Wildfire Analysis and Healthcare Impact
Del Rio, Val Verde, Texas

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Introduction:

In recent years, the western United States has experienced an increasing frequency of wildfires, marking summers with billowing smoke that spans across vast regions. The causes behind this surge are many, compromising factors such as climate change, forestry policies, and growing awareness. The consequential impact of these wildland fires extends far beyond the immediate affected areas, affecting health, tourism, property, and various facets of society.

Del Rio, situated in Val Verde County, Texas, is a vibrant community that boasts a population of approximately 34,673 residents. Situated in the heart of the Lone Star State, this city experiences a Hot Semi-Arid climate, characterized by warm temperatures and relatively low precipitation. Del Rio's residents enjoy a unique blend of southwestern charm and Texan hospitality. The city's air quality is notably good, with an average Air Quality Index (AQI) of 40, indicating a relatively low level of air pollution. Del Rio's scenic landscapes and welcoming atmosphere make it a compelling destination for those seeking a taste of Texas living amidst a backdrop of arid beauty.

This analysis focuses on Del Rio, Texas, situated in Val Verde County, a region that has been immune to the encroaching consequences of wildfires. The motivation behind this exploration is rooted in the necessity to inform key decision-makers – including policymakers, city managers, and civic institutions – about the potential impact of wildfires on Del Rio. By delving into the correlations between wildfire-induced smoke exposure and various health outcomes, this study seeks to provide actionable insights that can guide the formulation of informed plans and strategies for mitigating future impacts.

Del Rio is situated on the border of Mexico and the USA, southwest in Texas. Most of the wildfires in Texas have been in the north eastern region of Texas. Thus, based on these facts, some important research questions we would like to answer using this analysis are:

1. Is Del Rio affected by smoke from wildfires in Texas?
2. Does this increase the Smoke or AQI values for Del Rio?
3. Does smoke from wildfires affect the health of residents of Del Rio?

The significance of this analysis lies in its potential to influence proactive decision-making. By understanding the historical patterns of wildfires, predicting future trends, and correlating these with health outcomes, we aspire to provide valuable insights that can shape public policies, environmental strategies, and healthcare interventions. Our ultimate goal is to contribute to the well-being and resilience of Del Rio and its residents in the face of an evolving environmental landscape.

Background/Related Work:

Research in the field of wildfire impacts on communities, especially in the western United States, has gained momentum due to the rising frequency and severity of wildfires. Existing studies delve into the multifaceted consequences of wildfires, encompassing health, environment, and socio-economic aspects. Research often explores the negative repercussions of wildfire smoke on air quality and public health.

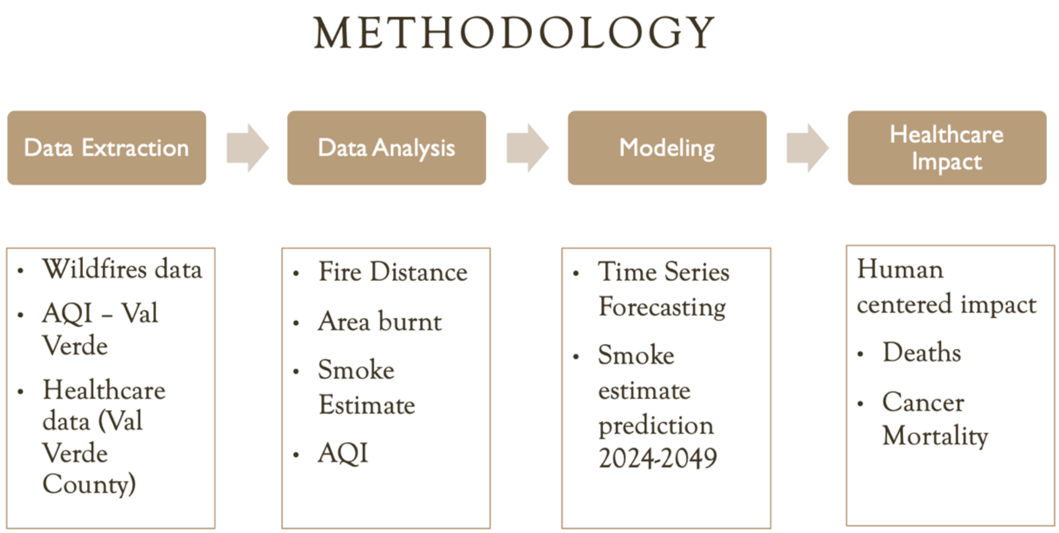
The hypotheses and research questions for this analysis were informed by the broader body of work on wildfire impacts. Questions such as the correlation between smoke exposure and health outcomes, the influence of wildfires on mortality rates, and the long-term effects on cancer incidences were shaped by the existing literature.

In developing Course Project - Part 2 - Extension Plan, the consideration of existing models was imperative. Notable models in the realm of predictive modeling for environmental health include various time series forecasting techniques. The selection of the Autoregressive Integrated Moving Average (ARIMA) model was influenced by its effectiveness in capturing temporal patterns and its suitability for predicting smoke estimates over the next 25 years.

Datasets used to extend Part 1 results were sourced from reputable repositories and agencies. The USGS Wildfire data provided a foundational dataset, enabling the extraction of relevant information on fires within proximity to Del Rio. Additionally, air quality data from monitoring stations, specifically the AQI values, were crucial in understanding the atmospheric conditions resulting from wildfires.

By integrating insights from prior research and leveraging established models, the analysis aimed to contribute to the existing knowledge base on wildfire impacts, offering a focused examination of Del Rio's unique context. The extension plan sought to build upon the groundwork laid in Part 1, addressing gaps identified during the initial analysis and incorporating more granular data to enhance the overall understanding of the relationship between wildfires and health outcomes in Del Rio.

Methodology:



To solve the research questions, we described the methodology [fig1]. The methodology for wildfire analysis for Del Rio, Texas, comprises of a comprehensive approach to data extraction, analysis, and predictive modeling. The choice of analytical methods was driven by a commitment to accuracy, interpretability, and ethical considerations, aligning with human-centered data science principles. The final outcome of this analysis was to evaluate the human centered impact of the smoke estimates of healthcare at Del Rio. We analyzed the impact of wildfire smoke on Deaths, Cancer Mortality, Infant/Fetal deaths, etc.

1. Data Extraction:

The analysis started with the extraction of wildfire data from the USGS dataset and Air Quality Index (AQI) data from monitoring stations. The decision to utilize the USGS Wildfire data was grounded in its comprehensive coverage of wildfire occurrences in the United States. The AQI data, sourced from monitoring stations, provided valuable insights into the air quality conditions resulting from wildfires.

