An Analysis of Wildfire Smoke Impact on Green Bay, Wisconsin

Elaine Zhang

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Introduction

Located on Lake Michigan, Green Bay, Wisconsin is the third-most populous city in the state [1]. Known for the Green Bay Packers and as the Toilet Paper Capital of the world [2], Green Bay is a city rich with history and culture.

As Wisconsin faces increasingly warm summers and longer dry periods, wildfires are becoming more frequent at an alarming rate. Wisconsin has experienced approximately 250 more wildfires this year compared to the average number recorded over the past decade [3]. While it is crucial to address the root issue of global warming, it is also imperative to understand the impacts of wildfire on a population to improve wildfire responses for the people of Green Bay.

As wildfires burn through trees, brush, and even homes, they produce a mixture of gaseous pollutants, hazardous air pollutants, water vapor, and particulate pollutants [4]. This mixture, hereafter known as wildfire smoke, can cause respiratory issues, especially for those with preexisting conditions. Wildfire smoke has been shown to have a clear association with acute effects on asthma [5]. In this analysis, we focused on people with asthma as the main population of interest. We aim to improve the well-being of the entire population by prioritizing the care and protection of the most vulnerable group.

We look to understanding the historical relationship between wildfire smoke and its impact on the community's health to gain deeper insight into how wildfire smoke affects the people of Green Bay and how to protect residents from the adverse effects of wildfire smoke. This report seeks to educate policymakers and city officials on potential health risks associated with wildfire smoke, particularly for people with asthma, and provide suggestions for strategies to mitigate impacts and improve the overall well-being of the residents of Green Bay.

Background

As mentioned in the previous section, wildfire smoke is comprised of many components, including gaseous and particulate pollutants. According to the EPA, particle pollution, also known as particulate matter (PM), is the main component of wildfire smoke and the primary public health threat [4]. Particulate matter can be split into coarse particles ($PM_{10-2.5}$) and fine particles ($PM_{2.5}$). Coarse particles have diameters larger than 2.5 µm and smaller than or equal to 10 µm, while fine particles have diameters 2.5 µm or smaller. Fine particles make up about 90% of the particles present in wildfire smoke and are therefore the most concerning type of PM impacting public health in wildfires [4].

In the formation of the smoke estimate, to be described in the following section, we spent time looking at daily Air Quality Index estimates for Green Bay as a reference point. The Air Quality Index, also known as AQI for short, covers five major pollutants: ozone (O_2), carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM). Particulate matter can be split into PM_{10}, $PM_{2.5}$, and Acceptable $PM_{2.5}$. Depending on the pollutant, each pollutant is assigned an index value based on either an 8-hour or 24-hour observation based according to the health-based national ambient air quality standard for that pollutant. The overall daily AQI index is calculated using each of the indexes from the five major pollutants. AQI includes six color-coded categories, with each category matching a range of index values. Each of these six categories has a description and recommendation for reducing exposure to air pollution. In this analysis, we used a generalized annual average AQI value for the sake of standardization and initial simplification. More on this in the methodology section.

The major research questions in this analysis are the following:

- What is the relationship between acute asthma metrics and wildfire smoke?
- Using historical smoke estimates, what is the predicted wildfire smoke trend and impacts on asthma for the next 25 years?

To address these questions, we start by quantifying wildfire smoke through a wildfire smoke estimate metric, factoring in fire size and distance to Green Bay for wildfires within 650 miles of the city. We then calculate an annual smoke estimate for each year in the past 60 years to create a model predicting the annual smoke estimates for 2025 through 2050. To represent the acute effects of asthma, we use asthma emergency room visit and hospitalization age-adjusted rates for Brown County, Wisconsin from 2002 to 2020. We then investigate the relationship between these asthma metrics and the previously calculated smoke estimates by calculating correlation. Finally, we look to create a predictive model using time-series methods for asthma emergency room visits and hospitalizations that factors in future smoke estimates.

We hypothesize that acute asthma metrics and wildfire smoke are positively correlated, since asthma symptoms usually occur anywhere between immediately to a few days after exposure to triggers [7]. As such, we expect to see an increase in asthma emergency visits and hospitalizations when smoke increases. According to the EPA, increased exposure to particulate matter is associated with increased asthma-related emergency room visits and hospitalizations [8]. Likewise, we hypothesize that wildfire smoke will increase over the next 25 years, with asthma emergency visits and hospitalizations increasing accordingly.

The data used in this analysis includes historical wildfire data, AQI data, and Brown County asthma emergency visit and hospitalization rates. The historical wildfire data is provided by the United States Geological Survey and includes metadata for United States wildland fires from the 1800s through 2020 in a GeoJSON format. This data is provided by USGS in the public domain with citation. We mainly use the geospatial polygons and year associated with each fire for our analysis. Historical daily AQI data is retrieved using the US EPA Air Quality System (AQS) API. AQI data for Green Bay is only available starting in 1985 due to the formation of the EPA in the 1970's and installation of stations in the 1980's. The Brown County asthma emergency room visit and hospitalization age-adjusted rates per 10,000 people were retrieved from the Environmental Public Health Tracking: Asthma Data dashboard provided by the Wisconsin Department of Health Services. As outlined in the Wisconsin.Gov Privacy Policy, material on the website is available for noncommercial use by the general public under fair use guidelines.

