

# Asthma and Air Pollution

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# Introduction & Background

## Current State

39% of Americans live in areas with poor air quality - an increase from last year

## Importance

Continuous exposure may lead to respiratory diseases

## Asthma Prevalence

7.6% of the U.S. population suffers from this condition



## Impact

Air pollution contributes to 334 million asthma cases worldwide

## Problem

Despite decades of effort and improvement, pollution levels are still unhealthy

## Racial Disparity

56% of people of color in the U.S. live in poor air quality regions

# Data Sources



# Air Quality Index

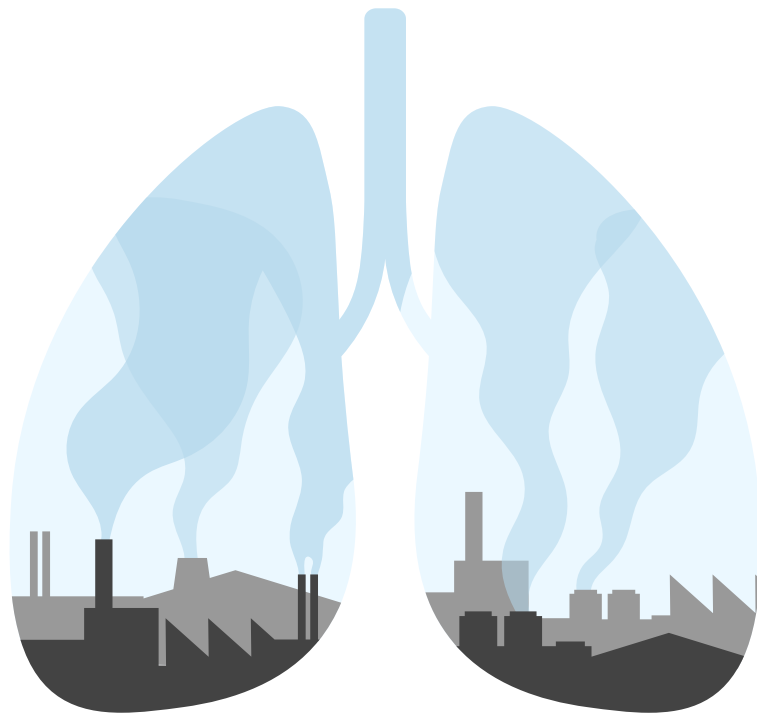
## WHAT IS IT?

AQI is a standard indicator for daily monitoring of how clean or polluted the air is.

## HOW IS IT USED?

Provided extensive data on the number of days each county records within each of these AQI categories.

Air Quality Index (AQI)	Levels of Health Concern
0-50	Good
51-100	Modest
101-150	Unhealthy For Sensitive Groups
151-200	Risky
201-300	Harmful
301-500	Dangerous



# Key Air Quality Indicators



PM

**Particulate Matter**  
Triggers inflammatory responses, including asthma attacks

NO<sub>2</sub>

**Nitrogen Dioxide**  
Asthmatic conditions and reduced lung function

CO

**Carbon Monoxide**  
Interferes with the blood's ability to carry oxygen

SO<sub>2</sub>

**Sulfur Dioxide**  
Worsen respiratory conditions and asthmatic symptoms

O<sub>3</sub>

**Ozone**  
Oxidative stress, airway inflammation, and lung failure

# Guiding Research Questions

## Main Question

What are the most significant environmental contaminants contribution to asthma incidence?

1

## Sub-Question

How do various environmental contaminants correlate differently with asthma incidence and health outcomes?