- **Wildfire Data:**

We extracted the fires data from the wildfire dataset and to filter it based on certain conditions using the city assigned. We used the fires which were within 1250 miles of the city - Del Rio, Texas. We found that there were 70861 fires which were under 1250 miles from Del Rio based on distance. The data was extracted based on 3 filters to create a smoke estimate at the end:

- The estimate only considers the last 60 years of wildland fires (1963-2023).

- The estimate only considers fires that are within 1250 miles of your assigned city.
- An annual fire season will run from May 1st through October 31st.

- **AQI Data:**

We extracted AQI values from 1963 to 2023 around Del Rio using US EPA API call to get the AQI information based on the fips for Del Rio, Texas. The AQI extraction was done for each year and ran from 1963 to 2023 for a specific fips number which we obtained by finding the local AQI measurement sites around Del Rio, Texas

Del Rio is very remote location and lies on the border of Mexico. Thus, to get the monitoring stations, we had to increase the bounding boxes to a higher range. We found 5 Monitoring stations around Del Rio, Texas, when we increased the bounding box scale to 250 Miles and thus finalized a fips number such that we have maximum AQI data.

We finalized the monitoring station - Brewster, Texas with fips=48043 which contained data starting in 1988 to get as close AQI data as possible to 1963

- **Healthcare Data:**

The data for analyzing the correlation between smoke estimates and potential healthcare concerns like mortality rates, cancer deaths, respiratory system-based deaths, etc. was procured from the official Texas Health Data Registry. The site contains reports and tables of public data and statistics on various health topics for Texas state and has reports/statistics based on each county. The official site covers data for Births, Deaths, Diseases, Drugs & Alcohol, Environmental Health, Hospitals, Injuries, etc., for Texas.

We also procured the data from Texas Vital Statistics and Cancer Data NIH (National Institute of Health) by the US government. The NIH contains numbers of cancer deaths and reasons for the death which will be obtained for Val Verde County from 1990-2020.

As we couldn’t find exact data for Del Rio as it is a small town, we used data from Val Verde county and Texas state as whole to scale it wherever need for the analysis.

2. Data Analysis:

Exploratory Data Analysis was done on the datasets procured and some derived variables were created. The 2 most important metrics derived were smoke estimate and AQI.

Smoke Estimate:

Smoke Estimate is basically a term which signifies the effect of wildfire smoke in the area. Thus we used metrics like distance from fire and area burned by the fires to calculate smoke estimates for each year.

Smoke Estimate = (Area burned in Acres/Distance from the city)*10

Smoke estimate is directly proportional to the area burnt i.e. it will have a higher impact on the city if the area is more and is inversely proportional to the distance from the city i.e. it will have higher impact for a shorter distance from the city. 10 is used to normalize the values.

AQI:

AQI is the air quality index values we extracted from the monitoring centers in Brewster Texas. The values collected are daily measurements of AQI values for multiple types of pollutants and they need to be converted to an annual AQI for comparison.

Annual AQI is calculated by taking max of AQI for each day based on Pollutant standards and then taking the Average of the top 30 AQI values for a year. This will ensure we calculate the right annual AQI

3. Predictive Modeling:

The Autoregressive Integrated Moving Average (ARIMA) model was used for predictive modeling of smoke estimates for the 2024-2049. ARIMA is well-established for capturing temporal patterns and proved effective in predicting smoke estimates for Del Rio over the next 25 years. The model's simplicity and interpretability were important considerations, ensuring that the results could be communicated effectively to diverse stakeholders, including policymakers and the public.

4. Healthcare Impact:

To see the impact of smoke on Healthcare in Del Rio, we Incorporated a comprehensive analysis of deaths, cancer deaths, and fetal/infant deaths as metrics to define the health.

Mortality Analysis:

The analysis of overall mortality rates serves as a fundamental component in gauging the healthcare impact of wildfires. We extracted data with number of deaths in Val Verde County over the years and compared it with the Smoke Estimates. We saw whether there is a discernible correlation between wildfires and mortality rates, providing crucial insights for healthcare planning and intervention.

Cancer Deaths Analysis:

This analysis acknowledges the potential long-term consequences of smoke exposure, specifically on cancer incidences and mortalities. By analyzing the patterns and trends in cancer deaths over the years, we seek to ascertain the extent to which wildfires might be implicated in cancer-related health outcomes within the Del Rio community. This is for deaths due to all cancers which include more than 60% deaths by Lung Cancer.

Fetal/Infant Deaths Analysis:

The analysis of fetal and infant deaths introduces a critical dimension to the methodology, examining the vulnerability of the youngest members of the population to wildfire-induced smoke. The goal here was to analyze whether there is a correlation between smoke estimates and adverse outcomes in fetal and infant health. This analysis is particularly sensitive, shedding light on potential risks that may necessitate targeted healthcare interventions.

5. Ethical Considerations:

Human-centered considerations were integral to the design of the study. Ethical guidelines were followed meticulously, particularly in the extraction of healthcare-related data. Privacy concerns were prioritized, and efforts were made to handle healthcare data at a county level to ensure the anonymity of individuals. The use of aggregated data aimed to mitigate privacy risks while still providing valuable insights into the correlation between smoke exposure and health outcomes.