In the formulation of this project, we hoped to use the relationship between the asthma metrics and smoke estimates to create a model for smoke impact, where the impact is defined as a combination of asthma hospitalizations and emergency department visit rates. We also wanted to predict the asthma hospitalization and emergency department visit rates for the next 25 years using the smoke estimate predictions. We planned on using time-series models for this extension, building off the smoke prediction model created in the common analysis section.

Methodology

Wildfire smoke is quantified through a smoke estimate metric based on two factors: wildfire size and wildfire distance to Green Bay, Wisconsin. The estimate is designed to produce a larger value for closer, larger fires and a smaller value for farther, smaller fires. Since the wildfire dataset provided by USGS does not contain an exact center for each wildfire, centers were estimated by averaging the distance of each coordinate on the fire polygon to Green Bay. Additionally, we assume that wildfires more than 650 miles away from Green Bay do not contribute to the city's smoke levels. To focus on more recent impacts and mitigate potential inaccuracies in older data collection methods, the data was filtered to include wildfires from the last 60 years, starting in 1964. Note that the source dataset ends in 2020 and does not include wildfires from 2021-2024.

The wildfire smoke estimate formula is defined as follows:

$$\text{smoke estimate} = \text{scaling factor} \cdot \frac{\text{fire size}}{\text{fire distance}^2}$$

We based our formula on the inverse-square law, which indicates that the observed intensity of a given physical quantity decreases in proportion to the square of the distance from its source. In this case, the severity of smoke is inversely proportional to the distance from the center of the fire. Fire size is used in the numerator to account for the fact that larger fires will produce more smoke, and smaller fires will produce less. The fire distance in the denominator penalizes fires that are far from Green Bay, effectively creating an estimate that produces larger values for closer fires vice versa as we intended. The scaling factor is used to bring our estimate to a comparable scale with the Air Quality Index (AQI), which we will discuss next. This scaling factor was manually adjusted to reach a desirable scale for easy visual comparison with AQI estimates, which we ultimately set to 1,000,000.

Using the formula defined above, we calculate a smoke estimate for each fire within 650 miles of Green Bay from 1964 through 2020. We took the mean smoke estimate for each year to create an annual estimate. For these estimates, we used a scaling factor of 2,000,000. After plotting these smoke estimates, we compared the estimates with a trend of the total acres burned per year within 650 miles of the city.

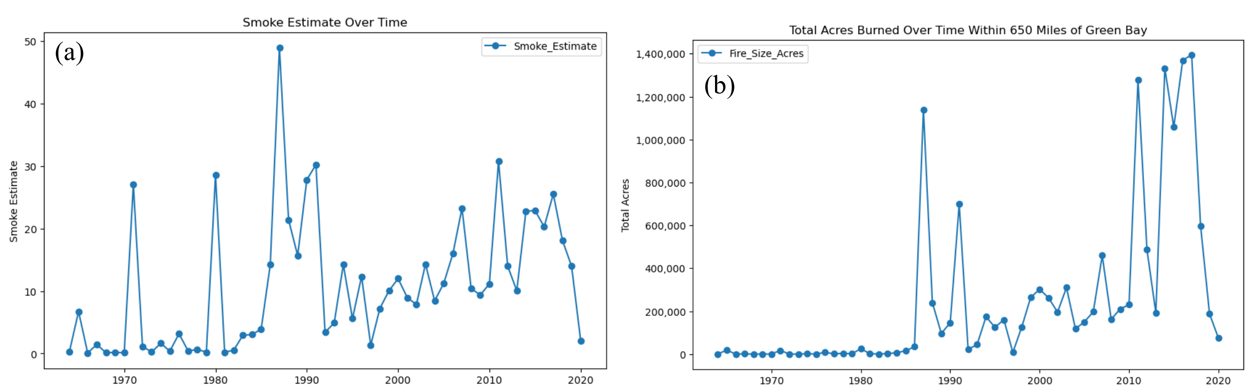

Fig. 1. Comparison of smoke estimate and acres burned: (a) initial smoke estimate (b) total acres burned over time

Upon comparison, we found ourselves wondering the following - would a year with one large fire moderately far away contribute more smoke to the annual estimate than multiple smaller, similarly sized fires that are close? By taking the average of all the smoke estimates without any weight on frequency, this estimate is not the most representative. As such, we adjusted the aggregation method to reflect fire frequency for each year. Rather than taking the mean, the smoke estimates for all fires in a year are summed up and then divided by the number of days in fire season, defined as May 1st through October 31st (184 days). The scaling factor is then adjusted to maintain a comparable scale with AQI. This approach represents the average daily smoke estimate during fire season and accounts for the compounded smoke effects of frequent, smaller fires.