2

## Sub-Question

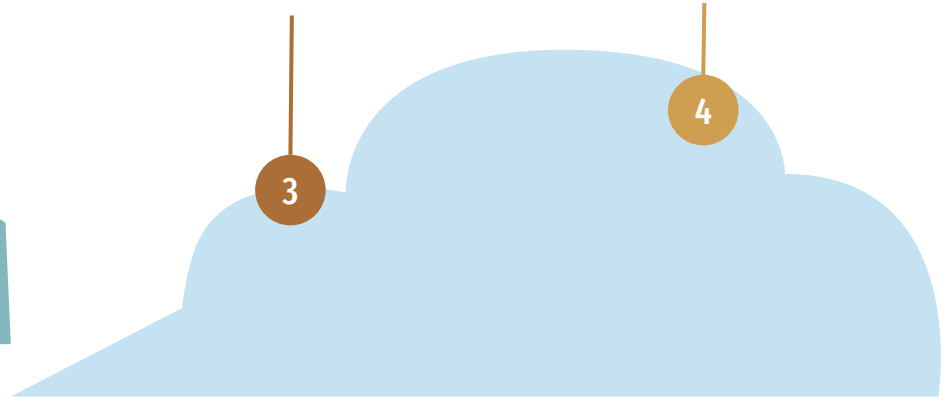
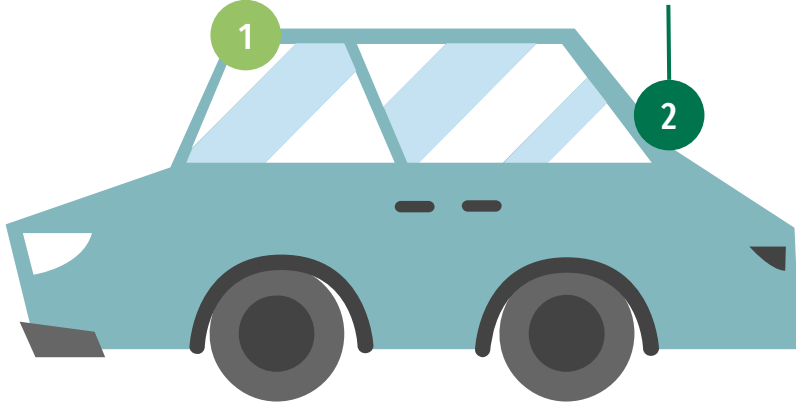
In what ways can machine learning algorithms utilize air quality and health data to predict asthma incidence?

3

## Sub-Question

Which machine learning algorithms demonstrate the highest accuracy and reliability in forecasting asthma trends?

4





# Methods Used

## PEARSON'S CORRELATION

1

Utilized to explore the relationship between air quality indicators and asthma-related health outcomes.

## RANDOM FOREST

2

Utilized to predict health outcomes based on air quality indicators. Focusing on a single county, we prepared our dataset and split it into training and test sets for validation.

## SARIMAX

3

An extension of ARIMA, for time series forecasting, considering both seasonality and external values.

# Exploratory Data Analysis

## Datasets

### 1. ER Visits

- Dropped years outside of 2005-2019

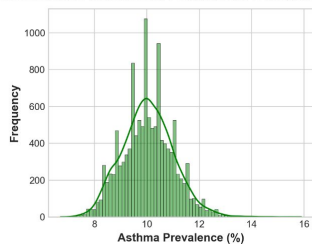
### 2. Hospitalizations

- Dropped years outside of 2005-2019

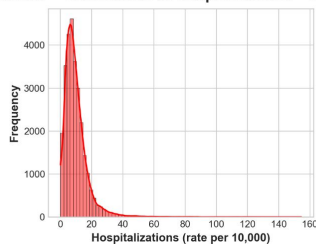
### 3. Prevalence

- Dropped due to insufficient and incomplete data

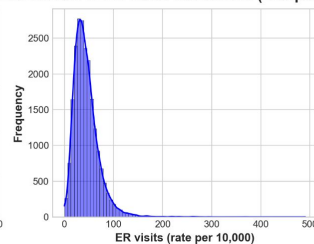
Distribution of Asthma Prevalence Percent Values