6. Human-Centered Design:

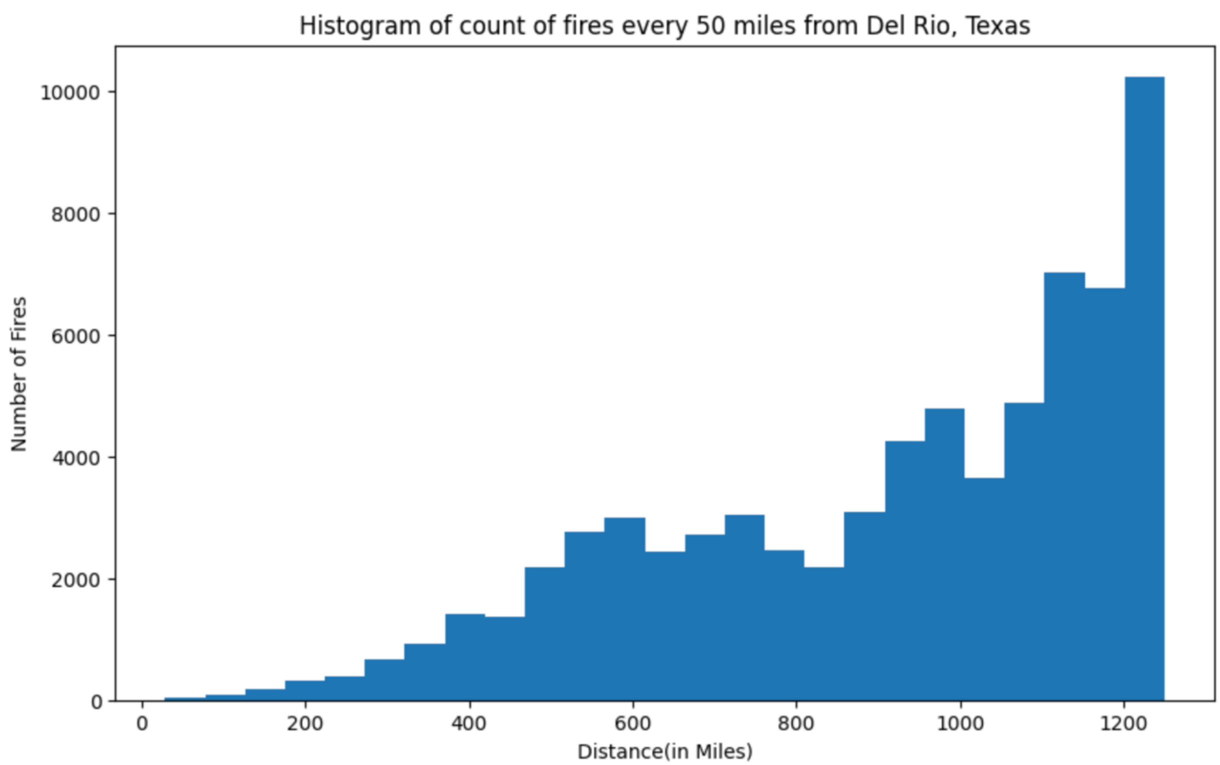
The study's design incorporated human-centered principles by focusing on public health implications and policy recommendations. Understanding the potential consequences of wildfires on the residents of Del Rio, the analysis aimed to provide actionable insights for city councils and civic institutions. The emphasis on smoke awareness campaigns, distribution of smoke resistance kits, and accessible treatment underscored a commitment to addressing the well-being of the community.

Findings:

- **EDA:**

Once we had the data and after deriving some metrics, we performed a through Exploratory Data Analysis. Some of the important findings from the same are:

1. **A Histogram showing the number of fires occurring every 50 mile distance from your assigned city up to the max specified distance.**

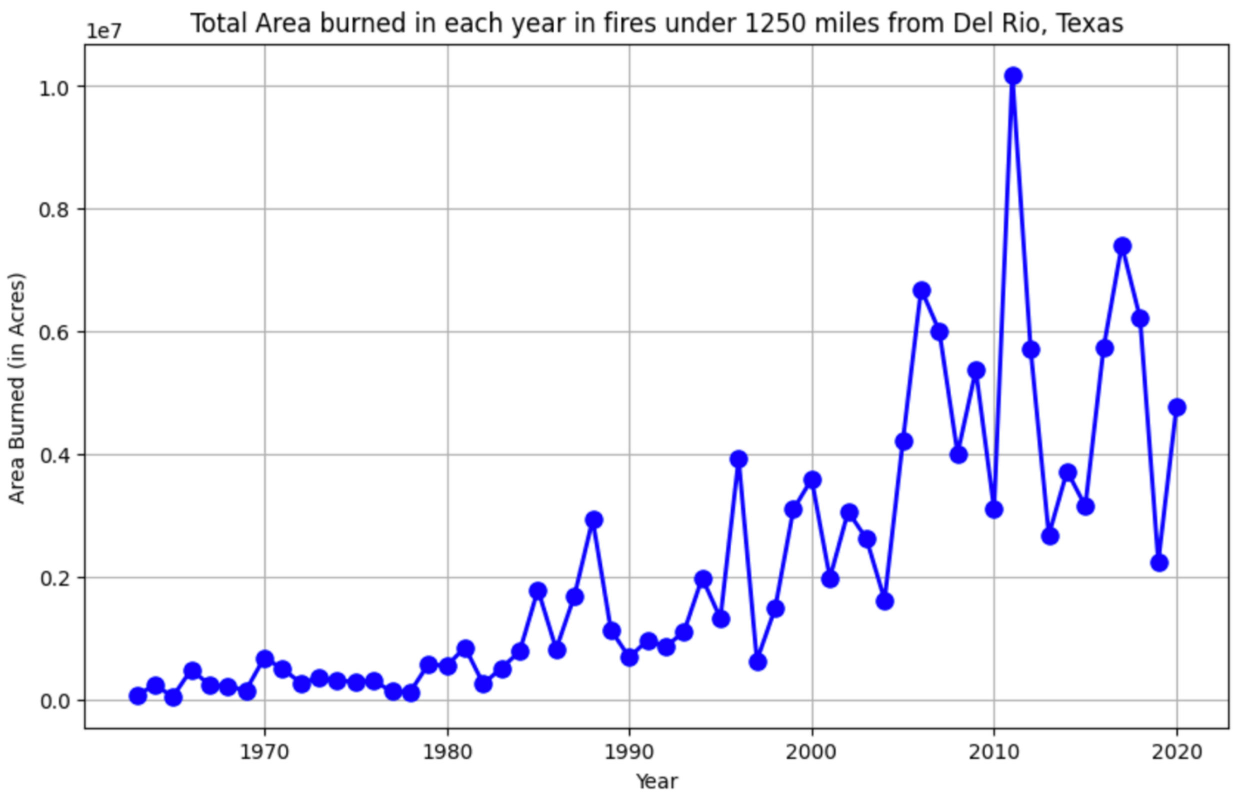


This visualization is depicting the number of fires occurring every 50 mile distance from Del Rio, Texas up to the max specified distance (1250 Miles). Each bin in this histogram is 50 miles. The X-axis for this graph is the Distance from Del Rio (in Miles) and the Y-axis is the number of fires corresponding to that distance. The left part of the graph shows a smaller number of fires which makes sense as Del Rio is a remote location on the border of Mexico. Thus, most of the US files will be far away from the city and which is evident by looking at the right part of the graph where the bars almost cross 10,000 fires.

