents on strategies to address and reduce these health challenges.

3. Methodology

The methodology for this analysis focuses on statistical modeling, predictive analytics and human centered approaches to explore the relationship between wildfires, smoke levels, air quality and respiratory health outcomes, specifically asthma, COPD, and TB. The methods in the analysis were chosen for their ability to reveal relationships between variables and to assess the temporal dynamics of the relationships.

a. Setting Project Scope

To set the scope of the project, the wildfire dataset from USGS was restricted for specific temporal range and geographic boundary. The analysis considered only wildfires from the last 60 years, spanning from 1964 to 2024 and are within a 650-mile radius of Madison. To filter for files within a specific distance, a new column '*shortest_dist*' was calculated as geodesic distance between the GPS coordinates of the Madison city center and the closest point on the perimeter of a wildfire. Specifically, the closest point was estimated by computing geodesic distances to all points on a wildfire perimeter before choosing the smallest value.

b. Handling Air Quality Data

AQI data from EPA's Air Quality System (AQS) API obtained for Madison using the monitoring stations in the vicinity was sparse, especially for the years 2001 to 2009. To address these gaps, the missing AQI values were calculated using the available fields. The calculation was carried out using the concentration levels of pollutants and the corresponding breakpoints defined in the technical assistance document of the data provider, ensuring consistency and accuracy with established methods. For each pollutant, breakpoints were established as *bp_high*, *bp_low*, *i_high*, *i_low*, where *bp_high* and *bp_low* represented the concentration range, and *i_high* and *i_low* denoted the corresponding AQI range. For each record in the dataset, the pollutant concentration was retrieved and checked against the defined breakpoint ranges. If the concentration fell within a range, the AQI was calculated using the below formula.

$$AQI = \frac{(bp_high - bp_low)}{(i_high - i_low)} \times (concentration - bp_low) + i_low$$

c. Smoke Estimation Calculation

Smoke estimation was calculated using direct fields from wildfire datasets like area, circleness, along with calculated fields for wind, intensity, duration and distance. The area burned plays a critical role, as smoke levels are directly proportional to the amount of fuel consumed, which was estimated using the **GIS_Acres** field. The **Circleness_Scale** field was used to evaluate the circularity of the fire, with more circular shapes containing smoke effectively, leading to higher local concentrations, and less circular shapes promoting greater dispersion and lower concentrations. This value is amplified by a constant to enhance its contribution to the smoke estimate.

Fire intensity is determined based on the **Assigned_Fire_Type**, with high-risk fires such as "Wildfire" and "Prescribed Fire" assigned an intensity factor of 5. Uncertain but potentially dangerous types, like "Likely Wildfire" and "Unknown - Wildfire," are assigned lower factors of 4 and 3, respectively, while minimal-impact fire types are given a factor of 0.5. The duration of the fire is inferred from the **Shape_Area**, with larger fires, indicated by thresholds such as 1,000,000 and 500,000 square units, associated with longer durations and higher duration factors. Smaller fires are expected to have shorter durations and lower duration factors. The impact of wind is assessed using the ratio of **Shape_Length** to **Shape_Area**, which indicates how elongated the fire shape is indirectly indicating wind behaviour. A higher ratio suggests elongated fires that allow smoke to disperse further, potentially increasing downwind concentrations, while a lower ratio indicates compact shapes with less dispersion. Distance inversely affects smoke concentration, as the diffusion and dispersion of particles reduce visibility and intensity with increasing distance from the source. This relationship is incorporated using the **shortest_dist** column.

All these factors are combined into a formula to compute the smoke estimate:

$$Smoke = \frac{Area \times FireIntensity \times Duration \times Wind \times Circleness}{Distance}$$

This comprehensive approach accounts for the key variables influencing smoke production and spread, leveraging the available data to provide a reliable estimation of smoke levels.

d. Smoke Estimates Prediction

A polynomial regression model was employed to forecast future trends in smoke exposure from 2021 to 2050, offering a suitable approach for capturing the observed non-linear patterns in the data. Unlike linear regression, which is limited to fitting straight lines, polynomial regression provides the flexibility to model complex upward or downward trends without clear seasonal patterns. By selecting an appropriate degree, such as two, the model balances accuracy with simplicity, avoiding unnecessary

complexity. In contrast, models like ARIMA, which are better suited for data with strong repeating patterns or autocorrelation, were deemed less appropriate for this analysis due to the absence of such features in the dataset.

e. Healthcare dataset processing

The extension plan utilized the readily available datasets of illness incidents from Wisconsin Department of Health services. The asthma and copd dataset includes information on county wise asthma-related hospitalizations and emergency department visits across Wisconsin from 2000 - 2023 aggregated at county level and below are the fields utilised.

County	Topic	Year	Crude Rate
County Name	Hospitalization or Emergency Visit	Cases recorded year	The number of cases divided by the total population of interest.

The TB dataset tracks the tuberculosis cases in Wisconsin from 2014 to 2023 aggregated at county level and below fields were of interest.

County	Year	Count
County Name	Cases recorded year	Number of cases recorded

The mortality dataset from IHME provides extensive data on mortality rates attributed to a variety of respiratory illnesses, including asthma, COPD, and TB, segmented by factors such as age and sex for the Wisconsin region for period 1980 - 2021 aggregated at state level and below fields were used.