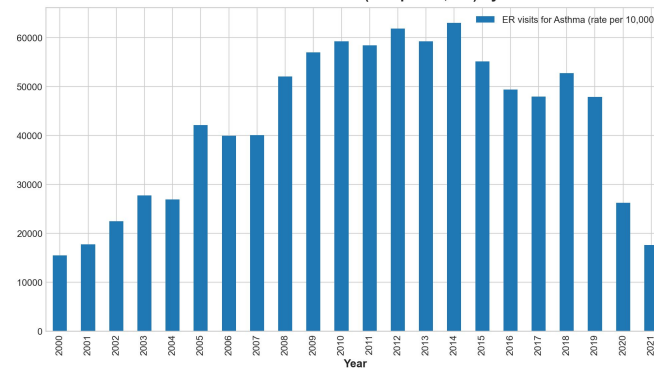
Distribution of Hospitalizations



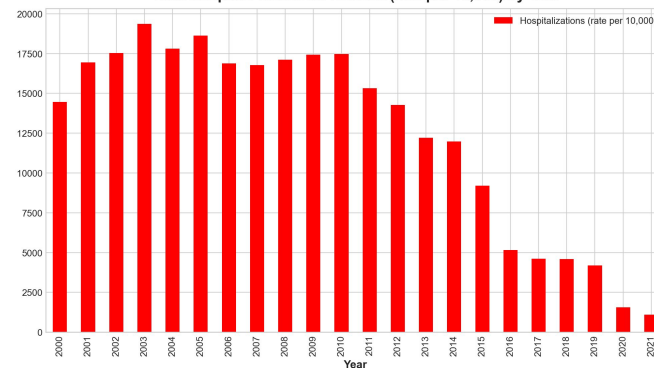
Distribution of ER visits for Asthma (rate per 10,000)



Total ER visits for Asthma (rate per 10,000) by Year



Total Hospitalizations for Asthma (rate per 10,000) by Year

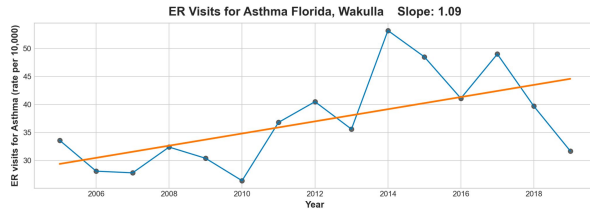




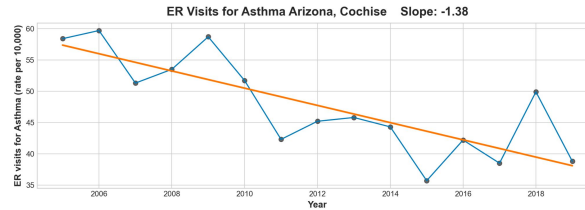
# Data Processing

## GROUPING

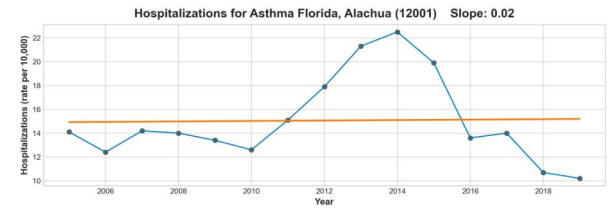
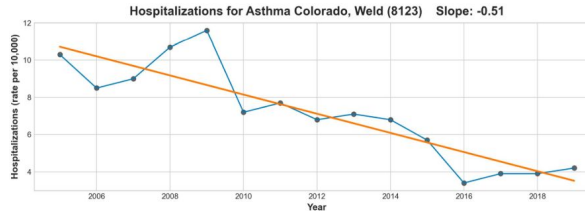
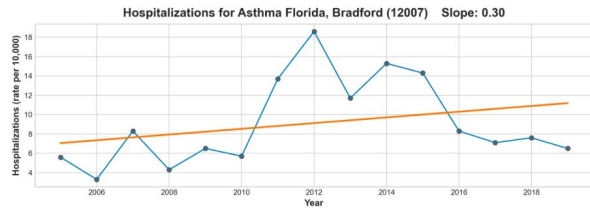
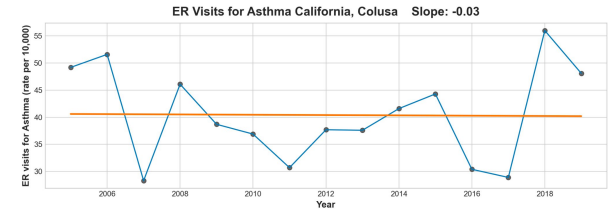
### Group A - Increasing Slope $> 0.1$



### Group B - Decreasing Slope $< -0.1$



### Group C - Neutral Slope $-0.1 < x < 0.1$



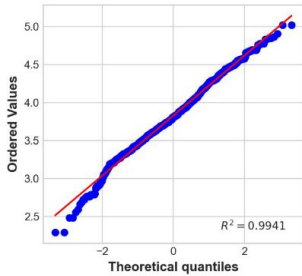
- Emergency Room visits group A consisted of 113 counties, group B contained 582 counties, and group C had 30.
- Hospitalizations group A contained data for 3 counties, group B had 671 counties, and group C contained 15 counties.
  - Due to the low number of counties in groups A and C for hospitalizations, these groups were dropped.