All the counts above 5000 fires are corresponding distance of more than 900-1000 miles from Del Rio. This graph was processed from the wildfire data extracted using GeoJSON

from the USGS. This data was extracted for each fire and then filtered for fires within 1250 miles of distance from Del Rio. The dataset had information like fire year, fir type, area burnt, and we calculated the distance of the fire from Del Rio.
Overall, the graph gives agreeable insight about fires corresponding to Del Rio.

2. **A time series graph of total acres burned per year for the fires occurring in the specified distance from your city.**

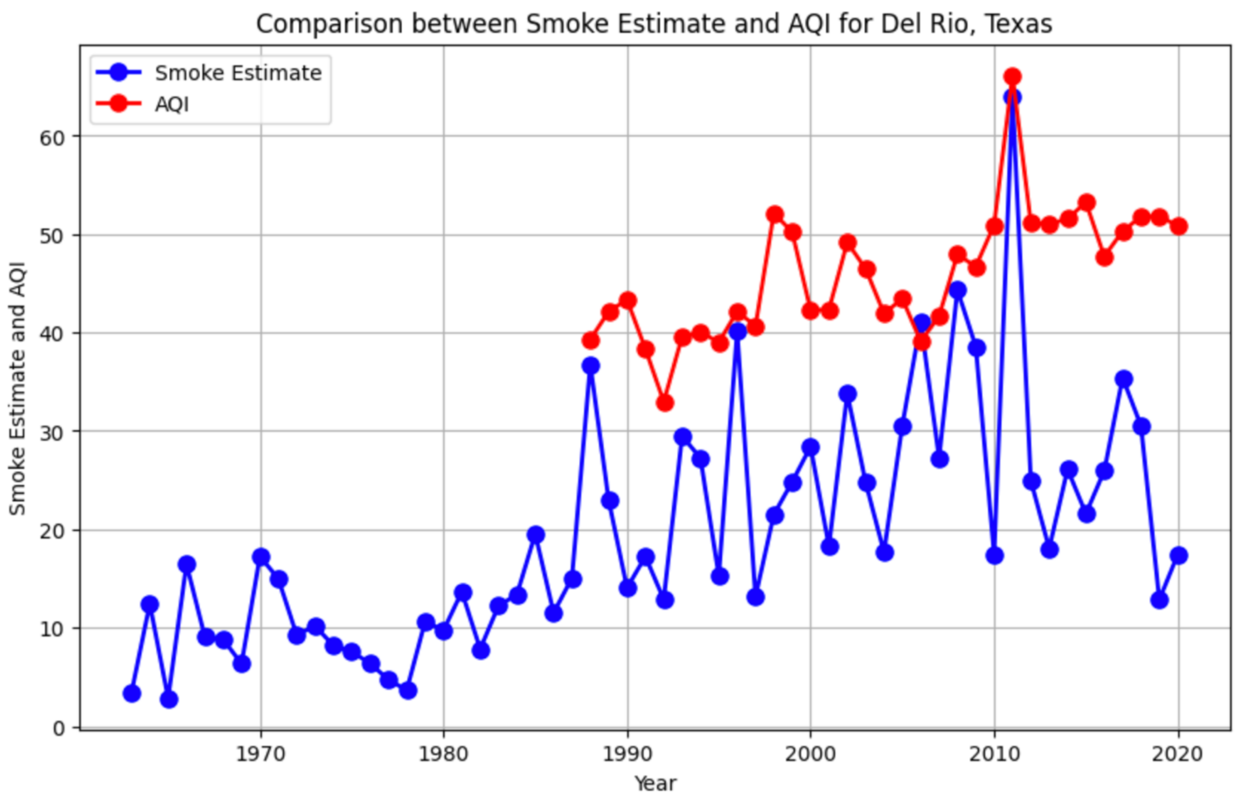


This visualization is a time series graph of total acres burned per year for the fires occurring in the specified distance from Del Rio, Texas. The X-axis in the graph represent the year of fire and the Y-axis is the area burned in acres due to fire. This graph is created from the wildfire data extracted for USGS using geojson. The data contains information for each fire and we extracted all those fires close to Del Rio. The data (Acres burned) is then aggregated per year to show this line chart.

We can see that there is a clear pattern with how the area of ground burned per year is increasing as the time passes and we can see a clear exponential increase. The line, although with some ups and downs, is comparatively increasing upwards towards the recent years. We can also find a sharp spike in the total area burned in 2011 and 2017.

Fires from 2006 to 2020 are of very high intensity and also more in number, thus resulting in very drastically large land burned in comparison to fires from 1963 to 1990.

3. **Produce a time series graph containing your fire smoke estimate for your city and the AQI estimate for your city.**

