ANALYSIS OF PM2.5 POLLUTION AND ITS IMPACT ON PUBLIC HEALTH: RACIAL AND NEIGHBORHOOD DISPARITIES IN NEW YORK CITY (2009-2022)

IST 652: Scripting for Data Analysis

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Abstract

Air pollution, particularly fine particulate matter (PM2.5), is a significant public health issue, contributing to increased morbidity and mortality from respiratory and cardiovascular diseases. Despite improvements in air quality over recent decades, New York City (NYC) continues to face elevated levels of PM2.5, especially in neighborhoods with higher populations of people of color. This study examines PM2.5 trends in NYC from 2009 to 2022, investigates racial and neighborhood disparities in exposure, and explores the impact of PM2.5 on hospitalizations for respiratory and cardiovascular diseases.

Using datasets from the NYC Environment and Health Data Portal, the study employs time-series, geospatial, and regression analysis techniques. The time-series analysis reveals a general decline in PM2.5 levels over the period, though certain neighborhoods persist with high pollution. Geospatial analysis identifies areas with the worst air quality, disproportionately affecting communities of color. Regression analysis shows a significant relationship between PM2.5 exposure and increased hospitalizations for respiratory and cardiovascular conditions in various age groups.

These findings highlight the need for targeted interventions to reduce air pollution in high-risk neighborhoods. While trends show improvements, disparities in exposure remain. Future research should incorporate additional variables and explore seasonal effects on PM2.5-related health outcomes.

Keywords: Air pollution, PM2.5, public health, racial disparities, New York City, hospitalizations, time-series analysis, geospatial analysis, regression analysis.

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1. Introduction

Pollution can be defined as harmful substances that are introduced into the air and cause significant damage to humans and other living organisms (Manisalidis, Stavropoulou, Starropoulos & Bezirtzoglou, 2020). As per Dockery (2012), air pollution can be defined as 11anything whether solid or liquid, that is suspended in the air. These contaminants could be from a vast source like soot, smoke, sulfates, nitrates, or even windblown dust and pollens.

Unfortunately, this has resulted in an international public health problem and various facets (Manisalidis, Stavropoulou, Starropoulos & Bezirtzoglou, 2020). Due to the increase in air pollution, many people are suffering from health implications like cardiovascular diseases, extensive respiratory illnesses, and some cases have even reported neurological disorders (Simkovich *et al.*, 2019). People with any pre-existing conditions related to health, children, and elderly are among the first to be targeted by the deteriorated air quality due to the presence of pollutants in the air (Naclerio *et al.*, 2020). Due to its profound impact on public health, it cannot be denied in stating that air pollution has now become a critical environmental problem (Sicard *et al.*, 2023).

Countless cities today are facing the same problem of the vast increase in pollutants causing air pollution. However, as per the United States Environmental Protection Agency (2024), outdoor air pollutants in the United States of America have been reduced by about 78%, from 1970 to 2020. Despite the reduced pollution levels, there remains a question of whether the pollutants responsible for an increase in diseases related to respiratory, cardiovascular, or any other illness have reduced or are demonstrating a declining pattern. In recent times, New York City (NYC) has been highlighted to be among the top three cities, with maximum pollution towards the east side of the Mississippi River (Christensen, 2023).

As a result, the main aim of this paper is to examine the impact of PM2.5 on public health in New York City by analyzing air quality trends from 2009 to 2022. It will highlight disparities in air quality across neighborhoods, particularly those with higher populations of people of color. The study would also link PM2.5 exposure to increased respiratory and cardiovascular hospitalizations, emphasizing the need for targeted pollution control measures.

1.1 Objective

- Composition identification based on the neighborhood and racial population air quality based on the NYC category segregation
- Comparative time-series analysis to identify the pattern of air quality from 2009 to 2022
- Understanding the number of asthma, and other respiratory and cardiovascular hospitalizations due to PM2.5 in various age groups.

1.2 Scope of the project

1.2.1 In-scope

- This project will focus on analyzing PM2.5 exposure data from the Air Quality dataset provided by the NYC Environment and Health Data Portal. The analysis will also incorporate three additional datasets that record hospitalizations due to respiratory diseases (age 20+), cardiovascular diseases (age 40+), and emergency asthma hospitalizations linked to PM2.5 exposure. These datasets will be primarily used to understand the impact of PM2.5 exposure on public health, particularly the increase in hospitalizations for respiratory and cardiovascular diseases in different age groups.

1.2.2 Assumptions

- It is assumed that PM2.5 levels have fluctuated or decreased over the years but continue to be a significant health risk in certain neighborhoods of NYC, particularly those with high industrial activity and traffic emissions.
- As part of this study, the focus will be on analyzing PM2.5 exposure and its correlation with hospitalization rates for respiratory and cardiovascular diseases.
- The study will analyze racial disparities in exposure to PM2.5, considering that these communities are more likely to be located in areas with worse air quality.
- Python (Jupyter Notebook) will be the primary tool for analysis, while Adobe Illustrator will be used for enhancing visualizations if necessary.

1.2.3 Out-of-scope

Any other business questions requiring additional datasets to be merged will not be a part of this project's scope.

1.3 Rationale

As outlined in the previous sections, despite the reduction in air pollution, there is still a significant impact resulting in public health issues with PM2.5 being one of the most harmful pollutants due to its ability to penetrate deep into the lungs and bloodstream. Given the prominent role that cities like NYC play as hubs of economic and population density, understanding and managing air quality becomes essential for improving public health. Despite the overall reduction in the air pollutants outdoors, NYC continues to be affected by high levels of PM2.5. By analyzing the trends in air quality over time, this term paper aims to create a clearer understanding of how pollutants influence public health in NYC, and ultimately contributes to a larger effort to protect urban populations from the detrimental effects of air pollution.

Additionally, the topic aligns with the interest in environmental health and data-driven decision-making. It also provides an opportunity to apply data analytics skills, especially Python and data manipulation techniques, that would assist in addressing this real-world problem. Using publicly available datasets on the NYC air quality, racial population and would allow the skills to help draw actional insights that can potentially influence public health policy and urban planning decisions aimed at improving air quality.

2. Literature review

Air pollution, particularly fine particulate matter (PM2.5), remains a pressing issue for public health, with a substantial body of research linking exposure to increased morbidity and mortality. In their study, Manisalidis, Stavropoulou, Starropoulos & Bezirtzoglou (2020) emphasize that particulate matter, including PM2.5, consists of small particles that pose significant health risks, particularly to the lungs and cardiovascular system. The paper also highlights how human activities such as industrialization and urbanization have significantly contributed and increased harmful pollutants. This aligns with Dockery (2012), which notes that long-term exposure to PM2.5 is associated with reduced life expectancy, especially in areas with high pollution levels like New York City. Simkovich *et al.* (2019) further underscores the widespread impact of

PM2.5, highlighting how air pollution is linked to an increase in respiratory diseases, including asthma and COPD, affecting vulnerable populations.

Goldstein (1972) extends this discussion by exploring how air pollution interacts with meteorological factors, exacerbating its health effects. The study shows that temperature inversions can trap pollutants near the ground, leading to higher concentrations of pollutants like PM2.5, which significantly increase the risk of respiratory and cardiovascular issues. This finding is particularly relevant to cities like New York, where weather conditions and high pollution levels often combine to create severe air quality events. Similarly, Cifuentes, Borja-Aburto, Gouveia, Thurston & Davis (2001) demonstrate the potential health benefits of reducing air pollution, estimating that even a modest reduction in PM10 and ozone could prevent thousands of deaths and hospitalizations, reinforcing the need for continued air quality management in urban environments. This aligns with Chen *et al.* (2024), who identifies the broad array of health complications linked to air pollution, including exacerbated respiratory conditions and increased rates of cardiovascular events. The global disease burden attributable to air pollution is substantial, and as Sicard *et al.* (2023) assert, addressing air quality issues could substantially reduce healthcare costs, making pollution control a key public health intervention.

While PM2.5 is a significant concern, Kinney, Chillrud, Ramstrom, Ross & Spengler (2002) highlight the emerging issue of ultrafine particles (UFPs), which can bypass natural respiratory defenses and cause even more severe health effects. Their study in New York City emphasizes how urban pollution, driven by traffic and industrial emissions, worsens the effects of both PM2.5 and UFPs. These pollutants contribute to chronic respiratory diseases, including asthma, particularly among those living in high-traffic urban areas like Harlem, where exposure levels to VOCs and PM2.5 are elevated.

The historical perspective provided by Greenburg, Jacobs, Drolette, Field & Braverman (1962) offers additional context, showing that New York City's air pollution problems date back decades. The temperature inversion incident of 1953, which caused a severe spike in sulfur dioxide levels, led to a noticeable increase in mortality, demonstrating the acute risks of high pollution levels. This historical evidence mirrors the ongoing concerns about PM2.5 and its health effects today.

Additionally, Goldstein (1972) delve into the interaction between weather conditions and air pollution, showing that temperature inversions can trap pollutants close to the ground, exacerbating the effects of PM2.5 in urban areas. Their research, combined with insights from Cifuentes, Borja-Aburto, Gouveia, Thurston & Davis (2001), underscores the urgent need to consider meteorological factors in air quality management strategies.

In terms of technological advancements, Sahu, Mangaraj, Beig, Tyagi, Tikle & Vinoj (2021) explore new methods for monitoring air pollution, such as satellite remote sensing and the integration of big data analytics, which have allowed for more precise tracking of PM2.5 levels and their sources. Additionally, the use of predictive models and machine learning can help forecast pollution trends, allowing policymakers to intervene proactively (Gulan *et al*., 2023).

The integration of these findings into a cohesive understanding of the air pollution-health relationship supports the need for enhanced air quality management. It is clear from the research that while substantial progress has been made in reducing overall pollution levels, targeted efforts to reduce specific pollutants like PM2.5 and UFPs, particularly in high-density urban areas, are essential. As Cifuentes, Borja-Aburto, Gouveia, Thurston & Davis (2001) suggest, reducing PM10 and PM2.5 levels through regulatory measures could have wide-reaching public health benefits, further emphasizing the importance of data-driven policy interventions in improving urban air quality and reducing hospitalizations related to respiratory and cardiovascular diseases.

This historical evidence highlights the need for continued air quality monitoring and stricter pollution controls. The goal of this paper is to analyze PM2.5 trends in NYC from 2009 to 2022, focusing on racial disparities and health impacts. By examining these factors, the study addresses three key hypotheses related to air quality and public health outcomes. This approach underscores the importance of targeted pollution control measures.

2.1 Hypotheses

H_1: Areas with a higher proportion of people of color have worse air quality (higher PM2.5 levels) compared to predominantly white neighborhoods.

H_2: PM2.5 levels in New York City have shown a decreasing trend from 2009 to 2022, indicating an improvement in air quality.

H_3: PM2.5 exposure has contributed to an increase in respiratory and cardiovascular hospitalizations, particularly in the age groups 20+ and 40+ over the past decade.

3. Methodology

The methodology for this term paper adopts a Quantitative Data Analysis approach to examine the trends in air quality in New York City, with a particular focus on fine particulate matter (PM2.5) and its effects on public health.

3.1 Methods

Time-Series Analysis:

- PM2.5 data from 2009 to 2022 was used for the time-series analysis. The dataset includes monthly air quality measurements for various neighborhoods in New York City.
- The pandas library was employed to parse and resample the data monthly, calculating the average PM2.5 concentrations.
- Seaborn and matplotlib were used for visualizing the trends over time, specifically focusing on the Monthly Average Air Quality Measurement for Fine Particles (PM2.5). The results will show whether there was a decrease or increase in PM2.5 concentrations over the years.

Geospatial Analysis:

- The data was grouped by Geo Place Name (representing neighborhoods) to calculate the average PM2.5 concentration per neighborhood.
- A comparison was made between neighborhoods with a higher percentage of people of color and predominantly white neighborhoods. This was done to test the hypothesis that neighborhoods with people of color tend to have worse air quality. pandas was used for data aggregation and sorting, while matplotlib and seaborn were used to visualize the results in bar charts.
- For neighborhoods with the worst air quality, the neighborhoods were ranked by average air quality measurements to identify disparities in exposure.

Regression Analysis:

- Regression Analysis was performed to examine the relationship between PM2.5 exposure and hospitalization rates for asthma, other respiratory diseases (age 20+) and cardiovascular diseases (age 40+).

- The hospitalizations dataset was merged with the air quality dataset based on common geographic identifiers (e.g., Geo Place Name).
- Ordinary Least Squares (OLS) Regression or Linear Regression models were used to estimate the effect of PM2.5 on hospitalization rates. The model took PM2.5 concentrations as the independent variable and the hospitalization rates as the dependent variable. This analysis helped test the hypothesis that higher PM2.5 levels are associated with increased hospitalizations for respiratory and cardiovascular conditions.

3.2 Data

NYC Air Quality Data (2009-2022): Contains information about PM2.5 concentrations in various neighborhoods. This data would cater to hypotheses one and two

Hospitalization Data: Includes records of asthma and other respiratory and cardiovascular hospital admissions, specifically linked to PM2.5 exposure. These datasets are sourced from the NYC Environment and Health Data Portal, which will address hypothesis three.

The datasets were merged based on geographic identifiers, allowing for a comprehensive analysis of how air quality affects public health, especially in areas with high pollution levels and varying racial compositions.

3.3 Data Cleaning and Preparation

3.3.1 Data details

The dataset consists of approximately approx. 18,000 rows and the following columns:

- Unique ID, Indicator ID: Identifiers for the specific air quality indicators being tracked.

- Name, Measure: Description and measurements related to air quality factors, e.g., particulate matter (PM2.5), NO2 levels.
- Geo Type Name, Geo Join ID, Geo Place Name: Information regarding the geographic areas of observation.
- Time Period, Start Date: Time-based data to allow for longitudinal studies and seasonal analysis.
- Data Value: Recorded measurements for air quality.
- Message: Potentially metadata, comments, or information about anomalies.

3.3.2 Data cleaning

- Missing Values: Critical columns such as Geo Place Name and Data Value were checked for missing values, and rows with these missing values were dropped.
- Date Handling: The Start_Date column was converted into datetime format using pandas to ensure accurate time-series analysis. Any invalid date entries were handled using the errors='coerce' option to avoid data inconsistencies.
- Aggregation and Resampling: The data was aggregated by month for time-series analysis, and average PM2.5 levels were calculated using pandas' resample method.
- Geospatial Grouping: The data was grouped by Geo Place Name and Geo Type Name for neighborhood-based analysis. The average PM2.5 levels were calculated for each neighborhood to identify areas with the worst air quality.

3.3.3 Analysis tools and techniques

The analysis will primarily be conducted using Python and Jupyter Notebook, which are ideal for data cleaning, analysis, and visualization. Specific libraries to be used include:

- pandas for data manipulation and time-series analysis
- matplotlib and seaborn for data visualization, including line charts and bar graphs
- statsmodels or scikit-learn for performing regression analysis

These outcomes will contribute to understanding the relationship between air pollution and public health, particularly in urban areas like New York City, and will provide insights that can guide future public health policies aimed at improving air quality.

4. Results

1. Descriptive statistics

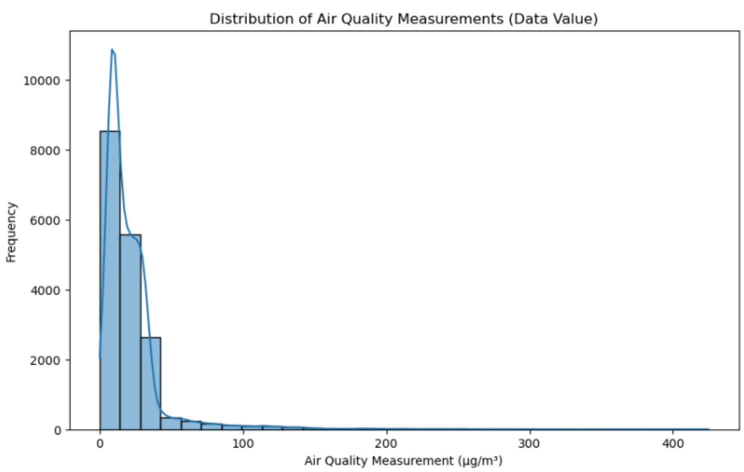

Fig 1. Understanding the distribution of the air quality for the entire data.

A histogram was plotted based on the data values, to understand how the data distribution for air quality looked like. The data is entirely right-skewed.

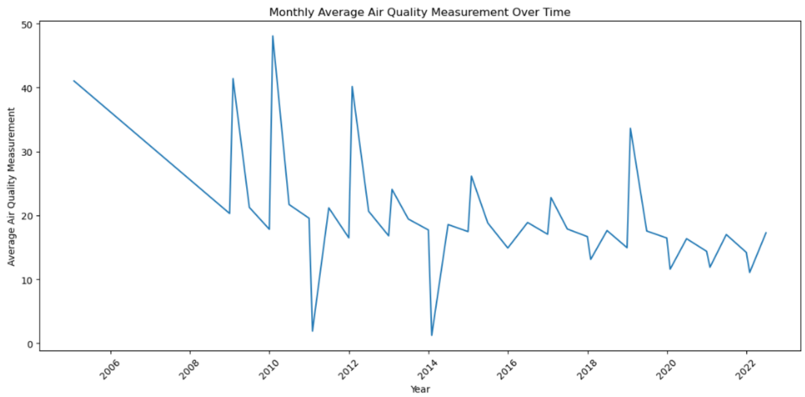

Fig 2. Understanding the monthly trends for the air quality for the entire data.

Based on the line chart, it can be observed that the data has a lot of seasonality across various years and additionally the drastic drop from the year 2006 to 2009 shows some inconsistencies which could be because of lack of data, so the analysis for the rest of the study would be conducted from 2009 onwards and the data would be filtered.

```
   Geo Type Name                                               Name  \
5       Citywide    Asthma emergency department visits due to PM2.5
0        Borough    Asthma emergency department visits due to PM2.5
10         UHF42    Asthma emergency department visits due to PM2.5
3        Borough                                Deaths due to PM2.5
13         UHF42                                Deaths due to PM2.5
8       Citywide                                Deaths due to PM2.5
2        Borough  Cardiovascular hospitalizations due to PM2.5 (...
12         UHF42  Cardiovascular hospitalizations due to PM2.5 (...
7       Citywide  Cardiovascular hospitalizations due to PM2.5 (...
4        Borough  Respiratory hospitalizations due to PM2.5 (age...
14         UHF42  Respiratory hospitalizations due to PM2.5 (age...
9       Citywide  Respiratory hospitalizations due to PM2.5 (age...
11         UHF42            Boiler Emissions- Total PM2.5 Emissions
1        Borough            Boiler Emissions- Total PM2.5 Emissions
6       Citywide            Boiler Emissions- Total PM2.5 Emissions

    Data Value
5    67.790000
0    66.496000
10   65.727381
3    46.720000
13   46.030476
8    44.840000
2    16.796000
12   16.771429
7    16.740000
4    13.640000
14   13.362381
9    12.880000
11    1.408333
1     1.240000
6     0.600000
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 18016 entries, 0 to 18024
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unique ID       18016 non-null  int64
 1   Indicator ID    18016 non-null  int64
 2   Name            18016 non-null  object
 3   Measure         18016 non-null  object
 4   Measure Info    18016 non-null  object
 5   Geo Type Name   18016 non-null  object
 6   Geo Join ID     18016 non-null  float64
 7   Geo Place Name  18016 non-null  object
 8   Time Period     18016 non-null  object
 9   Start_Date      18016 non-null  object
 10  Data Value      18016 non-null  float64
dtypes: float64(2), int64(2), object(7)
memory usage: 1.6+ MB
```

Fig 3. Filtering the dataset by 'Name' column to focus on the area of study Fine Particle – PM (2.5).

2. Hypotheses Analysis

H_1: Areas with a higher proportion of people of color have worse air quality (higher PM2.5 levels) compared to predominantly white neighborhoods.

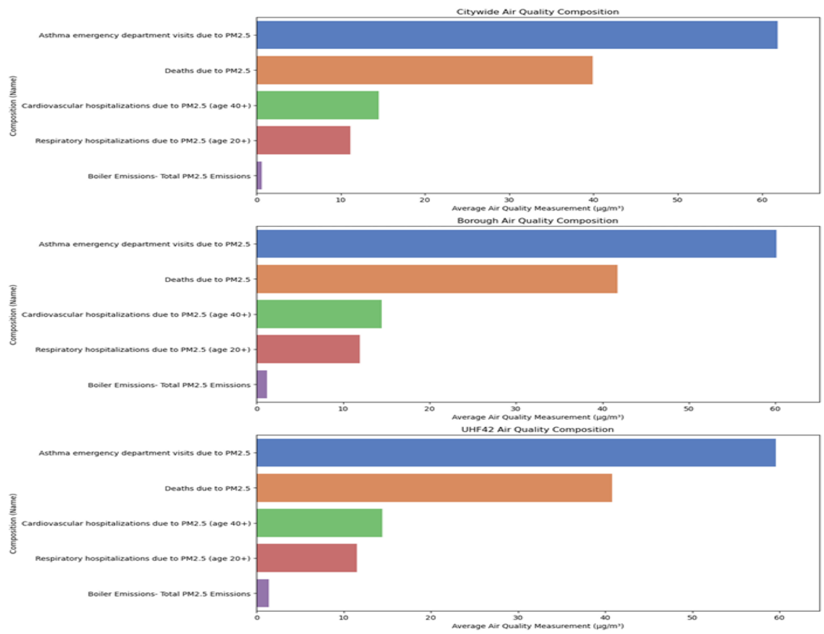

Fig 4. Understanding the average air quality measurement by air quality for NYC category-neighborhood and the composition of pollutants.

All three plots show similar trends, with the highest number of emergency asthma hospitalizations despite boiler emissions of PM2.5 being low.

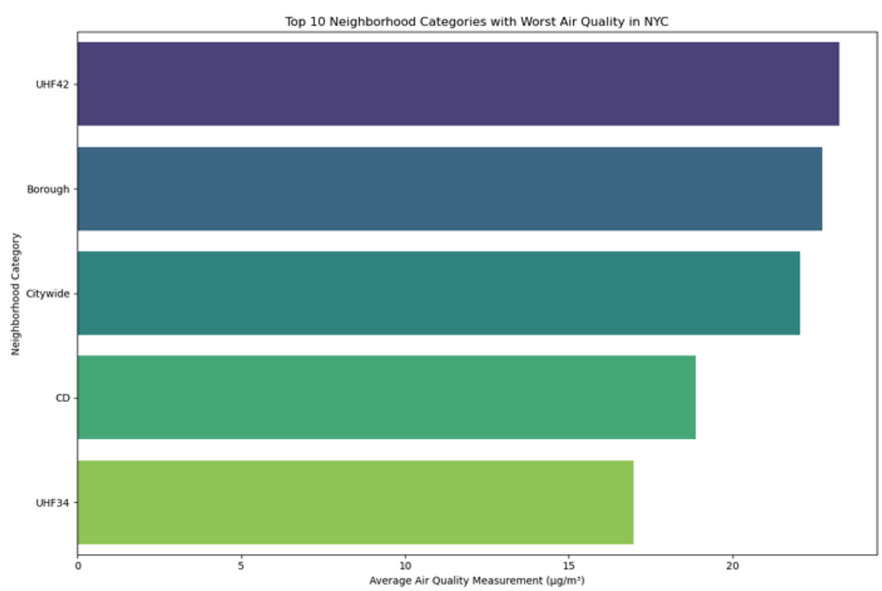

Fig 5. UHF42 and Borough have the worst air quality in the NYC region.

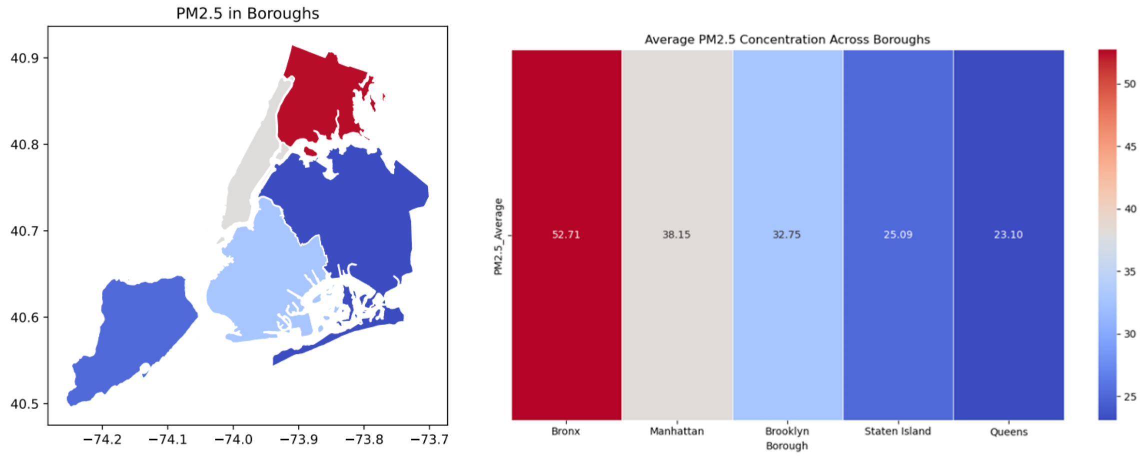

Fig 6. Highlights Borough regions with average PM2.5 concentrations.