Location	Cause	Metric	Year	Val
State Name	Respiratory illness name	Number or Percentage	Year	Rate of mortality or count of mortality based on metric

The aggregation of data at county and state levels helps mitigate individual identification risks, aligning with ethical standards of data privacy and confidentiality. Furthermore, the true value of these datasets lies in their potential to drive targeted healthcare improvements, emphasizing a human-centered approach.

To enhance the accuracy of asthma and COPD illness trends, a new measure, ***Illness_crude_rate***, was created by combining emergency room (ER) and hospitalization metrics. This approach provides a more holistic view of data, eliminating the need to analyze these two possibly dependent metrics separately.

The combined measure was computed as a weighted average of the crude rates for ER visits and hospitalizations, with the weights determined by their respective counts. This method ensures proportional importance is assigned to each measure, accurately reflecting their contribution to the overall illness rate.

$$Illness_crude_rate = \frac{(ER_crude_rate \times ER_count) + (Hosp_crude_rate \times Hosp_count)}{ER_count + Hosp_count}$$

Adopting this combined metric also helps address multicollinearity issues in predictive modeling by reducing redundancy in the dataset, as ER and hospitalization data are highly correlated.

f. Health Impact Prediction

VARMAX (Vector Autoregression Moving-Average with eXogenous variables) was deemed highly suitable for forecasting future respiratory health trends, for its ability to handle multiple interdependent time series, reflecting the interconnected nature of smoke levels, illness and mortality. A multivariate approach was employed, recognizing the strong links among various health metrics. The model captures both the relationships between these variables and their historical values, offering a comprehensive understanding of trends and interactions over time. Additionally, the model's structure permits future enhancements by incorporating external factors that may influence health metrics.

Throughout the analysis, Pearson's correlation analysis served as the core statistical method to quantify the relationship between variables. This method was chosen because it is effective in measuring the strength and direction of relationships between two continuous variables, making it suitable for this analysis. By calculating p-value, the study also assessed the statistical significance of the correlations, to confirm the reliability of our analysis, ensuring robust interpretation of the findings.

This study ensured strict adherence to all legal constraints on data usage and all license agreements for data use were meticulously followed, with the analysis conducted on a non-profit and open-source basis. Most importantly it was designed with strict adherence to ethical considerations, ensuring that protected health records were used responsibly and without attempts to identify specific individuals or access information beyond the data compiled with the legal consent of all involved. Data was exclusively sourced from reliable entities such as the Wisconsin State Department and IHME both of which uphold stringent privacy and ethical standards. Reproducibility was ensured through a Git repository that includes narrative notebooks, license and relevant data files. At every stage, efforts were made to maintain local relevance to the Madison community by prioritizing accuracy, integrity, and transparency.

Overall by integrating statistical analysis and predictive modeling and emphasizing on human centered approach and ethical considerations, the study aims to provide a comprehensive understanding of the trends in wildfire smoke and its relationship with respiratory health.

4. Findings

The analysis uncovered several crucial insights about the trends in wildfire smoke and its impact of wildfire smoke on respiratory health.

a. Initial findings

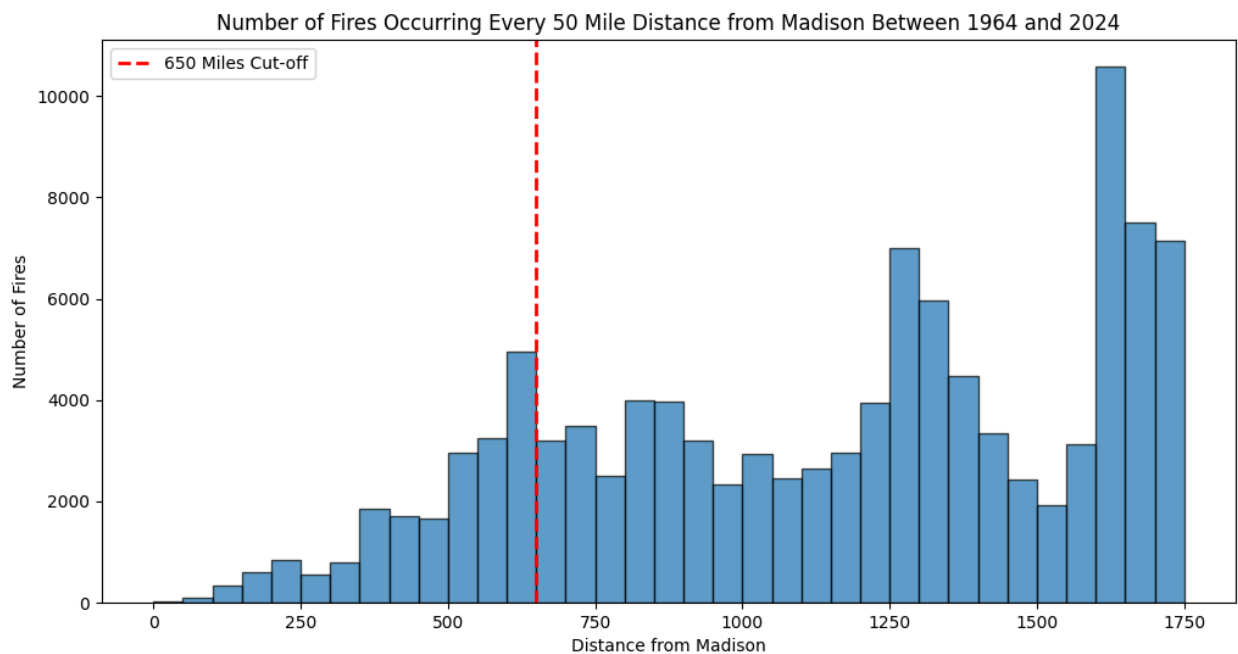


Figure 4.1: Histogram showing the number of fires occurring every 50 miles from Madison.