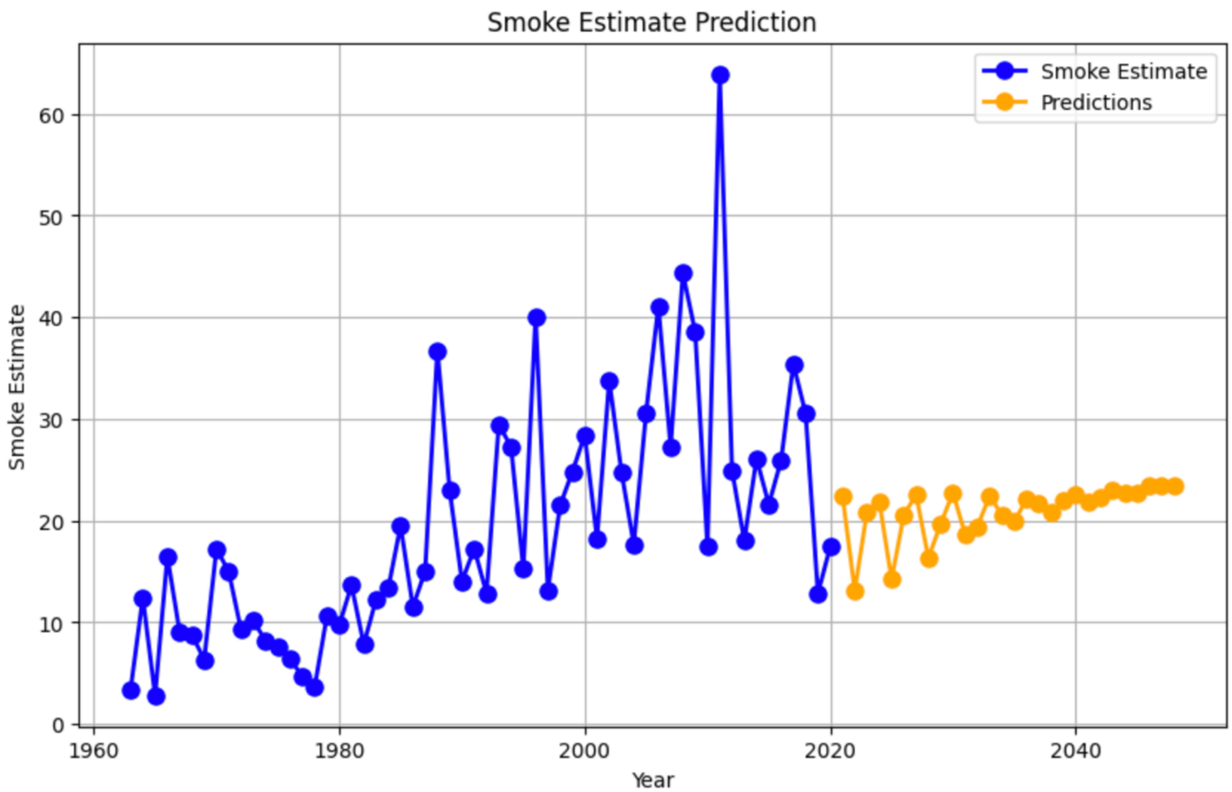


This visualization is a time series graph containing the fire smoke estimate created for Del Rio and the AQI estimate for Del Rio. The graph is basically a comparison between the annual smoke estimate derived from the wildfire data and the actual annual AQI values from the monitoring sites near Del Rio. The X-axis of the graph represents the year of the fire and the Y-axis Is basically the value of Smoke Estimate/AQI.

We can see that there is clear correlation between these two values. We also calculated the correlation which was **44%,** a pretty good percentage of correlation. Even though due to lack of monitoring stations in Del Rio and AQI values starting from 1988, the lines are following a clear pattern and also seasonality. The Blue line is the Smoke Estimate, and the Red line is the AQI value. We can also see that the values are in the 0-60 which is the indicator for Good Air Quality. This also matches to our initial finding that the fires are very far away from Del Rio thus confirming that there is very little or negligible impact of the fires on Del Rio.

The spike in 2011 is the perfect match between the AQI and smoke estimate curve. Deep diving more into it, we found that, during 2011 in Texas, around 31,453 fires had burned 4,000,000 acres of land which was one of the worst wildfires ever. Thus, this completely justifies the spike in both smoke estimate and AQI values.

4. **Prediction of smoke estimates for next 25 years:**

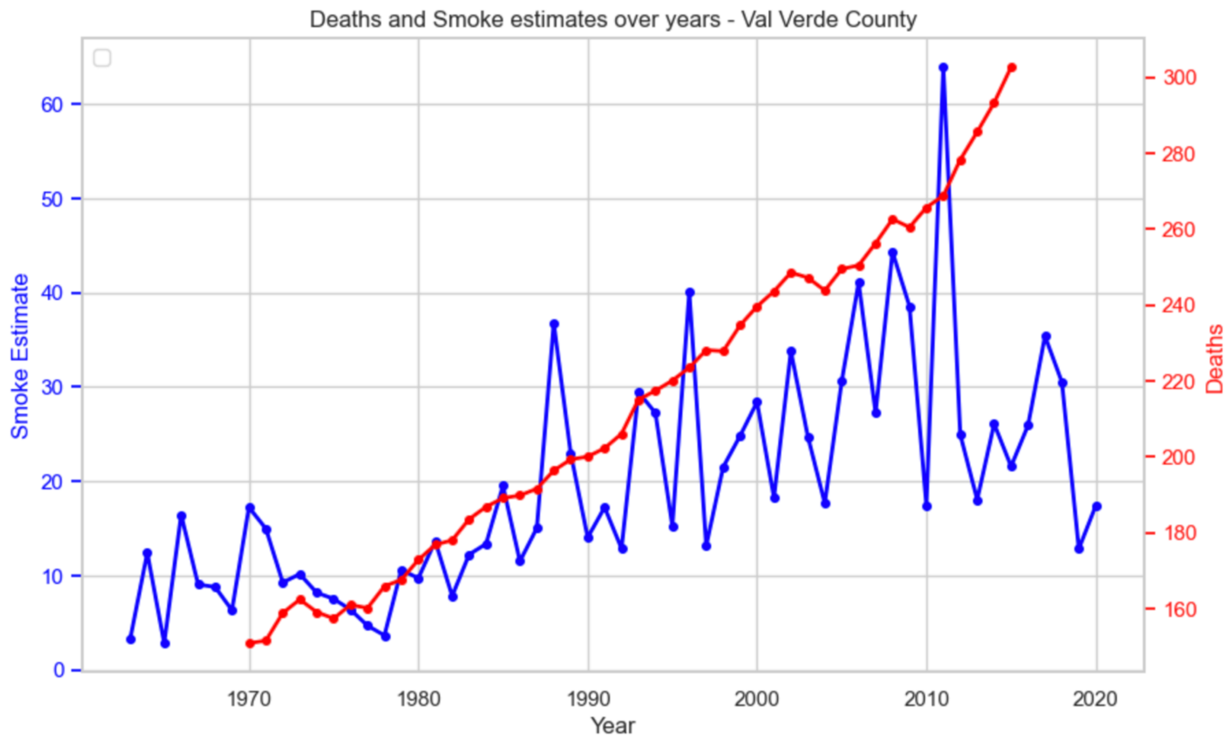


In this visualization we are predicting the smoke estimates calculated based on current data into future upto 2049. We are using ARIMA time series model for the prediction and displaying the final predictions using the model.

- ## Healthcare Impact:

