

Part 1 - Common Analysis

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Visualization Descriptions

1. Fire smoke estimate forecast

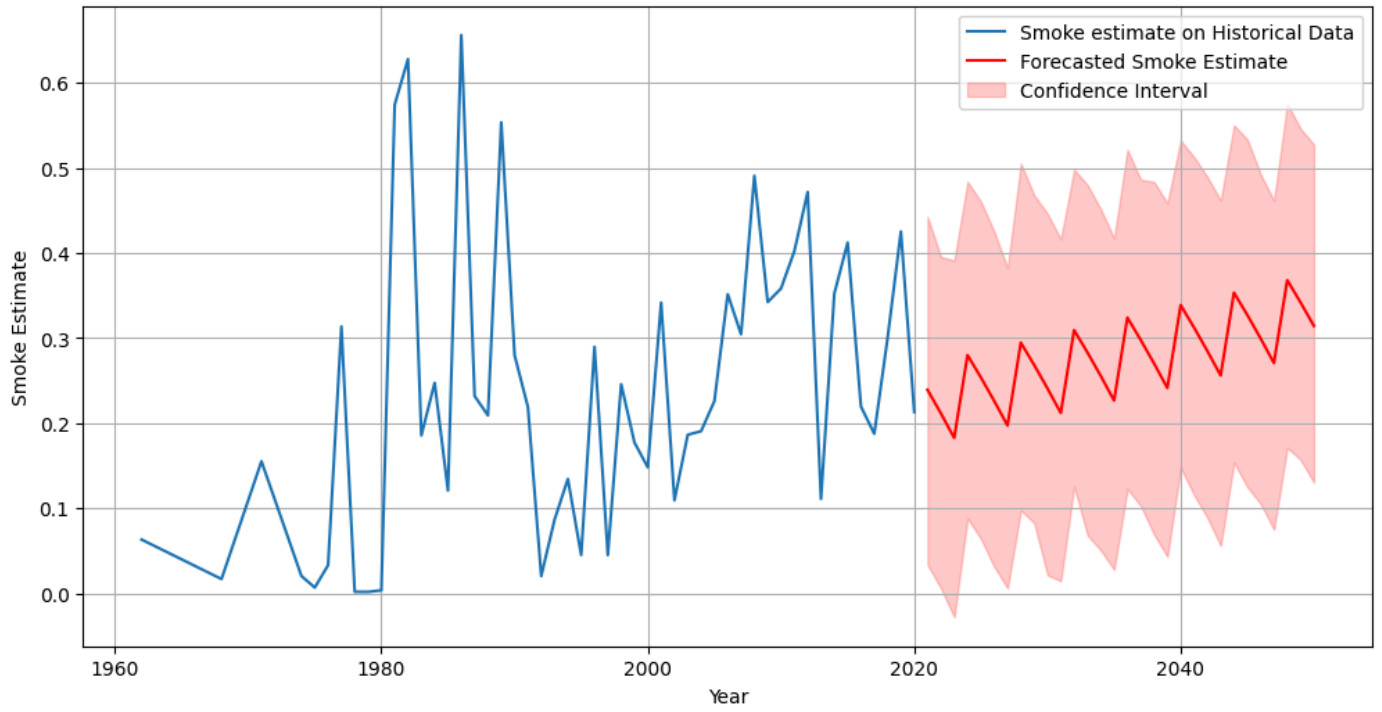
The following chart shows the historical and projection analysis of smoke impact estimates from fires on an annual basis. This figure should provide an understanding of past trends in smoke impact and allow informed predictions about possible future levels.

The years run from the early 1960s to 2050 and are divided into historical data-1960 to 2020 and forecasted data-2021-2050. The y-axis gives the "Smoke Estimate," a metric that approximates the smoke impact on St. Petersburg, Florida. The logarithmic transformation of the ratio between the area burnt by fire in acres and the shortest distance of the fire polygon from the city in miles was used. The distance was calculated by doing a geodetic computation to include the curvature of Earth's surface and terrain difference. This nonlinear transformation is used for the standardization of values having large values or outliers and accounts for the spread of smoke over distances.