Figure 4.1 shows the number of fires that occurred at various distances from Madison between 1964 and 2024. A red dashed line marks a 650-mile cut-off point, marking project scope. The histogram reveals that, within the cut off line, the fire activity is concentrated within 500 to 600 miles of Madison, suggesting that areas with dense forests, probably in the Northern Plains and parts of the upper Midwest, are more prone to wildfires. We see a linear trend within the cut off distance indicating more wildfires as we move farther away from Madison. But it is worthy to note that distant fires can affect air quality in Madison due to smoke being transported by winds, even if the fires themselves are far away.

The figure 4.2 displays the total acres burned(in millions) in fire incidents within a 650-mile radius of Madison from 1964 to 2024. Sharp increases in the total acres burned are observed starting in the late 1990s and early 2000s, peaking around the mid-2010s. This pattern aligns with a global rise in more intense wildfires, which have been linked to longer fire seasons and drier conditions caused by climate change. Additionally, year-to-year fluctuations in burned acres are evident, with some years showing significant

spikes that may be attributed to extreme weather events, such as droughts or heatwaves. Recently, a slight decline in the total acres burned has been noted after the peak around 2011, 2016. This decrease may be due to improved fire management practices or natural variations in weather conditions. Factors such as extended fire seasons, changes in forest management, and natural climate variability contribute to the complexity of fire activity in the region.

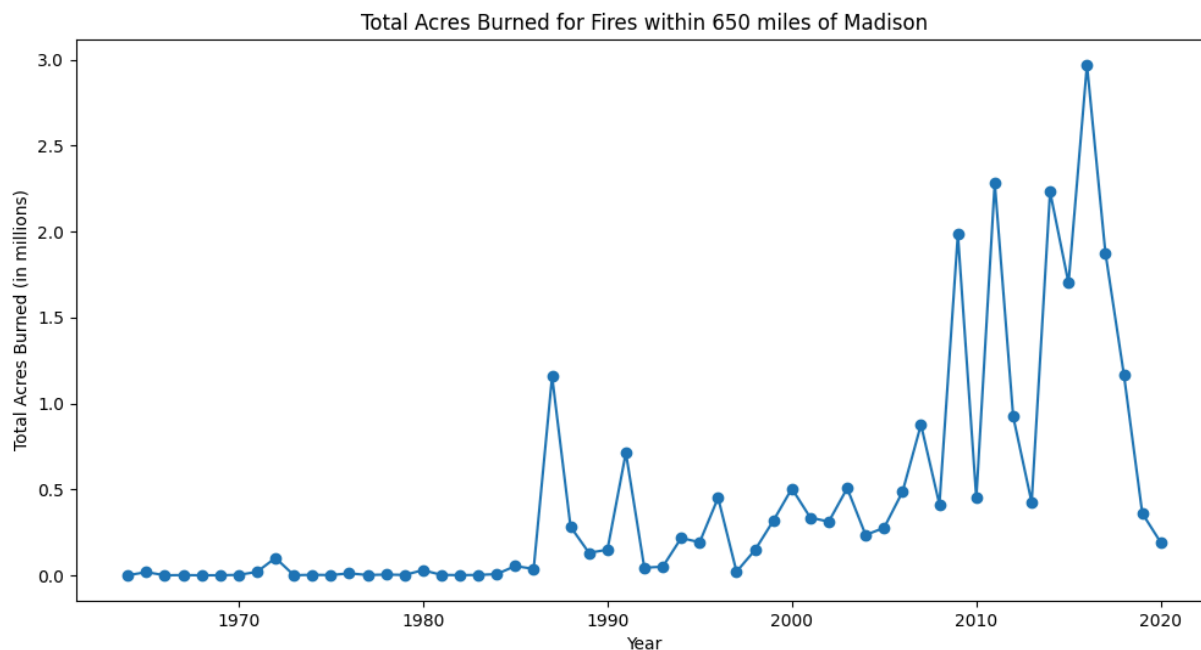


Figure 4.2: A time series graph of total acres burned from the fires near Madison