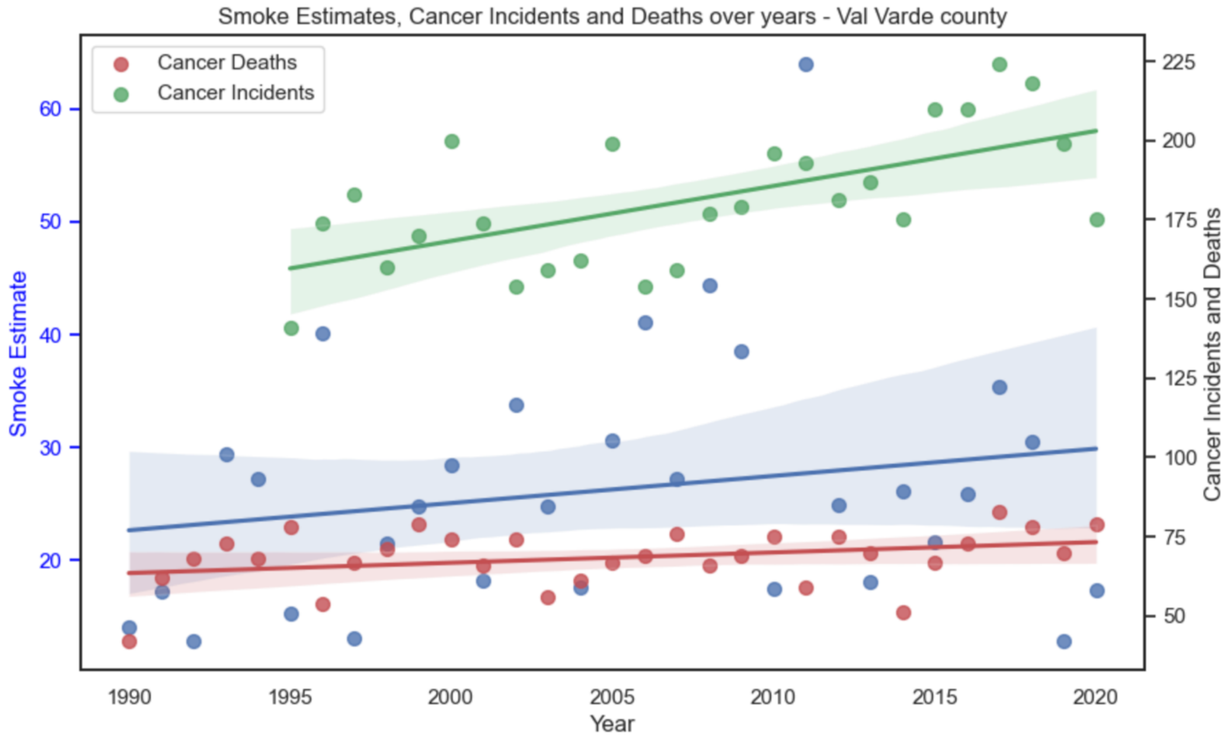
The wildfire analysis for Del Rio, Texas, yielded insightful findings across key dimensions, shedding light on the intricate relationship between wildfires, smoke exposure, and health outcomes.

1. **Smoke Estimates vs Deaths:**



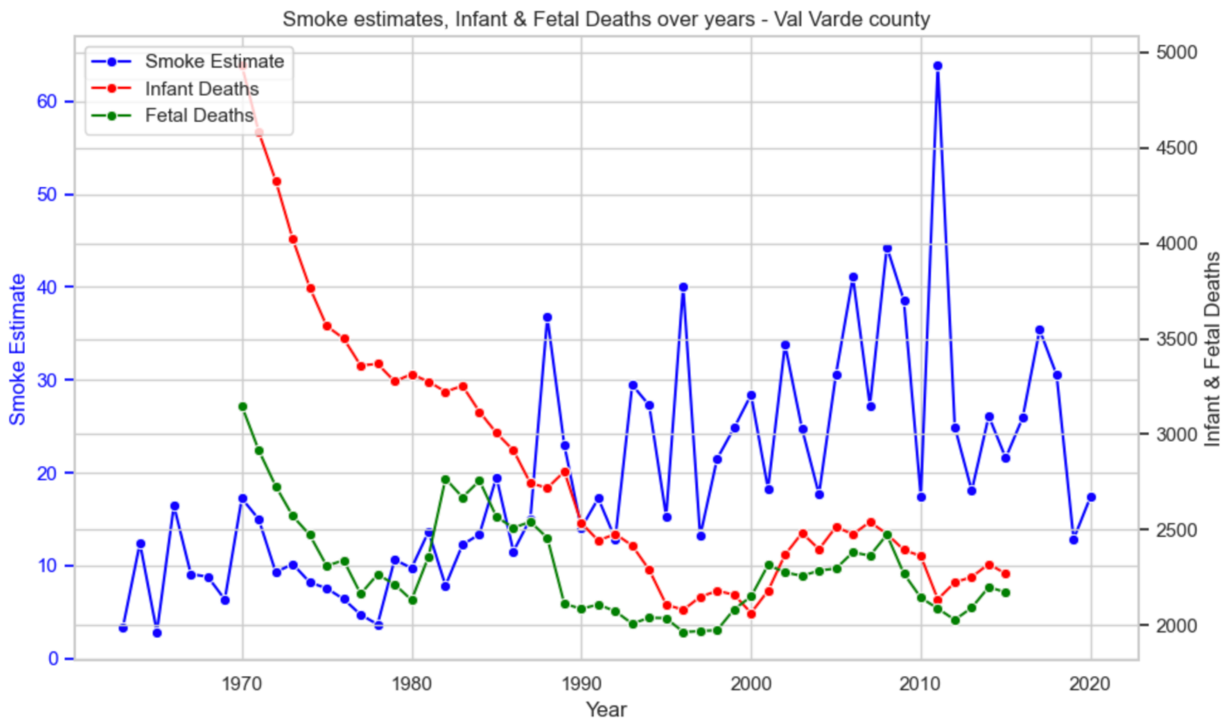
The analysis revealed a robust positive correlation of **64%** between smoke estimates and overall deaths in Del Rio. Over the examined period (1970-2015), the number of deaths consistently increased in tandem with rising smoke estimates. This correlation suggests that smoke exposure from wildfires is a significant contributing factor to overall mortality in the region.

2. **Smoke Estimates vs Cancer Mortality and Incidence:**



We can see through the visualization that the trends of cancer deaths, cancer incidents and smoke estimates have increasing curve, but contrary to the strong visual correlation observed for overall deaths, the relationship between smoke estimates and cancer mortality displayed a weaker correlation of 12%. While the number of cancer incidents and deaths increased (1995-2020 and 1990-2020, respectively), the correlation with smoke estimates was less pronounced. This suggests that other factors may play a more substantial role in cancer outcomes. This can be also because we are considering all types of cancers. Even though 60% died by Lung cancer, other cancer reasons could be also a reason for this weak correlation.

3. **Smoke Estimates vs Infant/Fetal Mortality:**



Unexpectedly, a negative correlation was identified for smoke estimates and infant/fetal mortality, with correlations of -53% and -25% respectively. The data indicates a decline in infant and fetal deaths, contrasting with the overall trend of increasing smoke estimates. This unexpected finding warrants further investigation into additional factors influencing infant and fetal mortality in the presence of wildfires.

It seems like the smoke is not affecting the infant and fetal deaths at all. Even though due to improvement in the hospitalization and technology, the deaths have reduced but the smoke has increased which should have affected the deaths.

