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Using R Programming Tools to Visualize Air Quality Index in USA

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Abstract: One of the prominent programming languages in data visualization and statistics is R. The author deployed R programming tools to analyze the air quality across the United States from 1980 to 2022, which provided valuable insights into the patterns of the national Air Quality Index (AQI). The findings indicate that some states have improved air quality through stringent environmental regulations. In contrast, others struggle with high AQI levels due to industrial activities, urbanization, and natural factors such as wildfires. The study identified that ozone and PM2.5 are the most persistent pollutants, significantly contributing to poor air quality. States such as California and Texas exhibited persistently high AQI values, while others, such as Vermont and Maine, showed relatively stable or improving air quality.

Keywords: R Programming Tools; Exploratory Data Analysis; Data Visualization; Air Quality Index; Particulate Matter

I. INTRODUCTION

Clean air is essential for life. Impure air impacts negatively on health. Air pollution is one of the crucial issues affecting the environment globally. Pure air is chiefly composed of 78% Nitrogen and 21% Oxygen, along with other gases like carbon dioxide and noble gases. Harmful gases and germs can make the air impure; hence, there is a need to know the quality of breathable air. In the USA, air quality data is collected by numerous monitoring stations. The data provides the levels of pollutants in the air. There is a growing degradation of air quality in both urban and industrial areas due to increased baseline concern toward monitoring pollution levels. Hence, environmental agencies developed the Air Quality Index (AQI) as a standardized metric to indicate safety regarding human health. AQI is a great tool that helps describe air pollution levels to the public, that is, whether the air is breathable or not [1].

AQI is an internationally accepted measure for presenting air quality to the public. It integrates multiple pollutants, like particulate matter (PM10 and PM2.5), ozone (O3), nitrogen dioxide (NO2), sulfur dioxide (SO2), and carbon monoxide (CO), into a single number representing a range of air quality categories from good to hazardous [2]. Environmental agencies adopt the values of AQI for disseminating information to the public and enforcing pollution control. Before the USA Environmental Protection Agency (EPA) created the AQI, air quality reporting varied nationwide, making it difficult to understand and compare pollution levels. The AQI standardized this reporting, using a consistent scale and framework that can adapt to new scientific findings and regulations. This has increased public awareness of air pollution and supported the development of regulations to improve air quality. The AQI is directly related to the National Ambient Air Quality Standards (NAAQS), which define acceptable levels of common pollutants like carbon monoxide, lead, nitrogen dioxide, ozone, particulate matter, and sulfur dioxide [19].

Ambient air pollution significantly threatens global health, necessitating effective monitoring and public communication strategies [18]. By quantifying the concentration of key pollutants, including particulate matter (PM10 and PM2.5), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO), the AQI provides a standardized and readily interpretable metric of air quality. The resulting index values, ranging from 0 to 500, are categorized into six color-coded levels, each corresponding to a specific level of health concern. This system enables public health agencies to issue timely advisories and empowers individuals, particularly vulnerable groups, to make informed decisions to minimize exposure to harmful pollutants [3].

The AQI serves several key purposes in public health and environmental policy. Firstly, it raises public awareness by providing an easily interpretable measure of air pollution, which allows individuals to take appropriate actions, such as reducing outdoor activities or using air purifiers during high pollution periods. Governments use the AQI to monitor air quality trends and inform regulatory measures to improve environmental standards [18]. In addition, the AQI is critical for emergency preparedness. During extreme events such as wildfires or industrial accidents, the AQI helps public health agencies issue timely warnings to mitigate health risks [19]. Moreover, the AQI allows for predictive modelling of health outcomes based on pollutant concentrations, thus guiding public health initiatives and interventions for at-risk populations.

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As depicted in Table 1, the AQI is roughly divided into six categories, each representing a different level of health concern based on the concentration of pollutants in the air. These categories range from "Good" (AQI 0-50), where air quality is satisfactory and poses little or no risk, to "Hazardous" (AQI over 300), where emergency conditions are triggered, and the entire population is likely to be affected. In between, "Moderate" (AQI 51-100) indicates acceptable air quality, though sensitive individuals, such as those with respiratory issues, may experience mild symptoms. "Unhealthy for Sensitive Groups" (AQI 101-150) signals a potential risk for people with lung or heart conditions, though the public is not usually impacted. At AQI values between 151 and 200, the air quality is considered "Unhealthy," meaning that health effects may begin to affect everyone, with more serious consequences for sensitive individuals. When the AQI reaches between 201 and 300, it is categorized as "Very Unhealthy," and a health alert is issued, warning that everyone may experience serious health effects. Finally, values above 300 represent "Hazardous" air quality, prompting warnings of emergency conditions where significant health impacts are expected across the entire population ([3], [19]).