The blue line in this figure shows the smoke estimates from historical data gathered over several decades. First, we implemented an Augmented Dickey-Fuller test to verify the stationarity nature of the time series. The null hypothesis of the test is that the series is not stationary. The results came as expected; namely, that the series was non-stationary ($p > 0.05$). Due to the non-stationarity of the series, we chose not to use standard Auto-Regressive models like ARIMA, as these models typically assume stationarity. Additionally, since the data lacked any strong seasonal patterns, we did not pursue ETS (Exponential smoothening) or SARIMAX (Seasonal Auto-Regressive Integrated Moving Average with exogenous factors), which do well on more granular seasonal patterns.

Instead, we opted to use the Prophet model, developed by Facebook which is well-suited for handling non-stationary data with irregular trends and potential changepoints. In the visualization, the red line represents the forecasted smoke estimates from 2021 to 2050 obtained by using the model. The shaded red region around this line illustrates the confidence interval of the forecast, capturing a range of uncertainty in the forecasted values.

Fire Smoke Estimates Forecast: 2021-2050



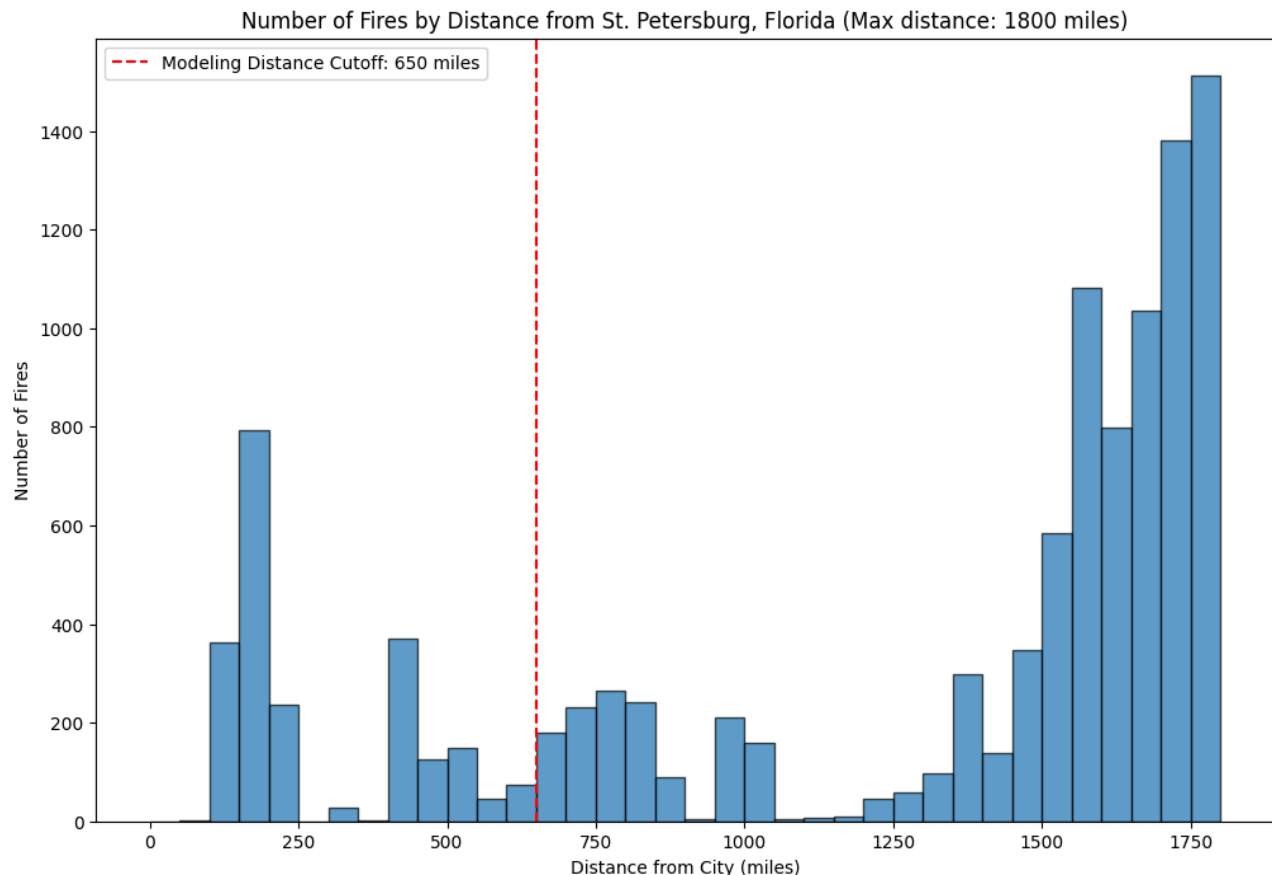
2. Number of fires by distance from St. Petersburg, Florida

The histogram visualization shows the distribution of fires based on their distance from St. Petersburg, Florida, up to a maximum distance of 1800 miles. The x-axis represents the distance from the city in 50-mile increments, while the y-axis shows the number of fires within each distance range.