Discussion/Implications:

The findings of the wildfire analysis for Del Rio are very significant for city stakeholders, prompting thoughtful considerations and potential interventions. The identified correlations between smoke estimates and health outcomes underscore the multifaceted impact of wildfires on the community's well-being. The positive correlation with overall deaths suggests that proactive measures are essential to address the health consequences of smoke exposure.

Recommendations for Stakeholders:

1. **City Council:**
    - The City Council should prioritize the development and implementation of smoke awareness campaigns. These campaigns could educate residents on the potential health risks associated with wildfire smoke and provide guidance on protective measures.
    - Consider allocating resources for the distribution of smoke resistance kits to vulnerable populations, ensuring that residents have access to tools that can mitigate the adverse effects of smoke exposure.
    - Collaborate with environmental agencies to enhance air quality monitoring systems and implement early warning systems to alert residents when air quality is compromised.

2. **City Manager/Mayor:**
    - Engage with healthcare professionals and public health organizations to establish accessible treatment and diagnosis services. Timely medical interventions can help manage health issues arising from smoke exposure.
    - Implement air purifying mechanisms in public spaces, such as parks and community centers, to provide residents with areas of respite during periods of elevated smoke.
    - Advocate for regional cooperation and policy changes that address the root causes of wildfires and contribute to long-term solutions for reducing the impact on public health.

3. **City Residents:**
    - Stay informed about air quality conditions by regularly checking local AQI values and heeding warnings issued by relevant authorities.
    - Actively participate in smoke awareness campaigns, implementing recommended measures to reduce personal exposure during wildfire events.

- Seek medical attention promptly if experiencing respiratory issues or other symptoms related to smoke exposure.

Timeline for Concrete Plans:

The urgency of addressing the findings necessitates prompt action. The City Council, City Manager/Mayor, and residents should collaborate to formulate and execute concrete plans within the next year. Immediate action is crucial to mitigate the impact of smoke exposure on public health, particularly given the foreseeable increase in wildfires.

Human-Centered Data Science Principles:

The project's decision-making was anchored in human-centered data science principles, emphasizing the well-being of the community. The focus on actionable recommendations, such as smoke awareness campaigns and accessible treatment, reflects a commitment to addressing the specific needs of Del Rio residents. Ethical considerations, privacy safeguards, and transparent communication of findings were paramount, ensuring that the study aligns with the best interests of the community it aims to serve.

Limitations:

While the wildfire analysis for Del Rio provides valuable insights, it is essential to address certain limitations that may impact the robustness and accuracy of the findings.

1. **Data Quality and Completeness:**
   The analysis heavily relies on open-source data, particularly the USGS Wildfire data. The quality and completeness of this data may vary, potentially introducing biases and inaccuracies into the smoke estimates. The lack of comprehensive information on all influencing variables may limit the accuracy of predictions and correlations.

2. **Assumptions in Predictive Modeling:**
   The ARIMA predictive model is based on assumptions about the stationarity and linearity of the data. Deviations from these assumptions may compromise the model's accuracy. Assumptions about the stability of future emissions and environmental conditions could introduce uncertainties into the long-term smoke estimates.

3. **Unknown Variables:**
   The analysis primarily focuses on smoke estimates as a factor influencing health outcomes. However, there may be other unaccounted variables and confounding factors, such as socio-economic status, individual health conditions, and regional policy changes, that can impact the observed correlations. Identifying and controlling for these unknowns is challenging and may introduce bias.

4. **Privacy Concerns in Healthcare Data:**
   Extracting healthcare data from public registries introduces privacy and security concerns. While efforts were made to aggregate data at a county level, potential risks to individual privacy cannot be entirely eliminated. The reliance on aggregated data might limit the granularity of the analysis.

5. **Future Prediction Uncertainties:**
   Predicting smoke estimates and healthcare effects over the next 25 years introduces uncertainties related to technological, economic, and policy changes. Environmental regulations and interventions may evolve, influencing the accuracy of long-term predictions.

6. **Weather Conditions and Meteorological Data:**
   The analysis does not deeply explore the influence of weather conditions, wind patterns, and temperature on smoke dispersion. Dependencies on accurate meteorological data for a detailed understanding of smoke behavior and its potential impact on health were not fully addressed.

7. **Temporal Scope and Historical Data:**
   The analysis considers historical data from 1963 to 2023. While this timeframe provides substantial insights, it may not capture the full spectrum of long-term trends and variations. The historical scope might not fully reflect changes in healthcare infrastructure, public awareness, and environmental policies.

8. **Regulatory and Policy Changes:**
   The analysis does not comprehensively account for potential changes in regulations and policies over the study period. Shifts in regulatory frameworks could significantly impact the relationship between wildfires, smoke exposure, and health outcomes.

9. **Incomplete Information on Individual Demographics:**
   The analysis assumes generalized effects of smoke exposure on the population without accounting for individual demographics. Variability in susceptibility based on age, pre-existing health conditions, and socio-economic status might not be fully captured.

10. **Data Extraction and Source Selection:**
    The extraction of AQI values relied on monitoring stations within a specific radius, potentially influencing the representativeness of the air quality data for Del Rio. The selection of specific monitoring stations and the increased bounding box scale may introduce biases.

Conclusion:

In examining the impacts of wildfires on Del Rio, Texas, this study aimed to address key research questions, evaluate hypotheses, and provide actionable insights grounded in human-centered data science principles.

Research Questions/Hypotheses:

- Are wildfires affecting healthcare in Del Rio and Val Verde County?

  The findings indicate a substantial correlation (64%) between smoke estimates from wildfires and overall deaths in Del Rio. This correlation underscores the significant impact of wildfires on public health.

- Are the death rates correlated to the smoke estimate calculated and also AQI values extracted from 1963 to 2023?

  The analysis reveals a positive correlation between smoke estimates and death rates, emphasizing the importance of considering environmental factors when assessing mortality trends.

- How much is the number of patients with cancer or cancer prevalence affected by smoke in the area over the years?

  \While an increase in the number of cancer incidents and deaths was observed, the correlation with smoke estimates was weaker (12%). This suggests that factors other than smoke exposure may contribute to cancer outcomes.

- Are the trends in deaths due to Chronic Lower Respiratory Diseases in Del Rio matching the smoke estimates and AQI values over the years?

  The study did not specifically address Chronic Lower Respiratory Diseases; however, the positive correlation with overall deaths implies a potential influence of smoke exposure on respiratory health.