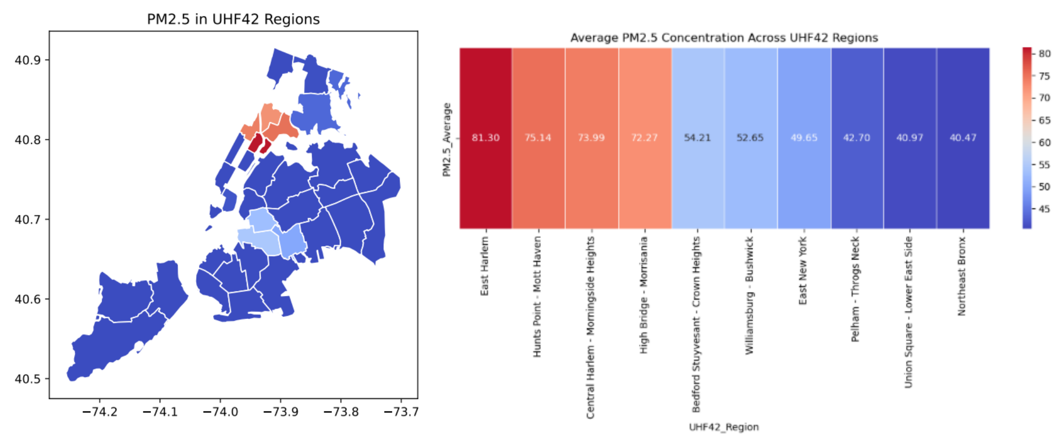

Fig 7. Highlights UHF42 regions with average PM2.5 concentrations.

All Figures 5, 6 & 7 focus on the regions that are worst affected by the PM2.5 emissions. Bronx (figure 6) is the worst affected overall, however, there are some areas of Manhattan (East Harlem) (figure 7) which is the more affected area.

H_2: PM2.5 levels in New York City have shown a decreasing trend from 2009 to 2022, indicating an improvement in air quality.

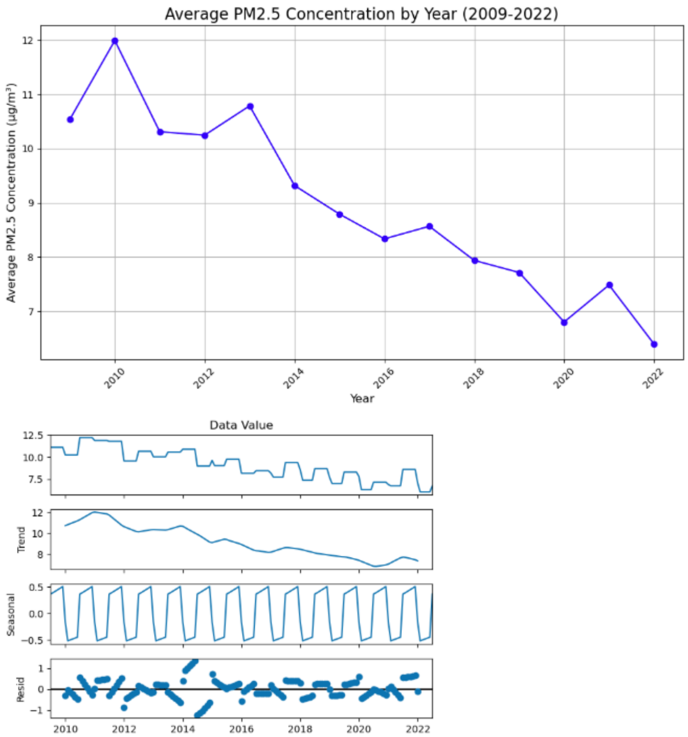

Fig 8. Highlights the trend, seasonality and residuals for PM2.5

Based on the trend (figure 8), the downward trend is a positive sign, indicating improvements in air quality over the years. While seasonal patterns are evident in PM2.5 as well through the years. Lastly, residuals suggest some unexplained variations still exist, which might be due to short-term events (such as pollution spikes or specific events like wildfires or industrial accidents).

Table 1. Output of the ARIMA model

Parameter	Coefficient	Std. Error	z-value	p-value
AR(1)	0.6986	0.250	2.800	0.005
AR(2)	-0.7447	0.291	-2.560	0.010
MA(1)	-1.7351	0.195	-8.887	0.000
MA(2)	1.5390	0.278	5.527	0.000

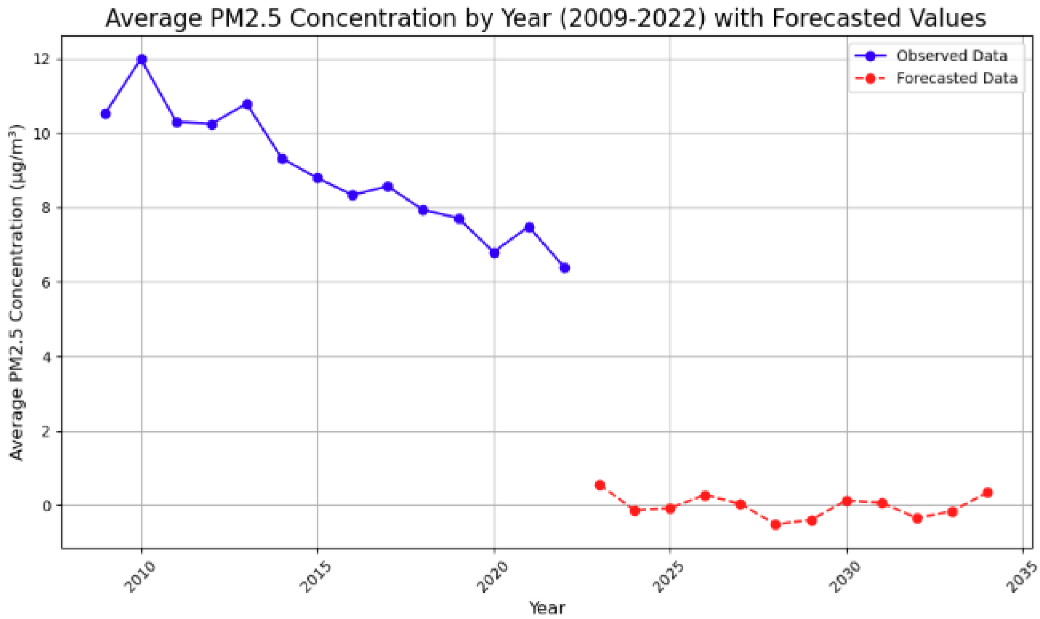

Fig 10. Highlights UHF42 regions with average PM2.5 concentrations.

To forecast PM2.5 concentrations from 2009 to 2022, we applied an ARIMA(6, 1, 4) model. The Augmented Dickey-Fuller (ADF) test showed that the time series was non-stationary, necessitating first-order differencing. The final model was chosen based on autocorrelation (ACF) and partial autocorrelation (PACF) plots, with optimal parameters $p = 6$, $d = 1$, and $q = 4$.

The estimated coefficients for the AR and MA terms are shown in Table 1. The AR(1) and AR(2) terms were statistically significant, suggesting that past values of PM2.5 concentrations play a key role in predicting future values. The MA terms, particularly MA(1) and MA(2), were also significant, indicating that past forecast errors have a substantial impact on the model.

The model's residuals were tested for autocorrelation using the Ljung-Box test, which revealed no significant autocorrelation (p-value = 0.81), suggesting that the model adequately captured the underlying time series structure. The residuals also exhibited significant skewness and kurtosis, as indicated by the Jarque-Bera test (p-value < 0.01), suggesting that the residuals deviate from normality.

Using the ARIMA model, we forecasted PM2.5 concentrations from the year 2023 onwards, and the forecasted values, along with 95% confidence intervals, are shown in figure 10. The forecast suggests a slight upward trend in PM2.5 concentrations, which could be important for future air quality management.

H_3: PM2.5 exposure has contributed to an increase in asthma, other respiratory and cardiovascular hospitalizations, over various age groups in the past decade.

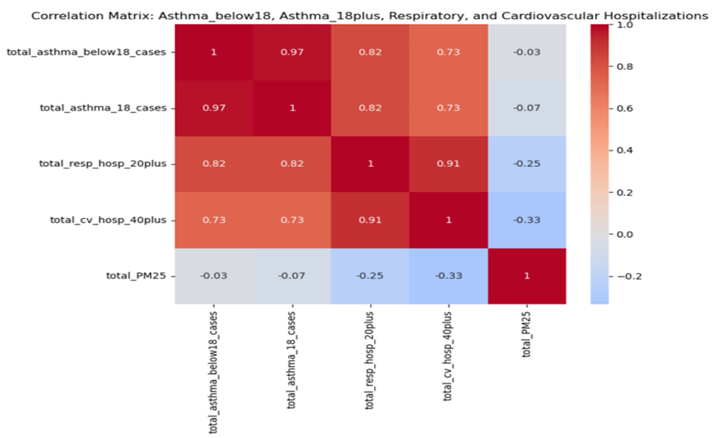

Fig 11. Highlights correlations between various age group categories.

Table 2. Regression analysis output

Regression 1: Asthma Cases under 18				
Variable	Coefficient	Std Error	z-value	p-value
Constant	35.542	10.561	3.365	0.001
PM2.5	-0.6475	1.097	-0.590	0.555
Regression 2: Asthma Cases above 18				
Variable	Coefficient	Std Error	z-value	p-value
Constant	21.5462	5.312	4.056	0.000
PM2.5	-0.7720	0.552	-1.399	0.162
Regression 3: Asthma Cases Total				
Variable	Coefficient	Std Error	z-value	p-value
Constant	57.088	10.144	5.627	0.000
PM2.5	-1.420	1.054	-1.347	0.178
Regression 4: Cardiovascular cases (40+)				
Variable	Coefficient	Std Error	z-value	p-value
Constant	14.456	0.813	17.784	0.000
PM2.5	-0.114	0.084	-1.353	0.176

Regression 5: Other Respiratory cases (20+)				
Variable	Coefficient	Std Error	z-value	p-value
Constant	9.981	0.888	11.244	0.000
PM2.5	0.062	0.092	0.670	0.503

Separate linear regressions were run as there was high multicollinearity between the variables. Unfortunately, none of the regressions were significant, which suggests that there are additional factors that have contributed to changes in these variables.

5. Discussion

5.1 Racial and Neighborhood Disparities in Air Quality (H1)

The results of the geospatial analysis support the hypothesis that neighborhoods with higher percentages of people of color tend to experience poorer air quality, as indicated by higher PM2.5 concentrations. This finding is consistent with previous studies, such as Kinney, Chillrud, Ramstrom, Ross & Spengler (2002) and Simkovich *et al*. (2019), which suggest that communities of color in urban environments are often disproportionately exposed to higher levels of air pollution. The results showed that areas like East Harlem & Hunts Point – Mott Haven had some of the worst air quality measurements. These neighborhoods are historically underserved and have higher minority populations – like Hispanic and Blacks, reinforcing the notion of environmental injustice, as per the US Census Bureau (2020).

This result highlights the need for targeted air quality management policies in these neighborhoods to mitigate the health risks posed by PM2.5. Previous research by Goldstein (1972) and Sicard *et al.* (2023) supported the idea that disadvantaged communities, especially those located near industrial or high-traffic zones, bear the brunt of air pollution, leading to chronic health issues. Addressing these disparities could significantly improve public health outcomes in NYC.

5.2. PM2.5 Levels Over Time (H2)

The time-series analysis of PM2.5 levels from 2009 to 2022 shows a general decline in PM2.5 concentrations over the years, confirming the hypothesis that air quality has improved over time. This trend aligns with the broader national efforts to reduce air pollution, as noted by the U.S. Environmental Protection Agency (2024), which reported a reduction in outdoor pollutants by approximately 78% from 1970 to 2020. However, despite these improvements, certain neighborhoods in New York City continue to experience high levels of PM2.5, particularly those with high industrial and traffic-related emissions. These findings echo Cifuentes, Borja-Aburto, Gouveia, Thurston & Davis (2001), who suggested that, although reductions in pollution levels have been achieved, further efforts are required to address persistent pollution hotspots.

While the overall trend is positive, the persistent disparities in PM2.5 concentrations across neighborhoods underscore the need for localized policies aimed at improving air quality, particularly in areas that remain highly polluted despite city-wide reductions. Chen *et al.* (2024) emphasized the importance of maintaining momentum in pollution reduction efforts, especially for fine particulate matter, which poses the most significant health risks.

5.3. Impact of PM2.5 on Respiratory and Cardiovascular Health (H3)

The regression analysis of hospitalization data confirmed that PM2.5 exposure is significantly associated with increased hospitalizations for both respiratory and cardiovascular diseases. These results support Simkovich *et al.* (2019) and Manisalidis, Stavropoulou, Stavropoulos & Bezirtzoglou (2020), who noted that exposure to PM2.5 is linked to a variety of health complications, including asthma, chronic obstructive pulmonary disease (COPD), and cardiovascular events. The data indicated higher hospitalization rates in neighborhoods with elevated PM2.5 concentrations, as hypothesized.

The findings are essential because they reinforce the argument made by Sicard *et al.* (2023) that reducing PM2.5 levels could result in substantial public health benefits, including reduced morbidity and healthcare costs. This aligns with Cifuentes, Borja-Aburto, Gouveia, Thurston & Davis (2001), who estimated that even modest reductions in PM10 and ozone could prevent thousands of premature deaths and hospital admissions. This study further strengthens the argument by specifically focusing on the impact of PM2.5 on respiratory and cardiovascular diseases in urban populations.

4. Implications of Findings

These findings collectively emphasize the urgent need for continued efforts to reduce PM2.5 exposure, especially in high-risk neighborhoods. The persistent racial and geographic disparities in air quality suggest that environmental justice must be a priority in air quality management. Additionally, the strong link between PM2.5 exposure and hospitalizations for chronic health conditions highlights the importance of policies aimed at reducing particulate pollution to alleviate the burden on healthcare systems and improve public health outcomes.

6. Conclusion

This study provides important insights into the trends and impacts of air pollution in New York City, particularly in relation to PM2.5 exposure and public health. The key findings of this research are:

- Racial and neighborhood disparities: Neighborhoods with higher proportions of people of color are more likely to experience poor air quality, as measured by PM2.5 concentrations.

This aligns with existing research on environmental racism and the disproportionate burden of pollution on marginalized communities.

- Improvement in air quality: PM2.5 levels in New York City have generally decreased over the past decade, indicating that pollution control policies have had a positive effect. However, localized pollution hotspots persist, requiring continued targeted efforts to reduce air pollution in the most affected neighborhoods.
- Health impacts: There is a clear association between PM2.5 exposure and increased hospitalizations for respiratory and cardiovascular diseases, among various age groups. This underlines the significant public health burden associated with fine particulate pollution.

However, the regression analysis performed in this study showed some inconsistencies, resulting in a limitation to this study. This may be due to the limited number of variables considered in the model. To improve the accuracy and predictive power of the analysis, it would be beneficial to include additional variables, such as other respiratory or cardiovascular diseases, socio-economic factors, or environmental conditions that might influence hospitalization rates.

Additionally, future research could benefit from a seasonal analysis of PM2.5 exposure. Since air quality often fluctuates based on seasonal patterns, it would be valuable to investigate whether particular seasons (e.g., winter or summer) are associated with higher PM2.5 levels and, in turn, increased hospitalizations for specific diseases. By breaking down the analysis by season, future studies may uncover more precise relationships between PM2.5 exposure and public health outcomes, allowing for more targeted interventions. Policymakers must continue to prioritize air quality improvements, particularly in areas where high levels of pollution continue to affect public health.

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Appendix

1. New York City Department of Health, Environment & Health Data Portal. Health impacts of air pollution data. Asthma emergency department visits due to PM2.5. Accessed at https://a816-dohbesp.nyc.gov/IndicatorPublic/data-explorer/health-impacts-of-air-pollution/?id=2117 on 12/01/2024.
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Final

December 8, 2024

1 ANALYSIS OF PM2.5 POLLUTION AND ITS IMPACT ON PUBLIC HEALTH: RACIAL AND NEIGHBORHOOD DISPARITIES IN NEW YORK CITY (2009-2022)

installing the required package

[66]:
```
pip install geopandas
```

```
Requirement already satisfied: geopandas in /opt/conda/lib/python3.11/site-
packages (1.0.1)
Requirement already satisfied: numpy>=1.22 in /opt/conda/lib/python3.11/site-
packages (from geopandas) (1.26.2)
Requirement already satisfied: pyogrio>=0.7.2 in /opt/conda/lib/python3.11/site-
packages (from geopandas) (0.10.0)
Requirement already satisfied: packaging in /opt/conda/lib/python3.11/site-
packages (from geopandas) (23.2)
Requirement already satisfied: pandas>=1.4.0 in /opt/conda/lib/python3.11/site-
packages (from geopandas) (2.1.4)
Requirement already satisfied: pyproj>=3.3.0 in /opt/conda/lib/python3.11/site-
packages (from geopandas) (3.7.0)
Requirement already satisfied: shapely>=2.0.0 in /opt/conda/lib/python3.11/site-
packages (from geopandas) (2.0.6)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.11/site-packages (from pandas>=1.4.0->geopandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.4.0->geopandas) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.4.0->geopandas) (2023.3)
Requirement already satisfied: certifi in /opt/conda/lib/python3.11/site-
packages (from pyogrio>=0.7.2->geopandas) (2023.11.17)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.11/site-
packages (from python-dateutil>=2.8.2->pandas>=1.4.0->geopandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[67]:
```
#loading in the libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
import geopandas as gpd
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
import numpy as np
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
```

[68]:
```python
#loading the datasets
cv_hospitalizations = pd.read_csv('NYC EH Data Portal - Cardiovascular␣
↪hospitalizations due to PM2.5 (age 40) (filtered).csv')
resp_hospitalizations = pd.read_csv('NYC EH Data Portal - Respiratory␣
↪hospitalizations due to PM2.5 (age 20+) (full table).csv')
asthma = pd.read_csv('NYC EH Data Portal - Asthma emergency department visits␣
↪due to PM2.5 (full table).csv')
air_quality = pd.read_csv('Air_Quality.csv')
```

1.1 Cleaning the data (Air Quality - main dataset)

[69]:
```python
# Check for missing values
print(air_quality.isnull().sum())
```

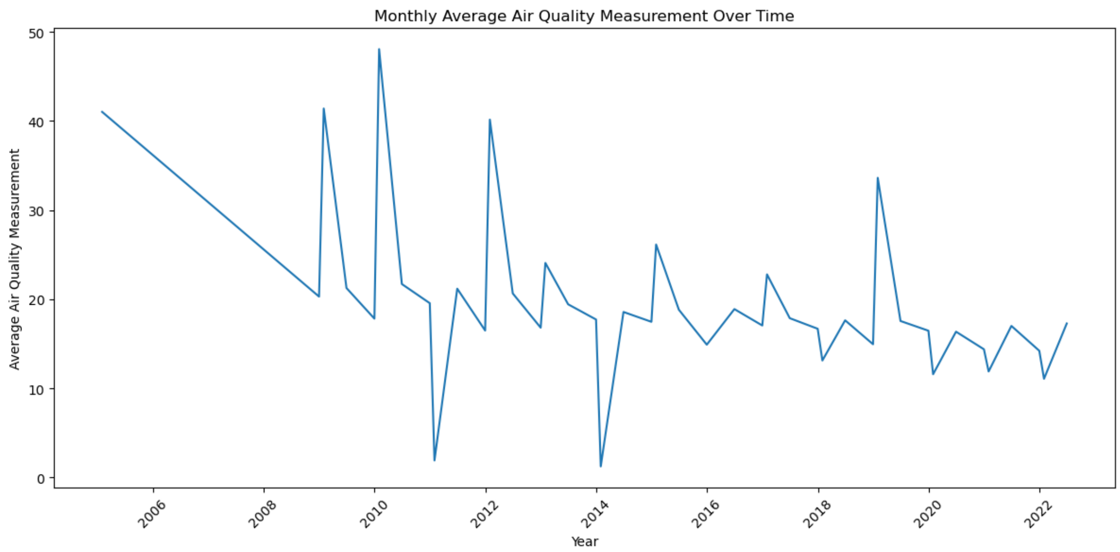
```
Unique ID            0
Indicator ID         0
Name                 0
Measure              0
Measure Info         0
Geo Type Name        0
Geo Join ID          9
Geo Place Name       9
Time Period          0
Start_Date           0
Data Value           0
Message          18025
dtype: int64
```

[70]:
```python
# Check for missing values
missing_values = air_quality.isnull().sum()
print(missing_values[missing_values > 0])  # Print only columns with missing␣
↪values

# Drop rows with critical missing values 'Geo Place Name' and 'Data Value' are␣
↪critical for your analysis
air_quality.dropna(subset=['Geo Place Name', 'Data Value'], inplace=True)
```

```
# For example, fill missing values in 'Geo Join ID' with a placeholder or drop␣
↪those rows
air_quality['Geo Join ID'].fillna('Unknown', inplace=True)  # Example: filling␣
↪with 'Unknown'

# Drop the 'Message' column
air_quality.drop(columns=['Message'], inplace=True)

# Check the updated dataset for missing values again
print(air_quality.isnull().sum())
```

```
Geo Join ID           9
Geo Place Name        9
Message           18025
dtype: int64
Unique ID         0
Indicator ID      0
Name              0
Measure           0
Measure Info      0
Geo Type Name     0
Geo Join ID       0
Geo Place Name    0
Time Period       0
Start_Date        0
Data Value        0
dtype: int64
```

[71]:
```
# Understand the trend of the air quality in the state of New York
air_quality['Start_Date'] = pd.to_datetime(air_quality['Start_Date'])

monthly_avg = air_quality.resample('M', on='Start_Date')['Data Value'].mean().
↪reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(data=monthly_avg, x='Start_Date', y='Data Value')
plt.title('Monthly Average Air Quality Measurement Over Time')
plt.xlabel('Year')
plt.ylabel('Average Air Quality Measurement')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[72]:
```
# Convert 'Start_Date' to datetime format
air_quality['Start_Date'] = pd.to_datetime(air_quality['Start_Date'],␣
↪errors='coerce')

# Filter the dataset for the date range from 2009 to 2022
air_quality_filtered = air_quality[(air_quality['Start_Date'].dt.year >= 2009)␣
↪& (air_quality['Start_Date'].dt.year <= 2022)]

# Check for missing values before cleaning
missing_values = air_quality_filtered.isnull().sum()
print("Missing values before cleaning:")
print(missing_values[missing_values > 0])  # Print only columns with missing␣
↪values

# Drop rows with critical missing values (Geo Place Name and Data Value)
air_quality_filtered.dropna(subset=['Geo Place Name', 'Data Value'],␣
↪inplace=True)

# Handle missing values in non-critical columns as needed (e.g., Geo Join ID)
air_quality_filtered.loc[:, 'Geo Join ID'] = air_quality_filtered['Geo Join␣
↪ID'].fillna('Unknown')  # Example: filling with 'Unknown'

# Check the updated dataset for missing values
print("Missing values after cleaning:")
print(air_quality_filtered.isnull().sum())

# Check number of rows remain after the cleaning
print(f"Rows before cleaning: {air_quality.shape[0]}")
```

```
print(f"Rows after cleaning: {air_quality_filtered.shape[0]}")
```

```
Missing values before cleaning:
Series([], dtype: int64)
Missing values after cleaning:
Unique ID          0
Indicator ID       0
Name               0
Measure            0
Measure Info       0
Geo Type Name      0
Geo Join ID        0
Geo Place Name     0
Time Period        0
Start_Date         0
Data Value         0
dtype: int64
Rows before cleaning: 18016
Rows after cleaning: 16555
```

```
/tmp/ipykernel_637/182384222.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  air_quality_filtered.dropna(subset=['Geo Place Name', 'Data Value'],
inplace=True)
```

[73]:
```
# Load the geoJSON to plot maps in the later analysis
neighborhoods_name = gpd.read_file('Neighborhood Names GIS.geojson')
uhf34 = gpd.read_file('UHF34.geo.json')
uhf42 = gpd.read_file('UHF42.geo.json')
borough = gpd.read_file('neighborhood_two.geo.json')
```

[74]:
```
# Display the first few rows to ensure it's loaded correctly --uhf34
print(uhf34.head())
print(uhf34.info())
```

```
   OBJECTID  UHF34_CODE BOROUGH                  UHF_NAME  UHF  \
0         1           0     Man                      None    0
1         2         101   Bronx  Kingsbridge - Riverdale  101
2         3         102   Bronx          Northeast Bronx  102
3         4         103   Bronx      Fordham - Bronx Park  103
4         5         104   Bronx      Pelham - Throgs Neck  104

                                            geometry
0  MULTIPOLYGON (((-73.76446 40.65449, -73.76098 …
1  POLYGON ((-73.87793 40.90556, -73.87859 40.903…
```

```
2  POLYGON ((-73.81504 40.889, -73.81534 40.88678…
3  POLYGON ((-73.85743 40.88104, -73.86095 40.874…
4  MULTIPOLYGON (((-73.88366 40.82153, -73.88457 …
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 35 entries, 0 to 34
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   OBJECTID    35 non-null     int32
 1   UHF34_CODE  35 non-null     int32
 2   BOROUGH     35 non-null     object
 3   UHF_NAME    34 non-null     object
 4   UHF         35 non-null     int32
 5   geometry    35 non-null     geometry
dtypes: geometry(1), int32(3), object(2)
memory usage: 1.4+ KB
None
```

