Saisriram Gurajala
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Final Report
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Introduction

Resolving the connection between wildfire smoke and respiratory disease incidence is a salient and essential investigation for current times. In 2022 Chronic lower respiratory diseases, including asthma, have caused over 147,000 deaths at a rate of 44.2 per 100,000 people in the United States[1]. Additionally, the EPA has reported that prolonged exposure to wildfire smoke exacerbates lung disease in the short term and reduces lung function in the long term[2]. Reinforcing the potentially dire consequences of this connection, wildland fire smoke $PM_{2.5}$ exposure has been linked to adverse health outcomes and mortality in the United States[3]. The rising frequency and intensity of wildfires driven by climate change makes this potential causal relationship even more pressing. This analysis seeks to uncover how wildfire smoke impacts the incidence of respiratory diseases in the community of Dearborn, Michigan. This research unites the fields of ecological research and public health, orienting current knowledge towards an interdisciplinary phenomenon. In investigating this research question, I aim to establish a data-driven framework connecting natural disasters with chronic respiratory health outcomes.

The real-world implications of this work include enablement of public policy officials to design targeted interventions, effectively allocate resources, and mitigate the health impacts of wildfire smoke exposure. Moreover, the citizens of Dearborn may benefit from actionable findings which lead to better understanding of their real-world health risks. This work also contributes to a growing body of interdisciplinary research linking environmental phenomena and public health. Escalating climate-related disasters in recent years necessitate through and rigorous evaluation of this question. Refining our understanding of wildfire smoke's impact on human health empowers effective planning, containment, and proactivity from impacted communities.

Background/Related Work

Previous efforts in this project focused on creating a framework to quantify wildfire smoke impacts on Dearborn, Michigan, based on geospatial and temporal wildfire data. To source wildfires and generate an initial metric, I utilized United States Geological Survey data of wildland fires in the US and territories from 1800 to the present. The goal was to generate annual estimates of wildfire smoke impacts over the past 60 years (1961–2021), and to compare these estimates with available Air Quality Index (AQI) data. These efforts laid the groundwork for developing predictive models exploring the relationship between wildfire smoke

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and chronic respiratory disease incidence. To estimate wildfire smoke impacts, fires within a 650-mile radius of Dearborn during the fire season (May 1–October 31) were analyzed. The metric considered two factors: fire size (measured in acres burned) and proximity to the city. Larger and closer fires were assumed to contribute more significantly to smoke exposure. Robustness of these estimates was evaluated by comparing them with AQI data from the U.S. EPA's Air Quality System (AQS). These comparisons provided initial insights into the alignment between modeled smoke impacts and observed air quality trends.

The initial smoke metric, calculated as the ratio of fire acreage burned to the squared distance from Dearborn, served as a foundational estimate. A 2018 study found wildfire smoke trended with the Palmer drought severity Index in California[4]. Therefore, I sought to refine the smoke metric via local climate metrics, including temperature, precipitation, and drought severity index, to capture the multifaceted factors influencing wildfire smoke impacts. To source this information, the National Oceanic and Atmospheric Administration's (NOAA) "Climate at a Glance" dataset, provided by the National Center for Environmental Information (NCEI), was utilized. This dataset furnished county-level coverage for Wayne County, Michigan, including temperature metrics such as average, maximum, and minimum temperatures; precipitation metrics including monthly and annual precipitation data; and drought metrics such as the Palmer Drought Severity Index. The key variables of average temperature, average precipitation, and palmer-drought severity index were selected for inclusion in the refined smoke metric (**Figure 1**).