To benchmark our smoke estimate and understand its performance, we look at Air Quality Index (AQI) values from 1985 through 2023. The AQI dataset consists of daily values for each of the five pollutants during the fire season. To create an annual value for comparison with annual smoke estimates, we take the average of all five values for the entire fire season. This is used as a representation of the average AQI value for the fire season. Smoke estimates are scaled to match the AQI value range from 0 through 500 for better visual comparison.

For our forward-looking insights, we create a predictive model to predict the future annual smoke estimates for the next 25 years, from 2025 to 2050. We start by fitting a linear regression model on our annual smoke estimates, where year is the sole predictor. The reasoning behind this is that although the smoke estimate trend looks quite complex, it has a generally upwards trend, especially in recent years.

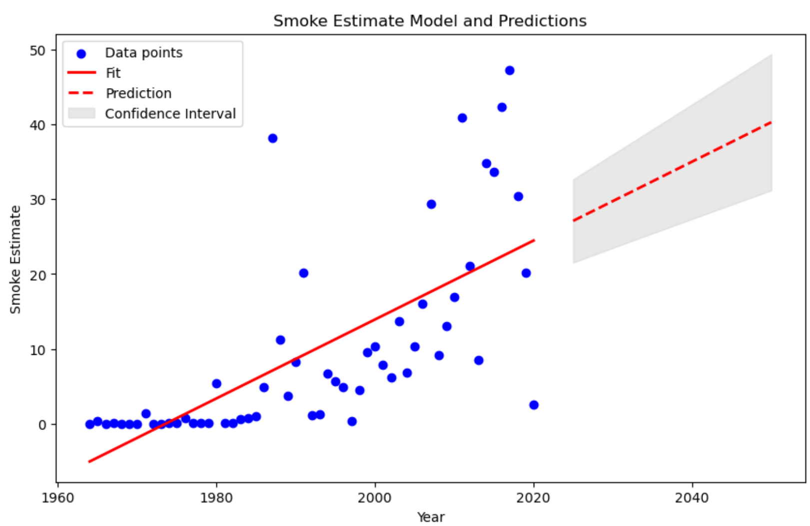

Fig. 2. Linear regression model for smoke estimates with predictions for 2025-2050 and 95% confidence intervals

Upon plotting the data for the initial linear model, we see that the smoke estimate for 1987 is much higher than the surrounding years, signaling that this could be an influential outlier. We replace this point with the average of the two smoke estimates of the year preceding and year following 1987 and refit the model.

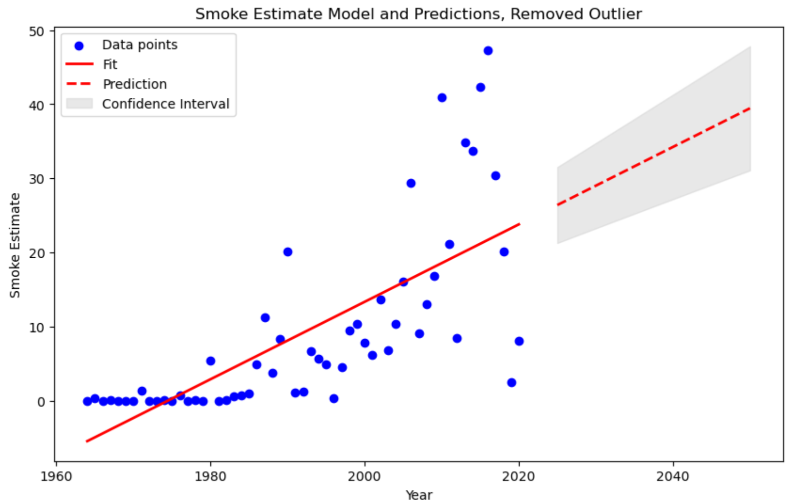

Fig. 3. Linear regression model for smoke estimates with predictions for 2025-2050 and 95% confidence intervals, with 1987 replaced

Though the R^2 value for this linear regression is a bit higher than the previous iteration (0.508 compared to 0.472), it is not apparent that this model is a good fit. Next, we try fitting an Autoregressive Integrated Moving Average (ARIMA) model to capture the time-series nature of our data. We use Auto-ARIMA, an automated approach to selecting the best-fitting ARIMA model, to select the best model parameters. This automated method was chosen due to lack of prior experience with the model and the expectation that it would provide an objectively well-chosen set of parameters. We fit the model and predict the next 25 years of smoke estimates as shown below.