The distance calculation between St. Petersburg, Florida, and various fire perimeters is achieved using a geodetic computation. This method utilizes the WGS84 ellipsoid model, which is ideal for accurately measuring distances on the Earth's surface. We iterate through the perimeter coordinates of each fire (converted to the EPSG:4326 coordinate system) to determine the shortest geodetic distance to the city.

Interestingly, there are peaks at some of the distances, especially between 200-300 miles, and further out at over 1500 miles. The peak between 200-300 miles could correspond to areas within Florida and immediate neighboring southeastern states, like Georgia and Alabama. Such regions have heavy forests, wetlands, and grasslands that are very prone to wildfire incidents, especially in the pine flatwoods of Florida and areas like the Okefenokee Swamp near the Florida-Georgia border. Controlled burns for maintaining the health of the forest, aside from natural ones, could be some of the reasons for the increased frequency within this range of distance.

The red dotted vertical line shows a cut-off distance of 650 miles which was the maximum range considered in the modeling work. Fires beyond this distance are excluded from the time series model because they likely have less direct impact on St. Petersburg in terms of smoke.

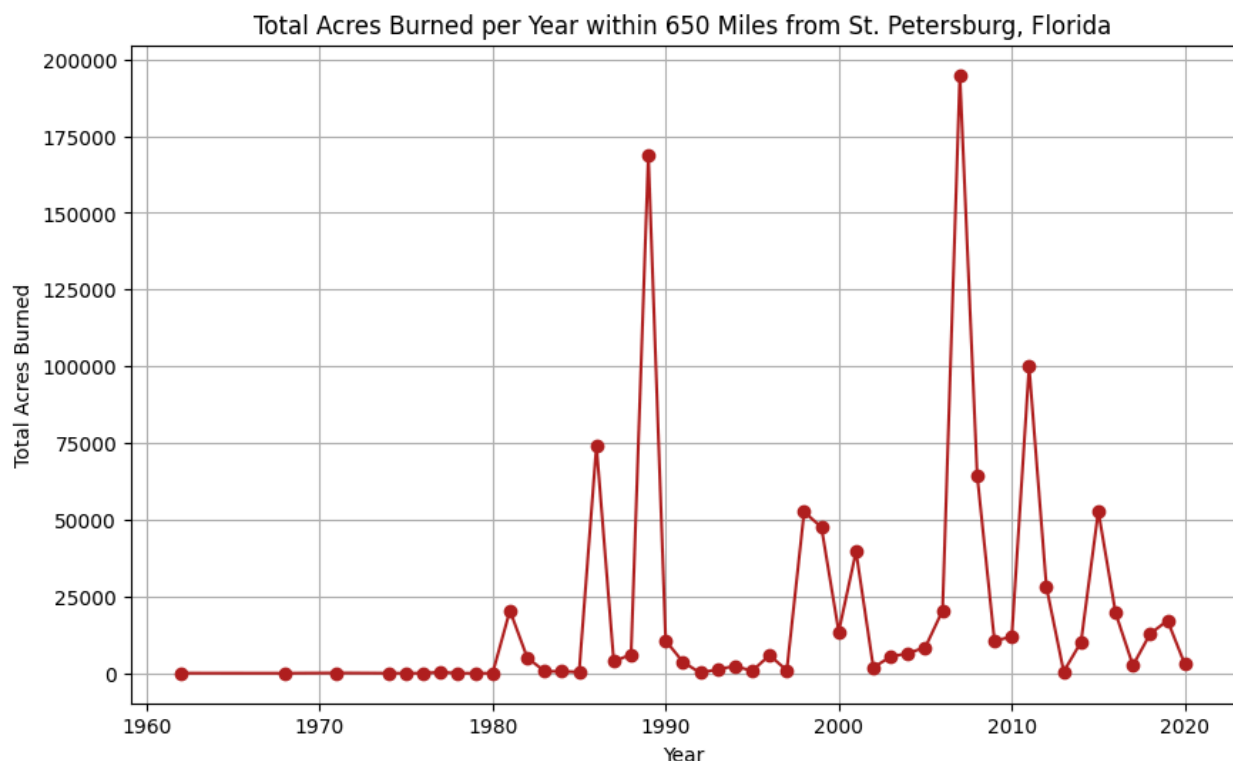


3. Total Acres Burned per Year within 650 miles from St. Petersburg, FL

The following visualization shows the total acres burned by wildfires over a radius of 650 miles from St. Petersburg, Florida, each year. This time series graph helps describe how the amount of wildfire activity has changed from year to year and conveys important information about the impact the wildfires are having on the surrounding environment.

In this graph, the x-axis represents the year in which the fires occurred, while the y-axis is the total acres burned, measured in acres. This information was extracted from a set of records of wildfire incidents for the geographical area under consideration-that is, incidents within 650 miles of St. Petersburg. The total acres burned in each year were obtained by summation, yielding a series of annual totals.

This plot contains a number of obvious peaks, such as those for the years 1989, 2005/6, and 2011. These spikes tentatively could be due to in 1989 could be because of the Big Cypress National Preserve Fire[1], or the years 2006 and 2007 were marked by major events like the Myakka Fire and Hurricane Wilma Fire [2][3], and in 2011, the wildfire season had the Jarhead fire[4]. These incidents were characterized by dry conditions and high winds, contributing to the rapid spread of flames and substantial acreage affected.