After formulating a refined smoke metric, I proceeded to focus on assessing the metric's broader implications for public health. I specifically selected the incidence of chronic respiratory diseases after observing the number of deaths to be essentially a linear function of time. Information about chronic respiratory disease incidence was sourced from the Global Burden of Disease (GBD) dataset from the University of Washington's Institute of Health Metrics and Evaluation (IHME). The analysis delved into disease trends with state-level specificity for Michigan, spanning from 1990 to 2021. To predict the future incidence of chronic respiratory disease in Michigan, I needed to predict the wildfire smoke metric. To do this I employed Holt-Winters Exponential Smoothing, which was previously applied in the prior work conducted in the common analysis section. Exponential Smoothing is a time series forecasting technique that accounts for seasonality, trends, and noise in the data. I next needed to predict the incidence of respiratory diseases as a function of wildfire smoke. I used cubic polynomial regression of the smoke metric to predict future incidence values, incorporating a linear term for the year to capture long-term trends over time.

Methodology

In designing this study, I sought to integrate robust analytical methods with a human-centered approach. Thereby, I sought to ensure that the outcomes would scientifically valid and accessible as well as actionable for the communities affected. The goal of this project was to understand the long-term health impacts of wildfire smoke on populations in Dearborn, Michigan. I placed a particular focus on chronic respiratory diseases like asthma and chronic obstructive pulmonary disease (COPD). To achieve this, I selected methods that would provide clear, understandable insights for health officials, policymakers, and the public. These methods ensure the findings can be effectively communicated and used to inform decisions such as public health interventions and resource allocation. Additionally, I filtered the data to wildfires within 500 miles to select for fires more impactful to the citizens of Dearborn, Michigan.

To forecast the impact of wildfire smoke, I employed Holt-Winters Exponential Smoothing. This forecasting method was chosen for its ability to capture both the short-term fluctuations and long-term trends in wildfire data. In my dataset wildfires were found to exhibit periodic (approximately three years in length) spikes, making Holt-Winters particularly well-suited to model this cyclical behavior. This method allowed me to generate reliable estimates of future smoke levels, providing health professionals with critical foresight to anticipate periods of elevated risk. Therefore, proactive public health strategies, such as the deployment of medical resources or public advisories became accessibility. Additionally, model results are simple to communicate with stakeholders without a deep technical background, resulting in accessibility and high impact.

To model the relationship between wildfire smoke and respiratory disease incidence, I utilized polynomial ordinary least squares regression. I selected this approach for its interpretability, which is crucial when communicating complex relationships to non-experts. Additionally, polynomial regression allows for both linear and non-linear relationships. Therefore, this method provides flexibility in capturing the intricate effects of wildfire smoke on public health over time. The linear year term helped assess whether the health impacts of wildfire smoke have evolved in a predictable pattern or whether the effects are becoming more pronounced. This interpretability made it easier to translate the results into actionable insights, enabling policymakers to understand the specific impact of smoke exposure on health outcomes and plan accordingly. The straightforward nature of the model supports its use in public health communication, ensuring that its results could be translated into real-world interventions.

Ethical considerations were woven throughout the design and execution of the study. For instance, the health data sourced from the Global Burden of Disease (GBD) dataset was handled in strict accordance with the terms set by the University of Washington's Institute for Health Metrics and Evaluation (IHME), ensuring that the privacy and confidentiality of individuals represented in the dataset were maintained. In addition to ethical data handling, I emphasized the importance of transparency and clarity in communicating the results. The goal was to make the findings not only scientifically sound but also accessible to communities who might be directly affected by wildfire smoke. This meant using clear visualizations, avoiding complex jargon, and ensuring that the results could be used to inform decisions on public health and resource allocation. The design of the study was aimed at empowering the Dearborn community by providing them with understandable tools to anticipate and mitigate the impacts of wildfire smoke.

Findings

The integration of climate measurements into the smoke metric formulation improved correspondence of the metric with air quality data. This refined metric extended the original inverse square law-based formulation by incorporating the squared ratio of temperature to the product of average precipitation and drought severity index. Therefore, the original metric was scaled by average climate conditions in the year the fire occurred (**Figure 1**). The enhanced formulation demonstrated a significant improvement in its alignment with annual Air Quality Index (AQI) values, achieving a Pearson correlation coefficient of $R=0.425$ and a p-value of 0.008. The previous metric, when filtered to fires within 500 miles of Dearborn, achieves a Pearson correlation coefficient of -0.04 and a p-value of 0.828. Therefore, the new smoke metric exhibits a statistically significant correspondence with air quality trends over time represents a substantial improvement to the previous metric (**Figure 2**).