TABLE 1 CATEGORIZATION OF AIR QUALITY CONTENTS AFTER [3]

Breakpoints							AQI	Category
O_3 (ppm) 8-hour	O_3 (ppm) 1-hour	PM2.5 ($\mu g/m^3$) 24-hour	PM10 ($\mu g/m^3$) 24-hour	CO (ppm) 8-hour	SO_2 (ppb) 1-hour	NO_2 (ppb) 1-hour		
0.000-0.054	N/A	0.0-12.0	0-54	0.0-4.4	0-35	0-53	0-50	Good
0.055-0.070	N/A	12.1-35.4	55-154	4.5-9.4	36-75	54-100	51-100	Moderate
0.071-0.085	0.125-0.164	35.5-55.4	155-254	9.5-12.4	76-185	101-360	101-150	Unhealthy for selected groups
0.086-0.105	0.165-0.204	**55.5-150.4**	255-354	12.5-15.4	*186-304*	361-649	151-200	Unhealthy
0.106-200	0.205-0.404	**150.5-250.4**	355-424	15.5-30.4	*305-604*	650-1249	201-300	Very unhealthy
N/A	0.405-0.504	**250.5-350.4**	425-504	30.5-40.4	*605-804*	1250-1649	301-400	Hazardous
N/A	0.505-0.604	**350.5-500.4**	505-604	40.5-50.4	*805-1004*	1650-2049	401-500	Hazardous

While AQI serves as a valuable communication tool for air quality, it is not without limitations. The index's reliance on broad categories may not fully capture the nuanced health risks associated with specific regional pollution sources, such as high particulate matter concentrations in urban areas [5]. Furthermore, the AQI's generalized risk assessment fails to account for local factors like healthcare access and the disproportionate vulnerability of specific populations, including those with chronic respiratory illnesses [6]. Limited monitoring infrastructure in some regions challenges real-time data availability, hindering timely public health responses [5]. Finally, the AQI's focus on short-term exposures neglects the cumulative health impacts of long-term pollutant exposure, particularly for vulnerable individuals.

Air quality data generates big data sets. Access to AQI analysis has become easier with data analysis and visualization techniques. Big data and visualization technologies have improved to the extent that analyzing AQI temporal trends can provide sources of pollution, seasonal variations, and the effectiveness of pollution control measures [2]. This study helps concerned parties to understand how visualized AQI data can aid informed decision-making and public awareness of air pollution.

This project aims to analyze historical AQI data from 1980 to 2022 to identify long-term air quality trends, assess the effectiveness of environmental policies, and evaluate the impact of pollution levels on public health. By leveraging this extensive dataset, we will examine variations in AQI across different regions, investigate correlations between pollutant

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concentrations and health advisories, and assess the frequency of extreme pollution events. Additionally, it explored the limitations of the AQI framework, including its ability to reflect localized pollution sources and long-term exposure risks

II. METHOD

The dataset used in this study is sourced from Kaggle, a popular platform known for its vast collection of publicly available datasets - Air Quality Index by State 1980 - 2022 [20]. Kaggle is an online hub where people can find datasets, work on data science projects, and join competitions. Indeed, it boasts several free datasets ranging from healthcare and finance to environmental studies.

The Air Quality Index by State dataset of 1980-2022 is used for this project. This is a dataset on the air quality level in different USA states from 1980 to 2022. This dataset contains yearly AQI values, data for USA state counties, and pollutant levels over time. Data in this dataset comes from government sources, such as the EPA air quality monitoring stations. The following is tracked at the stations across the nation through active measurement of these substances: fine particles in the air (PM2.5), coarse particles in the air (PM10), nitrogen dioxide (NO2), and carbon monoxide (CO).