b. Smoke Patterns

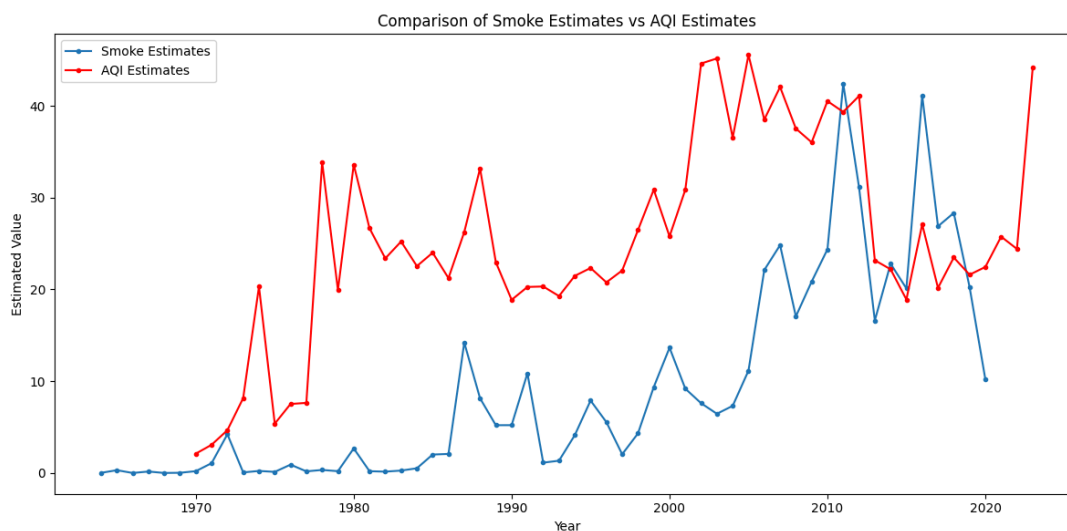


Figure 4.3: Comparison graph of Smoke estimates and AQI estimates

Figure 4.3 compares the estimated smoke levels and estimated average Air Quality Index (AQI) trends annually from 1964 to 2024. Blue line indicates the trend in smoke estimates and red line indicates the trend in AQI estimates both marked with data points. This layout allows us to see year-by-year variations in the smoke and AQI estimates along with any correlation or divergence between smoke and AQI levels. Over the years, both Smoke estimates and AQI estimates have generally increased, especially since the late 1990s, likely due to a rise in global wildfire activity linked to climate change factors like longer droughts and higher temperatures. After 2000, noticeable fluctuations in smoke and AQI values were observed, with few peaks in Smoke corresponding to major wildfires in North America during the 2000s and 2010s. The major peaks in smoke estimate in 2011 and 2016 can be attributed to the large number of wildfires that occurred in that year within 650 miles and highest area burned as seen in above two graphs. There are instances when AQI levels increased without a rise in smoke and vice versa, indicating that while wildfire smoke significantly impacts air quality, other factors such as industrial emissions, urban pollution, and agricultural activities also play a role.

The predictive modeling using polynomial regression model of degree 2 also provided critical insights. As per model metrics, the model explained about only 71% of the variance in the data and showed a small to moderate level of prediction error indicating room for improvement in future work.

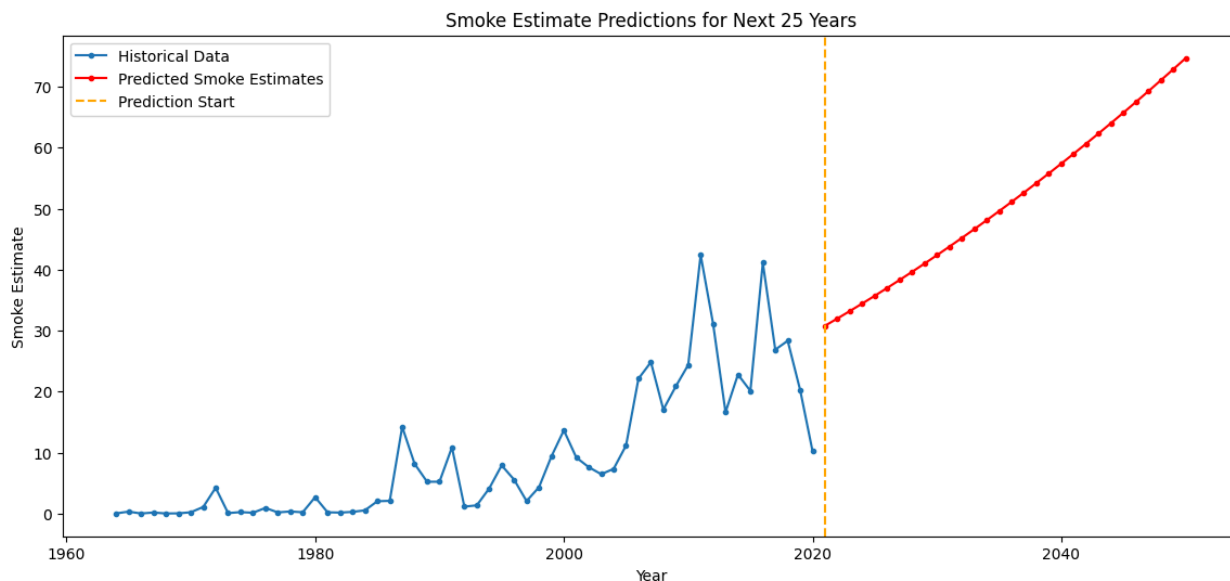


Figure 4.4: Forecast of Annual Smoke Estimates

The plot shows historical data and predicted smoke estimates for the next 25 years. The historical data shows fluctuations in smoke levels from 1960 to 2020, with some peaks and valleys. The predicted smoke estimates show a steady increase in smoke levels over the next 25 years reaching a much higher level by 2040 without action.