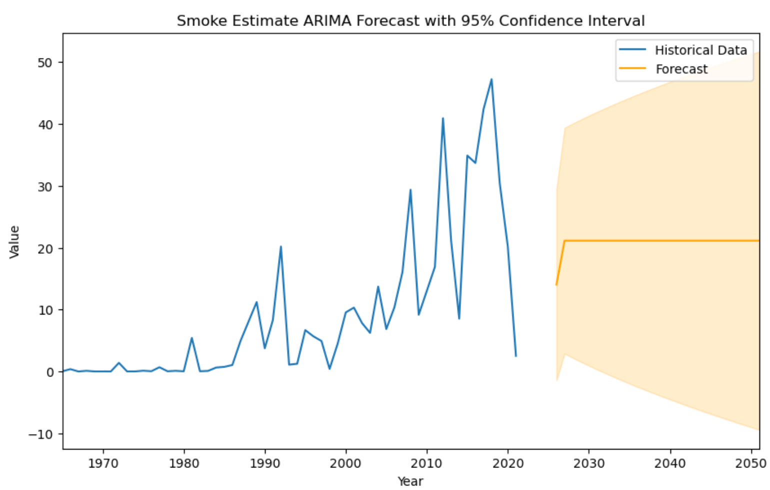

Fig. 4. ARIMA model for smoke estimates with predictions for 2025-2050 and 95% confidence intervals

The forecast is largely a flat line, which seems inaccurate. To validate this result, the data is fitted to another time-series model: the Exponential Smoothing State Space Model (ETS). This model extends exponential smoothing, assigning exponentially decreasing weights to past observations, into a formal state space framework. Unlike ARIMA, ETS captures seasonality in the data. Using the statsmodels

Python package, the ETS model with an additive component is fitted to predict smoke estimates for the next 25 years with a 95% confidence interval.

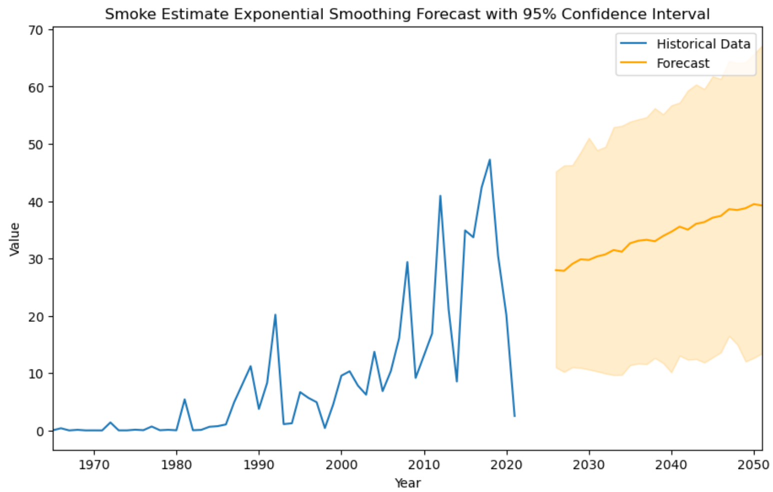

Fig. 5. Exponential Smoothing model (ETS) for smoke estimates with predictions for 2025-2050 and 95% confidence intervals

This model captures the overall upwards trend and the variability of the smoke estimates that the previous models do not. As such, we choose this model as our primary smoke estimate predictions.

To focus on the human aspect of wildfire smoke impact, we turn to our asthma data. We use Brown County annual age-adjusted rates per 10,000 people for asthma hospitalizations and emergency room visits from 2002 through 2020. We use age-adjusted rates to account for the possibility that asthma emergency room visit and hospitalization rates may be more frequent for different age groups, and thus avoiding misrepresentation and overgeneralizing. We start by validating if pairwise correlations between the asthma metrics and our smoke estimates follow our hypothesis. We planned to create a predictive model for asthma metrics upon confirmation of our hypothesis, however this fell through as the correlations did not align. To check if the asthma metrics and smoke estimates were correlated with lag, we computed cross-correlation with a lag of 4 years. This proved to be illogical even with statistically significant results, as it meant that it would take 4 years for the effects of wildfire smoke to show in people with asthma. Knowing that asthma symptoms show in a relatively immediate manner, this possibility makes little logical sense. To ensure data integrity and prevent misrepresenting the data, we chose not to create a predictive model with this asthma dataset and smoke. We choose to be honest to the data by not fitting models that will cause flawed decision-making.

In working with sensitive health-related data, we followed best practices and license agreements by using data provided by a government entity in a manner that was already aggregated and unidentifiable. This work is noncommercial and follows the fair use guidelines and is also published publicly under the MIT license for reproducibility and includes a well-documented commit history for transparency.

Findings

We start by looking into a couple exploratory plots regarding fire frequency, total acres burned, and a comparison of our AQI and smoke estimates over the years.