Air quality analysis was implemented using R, based on several packages designed for data visualization and manipulation. Such packages include ggplot2, tidyverse, maps, plotly, and viridis. These packages ensure the data are efficiently processed for statistical tests and visualized as required [4]. The analysis followed a structured approach: data preprocessing, followed by visualization. A code was used to extract data from the Kaggle hub package in R, which facilitated direct download of the dataset air-quality-index-by-state-1980-2022. Data preprocessing involved downloading the dataset from Kaggle using the kagglehub Python package, which is integrated into R using the reticulate library. Secondly, after downloading, the dataset is moved to a specified directory and loaded into an R data frame. Preprocessing involves renaming the columns for better readability and converting variables into suitable data types. This entails year to integer, population estimates to numeric, and state names to character. Still, cleaning the data, it filtered out all the rows containing all NA values and replaced all negative values with NA in a bid to retain the integrity of the data. It arranged the data chronologically in an order based on the state and year for conducting the analysis ([4], [7]).

The key activities composing the workflow in data preprocessing include ensuring consistency and the accuracy of the data for analysis, standardizing the column names across datasets, making changes to the variable types in order to represent numerical and categorical data accurately; and handling missing or negative values correctly to avoid biases in the analysis ([8], [17]). The geographic data is standardized for accurate mapping and visualization. Besides, the derived metrics are computed for percent change to show the variation over time. Finally, time series data is aggregated at yearly and decadal levels to identify long-term trends and patterns in air quality.

Exploratory data analysis (EDA) was conducted, consisting of a miscellaneous set of analytical methods that aim at understanding the structure and distribution of the data ([15], [16]). Spatial variation of the AQI was constructed to enable a geographic distribution understanding of air pollution. Decadal trend analysis puts forward the variation in air quality over long periods. Correlation analysis tests the various pollutants' relations; distribution analysis of pollutants calculates patterns and anomaly detection. How population changes with the AQI level will indicate the consequences of urbanization regarding air quality variation. For state-wise trends, regional variation, and for AQI distributions in categorical analysis for classification into different regions based on their air quality levels.

The evaluation strategy here is based on deriving meaningful insight from the various analyses conducted [13]. The long-term AQI trend across different states is discussed to assess their improvements or deterioration in air quality over time. Relationships among different pollutants are checked to understand how different pollutants interact and contribute to pollution levels. It checks the impact of increasing population on air quality, showing the places around where urbanization has resulted in the highest levels of concern for the environment. Geographic patterns in air quality are mapped to detect regional disparities; state-specific air quality challenges are highlighted to inform policy decisions and targeted interventions to mitigate pollution.

Visualizations were done to analyse the trend for air quality across different states and years. A choropleth or geographical distribution of median AQI values across the United States for the most recent year, 2022, was created. The AQI data was overlaid on a base USA map with colour gradients to represent AQI levels. This helped develop a scatter plot showing the dependence of PM2.5 and ozone pollution, including a linear regression trend line that helps indicate any kind of correlation. The latter part represents the comparison of growth in population versus the change in AQI between 1980 and 2022, decade-wise for each state. A decade-wise plot of population-AQI by bar and line plot showed trends in states with high AQI values. Summary statistics were generated to highlight key insights, including average AQI, peak AQI, and population growth percentages for the most affected states ([12], [14]). A box plot of distribution across different states for days affected by various pollutants like CO, NO2, Ozone, PM2.5, and PM10 were developed.

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III. RESULTS

The study evaluated the US states' air quality index using R programming and visualization tools. Fig. 1 illustrates the maximum Air Quality Index across USA states from 1980 to 2022, which is roughly reflected in Fig. 2, which shows the values for the year 2022. The dark blue shading in Fig. 1 represents the maximum AQI. The highest AQI, mostly above 500 in some instances, was obtained in the western states, with California on top, probably because of various reasons: wildfire, industrial activity, and generally high urban density. Contrasting that, states located in the Midwestern and Northeastern parts show lighter colours, reflecting lower maximum AQI values, probably due to different population density, industrial emissions, and environmental conditions [19]. The significant regional differences underpin the influence of geographical and environmental factors on air quality. States with record levels of extreme AQI, especially in the West, must deal with air quality problems more frequently and thus are more responsive regarding environmental law and natural disaster management. This visualization underscores the importance of focused interventions to enhance air quality, especially in regions highly prone to hazardous conditions.

