
# COVID-19 Impacts on Air Quality

## Predicting $NO_2$ Air Concentrations using Meteorological Data

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# Introduction and Background

- COVID-19 led to widespread lockdowns across the U.S.
  - Many workers transitioned to remote work, reducing daily commuting.
  - This shift significantly impacted transportation-related emissions and air quality, especially in major cities.

- Over 200 studies have analyzed pandemic-related air quality changes using key pollutants ($NO_2$, $O_3$, CO, PM2.5).
  - Initial studies often relied on preliminary data; more robust data is now available.

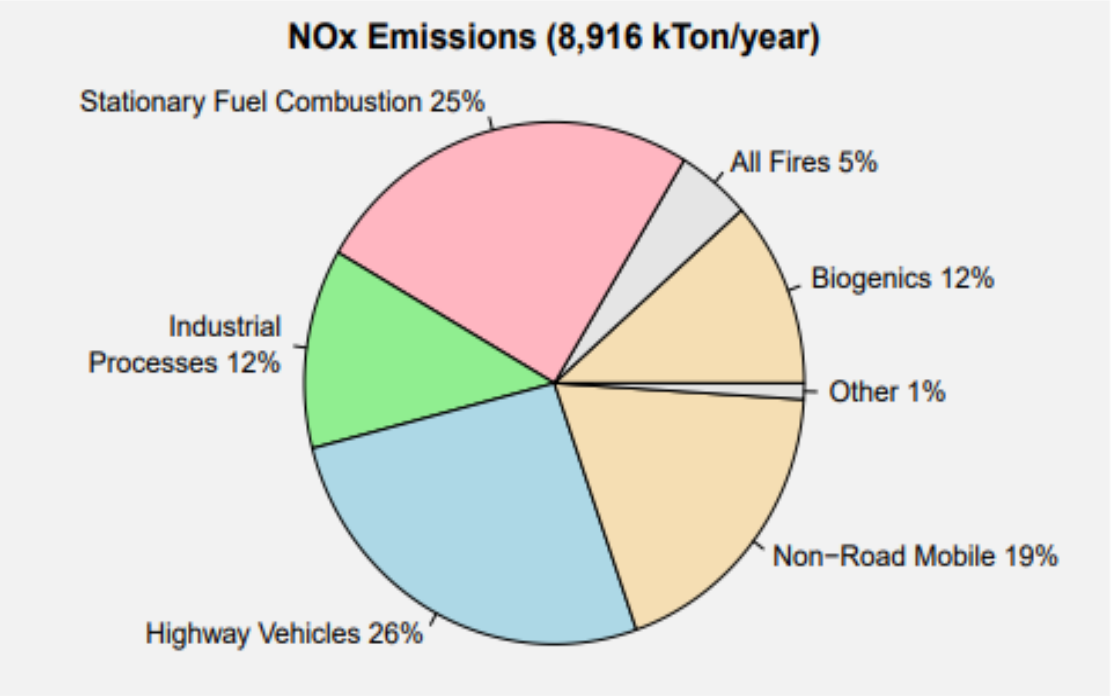
- The U.S. EPA Air Data repositories offer high-quality, comprehensive pollutant data.

# Purpose

- Investigate the impact of COVID-19 lockdowns on air quality in major U.S. metropolitan areas.
- Analyze $NO_2$ daily summary data from EPA in-situ sensors.
- Study five cities:
  - Chicago, IL
  - Los Angeles, CA
  - New York City, NY
  - Denver, CO
  - Washington, DC
- Incorporate meteorological data to account for weather-related influences on air quality.
- Use EPA data on hourly wind, temperature, barometric pressure, relative humidity, and dew point.

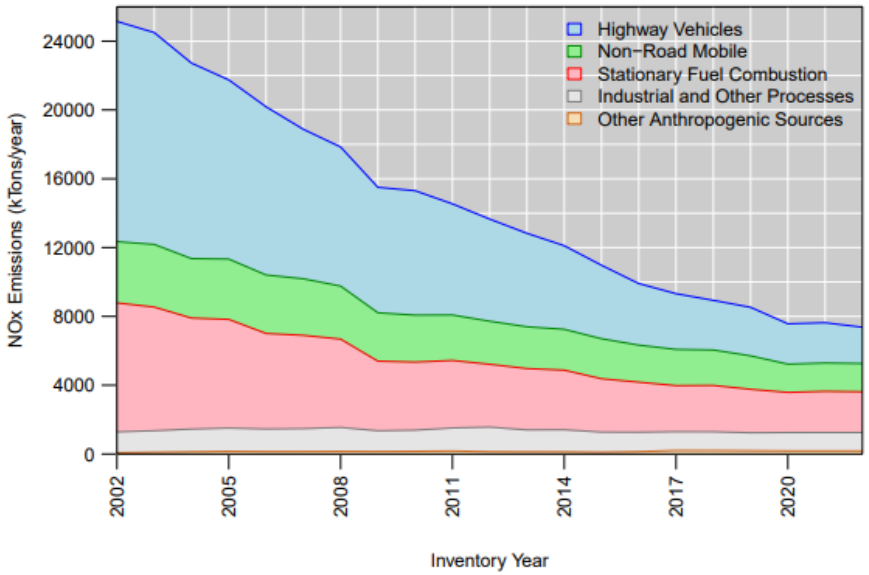
# Research Questions

- What factors impact $NO_2$ air concentration as measured from EPA ground-based sensors?
  - How well do these factors predict $NO_2$ air concentrations?
- Did COVID-19 lockdowns impact $NO_2$ air concentration?
  - To what extent did the lockdowns impact $NO_2$ air concentration




$NO_x$ Emissions by sector [1]

# Background ($NO_2$ Trends)




US Anthropogenic $NO_x$ Emissions Trend 2022-2022 [1]

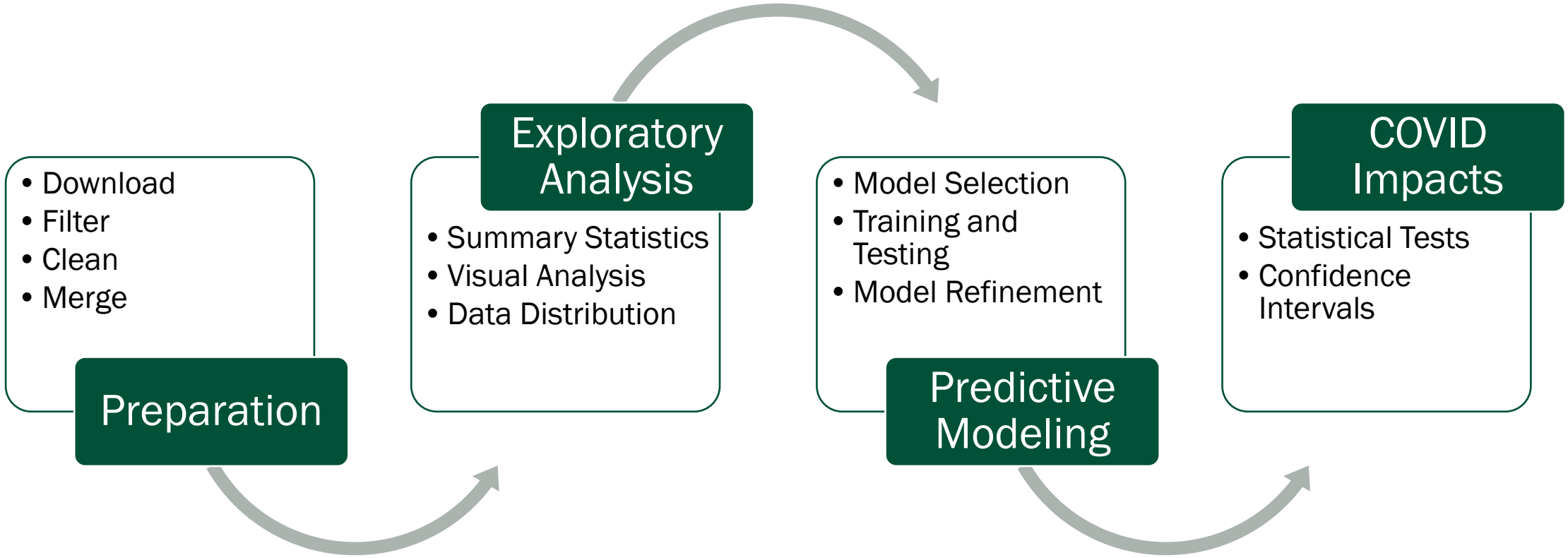
- EPA $NO_2$ Overview [1]
  - $NO_2$ concentrations are generally higher during fall and winter months, and lower during spring and summer.
  - Most monitoring sites show decreasing trends in $NO_2$ concentrations.
  - Annual mean and 98th percentile daily maximum 1-hour $NO_2$ concentrations have remained relatively constant over the past decade, well below the National Ambient Air Quality Standards (NAAQS)

# Data Sources

- US EPA Monitoring Network for Nitrogen Dioxide [1] [2]
  - 481 monitoring sites reported hourly $NO_2$ data to the EPA.
  - Monitoring networks include:
    - State and Local Air Monitoring Stations (SLAMS): Over 80% of sites
    - National Core (NCore) multi-pollutant monitoring network
    - Photochemical Assessment Monitoring Stations (PAMS)
    - Near-road monitoring network: 71 monitors
  - Hourly data is aggregated to daily and yearly data sets

- EPA Hourly Meteorological Data [2]
  - Hourly wind, temperature, barometric pressor, relative humidity, and dew-point measurements.

# Computational Workflow

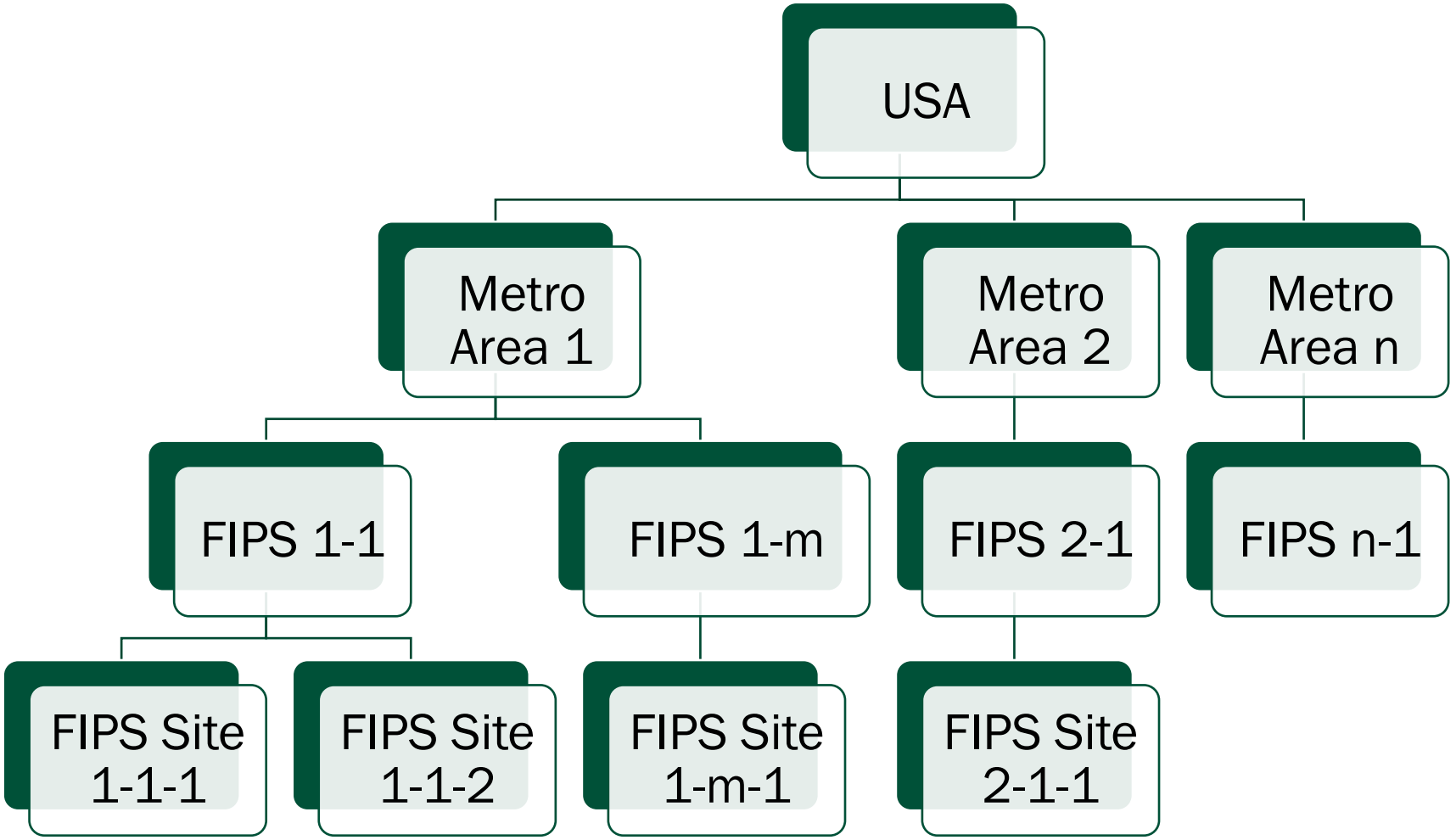


# Data Preparation (Metro Statistical Area Data)

- Defining a region of interest
  - Metropolitan Statistical Area (MSA) Geography Reference File [3]
    - MSA Area
    - County Name
    - Federal Information Processing Standards (FIPS) codes
      - State and County (example: Los Angeles is 06037 and 06059)

| Metro Areas | MSA name | FIPS Codes |
|---|---|---|
| Chicago | Chicago-Naperville-Elgin, IL-IN-WI Metro Area | 14 |
| Denver | Denver-Aurora-Lakewood, CO Metro Area | 10 |
| Los Angeles | Los Angeles-Long Beach-Anaheim, CA Metro Area | 2 |
| New York | New York-Newark-Jersey City, NY-NJ-PA Metro Area | 25 |
| Washington DC | Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area | 24 |
| | Total | 75 |

# Data Preparation (Geographic Level of Detail)



# Data Preparation ($NO_2$ Download)

- $NO_2$ Data Daily [2]
  - Average $NO_2$ measurement (ppb)
  - Max $NO_2$ measurement (ppb)
  - Hour of max measurement
  - Indexed by FIPS (state and county), and Site Number (non-fips)
  - Site details (name, address, latitude, longitude)

- Reducing to Area of Interest
  - Filter by FIPS codes
  - Index by FIPS codes and site number (example: 06037_1103)

- Clean
  - 2 FIPS-Sites have multiple same-day measurements
    - ~1500 observations (mean difference of about 1.2ppb (15%)
  - Outliers
    - ~1,000 observations less than 1ppb

- Downloaded Data Summary
  - 24 FIPS Codes (54 FIPS-Sites)
  - 5 Years of daily data (1826 days)
  - 86,165 Total Observations
    - Of a possible 98,604 (~90%)

# Data Preparation ($NO_2$ Download)

| Year | Chicago | Denver | Los Angeles | New York | Washington |
|---|---|---|---|---|---|
| 2017 | 1,802 | 1,904 | 6,054 | 3,780 | 3,275 |
| 2018 | 1,309 | 1,739 | 5,947 | 3,799 | 3,246 |
| 2019 | 1,818 | 2,092 | 6,155 | 4,120 | 3,232 |
| 2020 | 2,196 | 2,098 | 6,483 | 3,880 | 3,283 |
| 2021 | 2,295 | 2,036 | 6,390 | 3,967 | 3,265 |

# Data Preparation (Weather Download)

- Weather Data Hourly [2]
  - WIND: Wind direction and speed
  - TEMP: Temperature
  - PRESS: Pressure
  - RH_DP: Humidity and Dew Point
- Reducing to Area of Interest
  - Filter by FIPS codes
  - Index by FIPS codes and site number (example: 06037_1103)
- Clean
  - Outliers
    - 103 observations with wind speeds greater than 47 knots (Gale force winds @ 4 FIPS-Sites)
  - Summarized to Daily
- Downloaded Data Summary
  - 31 FIPS Codes (70 FIPS-Sites)
  - 5 Years of hourly data (1826 days)
  - 95,069 Total Observations
    - Of a possible 127,838 (~75%)

# Data Preparation (Weather Download)

- Weather data is not *complete
  - 1667 observations with full data
- Dropping barometric pressure and dew point increases observations
  - ~47,00 (still less than half)
- Dew point only measured in Chicago

| Measure | Missing | Unique | Observed |
|---|---|---|---|
| bar_pressure | 50,013 | 9,637 | 45,056 |
| dew_point | 91,818 | 1,789 | 3,251 |
| out_temperature | 10,046 | 13,159 | 85,023 |
| rel_humidity | 37,813 | 8,549 | 57,256 |
| wind_direction | 20,846 | 24,414 | 74,223 |
| wind_speed | 20,402 | 6,521 | 74,667 |

# Exploratory Analysis Questions

## Factor Analysis

- What weather factors are important?
- Are there time-series trends to account for?
- At what geographics scale should we model?

## Model Selection

- How is the data distributed?
- What models are reasonable based on the distributions?

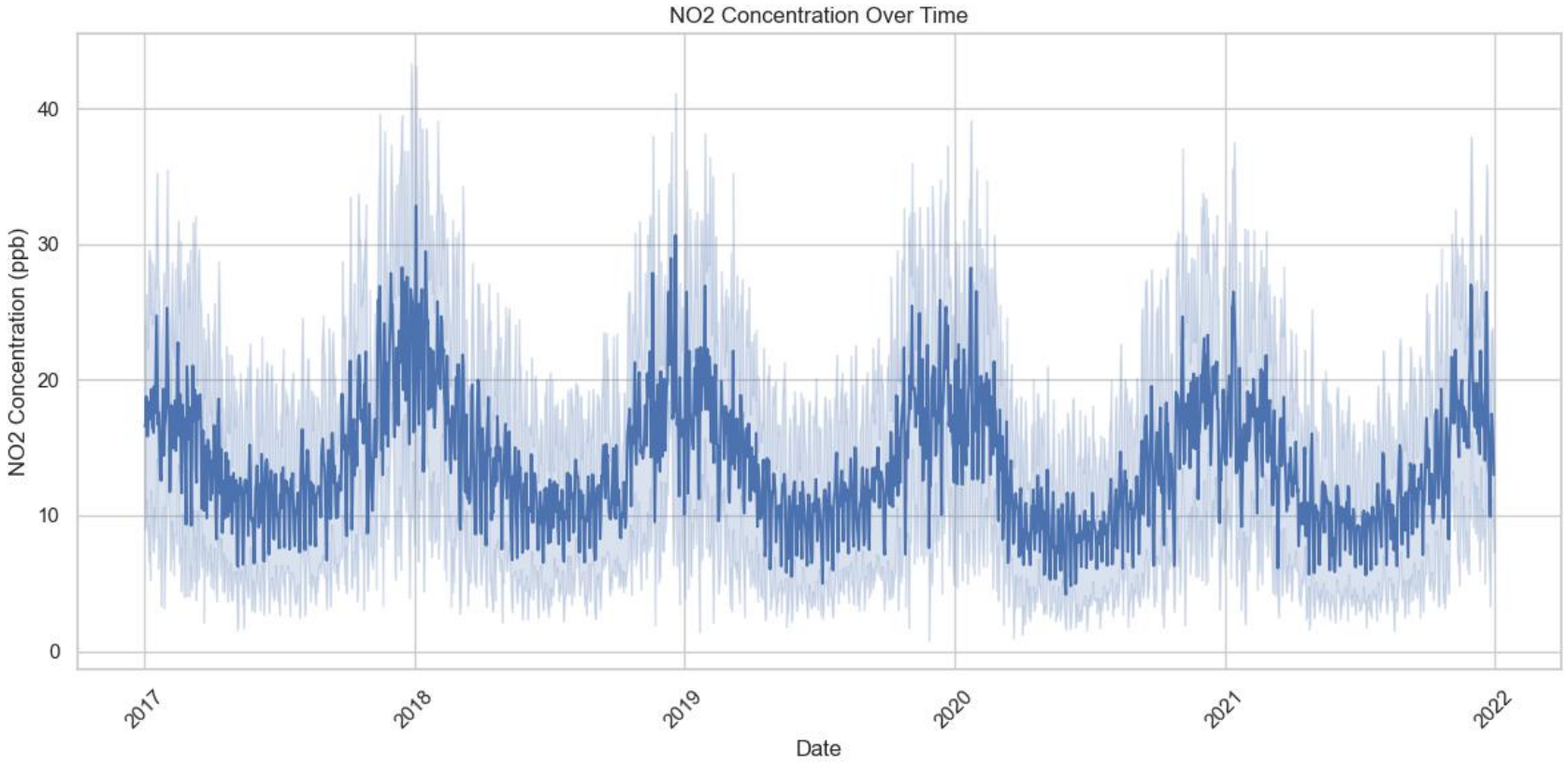
# Exploratory Data Analysis ($NO_2$ Data Summary)

**$NO_2$ average concentrations vary across metro areas**
**$NO_2$ average concentrations vary from year to year**

| | |
|---|---|
| count | 86,165 |
| mean | 13.74 |
| std | 8.79 |
| min | 1.00 |
| 25% | 7.00 |
| 50% | 12.03 |
| 75% | 18.72 |
| max | 70.62 |