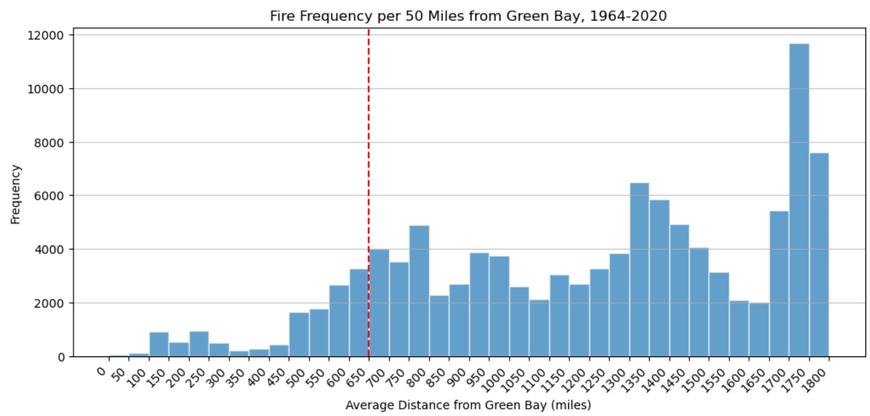

Fig. 6. Fire frequency histogram per 50 miles from Green Bay from 1964-2020

This visualization shows the total frequency of fires at different distances from Green Bay, Wisconsin in 50-mile buckets, from 0 to 1800 miles. The visualization includes a red dashed line marking the cut-off at 650 miles for inclusion in the smoke estimate analysis. Wildfires were filtered to include only those with an average distance less than 1800 miles to Green Bay, and then grouped into 50-mile buckets to create the count for each 50-mile grouping. There is no distinction for if the fire was east or west of the city, and no distinction for which year the fire occurred. This figure shows that there have not been a substantial number of fires less than 500 miles of Green Bay. Though it looks like Green Bay has not been affected heavily by wildfires in the last 60 years, keep in mind that this histogram does not account for fire size or year. We continue by plotting the total acres burned per year within 650 miles of Green Bay.

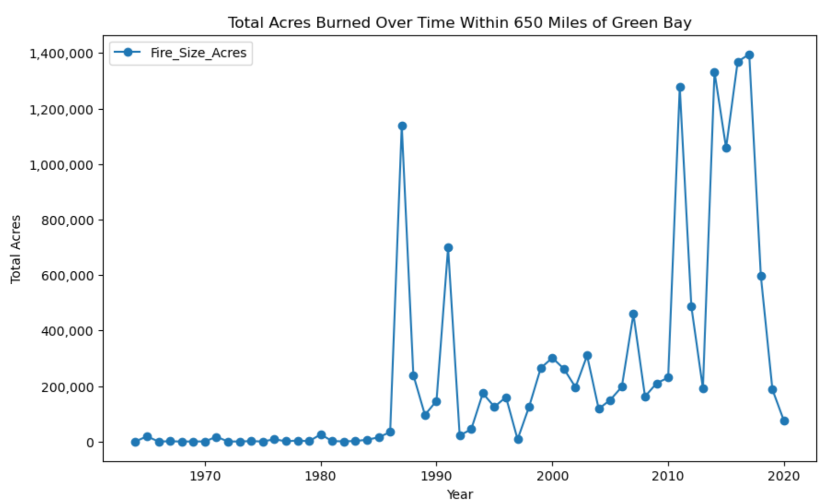

Fig. 1(b). Total acres burned per year within 650 miles of Green Bay

This visualization displays the total number of acres burned each year in the last 60 years where the center of the fire is within 650 miles of Green Bay, Wisconsin. We plot years on the x-axis, and total acres on the y-axis. It is possible for a fire's center to be within 650 miles but have a portion of the fire outside of the 650-mile boundary. In such cases, the fire's total burned acreage is included in this visualization regardless of how much of the fire was within 650 miles of Green Bay. Notice that there is a substantial spike in total acres burned in the year 1987, lining up with the outlier we discussed in the methodology section. Also note that the overall variability of total acres burned increases after the first spike in 1987, and the upper limit of total acres burned continues to increase over time.

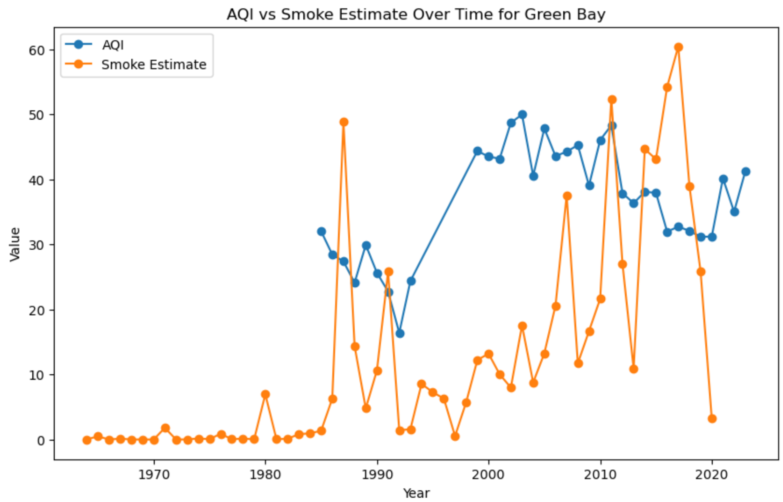

Fig. 7. AQI vs Smoke Estimate trends from 1964-2023, smoke estimates scaled to display with AQI

This visualization compares the AQI estimates acquired from the AQS API to the smoke estimate we created in the common analysis. Years are on the x-axis, and AQI and smoke estimate values are plotted on the y-axis. This figure is used for comparison between the AQI and smoke estimate trends. Visually, it is hard to see if there is any strong correlation between AQI and the smoke estimate, especially with the lack of AQI data from 1994 through 1998. Limitations of comparing with AQI and our smoke estimate is discussed further in later sections.