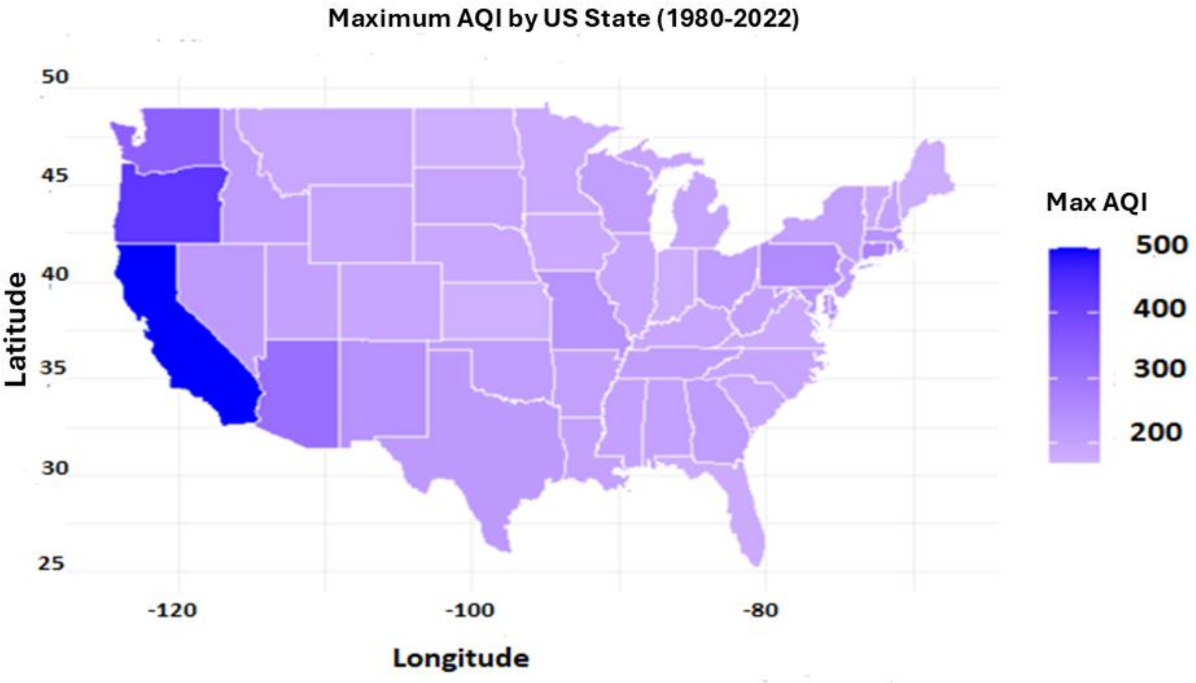

Fig. 1 Maximum AQI across United States 1980-2022.

To analyse the percentage change in air quality, the AQI data was overlaid with population for some states, decade-wise. Fig. 3 combines the population growth with the AQI trend in Virginia for every decade. Blue bars show the population in millions, and a red line illustrates the median AQI for the same periods. From this chart, the population has continued to increase over the years in Virginia from the 1980s to the 2020s, and it shows growth into the millions. In contrast, the red line, representing a decrease in the median AQI over time, suggests improvement. The peak of the median AQI was reached during the 1980s, and afterward, it went down in the next twenty years, whereas the population grew continuously. It reflects successful environmental policy and/or pollution control technologies amid rapid urbanization and high population density. The contrasting trends demonstrate an essential balance between population growth and environmental management.

Fig. 4 illustrates Texas's population and air quality index trend for several decades. The blue bars reflect the population growth, in millions, whereas the red line gives the median AQI. Texas has grown continuously over these decades, doubling between the 1980s and the 2020s. It goes to say that Texas is fast emerging as a new growth pole at an economic and cultural level. Median AQI increases slightly from the 1980s to the 1990s and then remains almost constant for the rest of the decades. The slight improvement in air quality over the years may mean increasing difficulties in pollution abatement, with increased technological and regulatory controls abounding. While other states reflect improvements in AQI with growing populations, the uniformity in the AQI plot of Texas denotes continuous environmental degradation associated with industry, energy, and urban growth. This place demands further escalating air quality management in Texas. Alongside these increases in population, even stronger controls of pollutants will need to be imposed, along with sustainable development, to prevent further deterioration.