# Data Processing

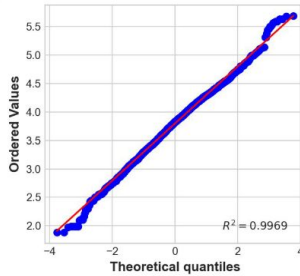
## NORMALIZING

### No Transformation

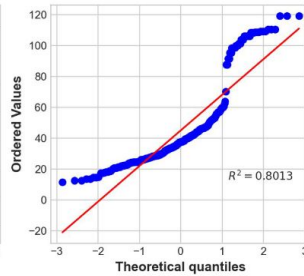
QQ Plot - ER Group A



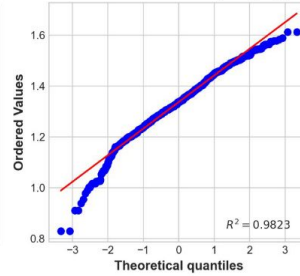
QQ Plot - ER Group B



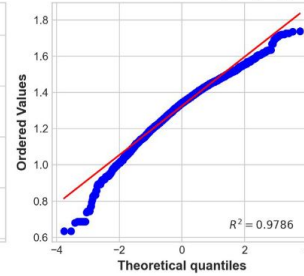
QQ Plot - ER Group C



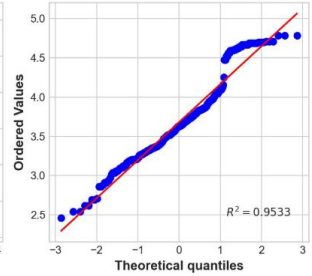
QQ Plot - ER Group A (log)



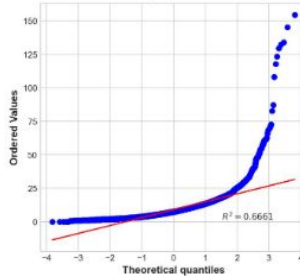
QQ Plot - ER Group B (log)



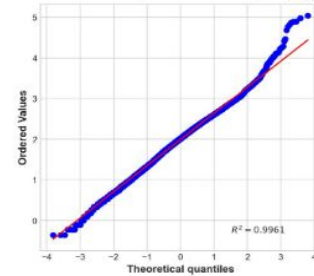
QQ Plot - ER Group C (log)