Holt-Winters exponential smoothing was employed to forecast the smoke metric over time, and an eight-year rolling average was used to examine temporal trends. The results revealed an overall upward trajectory in the smoke metric, with intermittent spikes corresponding to periods of heightened wildfire activity. Figure 3 illustrates these trends, with the blue line representing computed respiratory disease incidence from observed data and the red line depicting predicted incidence based on the forecasted smoke metric. The predicted incidence mirrored the temporal patterns of the observed values, showing a general increase over time punctuated by specific peaks.

Polynomial regression modeling was used to predict current chronic respiratory disease incidence, incorporating year, and exponentiated terms of the moving average of smoke metric as predictors. Several different versions of the smoke metric were tried, including a moving average, an exponentially weighted moving average, and the raw smoke metric. Of these the moving average performed the bets, with the model achieved an adjusted R-squared value of 0.669. This model indicates that the chosen variables accounted for a significant portion of the variance in the observed incidence data. The p-value of 2.10×10^{-5} further confirmed the statistical significance of the model (**Figure 4**). The alignment between predicted and observed incidence demonstrated the model's capacity to capture the complex relationship between these variables and chronic respiratory health disease incidence (**Figure 5**).

Projections of chronic respiratory disease incidence from 2021 to 2050, derived from the forecasted smoke metric, revealed a steady upward trend over the analyzed period. After a slight dip post-2020, incidence values began to rise consistently, surpassing 2020 levels by the mid-2020s. The model predicts a year-over-year increase in incidence rates, highlighting a continuous upward trajectory throughout the projection period. Figure 6 depicts these forecasts, with clear evidence of rising incidence values as time progresses, reflecting the sustained influence of smoke exposure on chronic respiratory disease outcomes.

Discussion/Implications

The findings from this study shed light on several clear and actionable links between wildfire smoke, air quality, and public health for citizens and agencies in Dearborn, Michigan. The refined smoke metric integrates local climate variables such as temperature, precipitation, and drought severity with the much broader USGS datasets. Therefore, it has allowed for a more nuanced understanding of how these factors collectively influence air quality in the region. By incorporating these measurements into the smoke metric, I was able to improve its predictive power and enabled more accurate forecasting of the impact of wildfire smoke on air quality. This refinement bridges the gap between distant wildfire events and their real-world consequences for Dearborn’s residents.

The relationship between wildfire smoke and chronic respiratory diseases, such as asthma and chronic obstructive pulmonary disease (COPD), is particularly striking. The data clearly demonstrate a correlation between increasing levels of wildfire smoke and rising incidences of these respiratory conditions. This connection is especially concerning, given the projected rise in wildfire smoke intensity over the next several years. In my analysis, I found that the cumulative effect of multiple years of exposure to wildfire smoke will likely result in a steady increase in chronic respiratory diseases. This raises urgent questions about public health preparedness in the face of increasing wildfires, especially since the health impacts of wildfire smoke may not be immediately apparent but can accumulate over time.

Given the projections of increasing wildfire smoke impact, it is imperative that the city of Dearborn take immediate action to address these findings. City council members, the city manager, and the mayor must prioritize the implementation of both short-term and long-term strategies to mitigate the effects of wildfire smoke on public health. Short-term measures might include expanding air quality monitoring infrastructure, improving access to air filtration systems for vulnerable populations, and issuing public health advisories during periods of high smoke exposure. Public education campaigns to inform residents about how to protect themselves during wildfire season could also be an immediate step. However, it is the long-term actions that will likely have the most substantial impact. Healthcare infrastructure supporting chronic respiratory conditions, air quality regulations, and urban planning accounting for growing impact of wildfire smoke will all be essential in minimizing the future health burden. The city has a limited window of time to act, and the implementation of concrete plans should begin as soon as possible to ensure that public health risks are addressed proactively,