c. Respiratory Health Analysis

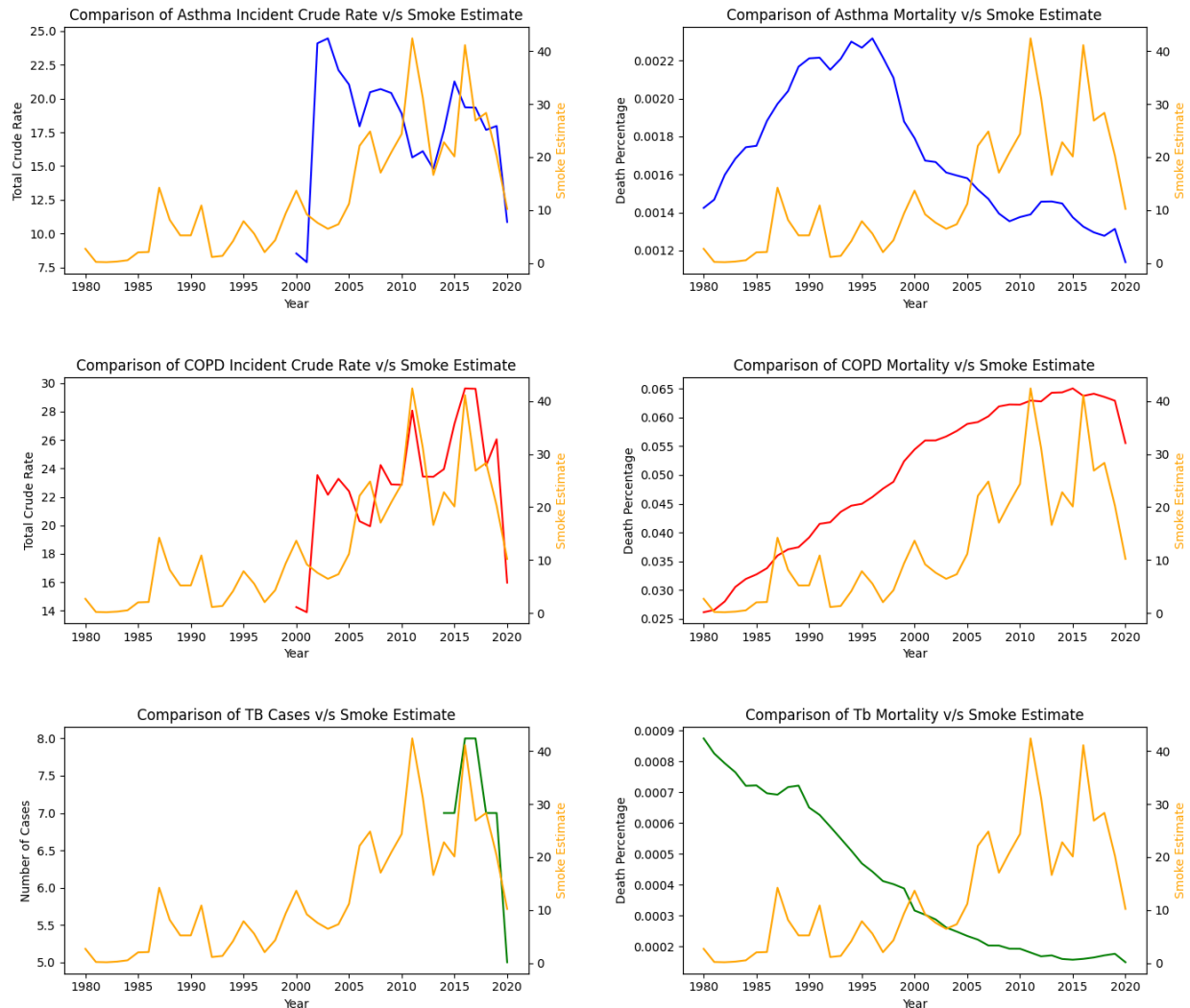


Figure 4.5: Comparison of Smoke and Respiratory Health

Figure 4.5 compares the estimated smoke levels and respiratory health indicators (Illness and mortality rate) for asthma, COPD and tuberculosis. Yellow lines indicate the trend in smoke estimates and other lines indicate the trend in health indicators. This layout allows us to see year-by-year variations in the health indicators along with any correlation or divergence between smoke and health indicators. The plots show that the trends in the health metrics generally correlate with the fluctuations in smoke estimates, with periods of higher smoke levels corresponding to higher values in health indicators, especially the incidents and cases.