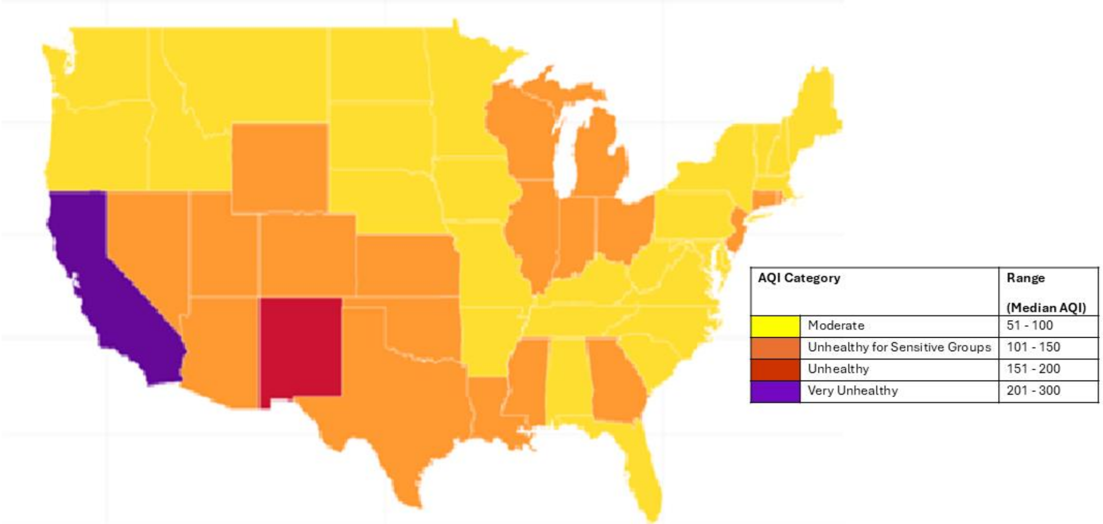

Fig. 2 Air Quality Index across United States 2022.

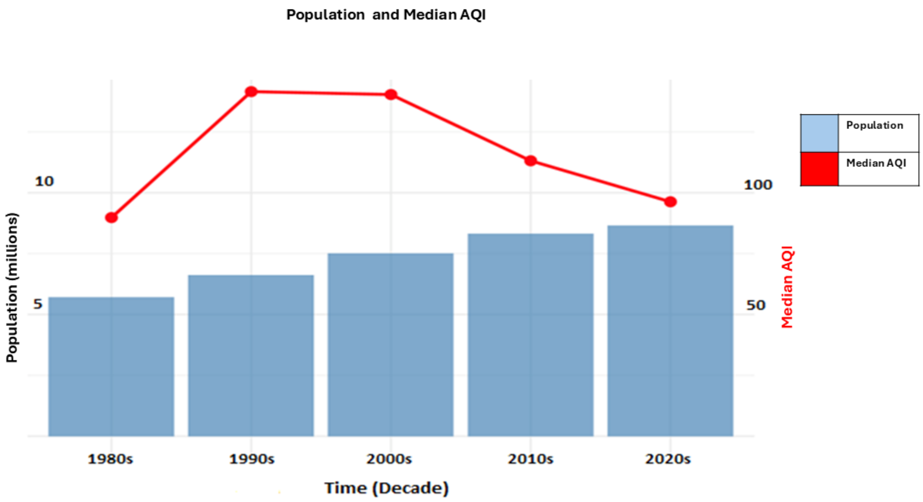

Fig. 3 Population growth with AQI trend in Virginia

This chart compares the percentage change in population (blue bars) and Air Quality Index (AQI) (red bars) for US states between 1980 and 2022. Most states exhibit significant population growth, with notable increases in Nevada (650.9%) and Arizona (482.8%). Despite population surges, AQI changes vary dramatically across states. While West Virginia saw an AQI increase of 878.9%, states like Vermont and Maine show very minimal growth in AQI, or even slight declines. This suggests that the relation of population growth to environmental degradation can be quite complex, and areas of rapid growth might not relate to significant increases in AQI. This further underlines the different effectiveness of environmental policies and other factors, such as industrial activity, geographic conditions, and urbanization, in affecting air quality trends in concert with population changes. The chart dramatically presents state-by-state disparities in managing growth and environmental sustainability.

A boxplot was constructed to illustrate the distribution of pollutant types by day. Fig. 5 illustrates the distribution of days by pollutant type, including carbon monoxide (CO), nitrogen dioxide (NO2), ozone (O3), particulate matter smaller than 10 microns (PM10), and particulate matter smaller than 2.5 microns (PM2.5). Among the pollutants, ozone and PM2.5 have the highest number of days, reflecting their persistent and widespread presence in the environment. Among these, PM2.5 has the highest range and median, and therefore contributes most to air quality concerns. Note also that the distribution in both CO and NO_2 is much smaller, indicating only a few days with notably high levels. PM10 falls between these extremes but is less important than PM 2.5. There are outliers, especially for ozone and PM2.5, to indicate extreme events of pollution on those days, which again points to how important these pollutants are ([9], [11]). This analysis indicates that measures on ozone and particulate matter would have to be prioritized to improve air quality.