The human-centered data science principles I applied in this project were key to ensuring that my findings were not only scientifically robust but also practical and relevant to the people of Dearborn. One such principle was my decision to model the smoke metric as a rolling average. The effects of wildfire smoke are not always immediate, and often the cumulative impact over several years is more relevant than the specific impact of a single year. By using a rolling average with an eight-year window, I was able to capture the delayed and compounded effects of repeated smoke exposure. Therefore, the model reflects the lived experiences of residents who may experience health impacts long after a wildfire has occurred. Additionally, I selected Holt-Winters exponential smoothing for forecasting because of its ability to handle seasonal and cyclical patterns, which are inherent in both wildfire occurrences and air quality trends. The flexibility of this approach is crucial from a human-centered perspective, as it provides city officials and residents with practical, forward-looking insights that can inform decision-making in the face of an uncertain future.

Another human-centered design principle central to this project was the use of polynomial ordinary least squares (OLS) regression to predict chronic respiratory disease incidence. This model captures both linear and non-linear relationships between the smoke metric, year, and chronic respiratory disease incidence. The flexibility of polynomial regression makes it a powerful tool for interpreting and modeling complex phenomena such as human health. The model's transparency and ease of understanding ensure that stakeholders—whether public health officials, policymakers, or residents—can grasp the key drivers of respiratory disease trends and make informed decisions. This interpretability is critical for ensuring that the findings are accessible and actionable and allows for effective communication of complex health risks to those who need it most.

Additionally, as much as possible I have integrated principles of reproducibility and access of my work, code, and datasets. This effort has improved the accuracy and reliability of my findings. In the context of enabling accessibility of my results, I have ensured the findings are relevant, actionable, and understandable for the people most affected. My work has focused on long-term impacts and ensured the flexibility of my models while also prioritizing explainability. I have thereby developed a framework that can help Dearborn's leadership and residents respond to the growing challenge of wildfire smoke in a way that is both effective and equitable. My sincere hope is that the citizens and municipality of Dearborn swiftly and strategically plan and execute mitigation efforts for the rising risk of wildfire smoke.

Limitations

While the study offers valuable insights into the relationship between wildfire smoke and chronic respiratory diseases, there are several key limitations and assumptions that must be considered when interpreting the results.

First, there are licensing restrictions associated with the use of the Global Burden of Disease (GBD) dataset, which limits its accessibility and potential for broader dissemination. According to the terms of use, users are prohibited from copying, reproducing, or redistributing the dataset outside of their organization or to individuals who do not require access. Additionally, actions like decrypting, reverse-engineering, or compiling a similar dataset from the GBD data are prohibited.

Therefore, I am unable to share the respiratory disease data used for this work, significantly impacting reproducibility of the study.

Data-related limitations also exist in terms of the temporal and spatial scope of the datasets used. The GBD dataset only provides health data from 1990 onward, limiting exploration of long-term trends extending further into the past. The wildfire data, while useful, comprises only about 1,500 fires with an uneven distribution across years. The number of fires per year ranged from a minimum of four to a maximum of 130. This source of variability resulted in uncertain approximation of health events for a given year when modeling with smoke metric. This uneven distribution could potentially skew the analysis, and result in poor modeling in years with fewer fire events.

Another challenge encountered was the need to rescale the drought severity index when constructing the smoke metric. The original drought index values included negative numbers, which could result in inconsistency for the smoke metric. To address this, I rescaled the drought severity index to lie within zero and one. While this approach preserved the relative distance between points, it may have resulted in loss of nuance for negative drought severity values, thereby affecting the accuracy of the smoke metric in certain regions or years.

From a methodological standpoint, both the polynomial regression and Holt-Winters exponential smoothing methods have their own assumptions and limitations. Polynomial regression shares its assumptions with ordinary least square regression. Errors are assumed to be normally distributed with constant variance, which may not be true for complex and non-linear temporal phenomena. Additionally, it assumes that the relationship between the predictors and the outcome can appropriately modeled as a linear function. Additionally, the polynomial regression model does not account for potential autocorrelation between observations which may occur in time series datasets, affecting the reliability of predictions[5].