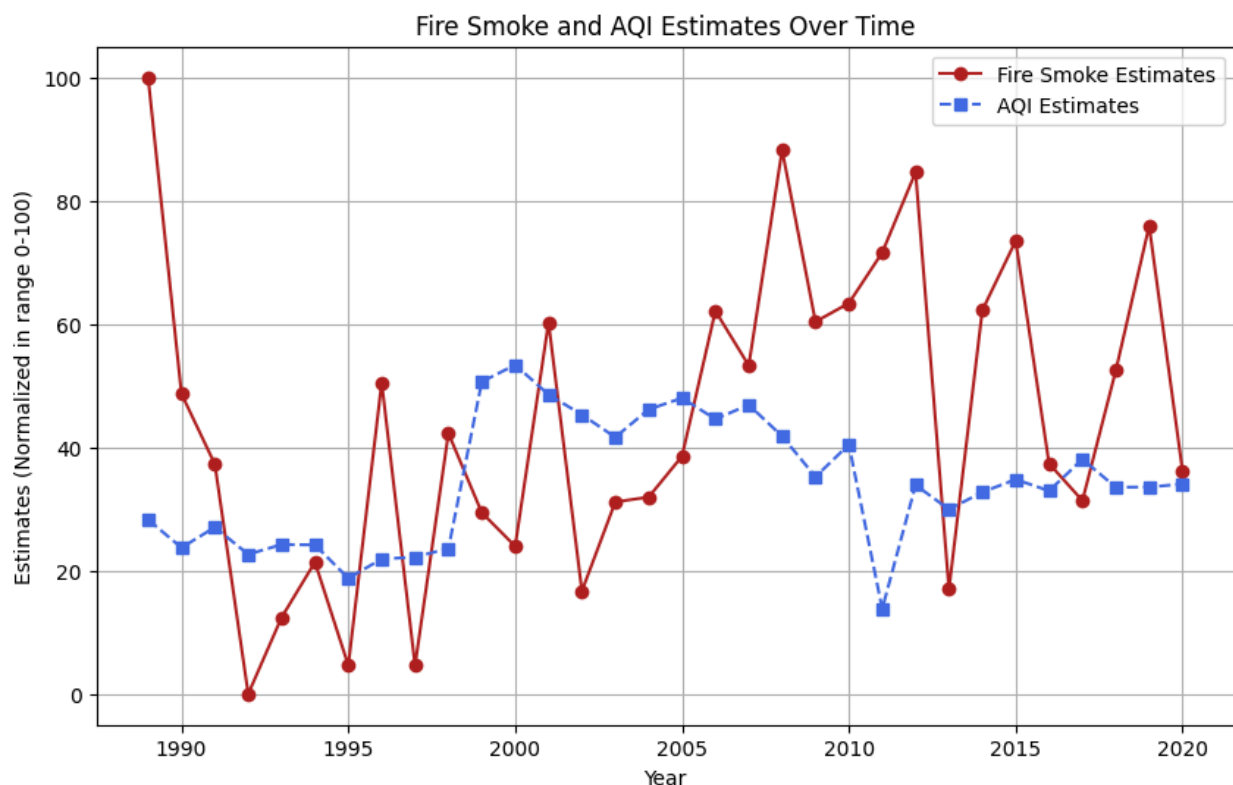


4. Time series graph for comparing trends in Smoke Impact estimates and AQI values

The following visualization shows the relationship between fire smoke and air quality in St. Petersburg, Florida, as a combined time series graph of fire smoke estimates, with data ranging from 1989 to 2020. The smoke impact estimate is calculated using the logarithmic transformation of the ratio between the area burned by fire in acres and the shortest distance from the fire polygon to the city in miles.

The AQI data were obtained from the US EPA (Environmental Protection Agency), which provides AQI levels for various gaseous and particulate compounds daily across the US. We are primarily interested in PM2.5 and PM10, as these are critical byproducts of smoke emanating from wildfires. We searched for monitoring stations close to St. Petersburg and requested daily summary data from monitors across several sites. Because this API has limited requests, we looped through each year between 1989 and 2020, importing the AQI values from May 1 to October 31 (fire season) and averaging the data from multiple sources for that period.

In the visualization, we plot the years on the x-axis and the normalized estimates on a scale of 0-100 on the y-axis. Since the smoke impact estimates are only a relative metric, we have used min-max scaling to adjust the smoke estimate values to a similar 0-100 range for better visualization and to align with the range of the AQI values. This approach helps to clarify the trend. Further analysis showed that the Pearson correlation coefficient was approximately 0.117, indicating a weak positive trend in fire smoke estimates over the years concerning AQI levels. This suggests that, although there may not be a clear, direct trend, there is a slight upward trajectory in smoke estimates with increasing years. This small increase in smoke estimates may also imply that, with global warming and the rising incidence of wildfires, air quality could become a deteriorating problem.



Reflection:

The proposed research question—analyzing the impact of wildfire smoke on air quality in St. Petersburg, Florida—provided an excellent opportunity to apply statistical testing, data aggregation, cleaning, and visualization techniques to uncover patterns and trends in the data. This assignment has deepened my understanding of wildfire impacts, specifically the frequency and increasing magnitude of smoke effects on air quality, which are critical concerns for local environments and public health.