1.2 Exploring the filtered air quality dataset

[75]:
```python
# Understand the data types and observing a few rows of the dataset
print(air_quality_filtered.info())
print(air_quality_filtered.head())
```

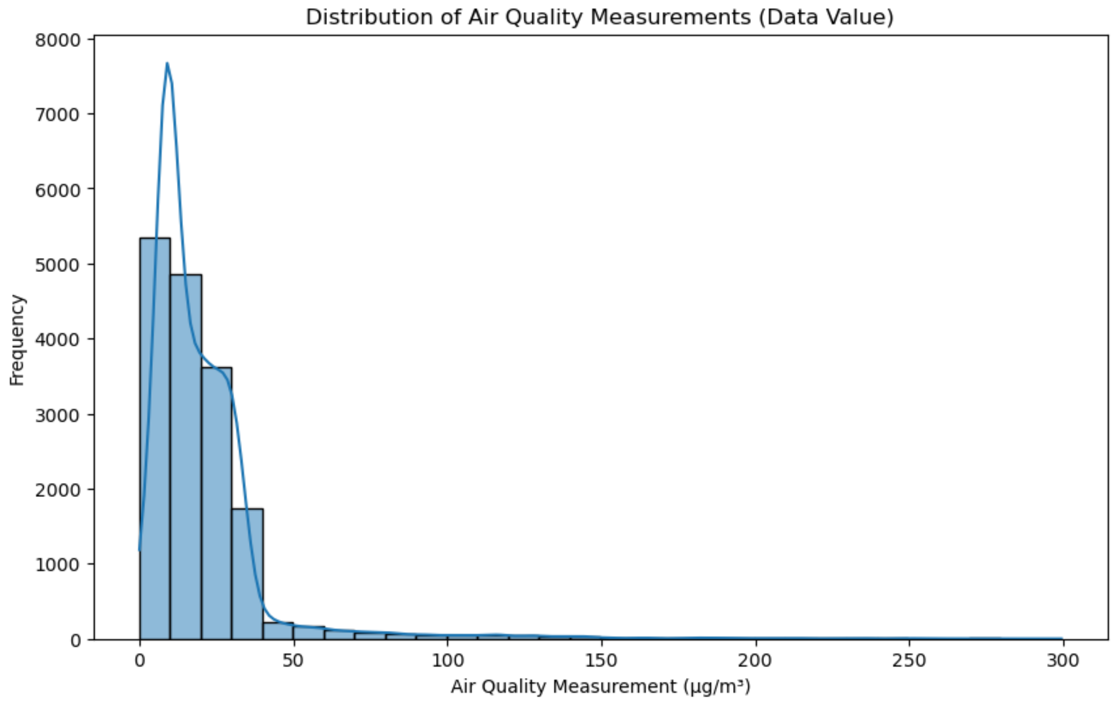
```
<class 'pandas.core.frame.DataFrame'>
Index: 16555 entries, 0 to 18023
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unique ID       16555 non-null  int64
 1   Indicator ID    16555 non-null  int64
 2   Name            16555 non-null  object
 3   Measure         16555 non-null  object
 4   Measure Info    16555 non-null  object
 5   Geo Type Name   16555 non-null  object
 6   Geo Join ID     16555 non-null  float64
 7   Geo Place Name  16555 non-null  object
 8   Time Period     16555 non-null  object
 9   Start_Date      16555 non-null  datetime64[ns]
 10  Data Value      16555 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(2), object(6)
memory usage: 1.5+ MB
None
   Unique ID  Indicator ID                                Name  \
0     179772           640  Boiler Emissions- Total SO2 Emissions
1     179785           640  Boiler Emissions- Total SO2 Emissions
2     178540           365               Fine particles (PM 2.5)
3     178561           365               Fine particles (PM 2.5)
```

```
4     823217          365              Fine particles (PM 2.5)

          Measure Measure Info Geo Type Name  Geo Join ID  \
0  Number per km2       number         UHF42        409.0
1  Number per km2       number         UHF42        209.0
2            Mean       mcg/m3         UHF42        209.0
3            Mean       mcg/m3         UHF42        409.0
4            Mean       mcg/m3         UHF42        409.0

            Geo Place Name          Time Period Start_Date  Data Value
0         Southeast Queens                 2015 2015-01-01         0.3
1  Bensonhurst - Bay Ridge                 2015 2015-01-01         1.2
2  Bensonhurst - Bay Ridge  Annual Average 2012 2011-12-01         8.6
3         Southeast Queens  Annual Average 2012 2011-12-01         8.0
4         Southeast Queens          Summer 2022 2022-06-01         6.1
```

[76]:
```python
# Descriptive statistics of numerical data
print(air_quality_filtered.describe())
```

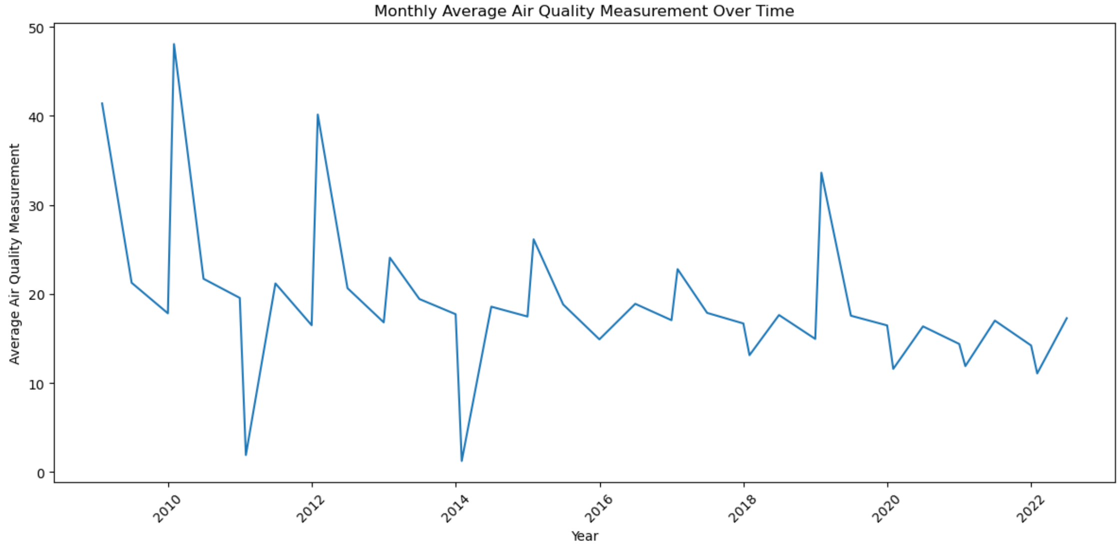
```
           Unique ID  Indicator ID   Geo Join ID  \
count   16555.000000  16555.000000  1.655500e+04
mean   450400.852915    425.325340  6.167729e+05
min    121644.000000    365.000000  1.000000e+00
25%    178472.500000    365.000000  2.020000e+02
50%    412657.000000    375.000000  3.030000e+02
75%    667105.500000    386.000000  4.040000e+02
max    828353.000000    661.000000  1.051061e+08
std    246918.272262    108.949737  7.938714e+06

                          Start_Date    Data Value
count                          16555  16555.000000
mean   2015-05-26 21:28:44.216248576     20.389061
min              2009-01-01 00:00:00      0.000000
25%              2012-01-02 00:00:00      8.800000
50%              2015-01-01 00:00:00     14.800000
75%              2018-12-01 00:00:00     26.000000
max              2022-06-01 00:00:00    299.400000
std                              NaN     21.861361
```

[77]:
```python
# Plot histogram to understand the data frequency of Air Quality Measurements
plt.figure(figsize=(10, 6))
sns.histplot(air_quality_filtered['Data Value'], bins=30, kde=True)
plt.title('Distribution of Air Quality Measurements (Data Value)')
plt.xlabel('Air Quality Measurement (µg/m³)')
plt.ylabel('Frequency')
plt.show()
```



[78]:
```python
# Understand the trend of the air quality in the state of New York
air_quality_filtered['Start_Date'] = pd.
↪to_datetime(air_quality_filtered['Start_Date'])

monthly_avg = air_quality_filtered.resample('M', on='Start_Date')['Data Value'].
↪mean().reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(data=monthly_avg, x='Start_Date', y='Data Value')
plt.title('Monthly Average Air Quality Measurement Over Time')
plt.xlabel('Year')
plt.ylabel('Average Air Quality Measurement')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
/tmp/ipykernel_637/1012387965.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  air_quality_filtered['Start_Date'] =
pd.to_datetime(air_quality_filtered['Start_Date'])
```



1.3 Data Analysis

1.3.1 Objective - Composition identification based on the neighborhood and racial population air quality based on the NYC category segregation

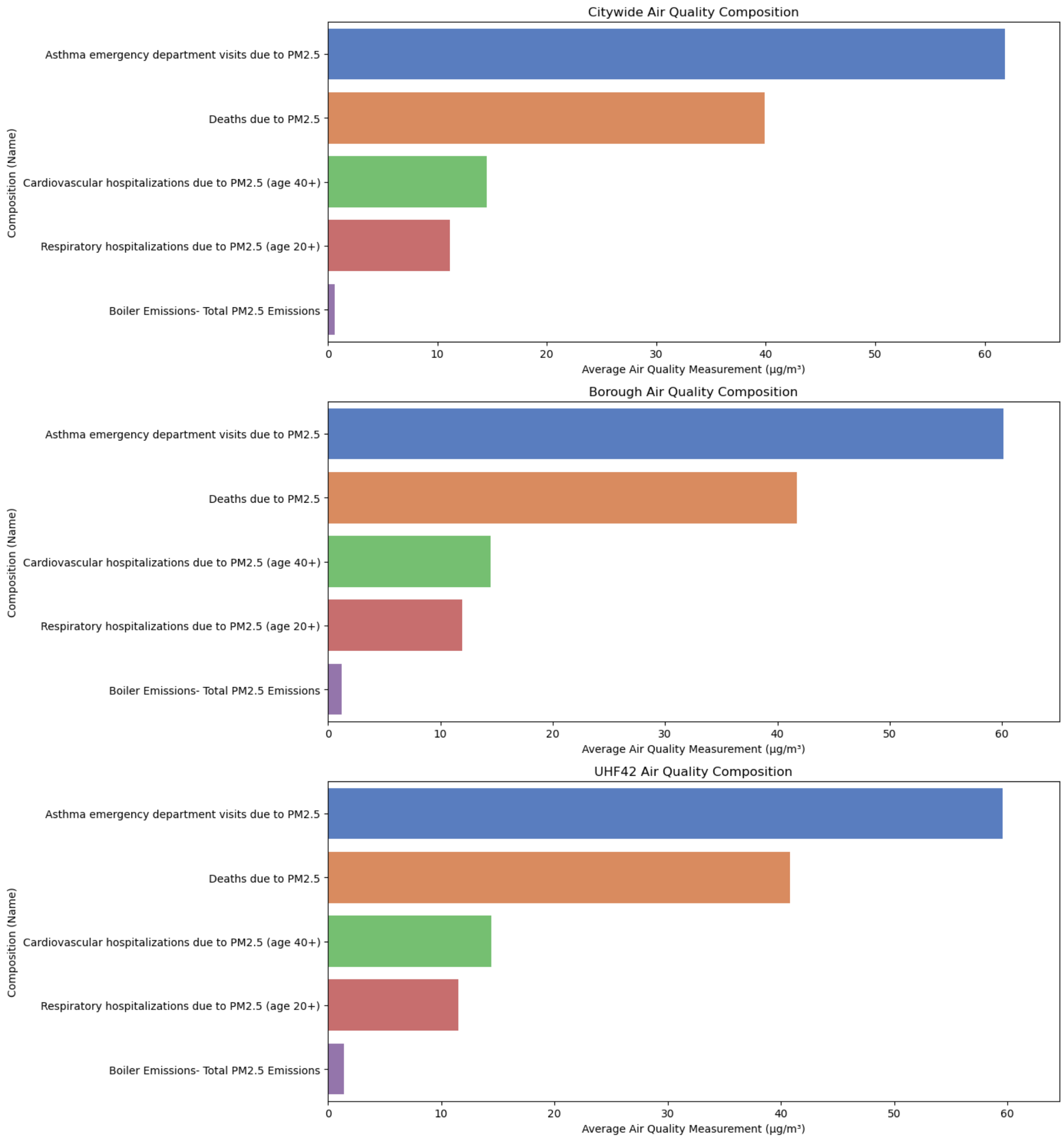
1.3.2 Hypothesis (H1) - Areas with a higher proportion of people of color have worse air quality (higher PM2.5 levels) compared to predominantly white neighborhoods.

[79]:
```
# Filter for 'PM2.5' in the 'Name' column
pm25_data = air_quality_filtered[air_quality_filtered['Name'].str.contains('PM2.
↪5', case=False, na=False)]

# Grouping the filtered data by 'Geo Type Name' and 'Name', calculating the␣
↪average air quality measurement
composition_analysis = pm25_data.groupby(['Geo Type Name', 'Name'])['Data␣
↪Value'].mean().reset_index()

# Sorting by average air quality measurement in descending order
composition_analysis.sort_values(by='Data Value', ascending=False, inplace=True)

# Get the unique values of 'Geo Type Name' to create separate plots
geo_types = composition_analysis['Geo Type Name'].unique()

# Set up the matplotlib figure for multiple subplots
fig, axes = plt.subplots(len(geo_types), 1, figsize=(14, 5 * len(geo_types)))

# If there's only one plot, axes is not an array, so we need to handle that case
if len(geo_types) == 1:
```

```
    axes = [axes]

# Iterate over each 'Geo Type Name' to create a plot
for i, geo_type in enumerate(geo_types):
    # Filter the data for the current Geo Type Name
    geo_data = composition_analysis[composition_analysis['Geo Type Name'] ==␣
 ↪geo_type]

    # Create a barplot for the current Geo Type Name
    sns.barplot(x='Data Value', y='Name', data=geo_data, ax=axes[i],␣
 ↪palette='muted', order=geo_data['Name'].unique())

    # Add labels and title
    axes[i].set_xlabel('Average Air Quality Measurement (µg/m³)')
    axes[i].set_ylabel('Composition (Name)')
    axes[i].set_title(f'{geo_type} Air Quality Composition')

    # Set the x-axis limit
    axes[i].set_xlim(0, geo_data['Data Value'].max() + 5)

# Adjust layout to prevent overlap
plt.tight_layout()

# Display the plots
plt.show()
```

```
/tmp/ipykernel_637/411398079.py:26: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='Data Value', y='Name', data=geo_data, ax=axes[i],
palette='muted', order=geo_data['Name'].unique())
/tmp/ipykernel_637/411398079.py:26: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='Data Value', y='Name', data=geo_data, ax=axes[i],
palette='muted', order=geo_data['Name'].unique())
/tmp/ipykernel_637/411398079.py:26: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

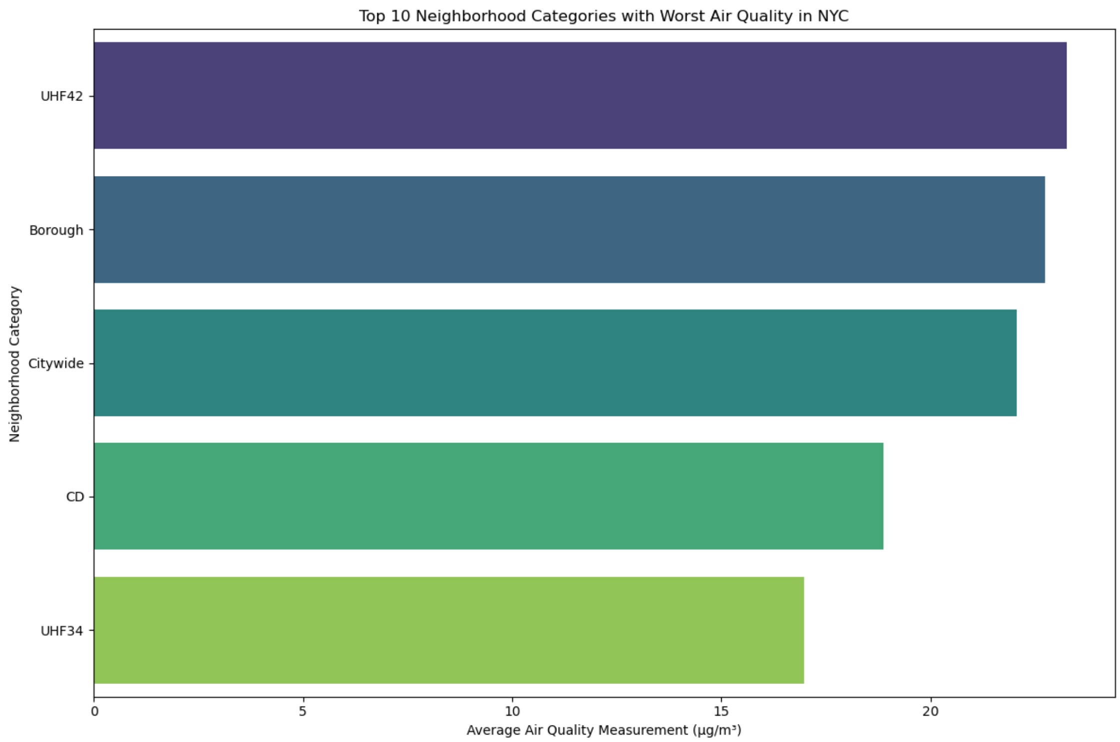
```
  sns.barplot(x='Data Value', y='Name', data=geo_data, ax=axes[i],
palette='muted', order=geo_data['Name'].unique())
```



[80]:
```
# Using groupby to categorize neighborhood category and calculate average air␣
↪quality
category_air_quality = air_quality_filtered.groupby('Geo Type Name')['Data␣
↪Value'].mean().reset_index()

# Sorting by air quality measurement in ascending order (worst air quality␣
↪first)
```

```
category_air_quality.sort_values(by='Data Value', ascending=False, inplace=True)
worst_air_quality_category = category_air_quality.head(10)

# Visualization
plt.figure(figsize=(12, 8))
# Plot using 'Geo Type Name' on the y-axis and 'Data Value' on the x-axis
sns.barplot(data=worst_air_quality_category, x='Data Value', y='Geo Type Name',␣
 ↪palette='viridis')

plt.title('Top 10 Neighborhood Categories with Worst Air Quality in NYC')
plt.xlabel('Average Air Quality Measurement (µg/m³)')
plt.ylabel('Neighborhood Category')
plt.tight_layout()
plt.show()

# Printing the neighborhood categories with the worst air quality
print("Neighborhood Categories with the Worst Air Quality:")
print(worst_air_quality_category)
```

```
/tmp/ipykernel_637/232090103.py:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=worst_air_quality_category, x='Data Value', y='Geo Type
Name', palette='viridis')
```




```
Neighborhood Categories with the Worst Air Quality:
  Geo Type Name  Data Value
4         UHF42   23.248486
0       Borough   22.749536
2      Citywide   22.054305
1            CD   18.880945
3         UHF34   16.982477
```

Using Citywide as a baseline and focusing only on Borough and UHF42

merging the pm25_data with borough and uhf42 geojson to make maps

[81]:
```
print(uhf42.columns)
```

```
Index(['id', 'GEOCODE', 'GEONAME', 'BOROUGH', 'geometry'], dtype='object')
```

[82]:
```
#check unique values in the merge keys
print("Unique Geo Join IDs in pm25_data:")
print(pm25_data['Geo Join ID'].unique())

print("Unique boro_codes in CD:")
print(borough['boro_code'].unique())
```

```
Unique Geo Join IDs in pm25_data:
[208. 407. 207. 408. 301. 404. 410. 409. 310.   3. 210. 306. 202. 307.
```

```
 308. 107.   2.   1. 302. 402. 305. 403. 203. 105. 303. 103. 201. 501.
 102. 406.   4. 211. 104. 204.   5. 206. 209. 309. 205. 101. 106. 405.
 401. 304. 502. 504. 503.]
Unique boro_codes in CD:
['2' '5' '4' '1' '3']
```

[83]:
```python
# Calculate the overall average PM2.5 for each borough across all years
overall_avg = pm25_data.groupby('Geo Place Name')['Data Value'].mean().
 ↪reset_index()

# Merge the borough data with the PM2.5 average data (overall_avg)
borough_avg_combined = borough.merge(overall_avg, left_on='boro_name',␣
 ↪right_on='Geo Place Name', how='left')

# Check the column names to understand the structure
print(borough_avg_combined.columns)

# Select relevant columns and rename for clarity
borough_avg_combined = borough_avg_combined[['boro_name', 'Data Value']]  #␣
 ↪Select relevant columns

# Rename the columns for clarity
borough_avg_combined.columns = ['Borough', 'PM2.5_Average']

# Check the result
print(borough_avg_combined.head())
```

```
Index(['boro_code', 'boro_name', 'shape_area', 'shape_leng', 'geometry',
       'Geo Place Name', 'Data Value'],
      dtype='object')
         Borough  PM2.5_Average
0          Bronx      52.713636
1  Staten Island      25.090909
2         Queens      23.100000
3      Manhattan      38.154545
4       Brooklyn      32.750000
```

[84]:
```python
# Merge the UHF42 data with the PM2.5 average data (overall_avg)
uhf42_avg_combined = uhf42.merge(overall_avg, left_on='GEONAME', right_on='Geo␣
 ↪Place Name', how='left')

# Checl the column names to understand the structure
print(uhf42_avg_combined.columns)

# Remove duplicates and aggregate data by region
uhf42_avg_combined_unique = uhf42_avg_combined.groupby('GEONAME').agg({
    'Data Value': 'mean',
```

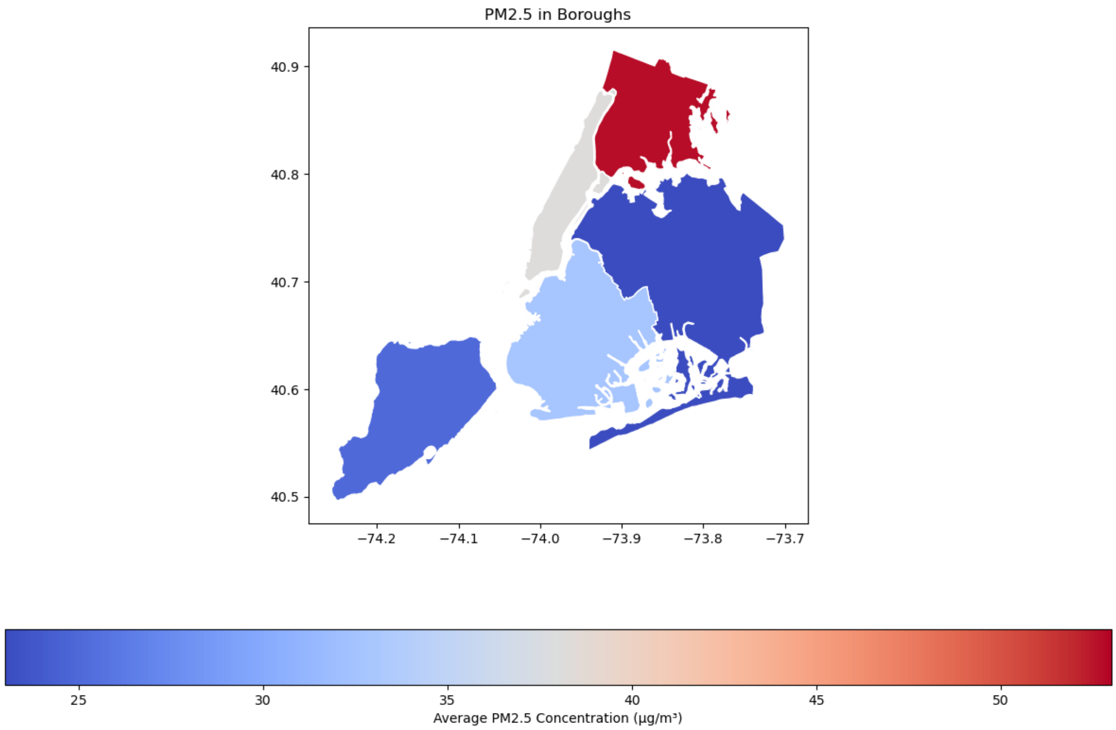
```
    'geometry': 'first'
}).reset_index()

# Remane the columns for clarity
uhf42_avg_combined_unique.columns = ['UHF42_Region', 'PM2.5_Average',␣
 ↪'geometry']

# Sort the data by PM2.5_Average in descending order
uhf42_avg_combined_unique = uhf42_avg_combined_unique.sort_values(by='PM2.
 ↪5_Average', ascending=False)