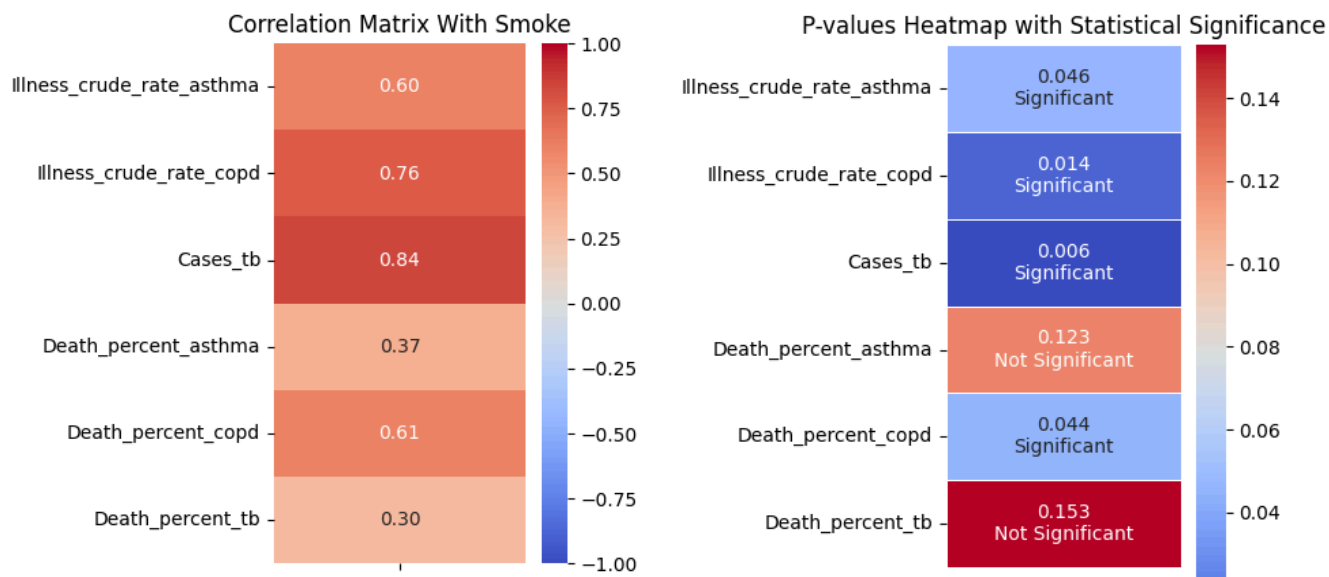


Figure 4.6: Correlation and Statistical Significance Matrix

From figure 4.5 , we see that a strong positive correlation was identified between smoke exposure and the incidence rates of respiratory conditions like asthma, COPD, and TB, highlighting how significantly air quality degradation can influence the prevalence of such illnesses. Regarding mortality, the relationship with smoke exposure was less pronounced compared to incidence rates except for COPD mortality. Based on p-values heatmap, all correlations exhibited statistically significant links except for asthma and TB mortality. This suggests that mortality outcomes are influenced by additional factors such as healthcare access, timely treatment, and pre-existing health conditions. It indicates that while smoke exposure plays a role in increasing disease prevalence, its impact on mortality may be moderated by systemic healthcare variables.

Figure 4.7 presents projections for respiratory health metrics in the coming decades. A key trend is the steady increase in Asthma Illness Incident Rate, rising from around 15 in 2025 to over 35 by 2050. Similarly, Asthma Mortality Rate is projected to increase, though at a slower pace, going from around 0.0014% in 2025 to 0.0020% by 2050. The projections also show a rise in COPD Illness Incident Rate, from around 17.5 in 2025 to over 27.5 by 2050. COPD Mortality Rate is expected to increase as well. While less pronounced, TB Cases and TB Mortality Rate are also projected to increase gradually over the same time period.

These trends indicate a growing burden of respiratory health challenges, particularly asthma and COPD, driven by increasing smoke exposure. This highlights the urgent need for targeted public health interventions, including policies to improve air quality, proactive health measures, and public awareness campaigns, to mitigate the long-term impacts on respiratory health.