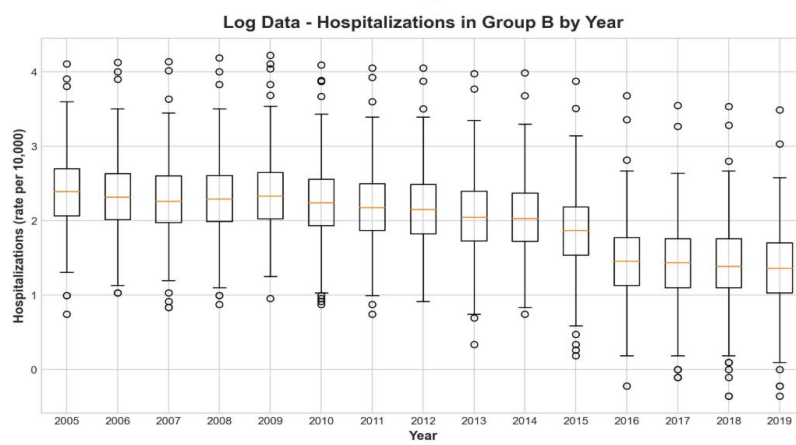
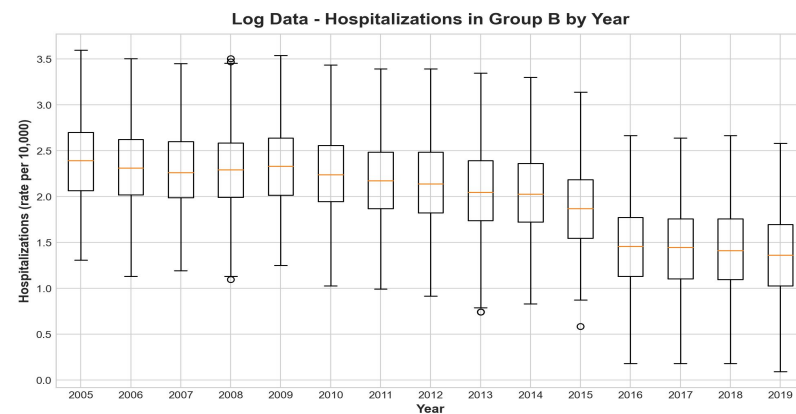
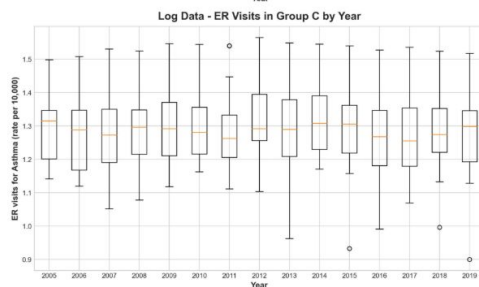
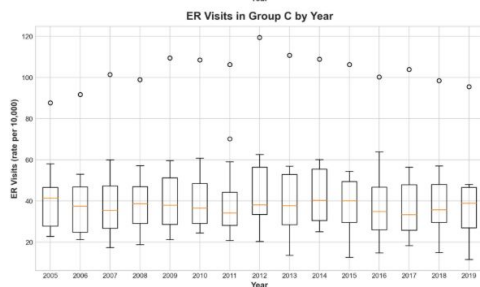
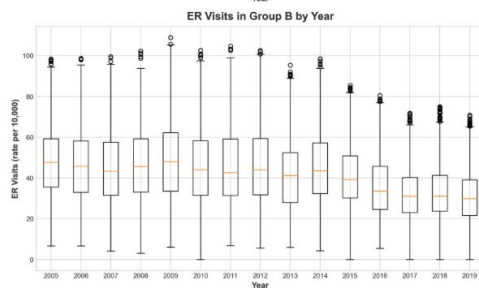
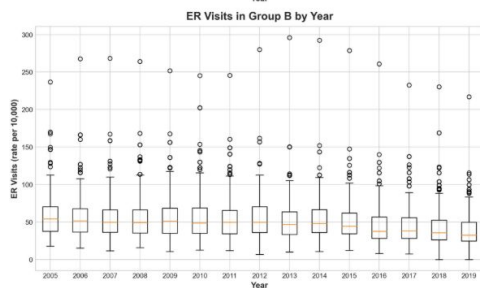
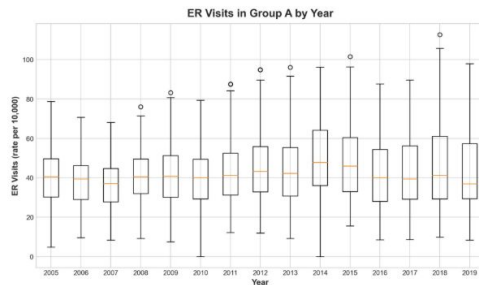
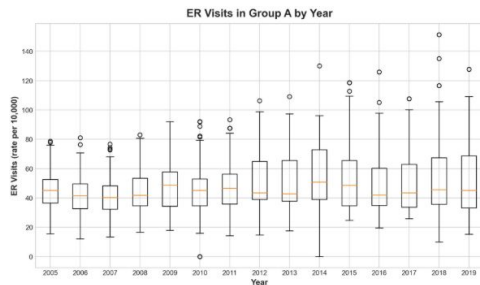
QQ Plot - Hospitalizations Group B



QQ Plot - Hospitalizations Group B (log)