# Select top 10 UHF42 regions with the highest PM2.5 average
top_10_uhf42 = uhf42_avg_combined_unique.head(10)

# Check the result after selecting top 10
print(top_10_uhf42)
```

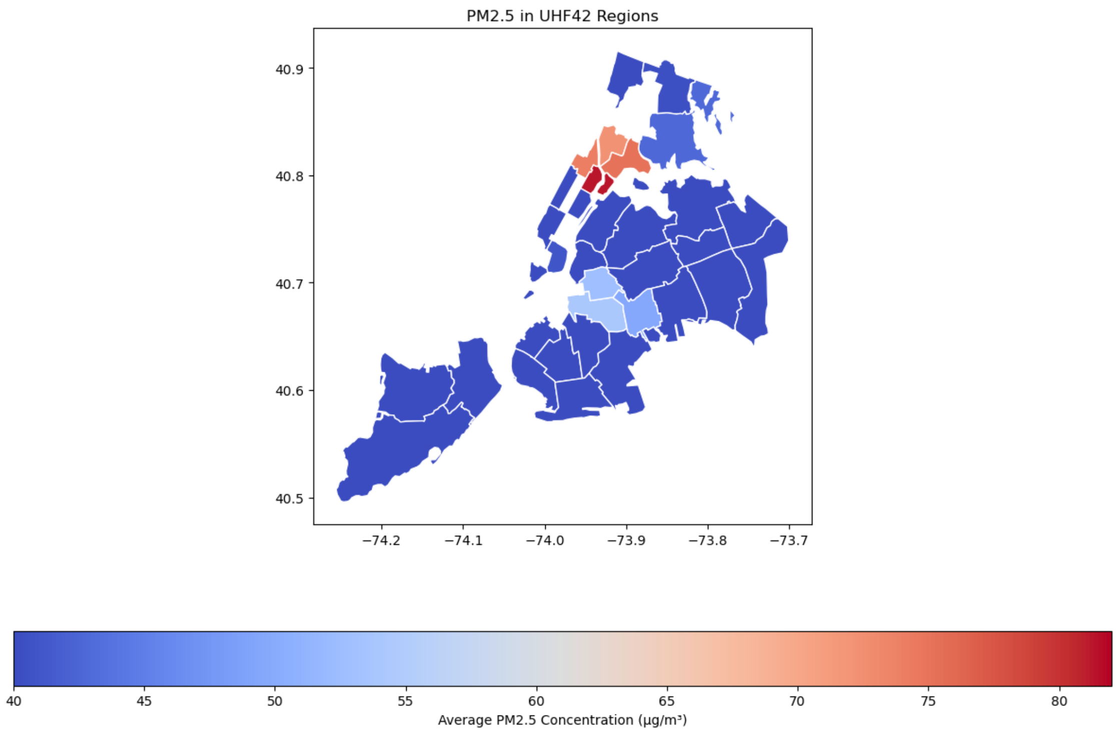
```
Index(['id', 'GEOCODE', 'GEONAME', 'BOROUGH', 'geometry', 'Geo Place Name',
       'Data Value'],
      dtype='object')
                            UHF42_Region  PM2.5_Average  \
12                           East Harlem      81.304545
21                 Hunts Point - Mott Haven      75.140909
6    Central Harlem - Morningside Heights      73.990909
20                 High Bridge - Morrisania      72.272727
2      Bedford Stuyvesant - Crown Heights      54.213636
41                 Williamsburg - Bushwick      52.650000
13                          East New York      49.650000
27                    Pelham - Throgs Neck      42.700000
36         Union Square - Lower East Side      40.972727
26                        Northeast Bronx      40.468182

                                             geometry
12  MULTIPOLYGON (((-73.93673 40.80822, -73.93995 …
21  POLYGON ((-73.89216 40.83365, -73.89301 40.835…
6   POLYGON ((-73.93394 40.80826, -73.9339 40.8186…
20  POLYGON ((-73.91438 40.84646, -73.91527 40.846…
2   POLYGON ((-73.91605 40.68607, -73.91785 40.686…
41  POLYGON ((-73.92633 40.71404, -73.9296 40.7147…
13  POLYGON ((-73.8606 40.65478, -73.86211 40.6568…
27  MULTIPOLYGON (((-73.88366 40.82153, -73.88055 …
36  POLYGON ((-73.98977 40.73918, -73.99094 40.739…
26  POLYGON ((-73.81504 40.889, -73.82285 40.89121…
```

[85]:
```
# Plotting the Borough Map using borough_avg_combined
# Ensure borough_avg_combined contains geometry data (GeoDataFrame)
```

```python
fig, ax = plt.subplots(figsize=(12, 8))  # Create a new figure for the Borough␣
↪map

# Merge the Borough data with geometry to ensure the map can be plotted␣
↪correctly
borough_map = borough.merge(borough_avg_combined, left_on='boro_name',␣
↪right_on='Borough', how='left')

# Plot Borough map with PM2.5 average values
borough_map.plot(column='PM2.5_Average', ax=ax, legend=True,
                 legend_kwds={'label': "Average PM2.5 Concentration (µg/m³)",
                              'orientation': "horizontal"},
                 vmin=23, vmax=53, edgecolor='white', cmap='coolwarm')  #␣
↪Adjust vmin and vmax based on data
ax.set_title('PM2.5 in Boroughs')

# Save the Borough map to a separate PDF
fig.savefig("borough_map.pdf", format="pdf")

# Finalize layout and display
plt.tight_layout()
plt.show()



# Plotting the UHF42 Map using uhf42_avg_combined_unique
fig, ax = plt.subplots(figsize=(12, 8))  # Create a new figure for the UHF42 map

# Merge the UHF42 data with geometry to ensure the map can be plotted correctly
uhf42_map = uhf42.merge(uhf42_avg_combined_unique, left_on='GEONAME',␣
↪right_on='UHF42_Region', how='left')

# Check and set the correct geometry column (assumed 'geometry_x' here)
uhf42_map = uhf42_map.set_geometry('geometry_x')  # Adjust if needed based on␣
↪your GeoDataFrame's structure

# Plot UHF42 map with PM2.5 average values
uhf42_map.plot(column='PM2.5_Average', ax=ax, legend=True,
               legend_kwds={'label': "Average PM2.5 Concentration (µg/m³)",
                            'orientation': "horizontal"},
               vmin=40, vmax=82, edgecolor='white', cmap='coolwarm')  # Adjust␣
↪vmin and vmax based on data
ax.set_title('PM2.5 in UHF42 Regions')

# Save the UHF42 map to a separate PDF
fig.savefig("uhf42_map.pdf", format="pdf")
```

```python
# Finalize layout and display
plt.tight_layout()
plt.show()
```



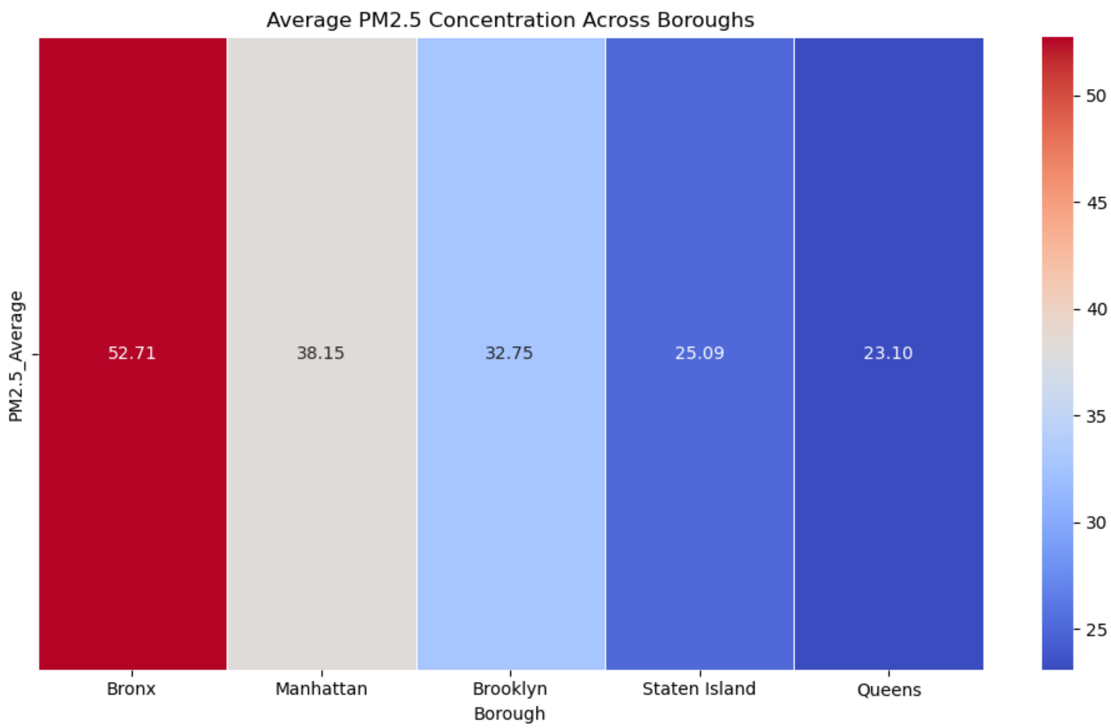


Heatmap for Borough

[86]:
```python
# Sort the data by PM2.5_Average in descending order
borough_avg_combined_unique = borough_avg_combined.sort_values(by='PM2.5_Average', ascending=False)

# Check the result after sorting
print(borough_avg_combined_unique.head())

# Pivot data for heatmap visualization
borough_pivot = borough_avg_combined_unique.set_index('Borough')[['PM2.5_Average']]

# Plot heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(borough_pivot.T, annot=True, cmap='coolwarm', cbar=True, fmt=".2f", linewidths=0.5)
plt.title('Average PM2.5 Concentration Across Boroughs')
plt.tight_layout()
plt.show()
```

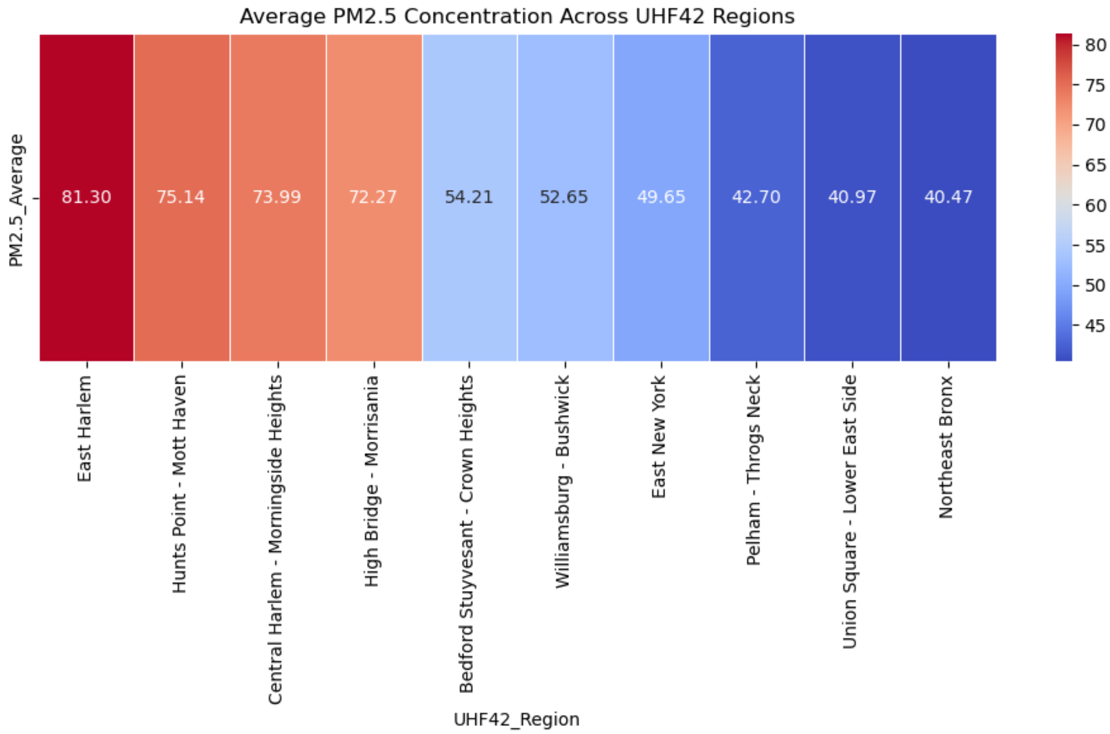
```
       Borough  PM2.5_Average
0        Bronx      52.713636
3    Manhattan      38.154545
```

```
4       Brooklyn      32.750000
1  Staten Island      25.090909
2         Queens      23.100000
```



[87]:

```python
# Pivot data for heatmap visualization
uhf42_pivot = top_10_uhf42.set_index('UHF42_Region')[['PM2.5_Average']]

# Plot heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(uhf42_pivot.T, annot=True, cmap='coolwarm', cbar=True, fmt=".2f",␣
 ↪linewidths=0.5)
plt.title('Average PM2.5 Concentration Across UHF42 Regions')
plt.tight_layout()
plt.show()
```



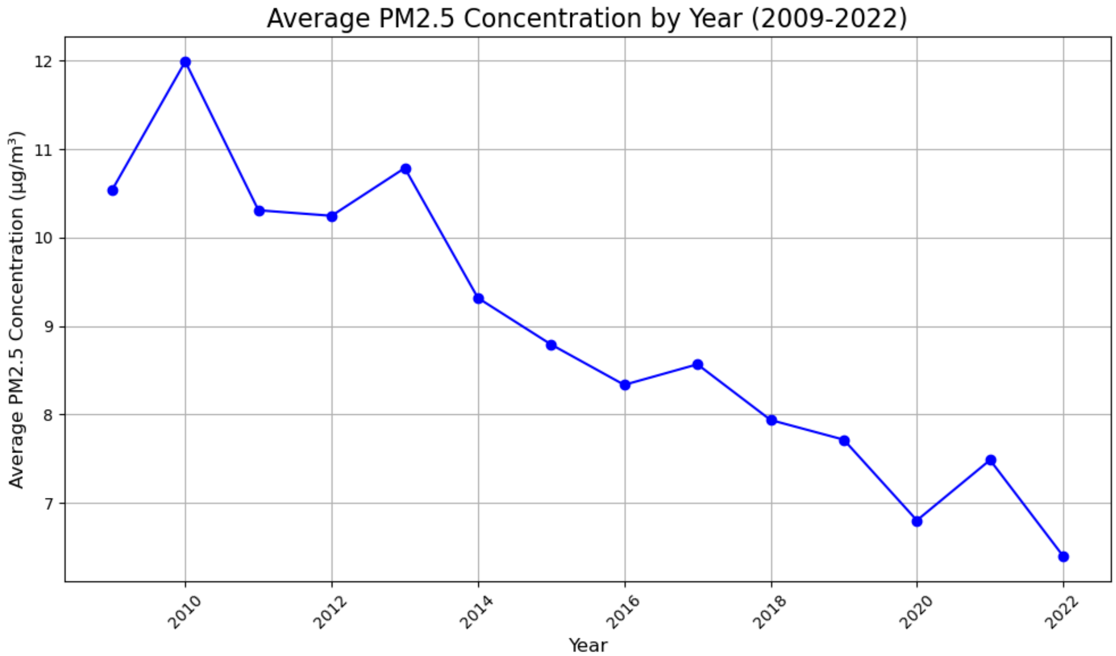
1.3.3 Objective - Comparative time-series analysis to identify the pattern of air quality from 2009 to 2022

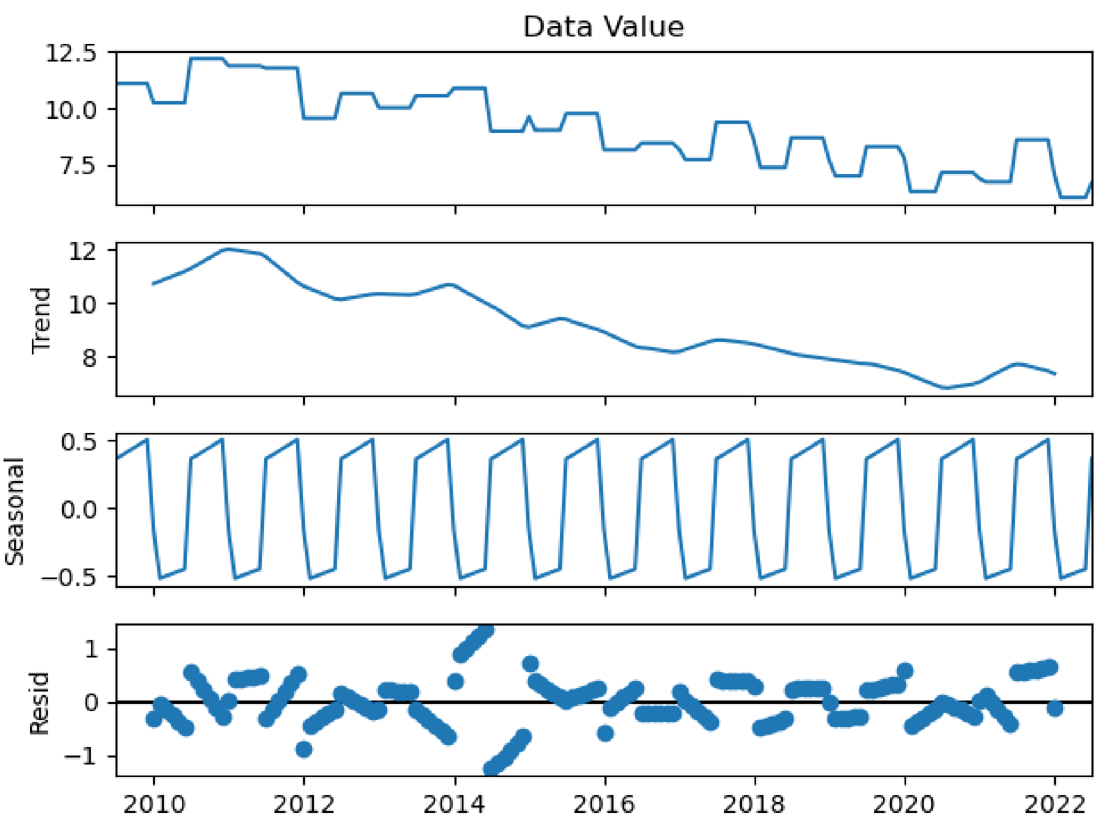
1.3.4 Hypothesis (H2): PM2.5 levels in New York City have shown a decreasing trend from 2009 to 2022, indicating an improvement in air quality.

[88]:
```
# Filter and data for "Fine particles (PM 2.5)" in 'Name' column
pm25_data_filtered = air_quality_filtered[air_quality_filtered['Name'] == 'Fine␣
↪particles (PM 2.5)']

# Convert 'Start_Date' to datetime
pm25_data_filtered['Start_Date'] = pd.
↪to_datetime(pm25_data_filtered['Start_Date'], errors='coerce')

# Filter data for the period 2009-2022
pm25_data_filtered = pm25_data_filtered[(pm25_data_filtered['Start_Date'].dt.
↪year >= 2009) &
                                        (pm25_data_filtered['Start_Date'].dt.
↪year <= 2022)]

# Group by year and calculate the average PM2.5 concentration
pm25_data_filtered['Year'] = pm25_data_filtered['Start_Date'].dt.year
pm25_data_filtered['Month'] = pm25_data_filtered['Start_Date'].dt.month
```

```
# Group by Year and calculate the average PM2.5 concentration per year
pm25_yearly = pm25_data_filtered.groupby('Year')['Data Value'].mean().
↪reset_index()

# Plot the Time Series for PM2.5
plt.figure(figsize=(10, 6))
plt.plot(pm25_yearly['Year'], pm25_yearly['Data Value'], marker='o',␣
↪linestyle='-', color='b')
plt.title('Average PM2.5 Concentration by Year (2009-2022)', fontsize=16)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Average PM2.5 Concentration (µg/m³)', fontsize=12)
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Time Series Decomposition
pm25_data_filtered.set_index('Start_Date', inplace=True)

# Resample the data to monthly frequency and calculate the mean PM2.5 value per␣
↪month
pm25_monthly = pm25_data_filtered['Data Value'].resample('M').mean()

# Fill missing values using forward fill
pm25_monthly_filled = pm25_monthly.ffill()

# Check if we have enough data points (at least 24)
if len(pm25_monthly_filled) >= 24:
    decomposition = sm.tsa.seasonal_decompose(pm25_monthly_filled,␣
↪model='additive', period=12)
    decomposition.plot()
    plt.tight_layout()
    plt.show()
else:
    print("Not enough data points for seasonal decomposition.")
```

```
/tmp/ipykernel_637/2287160137.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  pm25_data_filtered['Start_Date'] =
pd.to_datetime(pm25_data_filtered['Start_Date'], errors='coerce')
```

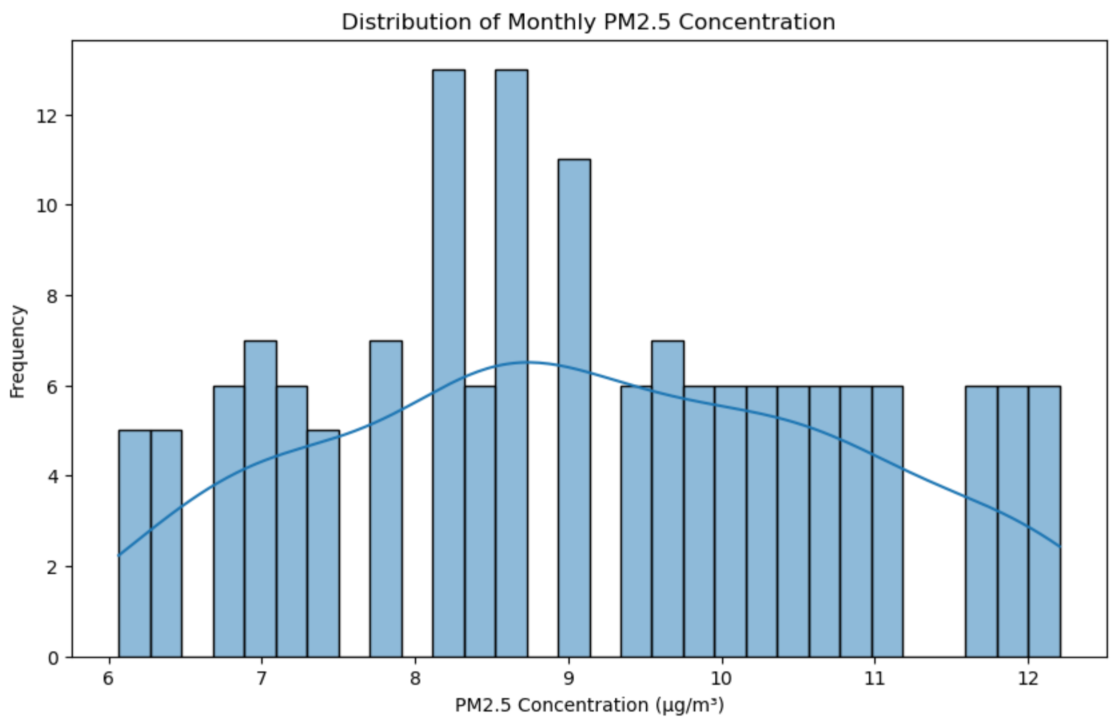

Average PM2.5 Concentration by Year (2009-2022)
Average PM2.5 Concentration (µg/m³)
Year
12
11
10
9
8
7
2010
2012
2014
2016
2018
2020
2022


Data Value
12.5
10.0
7.5
Trend
12
10
8
Seasonal
0.5
0.0
−0.5
Resid
1
0
−1
2010
2012
2014
2016
2018
2020
2022

[89]:
```
# Check if the data is skewed, before performing the analysis
skewness = pm25_monthly_filled.skew()
print(f"Skewness of PM2.5 data: {skewness}")
```

```
Skewness of PM2.5 data: 0.05312041061060736
```

[90]:
```
# Plot histogram for the distribution of PM2.5 (monthly filled data)
plt.figure(figsize=(10, 6))
sns.histplot(pm25_monthly_filled, bins=30, kde=True)
plt.title('Distribution of Monthly PM2.5 Concentration')
plt.xlabel('PM2.5 Concentration (µg/m³)')
plt.ylabel('Frequency')
plt.show()
```



Augmented Dickey-Fuller Test

[91]:
```
# Perform ADF test on the PM2.5 data
result = adfuller(pm25_monthly_filled.dropna())  #Dropping NaN
print('ADF Statistic:', result[0])
print('p-value:', result[1])