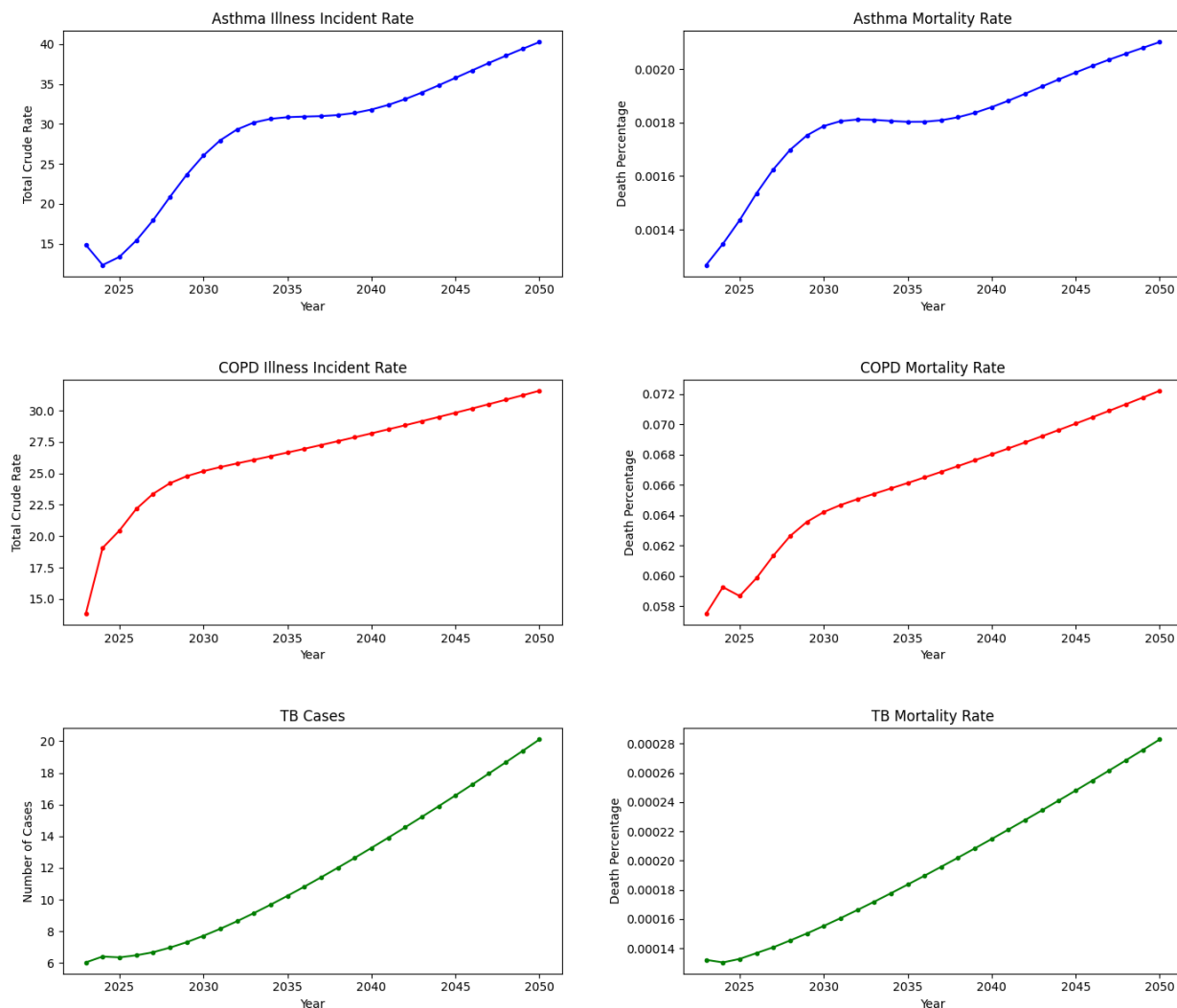


Figure 4.7: Forecast of respiratory illness and mortality

Overall, the study emphasizes the urgent need to address smoke exposure as a public health priority. By understanding its effects on both disease incidence and mortality, stakeholders can better prepare for future challenges and work towards managing and preventing respiratory health issues associated with wildfire smoke.

5. Discussion

During the analysis, a strong, positive and statistically significant correlation was identified between smoke and the incidence rates of asthma, COPD, TB and mortality rate of COPD. The analysis also predicts a substantial increase in smoke, incidents and mortality rates of all 3 respiratory conditions in future if no action is taken to reduce wildfires. These results go beyond statistical data, they represent a real and immediate threat to the well-being of the Madison community.

To gain better control over the issue, the city council must prioritize more frequent tracking of health indicators, enabling a deeper understanding of both the short- and long-term healthcare impacts associated with wildfires. Enhanced data collection will support the development of a comprehensive and effective healthcare response strategy. Additionally, expanding air monitoring systems is essential to obtain detailed air quality data, ensuring accurate tracking of pollutants and their impacts on public health.

To address the possible impacts, the city council must raise environmental awareness among the public, emphasizing the importance of reducing wildfires. Expanding medical resources, such as increasing the number of respiratory therapy centers, hospital beds, and emergency care facilities, will ensure timely treatment for those affected by smoke-related illnesses. Another critical measure is the establishment of clean air shelters in areas most vulnerable to smoke, providing safe spaces for individuals to take refuge during wildfire smoke days. For city planners, healthcare professionals, and policymakers, addressing both the environmental and healthcare factors will be crucial for improving public health outcomes over the next few decades.

Reflecting on the project, the principles of human-centered data science were crucial in shaping the research methodology and interpreting the results for Madison, Wisconsin. The study was designed with a clear focus on the local community, aiming to address specific health outcomes that directly impact Madison residents. By using methods that deliver actionable insights for the welfare of the community, the research aligns with the core values of human-centered data science. This approach ensured that the findings were not only statistically robust but also practical to possible extent and completely relevant for the community. The ethical considerations of the study, especially regarding public health and privacy, were carefully addressed to ensure that the conclusions prioritized the well-being and interests of Madison's population.

6. Limitations

The analysis conducted in this study has several limitations worth noting for accurate interpretation and practical application of findings.

Firstly, the wildfire dataset presents inconsistencies due to overlapping records within the same geographic area and timeframe, introducing potential duplication. The tool used to measure fire distances excludes fires with non-ring shapes, resulting in the omission of 36 fires. Additionally, the model simplifies smoke impact estimation by overlooking critical variables such as wind direction, duration and actual intensity due to data unavailability. Sparse AQI data (2001–2009) further limits the reliability of smoke estimates. The health indicator data is aggregated at different levels for different topics (for example asthma incidents at county level, asthma mortality at state level) further exacerbating these challenges.

Despite having access to smoke data spanning the last 60 years, the shorter temporal range of healthcare data, particularly hospitalization records (2000-2023 for asthma and COPD, 2014-2023 for TB), limits our ability to fully explore the historical health impacts of smoke. County-specific mortality rate data is unavailable, compelling us to use aggregate data for the entire state of Wisconsin. By relying on statewide data, we risk obscuring local trends and nuances in mortality that might otherwise reveal significant insights. This limitation could lead to correlation errors and impact the precision of our findings regarding the health effects of smoke specifically in Madison, Dane county.

The predictive smoke model, with an R^2 value of 0.71, explains only 71% of the variance in the data but falls short of optimal accuracy due to less features. Predictions are prone to errors of at least two units, which is notable given the scale of smoke estimates. The extended health model performs adequately, but the varying temporal range of health data compromises its uniform effectiveness across indicators.

Another critical limitation lies in the exclusion of confounding factors such as smoke generated from other sources, preexisting health conditions, diet, and exposure to other pollutants, all of which can influence both smoke and health outcomes. Moreover, while the focus is on U.S. wildfires, Madison is significantly affected by Canadian wildfires due to its geographical location. Wildfires in Canada often produce large-scale smoke plumes that travel longer distances due to prevailing atmospheric winds, impacting air quality in Madison, WI, more significantly than closer U.S. wildfires. These plumes contain higher particulate matter concentrations due to the dense, boreal vegetation burned in Canadian fires. Since our analysis focuses only on smoke estimates generated purely only from U.S. wildfires, it might miss the dominant contributors to poor air quality, leading to weaker than expected correlations with respiratory health trends.

Despite these limitations, the findings demonstrate significant relationships between wildfire smoke and respiratory health outcomes, particularly for conditions like asthma, COPD, and TB. The research underscores the importance of improving data quality, incorporating additional variables, and refining models to support more accurate forecasting and informed public health strategies. These measures would enhance the reliability of insights.