# Outlier Removal



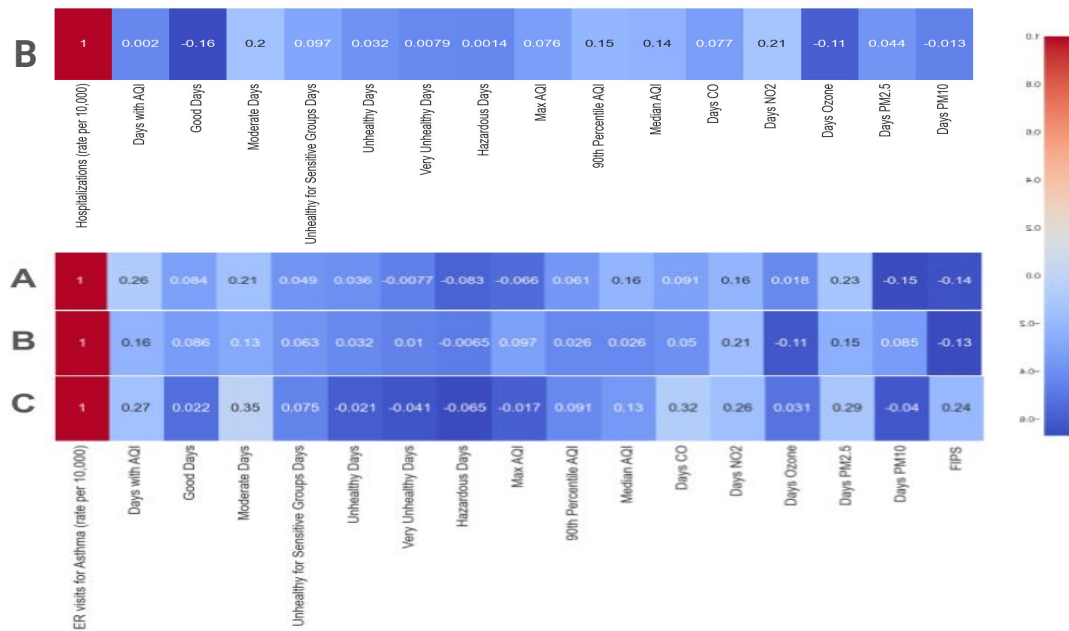
# Feature Selection

**Hospitalizations Group B:**  
Days NO2 and Moderate Days

**ER Visits Group A:**  
Days AQI and PM2.5

**ER Visits Group B:**  
Days AQI and NO2

**ER Visits Group C:**  
Moderate Days and CO



# Random Forest

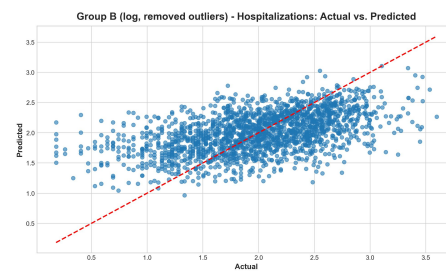
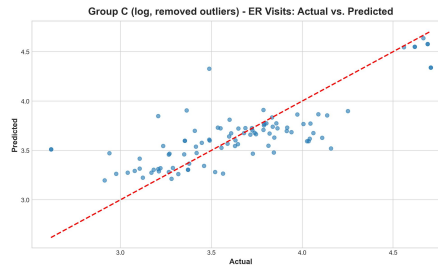
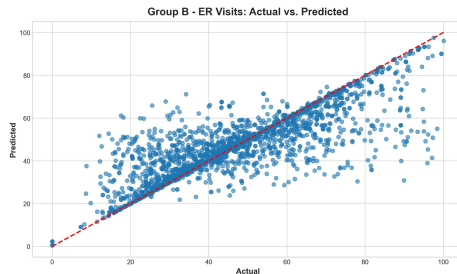
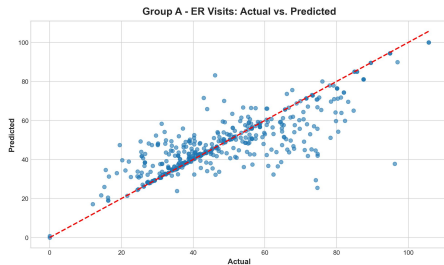
## 1. Test train split for each group:

- Test size = 0.3
- Random state = 42

## 2. Random Forest Regressor

- Features: all air quality metrics
- Target: ER visits and hospitalizations

Random Forest Summary			
Group	$R^2$ Score	MSE	RMSE
ER Visits Group A	0.65	105.84	10.29
ER Visits Group B	0.68	119.77	10.94
ER Visits Group C	0.63	0.08	0.27
Hospitalizations Group B	0.25	0.26	0.51