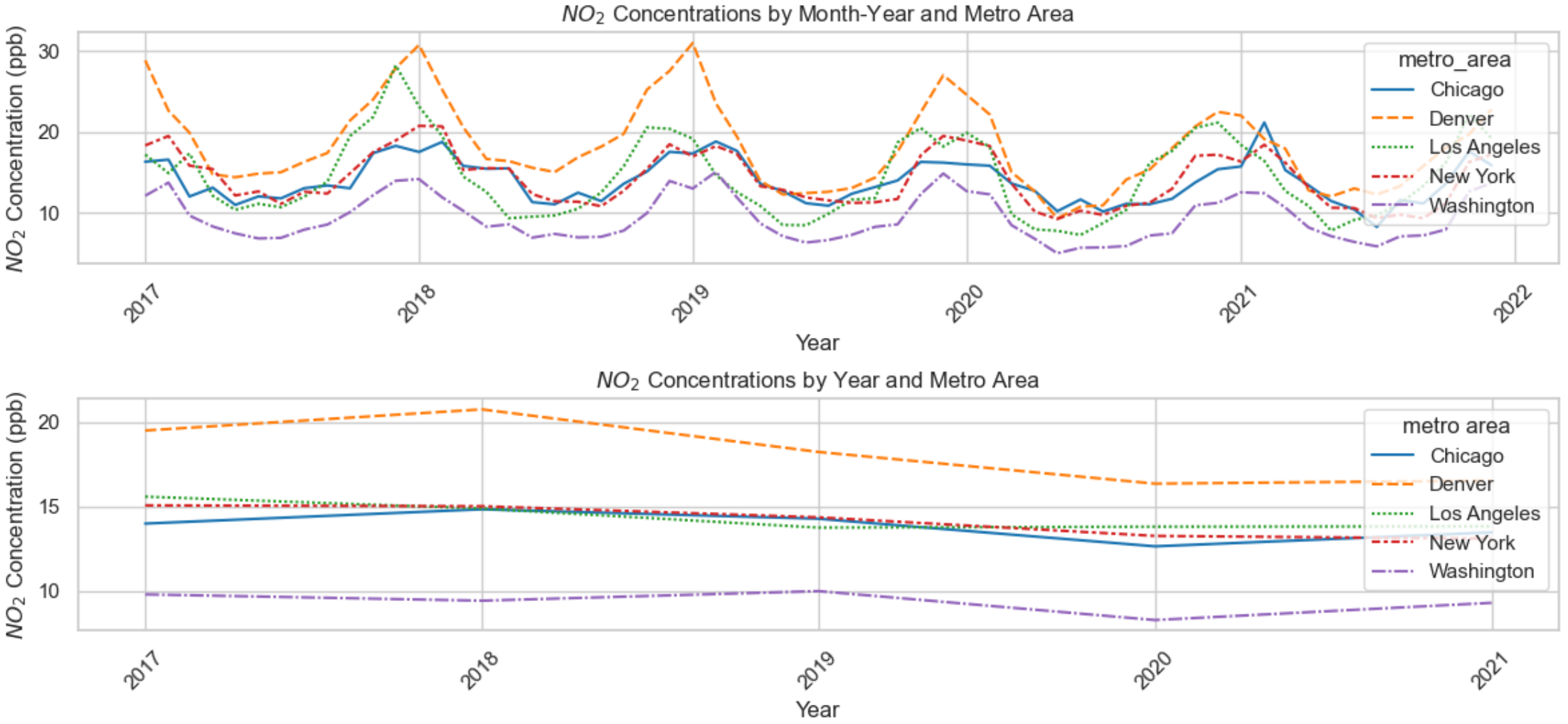
| Year | Chicago | Denver | Los Angeles | New York | Wash DC. | AVG |
|---|---|---|---|---|---|---|
| **2017** | 14.00 | 19.51 | 15.59 | 15.07 | 9.81 | **14.62** |
| **2018** | 14.84 | 20.75 | 14.89 | 15.02 | 9.44 | **14.45** |
| **2019** | 14.28 | 18.23 | 13.76 | 14.37 | 10.00 | **13.81** |
| **2020** | 12.65 | 16.36 | 13.82 | 13.27 | 8.29 | **12.81** |
| **2021** | 13.47 | 16.54 | 13.84 | 13.11 | 9.31 | **13.11** |
| **AVG** | **13.73** | **18.18** | **14.36** | **14.16** | **9.37** | **13.74** |

# Exploratory Analysis ($NO_2$ Concentration Over Time)




$NO_2$ average concentrations have seasonality

# Exploratory Analysis ($NO_2$ Concentration Over Time)



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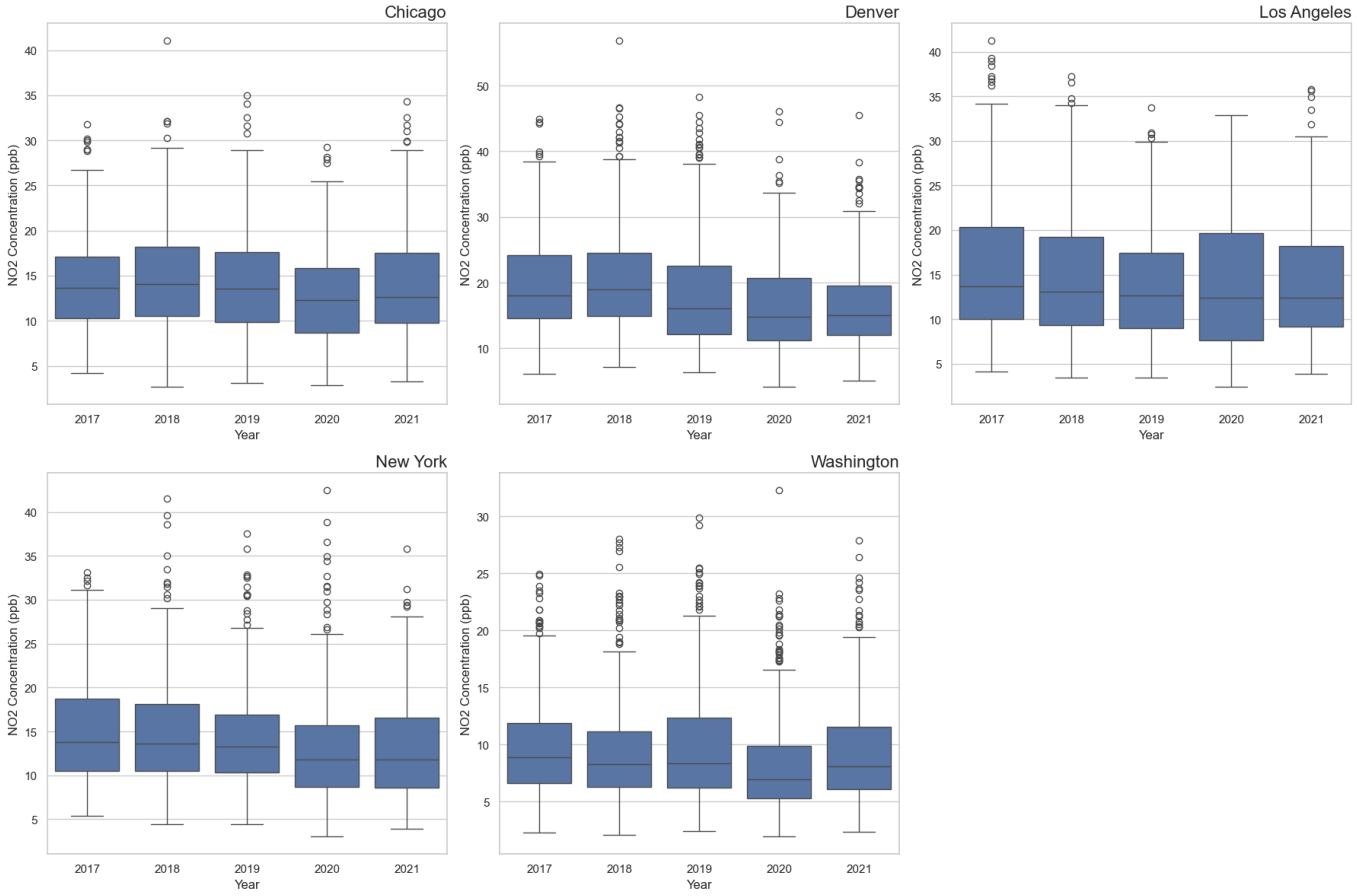
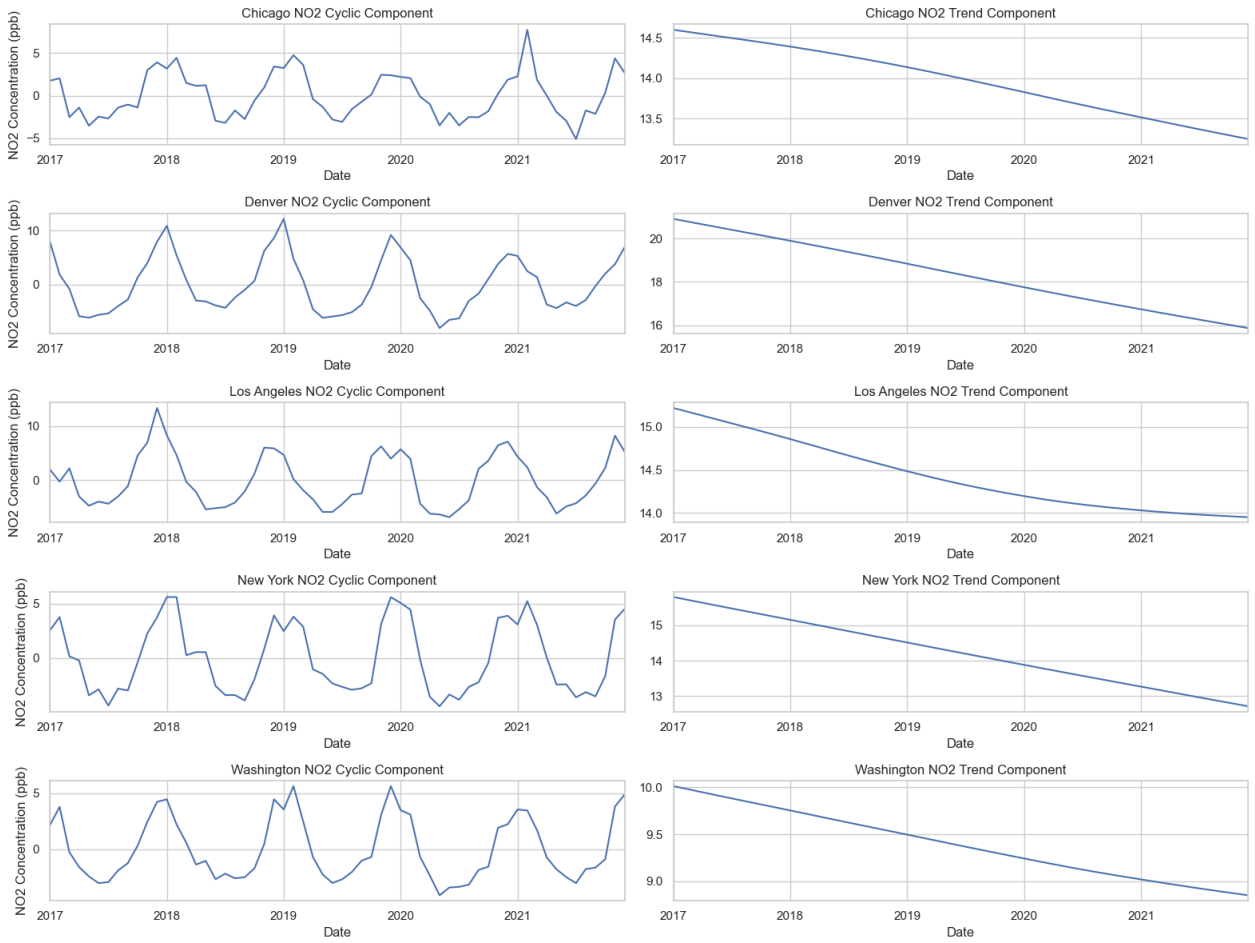



**Year is likely an important factor**

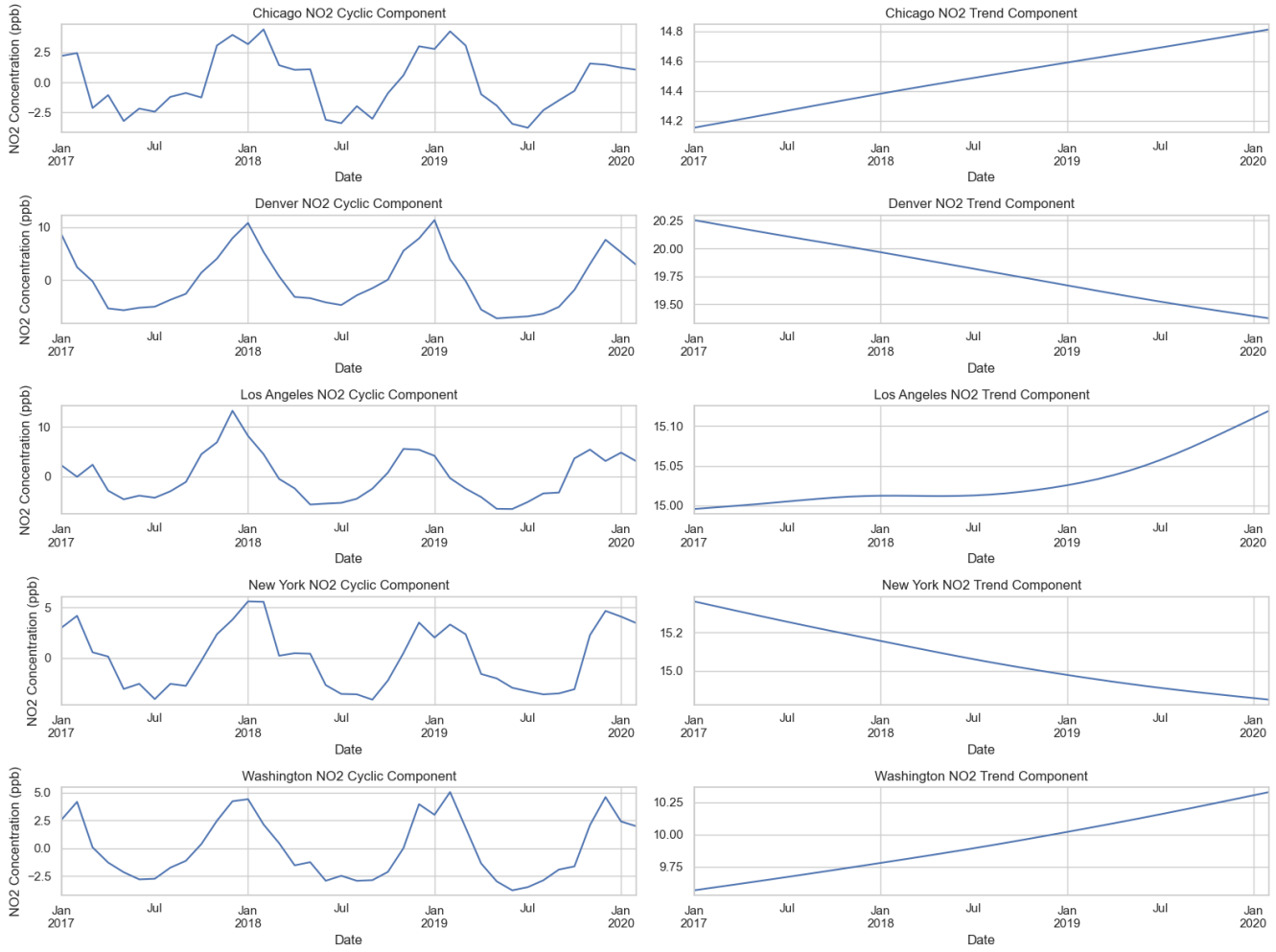
# Exploratory Analysis ($NO_2$ Concentration Over Time)

- Hodrick-Prescott filter
  - $\lambda = 129600$
- $NO_2$ concentration has a cyclic component (yearly period)
- $NO_2$ concentration has a trend component (decreasing)

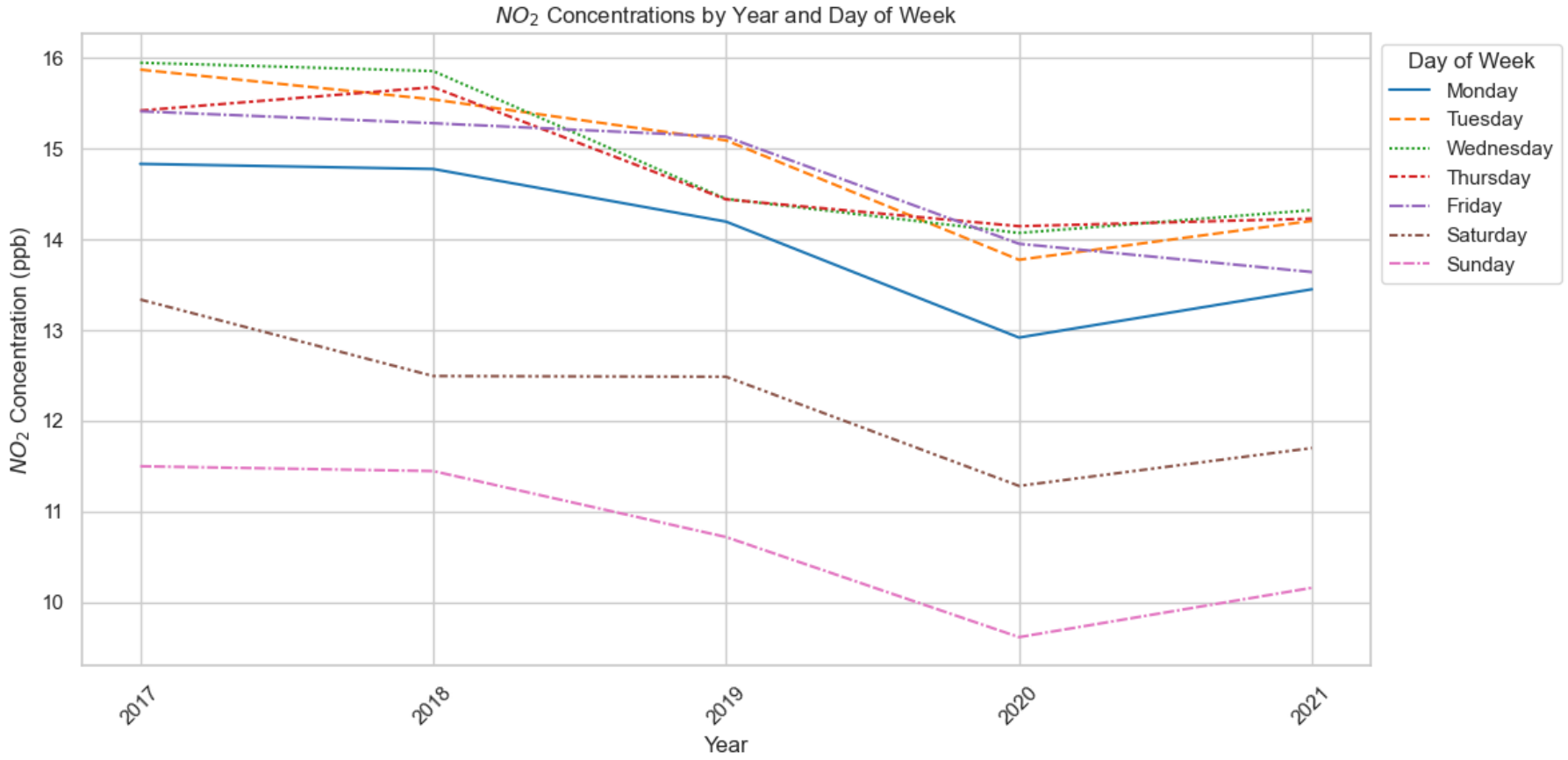


# Exploratory Analysis ($NO_2$ Concentration Over Time)

- HP Filter is sensitive to shocks. One-time shifts can cause trend shifts that do not occur
- Remove post COVID data results in same cyclical pattern but different trends