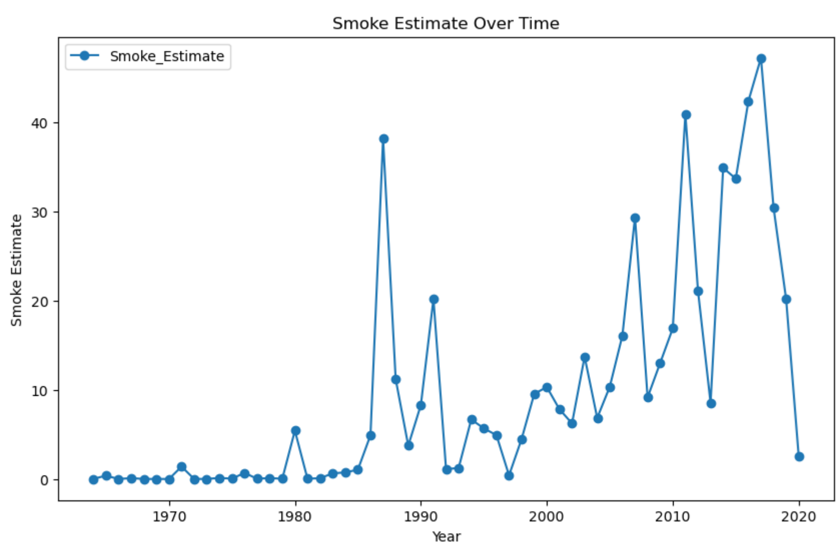

Fig. 8. Finalized smoke estimate trend, where smoke estimates are normalized to fire season

Above is the final smoke estimate trend created by the second method of aggregating and normalizing smoke estimates to fire season. We see the spike in 1987, and the subsequent increase in variability and peak smoke estimates, like Fig. 1(b) above.

As shown in Fig. 5, our predicted smoke estimates fitted using the ETS exponential smoothing model for 2025 through 2050 are steadily increasing, shown above. The width of the 95% confidence interval in orange shows that the predictions can range anywhere from a little over 10 to about 40 to 50. We also take note that the upper limit of the confidence interval is much steeper than the lower limit, meaning that the variability is predicted to increase, and the increasing upper limit trend is expected to continue as well.

Moving to the asthma analysis, we start by looking at a couple exploratory plots as well.

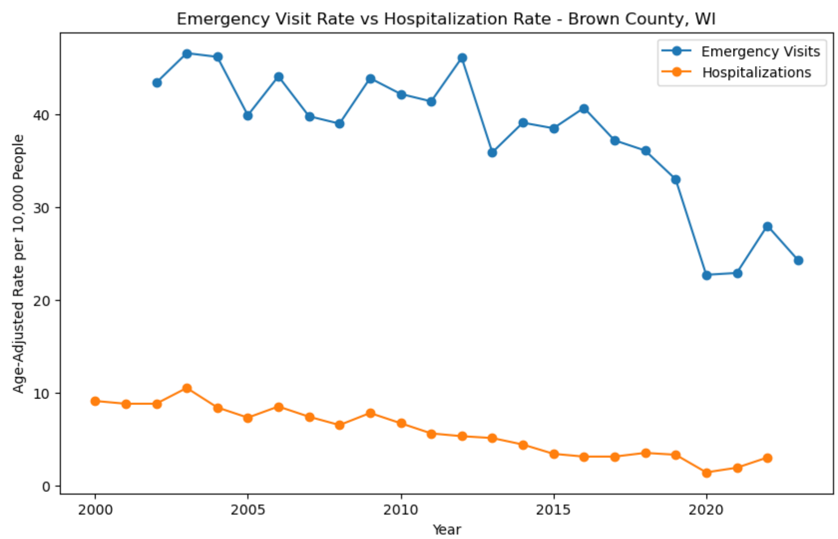

Fig. 9. Emergency visit rate vs hospitalization rate trends for Brown County, WI from 2000-2023

Both hospitalization and emergency visit rates are decreasing over time, with emergency visits having more variability over time. Decreasing emergency visits could mean that less asthma triggers are present over time, while decreasing hospitalizations could mean that asthma treatment quality is improving and thereby reducing the need for asthma-related hospitalizations. We keep this in mind as we look at correlation between these asthma metrics and smoke estimates.