Holt-Winters exponential smoothing also has inherent limitations. The method assumes that future values are a weighted average of past observations, with more recent data given higher weight. While this method is useful for forecasting trends, it may not fully capture sudden, unforeseen changes or outliers, such as extreme wildfire seasons or shifts in environmental conditions. Moreover, exponential smoothing is sensitive to the choice of smoothing parameters, and improper selection can lead to inaccurate forecasts. Additionally, the method assumes that the time series is stationary in terms of its overall trend, which may not be the case in a dynamic and rapidly changing environment like wildfire smoke and air quality. Finally, the model itself can provide erroneous long-term forecasting, so predictions 30 years into the future may not be reliable[6].

Conclusions

This study reveals several important insights into the relationship between wildfire smoke and chronic respiratory disease incidence in Dearborn, Michigan. The improved smoke metric, which integrates climate variables such as temperature, precipitation, and drought severity, significantly enhanced its alignment with the Air Quality Index (AQI), achieving a statistically significant Pearson correlation ($R=0.425$, $p=0.008$). Forecasting the smoke metric with Holt-Winters exponential smoothing indicated a general upward trend in smoke exposure, with intermittent spikes linked to heightened wildfire activity. These trends were reflected in the predicted respiratory disease incidence, showing a consistent increase over time. The model, with an adjusted R-squared of 0.669, accurately captured the complex relationship between smoke exposure and disease outcomes. Projections indicate a steady rise in chronic respiratory disease incidence from 2021 to 2050, surpassing 2020 levels by the mid-2020s.

The findings underscore the importance of integrating environmental factors into public health models and emphasize the growing impact of wildfire smoke on respiratory health. Through human-centered data science principles, this study prioritized interpretability, reproducibility, and accessibility. Decisions such as employing rolling average for the smoke metric reflect the heuristic knowledge that people experience and react to environmental changes over time. Similarly, the use of polynomial regression highlights the need for models that can capture the complexities of human life while making the results meaningful for stakeholders.

Incorporating these human-centered approaches facile communication, and in term actionability, with city officials, public health planners, and residents alike. The model's transparency and the ability to explore its outputs contribute to informed decision-making, understanding, and trust of the results of my work. Conducting this study has been a reminder of the importance of keeping people at the heart of data science. The work isn't just about numbers, algorithms, or metrics—it's about the lives, health, and well-being of the individuals who make up a community like Dearborn. Chronic respiratory diseases aren't just statistics; they represent the struggles of individuals who face tangible challenges in their daily lives, exacerbated by factors like wildfire smoke. For me, this study has been about grounding abstract data science work in the lived experience of real people.

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Data Sources

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Figures

Figure 1: Improved Smoke Metric Formulation

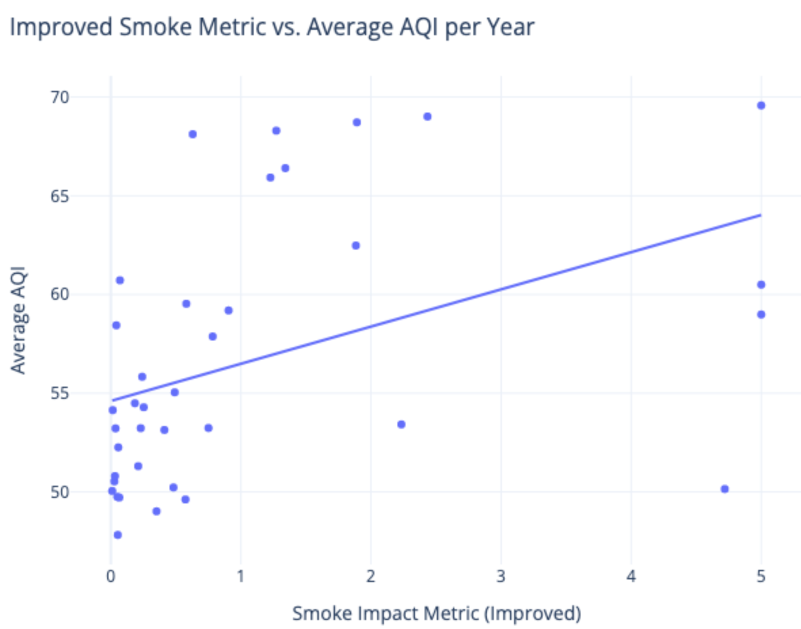
$$SmokeMetric_{fire} = f(acreage_{fire}, distance_{fire}, temperature_{fire}, dsi_{fire}, precipitation_{fire})$$