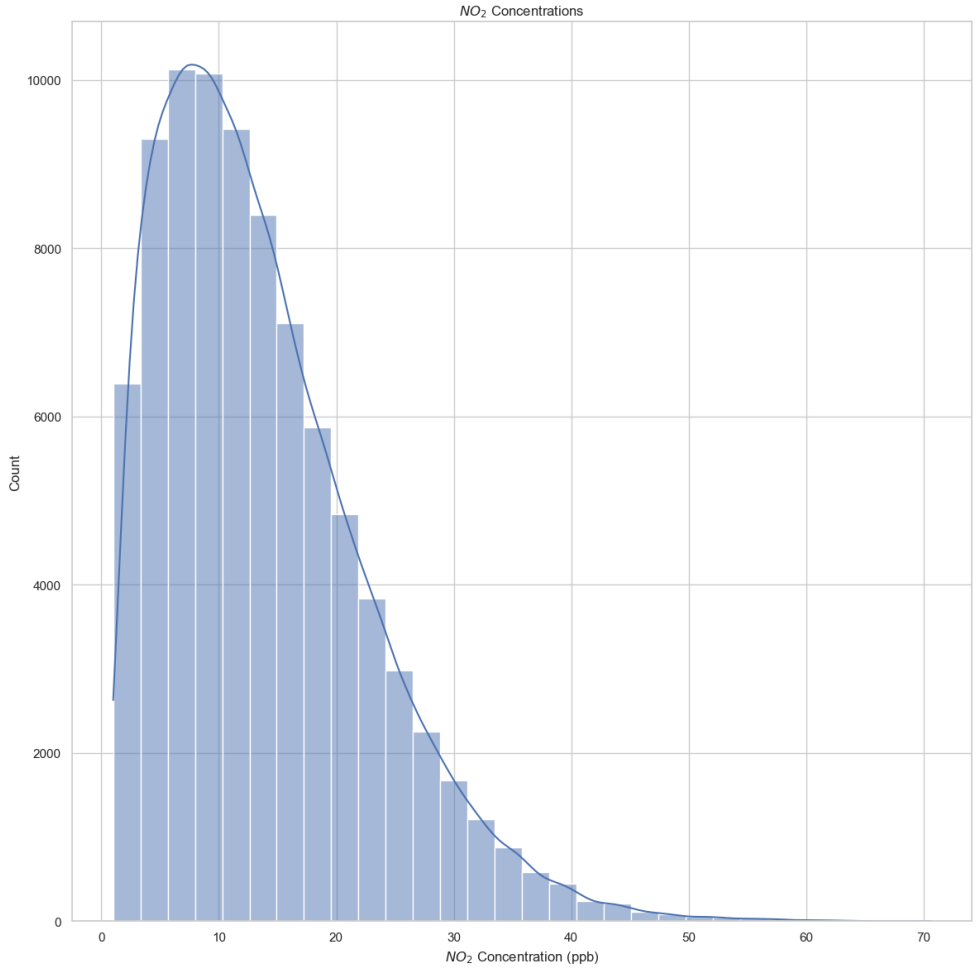


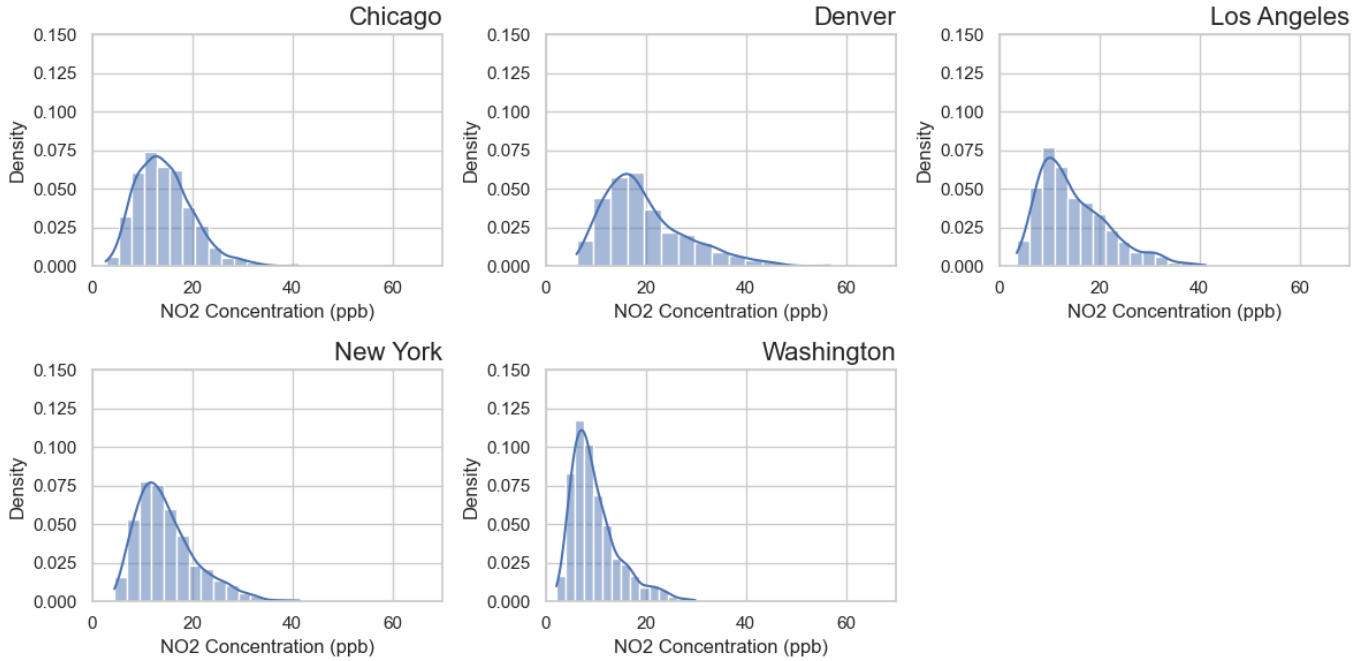
# Exploratory Analysis ($NO_2$ Concentration by Day of Week)




**Day of the weeks is likely an important factor**

# Exploratory Analysis ($NO_2$ Concentration Distribution)



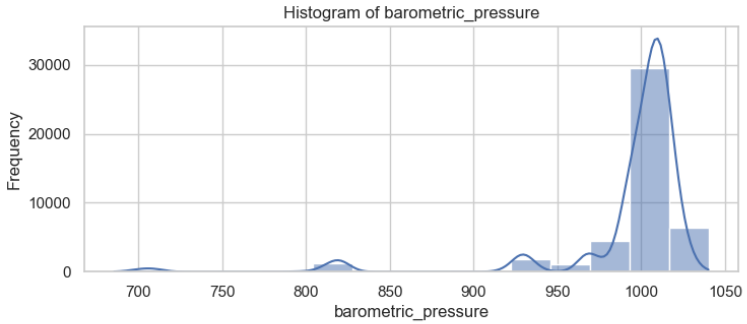



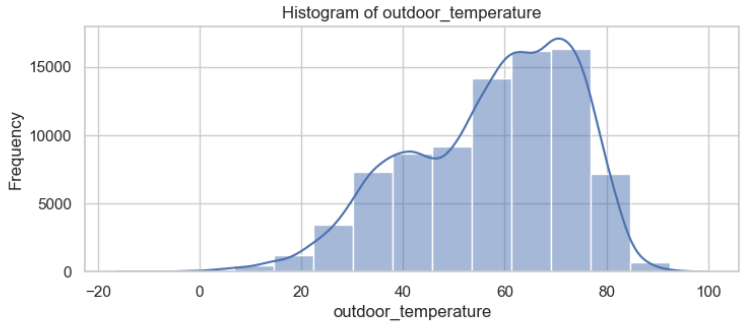

**Data appears log-normal distributed**

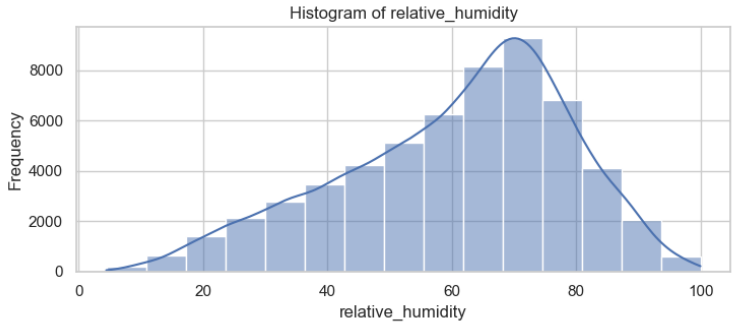
# Exploratory Analysis (Weather Summary Data)

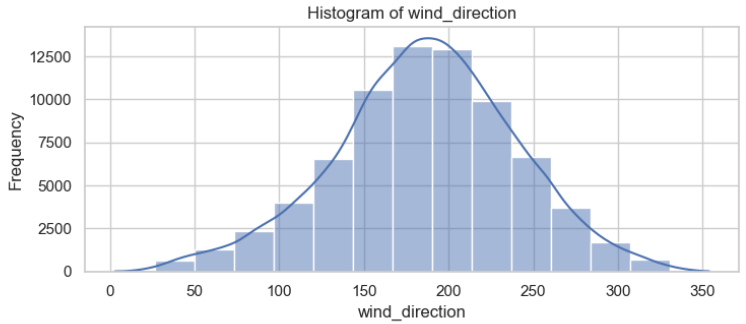
| | Barometric Pressure (mb) | | Dew Point (F) | | Outdoor Temperature (F) | | Relative Humidity (%) | | Wind Direction (card degree) | | Wind Speed (knots) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Metro Area | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD |
| Chicago | 993 | 6.8 | 40.23 | 19.54 | 51.8 | 18.6 | 72.1 | 13.3 | 183.0 | 68.2 | 6.3 | 2.7 |
| Denver | 790 | 48.9 | | | 52.1 | 17.8 | 45.3 | 18.7 | 183.9 | 44.4 | 4.5 | 2.5 |
| Los Angeles | 992 | 25.6 | | | 65.1 | 8.8 | 59.9 | 18.8 | 186.8 | 47.0 | 2.7 | 1.1 |
| New York | 1,001 | 13.1 | | | 54.3 | 17.5 | 62.4 | 14.7 | 198.8 | 68.3 | 4.6 | 2.6 |
| Washington | 1,010 | 8.5 | | | 57.7 | 16.5 | 64.0 | 15.1 | 189.7 | 67.7 | 3.4 | 2.6 |

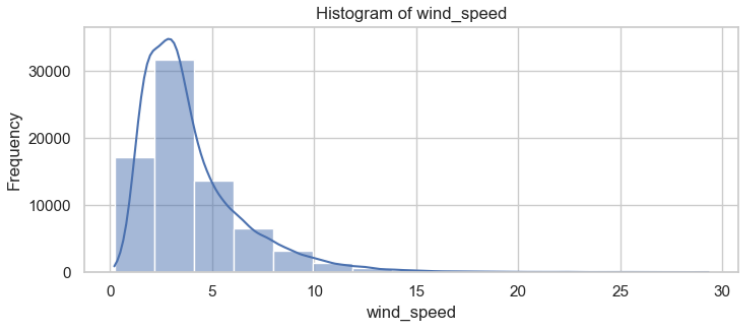
# Exploratory Analysis (Weather Distributions)



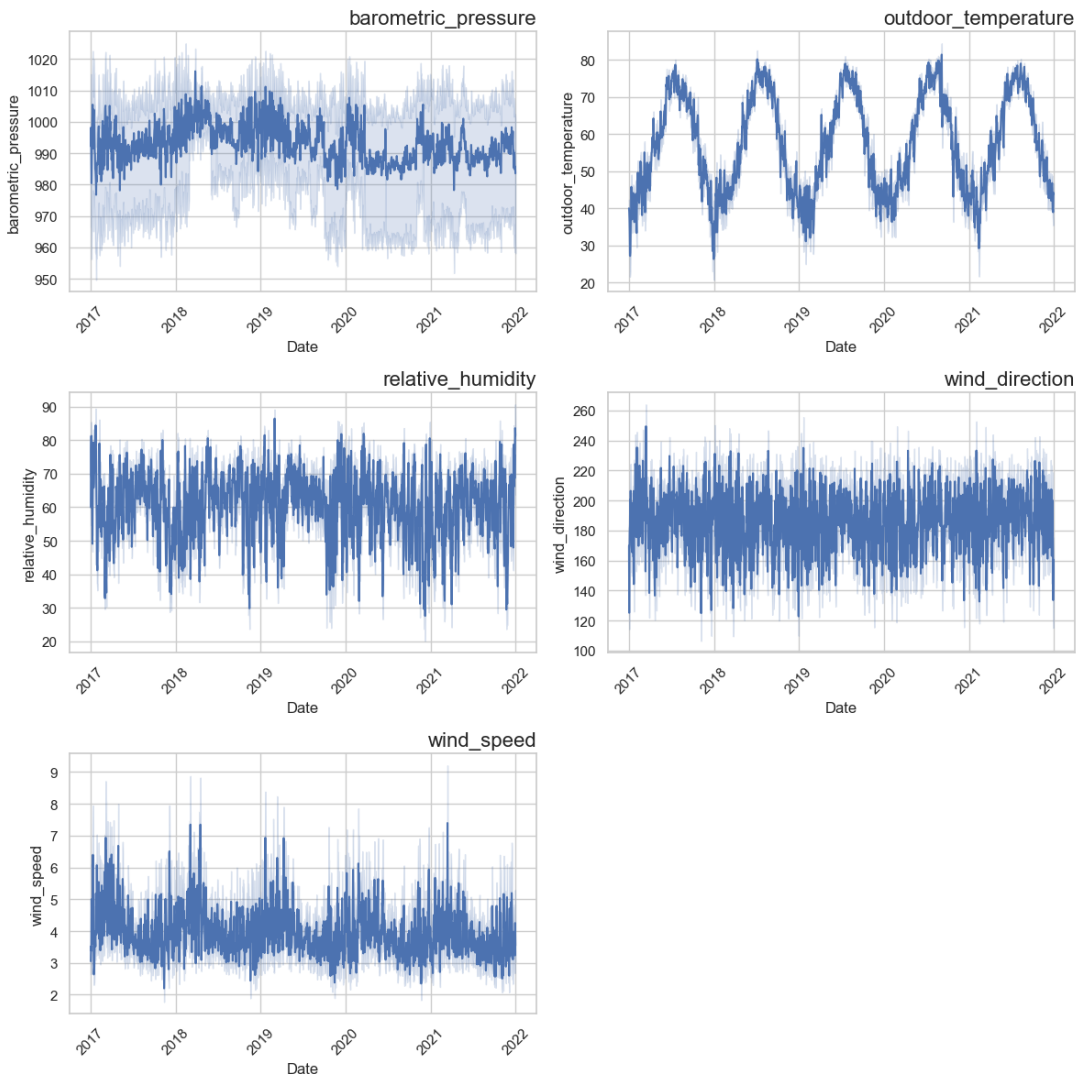




- Barometric pressure is dependent on metro area
- Wind direction is normal with average direction around 180º
- Windspeed appears log-norm

# Exploratory Analysis (Weather Time Series)

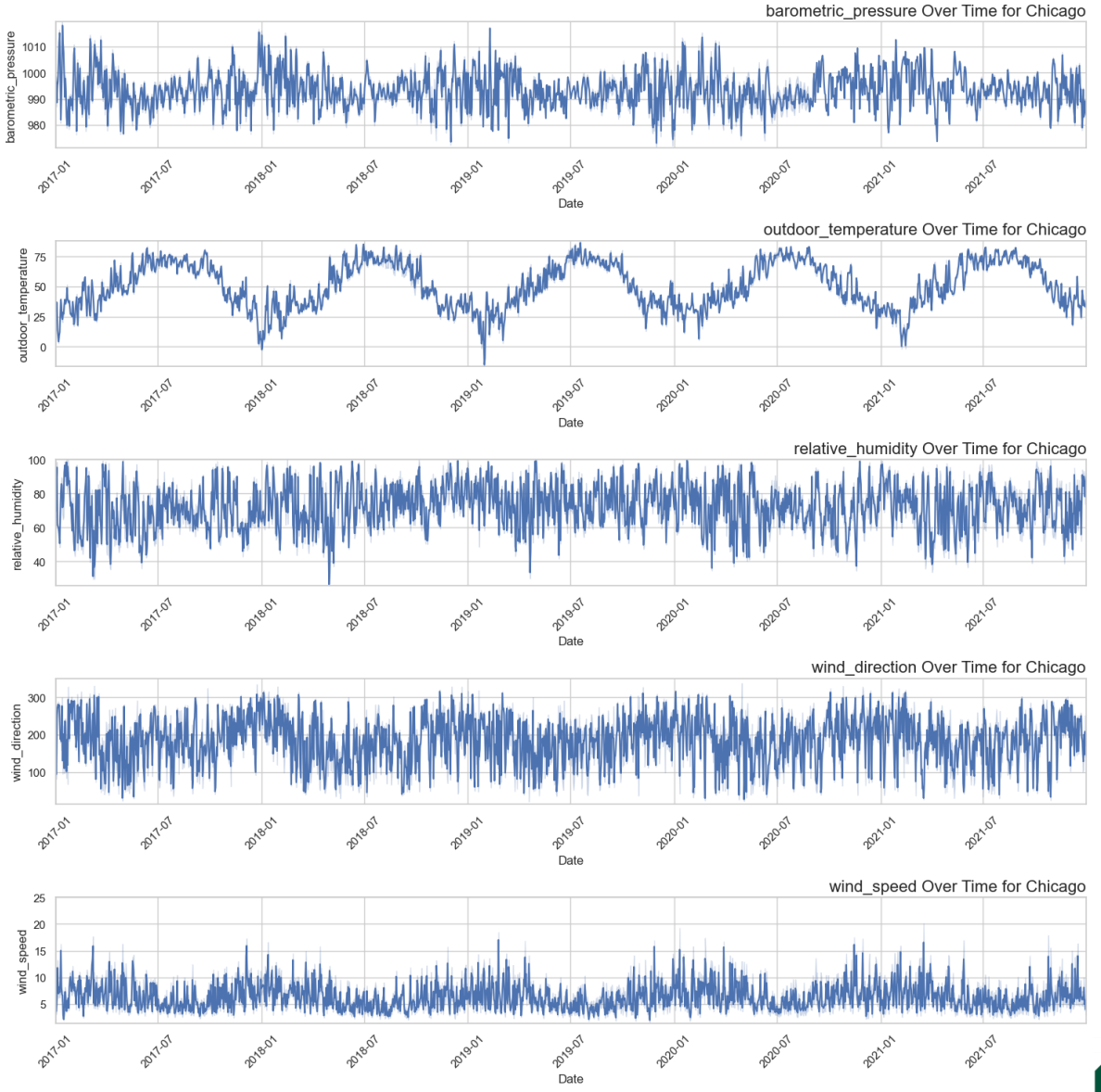
- Outdoor temperature shows cyclical component
- Relative humidity shows increased variability in the winter
- Windspeed shows increased variability in the winter



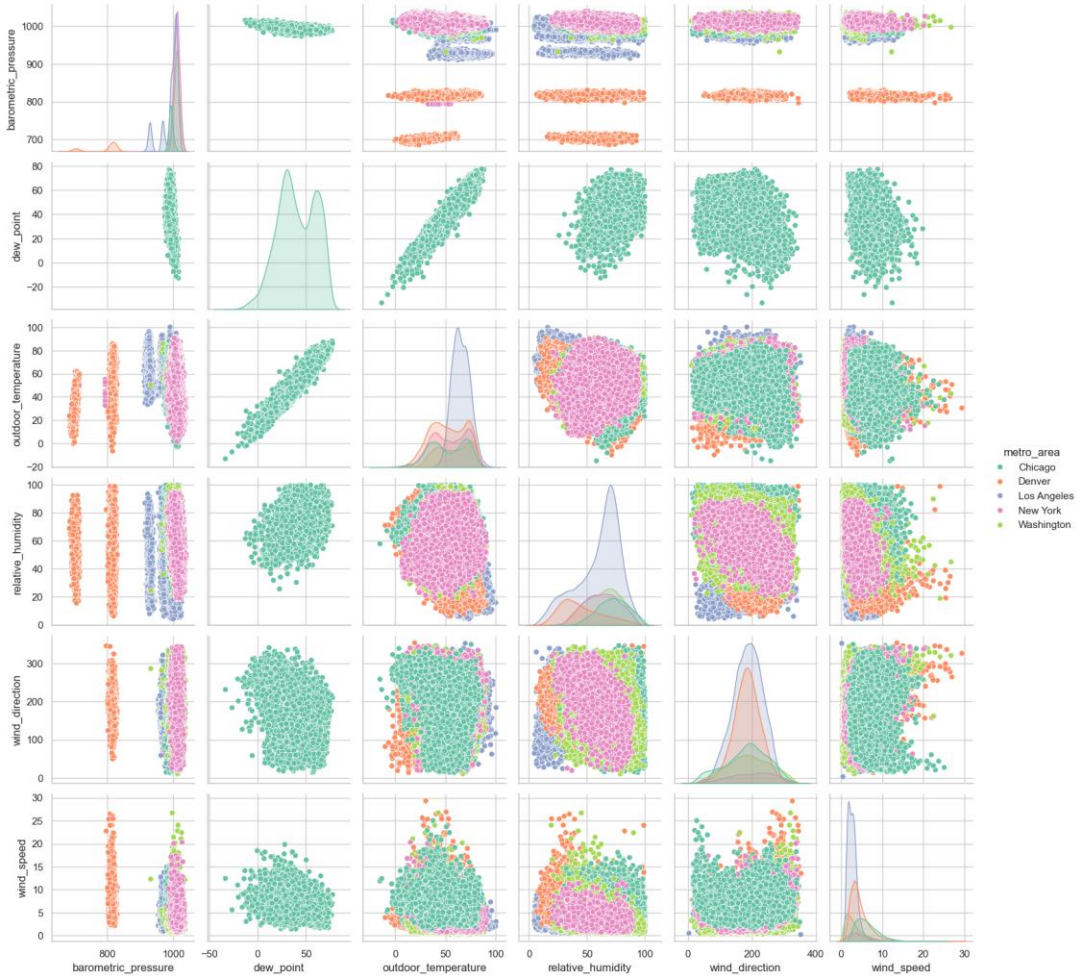
# Exploratory Analysis (Weather Time Series)

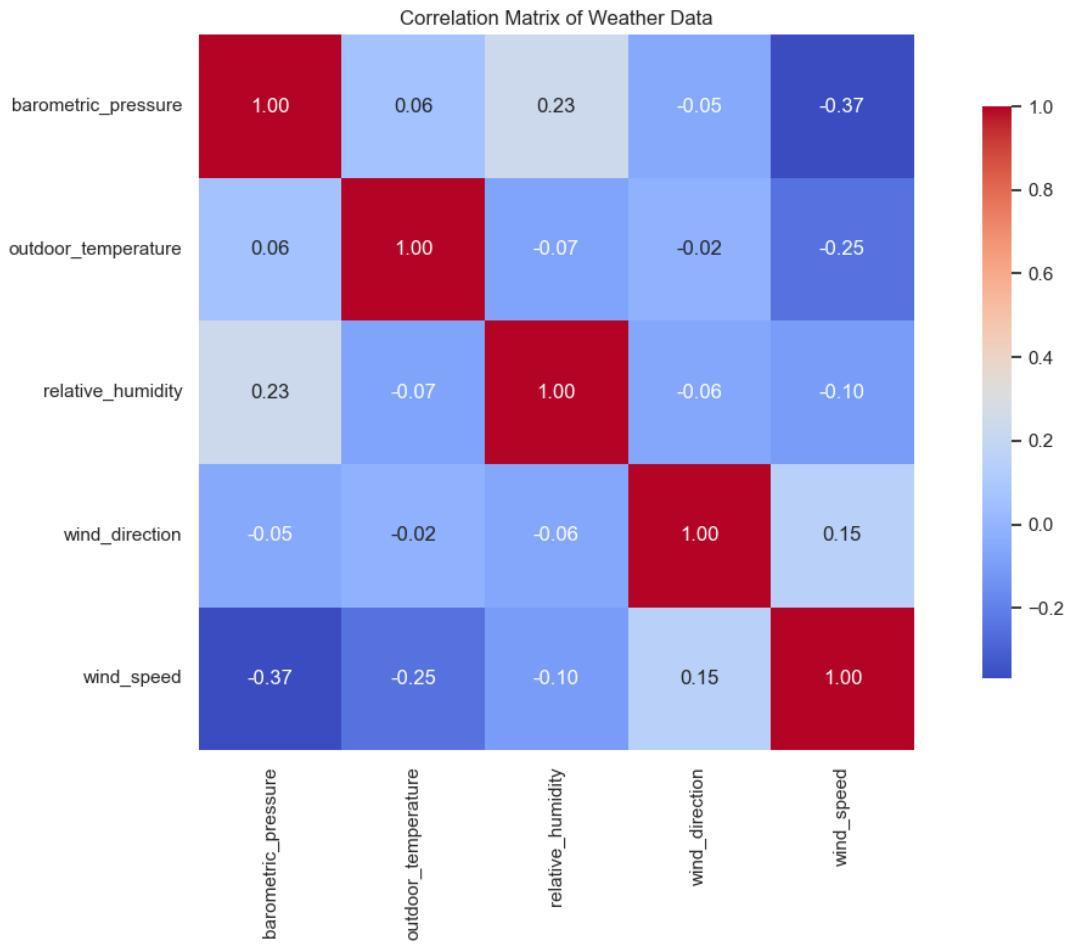
- By Region
- Outdoor temperature shows cyclical component
- Relative humidity shows increased variability in the winter
- Windspeed shows increased variability in the winter

- Plots for all metro areas available in back-up slides.