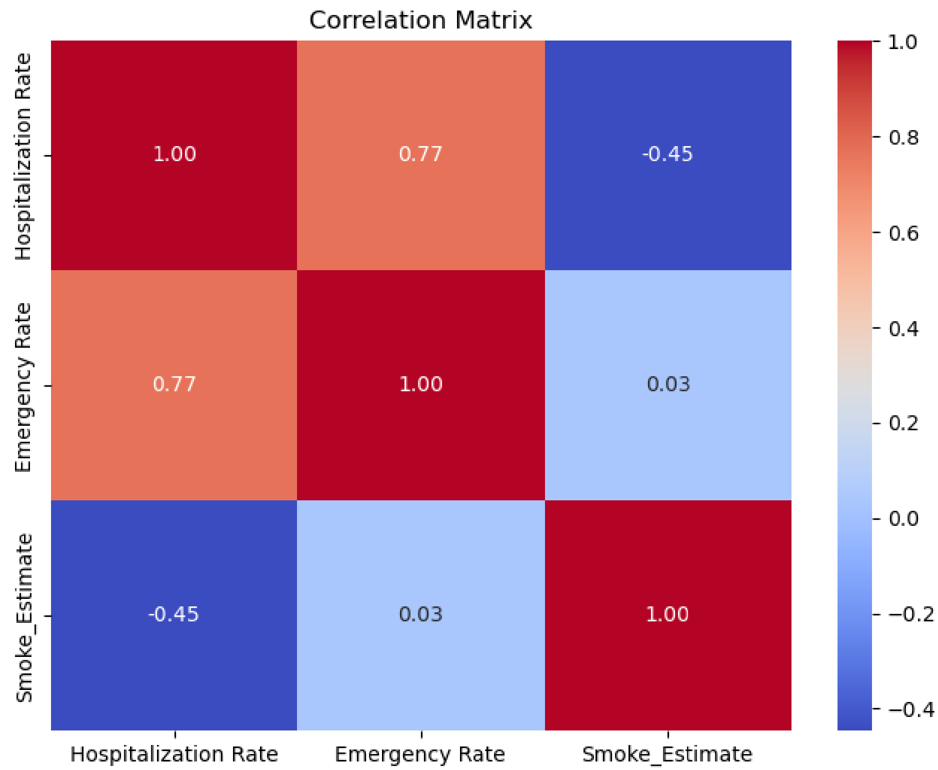

Fig. 10. Correlation matrix between hospitalization rate, emergency rate, and smoke estimate. Correlation value is shown at the intersection between any two variables.

This correlation matrix shows the correlation between each of the asthma metrics and smoke estimates. The 0.77 correlation between emergency visits and hospitalizations aligns with the fact that emergency visits can lead to hospitalizations, and with a p-value of 0.00013 this result is statistically significant. The 0.03 correlation between emergency visit rates and smoke estimates has a p-value of 0.895, making it statistically insignificant and practically insignificant. Lastly, the correlation between smoke estimates and hospitalization rates is -0.45 with a p-value of 0.055. Though this p-value means it is not statistically significant, we investigate this as it may prove to be of some practical significance. A correlation value of -0.45 means that the two are moderately negatively correlated, much unlike our hypothesis and background research. This means that a larger smoke estimate is associated with a lower hospitalization rate. This result signals that we require more representative, detailed asthma data as well as a more holistic approach to calculating our smoke estimate to validate our findings before we can provide an accurate model for predicting future smoke-related asthma impacts.

Discussion

The findings from this analysis confirm that wildfire smoke is becoming an increasingly important issue as wildfires are becoming increasingly common. Though the asthma analysis in this initial study showed unexpected results, it still serves as a starting point for investigation into an important issue for the community.

To better protect the people of Green Bay, especially at-risk populations like those with asthma, city officials should educate city residents on preventative measures and responses to wildfires and wildfire smoke. The city should implement policies to regularly clean up flammable debris, as debris is responsible for about one-third of fires [3]. The city should also educate city residents on the dangers of fires started by equipment like lawnmowers and recreational vehicles and methods to prevent these fires. We also recommend city officials to educate residents on procedures to follow when wildfire smoke becomes an issue, such as mask usage and ways to keep buildings well ventilated. In the case that this analysis is extended to create an effective predictive model for smoke-related asthma hospitalizations and emergency visits, city officials can use the model to better prepare hospitals for spikes in asthma hospitalizations and emergency visits due to wildfire smoke.

Since this analysis is for the benefit of the community and to better the lives of Green Bay residents, we implement human centered data science principles to make sure that this work is ethical, inclusive, and impactful for the people who will be affected by the results of this analysis. To ensure fairness and accurate representation among age groups, we use age-adjusted asthma emergency visit and hospitalization rates instead of raw counts and rates. We enforce data stewardship through the ethical use of secondary data through upholding ethical standards when working with the asthma dataset. In the formulation of the predictive smoke estimate model, we iterate on the models to improve and leave the door open for iteration based on societal feedback. We also take ownership and accountability by knowing when to stop and question results instead of plowing ahead and creating a nonsensical model that may negatively impact people's decision-making and consequently, their lives. We ensure reproducibility and explainability in our work through creating well-documented code artifacts and writing reports and figure descriptions.