Summary of Findings:

- The analysis indicates that Del Rio, though moderately affected by wildfire smoke, experiences a notable correlation between smoke estimates and overall deaths.
- While the impact on overall mortality is clear, the relationship with cancer mortality is more nuanced, suggesting the presence of other contributing factors.

- Unexpectedly, smoke exposure does not appear to be positively correlated with infant and fetal mortality, indicating the need for further investigation into additional influencing variables.
- Informed Understanding of Human-Centered Data Science:
- This study contributes to the understanding of human-centered data science by prioritizing the well-being of the Del Rio community. The application of data science principles, such as privacy safeguards, transparency, and interpretability, ensured that the findings were ethically sound and actionable.
- By focusing on public health implications and providing recommendations tailored to the community's needs, the study exemplifies the human-centered approach. Stakeholders, including City Council, City Manager/Mayor, and residents, are now equipped with insights to make informed decisions and implement strategies that prioritize health and resilience.
- This study serves as a blueprint for how human-centered data science can be leveraged to address real-world challenges. It not only uncovers correlations but also emphasizes the importance of translating data-driven insights into tangible actions that positively impact the lives of individuals in the community.

References:

1. https://aqs.epa.gov/aqsweb/documents/data_api.html
2. https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf
3. https://www.sciencebase.gov/catalog/item/61aa537dd34eb622f699df81
4. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8352067/
5. https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2019MS001955

Data Sources:

1. USGS Wildfire Data
   https://www.sciencebase.gov/catalog/item/61aa537dd34eb622f699df81
   File: USGS_Wildland_Fire_Combined_Dataset.json

2. US EPA Air Quality Index (AQI) Data
   https://aqs.epa.gov/aqsweb/documents/data_api.html

3. Texas Health Data – Val Verde County death rates
   https://healthdata.dshs.texas.gov/dashboard/births-and-deaths/deaths

4. Texas Vital Statistics
   https://www.dshs.texas.gov/vital-statistics-data

5. Texas Cancer Registry – Val Verde County cancer rates from 1990 to 2020
   https://www.cancer-rates.com/tx/

6. National Cancer Institute (NIH)
   https://seer.cancer.gov/

Data Description:

1. Wildfire Data:

Column Name	Data Type	Description
OBJECTID	Integer	Unique identifier for each record in the dataset.
USGS_Assigned_ID	Numeric/String	Assigned identifier by the US Geological Survey (USGS) for the fire.
Assigned_Fire_Type	String	Type or classification of the assigned fire.
Fire_Year	Integer	The calendar year in which the fire occurred.
Fire_Polygon_Tier	String	Tier or level of classification for the fire polygon.
Fire_Attribute_Tiers	String	Tiers or levels of attributes associated with the fire.
GIS_Acres	Float	Area of the fire in acres according to the GIS data.
GIS_Hectares	Float	Area of the fire in hectares according to the GIS data.
Source_Datasets	String	List of datasets used as sources for fire information.
Listed_Fire_Types	String	Types of fires listed for the particular record.
Overlap_Within_1_or_2_Flag	String	Flag indicating overlap within 1 or 2 units.
Circleness_Scale	Float	Scale related to the circular shape of the fire.
Circle_Flag	String	Flag indicating whether the fire has a circular shape.
Exclude_From_Summary_Rasters	String	Flag indicating whether the fire should be excluded from summary rasters.
Shape_Length	Float	Length of the shape representation of the fire.
Shape_Area	Float	Area of the shape representation of the fire.
fire_lat	Float	Latitude of the fire location.
fire_lon	Float	Longitude of the fire location.
distance_from_del_rio	Float	Distance from Del Rio, a reference point, to

		the fire location.
smoke_estimate	Numeric	Estimate of smoke associated with the fire.

2. AQI Data:

Column Name	Data Type	Description
date_local	Date	The local date for which air quality information is recorded.
pollutant_standard	String	The air quality pollutant standard being measured, such as PM2.5, PM10, Ozone, etc.
aqi	Integer	The Air Quality Index (AQI) value corresponding to the pollutant_standard for the given date_local. The AQI provides a numerical representation of the air quality level.

3. Deaths by Race Data:

Column Name	Data Type	Description
Year	Integer	The calendar year in which the data was recorded.
All Races Total Deaths - Texas	Integer	The total number of deaths for all races in the state of Texas during the specified year.
All Races Total Deaths	Integer	The total number of deaths for all races across all regions during the specified year.
All Races Male Deaths	Integer	The total number of deaths for all races among males during the specified year.
All Races Female Deaths	Integer	The total number of deaths for all races among females during the specified year.
White Total Deaths	Integer	The total number of deaths among individuals identified as White during the specified year.
White Male Deaths	Integer	The total number of deaths among White males during the specified year.
White Female Deaths	Integer	The total number of deaths among White females during the specified year.
Black Total Deaths	Integer	The total number of deaths among individuals identified as Black during the specified year.
Black Male Deaths	Integer	The total number of deaths among Black males during the specified year.
Black Female Deaths	Integer	The total number of deaths among Black females during the specified year.
Hispanic* Total Deaths	Integer	The total number of deaths among individuals identified as Hispanic* during the specified year.
Hispanic* Male Deaths	Integer	The total number of deaths among Hispanic* males during the specified year.
Hispanic* Female Deaths	Integer	The total number of deaths among Hispanic* females during the specified year.

Other** Total Deaths	Integer	The total number of deaths among individuals identified as Other** during the specified year.
Other** Male Deaths	Integer	The total number of deaths among Other** males during the specified year.
Other** Female Deaths	Integer	The total number of deaths among Other** females during the specified year.

4. Cancer Deaths Data:

Column Name	Data Type	Description
Year	Integer	The calendar year in which the data was recorded.
Population	Integer	The total number of individuals in a specified region or demographic during the year.
Cancer Deaths	Integer	The number of deaths attributed to cancer within the specified population and year.
Population affected	Integer	The count of individuals who have been diagnosed or affected by cancer in any form.
Cancer Incidents	Integer	The number of new cases of cancer reported or diagnosed within the specified population.

5. Infants and Fetal Deaths Data:

Column Name	Data Type	Description
Year	Integer	The calendar year in which the data was recorded.
Infant Deaths	Integer	The number of deaths of infants (children below one year of age) during the year.
Infant Death Rate	Float	The rate of infant deaths per 1,000 live births during the specified year.
Fetal Deaths	Integer	The number of fetal deaths (stillbirths) during the specified year.
Fetal Death Ratio	Float	The ratio of fetal deaths to the total number of births during the specified year.