# Exploratory Analysis (Weather Correlations)



# Exploratory Analysis (Conclusions)

## Factor Analysis

- What weather factors are important?
  - **Wind speed, wind direction, outdoor temperature, and relative humidity should be considered**
- Are there time-series trends to account for?
  - **Weekly and Yearly cyclical trends**
- At what geographics scale should we model?
  - **Metro Area scale is appropriate but should include FIPS or FIPS-Site** (backup slides available)

# Exploratory Analysis (Conclusions)

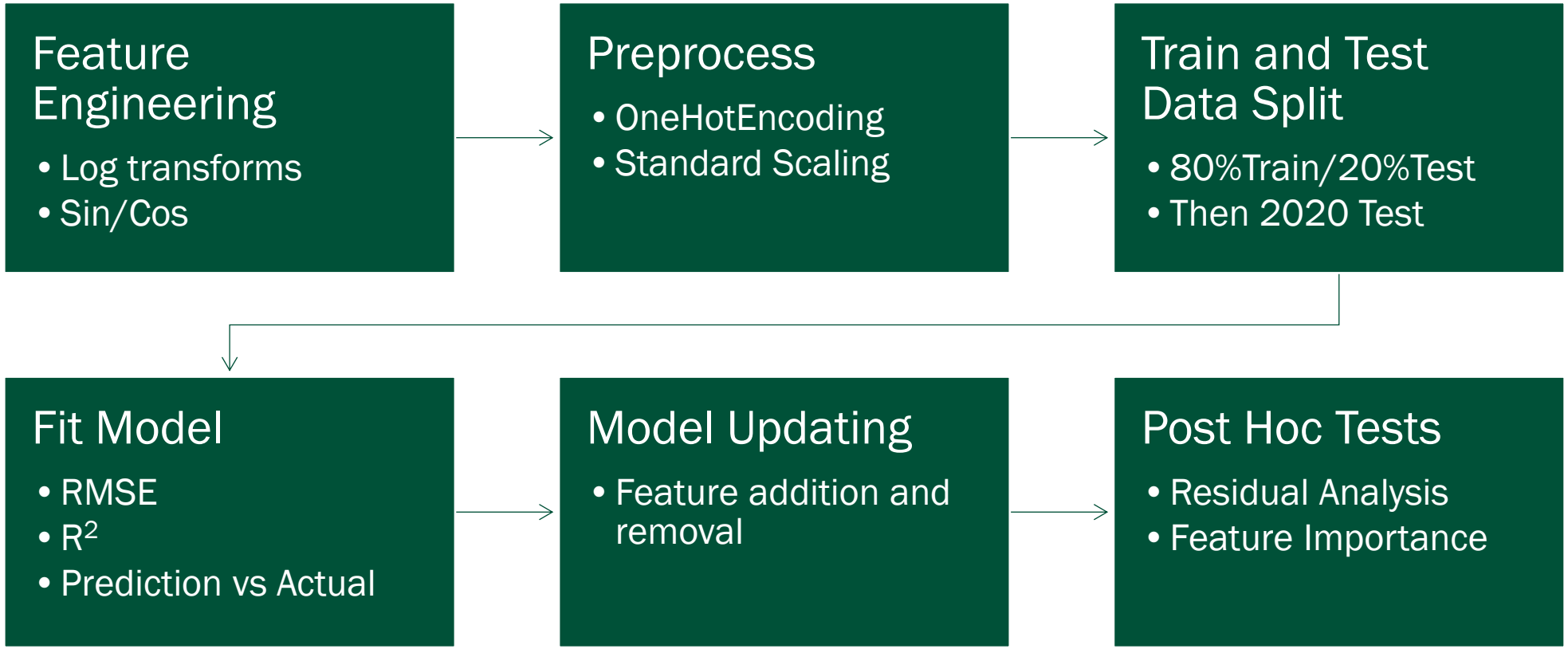
## Model Selection

- How is the data distributed?
  - **$NO_2$ is log-normal while weather data is a mix of normal and log-normal**
- What models are reasonable based on the distributions?
  - **Generalize linear models are appropriate for the data.**
  - **Other regression models should also be explored**
  - **Time-series models like ARIMA/SARIMA or rolling averages will likely have good prediction accuracy of short time scales because of their ability to “adjust” to shocks**

# Predictive Modeling (Linear Regression)

- **Purpose:**
  Predict a continuous outcome ($\hat{y}$) based on one or more input features($x_n$).
  $$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$
- **Training Objective:**
  Minimize the **sum of squared errors (SSE)** between predicted and actual values:
  $$SSE = \sum (y_i - \hat{y}_i)^2$$
- **Interpretation:**
  Each coefficient $\beta_i$ shows the expected change in $y$ for a one-unit increase in $x_i$, holding others constant.

# Predictive Modeling (Method)



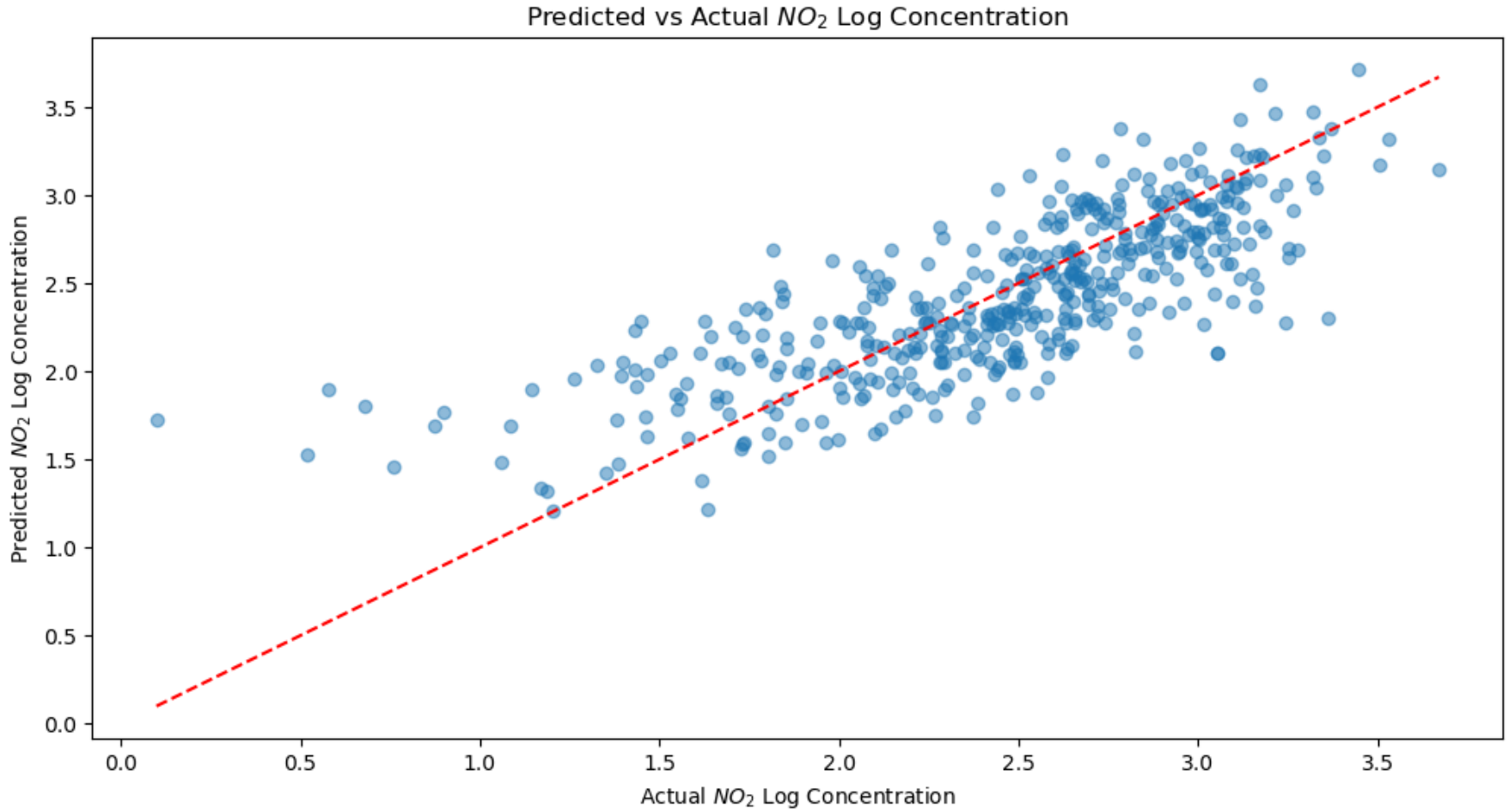
# Predictive Modeling (Factor Engineering)

- Time Series Factors
  - Yearly trends by metro area
  - Yearly cyclical components by metro area
    - $day_{yearSin} = \sin\left(\frac{2\pi\, day_{year}}{365}\right)$
    - $day_{yearCos} = \cos\left(\frac{2\pi\, day_{year}}{365}\right)$
  - Weekly component by metro area
    - Day of the week (oneHotEncoder)
- Weather Factors
  - Wind Speed
    - $wind_{speedLog} = \log(wind_{speed})$
- Location Factor
  - FIPS-Site (oneHotEncoder)

# Predictive Modeling (Model Fit – Chicago Example)

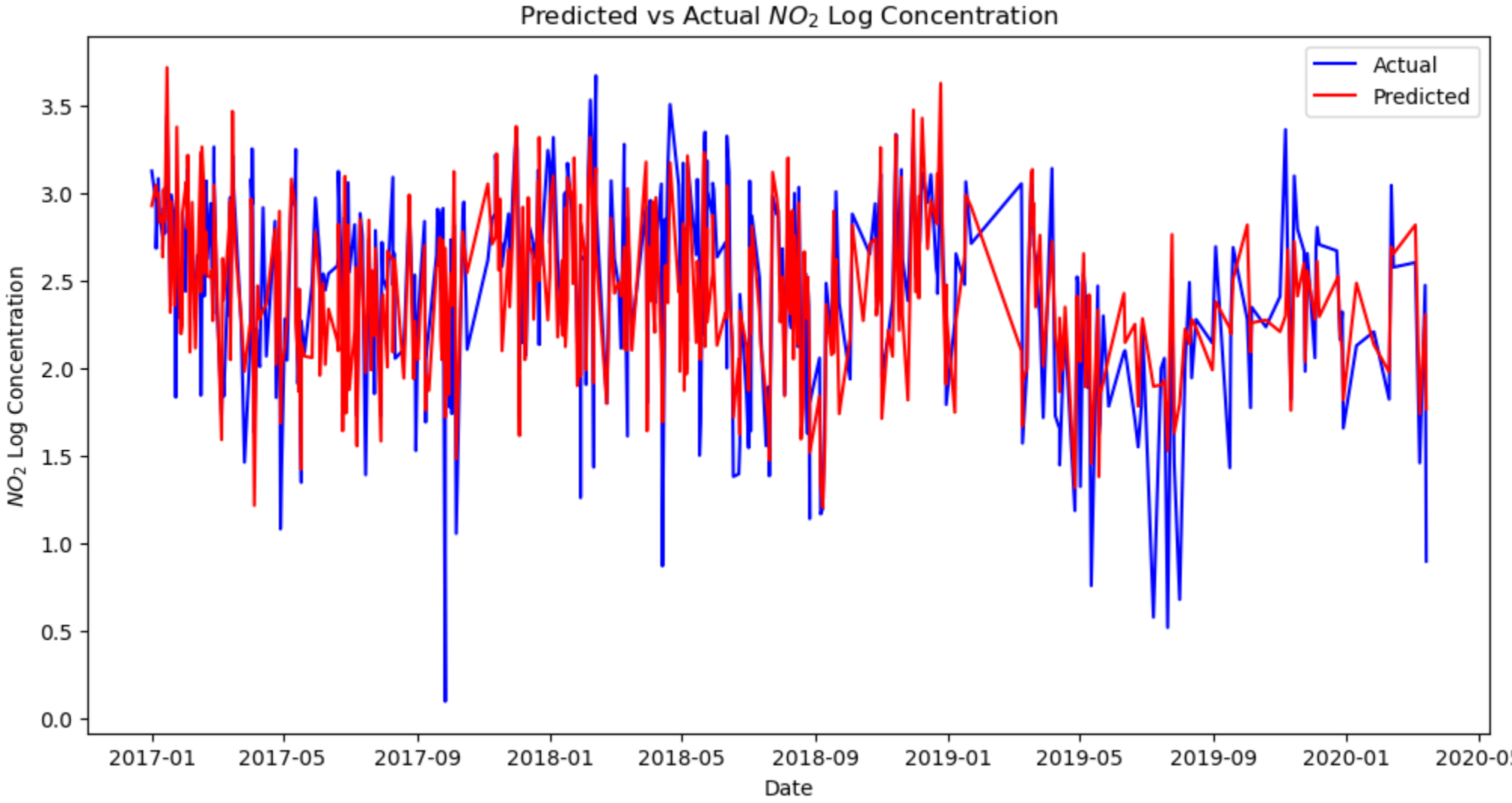
- Using only 2017 to Pre-COVID (14 March 2020)
- 80% train vs 20% test
- Log($NO_2$) vs
  - fip_site,
  - day_of_week, day_of_year_sin, day_of_year_cos,
  - outdoor_temp, relative_humidity, wind_direction, wind_speed_log
- Results
  - `Mean Squared Error: 0.123`
  - `Root Mean Squared Error: 0.350`
  - `R-squared: 0.593`