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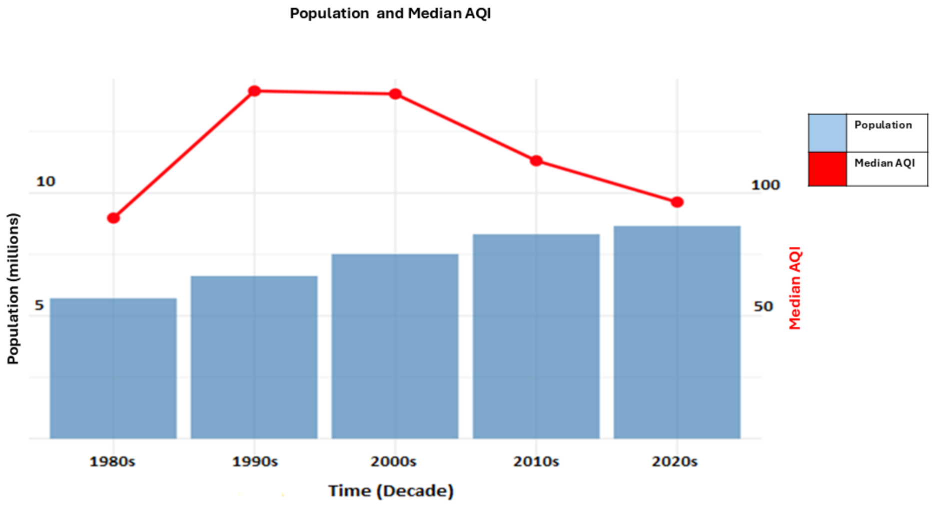

Fig. 4 Population growth with AQI trend in Texas

IV. DISCUSSION

This study of AQI across the United States, from 1980 to 2022, has shown dramatic contrasts in various regions. It is distressing to note that in 2022, states like Texas had an index value of 1737, and Wisconsin had an index value of 1022. Generally, higher AQI values are recorded within the southeastern and midwestern states than in other regions. Despite maintaining very strict environmental rules, California has struggled with significant air quality issues in 2022, managing an AQI of 2248 [19]. The distribution analysis of the pollutant types shows that ozone has the highest number of affected days among all pollutant categories, with PM2.5 reflected with high variation in its distribution. While CO and NO2 present relatively lower occurrences on a day-to-day basis, they nonetheless constitute persistent urban concerns. In addition, it is seen from the statistical results that ozone and PM2.5 have big outliers, which means there will be periodic severe pollution events [18].

Decadal analysis reveals the relative success of pollution control. For example, states such as California demonstrate relative stability in AQI despite population increases, indicating successful pollution control. Other states, such as Indiana and Kentucky, demonstrate disturbing trends of large increases in AQI during the 2000s followed by gradual decreases, highlighting the effect of industrial activity and environmental policy (American Lung Association). Analysis of AQI change versus population, 1980-2022, presents complex relationships between demographic growth and air quality. States with rapid growth in population, such as Nevada with 292.2% and Arizona with 229.9%, show corresponding increases in AQI, hence showing difficulties in maintaining air quality in the wake of rapid urbanization. Most northeastern states generally exhibit more modest changes in both measures and reflect more sustainable development patterns. Temporal analysis reveals AQI peaks in the 2000s for many states, with subsequent improvements in recent decades, particularly evident in southeastern states like Georgia, North Carolina, and Tennessee. Florida and Texas show distinct patterns with gradual AQI increases correlating with sustained population growth.

Based on the analysis, several key recommendations emerge for improving air quality management across the United States. First, introducing improved monitoring systems is relevant, especially within states that have represented hazardous AQI levels over time. In addition, these should be done through more sophisticated measuring tools and increased frequency of data collection to monitor or respond to variations in air quality [18]. Second, interstate collaboration frameworks are equally fundamental since air pollution respects no state borders. It would allow the states to share resources, coordinate pollution control efforts, and pursue joint strategies for managing air quality across interconnected regions.