# Interpretation of p-value
if result[1] < 0.05:
    print("The time series is stationary.")
```

```python
else:
    print("The time series is non-stationary.")
```

```
ADF Statistic: -0.614285084118284
p-value: 0.8677214026498994
The time series is non-stationary.
```

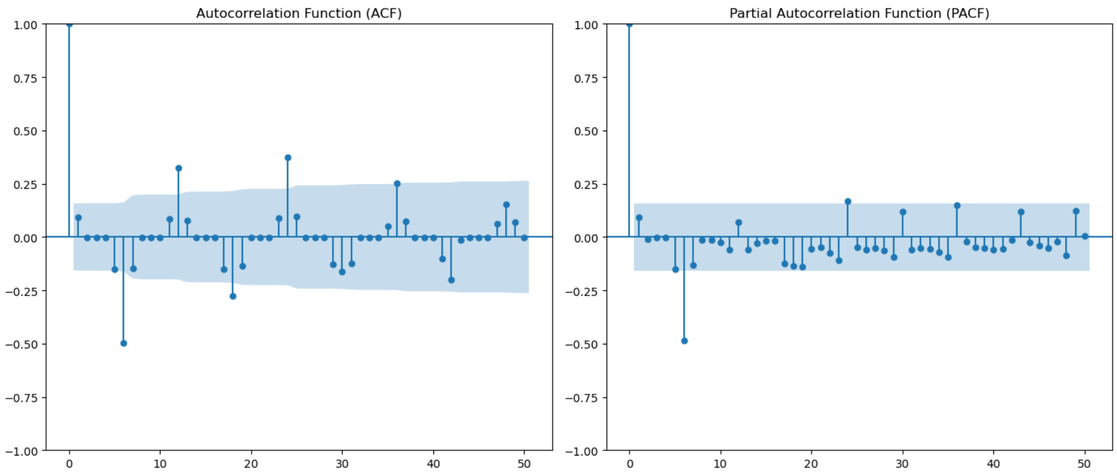
Differencing the timeseries data - to make it stationary

[92]:
```python
# First-order differencing
pm25_diff = pm25_monthly_filled.diff().dropna()

# Perform the ADF test again to check if the differenced series is stationary
result = adfuller(pm25_diff)
print('ADF Statistic:', result[0])
print('p-value:', result[1])

if result[1] < 0.05:
    print("The differenced time series is stationary.")
else:
    print("The differenced time series is still non-stationary.")
```

```
ADF Statistic: -8.593892429770564
p-value: 7.163528322744075e-14
The differenced time series is stationary.
```

ACF and PACF to understand the structure of time series

[93]:
```python
# Plot ACF and PACF for the differenced data
plt.figure(figsize=(14, 6))

# ACF plot
plt.subplot(121)
plot_acf(pm25_diff, lags=50, ax=plt.gca())
plt.title('Autocorrelation Function (ACF)')

# PACF plot
plt.subplot(122)
plot_pacf(pm25_diff, lags=50, ax=plt.gca())
plt.title('Partial Autocorrelation Function (PACF)')

plt.tight_layout()
plt.show()
```



ARIMA

[94]:
```
# Fitting an ARIMA model with the parameters (p=6, d=1, q=4)
model = ARIMA(pm25_diff, order=(6, 1, 4))  # Adjust p and q based on ACF/PACF␣
 ↪results
model_fit = model.fit()

# Print the summary of the model
print(model_fit.summary())
```

```
/opt/conda/lib/python3.11/site-
packages/statsmodels/tsa/statespace/sarimax.py:978: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:             Data Value   No. Observations:                  156
Model:                 ARIMA(6, 1, 4)   Log Likelihood                 -93.499
Date:                Sun, 08 Dec 2024   AIC                            208.998
Time:                        14:42:43   BIC                            242.476
Sample:                    07-31-2009   HQIC                           222.596
                         - 06-30-2022
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.6986      0.250      2.800      0.005       0.210       1.188
ar.L2         -0.7447      0.291     -2.560      0.010      -1.315      -0.174
ar.L3          0.5365      0.323      1.662      0.097      -0.096       1.169
ar.L4         -0.0585      0.318     -0.184      0.854      -0.683       0.566
ar.L5         -0.1369      0.277     -0.494      0.621      -0.680       0.406
```

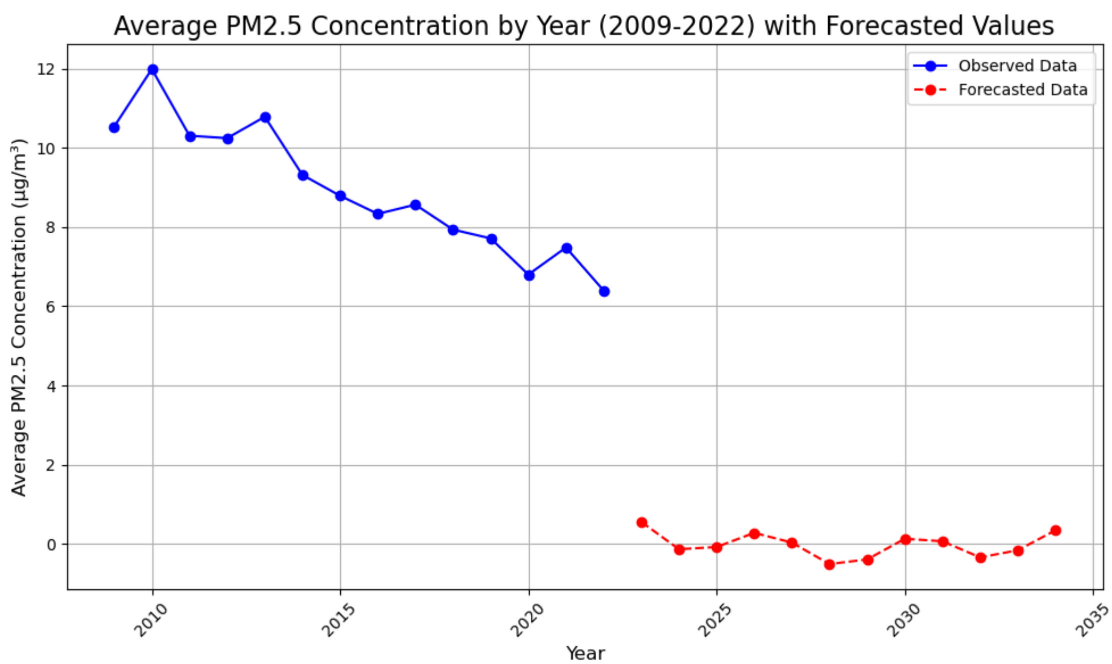
```
ar.L6         -0.2845      0.217     -1.310      0.190     -0.710      0.141
ma.L1         -1.7351      0.195     -8.887      0.000     -2.118     -1.352
ma.L2          1.5390      0.278      5.527      0.000      0.993      2.085
ma.L3         -1.4180      0.239     -5.936      0.000     -1.886     -0.950
ma.L4          0.6195      0.164      3.771      0.000      0.297      0.941
sigma2         0.1841      0.015     12.631      0.000      0.156      0.213
================================================================================
===
Ljung-Box (L1) (Q):                   0.06   Jarque-Bera (JB):
476.44
Prob(Q):                              0.81   Prob(JB):
0.00
Heteroskedasticity (H):               0.88   Skew:
-0.71
Prob(H) (two-sided):                  0.66   Kurtosis:
11.47
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

```
/opt/conda/lib/python3.11/site-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Forecasting

[95]:
```python
# Forecast the next few years
forecast_steps = 12
forecast = model_fit.forecast(steps=forecast_steps)

# Create a date range for the forecast period
forecast_years = range(pm25_yearly['Year'].iloc[-1] + 1, pm25_yearly['Year'].
 ↪iloc[-1] + 1 + forecast_steps)

# Create a DataFrame for the forecasted values
forecast_df = pd.DataFrame({
    'Year': forecast_years,
    'Data Value': forecast
})

# Plot the Time Series for PM2.5 (Observed data)
plt.figure(figsize=(10, 6))

# Plot the observed data (Yearly)
```

```
plt.plot(pm25_yearly['Year'], pm25_yearly['Data Value'], marker='o',␣
↪linestyle='-', color='b', label='Observed Data')

# Plot the forecasted data (Next 12 months)
plt.plot(forecast_df['Year'], forecast_df['Data Value'], marker='o',␣
↪linestyle='--', color='r', label='Forecasted Data')

# Adding titles and labels
plt.title('Average PM2.5 Concentration by Year (2009-2022) with Forecasted␣
↪Values', fontsize=16)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Average PM2.5 Concentration (µg/m³)', fontsize=12)
plt.grid(True)
plt.xticks(rotation=45)

# Add legend
plt.legend()

plt.tight_layout()
plt.show()
```



Objective - Understanding the number of asthma, and respiratory and cardiovascular hospitalization due to PM2.5 in the age group of 20+ and 40+, respectively

Hypothesis 3 (H3): PM2.5 exposure has contributed to an increase in asthma, and other respiratory and cardiovascular hospitalizations, particularly in the age groups 20+ and 40+ over the past decade.

[96]:
```
# Prepare to merge the three datasets asthna, resp_hospitalizations and
 ↪cv_hospitalizations
print(cv_hospitalizations.head())
print(cv_hospitalizations.info())
```

```
  TimePeriod GeoTypeDesc  GeoID  GeoRank      Geography  \
0  2017-2019    Citywide      1        0  New York City
1  2017-2019     Borough      1        1          Bronx
2  2017-2019     Borough      2        1       Brooklyn
3  2017-2019     Borough      3        1      Manhattan
4  2017-2019     Borough      4        1         Queens

   Estimated annual number Estimated annual rate per 100,000 adults
0                    387.0                                     10.0
1                     75.0                                     12.0
2                    126.0                                     11.0
3                     70.0                                      9.0
4                     89.0                                      8.0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   TimePeriod                                240 non-null    object
 1   GeoTypeDesc                               240 non-null    object
 2   GeoID                                     240 non-null    int64
 3   GeoRank                                   240 non-null    int64
 4   Geography                                 240 non-null    object
 5   Estimated annual number                   240 non-null    float64
 6   Estimated annual rate per 100,000 adults  240 non-null    object
dtypes: float64(1), int64(2), object(4)
memory usage: 13.3+ KB
None
```

[97]:
```
print(resp_hospitalizations.head())
print(resp_hospitalizations.info())
```

```
  TimePeriod GeoType  GeoID  GeoRank                Geography  \
0  2017-2019   UHF42    101        4  Kingsbridge - Riverdale
1  2017-2019   UHF42    102        4          Northeast Bronx
2  2017-2019   UHF42    103        4       Fordham - Bronx Pk
3  2017-2019   UHF42    104        4      Pelham - Throgs Neck
4  2017-2019   UHF42    105        4         Crotona -Tremont
```

```
  Estimated annual number  Estimated annual rate per 100,000 adults
0                     7.0                                       9.0
1                    16.0                                      10.0
2                    23.0                                      11.0
3                    24.0                                      10.0
4                    20.0                                      13.0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   TimePeriod                                240 non-null    object
 1   GeoType                                   240 non-null    object
 2   GeoID                                     240 non-null    int64
 3   GeoRank                                   240 non-null    int64
 4   Geography                                 240 non-null    object
 5   Estimated annual number                   240 non-null    object
 6   Estimated annual rate per 100,000 adults  156 non-null    float64
dtypes: float64(1), int64(2), object(4)
memory usage: 13.3+ KB
None
```

[98]:
```python
print(air_quality_filtered.head())
print(air_quality_filtered.info())
```

```
   Unique ID  Indicator ID                                  Name  \
0     179772           640  Boiler Emissions- Total SO2 Emissions
1     179785           640  Boiler Emissions- Total SO2 Emissions
2     178540           365                 Fine particles (PM 2.5)
3     178561           365                 Fine particles (PM 2.5)
4     823217           365                 Fine particles (PM 2.5)

          Measure Measure Info Geo Type Name  Geo Join ID  \
0  Number per km2       number         UHF42        409.0
1  Number per km2       number         UHF42        209.0
2            Mean       mcg/m3         UHF42        209.0
3            Mean       mcg/m3         UHF42        409.0
4            Mean       mcg/m3         UHF42        409.0

            Geo Place Name          Time Period Start_Date  Data Value
0         Southeast Queens                 2015 2015-01-01         0.3
1  Bensonhurst - Bay Ridge                 2015 2015-01-01         1.2
2  Bensonhurst - Bay Ridge  Annual Average 2012 2011-12-01         8.6
3         Southeast Queens  Annual Average 2012 2011-12-01         8.0
4         Southeast Queens          Summer 2022 2022-06-01         6.1
<class 'pandas.core.frame.DataFrame'>
Index: 16555 entries, 0 to 18023
Data columns (total 11 columns):
```

```
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unique ID       16555 non-null  int64
 1   Indicator ID    16555 non-null  int64
 2   Name            16555 non-null  object
 3   Measure         16555 non-null  object
 4   Measure Info    16555 non-null  object
 5   Geo Type Name   16555 non-null  object
 6   Geo Join ID     16555 non-null  float64
 7   Geo Place Name  16555 non-null  object
 8   Time Period     16555 non-null  object
 9   Start_Date      16555 non-null  datetime64[ns]
 10  Data Value      16555 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(2), object(6)
memory usage: 1.5+ MB
None
```

[99]:

```python
print(asthma.head())
print(asthma.info())
```

```
  TimePeriod GeoType  GeoID  GeoRank                Geography  \
0  2017-2019   UHF42    101        4  Kingsbridge - Riverdale
1  2017-2019   UHF42    102        4          Northeast Bronx
2  2017-2019   UHF42    103        4       Fordham - Bronx Pk
3  2017-2019   UHF42    104        4     Pelham - Throgs Neck
4  2017-2019   UHF42    105        4         Crotona -Tremont

  Estimated annual number (age 18+) Estimated annual number (under age 18)  \
0                              13.0                                    9.0
1                              61.0                                   37.0
2                             101.0                                   79.0
3                              83.0                                   58.0
4                             110.0                                   74.0

   Estimated annual rate (age 18+) per 100,000 adults  \
0                                               16.0
1                                               36.0
2                                               49.0
3                                               34.0
4                                               67.0

   Estimated annual rate (under age 18) per 100,000 children
0                                               48.0
1                                               81.0
2                                              112.0
3                                               80.0
4                                              119.0
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 240 entries, 0 to 239
Data columns (total 9 columns):
 #   Column                                                 Non-Null Count
Dtype
---  ------                                                 --------------
-----
 0   TimePeriod                                             240 non-null
object
 1   GeoType                                                240 non-null
object
 2   GeoID                                                  240 non-null
int64
 3   GeoRank                                                240 non-null
int64
 4   Geography                                              240 non-null
object
 5   Estimated annual number (age 18+)                      240 non-null
object
 6   Estimated annual number (under age 18)                 240 non-null
object
 7   Estimated annual rate (age 18+) per 100,000 adults     156 non-null
float64
 8   Estimated annual rate (under age 18) per 100,000 children  156 non-null
float64
dtypes: float64(2), int64(2), object(5)
memory usage: 17.0+ KB
None
```

[100]:

```
# For cv_hospitalizations: Normalizing the 'TimePeriod' column to extract the␣
↪starting year
cv_hospitalizations['Start_Year'] = cv_hospitalizations['TimePeriod'].str.
↪split('-').str[0].astype(int)

# Check the changes for cv_hospitalizations
print("cv_hospitalizations - Start Year Extraction:")
print(cv_hospitalizations[['TimePeriod', 'Start_Year']].head())

# For resp_hospitalizations: Extracting start year from 'TimePeriod'
resp_hospitalizations['Start_Year'] = resp_hospitalizations['TimePeriod'].str.
↪split('-').str[0].astype(int)

# Check the changes for resp_hospitalizations
print("resp_hospitalizations - Start Year Extraction:")
print(resp_hospitalizations[['TimePeriod', 'Start_Year']].head())

# For asthma: Extracting start year from 'TimePeriod'
asthma['Start_Year'] = asthma['TimePeriod'].str.split('-').str[0].astype(int)
```

```
# Check the changes for asthma
print("asthma - Start Year Extraction:")
print(asthma[['TimePeriod', 'Start_Year']].head())

# Additional check: Rows with missing Start_Year
missing_start_year_cv = cv_hospitalizations[cv_hospitalizations['Start_Year'].
  ↪isnull()]
missing_start_year_resp =␣
  ↪resp_hospitalizations[resp_hospitalizations['Start_Year'].isnull()]
missing_start_year_asthma = asthma[asthma['Start_Year'].isnull()]

print(f"Rows with missing Start_Year in cv_hospitalizations:␣
  ↪{missing_start_year_cv.shape[0]}")
print(f"Rows with missing Start_Year in resp_hospitalizations:␣
  ↪{missing_start_year_resp.shape[0]}")
print(f"Rows with missing Start_Year in asthma: {missing_start_year_asthma.
  ↪shape[0]}")

# Fill missing Start_Year in both datasets
cv_hospitalizations['Start_Year'].fillna(0, inplace=True)  # Filling with 0
resp_hospitalizations['Start_Year'].fillna(0, inplace=True)  # Same for␣
  ↪resp_hospitalizations
asthma['Start_Year'].fillna(0, inplace=True)  # Same for asthma

# Recheck after filling missing values
print("After filling missing Start_Year:")
print(cv_hospitalizations[['TimePeriod', 'Start_Year']].head())
print(resp_hospitalizations[['TimePeriod', 'Start_Year']].head())
print(asthma[['TimePeriod', 'Start_Year']].head())
```

```
cv_hospitalizations - Start Year Extraction:
  TimePeriod  Start_Year
0  2017-2019        2017
1  2017-2019        2017
2  2017-2019        2017
3  2017-2019        2017
4  2017-2019        2017
resp_hospitalizations - Start Year Extraction:
  TimePeriod  Start_Year
0  2017-2019        2017
1  2017-2019        2017
2  2017-2019        2017
3  2017-2019        2017
4  2017-2019        2017
asthma - Start Year Extraction:
  TimePeriod  Start_Year
```

```
0  2017-2019        2017
1  2017-2019        2017
2  2017-2019        2017
3  2017-2019        2017
4  2017-2019        2017
Rows with missing Start_Year in cv_hospitalizations: 0
Rows with missing Start_Year in resp_hospitalizations: 0
Rows with missing Start_Year in asthma: 0
After filling missing Start_Year:
  TimePeriod  Start_Year
0  2017-2019        2017
1  2017-2019        2017
2  2017-2019        2017
3  2017-2019        2017
4  2017-2019        2017
  TimePeriod  Start_Year
0  2017-2019        2017
1  2017-2019        2017
2  2017-2019        2017
3  2017-2019        2017
4  2017-2019        2017
  TimePeriod  Start_Year
0  2017-2019        2017
1  2017-2019        2017
2  2017-2019        2017
3  2017-2019        2017
4  2017-2019        2017
```

[101]:

```
#Checl unique geography values for both datasets
print(cv_hospitalizations['Geography'].unique())
print(resp_hospitalizations['Geography'].unique())
print(asthma['Geography'].unique())
print(air_quality_filtered['Geo Place Name'].unique())
```

```
['New York City' 'Bronx' 'Brooklyn' 'Manhattan' 'Queens' 'Staten Island'
 'Kingsbridge - Riverdale' 'Northeast Bronx' 'Fordham - Bronx Pk'
 'Pelham - Throgs Neck' 'Crotona -Tremont' 'High Bridge - Morrisania'
 'Hunts Point - Mott Haven' 'Greenpoint' 'Downtown - Heights - Slope'
 'Bedford Stuyvesant - Crown Heights' 'East New York' 'Sunset Park'
 'Borough Park' 'East Flatbush - Flatbush' 'Canarsie - Flatlands'
 'Bensonhurst - Bay Ridge' 'Coney Island - Sheepshead Bay'
 'Williamsburg - Bushwick' 'Washington Heights'
 'Central Harlem - Morningside Heights' 'East Harlem' 'Upper West Side'
 'Upper East Side' 'Chelsea - Clinton' 'Gramercy Park - Murray Hill'
 'Greenwich Village - SoHo' 'Union Square - Lower East Side'
 'Lower Manhattan' 'Long Island City - Astoria' 'West Queens'
 'Flushing - Clearview' 'Bayside - Little Neck' 'Ridgewood - Forest Hills'
 'Fresh Meadows' 'Southwest Queens' 'Jamaica' 'Southeast Queens'
```

```
 'Rockaways' 'Port Richmond' 'Stapleton - St. George' 'Willowbrook'
 'South Beach - Tottenville']
['Kingsbridge - Riverdale' 'Northeast Bronx' 'Fordham - Bronx Pk'
 'Pelham - Throgs Neck' 'Crotona -Tremont' 'High Bridge - Morrisania'
 'Hunts Point - Mott Haven' 'Greenpoint' 'Downtown - Heights - Slope'
 'Bedford Stuyvesant - Crown Heights' 'East New York' 'Sunset Park'
 'Borough Park' 'East Flatbush - Flatbush' 'Canarsie - Flatlands'
 'Bensonhurst - Bay Ridge' 'Coney Island - Sheepshead Bay'
 'Williamsburg - Bushwick' 'Washington Heights'
 'Central Harlem - Morningside Heights' 'East Harlem' 'Upper West Side'
 'Upper East Side' 'Chelsea - Clinton' 'Gramercy Park - Murray Hill'
 'Greenwich Village - SoHo' 'Union Square - Lower East Side'
 'Lower Manhattan' 'Long Island City - Astoria' 'West Queens'
 'Flushing - Clearview' 'Bayside - Little Neck' 'Ridgewood - Forest Hills'
 'Fresh Meadows' 'Southwest Queens' 'Jamaica' 'Southeast Queens'
 'Rockaways' 'Port Richmond' 'Stapleton - St. George' 'Willowbrook'
 'South Beach - Tottenville' 'Bronx' 'Brooklyn' 'Manhattan' 'Queens'
 'Staten Island' 'New York City']
['Kingsbridge - Riverdale' 'Northeast Bronx' 'Fordham - Bronx Pk'
 'Pelham - Throgs Neck' 'Crotona -Tremont' 'High Bridge - Morrisania'
 'Hunts Point - Mott Haven' 'Greenpoint' 'Downtown - Heights - Slope'
 'Bedford Stuyvesant - Crown Heights' 'East New York' 'Sunset Park'
 'Borough Park' 'East Flatbush - Flatbush' 'Canarsie - Flatlands'
 'Bensonhurst - Bay Ridge' 'Coney Island - Sheepshead Bay'
 'Williamsburg - Bushwick' 'Washington Heights'
 'Central Harlem - Morningside Heights' 'East Harlem' 'Upper West Side'
 'Upper East Side' 'Chelsea - Clinton' 'Gramercy Park - Murray Hill'
 'Greenwich Village - SoHo' 'Union Square - Lower East Side'
 'Lower Manhattan' 'Long Island City - Astoria' 'West Queens'
 'Flushing - Clearview' 'Bayside - Little Neck' 'Ridgewood - Forest Hills'
 'Fresh Meadows' 'Southwest Queens' 'Jamaica' 'Southeast Queens'
 'Rockaways' 'Port Richmond' 'Stapleton - St. George' 'Willowbrook'
 'South Beach - Tottenville' 'Bronx' 'Brooklyn' 'Manhattan' 'Queens'
 'Staten Island' 'New York City']
['Southeast Queens' 'Bensonhurst - Bay Ridge' 'Rockaways'
 'Coney Island - Sheepshead Bay' 'Williamsburg - Bushwick'
 'Bayside - Little Neck' 'Pelham - Throgs Neck' 'Upper West Side'
 'East New York' 'Canarsie - Flatlands' 'Jamaica'
 'Gramercy Park - Murray Hill' 'Hunts Point - Mott Haven'
 'Southwest Queens' 'Greenwich Village - SoHo' 'Brooklyn'
 'Downtown - Heights - Slope' 'Washington Heights' 'Northeast Bronx'
 'Greenpoint' 'Long Island City - Astoria' 'Port Richmond'
 'Kingsbridge - Riverdale' 'Throgs Neck and Co-op City (CD10)'
 'Williamsbridge and Baychester (CD12)' 'Jamaica and Hollis (CD12)'
 'South Ozone Park and Howard Beach (CD10)'
 'Kingsbridge Heights and Bedford (CD7)' 'Sunset Park (CD7)'
 'Rockaway and Broad Channel (CD14)' 'Upper West Side (CD7)'
 'Flushing and Whitestone (CD7)' 'Bushwick (CD4)'
```