# Predictive Modeling (Model Fit – Chicago Example)

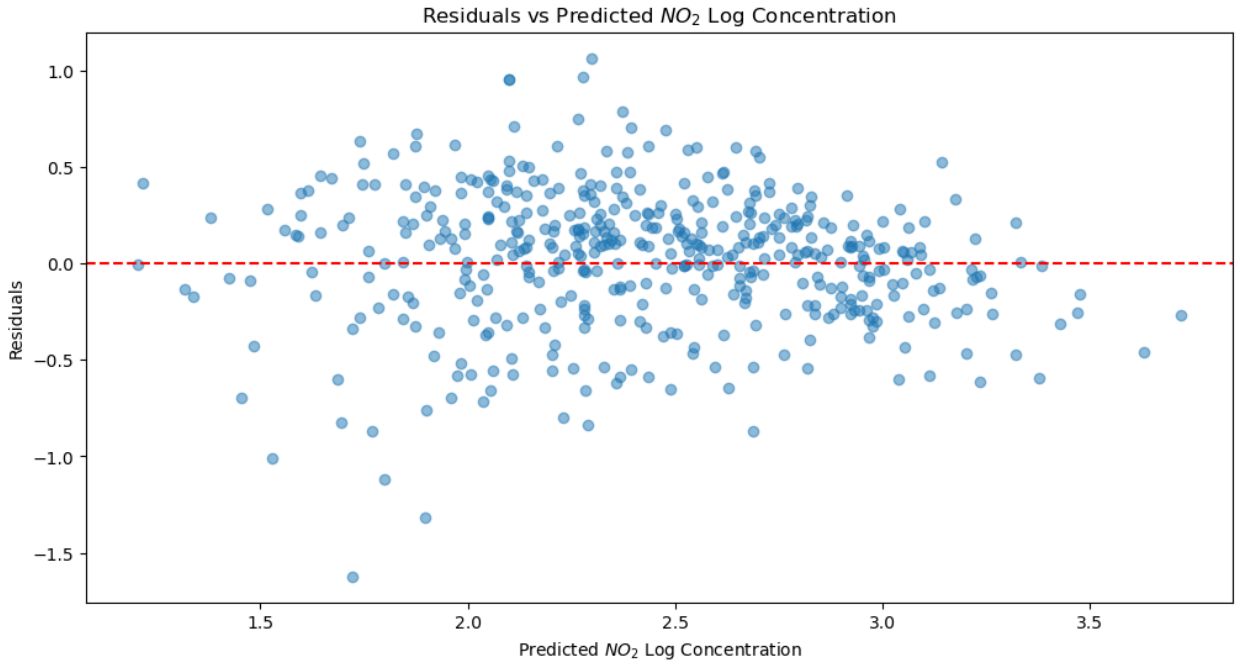


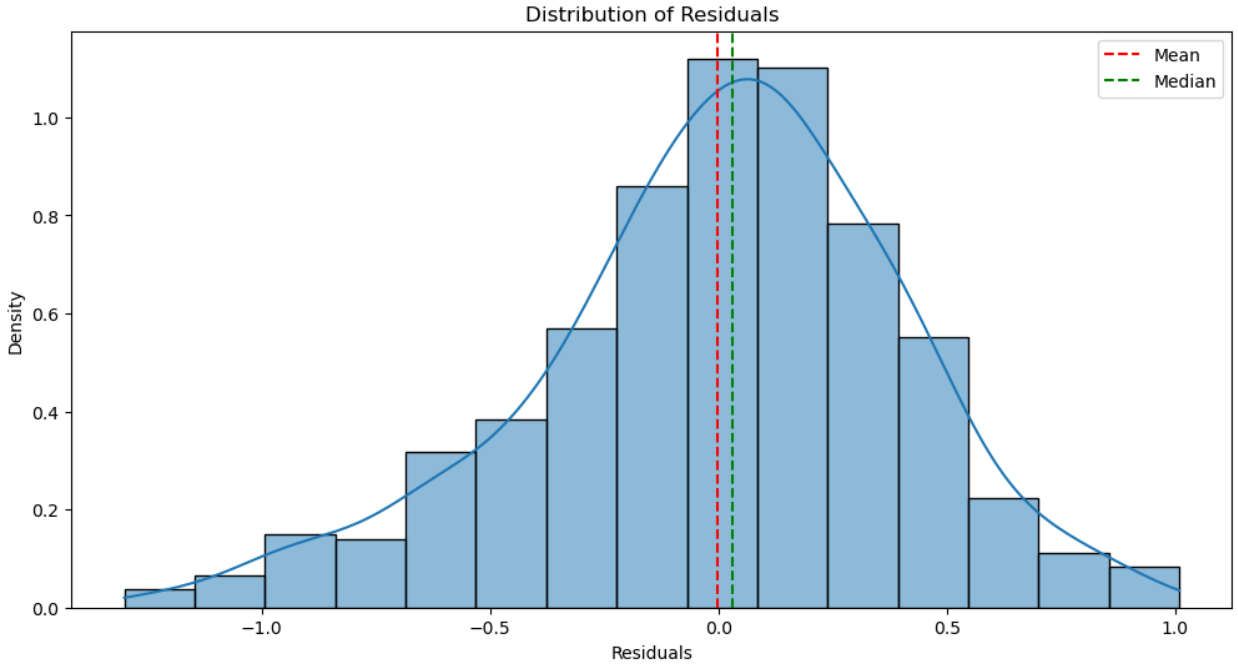

Low log(NO2) concentrations are predicted to be higher

# Predictive Modeling (Model Fit – Chicago Example)



# Predictive Modeling (Residual Analysis – Chicago Example)

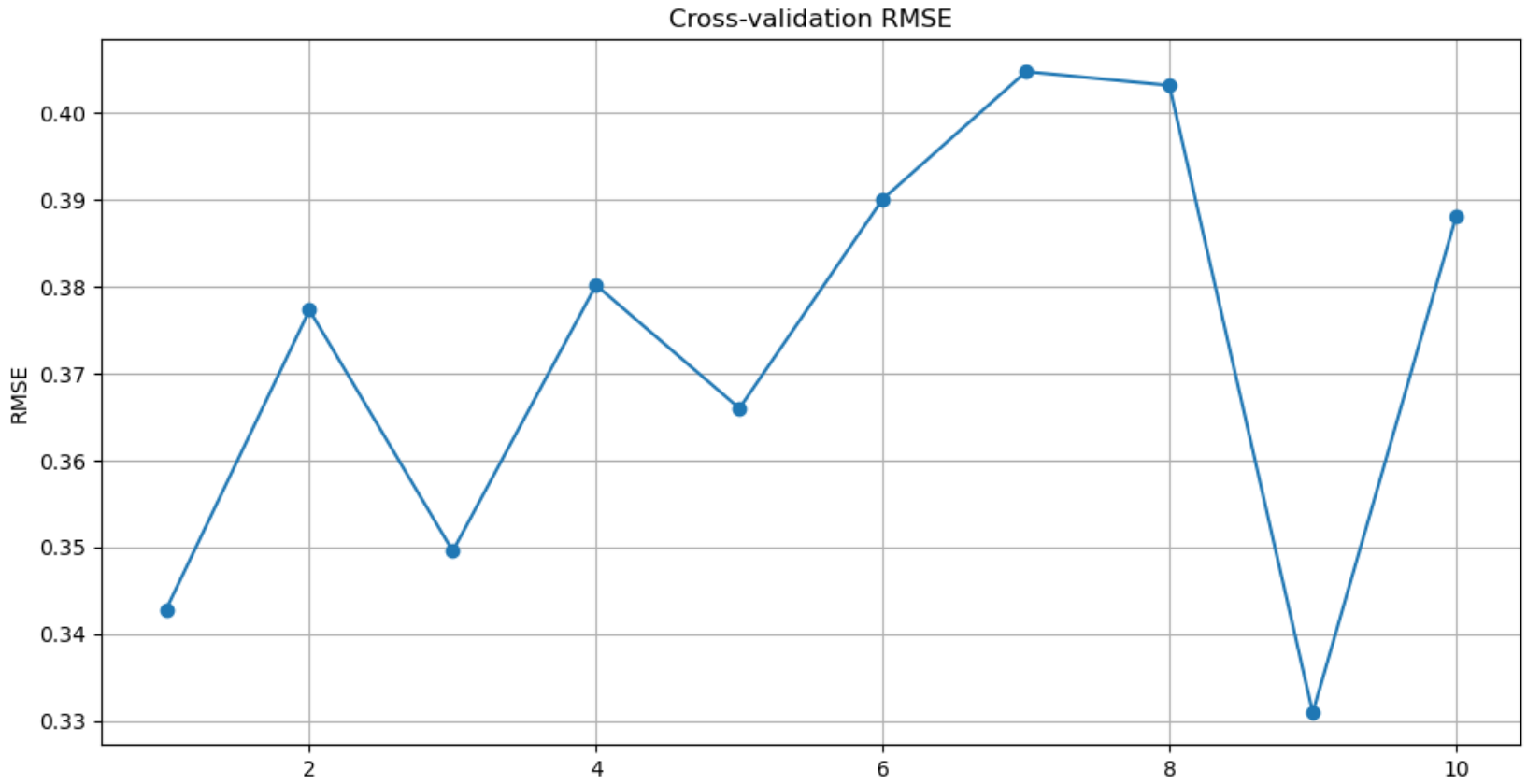



Shapiro-Wilk test statistic: 0.978, p-value: 0.000

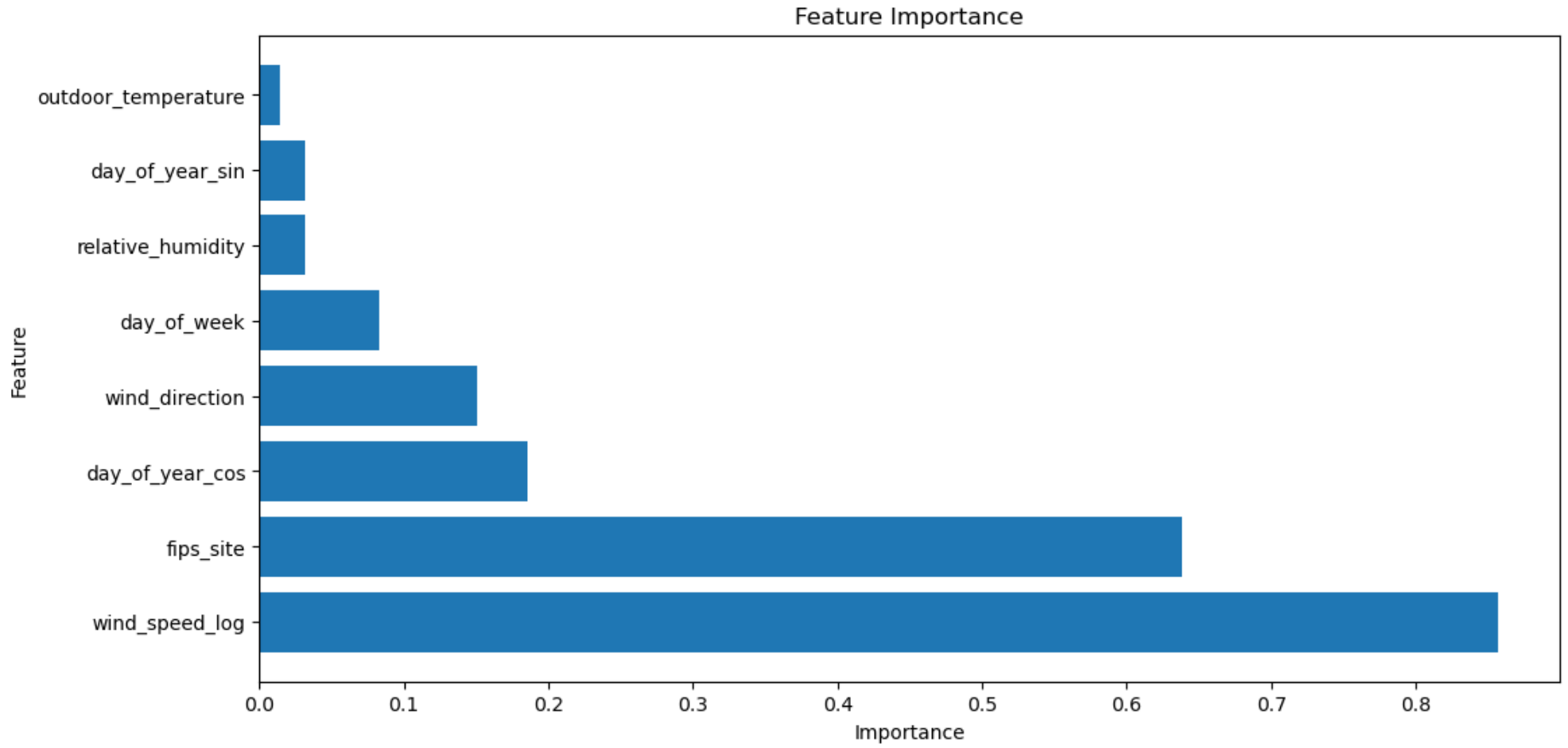
# Predictive Modeling (Validation – Chicago Example)

K-fold Cross Validation (10 Folds)




```
Cross-validation RMSE: 0.372
```

# Predictive Modeling (Feature Importance – Chicago Example)



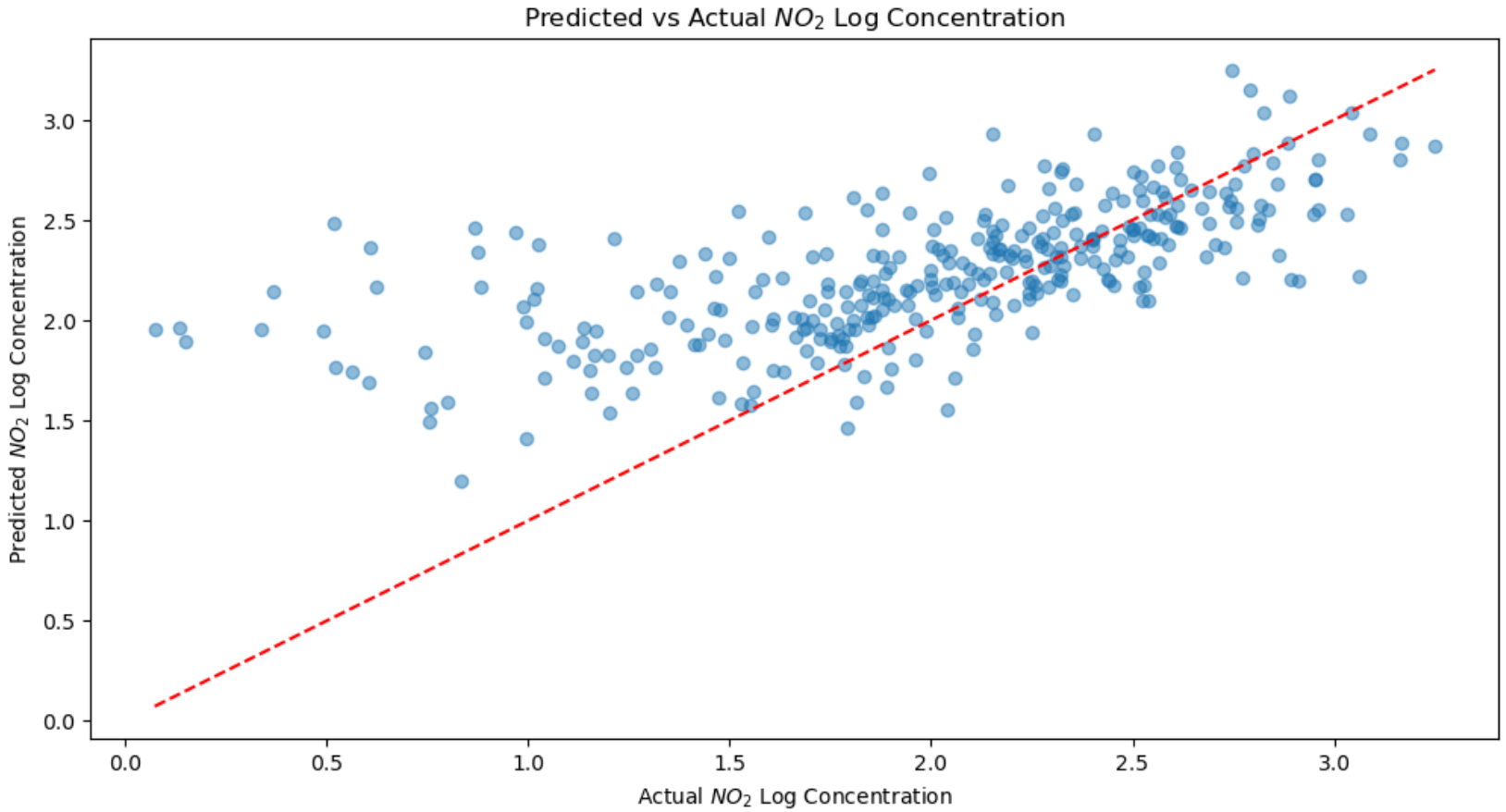
# Predictive Modeling
# (All Metro Area Results Pre-COVID)

| Metro Area | MSE | RMSE | $R^2$ |
|---|---|---|---|
| Chicago | 0.12 | 0.35 | 0.60 |
| Denver | 0.09 | 0.3 | 0.85 |
| Los Angeles | 0.15 | 0.38 | 0.66 |
| New York | 0.14 | 0.37 | 0.45 |
| Washington | 0.16 | 0.4 | 0.60 |

# COVID-19 Impacts (Predictive Difference – Chicago Example)

- Using 100% Pre-COVID as training data
- Post COVID (2020-03-15 to 2021-03-15) as the testing data
- Log($NO_2$) vs
  - fip_site,
  - day_of_week, day_of_year_sin, day_of_year_cos,
  - outdoor_temp, relative_humidity, wind_direction, wind_speed_log
- Results
  - `Mean Squared Error: 0.271`
  - `Root Mean Squared Error: 0.521`
  - `R-squared: 0.274`

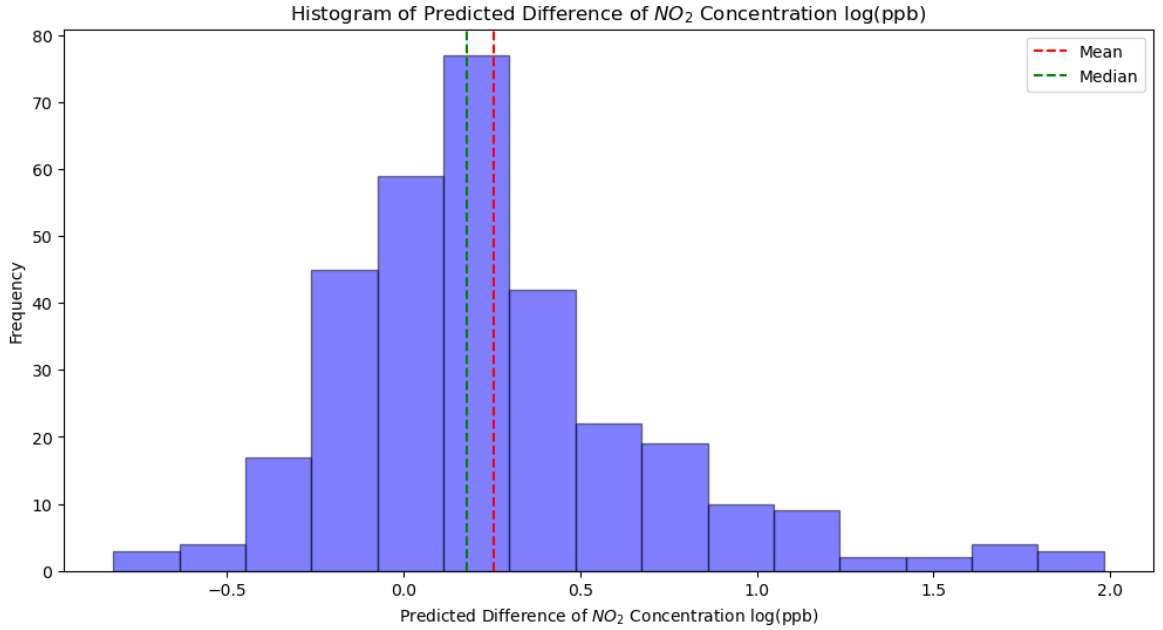
# COVID-19 Impacts (Predictive Difference – Chicago Example)




Predictions are higher than actual observed values

# COVID-19 Impacts (Predictive Difference – Chicago Example)

- Mean of predicted difference: 0.26
- Median of predicted difference: 0.18
- 95% confidence interval for the mean of the predicted difference:
  (0.19, 0.29)



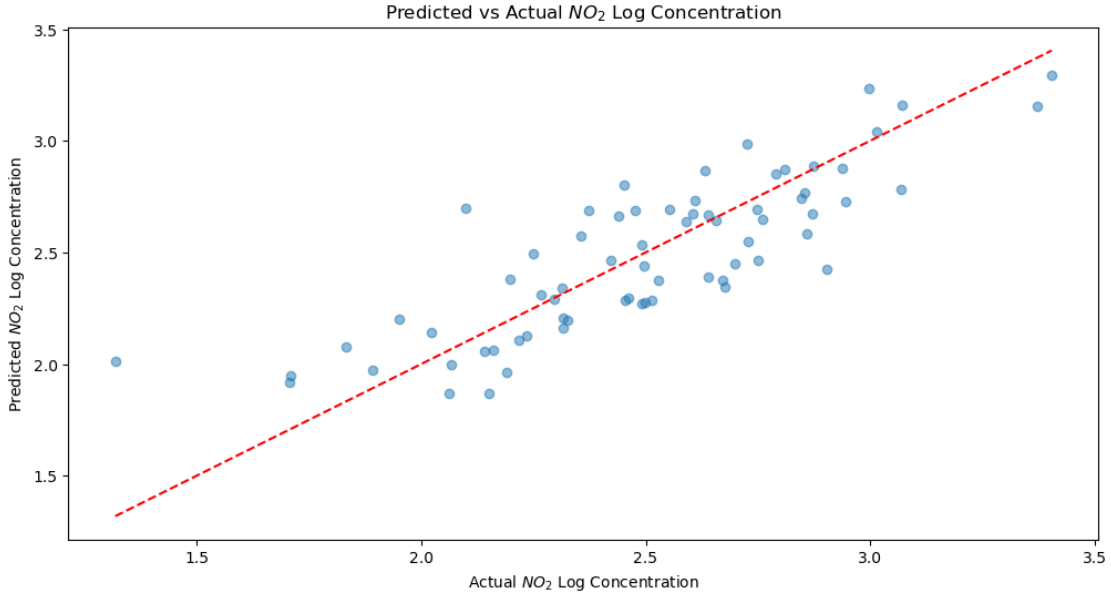
# COVID-19 Impacts (Predictive Difference – All Metro Areas)

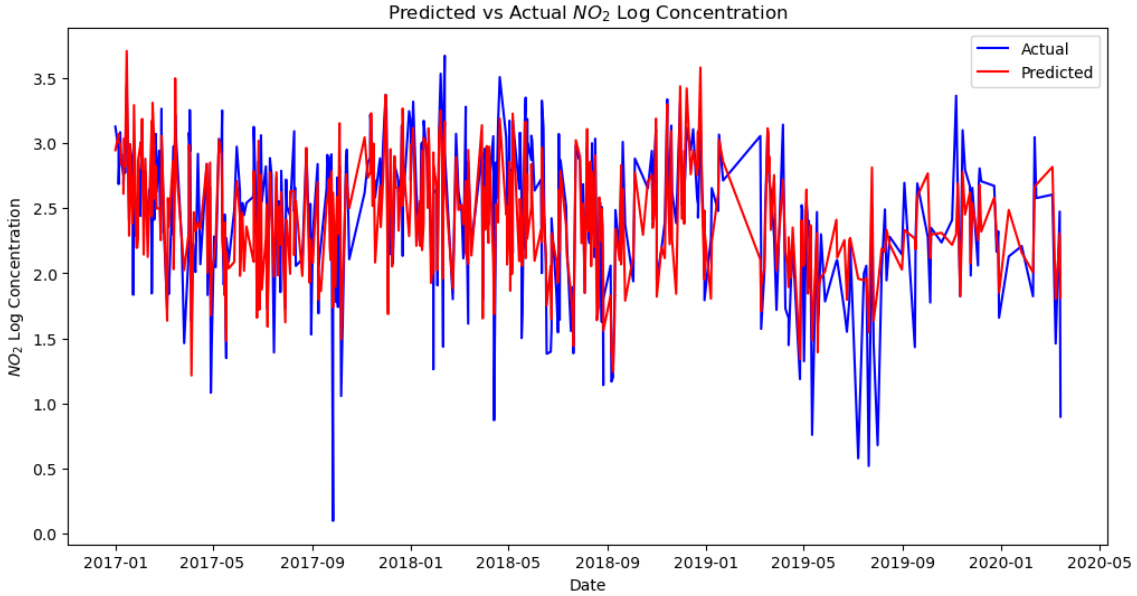
| Metro Area | $R^2$ Pre-COVID | $R^2$ Pos-COVID | Mean Difference | 95% CI Lower | 95% CI Higher |
|---|---|---|---|---|---|
| Chicago | 0.60 | 0.26 | 0.25 | 0.20 | 0.30 |
| Denver | 0.85 | 0.8 | 0.18 | 0.17 | 0.20 |
| Los Angeles | 0.66 | 0.63 | 0.13 | 0.12 | 0.14 |
| New York | 0.45 | 0.17 | 0.21 | 0.17 | 0.26 |
| Washington | 0.60 | 0.06 | 0.38 | 0.36 | 0.41 |

# COVID-19 Impacts (Weekly Averaged Data–Chicago)

- Using only 2017 to Pre-COVID (14 March 2020)
- Averaged weekly values
- 80% train vs 20% test
- Log($NO_2$) vs
  - fip_site,
  - **week_of_year_sin, week_of_year_cos,**
  - outdoor_temp, relative_humidity, wind_direction, wind_speed_log
- Results
  - `Mean Squared Error: 0.047`
  - `Root Mean Squared Error: 0.217`
  - `R-squared: 0.678`