$$f(acreage_{fire}, distance_{fire}, temperature_{fire}, dsi_{fire}, precipitation_{fire}) = \frac{acreage_{fire}}{distance_{fire}^2} * \left(\frac{temperature_{fire}}{precipitation_{fire} * dsi_{fire}}\right)^2$$

$$SmokeMetric_{year} = \sum_{x=0}^{n} f(acreage_x, distance_x, temperature_x, dsi_x, precipitation_x)$$

Description: The improved smoke metric leverages the inverse square law formulation devised in previous work. It additionally incorporates the ratio of temperature to the product of average precipitation and drought severity index. It squares this ratio and multiples by the original metric.

Figure 2: Correspondence of improved smoke metric with Air Quality Index



Description: The improved smoke metric showed significantly higher correlation relative to the previous version. A pearson correlation between the two was highly significant at a p-value of 0.008 and R = 0.425.

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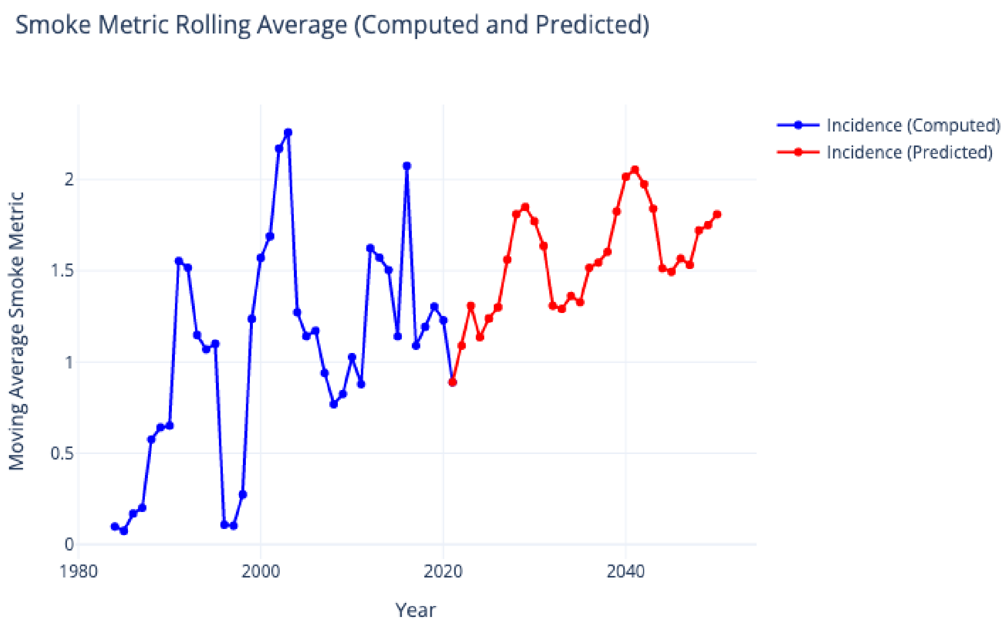
Figure 3: Rolling Smoke Metric Forecasting



Description: The smoke metric was forecasted with Holt-Winters forecasting, and a rolling average was computed with a window size of eight years. The computed incidence (from the source data) is represented via the blue line, whereas the predicted incidence is represented via the red line. The red line replicates the trend seen in the blue line, which is a general increase punctuated with occasional spikes.