```
'Bedford Stuyvesant (CD3)' 'Jackson Heights (CD3)'
'East Flatbush - Flatbush' 'Elmhurst and Corona (CD4)'
'Highbridge and Concourse (CD4)' 'Lower East Side and Chinatown (CD3)'
'Morrisania and Crotona (CD3)' 'Upper East Side (CD8)'
'Central Harlem (CD10)' 'Washington Heights and Inwood (CD12)'
'Union Square - Lower East Side' 'Manhattan'
'Bedford Stuyvesant - Crown Heights' 'High Bridge - Morrisania'
'Woodside and Sunnyside (CD2)' 'Hunts Point and Longwood (CD2)'
'Greenwich Village and Soho (CD2)' 'Upper East Side' 'Crotona -Tremont'
'Flushing - Clearview' 'East Harlem' 'Fordham - Bronx Pk'
'Chelsea - Clinton' 'Central Harlem - Morningside Heights'
'Fresh Meadows' 'Bay Ridge and Dyker Heights (CD10)'
'Fort Greene and Brooklyn Heights (CD2)'
'Greenpoint and Williamsburg (CD1)' 'Mott Haven and Melrose (CD1)'
'Lower Manhattan' 'West Queens' 'Parkchester and Soundview (CD9)'
'Kew Gardens and Woodhaven (CD9)' 'Morris Park and Bronxdale (CD11)'
'Bayside and Little Neck (CD11)'
'Morningside Heights and Hamilton Heights (CD9)' 'East Harlem (CD11)'
'South Crown Heights and Lefferts Gardens (CD9)'
'East New York and Starrett City (CD5)' 'Midtown (CD5)' 'Queens'
'Queens Village (CD13)' 'Park Slope and Carroll Gardens (CD6)'
'Stuyvesant Town and Turtle Bay (CD6)'
'Hillcrest and Fresh Meadows (CD8)' 'Bronx'
'Long Island City and Astoria (CD1)'
'Fordham and University Heights (CD5)' 'Riverdale and Fieldston (CD8)'
'Clinton and Chelsea (CD4)' 'Crown Heights and Prospect Heights (CD8)'
'Rego Park and Forest Hills (CD6)' 'Bensonhurst (CD11)' 'Sunset Park'
'Brownsville (CD16)' 'St. George and Stapleton (CD1)'
'Financial District (CD1)' 'Borough Park' 'Coney Island (CD13)'
'Sheepshead Bay (CD15)' 'Staten Island' 'Ridgewood - Forest Hills'
'Belmont and East Tremont (CD6)' 'Flatbush and Midwood (CD14)'
'Borough Park (CD12)' 'East Flatbush (CD17)'
'Ridgewood and Maspeth (CD5)' 'Willowbrook' 'Northern SI'
'Stapleton - St. George' 'Southern SI' 'Flatlands and Canarsie (CD18)'
'South Beach and Willowbrook (CD2)' 'Bayside Little Neck-Fresh Meadows'
'South Beach - Tottenville' 'South Bronx'
'Tottenville and Great Kills (CD3)' 'Upper East Side-Gramercy'
'Chelsea-Village' 'Union Square-Lower Manhattan' 'New York City']
```

[102]:
```python
# Check the data types of the columns
print(cv_hospitalizations['Start_Year'].dtype)
print(resp_hospitalizations['Start_Year'].dtype)
print(asthma['Start_Year'].dtype)
print(air_quality_filtered['Start_Date'].dtype)
```

```
int64
int64
int64
```

```
datetime64[ns]
```

[103]:
```python
# Print column names of air_quality to see if 'Start_Year' exists
print(air_quality_filtered.columns)
```

```
Index(['Unique ID', 'Indicator ID', 'Name', 'Measure', 'Measure Info',
       'Geo Type Name', 'Geo Join ID', 'Geo Place Name', 'Time Period',
       'Start_Date', 'Data Value'],
      dtype='object')
```

[104]:
```python
# Extract the year from 'Start_Date'
air_quality_filtered['Start_Year'] = air_quality_filtered['Start_Date'].dt.year.
 ↪astype(int)

# Check the conversion
print("air_quality - Start Year Conversion:")
print(air_quality_filtered[['Geo Place Name', 'Start_Year', 'Data Value']].
 ↪head())

# Confirm the data type change
print("Data type of 'Start_Year' in air_quality:",␣
 ↪air_quality_filtered['Start_Year'].dtype)
```

```
air_quality - Start Year Conversion:
            Geo Place Name  Start_Year  Data Value
0         Southeast Queens        2015         0.3
1   Bensonhurst - Bay Ridge        2015         1.2
2   Bensonhurst - Bay Ridge        2011         8.6
3         Southeast Queens        2011         8.0
4         Southeast Queens        2022         6.1
Data type of 'Start_Year' in air_quality: int64
```

```
/tmp/ipykernel_637/2330814497.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  air_quality_filtered['Start_Year'] =
air_quality_filtered['Start_Date'].dt.year.astype(int)
```

[105]:
```python
# Ensure 'Start_Year' in both datasets is an object type (string) to match the␣
 ↪format in air_quality
cv_hospitalizations['Start_Year'] = cv_hospitalizations['Start_Year'].
 ↪astype(int)
resp_hospitalizations['Start_Year'] = resp_hospitalizations['Start_Year'].
 ↪astype(int)
asthma['Start_Year'] = asthma['Start_Year'].astype(int)
```

```
# Clean the 'GeoPlaceName' columns for cv_hospitalizations,␣
↪resp_hospitalizations and asthma
cv_hospitalizations['Geography'] = cv_hospitalizations['Geography'].str.strip().
↪str.lower()
resp_hospitalizations['Geography'] = resp_hospitalizations['Geography'].str.
↪strip().str.lower()
asthma['Geography'] = asthma['Geography'].str.strip().str.lower()

# Clean the 'Geo Place Name' column in air_quality
air_quality_filtered['Geo Place Name'] = air_quality_filtered['Geo Place Name'].
↪str.strip().str.lower()
```

```
/tmp/ipykernel_637/275883514.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  air_quality_filtered['Geo Place Name'] = air_quality_filtered['Geo Place
Name'].str.strip().str.lower()
```

[106]:
```
# Check the columns in cv_hospitalizations to confirm if 'Start_Year' exists
print("cv_hospitalizations columns:", cv_hospitalizations.columns)

# Check the columns in resp_hospitalizations to confirm if 'Start_Year' exists
print("resp_hospitalizations columns:", resp_hospitalizations.columns)

# Check the columns in asthma to confirm if 'Start_Year' exists
print("asthma columns:", asthma.columns)

# Check if 'Start_Year' exists in both datasets before converting to int
if 'Start_Year' in cv_hospitalizations.columns:
    cv_hospitalizations['Start_Year'] = cv_hospitalizations['Start_Year'].
↪astype(int)
else:
    print("Start_Year column not found in cv_hospitalizations")

if 'Start_Year' in resp_hospitalizations.columns:
    resp_hospitalizations['Start_Year'] = resp_hospitalizations['Start_Year'].
↪astype(int)
else:
    print("Start_Year column not found in resp_hospitalizations")

if 'Start_Year' in asthma.columns:
    asthma['Start_Year'] = asthma['Start_Year'].astype(int)
else:
```

```
    print("Start_Year column not found in asthma")
```

```
cv_hospitalizations columns: Index(['TimePeriod', 'GeoTypeDesc', 'GeoID',
'GeoRank', 'Geography',
       'Estimated annual number', 'Estimated annual rate per 100,000 adults',
       'Start_Year'],
      dtype='object')
resp_hospitalizations columns: Index(['TimePeriod', 'GeoType', 'GeoID',
'GeoRank', 'Geography',
       'Estimated annual number', 'Estimated annual rate per 100,000 adults',
       'Start_Year'],
      dtype='object')
asthma columns: Index(['TimePeriod', 'GeoType', 'GeoID', 'GeoRank', 'Geography',
       'Estimated annual number (age 18+)',
       'Estimated annual number (under age 18)',
       'Estimated annual rate (age 18+) per 100,000 adults',
       'Estimated annual rate (under age 18) per 100,000 children',
       'Start_Year'],
      dtype='object')
```

[107]:
```
# Drop the specified columns from the asthma dataset as they are not required␣
↪in merging
asthma_cleaned = asthma.drop(columns=['Estimated annual number (age 18+)',␣
↪'Estimated annual number (under age 18)'])

# Check the result to confirm columns have been dropped
print(asthma_cleaned.head())
```

```
  TimePeriod GeoType  GeoID  GeoRank                Geography  \
0  2017-2019   UHF42    101        4  kingsbridge - riverdale
1  2017-2019   UHF42    102        4          northeast bronx
2  2017-2019   UHF42    103        4       fordham - bronx pk
3  2017-2019   UHF42    104        4     pelham - throgs neck
4  2017-2019   UHF42    105        4         crotona -tremont

   Estimated annual rate (age 18+) per 100,000 adults  \
0                                               16.0
1                                               36.0
2                                               49.0
3                                               34.0
4                                               67.0

   Estimated annual rate (under age 18) per 100,000 children  Start_Year
0                                               48.0                 2017
1                                               81.0                 2017
2                                              112.0                 2017
3                                               80.0                 2017
```

4   119.0   2017

[108]:
```
# Check for matching rows in the asthma dataset for each of the conditions
asthma_condition_1 = asthma[(asthma['Estimated annual rate (under age 18) per␣
↪100,000 children'].notnull())]
asthma_condition_2 = asthma[(asthma['Estimated annual rate (age 18+) per␣
↪100,000 adults'].notnull())]


# Output how many rows match each condition
print(f"Matching rows for under 18 per 100,000 children: {asthma_condition_1.
↪shape[0]}")
print(f"Matching rows for age 18+ per 100,000 adults: {asthma_condition_2.
↪shape[0]}")
```

```
Matching rows for under 18 per 100,000 children: 156
Matching rows for age 18+ per 100,000 adults: 156
```

[109]:
```
# Merge for 'Measure' = 'Estimated annual rate (under age 18)' and 'Measure␣
↪Info' = 'per 100,000 children'
asthma_merged_1 = pd.merge(
    air_quality_filtered[(air_quality_filtered['Measure'] == 'Estimated annual␣
↪rate (under age 18)') &
                         (air_quality_filtered['Measure Info'] == 'per 100,000␣
↪children')],
    asthma[['Start_Year', 'Geography', 'Estimated annual rate (under age 18)␣
↪per 100,000 children']],
    left_on=['Start_Year', 'Geo Place Name'],
    right_on=['Start_Year', 'Geography'],
    how='left'
)

# Merge for 'Measure' = 'Estimated annual rate (age 18+)' and 'Measure Info' =␣
↪'per 100,000 adults'
asthma_merged_2 = pd.merge(
    air_quality_filtered[(air_quality_filtered['Measure'] == 'Estimated annual␣
↪rate (age 18+)') &
                         (air_quality_filtered['Measure Info'] == 'per 100,000 adults')],
    asthma[['Start_Year', 'Geography', 'Estimated annual rate (age 18+) per␣
↪100,000 adults']],
    left_on=['Start_Year', 'Geo Place Name'],
    right_on=['Start_Year', 'Geography'],
    how='left'
)

# Concatenate the tables
final_merged_asthma = pd.concat([asthma_merged_1, asthma_merged_2])
```

```python
# Check
print(final_merged_asthma)
```

```
    Unique ID  Indicator ID                                          Name  \
0      131425           648  Asthma emergency department visits due to PM2.5
1      131445           648  Asthma emergency department visits due to PM2.5
2      131424           648  Asthma emergency department visits due to PM2.5
3      628472           648  Asthma emergency department visits due to PM2.5
4      628471           648  Asthma emergency department visits due to PM2.5
..        …          …                                            …
571    628525           657  Asthma emergency department visits due to PM2.5
572    518966           657  Asthma emergency department visits due to PM2.5
573    151588           661             Asthma hospitalizations due to Ozone
574    827392           657  Asthma emergency department visits due to PM2.5
575    628519           657  Asthma emergency department visits due to PM2.5

                                 Measure         Measure Info Geo Type Name  \
0    Estimated annual rate (under age 18)  per 100,000 children         UHF42
1    Estimated annual rate (under age 18)  per 100,000 children         UHF42
2    Estimated annual rate (under age 18)  per 100,000 children         UHF42
3    Estimated annual rate (under age 18)  per 100,000 children         UHF42
4    Estimated annual rate (under age 18)  per 100,000 children         UHF42
..                                    …                    …            …
571        Estimated annual rate (age 18+)    per 100,000 adults         UHF42
572        Estimated annual rate (age 18+)    per 100,000 adults         UHF42
573        Estimated annual rate (age 18+)    per 100,000 adults         UHF42
574        Estimated annual rate (age 18+)    per 100,000 adults         UHF42
575        Estimated annual rate (age 18+)    per 100,000 adults         UHF42

    Geo Join ID             Geo Place Name Time Period Start_Date  Data Value  \
0         208.0       canarsie - flatlands   2009-2011 2009-01-01        81.7
1         407.0           southwest queens   2009-2011 2009-01-01        80.0
2         207.0  east flatbush - flatbush   2009-2011 2009-01-01       115.8
3         408.0                    jamaica   2015-2017 2015-01-01        69.6
4         407.0           southwest queens   2015-2017 2015-01-01        43.0
..          …                        …         …        …         …
571       503.0                willowbrook   2015-2017 2015-01-01        12.9
572       403.0        flushing - clearview   2012-2014 2012-01-02         9.6
573       207.0  east flatbush - flatbush   2009-2011 2009-01-01         7.3
574       408.0                    jamaica   2017-2019 2017-01-01        23.0
575       407.0           southwest queens   2015-2017 2015-01-01        18.6

    Start_Year                 Geography  \
0         2009      canarsie - flatlands
1         2009          southwest queens
2         2009  east flatbush - flatbush
```

```
3          2015                  jamaica
4          2015          southwest queens
..          …                        …
571        2015               willowbrook
572        2012       flushing - clearview
573        2009  east flatbush - flatbush
574        2017                  jamaica
575        2015          southwest queens

     Estimated annual rate (under age 18) per 100,000 children  \
0                                                  NaN
1                                                  NaN
2                                                  NaN
3                                                 69.6
4                                                 43.0
..                                                  …
571                                                NaN
572                                                NaN
573                                                NaN
574                                                NaN
575                                                NaN

     Estimated annual rate (age 18+) per 100,000 adults
0                                                  NaN
1                                                  NaN
2                                                  NaN
3                                                  NaN
4                                                  NaN
..                                                  …
571                                               12.9
572                                                9.6
573                                                NaN
574                                               23.0
575                                               18.6

[1152 rows x 15 columns]
```

[110]:

```
# Change the asthma column names
final_merged_asthma.rename(columns={'Estimated annual rate (under age 18) per␣
↪100,000 children': 'Asthma_under18'}, inplace=True)
final_merged_asthma.rename(columns={'Estimated annual rate (age 18+) per␣
↪100,000 adults': 'Asthma_18+'}, inplace=True)
print(final_merged_asthma.head())
```

```
   Unique ID  Indicator ID                                         Name  \
0     131425           648  Asthma emergency department visits due to PM2.5
1     131445           648  Asthma emergency department visits due to PM2.5
2     131424           648  Asthma emergency department visits due to PM2.5
```

```
3     628472          648  Asthma emergency department visits due to PM2.5
4     628471          648  Asthma emergency department visits due to PM2.5

                                 Measure          Measure Info Geo Type Name  \
0  Estimated annual rate (under age 18)  per 100,000 children         UHF42
1  Estimated annual rate (under age 18)  per 100,000 children         UHF42
2  Estimated annual rate (under age 18)  per 100,000 children         UHF42
3  Estimated annual rate (under age 18)  per 100,000 children         UHF42
4  Estimated annual rate (under age 18)  per 100,000 children         UHF42

   Geo Join ID            Geo Place Name Time Period Start_Date  Data Value  \
0        208.0      canarsie - flatlands   2009-2011 2009-01-01        81.7
1        407.0          southwest queens   2009-2011 2009-01-01        80.0
2        207.0  east flatbush - flatbush   2009-2011 2009-01-01       115.8
3        408.0                   jamaica   2015-2017 2015-01-01        69.6
4        407.0          southwest queens   2015-2017 2015-01-01        43.0

   Start_Year                 Geography  Asthma_under18  Asthma_18+
0        2009      canarsie - flatlands             NaN         NaN
1        2009          southwest queens             NaN         NaN
2        2009  east flatbush - flatbush             NaN         NaN
3        2015                   jamaica            69.6         NaN
4        2015          southwest queens            43.0         NaN
```

[111]:

```python
# For cv_hospitalizations
cv_condition_1 = cv_hospitalizations[
    (cv_hospitalizations['GeoTypeDesc'].isin(air_quality_filtered['Geo Type␣
 ↪Name'].unique())) &
    (cv_hospitalizations['Start_Year'].isin(air_quality_filtered['Start_Year'].
 ↪unique())) &
    (cv_hospitalizations['Geography'].isin(air_quality_filtered['Geo Place␣
 ↪Name'].unique())) &
    (cv_hospitalizations['Estimated annual rate per 100,000 adults'].notnull())
]

print(f"Matching rows for cv_hospitalizations: {cv_condition_1.shape[0]}")

# For resp_hospitalizations
resp_condition_1 = resp_hospitalizations[
    (resp_hospitalizations['GeoType'].isin(air_quality_filtered['Geo Type␣
 ↪Name'].unique())) &
    (resp_hospitalizations['Start_Year'].
 ↪isin(air_quality_filtered['Start_Year'].unique())) &
    (resp_hospitalizations['Geography'].isin(air_quality_filtered['Geo Place␣
 ↪Name'].unique())) &
    (resp_hospitalizations['Estimated annual rate per 100,000 adults'].
 ↪notnull())
```

```
]

print(f"Matching rows for resp_hospitalizations: {resp_condition_1.shape[0]}")
```

```
Matching rows for cv_hospitalizations: 24
Matching rows for resp_hospitalizations: 150
```

[112]:

```
# Merge cv_hospitalizations with air_quality based on the specified logic
cv_hospitalization_merged = pd.merge(
    air_quality_filtered[air_quality_filtered['Name'] == 'Cardiovascular␣
 ↪hospitalizations due to PM2.5 (age 40+)'],  # Filter for matching 'Name'
    cv_hospitalizations[['Start_Year', 'Geography', 'Estimated annual rate per␣
 ↪100,000 adults']],  # Columns to merge
    left_on=['Start_Year', 'Geo Place Name'],  # Matching columns in␣
 ↪air_quality (removed Geo Type Name from merge criteria)
    right_on=['Start_Year', 'Geography'],  # Matching columns in␣
 ↪cv_hospitalizations
    how='left'  # Keep all air_quality data
)

cv_hospitalization_merged.rename(columns={'Estimated annual rate per 100,000␣
 ↪adults': 'cv_adults'}, inplace=True)

# Merge resp_hospitalizations with air_quality based on the specified logic
resp_hospitalization_merged = pd.merge(
    air_quality_filtered[air_quality_filtered['Name'] == 'Respiratory␣
 ↪hospitalizations due to PM2.5 (age 20+)'],
    resp_hospitalizations[['Start_Year', 'Geography', 'Estimated annual rate␣
 ↪per 100,000 adults']],
    left_on=['Start_Year', 'Geo Place Name'],
    right_on=['Start_Year', 'Geography'],
    how='left'
)

resp_hospitalization_merged.rename(columns={'Estimated annual rate per 100,000␣
 ↪adults': 'resp_adults'}, inplace=True)

# Check the merged datasets
print(cv_hospitalization_merged.head())
print(resp_hospitalization_merged.head())
```

```
   Unique ID  Indicator ID                                          Name  \
0     628611           651  Cardiovascular hospitalizations due to PM2.5 (…
1     518862           651  Cardiovascular hospitalizations due to PM2.5 (…
2     518837           651  Cardiovascular hospitalizations due to PM2.5 (…
3     518866           651  Cardiovascular hospitalizations due to PM2.5 (…
4     628586           651  Cardiovascular hospitalizations due to PM2.5 (…
```

```
                Measure       Measure Info Geo Type Name  Geo Join ID  \
0  Estimated annual rate  per 100,000 adults         UHF42        403.0
1  Estimated annual rate  per 100,000 adults         UHF42        305.0
2  Estimated annual rate  per 100,000 adults       Borough          3.0
3  Estimated annual rate  per 100,000 adults         UHF42        309.0
4  Estimated annual rate  per 100,000 adults         UHF42        106.0

                  Geo Place Name Time Period Start_Date  Data Value  \
0            flushing - clearview   2015-2017 2015-01-01        12.8
1                 upper east side   2012-2014 2012-01-02         9.2
2                       manhattan   2012-2014 2012-01-02        12.3
3  union square - lower east side   2012-2014 2012-01-02        12.7
4        high bridge - morrisania   2015-2017 2015-01-01        23.5

   Start_Year                       Geography cv_adults
0        2015            flushing - clearview      12.8
1        2012                 upper east side       9.2
2        2012                       manhattan      12.3
3        2012  union square - lower east side      12.7
4        2015        high bridge - morrisania      23.5
   Unique ID  Indicator ID                                               Name  \
0     518816           650  Respiratory hospitalizations due to PM2.5 (age…
1     131520           650  Respiratory hospitalizations due to PM2.5 (age…
2     518817           650  Respiratory hospitalizations due to PM2.5 (age…
3     628568           650  Respiratory hospitalizations due to PM2.5 (age…
4     628528           650  Respiratory hospitalizations due to PM2.5 (age…

                Measure       Measure Info Geo Type Name  Geo Join ID  \
0  Estimated annual rate  per 100,000 adults         UHF42        307.0
1  Estimated annual rate  per 100,000 adults         UHF42        207.0
2  Estimated annual rate  per 100,000 adults         UHF42        308.0
3  Estimated annual rate  per 100,000 adults         UHF42        408.0
4  Estimated annual rate  per 100,000 adults       Borough          1.0

              Geo Place Name Time Period Start_Date  Data Value  Start_Year  \
0  gramercy park - murray hill   2012-2014 2012-01-02         8.9        2012
1     east flatbush - flatbush   2009-2011 2009-01-01        10.5        2009
2     greenwich village - soho   2012-2014 2012-01-02         5.3        2012
3                      jamaica   2015-2017 2015-01-01        10.5        2015
4                        bronx   2015-2017 2015-01-01        19.6        2015

                    Geography  resp_adults
0  gramercy park - murray hill          8.9
1     east flatbush - flatbush          NaN
2     greenwich village - soho          5.3
3                      jamaica         10.5
4                        bronx         19.6
```

Final merging of datasets

[113]:
```
# Merge the final_merged_asthma, cv_hospitalization_merged, and␣
↪resp_hospitalization_merged datasets
final_merged = pd.merge(
    final_merged_asthma,
    cv_hospitalization_merged[['Start_Year', 'Geo Place Name', 'cv_adults']],
    on=['Start_Year', 'Geo Place Name'],
    how='left'
)

final_merged = pd.merge(
    final_merged,
    resp_hospitalization_merged[['Start_Year', 'Geo Place Name',␣
↪'resp_adults']],
    on=['Start_Year', 'Geo Place Name'],
    how='left'
)

# Check the merged dataset
print(final_merged.head())
```

```
   Unique ID  Indicator ID                                            Name  \
0     131425           648  Asthma emergency department visits due to PM2.5
1     131445           648  Asthma emergency department visits due to PM2.5
2     131424           648  Asthma emergency department visits due to PM2.5
3     628472           648  Asthma emergency department visits due to PM2.5
4     628471           648  Asthma emergency department visits due to PM2.5

                                Measure          Measure Info Geo Type Name  \
0  Estimated annual rate (under age 18)  per 100,000 children         UHF42
1  Estimated annual rate (under age 18)  per 100,000 children         UHF42
2  Estimated annual rate (under age 18)  per 100,000 children         UHF42
3  Estimated annual rate (under age 18)  per 100,000 children         UHF42
4  Estimated annual rate (under age 18)  per 100,000 children         UHF42

   Geo Join ID            Geo Place Name Time Period Start_Date  Data Value  \
0        208.0      canarsie - flatlands   2009-2011 2009-01-01        81.7
1        407.0          southwest queens   2009-2011 2009-01-01        80.0
2        207.0  east flatbush - flatbush   2009-2011 2009-01-01       115.8
3        408.0                   jamaica   2015-2017 2015-01-01        69.6
4        407.0          southwest queens   2015-2017 2015-01-01        43.0

   Start_Year                 Geography  Asthma_under18  Asthma_18+ cv_adults  \
0        2009      canarsie - flatlands             NaN         NaN         -
1        2009          southwest queens             NaN         NaN         -
2        2009  east flatbush - flatbush             NaN         NaN         -
3        2015                   jamaica            69.6         NaN      19.4
```

```
4         2015           southwest queens            43.0          NaN      18.5

   resp_adults
0          NaN
1          NaN
2          NaN
3         10.5
4          9.0
```

Merging and creating a new column PM2.5 for regression analysis

[114]:
```
# Rename the 'Data Value' column to 'PM2.5' and 'Year' to 'Start_Year'
pm25_data_filtered = pm25_data_filtered.rename(columns={'Data Value': 'PM2.5',␣
↪'Year': 'Start_Year'})

# Check the filtered data
print(pm25_data_filtered.head())
```

```
            Unique ID  Indicator ID                    Name Measure  \
Start_Date
2011-12-01     178540           365  Fine particles (PM 2.5)    Mean
2011-12-01     178561           365  Fine particles (PM 2.5)    Mean
2022-06-01     823217           365  Fine particles (PM 2.5)    Mean
2012-06-01     177910           365  Fine particles (PM 2.5)    Mean
2013-06-01     177952           365  Fine particles (PM 2.5)    Mean

           Measure Info Geo Type Name  Geo Join ID           Geo Place Name  \
Start_Date
2011-12-01       mcg/m3         UHF42        209.0  Bensonhurst - Bay Ridge
2011-12-01       mcg/m3         UHF42        409.0         Southeast Queens
2022-06-01       mcg/m3         UHF42        409.0         Southeast Queens
2012-06-01       mcg/m3         UHF42        209.0  Bensonhurst - Bay Ridge
2013-06-01       mcg/m3         UHF42        209.0  Bensonhurst - Bay Ridge