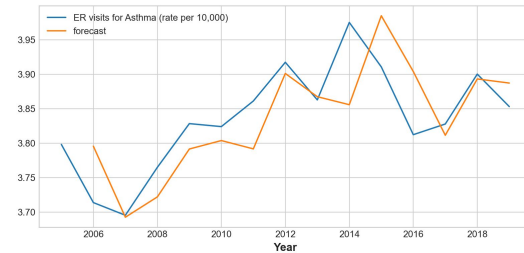
# SARIMAX

Autoregressive Integrated Moving Average with Exogenous Regressors

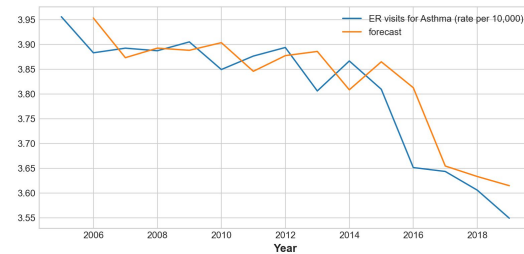
- Grouped by mean for each year
- Model order: (1,1,1) Seasonality Parameters: (1, 0, 0, 2).
- Exogenous variable: PM2.5

	ER Visits (A)	ER Visits (B)	ER Visits (C)	Hosp (B)
Ljung-Box (L1) (Q)	0.02	0.56	0.07	0.10
Prob(Q)	0.90	0.45	0.79	0.75
Heteroskedasticity (H)	0.22	4.01	3.06	10.64
Prob(H) (two-sided)	0.22	0.15	0.25	0.02
Jarque-Bera (JB)	0.60	1.01	0.78	3.24
Prob(JB)	0.74	0.60	0.68	0.20
Skew	0.44	-0.65	-0.02	-1.11
Kurtosis	2.51	3.11	1.84	3.81

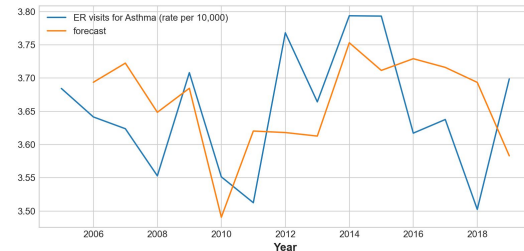
ER (A)



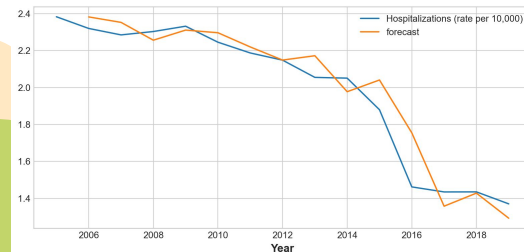
ER (B)



ER (C)



Hosp (B)



# Implications & Challenges

Our study highlights the importance of considering multiple air quality (AQI) for a more comprehensive understanding of asthma triggers

## **Broader Air Quality Assessment**

By pinpointing key pollutants and AQI factors, healthcare professionals can develop better strategies to manage asthma and reduce healthcare burden

## **Targeted Interventions**

Missing values and inconsistent geographical information limited the generalizability of our findings and required data grouping strategies

## **Incomplete Data**

Integrating data specific to county demographics could provide deeper insights into the environmental factors affecting asthma outcomes

## **Need For More Detailed Data**

# Discussion & Conclusions

The study confirms a link between air pollutants (PM2.5, NO2) and median AQI with asthma cases and hospitalizations.

While machine learning models offer promise for analyzing specific pollutants, their effectiveness in this study highlights the need for further refinement of these models for broader public health

Mitigating air pollution is crucial, but interventions should also address determinants of healthcare accessibility to achieve a more substantial reduction in asthma related injuries

The study lays the groundwork for utilizing machine learning as a tool to inform public health strategies and develop community-specific solutions to address asthma





# References

1. Andrew C. Leon. "3.12 - Descriptive and Inferential Statistics." In: *Comprehensive Clinical Psychology*. Oxford: Pergamon, 1998, pp. 243-285. ISBN: 978-0-042707-2.
2. Ioannis Mansialidis et al. "Environmental and Health Impacts of Air Pollution: A Review". In: 8.14 (Feb. 2020). DOI: 10.3389/fpubh.2020.00014.
3. Manuel Méndez, Mercedes G. Merayo, and Manuel Núñez. "Machine learning algorithms to forecast air quality: a survey". en. In: *Artificial Intelligence Review* 56.9 (Sept. 2023), pp. 10031-10066. ISSN: 1573-7462. DOI: 10.1007/s10462-023-10424-4.
4. *State of the Air*. 2023. URL: <https://www.lung.org/research/sota/key-findings#:~:text=The%20%E2%80%9CState%20of%20the%20Air,of%20ozone%20or%20particle%20pollution.>