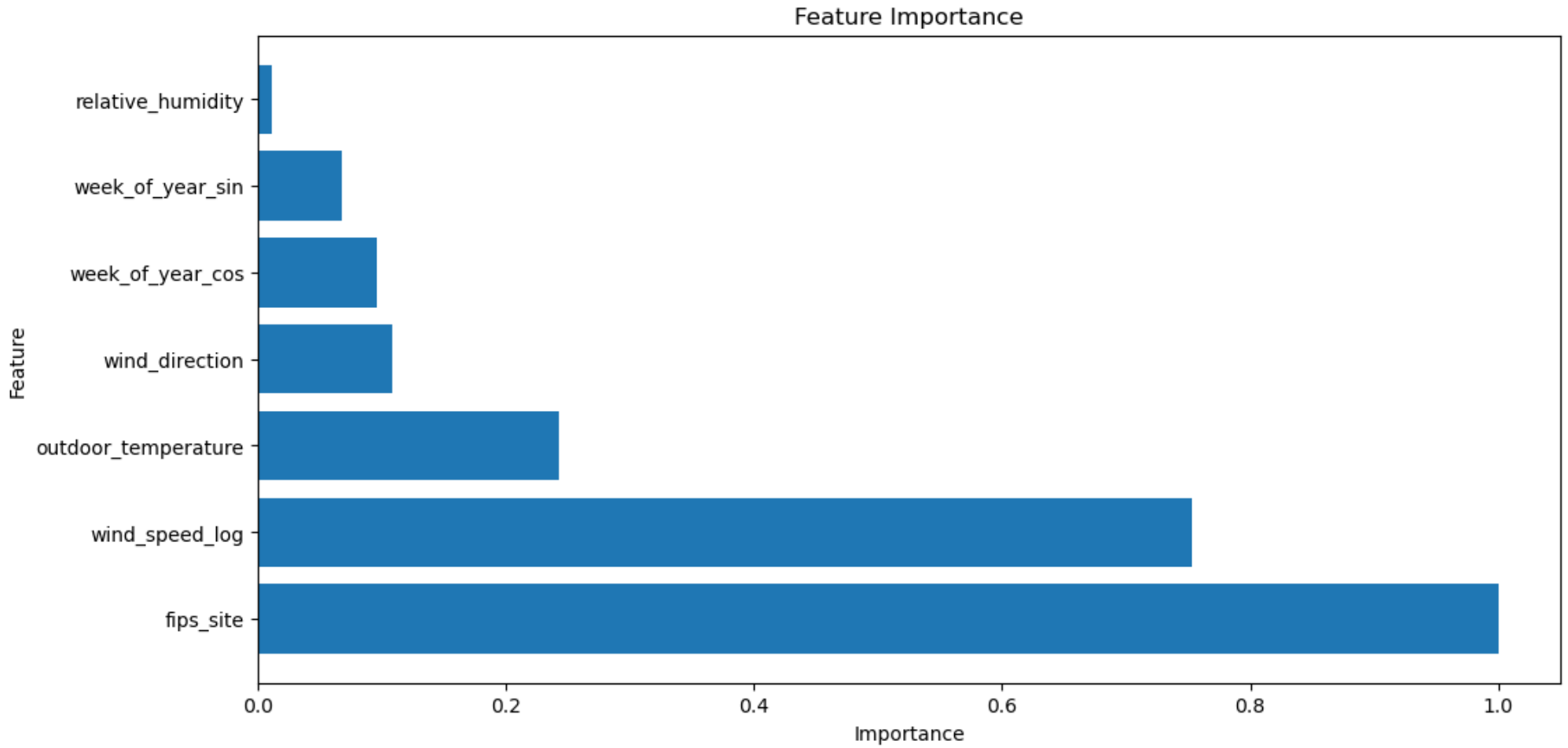
# COVID-19 Impacts (Weekly Averaged Data–Chicago)




**Model still have issues with very low $NO_2$ concentrations**

# COVID-19 Impacts (Weekly Averaged Data–Chicago)



# COVID-19 Impacts (Weekly Averaged Data—All Metro Areas)

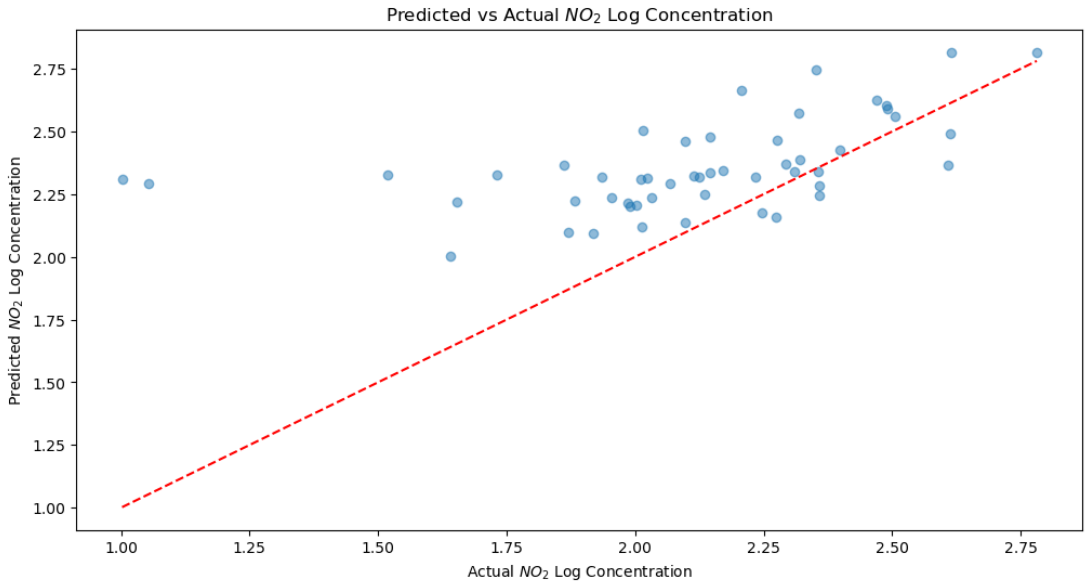
| Metro Area | Weekly MSE | Weekly RMSE | Weekly $R^2$ | Daily $R^2$ |
|---|---|---|---|---|
| Chicago | 0.05 | 0.22 | 0.68 | 0.60 |
| Denver | 0.03 | 0.17 | 0.96 | 0.85 |
| Los Angeles | 0.07 | 0.26 | 0.76 | 0.66 |
| New York | 0.04 | 0.19 | 0.60 | 0.45 |
| Washington | 0.08 | 0.28 | 0.67 | 0.60 |

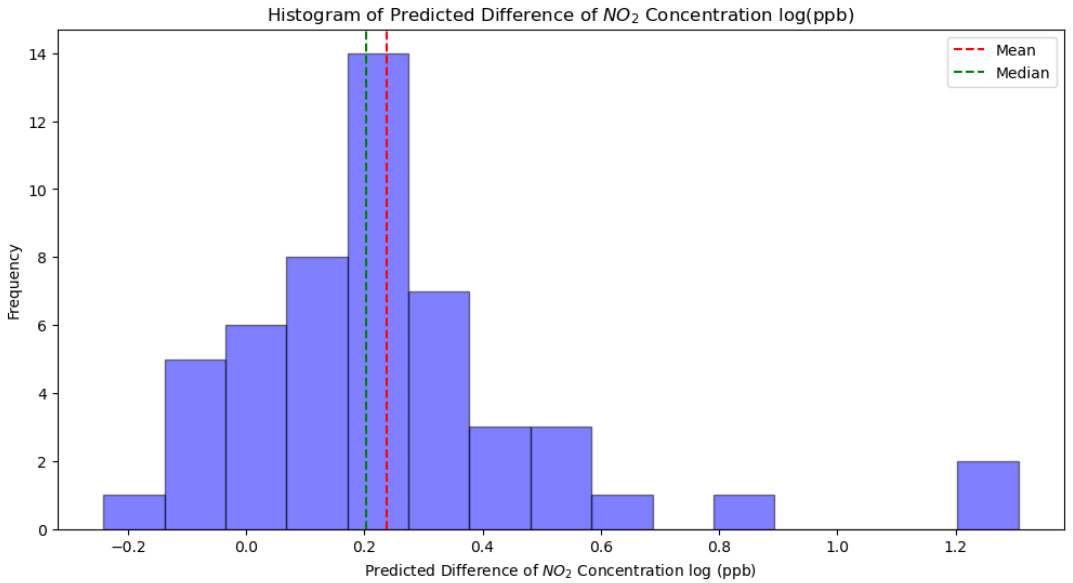
Weekly averaged model has better fit than daily model

# COVID-19 Impacts (Predictive Difference – All Metro Areas)

- Using 100% Pre-COVID as training data
- Post COVID (2020-03-15 to 2021-03-15) as the testing data
- Log($NO_2$) vs
  - fip_site,
  - **week_of_year_sin, week_of_year_cos,**
  - outdoor_temp, relative_humidity, wind_direction, wind_speed_log

# COVID-19 Impacts (Predictive Difference—Chicago)



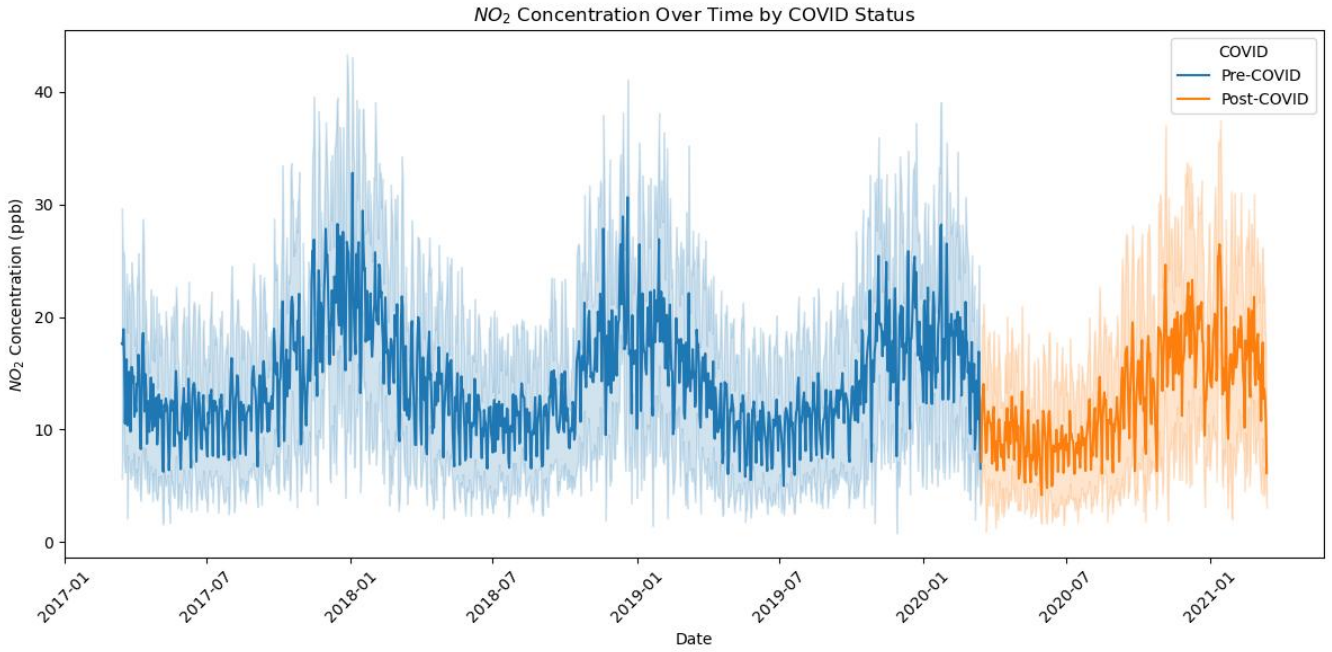

Mean Squared Error: 0.140
Root Mean Squared Error: 0.374
R-squared: -0.192

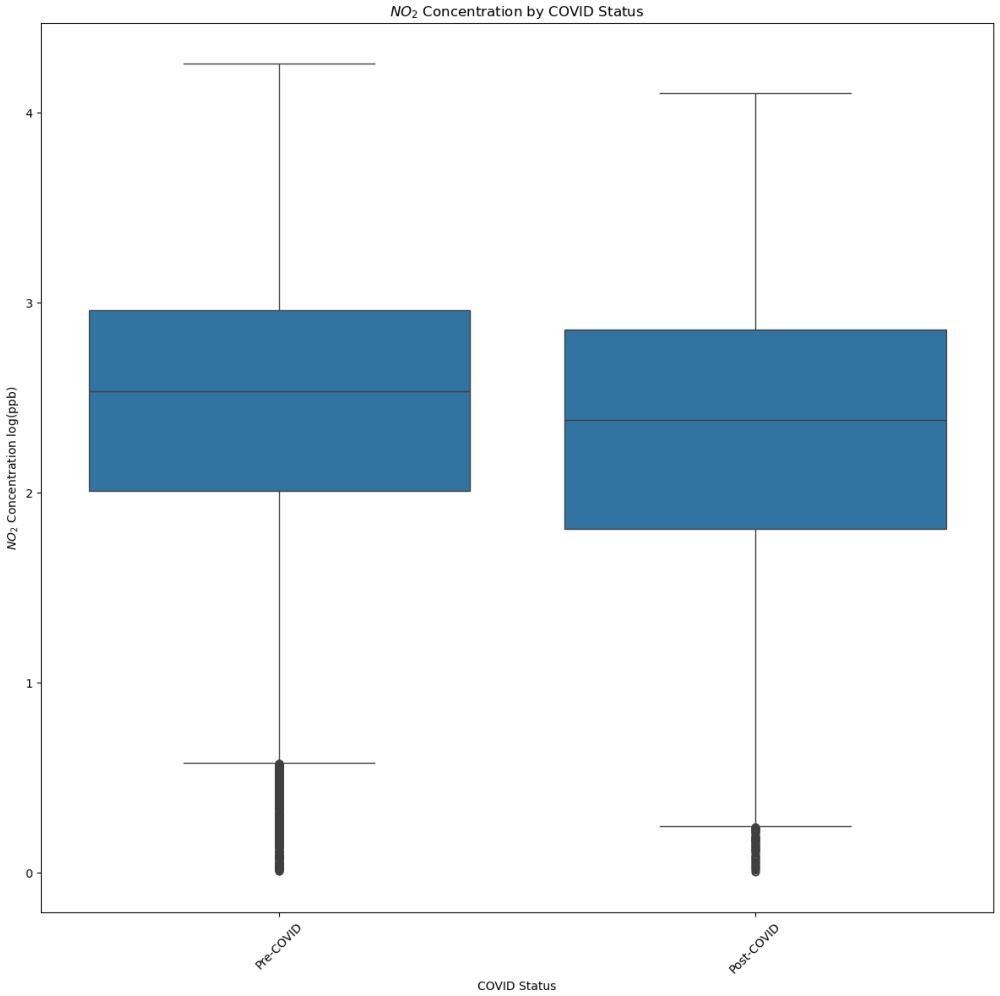
95% confidence interval for the mean of the predicted difference: (0.15, 0.32)

# COVID-19 Impacts (Predictive Difference – All Metro Areas)

| Metro Area | $R^2$ Pre-COVID | $R^2$ Pos-COVID | Mean Difference | 95% CI Lower | 95% CI Higher |
|---|---|---|---|---|---|
| Chicago | 0.68 | -0.19 | 0.24 | 0.16 | 0.32 |
| Denver | 0.96 | 0.87 | 0.18 | 0.16 | 0.21 |
| Los Angeles | 0.76 | 0.72 | 0.12 | 0.10 | 0.14 |
| New York | 0.60 | 0.4 | 0.18 | 0.14 | 0.23 |
| Washington | 0.67 | 0.30 | 0.29 | 0.25 | 0.34 |

# COVID-19 Impacts (Grouped Analysis)



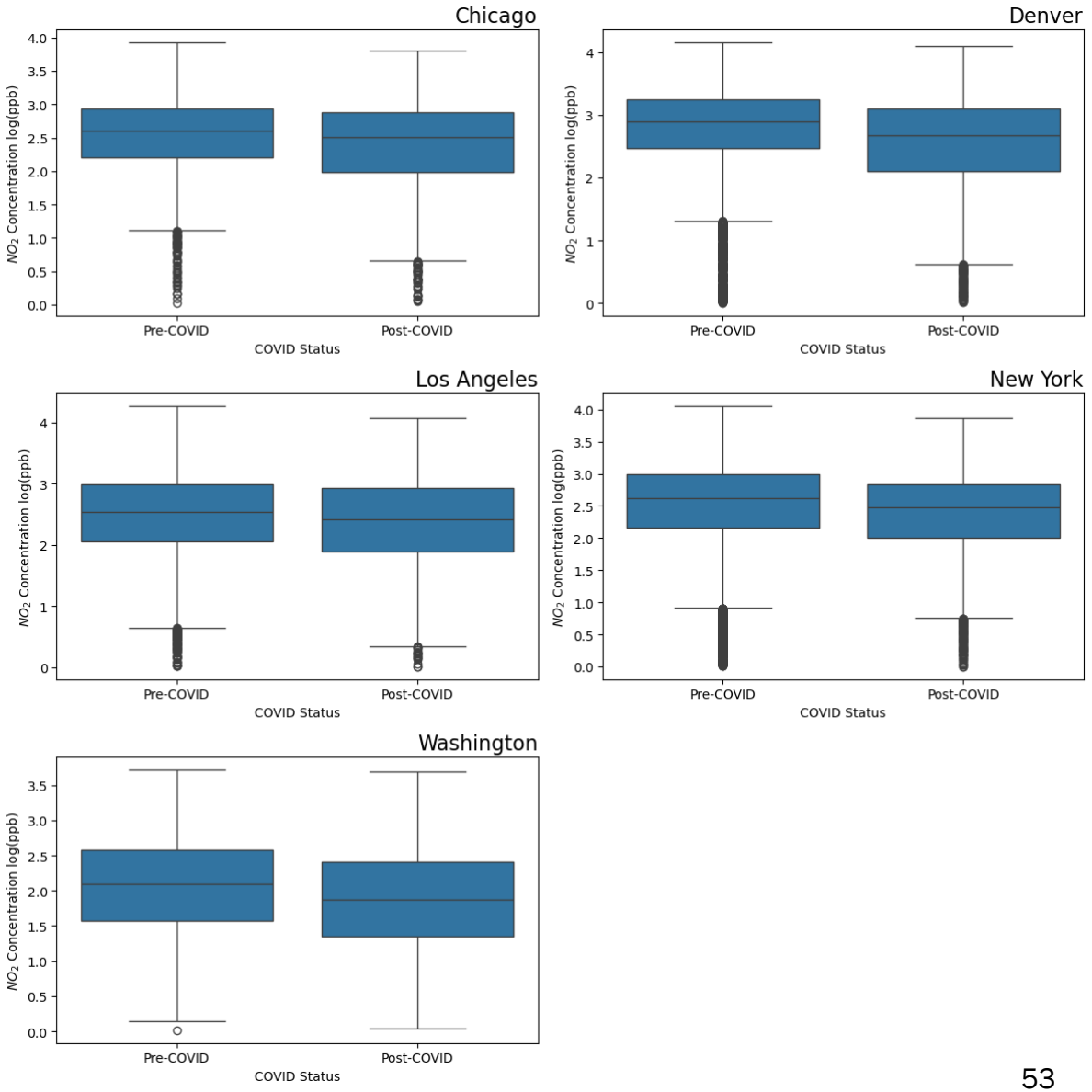
# COVID-19 Impacts (Generalized Linear Model)

- Python glm module with gaussian log-link

| | pval | R2 (psedo) | Diff | 95% CI Lower | 95% CI Upper | Percent Change | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Difference | 95%CI Lower | 95%CI Upper |
| Chicago | 0 | 0.01 | 0.09 | 0.06 | 0.11 | 9% | 6% | 12% |
| Denver | 0 | 0.02 | 0.19 | 0.16 | 0.22 | 21% | 17% | 25% |
| Los Angeles | 0 | 0.00 | 0.08 | 0.06 | 0.1 | 9% | 7% | 11% |
| New York | 0 | 0.01 | 0.14 | 0.12 | 0.16 | 15% | 12% | 17% |
| Washington | 0 | 0.01 | 0.16 | 0.13 | 0.18 | 17% | 14% | 20% |

# COVID-19 Impacts (Grouped Analysis)

| | Percent Change | | |
|---|---|---|---|
| | Diff | 95%CI Lower | 95%CI Upper |
| Chicago | 9% | 6% | 12% |
| Denver | 21% | 17% | 25% |
| Los Angeles | 9% | 7% | 11% |
| New York | 15% | 12% | 17% |
| Washington | 17% | 14% | 20% |

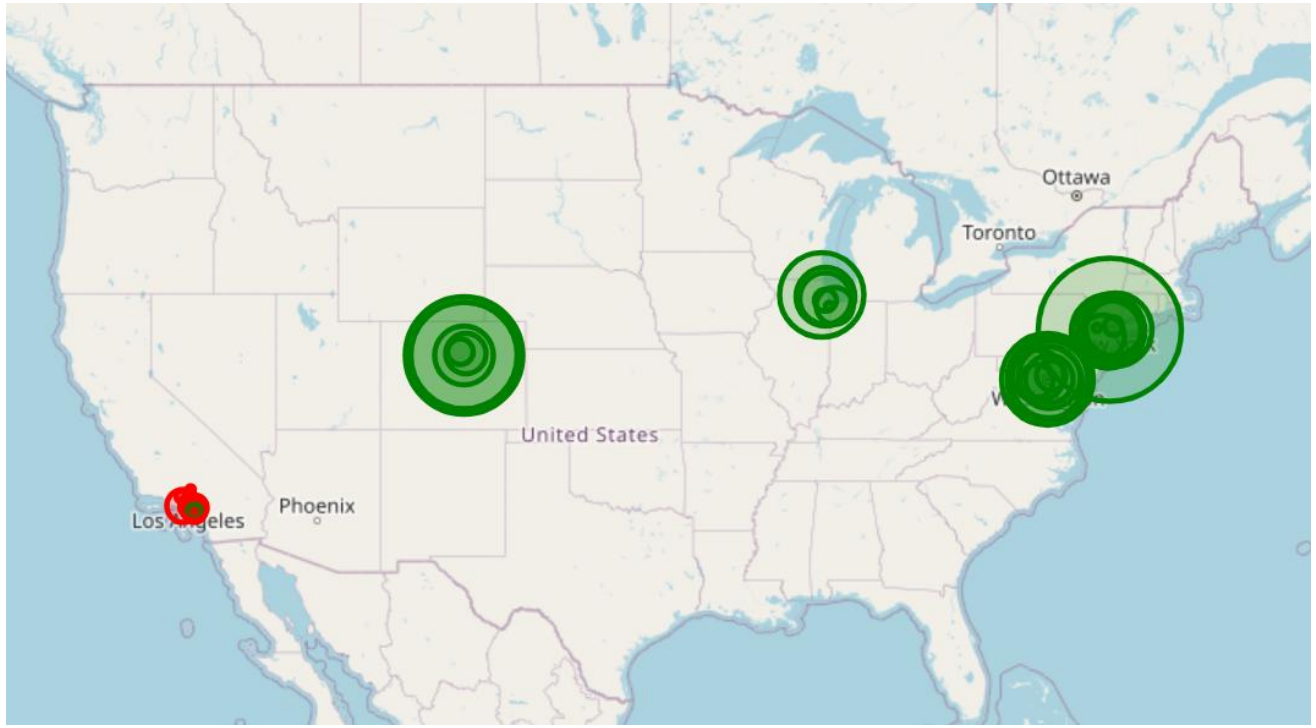


# COVID-19 Impacts (Interactive Map of $NO_2$ Difference)

- Difference between 2020 and 2019 average yearly $NO_2$ concentration at each FIPS Site [4]

- Styled by
  - Color: decrease (green) or increase (red)
  - Size: magnitude of change (absolute difference)

- Shows 2020 increase in $NO_2$ concentrations in Los Angles as compared to 2019




https://codepen.io/scout792/full/MYWNNpM

# Conclusions

- Predictions of daily $NO_2$ data with daily weather data was varied by metro area with Denver having the best predictability
- Daily fit-model has the worst performance for low $NO_2$ concentrations
- Predictive model fit with pre-COVID data generally predicted higher $NO_2$ concentrations than were observed during COVID
- COVID $NO_2$ concentrations were between 10-30% lower than predicted for all metro areas
  - Los Angels saw the lowest reduction at about 10%
  - Washington DC saw the highest reduction at about 20-35%
- Weekly averaged model has better overall fit but still does poorly at predicting low $NO_2$ concentrations

# Future Work

- Explore the low $NO_2$ concentration ranges to improve model performance
  - (Box-Cox transform did not significantly improve model performance)
- Build models for FIPS Code
  - Use factor permutations for each FIPS code for best fit
- Explore more detailed time-series analysis options including yearly (365 days) and week of year (52 week) differenced data to remove cyclical components
- Explore deep learning methods

# Acknowledgements

Much of the code used in the project was initially used in class as part of homework sets or in-class projects.