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Figure 4: Summarizing Polynomial Regression Results of Best Performing Model

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Incidence   R-squared:                       0.724
Model:                            OLS   Adj. R-squared:                  0.669
Method:                 Least Squares   F-statistic:                     13.12
Date:                Wed, 04 Dec 2024   Prob (F-statistic):           2.10e-05
Time:                        20:07:37   Log-Likelihood:                -264.41
No. Observations:                  25   AIC:                             538.8
Df Residuals:                      20   BIC:                             544.9
Df Model:                           4
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
const               -4.089e+06   7.32e+05     -5.584      0.000   -5.62e+06   -2.56e+06
Rolling_Avg         -2.053e+05   3.87e+04     -5.309      0.000   -2.86e+05   -1.25e+05
Rolling_Avg_Squared  1.642e+05   3.85e+04      4.263      0.000    8.39e+04    2.45e+05
Rolling_Avg_Cubed   -3.941e+04   1.08e+04     -3.657      0.002   -6.19e+04   -1.69e+04
Year                 2196.9498    368.625      5.960      0.000    1428.012    2965.888
==============================================================================
Omnibus:                        0.772   Durbin-Watson:                   0.764
Prob(Omnibus):                  0.680   Jarque-Bera (JB):                0.333
Skew:                           0.282   Prob(JB):                        0.847