Limitations

The data used in this analysis has many limitations. First, the wildfire data does not account for any fires in Canada. Considering Wisconsin's proximity to Canada, this is leaves out a big piece of the data needed to accurately capture wildfire smoke conditions in Green Bay. Second, the wildfire data does not contain details like wind direction, wind speed, fire duration, and other influential factors that will impact smoke. For the Air Quality Index (AQI) dataset used to benchmark the smoke estimate, we lack data from before 1985 as the United States Environmental Protection Agency (EPA) was created in the 1970s, and station installation began in the 1980s. There is also a missing chunk of data from 1994 through 1998 that was not filled in. Due to the sparsity of the data, we do not have a full, accurate representation of AQI for the period we are interested in. For the last dataset, the asthma emergency visit and hospitalization rates, our first limitation is that the data is at the county level. Though Green Bay is the county seat and the largest city in the county, using Brown County data leaves room for error. Since the dataset is provided by the Wisconsin Department of Health Services, the dataset does not include any federal hospitals. Another limitation of the asthma dataset is that the age-adjusted rates are annual and do not have a distinction for fire season. It also does not contain any information on the triggers leading to emergency visits or hospitalizations, thereby combining all possible triggers into one rate. This means that people who are hospitalized for asthma symptoms triggered by dust mites or pollen outside of May 1st through October 31st are also included in the analysis with wildfire smoke. We should be only looking at asthma hospitalizations and emergency visits triggered by wildfire smoke for the most accurate picture, if possible. This limitation may be a result of maintaining privacy standards for medical data and not feasible to get around. To get a better picture of asthma trends in general, we also need to understand how asthma treatment quality has changed over time.

Some calculation limitations and generalizations made in the analysis include the following. When calculating fire center, we use the average distance from each of the polygon's borders. This assumes that fires will have a symmetrical center, and that this center has the strongest fire. This may not accurately represent wildfire behavior and is a potential place for error. Likewise, we attributed every fire's entire size to the smoke estimate, regardless of how much of the fire was within the 650-mile radius. If the estimated center is within 650 miles of Green Bay, we assume that the entire fire contributes to the smoke estimate, leaving room for error. The smoke estimate formula is heavily simplified, as it only considers two properties of each wildfire. This estimate is therefore highly unrepresentative of the actual wildfire smoke conditions for Green Bay. For the AQI calculation, each of the five pollutants are weighed evenly. Knowing that wildfire smoke is mainly comprised of particulate matter, a more accurate benchmark for the smoke estimates would incorporate more weight to the particulate matter component of the AQI estimates and decrease the effects of the other four pollutants on the AQI estimate.

In creating the model to predict future smoke estimates, the ETS model was fitted without full confirmation that the assumptions are met. The ETS model assumes that there is regular seasonality, with residuals assumed to be independent and identically distributed, normally distributed with a mean of zero, and homoscedastic. In using the additive component, we assume that the seasonal trend has a linear relationship. Since we apply this model without full confidence in the underlying assumptions, our findings need to be tested and replicated by others before it can be used in decision-making.

Conclusion

In this study, we explore the impact of wildfire smoke on Green Bay, Wisconsin through looking at the relationship between asthma hospitalization and emergency visit rates and wildfire smoke estimates. We hypothesized that as wildfire smoke increases, asthma emergency visit and hospitalization rates should increase as well. We defined a smoke estimate, forecasted smoke estimates for the next 25 years, and analyzed the correlation between asthma hospitalization and emergency visit rates and wildfire smoke estimates. Results showed that smoke estimates are predicted to increase for the next 25 years in Green Bay, and asthma metrics are negatively correlated with the smoke estimates. These findings signal that further investigation is required before a meaningful predictive model can be created for wildfire smoke impacts on asthma in Green Bay.

This study explores solving data science problems from a human centered lens, where the impact and meaning of what we do for the people this study informs every decision we make in the process. We maintain reproducibility standards for our fellow data scientists while ensuring our process is well-documented for explainability for all audiences. Through focusing on human-centered research questions and goals, this study follows human centered data science principles to ensure that data science is used for the betterment of our community.

References

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Data Sources

Wildfire data - Initial wildfire dataset retrieved from USGS here. We use the USGS_Wildland_Fire_Combined_Dataset.json file found in the GeoJSON Files zip file. This dataset includes metadata for wildland fires from the 1800s to the present and provides fire polygons in a GeoJSON format.

AQI data - Daily Air Quality Index data is retrieved using the US EPA Air Quality System (AQS) API. We focus on Gaseous AQI pollutants CO, SO2, NO2, and O2 and Particulate AQI pollutants PM10, PM2.5, and Acceptable PM2.5. The API provides historical data starting in the 1980's and does not provide any data in real-time. The AQI index indicates how healthy or clean the air is on a specific day.

Asthma data – Annual asthma emergency room visit and hospitalization age-adjusted rates per 10,000 people were retrieved from the Environmental Public Health Tracking: Asthma Data dashboard provided by the Wisconsin Department of Health Services. Datasets were obtained by filtering the interactive dashboard to Brown County and downloading from the county-specific trend view.