- Dr. Kennedy: Foundational understanding of knowledge mining, model preparations, model tuning, and a reminder that data cleaning is 90% of the work.
- Dr. Miller: Applying statistical analysis to real world problems, namely ANOVA testing and linear regression.
- Dr Russo: Applying statistical visualization to real world problems, including the seaborn library.
- Dr Wolf (GGS): Applying time-series analysis to real world problems, including identifying cyclical and trend components in time-series data
- Dr Pfoser (GGS): Interactive map making, specifically deploying HTML in CodePen

# References


- [1] U.S. Environmental Protection Agency. (2023, June 29). *Overview of nitrogen dioxide ($NO_2$) air quality in the United States*.url: https://www.epa.gov/system/files/documents/2023-06/NO2_2022.pdf

- [2] U.S. Environmental Protection Agency. Air Data: Air Quality Data Collected at Outdoor Monitors Across the US. 2025. url: https://www.epa.gov/outdoor-air-quality-data.

- [3] U.S. Census Bureau. (n.d.). *Metro area geography reference*. U.S. Department of Commerce. Retrieved April 13, 2025, from https://www.census.gov/programs-surveys/cbp/technical-documentation/reference/metro-area-geography-reference.html

- [4] Folium Developers. (n.d.). *Folium documentation (latest)*. Python Visualization. Retrieved April 14, 2025, from https://python-visualization.github.io/folium/latest/index.html

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# Questions

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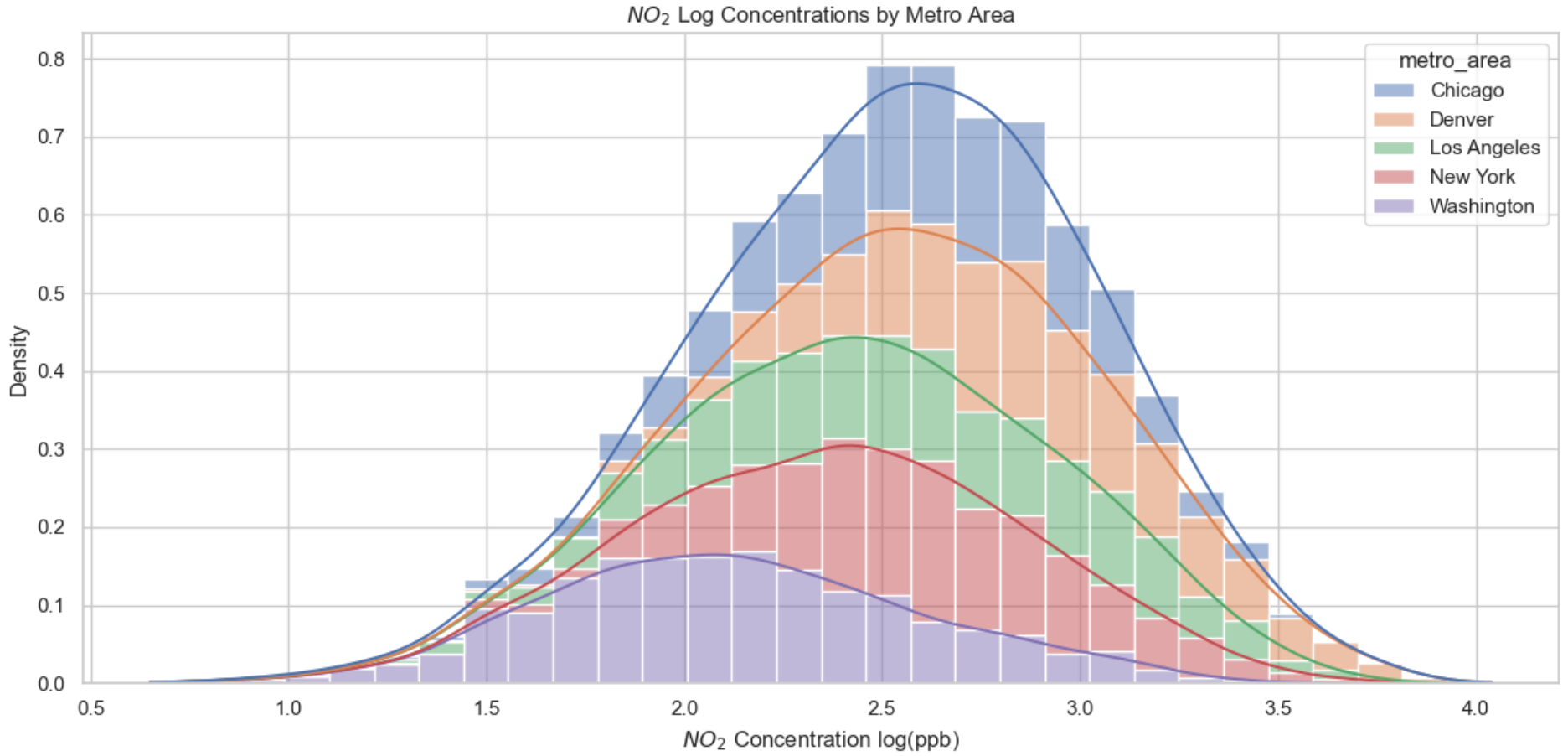
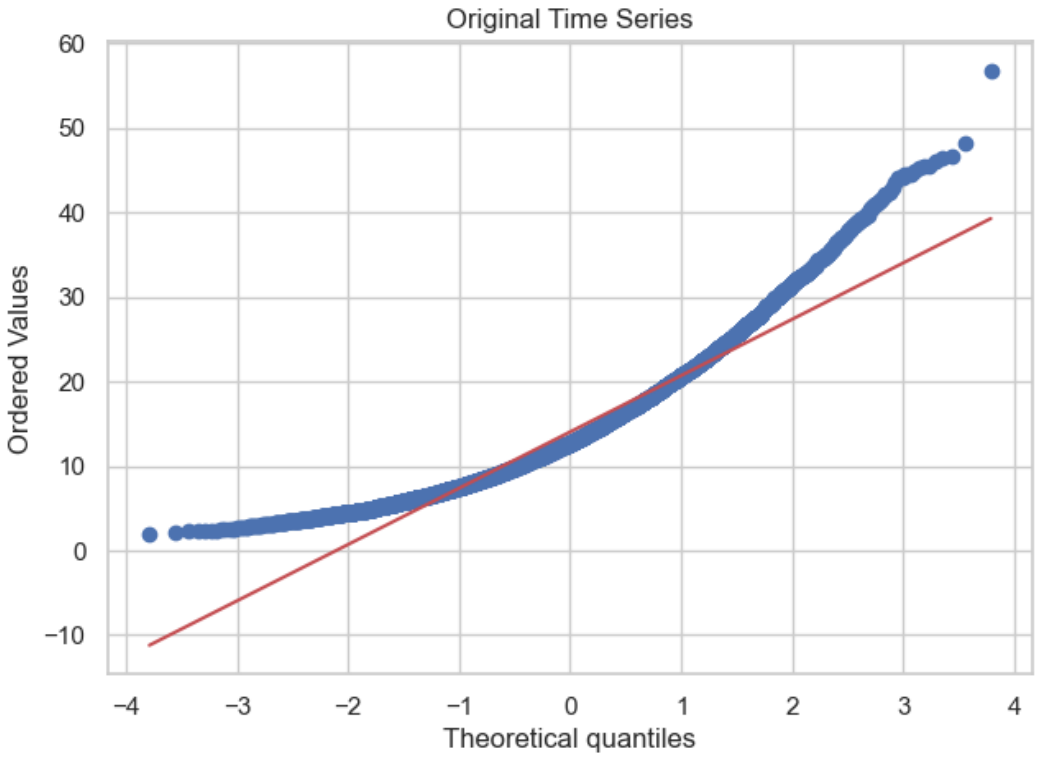
# Backup Material

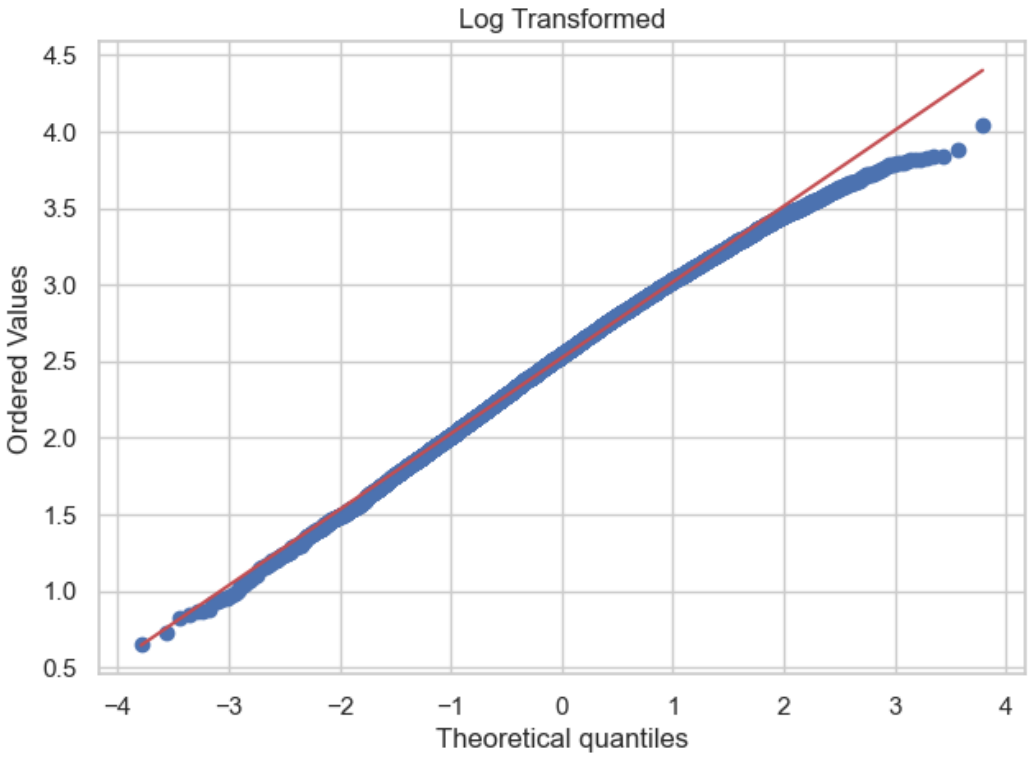
## Supporting Graphics and Model Assumptions

# Modeling Assumptions (Normality)



# Modeling Assumption (Normality)

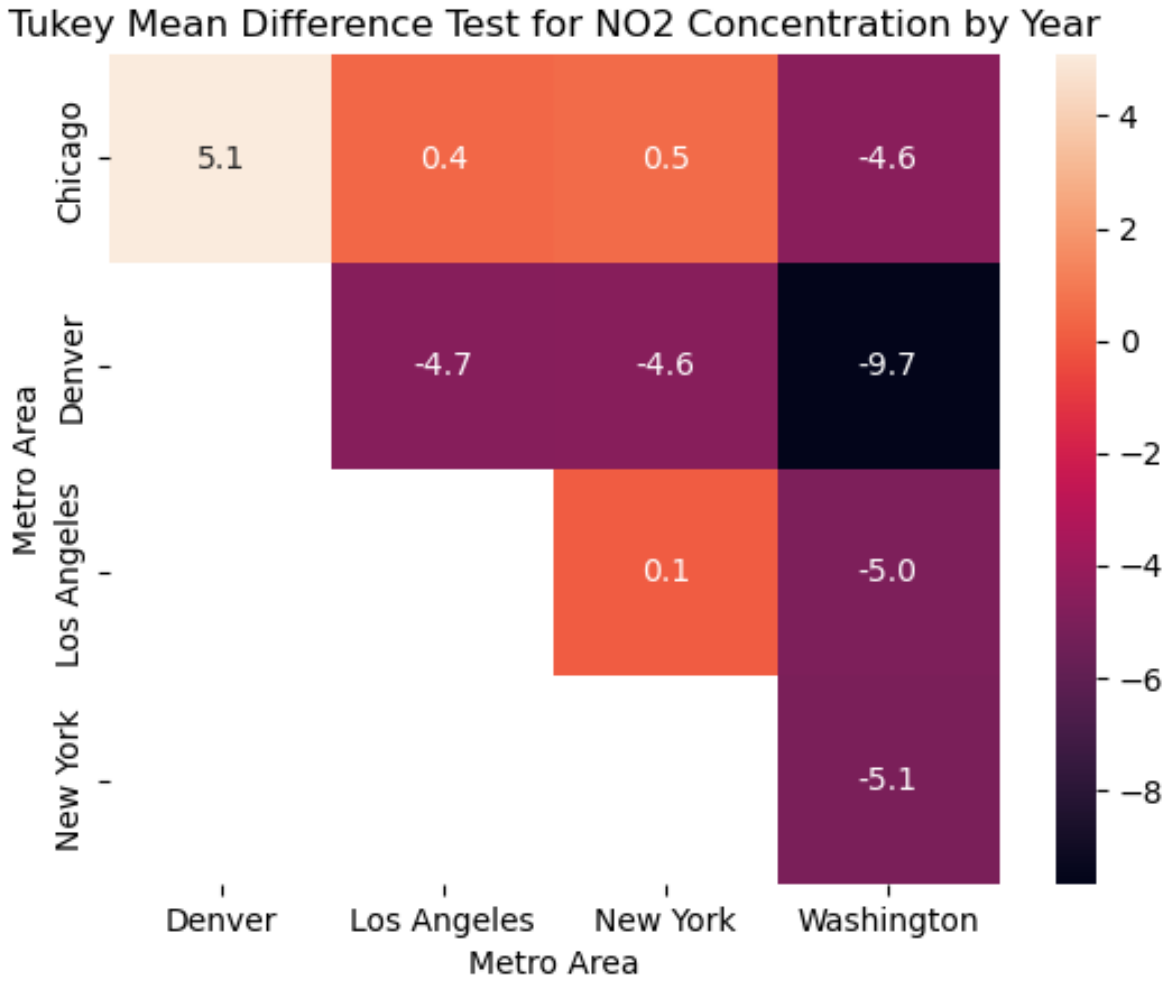


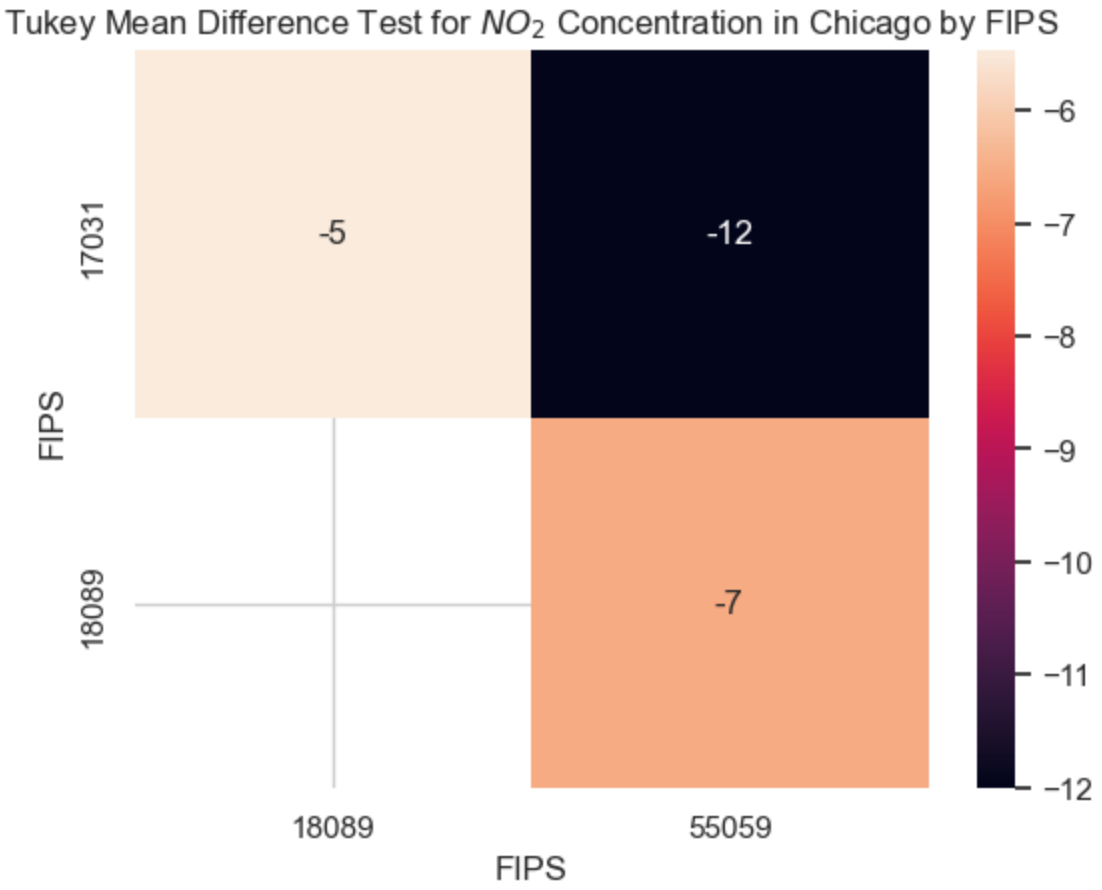

Log transformed data appears more normal

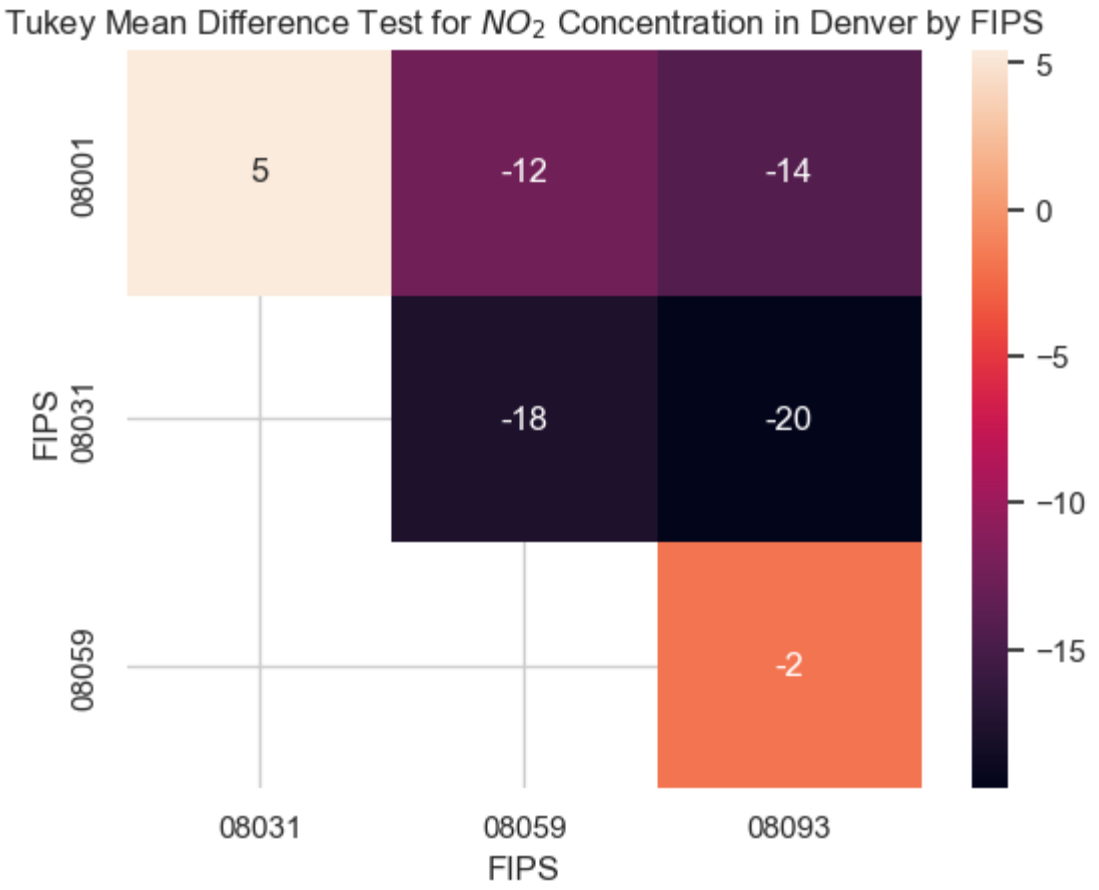
# $NO_2$ Concentration Difference Metro Area