Population-sensitive planning is another important aspect of air quality management, which in rapidly growing states may experience urbanization and development that seriously affects air quality. These estimates of population growth should be carefully integrated into the air quality management strategies to let states develop appropriate plans and prepare for potential challenges in advance [19]. Given the prevalence of certain pollutants from the data, specific attention is needed regarding strategies to reduce ozone and PM2.5. Such pollutant-specific approaches should include targeted controls of emissions, better public transport systems, and improved industrial regulations.

Lastly, the regulation of emissions through policy should be strengthened, especially in states showing declining air quality with a stable population. This includes revision and updating of the existing rule, stringency in enforcement, and new technologies for emission reduction. These policies need to be flexible and responsive to changing conditions but with steady movement toward improving air quality.

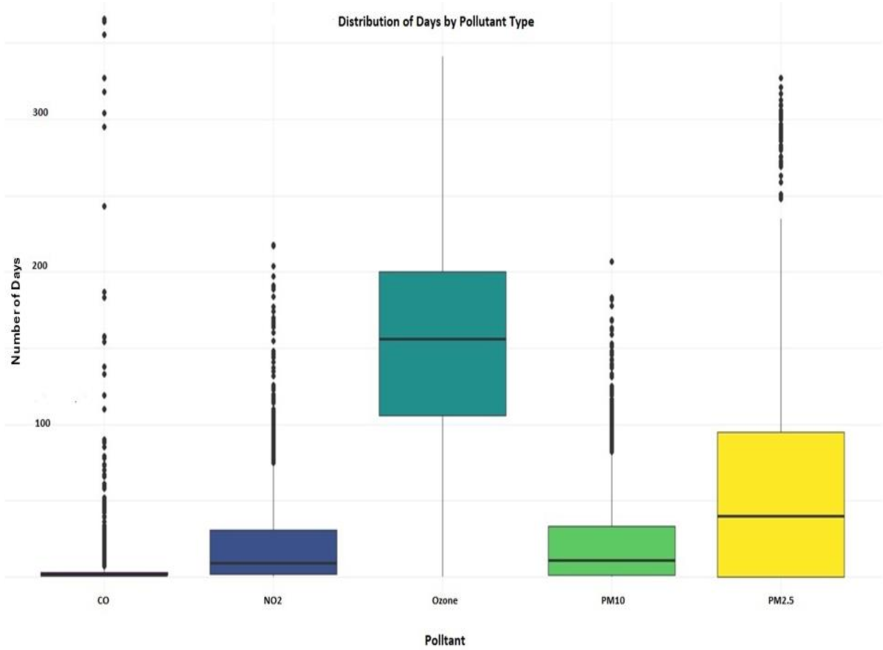

Fig. 5 Boxplot of pollutant values per day

V. CONCLUSION

Air quality analysis across the United States from 1980 to 2022 has provided valuable insights into the trends, patterns, and implications of the Air Quality Index (AQI). The findings indicate that while some states have improved their air quality through stringent environmental regulations, others continue to struggle with high AQI levels due to industrial activities, urbanization, and natural factors such as wildfires [3]. The study identified ozone and PM2.5 as the most persistent pollutants, significantly contributing to poor air quality [2]. States such as California and Texas exhibited persistently high AQI values, while others, such as Vermont and Maine, showed relatively stable or improving air quality. Furthermore, the correlation between population growth and AQI trends varied across states, suggesting that effective pollution control measures can mitigate the impact of urban expansion on air quality ([4], [13]). The various plots and visualizations have served well to pinpoint the geographical and temporal variations in the levels of air pollution. Therefore, these findings underscore the need for continuous monitoring, policy interventions, and public awareness to improve air quality and safeguard public health [18].

The Air Quality Index remains crucial for assessing and communicating air pollution levels to the public and policymakers [6]. The study reaffirms that air quality management requires a multi-faceted approach, incorporating data-driven decision-making, technological advancements, and regulatory frameworks [2]. Such visualization techniques underscore the role data science could play in research, especially in finding trends related to pollution and identifying the efficiency of intervention measures [16]. Although advanced monitoring and predictive analytics have boosted human understanding of air pollution, inconsistency in reporting from sources, site-specific emissions, and the chronicle of air pollution exposure, among others, are challenges that remain upfront [1]. Moving forward, improved AQI monitoring, real-time data collection, and cross-state collaboration will be essential in mitigating air pollution and promoting healthier living environments [19]. Addressing these challenges will require a collective effort from government agencies, researchers, industries, and the public to ensure sustainable air quality improvements and minimize the health risks associated with pollution [18].

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BIOGRAPHY

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