                   Time Period  PM2.5  Start_Year  Month
Start_Date
2011-12-01  Annual Average 2012    8.6        2011     12
2011-12-01  Annual Average 2012    8.0        2011     12
2022-06-01          Summer 2022    6.1        2022      6
2012-06-01          Summer 2012   10.0        2012      6
2013-06-01          Summer 2013    9.8        2013      6
```

[115]:
```
pm25_select = pm25_data_filtered[['Start_Year','Geo Type Name', 'Geo Place␣
↪Name', 'PM2.5']]

print(pm25_select.head())
pm25_select.info()
```

```
             Start_Year Geo Type Name         Geo Place Name  PM2.5
Start_Date
2011-12-01        2011         UHF42  Bensonhurst - Bay Ridge    8.6
2011-12-01        2011         UHF42         Southeast Queens    8.0
2022-06-01        2022         UHF42         Southeast Queens    6.1
2012-06-01        2012         UHF42  Bensonhurst - Bay Ridge   10.0
2013-06-01        2013         UHF42  Bensonhurst - Bay Ridge    9.8
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 5640 entries, 2011-12-01 to 2019-01-01
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Start_Year      5640 non-null   int32
 1   Geo Type Name   5640 non-null   object
 2   Geo Place Name  5640 non-null   object
 3   PM2.5           5640 non-null   float64
dtypes: float64(1), int32(1), object(2)
memory usage: 198.3+ KB
```

[116]:
```python
# Aggregate the PM2.5 data to get the mean PM2.5 value for each year, geo type,␣
↪and place
pm25_aggregated = pm25_data_filtered.groupby(['Start_Year', 'Geo Type Name',␣
↪'Geo Place Name'])['PM2.5'].mean().reset_index()

# Check the aggregated PM2.5 data
print(pm25_aggregated.head())
```

```
   Start_Year Geo Type Name Geo Place Name      PM2.5
0        2009       Borough          Bronx  10.600000
1        2009       Borough       Brooklyn  10.200000
2        2009       Borough      Manhattan  12.066667
3        2009       Borough         Queens   9.633333
4        2009       Borough  Staten Island   9.466667
```

[117]:
```python
pm25_aggregated['Geo Place Name'] = pm25_aggregated['Geo Place Name'].str.
↪strip().str.lower()
print(pm25_aggregated['Geo Place Name'].unique())

# Check unique values of merge columns in both datasets
print(final_merged[['Start_Year', 'Geo Type Name', 'Geo Place Name']].
↪drop_duplicates())
print(pm25_aggregated[['Start_Year', 'Geo Type Name', 'Geo Place Name']].
↪drop_duplicates())
```

```
['bronx' 'brooklyn' 'manhattan' 'queens' 'staten island'
 'bay ridge and dyker heights (cd10)' 'bayside and little neck (cd11)'
 'bedford stuyvesant (cd3)' 'belmont and east tremont (cd6)'
 'bensonhurst (cd11)' 'borough park (cd12)' 'brownsville (cd16)'
```

```
'bushwick (cd4)' 'central harlem (cd10)' 'clinton and chelsea (cd4)'
'coney island (cd13)' 'crown heights and prospect heights (cd8)'
'east flatbush (cd17)' 'east harlem (cd11)'
'east new york and starrett city (cd5)' 'elmhurst and corona (cd4)'
'financial district (cd1)' 'flatbush and midwood (cd14)'
'flatlands and canarsie (cd18)' 'flushing and whitestone (cd7)'
'fordham and university heights (cd5)'
'fort greene and brooklyn heights (cd2)'
'greenpoint and williamsburg (cd1)' 'greenwich village and soho (cd2)'
'highbridge and concourse (cd4)' 'hillcrest and fresh meadows (cd8)'
'hunts point and longwood (cd2)' 'jackson heights (cd3)'
'jamaica and hollis (cd12)' 'kew gardens and woodhaven (cd9)'
'kingsbridge heights and bedford (cd7)'
'long island city and astoria (cd1)'
'lower east side and chinatown (cd3)' 'midtown (cd5)'
'morningside heights and hamilton heights (cd9)'
'morris park and bronxdale (cd11)' 'morrisania and crotona (cd3)'
'mott haven and melrose (cd1)' 'park slope and carroll gardens (cd6)'
'parkchester and soundview (cd9)' 'queens village (cd13)'
'rego park and forest hills (cd6)' 'ridgewood and maspeth (cd5)'
'riverdale and fieldston (cd8)' 'rockaway and broad channel (cd14)'
'sheepshead bay (cd15)' 'south beach and willowbrook (cd2)'
'south crown heights and lefferts gardens (cd9)'
'south ozone park and howard beach (cd10)'
'st. george and stapleton (cd1)' 'stuyvesant town and turtle bay (cd6)'
'sunset park (cd7)' 'throgs neck and co-op city (cd10)'
'tottenville and great kills (cd3)' 'upper east side (cd8)'
'upper west side (cd7)' 'washington heights and inwood (cd12)'
'williamsbridge and baychester (cd12)' 'woodside and sunnyside (cd2)'
'new york city' 'bayside little neck-fresh meadows'
'bedford stuyvesant - crown heights' 'bensonhurst - bay ridge'
'borough park' 'canarsie - flatlands'
'central harlem - morningside heights' 'chelsea-village'
'coney island - sheepshead bay' 'downtown - heights - slope'
'east flatbush - flatbush' 'east harlem' 'east new york'
'flushing - clearview' 'fordham - bronx pk' 'greenpoint' 'jamaica'
'kingsbridge - riverdale' 'long island city - astoria' 'northeast bronx'
'northern si' 'pelham - throgs neck' 'ridgewood - forest hills'
'rockaways' 'south bronx' 'southeast queens' 'southern si'
'southwest queens' 'sunset park' 'union square-lower manhattan'
'upper east side-gramercy' 'upper west side' 'washington heights'
'west queens' 'williamsburg - bushwick' 'bayside - little neck'
'chelsea - clinton' 'crotona -tremont' 'fresh meadows'
'gramercy park - murray hill' 'greenwich village - soho'
'high bridge - morrisania' 'hunts point - mott haven' 'lower manhattan'
'port richmond' 'south beach - tottenville' 'stapleton - st. george'
'union square - lower east side' 'upper east side' 'willowbrook']
    Start_Year Geo Type Name            Geo Place Name
```

```
0          2009        UHF42      canarsie - flatlands
1          2009        UHF42          southwest queens
2          2009        UHF42    east flatbush - flatbush
3          2015        UHF42                   jamaica
4          2015        UHF42          southwest queens
..          …           …                        …
534        2009        UHF42    stapleton - st. george
541        2017     Citywide             new york city
544        2009     Citywide             new york city
547        2012     Citywide             new york city
548        2015     Citywide             new york city

[192 rows x 3 columns]
      Start_Year Geo Type Name           Geo Place Name
0           2009       Borough                    bronx
1           2009       Borough                 brooklyn
2           2009       Borough                manhattan
3           2009       Borough                   queens
4           2009       Borough            staten island
…            …           …                         …
1969        2022         UHF42          upper west side
1970        2022         UHF42       washington heights
1971        2022         UHF42             west queens
1972        2022         UHF42  williamsburg - bushwick
1973        2022         UHF42               willowbrook

[1974 rows x 3 columns]
```

[118]:
```
# Create a new column 'asthma_cases_under18' and fill it with values from the
↪asthma dataset
final_merged['asthma_cases_under18'] = final_merged['Asthma_under18']
final_merged['asthma_cases_18+'] = final_merged['Asthma_18+']

# Respiratory hospitalizations for 20+
final_merged['resp_hosp_20plus'] = final_merged['resp_adults']

# Cardiovascular hospitalizations for 40+
final_merged['cv_hosp_40plus'] = final_merged['cv_adults']

# Check the derived columns
print(final_merged[['Start_Year', 'Geo Type Name', 'Geo Place Name',
↪'asthma_cases_under18', 'asthma_cases_18+', 'resp_hosp_20plus',
↪'cv_hosp_40plus']].head())
```

```
   Start_Year Geo Type Name            Geo Place Name  asthma_cases_under18  \
0        2009         UHF42      canarsie - flatlands                   NaN
1        2009         UHF42          southwest queens                   NaN
2        2009         UHF42  east flatbush - flatbush                   NaN
```

```
3        2015         UHF42                   jamaica                  69.6
4        2015         UHF42          southwest queens                  43.0

   asthma_cases_18+  resp_hosp_20plus cv_hosp_40plus
0               NaN               NaN              -
1               NaN               NaN              -
2               NaN               NaN              -
3               NaN              10.5           19.4
4               NaN               9.0           18.5
```

[119]:
```python
# Create a new dataset with the relevant columns
final_merged_selected = final_merged[['Start_Year', 'Geo Type Name', 'Geo Place␣
↪Name',
                                       'asthma_cases_under18',␣
↪'asthma_cases_18+', 'resp_hosp_20plus', 'cv_hosp_40plus']]

# Merge the aggregated PM2.5 data with the final_merged dataset
final_merged_with_pm25 = pd.merge(
    final_merged_selected,  # The dataset with asthma, cardiovascular, and␣
↪respiratory hospitalization data
    pm25_aggregated[['Start_Year', 'Geo Type Name', 'Geo Place Name', 'PM2.
↪5']],  # Columns to merge
    on=['Start_Year', 'Geo Type Name', 'Geo Place Name'],  # Merge on␣
↪'Start_Year', 'Geo Type Name', 'Geo Place Name'
    how='left'  # Left join to retain all rows from final_merged
)

# Check the merged dataset
print(final_merged_with_pm25.head())
```

```
   Start_Year Geo Type Name            Geo Place Name  asthma_cases_under18  \
0        2009         UHF42      canarsie - flatlands                   NaN
1        2009         UHF42          southwest queens                   NaN
2        2009         UHF42  east flatbush - flatbush                   NaN
3        2015         UHF42                   jamaica                  69.6
4        2015         UHF42          southwest queens                  43.0

   asthma_cases_18+  resp_hosp_20plus cv_hosp_40plus      PM2.5
0               NaN               NaN              -   9.666667
1               NaN               NaN              -   9.666667
2               NaN               NaN              -  10.300000
3               NaN              10.5           19.4   7.925000
4               NaN               9.0           18.5   7.875000
```

[120]:
```python
# Remove rows where 'asthma_cases_under18', 'asthma_cases_18+',␣
↪'resp_hosp_20plus', 'cv_hosp_40plus' and 'PM2.5' are all NaN
```

```
final_merged_with_pm25 = final_merged_with_pm25.
 ↪dropna(subset=['asthma_cases_under18', 'asthma_cases_18+',␣
 ↪'resp_hosp_20plus', 'cv_hosp_40plus'], how='all')

# Check how many rows remain after the cleaning
print(f"Rows before cleaning: {final_merged_with_pm25.shape[0]}")
print(f"Rows after cleaning: {final_merged_with_pm25.shape[0]}")

# Check
final_merged_with_pm25.tail()
```

```
Rows before cleaning: 1152
Rows after cleaning: 1152
```

[120]:

```
      Start_Year Geo Type Name             Geo Place Name  \
1147        2015         UHF42                willowbrook
1148        2012         UHF42       flushing - clearview
1149        2009         UHF42  east flatbush - flatbush
1150        2017         UHF42                    jamaica
1151        2015         UHF42           southwest queens

      asthma_cases_under18  asthma_cases_18+  resp_hosp_20plus cv_hosp_40plus  \
1147                   NaN              12.9              14.1           16.8
1148                   NaN               9.6               8.9            9.2
1149                   NaN               NaN               NaN              -
1150                   NaN              23.0               6.0            9.0
1151                   NaN              18.6               9.0           18.5

          PM2.5
1147   7.950000
1148   9.466667
1149  10.300000
1150   7.800000
1151   7.875000
```

[121]:

```
# Check for any NaN or invalid values in the cv_hosp_40plus column before␣
 ↪grouping
print(final_merged_with_pm25[['Geo Place Name', 'cv_hosp_40plus']].isnull().
 ↪sum())
print(final_merged_with_pm25[['Geo Place Name', 'cv_hosp_40plus']].head())

# Replace hyphen ('-') with NaN and convert to numeric
final_merged_with_pm25['cv_hosp_40plus'] =␣
 ↪final_merged_with_pm25['cv_hosp_40plus'].replace('-', np.nan)

# Now convert the column to numeric, forcing errors to NaN (in case there are␣
 ↪other non-numeric values)
```

```
final_merged_with_pm25['cv_hosp_40plus'] = pd.
    ↪to_numeric(final_merged_with_pm25['cv_hosp_40plus'], errors='coerce')

# Verify the data after cleaning
print(final_merged_with_pm25[['Geo Place Name', 'cv_hosp_40plus']].head())

# Group by Start_Year and Geo Place Name to get the total cases for each␣
    ↪condition
grouped_data = final_merged_with_pm25.groupby(['Start_Year', 'Geo Place Name']).
    ↪agg(
    total_asthma_below18_cases=('asthma_cases_under18', 'sum'),
    total_asthma_18_cases=('asthma_cases_18+', 'sum'),
    total_resp_hosp_20plus=('resp_hosp_20plus', 'sum'),
    total_cv_hosp_40plus=('cv_hosp_40plus', 'sum'),
    total_PM25=('PM2.5', 'sum')
).reset_index()

# Check the grouped results again
print(grouped_data.head())
```

```
Geo Place Name    0
cv_hosp_40plus    0
dtype: int64
             Geo Place Name cv_hosp_40plus
0       canarsie - flatlands              -
1           southwest queens              -
2  east flatbush - flatbush              -
3                    jamaica           19.4
4           southwest queens           18.5
             Geo Place Name  cv_hosp_40plus
0       canarsie - flatlands             NaN
1           southwest queens             NaN
2  east flatbush - flatbush             NaN
3                    jamaica            19.4
4           southwest queens            18.5
   Start_Year                      Geo Place Name  total_asthma_below18_cases  \
0        2009              bayside - little neck                         0.0
1        2009  bedford stuyvesant - crown heights                         0.0
2        2009            bensonhurst - bay ridge                         0.0
3        2009                       borough park                         0.0
4        2009                              bronx                       384.6

   total_asthma_18_cases  total_resp_hosp_20plus  total_cv_hosp_40plus  \
0                    0.0                     0.0                   0.0
1                    0.0                     0.0                   0.0
2                    0.0                     0.0                   0.0
3                    0.0                     0.0                   0.0
```

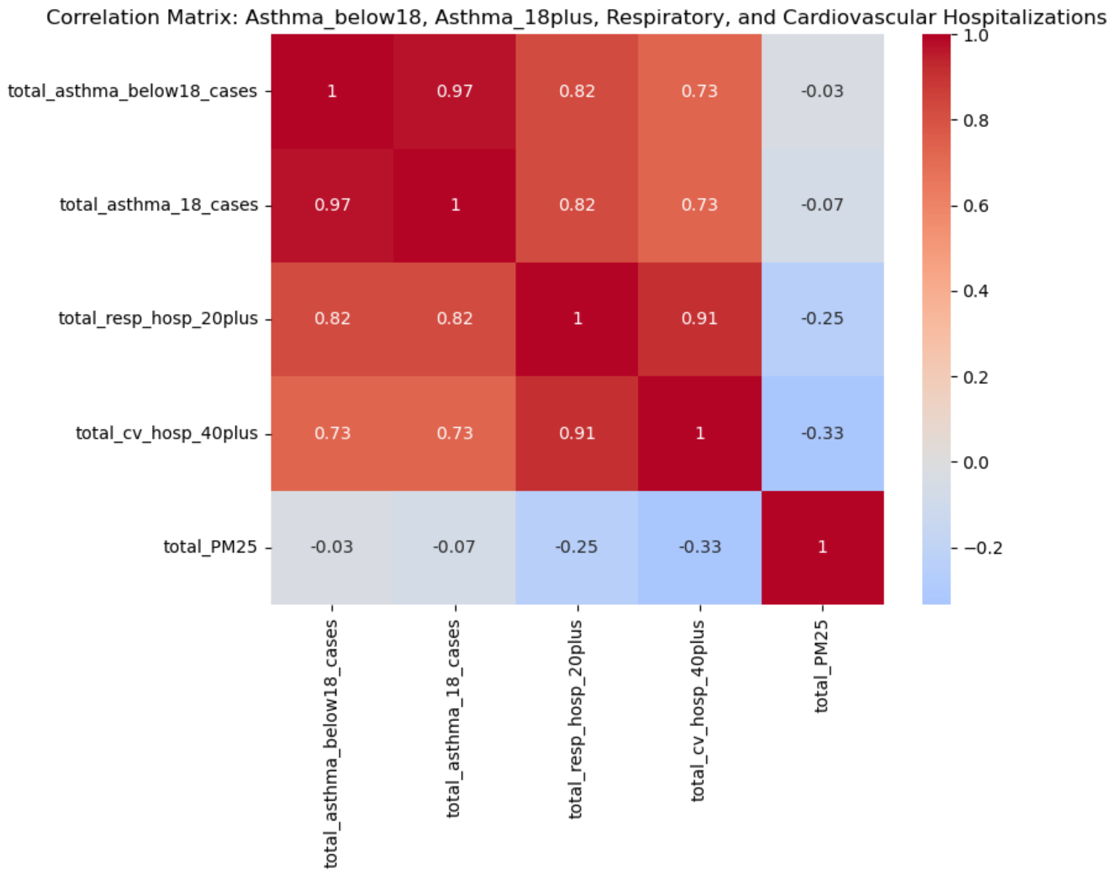
```
4                  201.0                    123.6                   112.8

   total_PM25
0        56.0
1        62.2
2        58.6
3        61.0
4        63.6
```

[122]:
```
# Get the summary statistics for each condition
summary_stats = grouped_data.describe()

# Display the summary statistics
print(summary_stats)
```

```
        Start_Year  total_asthma_below18_cases  total_asthma_18_cases  \
count   192.000000                  192.000000             192.000000
mean   2013.250000                  176.229687              85.139063
std       3.039013                  173.688094              89.182114
min    2009.000000                    0.000000               0.000000
25%    2011.250000                   42.000000              19.725000
50%    2013.500000                  137.250000              58.650000
75%    2015.500000                  253.875000             119.400000
max    2017.000000                  759.300000             391.800000

       total_resp_hosp_20plus  total_cv_hosp_40plus  total_PM25
count              192.000000            192.000000  192.000000
mean                50.293750             63.271875   57.172656
std                 36.818342             40.837115    8.129833
min                  0.000000              0.000000   41.100000
25%                 27.150000             42.000000   51.200000
50%                 52.500000             70.200000   56.600000
75%                 71.550000             90.750000   61.600000
max                159.000000            153.000000   87.200000
```

[123]:
```
#Correlation analysis
# Calculate the correlation matrix
correlation_matrix = grouped_data[['total_asthma_below18_cases',␣
↪'total_asthma_18_cases', 'total_resp_hosp_20plus',␣
↪'total_cv_hosp_40plus','total_PM25']].corr()

# Plot the correlation heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)

# Set the title
```

```
plt.title('Correlation Matrix: Asthma_below18, Asthma_18plus, Respiratory, and
    Cardiovascular Hospitalizations')

# Show the plot
plt.show()
```



[124]:

```
# Check the number of non-NaN rows for each dependent variable
print(final_merged_with_pm25[['PM2.5', 'asthma_cases_under18',
    'asthma_cases_18+', 'resp_hosp_20plus', 'cv_hosp_40plus']].notna().sum())

# Drop rows only where 'PM2.5' or any dependent variable of interest is NaN
final_merged_with_pm25_clean = final_merged_with_pm25.dropna(subset=['PM2.5'])

# Fill in missing health outcomes with a placeholder value (like 0 or median)
final_merged_with_pm25_clean['asthma_cases_under18'].fillna(0, inplace=True)
final_merged_with_pm25_clean['asthma_cases_18+'].fillna(0, inplace=True)
final_merged_with_pm25_clean['resp_hosp_20plus'].
    fillna(final_merged_with_pm25_clean['resp_hosp_20plus'].median(),
    inplace=True)
```

```
final_merged_with_pm25_clean['cv_hosp_40plus'].
 ↪fillna(final_merged_with_pm25_clean['cv_hosp_40plus'].median(), inplace=True)

# Check descriptive statistics
print(final_merged_with_pm25_clean.describe())
```

```
PM2.5                    1152
asthma_cases_under18      450
asthma_cases_18+          450
resp_hosp_20plus          900
cv_hosp_40plus            900
dtype: int64
        Start_Year  asthma_cases_under18  asthma_cases_18+  resp_hosp_20plus  \
count  1152.000000           1152.000000       1152.000000       1152.000000
mean   2013.250000             29.371615         14.189844         10.569792
std       3.032405             50.320333         25.327168          4.229895
min    2009.000000              0.000000          0.000000          2.000000
25%    2011.250000              0.000000          0.000000          8.275000
50%    2013.500000              0.000000          0.000000         10.000000
75%    2015.500000             45.625000         19.375000         11.925000
max    2017.000000            253.100000        130.600000         26.500000

       cv_hosp_40plus        PM2.5
count     1152.000000  1152.000000
mean        13.367188     9.528776
std          3.875569     1.352026
min          3.000000     6.850000
25%         11.100000     8.533333
50%         12.900000     9.433333
75%         15.125000    10.266667
max         25.500000    14.533333
```

1.3.5 Regression analysis - with separate asthma cases

[125]:
```
# Define the independent variable (PM2.5) and dependent variables (health␣
 ↪outcomes)
X = final_merged_with_pm25_clean['PM2.5']
y_asthma_below18 = final_merged_with_pm25_clean['asthma_cases_under18']
y_asthma_18plus = final_merged_with_pm25_clean['asthma_cases_18+']
y_resp_hosp = final_merged_with_pm25_clean['resp_hosp_20plus']
y_cv_hosp = final_merged_with_pm25_clean['cv_hosp_40plus']

# Add a constant to the independent variable for the intercept in the model
X = sm.add_constant(X)

# Perform regression for each dependent variable
model_asthma_below18 = sm.OLS(y_asthma_below18, X).fit()
```

```python
model_asthma_18plus = sm.OLS(y_asthma_18plus, X).fit()
model_resp_hosp = sm.OLS(y_resp_hosp, X).fit()
model_cv_hosp = sm.OLS(y_cv_hosp, X).fit()

# Print the summaries of the models
print("Regression results for Asthma Cases under 18:")
print(model_asthma_below18.summary())

print("\nRegression results for Asthma Cases above 18:")
print(model_asthma_18plus.summary())

print("\nRegression results for Respiratory Hospitalizations (20+):")
print(model_resp_hosp.summary())

print("\nRegression results for Cardiovascular Hospitalizations (40+):")
print(model_cv_hosp.summary())
```

```
Regression results for Asthma Cases under 18:
                            OLS Regression Results
===============================================================================
Dep. Variable:     asthma_cases_under18   R-squared:                       0.000
Model:                              OLS   Adj. R-squared:                 -0.001
Method:                   Least Squares   F-statistic:                    0.3482
Date:                  Sun, 08 Dec 2024   Prob (F-statistic):              0.555
Time:                          14:43:07   Log-Likelihood:                -6148.0
No. Observations:                  1152   AIC:                         1.230e+04
Df Residuals:                      1150   BIC:                         1.231e+04
Df Model:                             1
Covariance Type:              nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         35.5416     10.561      3.365      0.001      14.821      56.263
PM2.5         -0.6475      1.097     -0.590      0.555      -2.801       1.506
==============================================================================
Omnibus:                      483.020   Durbin-Watson:                   0.801
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1711.695
Skew:                           2.094   Prob(JB):                         0.00
Kurtosis:                       7.256   Cond. No.                         69.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

Regression results for Asthma Cases above 18:
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:       asthma_cases_18+   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.957
Date:                Sun, 08 Dec 2024   Prob (F-statistic):              0.162
Time:                        14:43:07   Log-Likelihood:                -5356.3
No. Observations:                1152   AIC:                         1.072e+04
Df Residuals:                    1150   BIC:                         1.073e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         21.5462      5.312      4.056      0.000      11.124      31.968
PM2.5         -0.7720      0.552     -1.399      0.162      -1.855       0.311
==============================================================================
Omnibus:                      552.400   Durbin-Watson:                   1.150
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2474.474
Skew:                           2.321   Prob(JB):                         0.00
Kurtosis:                       8.477   Cond. No.                         69.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

Regression results for Respiratory Hospitalizations (20+):
                            OLS Regression Results
==============================================================================
Dep. Variable:      resp_hosp_20plus   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.4484
Date:                Sun, 08 Dec 2024   Prob (F-statistic):              0.503
Time:                        14:43:07   Log-Likelihood:                -3295.3
No. Observations:                1152   AIC:                             6595.
Df Residuals:                    1150   BIC:                             6605.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          9.9813      0.888     11.244      0.000       8.240      11.723
PM2.5          0.0618      0.092      0.670      0.503      -0.119       0.243
==============================================================================
Omnibus:                      251.813   Durbin-Watson:                   1.552
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              540.425
Skew:                           1.224   Prob(JB):                    4.45e-118
Kurtosis:                       5.296   Cond. No.                         69.3
```