7. Conclusion

This study examined the impact of wildfire smoke on respiratory health outcomes in Madison, Wisconsin, with the hypothesis that increasing levels of smoke exposure correlate with a rise in respiratory illnesses, hospitalizations, and potentially mortality rates, particularly for asthma, COPD, and tuberculosis. The findings strongly support this hypothesis, revealing a significant positive correlation between smoke exposure and the incidence of asthma and COPD. While the relationship between smoke and tuberculosis was less pronounced, COPD mortality showed a notable connection to smoke levels, whereas asthma and tuberculosis mortality were more influenced by systemic factors such as

healthcare access and preexisting conditions. Projections suggest a steep rise in respiratory illnesses over the coming decades if current trends in wildfire smoke continue unabated.

These results emphasize the need for proactive, targeted public health interventions to mitigate the escalating risks posed by wildfire smoke. The study not only highlights the pressing environmental health challenges facing Madison but also illustrates the power of human-centered data science in addressing these issues. By integrating diverse datasets on smoke exposure, air quality, and health outcomes while upholding ethical standards of data aggregation and privacy, the research offers actionable insights that prioritize community welfare. The localized focus ensures relevance and provides a foundation for tailored interventions that directly benefit Madison's residents.

Beyond the statistical findings, this study exemplifies how data science can serve as a bridge between complex environmental data and real-world health outcomes. It underscores the importance of ethical considerations and a human-centered approach, ensuring that the research is not only robust but also aligned with the broader goal of improving quality of life. The conclusions offer valuable guidance for policymakers, healthcare providers, and urban planners in developing strategies such as enhancing air quality monitoring systems, preparing healthcare infrastructure for increased respiratory care demand, and raising public awareness about protective measures. This research reaffirms the potential of data-driven approaches to foster equitable, informed, and community-focused responses to pressing public health challenges.

8. References

- AirNow. AQI Calculation. <https://www.airnow.gov>
- GeoJSON. GeoJSON Python Library Documentation. <https://geojson.readthedocs.io/en/latest/>
- Pyproj. Pyproj Library Documentation. <https://pyproj4.github.io/pyproj/stable/>
- Wisconsin Department of Health Services. <https://www.dhs.wisconsin.gov/>
- The Institute for Health Metrics and Evaluation. <https://www.healthdata.org/>
- Public Health Madison and Dane County. Respiratory Illness Dashboard. <https://publichealthmdc.com/health-services/respiratory-illness/dashboard>
- U.S. Centers for Disease Control and Prevention. <https://www.cdc.gov/>
- Wisconsin Hospital Association Information Center. <https://www.whainfocenter.com/>
- Statsmodels VARMAX Model Documentation. <https://www.statsmodels.org/stable/generated/statsmodels.tsa.statespace.varmax.VARMAX.html>
- Wisconsin Department of Natural Resources. Wildfire Smoke Information. <https://dnr.wisconsin.gov/topic/AirQuality/WildfireSmoke.html>

- Wisconsin Wildfire Smoke Impact Analysis. Milwaukee Journal Sentinel. <https://www.jsonline.com/story/news/local/wisconsin/2024/08/09/2023-wildfire-smoke-affected-health-in-wisconsin-data-show/74157620007/>
- D'Evelyn, S.M., et al. Wildfire, Smoke Exposure, Human Health, and Environmental Justice Need to Be Integrated into Forest Restoration and Management. *Current Environmental Health Reports*, 9(3): 366–385, 2022. DOI: <https://doi.org/10.1007/s40572-022-00355-7>
- University of Wisconsin-Milwaukee Public Health Insights. <https://uwm.edu/publichealth/what-health-impacts-did-last-years-wildfire-smoke-have-on-wisconsin-new-data-tell-the-story/>
- Reid, C. E., Brauer, M., Johnston, F. H., Jerrett, M., Balmes, J. R., & Elliott, C. T. (2016). Critical review of health impacts of wildfire smoke exposure. *Environmental Health Perspectives*, 124(9), 1334-1343. DOI:[10.1289/ehp.1409277](https://doi.org/10.1289/ehp.1409277)
- Liu, J. C., Pereira, G., Uhl, S. A., Bravo, M. A., & Bell, M. L. (2017). A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research*, 136, 120-132. DOI: [10.1016/j.envres.2014.10.015](https://doi.org/10.1016/j.envres.2014.10.015)
- Ward, D.E., Hardy, C.C. Smoke emissions from wildland fires. *Environment International*, 17(2–3): 117–134, 1991. DOI: [https://doi.org/10.1016/0160-4120\(91\)90095-8](https://doi.org/10.1016/0160-4120(91)90095-8)

9. Data Sources

- Air Quality System (AQS) API(https://aqz.epa.gov/aqsweb/documents/data_api.html)
- USGS Wildfire Dataset (<https://www.sciencebase.gov/catalog/item/61aa537dd34eb622f699df81>)
- Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2021 (GBD 2021) Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2022. (<https://vizhub.healthdata.org/gbd-results/>).
- Asthma Data - Wisconsin DHS (<https://www.dhs.wisconsin.gov/epht/asthma.htm>)
- COPD Data - Wisconsin DHS (<https://www.dhs.wisconsin.gov/epht/copd.htm>)
- TB Data - Wisconsin DHS (<https://www.dhs.wisconsin.gov/tb/data.htm>)