- ANOVA test of $NO_2$ concentration by metro area for 2017-2019
- The difference in $NO_2$ concentrations for the metro areas is statistically significant
- The only exception is New York and Los Angeles

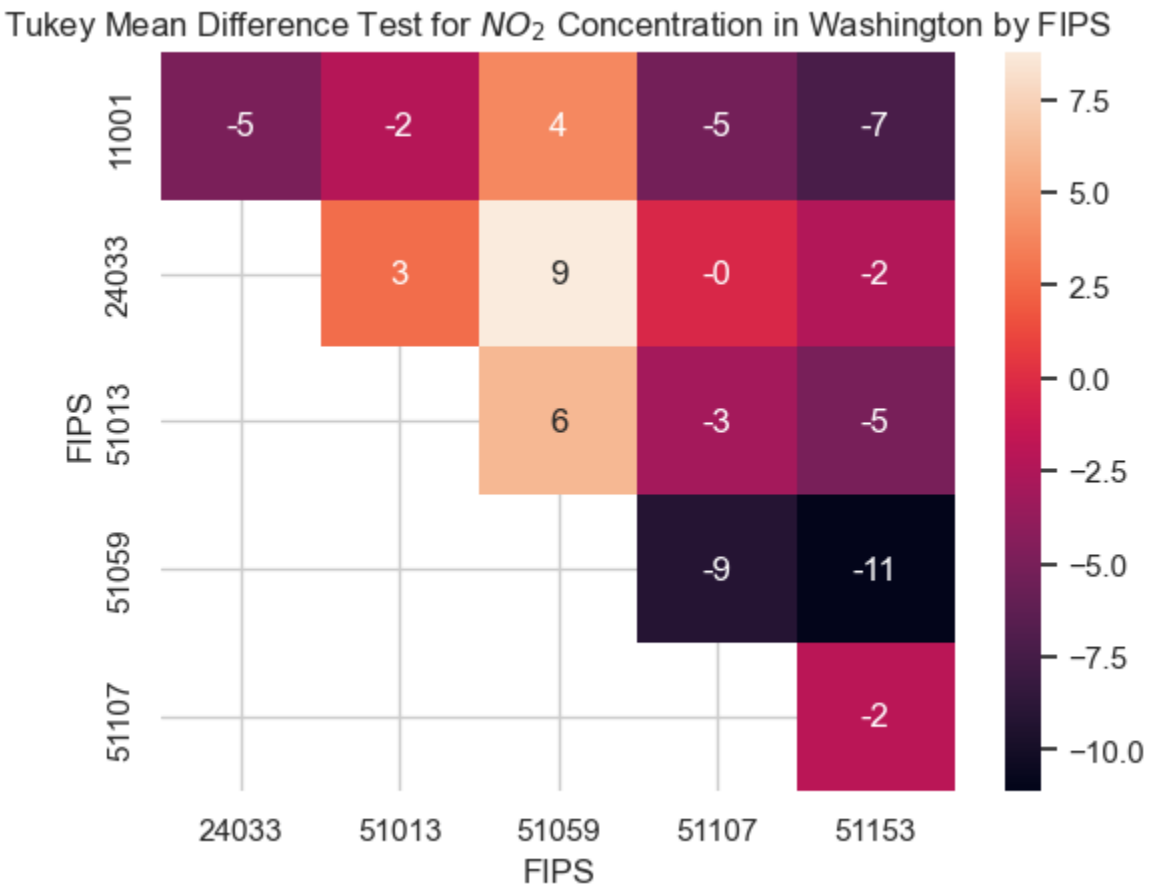


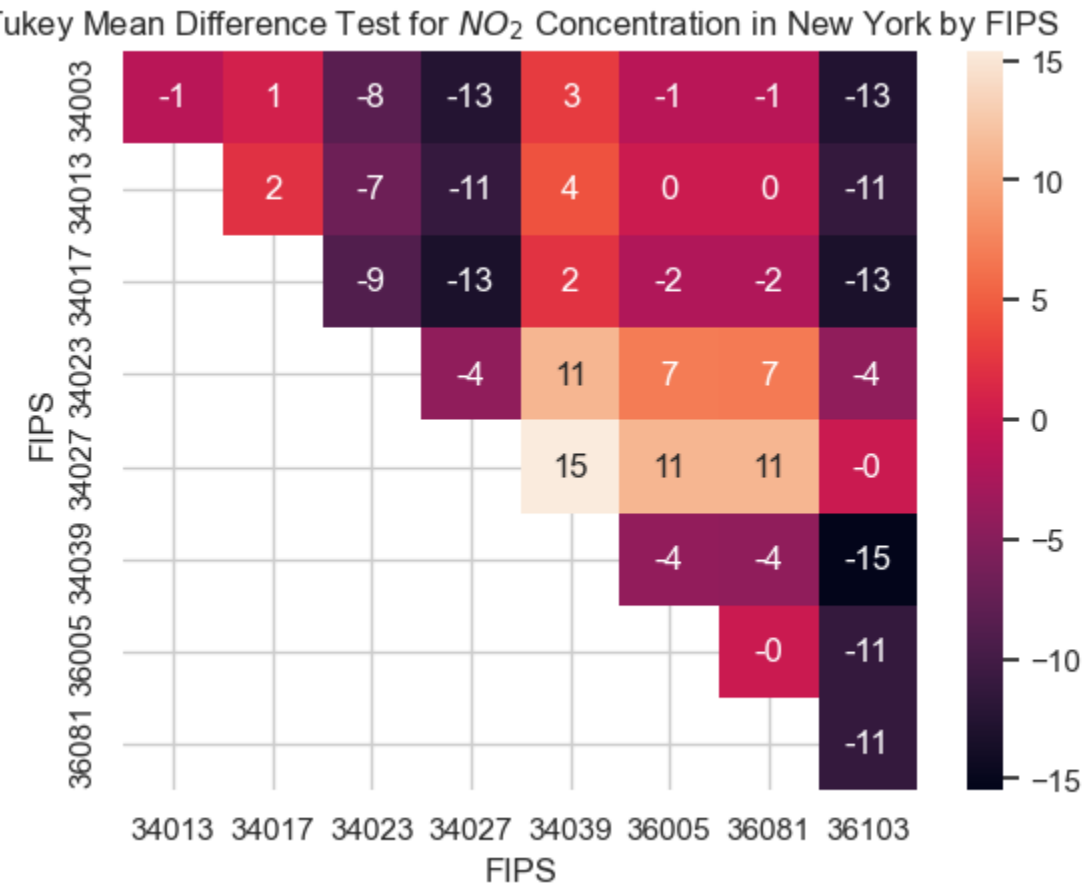
# $NO_2$ Concentration Difference FIPS Code



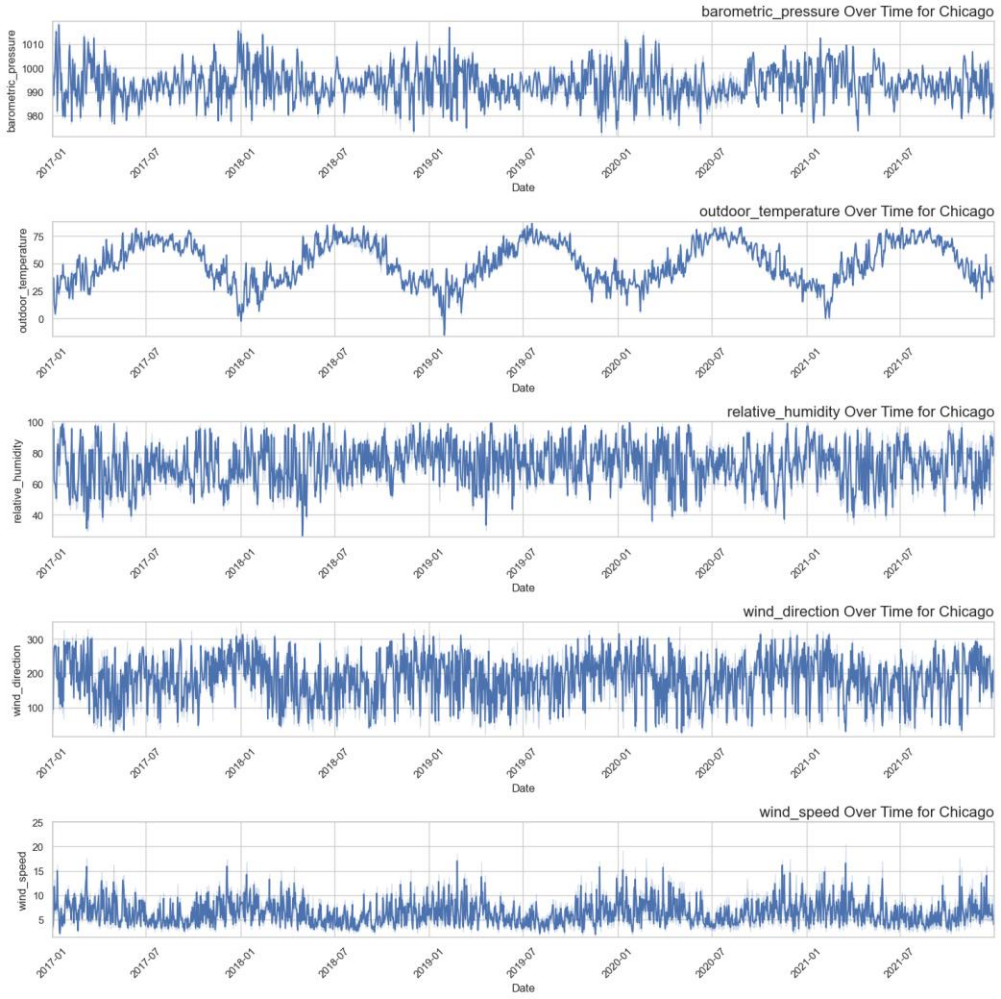



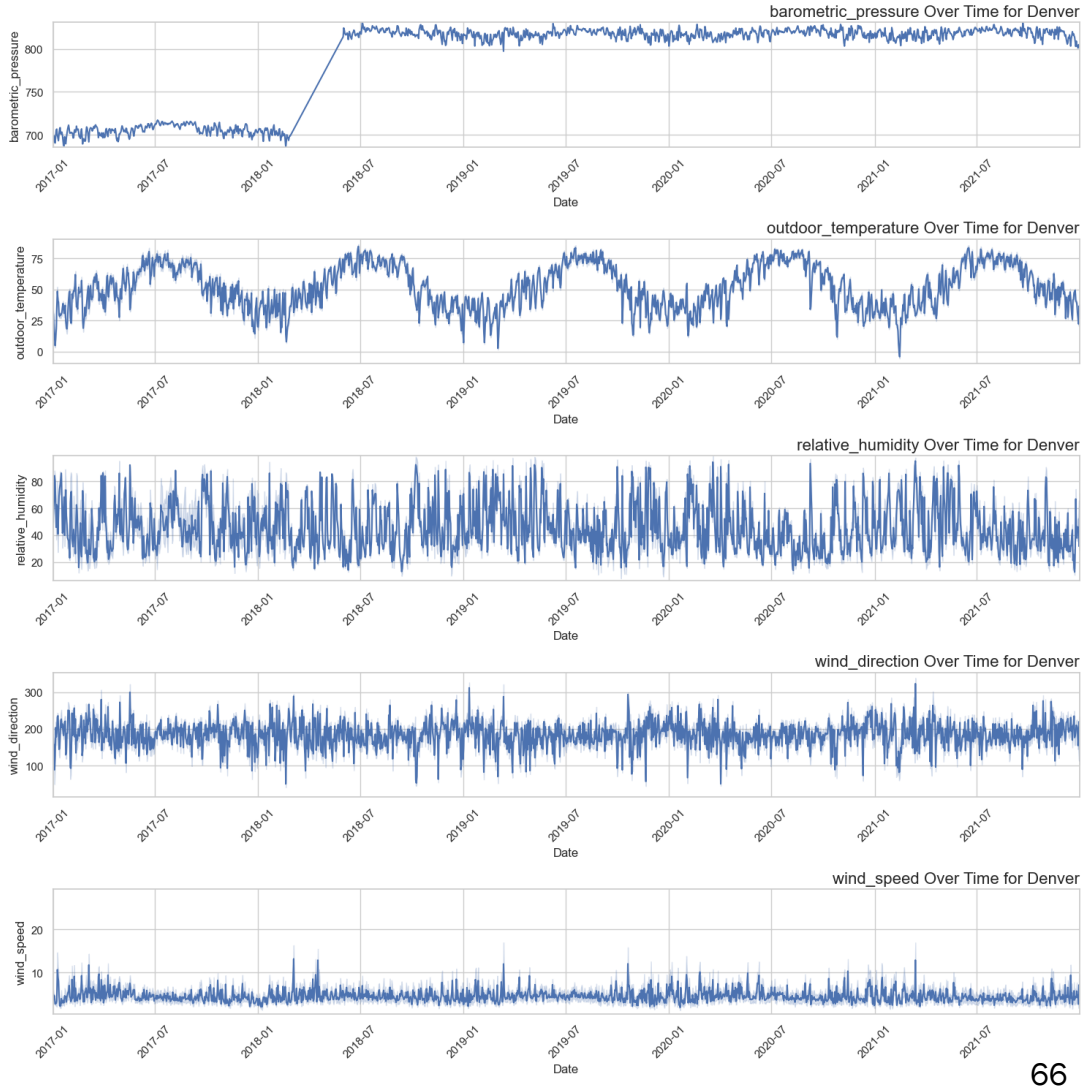
# $NO_2$ Concentration Difference FIPS Code



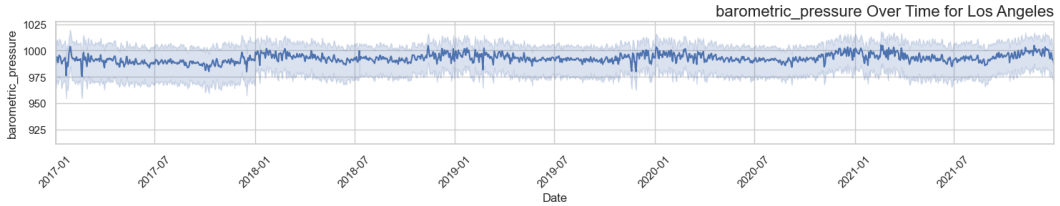



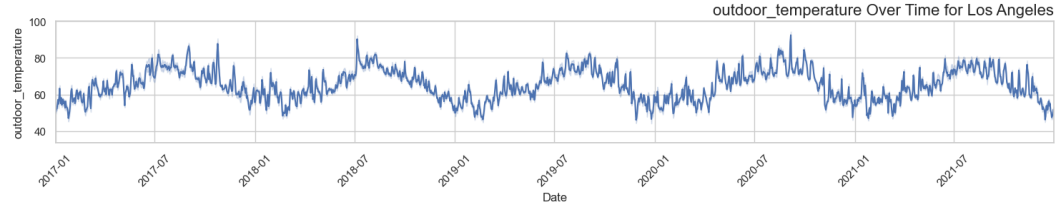
# Weather Data Over Time

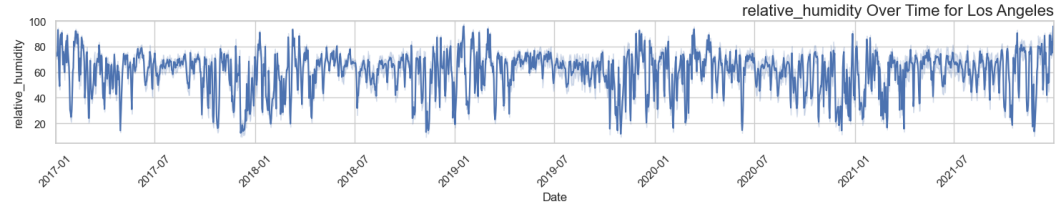


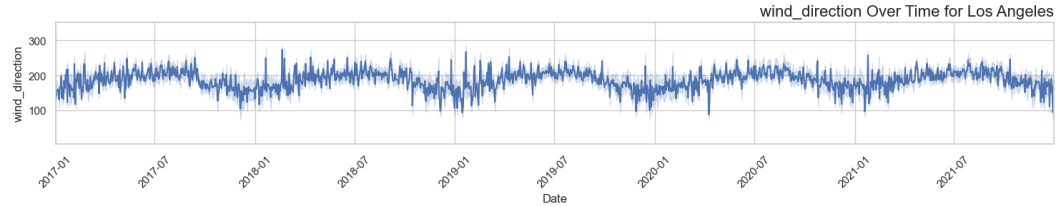



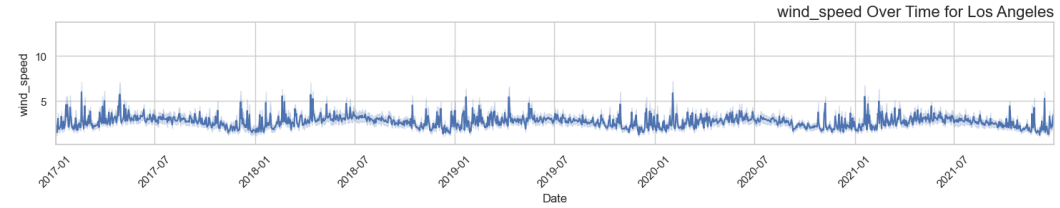
# Weather Data Over Time

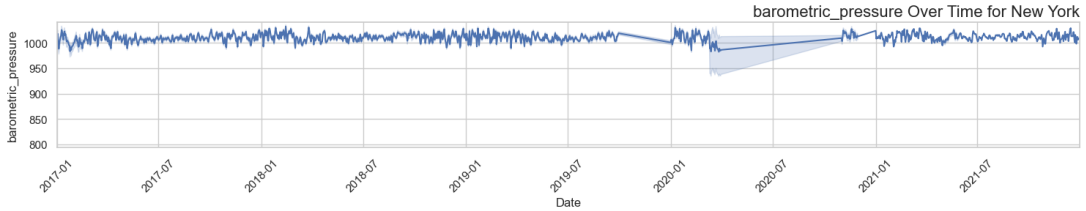


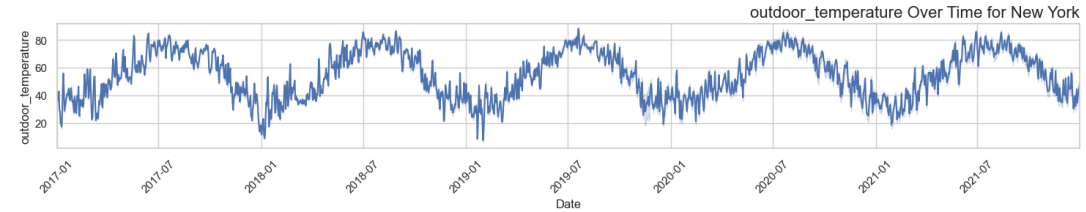



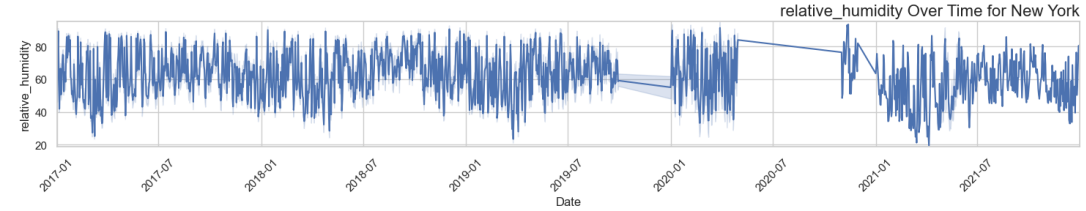



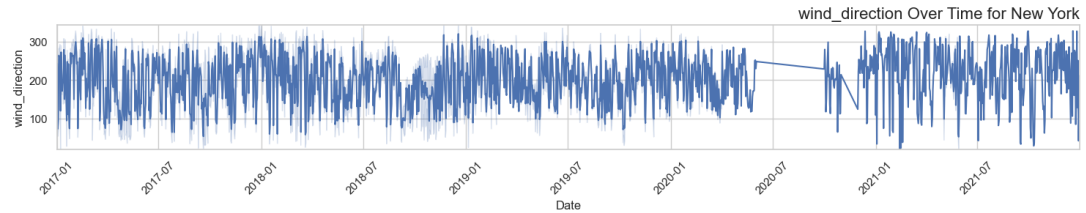



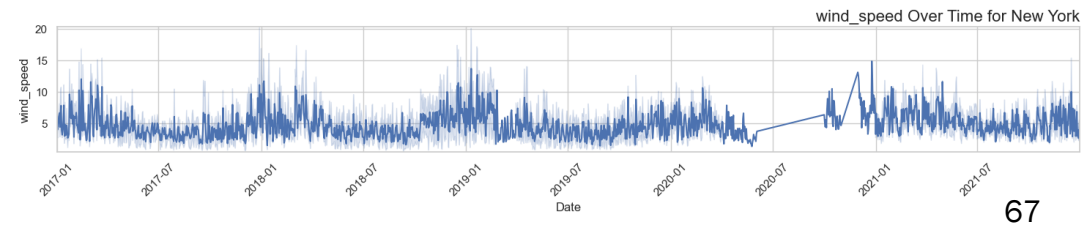



# Weather Data Over Time