```
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

Regression results for Cardiovascular Hospitalizations (40+):
                            OLS Regression Results
==============================================================================
Dep. Variable:          cv_hosp_40plus   R-squared:                       0.002
Model:                             OLS   Adj. R-squared:                  0.001
Method:                  Least Squares   F-statistic:                     1.831
Date:                 Sun, 08 Dec 2024   Prob (F-statistic):              0.176
Time:                         14:43:07   Log-Likelihood:                -3193.8
No. Observations:                 1152   AIC:                             6392.
Df Residuals:                     1150   BIC:                             6402.
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         14.4561      0.813     17.784      0.000      12.861      16.051
PM2.5         -0.1143      0.084     -1.353      0.176      -0.280       0.051
==============================================================================
Omnibus:                       52.123   Durbin-Watson:                   1.424
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               60.859
Skew:                           0.489   Prob(JB):                     6.09e-14
Kurtosis:                       3.556   Cond. No.                         69.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

1.3.6 Regression analysis - combines asthma cases

[126]:

```python
# Combine asthma cases under 18 and 18+ by summing them
final_merged_with_pm25_clean['total_asthma_cases'] =
 ↪final_merged_with_pm25_clean['asthma_cases_under18'] +
 ↪final_merged_with_pm25_clean['asthma_cases_18+']

# Define the independent variable and the new dependent variable (total asthma
 ↪cases)
X = final_merged_with_pm25_clean['PM2.5']
y_total_asthma = final_merged_with_pm25_clean['total_asthma_cases']

# Add a constant to the independent variable for the intercept in the model
```

```python
X = sm.add_constant(X)

# Run the regression for the combined asthma cases
model_total_asthma = sm.OLS(y_total_asthma, X).fit()

#Print regression results
print("Regression results for Total Asthma Cases:")
print(model_total_asthma.summary())
```

```
Regression results for Total Asthma Cases:
                            OLS Regression Results
==============================================================================
Dep. Variable:     total_asthma_cases   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.814
Date:                Sun, 08 Dec 2024   Prob (F-statistic):              0.178
Time:                        14:43:08   Log-Likelihood:                -6101.6
No. Observations:                1152   AIC:                         1.221e+04
Df Residuals:                    1150   BIC:                         1.222e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         57.0878     10.144      5.627      0.000      37.184      76.992
PM2.5         -1.4195      1.054     -1.347      0.178      -3.488       0.649
==============================================================================
Omnibus:                      388.601   Durbin-Watson:                   1.186
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1099.912
Skew:                           1.742   Prob(JB):                    1.44e-239
Kurtosis:                       6.282   Cond. No.                         69.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Analysis of PM2.5 Pollution and Its Impact on Public Health in NYC (2009-2022)

Team Members:
Shubhi Vyas
Srishti RV Singh

Contents covered

Introduction

Problem statement:

Air pollution, particularly PM2.5, poses a **severe public health risk**, causing respiratory and cardiovascular diseases. Despite a 78% reduction in U.S. pollutants since 1970, **NYC remains heavily impacted**, with significant racial and neighborhood disparities. Our project aims to examines PM2.5 trends (2009–2022) and their **health impacts & neighborhood disparities** to highlight the need for targeted interventions.

Motive:

Despite reductions in overall air pollution, PM2.5 continues to **significantly impact public health**, particularly in densely populated cities like NYC. Vulnerable neighborhoods, often home to marginalized communities, face persistent disparities in air quality. This study seeks to **analyze PM2.5 trends**, link exposure to **health outcomes**, and generate **actionable insights** to inform policies addressing environmental justice and public **health improvement**.

Data Source

1. **Air Quality Dataset** (Geographical type, Air Quality indicators & measurements & Time period)

2. **Datasets on PM2.5 levels and hospitalizations** (Geographical type & Annual estimated cases)
   a) Asthma emergency hospitalizations
   b) Cardiovascular hospitalizations = CV_hospitalizations
   c) Respiratory hospitalizations = resp_hospitalizations

3. **Tools: Python**
   a) pandas, numpy: data manipulation
   b) matplotlib, seaborn: visualization
   c) Statsmodels: regression modelling

Research Goals & Hypotheses

Goals:

1. Assess air quality disparities across neighborhoods
2. Evaluate the trend in PM2.5 levels
3. Link PM2.5 levels to hospitalization rates(asthma, other respiratory illness & cardio-vascular diseases)

Hypotheses:

1. Neighborhoods with more people of color(population density) have worse air quality.
2. PM2.5 levels have decreased over time from 2009 to 2022.
3. Higher PM2.5 exposure leads to increased hospitalizations.

Data Cleaning and Preparation

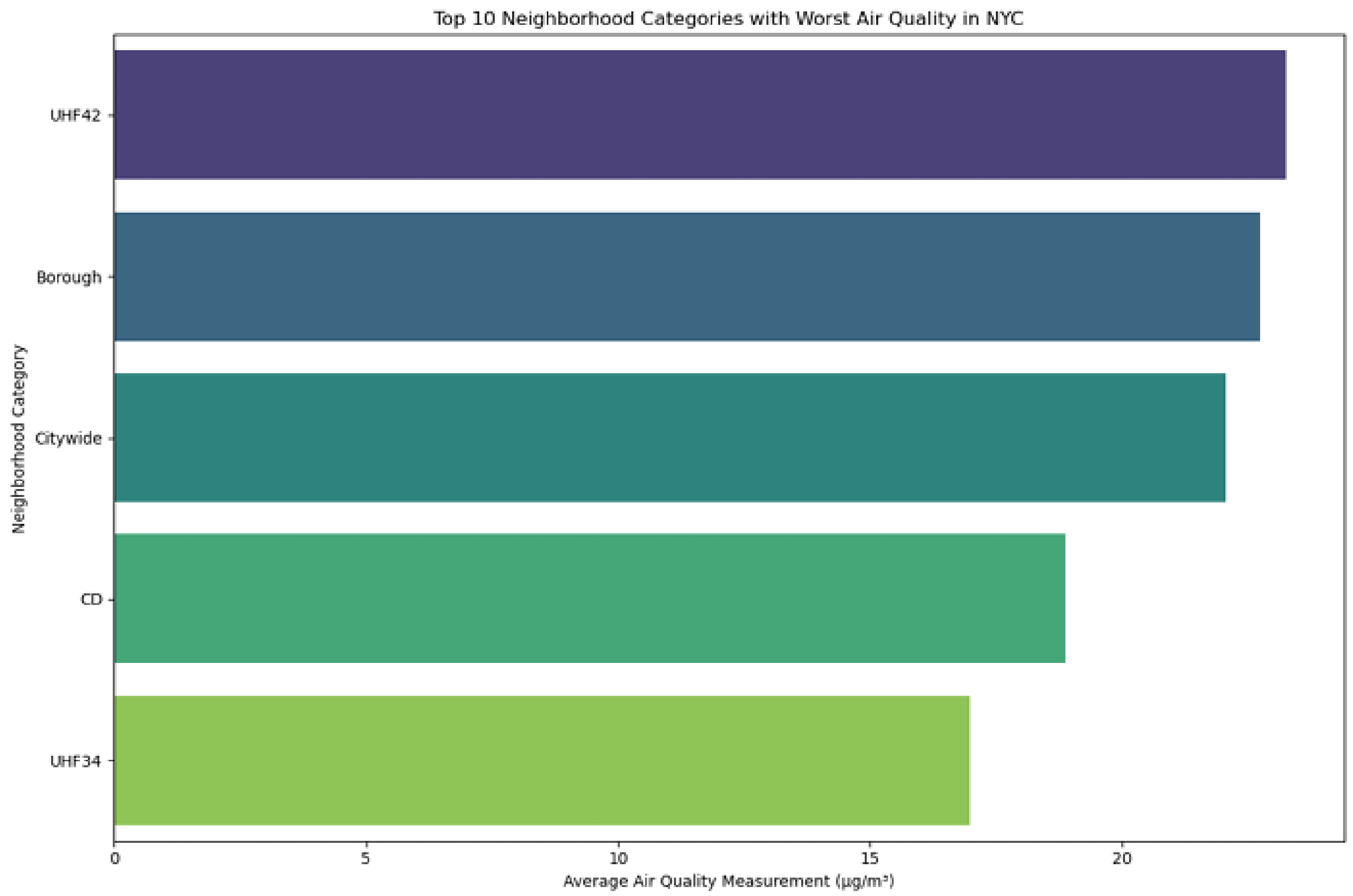
Air Quality Data Preparation

- Addressed missing values with **null value treatment based on geographic type**.
- Analyzed data for 2009–2022, excluding 2006–2008 due to incomplete **seasonality patterns**.
- Identified **PM2.5 as the primary pollutant** for analysis.
- Checked **data skewness** for distribution insights.

Asthma, Respiratory, and Cardiovascular Data Processing

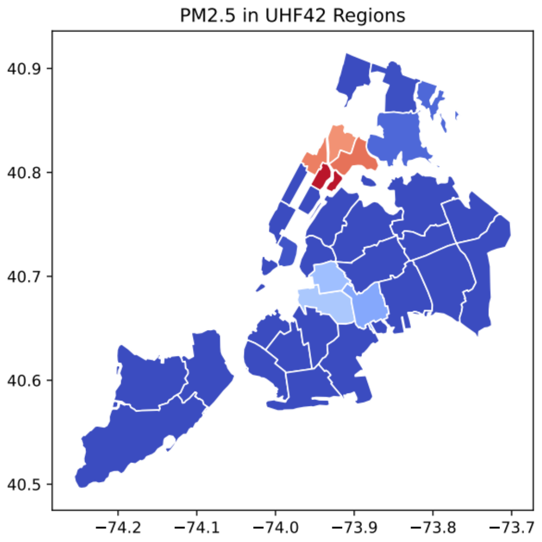
- **Integrated data** from three different sources.
- **Merged datasets** using geographic type (Geo Place Name) and year as common keys.
- **Extracted year** from date fields for **consistency**.
- Removed rows with **null values** across all three datasets.
- **Transposed** and merged data using pandas for a seamless analysis framework.

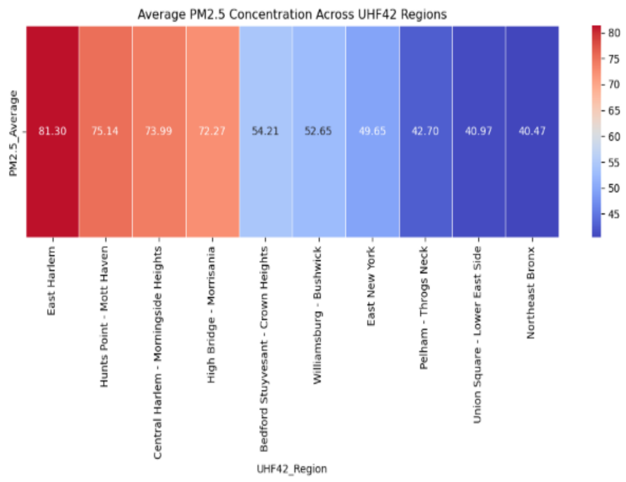
Results (H1 - Disparities in Air Quality)

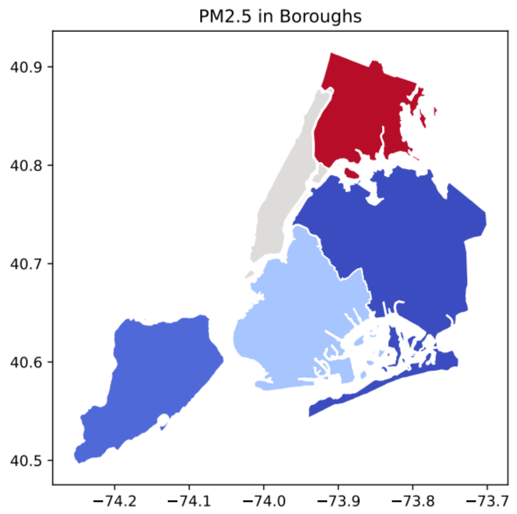


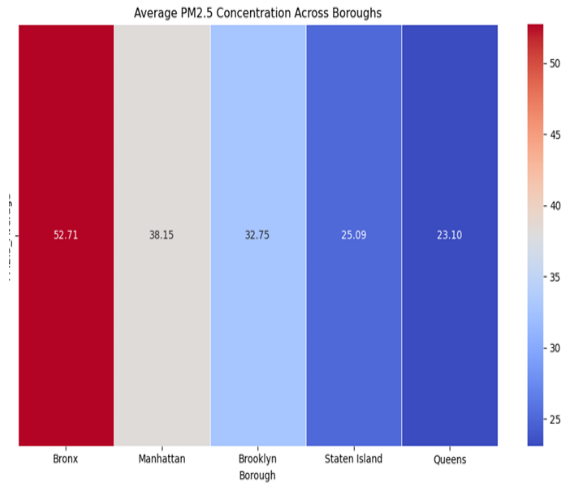
- Geospatial Analysis
- **Citywide** as **benchmark**
- Area of focus: **UHF42** and **Borough**
- UHF42 – United Hospital Fund, consisting of 42 city neighborhoods. Boundaries are based on the zip codes
- Borough – administrative units

Results (H1 - Disparities in Air Quality)



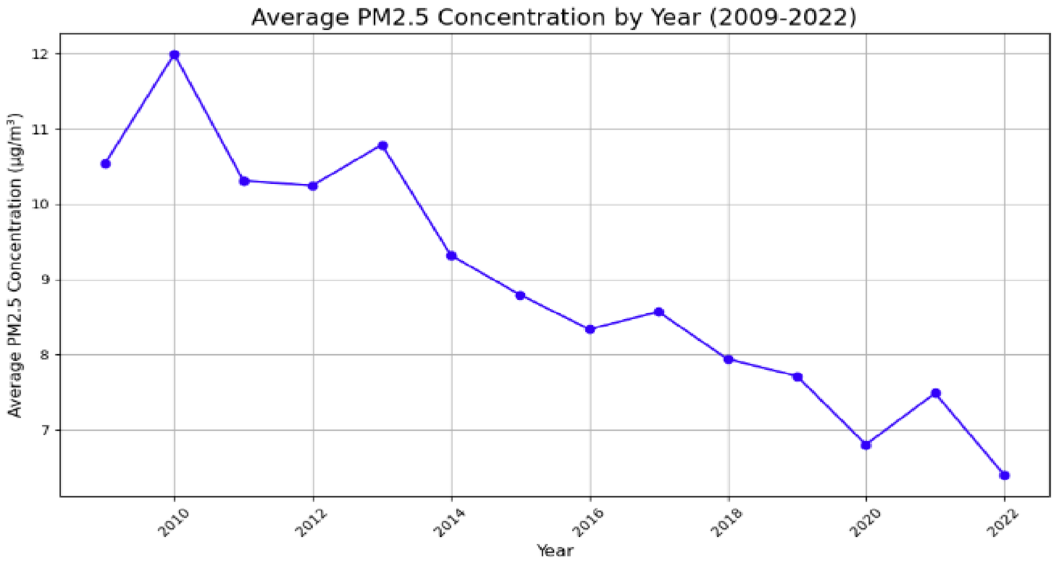


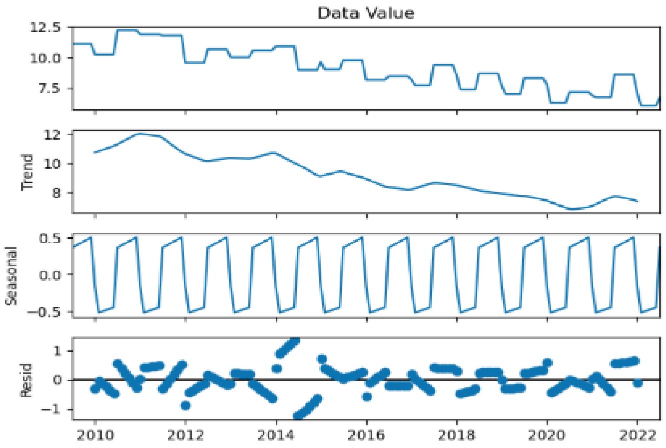




- Disparities in PM2.5 concentrations:
  - Higher levels in neighborhoods with people of color.
  - **Bronx**(Borough) and **East Harlem**(UHF42) among the worst-affected areas.
- These neighborhoods are historically **underserved and have higher minority populations** – like Hispanic and Blacks (US Census Data, 2020)
- Goldstein (1972) and Sicard *et al.* (2023) - **disadvantaged communities**, especially those **located near industrial or high-traffic zones**, bear the brunt of air pollution, leading to **chronic health issues**

Results (H2 - Time-Series Analysis)





- **General decline** in PM2.5 from **2009 to 2022**: indicating improvements in air quality over the years.
- While **seasonal patterns** are evident in PM2.5 as well through the years.
- **Residuals** suggest some unexplained variations due to **short-term events** (such as pollution spikes or specific events like wildfires or industrial accidents).

Results (H2 - Time-Series Analysis)

```
ADF Statistic: -0.614285084118284
p-value: 0.8677214026498994
The time series is non-stationary.
```

ADF Test 1 - Results

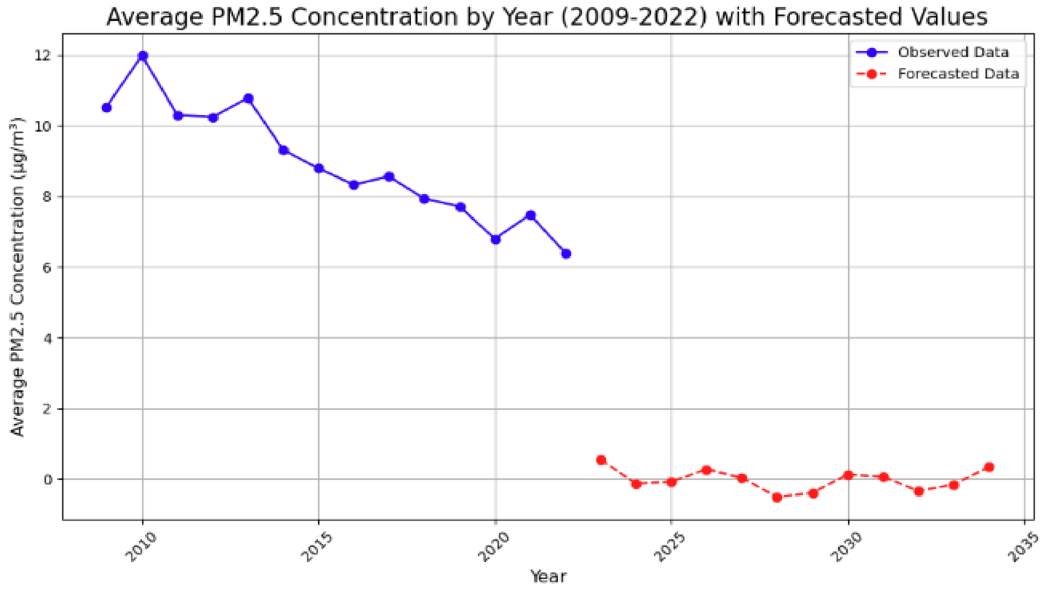
```
ADF Statistic: -8.593892429770564
p-value: 7.163528322744075e-14
The differenced time series is stationary.
```

ADF Test 2 - Results

Summary of ARIMA Model				
Parameter	Coefficient	Std. Error	z-value	p-value
AR(1)	0.6986	0.250	2.800	0.005
AR(2)	-0.7447	0.291	-2.560	0.010
MA(1)	-1.7351	0.195	-8.887	0.000
MA(2)	1.5390	0.278	5.527	0.000

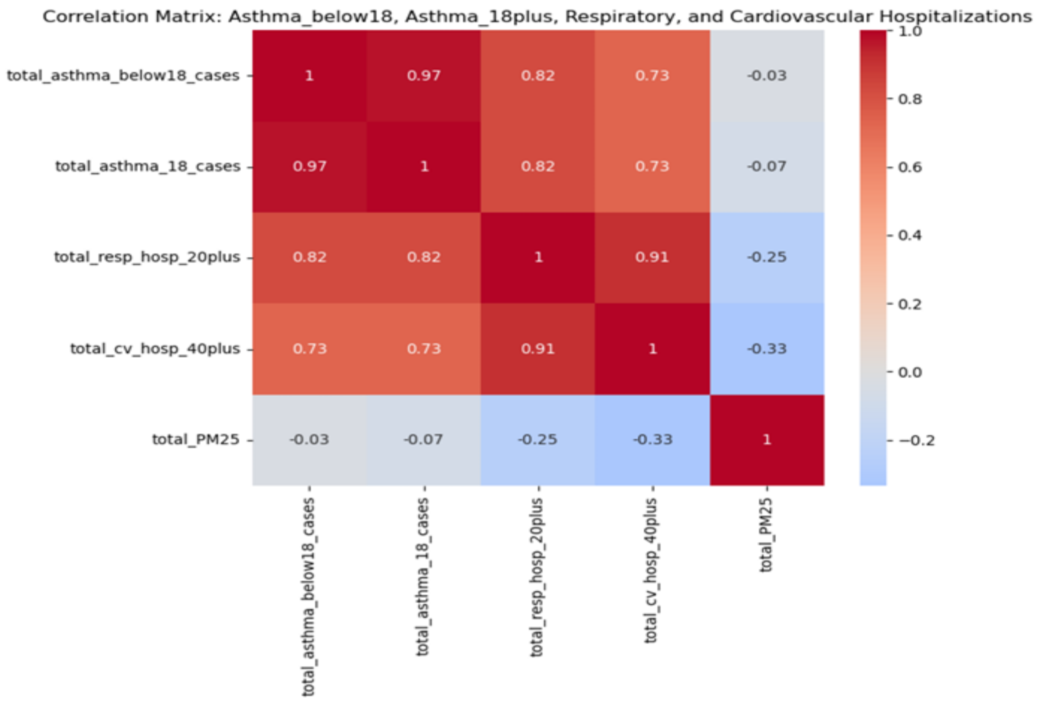
Approach:

- Stationary & Non-Stationary: ADF Test
    - Our data was non-stationary - First differencing to make data stationary
- ACF & PACF used to understand the structure of time series- **ARIMA Model(6,1,4)**
    - Forecasted the data



Results (H3 - Health Impacts)

Regression 1: Asthma Cases under 18				
Variable	Coefficient	Std Error	z-value	p-value
Constant	35.542	10.561	3.365	0.001
PM2.5	-0.6475	1.097	-0.590	0.555
Regression 2: Asthma Cases above 18				
Variable	Coefficient	Std Error	z-value	p-value
Constant	21.5462	5.312	4.056	0.000
PM2.5	-0.7720	0.552	-1.399	0.162
Regression 3: Asthma Cases Total				
Variable	Coefficient	Std Error	z-value	p-value
Constant	57.088	10.144	5.627	0.000
PM2.5	-1.420	1.054	-1.347	0.178
Regression 4: Cardiovascular cases (40+)				
Variable	Coefficient	Std Error	z-value	p-value
Constant	14.456	0.813	17.784	0.000
PM2.5	-0.114	0.084	-1.353	0.176
Regression 5: Other Respiratory cases (20+)				
Variable	Coefficient	Std Error	z-value	p-value
Constant	9.981	0.888	11.244	0.000
PM2.5	0.062	0.092	0.670	0.503



- **Correlation** between PM2.5 and hospitalizations
- Linear regressions – **results are non-significant**
- Need to incorporate additional variables

Discussion

- **Racial and Neighborhood Disparities**: Findings reveal that neighborhoods with higher populations of people of color face worse air quality (e.g., Kinney et al., 2002; Simkovich et al., 2019).
- **Declining Trends with Persistent Hotspots**: While PM2.5 levels have decreased citywide, persistent pollution hotspots, such as East Harlem and the Bronx
- **Health Impacts of PM2.5**: The association between PM2.5 exposure and hospitalizations aligns with studies linking fine particulate pollution to respiratory and cardiovascular illnesses (Manisalidis et al., 2020; Sicard et al., 2023). An aim should be made to focus on reducing particulate pollution.
- **Policy Implications**: The results highlight the need for targeted policies to reduce pollution in vulnerable areas and mitigate health risks, indicating the need for localized interventions and targeted interventions are necessary to address pollution hotspots
- **Broader Research Support**: Literature emphasizes how urbanization and industrial activity exacerbate pollution, reinforcing the importance of data-driven strategies to manage air quality (Dockery, 2012; Chen et al., 2024).

Conclusion, Limitation & Future Directions

Conclusion

- **Disparities exist** in the neighborhoods with a **higher population of people of color (H1)**
- PM2.5 trends have **reduced** over time from 2009 to 2022 **(H2)**
- **Insignificant results** to determine rising cases of respiratory illness and cardiovascular diseases due to PM2.5 **(H3)**

Limitations

- The analysis excluded **socio-economic factors** and other environmental variables that might influence hospitalization rates.
- Limited scope for **seasonal or short-term event analysis**, which may affect PM2.5 trends and health outcomes.

Future Directions

- Incorporate **additional variables**, such as income, occupation, and access to healthcare, for a more nuanced analysis.
- Conduct **seasonal studies** to identify periods of heightened risk and tailor interventions.
- Develop **predictive models** using real-time monitoring to proactively manage air quality and reduce health risks.

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Appendix

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Thank You!