Kurtosis:                       3.000   Cond. No.                     6.91e+05
==============================================================================
```

Description: Summary of ordinary least squares polynomial regression results for the best performing model (using rolling average) for prediction. This model resulted in an adjusted R-squared of 0.669 with an F statistic of 2.10e-05. We can see a clear and significant positive correlation with the squared rolling average with the incidence of diseases.

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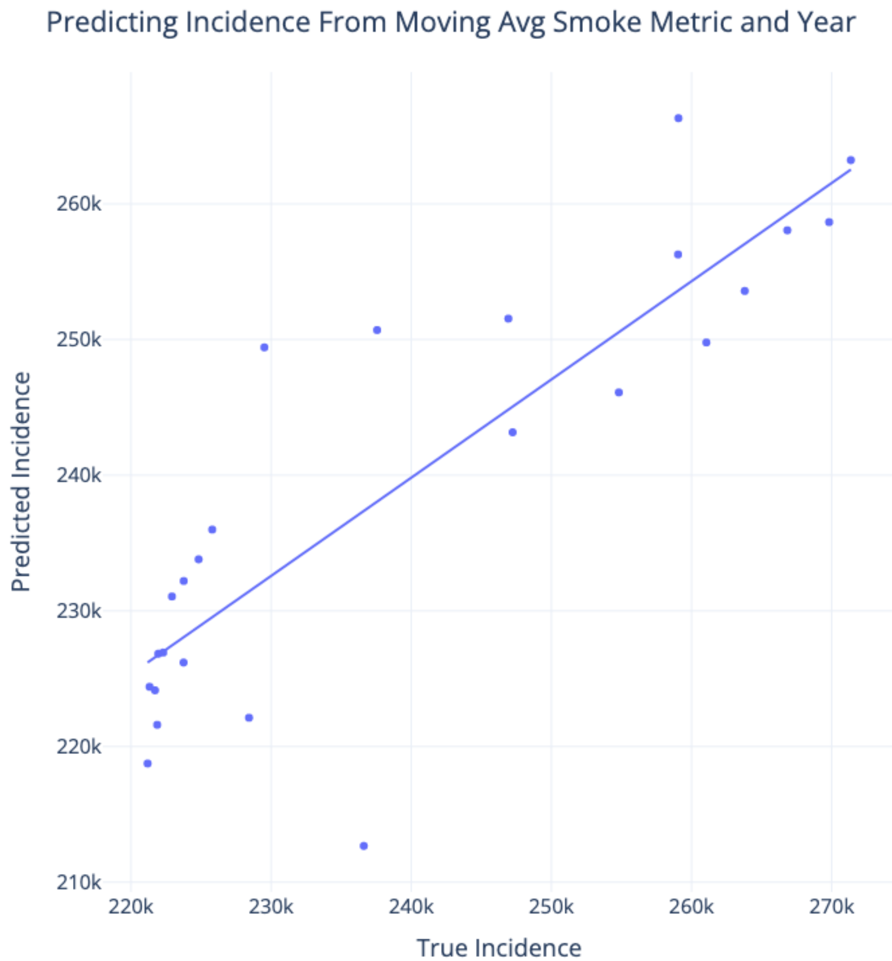
Figure 5: Predicting Incidence from Smoke Metric and Year



Description: Using a polynomial ordinary least squares regression model, we predicted incidence from a linear combination of year, and various exponentiated forms of the smoke metric. Here we found these variables serve as a high-quality prediction of existing incidence values, with an adjusted r-squared of 0.669 and a p-value of 2.10e-05 when modeling this relationship.

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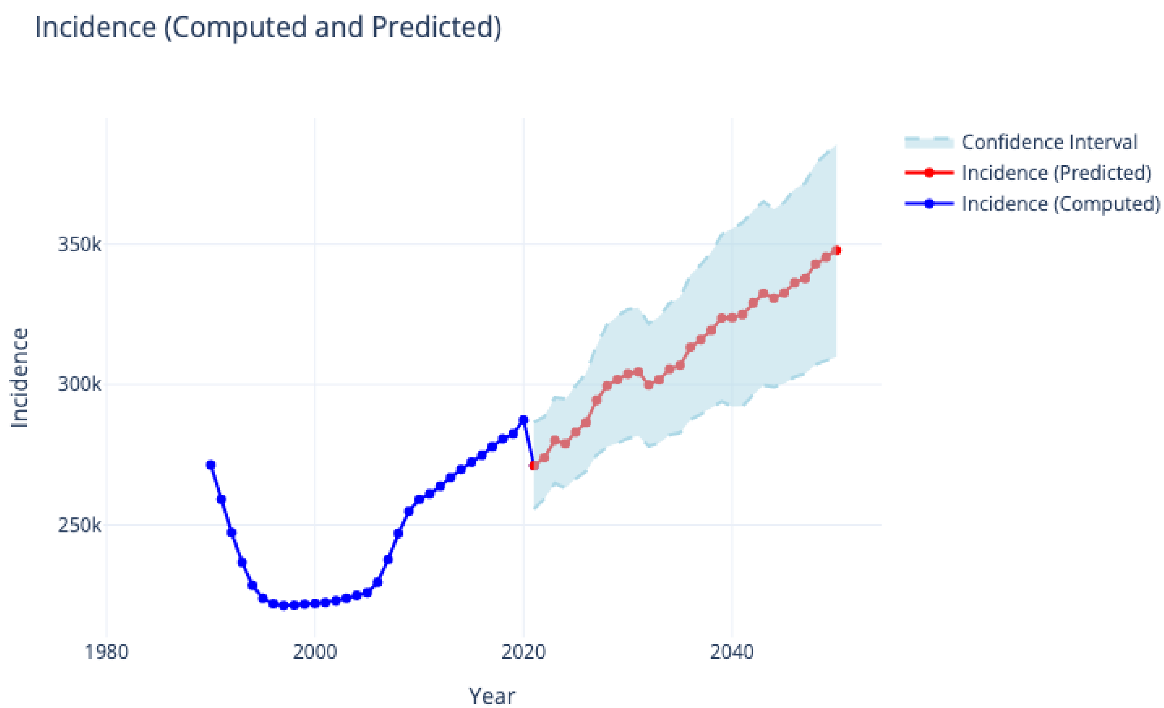
Figure 6: Predicting Future Chronic Respiratory Disease Incidence from Forecasted Rolling Smoke Metric



Description: Using polynomial regression, I predicted the incidence of chronic respiratory diseases for Michigan via the forecasted smoke impact metric values. While the model predicts a slight drop in 2020, it predicts a consistent increase year over year from 2021 onwards. Eventually the incidence will catch up to 2020 values and exceed it.