Collaboration was another highly valuable aspect of my approach to this open-ended analysis. Discussions with classmates helped shape our approach to estimating smoke impact, allowing us to consider different formulas—such as area burned and proximity to the city—and brainstorm additional features. Challenges, such as API limits and missing data for certain years, became more manageable with colleagues' support in identifying consistent patterns and reliable data filtering strategies. Additionally, ambiguous information, such as extracting accurate fire start and end dates from complex log strings, was clarified through multiple discussions with professors and peers. My readings on particulate matter, particularly PM2.5 and PM10, underscored its relevance to wildfire smoke, and sharing these insights fostered a valuable, shared understanding that informed our data preparation decisions.

Interestingly, there was a weaker-than-expected association between the smoke estimates and AQI values. Collaborative discussions allowed me to explore whether others observed similar trends and encouraged us to try more advanced statistical tests, such as the Augmented Dickey-Fuller test for time series stationarity. Ultimately, these conversations led us to evaluate FB Prophet as an alternative to ARIMA, given the nuances in our dataset.

Reflecting on this experience, the collaborative process greatly enhanced my understanding and analytical approach. The shared insights and support from peers and instructors enabled a comprehensive “common analysis” phase, strengthening our foundational understanding of wildfire impacts on air quality. This experience has provided critical insights and techniques that will guide further analysis and solutions as we expand this project’s scope.

References:

1. <https://www.latimes.com/archives/la-xpm-1989-05-30-me-1006-story.html>
2. <https://research.fit.edu/whirl/post-storm-damage-assessment/hurricane-wilma-2005>
3. <https://earthobservatory.nasa.gov/images/16580/fires-in-florida>
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5. <https://www.lni.wa.gov/safety-health/safety-topics/topics/wildfire-smoke>