Exploratory Data Analysis (EDA) of Air Quality Index (AQI) in Major Indian Cities

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Load AQI dataset
df = pd.read_csv("/content/Final_AQI.csv", parse_dates=['Date'])
df.head()
```

	Date	PM2.5	PM10	NO2	CO	Ozone	City	AQI_PM2.5	AQI_PM10	AQI_NO2	AQI_CO	AQI_Ozone	AQI
0	2024-01-02	104.79	146.30	44.64	1.35	53.47	Indore	248.076207	131.098658	55.573333	64.611111	53.47	248.076207
1	2024-01-04	114.69	161.47	39.49	1.54	38.37	Indore	281.872759	141.178054	49.362500	74.955556	38.37	281.872759
2	2024-01-06	88.81	122.08	48.94	1.53	43.09	Indore	195.937586	115.006174	60.975897	74.411111	43.09	195.937586
3	2024-01-07	66.61	93.93	46.25	1.25	30.89	Indore	120.151379	93.930000	57.596154	59.166667	30.89	120.151379
4	2024-01-08	94.56	141.99	51.93	1.64	49.13	Indore	213.153103	128.234966	64.732564	80.400000	49.13	213.153103

```python
df.info()
```

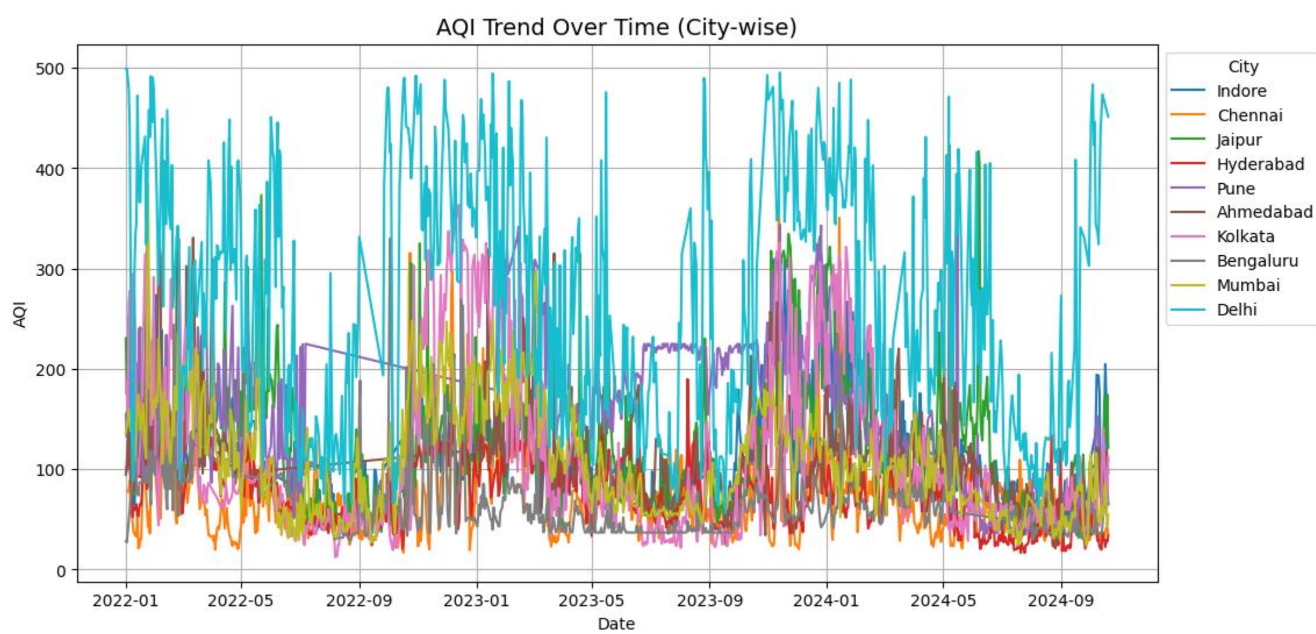
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8252 entries, 0 to 8251
Data columns (total 13 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       8252 non-null   datetime64[ns]
 1   PM2.5      8252 non-null   float64
 2   PM10       8252 non-null   float64
 3   NO2        8252 non-null   float64
 4   CO         8252 non-null   float64
 5   Ozone      8252 non-null   float64
 6   City       8252 non-null   object
 7   AQI_PM2.5  8252 non-null   float64
 8   AQI_PM10   8252 non-null   float64
 9   AQI_NO2    8252 non-null   float64
 10  AQI_CO     8252 non-null   float64
 11  AQI_Ozone  8252 non-null   float64
 12  AQI        8252 non-null   float64
dtypes: datetime64[ns](1), float64(11), object(1)
memory usage: 838.2+ KB
```

```
df.describe()
```

	Date	PM2.5	PM10	NO2	CO	Ozone	AQI_PM2.5	AQI_PM10	AQI_NO2	AQI_CO	AQI_Ozone	AQI
count	8252	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000	8252.000000
mean	2023-06-07 17:33:07.590886912	47.140606	111.592569	38.939124	1.053259	26.334747	87.105349	102.558761	47.247326	48.337511	26.374552	118.505874
min	2022-01-01 00:00:00	1.200000	4.946429	0.100000	0.000000	0.280000	2.000000	4.946429	0.125000	0.000000	0.280000	12.450000
25%	2022-09-24 00:00:00	20.842813	54.148958	13.125148	0.500000	11.462196	34.738021	54.148958	16.406434	25.000000	11.462196	60.025000
50%	2023-06-20 00:00:00	35.920000	87.692708	25.420000	0.744521	21.669792	59.313103	87.692708	31.775000	37.226066	21.669792	96.107292
75%	2024-02-18 00:00:00	57.998698	137.969808	51.062500	1.372370	35.997231	96.618490	125.563832	63.642628	65.829022	35.997231	145.079052
max	2024-10-20 00:00:00	424.810000	598.950000	281.830000	8.707407	181.700000	470.105181	499.384911	301.690504	183.801688	233.238462	499.384911
std	NaN	42.148336	88.505692	39.502543	0.807615	19.561330	82.616933	74.395676	45.196637	30.811572	19.799977	84.725075

AQI Trend Over Time

```
plt.figure(figsize=(12, 6))
sns.lineplot(x='Date', y='AQI', hue='City', data=df, palette="tab10")
plt.title("AQI Trend Over Time (City-wise)", fontsize=14)
plt.xlabel("Date")
plt.ylabel("AQI")
plt.legend(title="City", bbox_to_anchor=(1,1))
plt.grid()
plt.show()
```



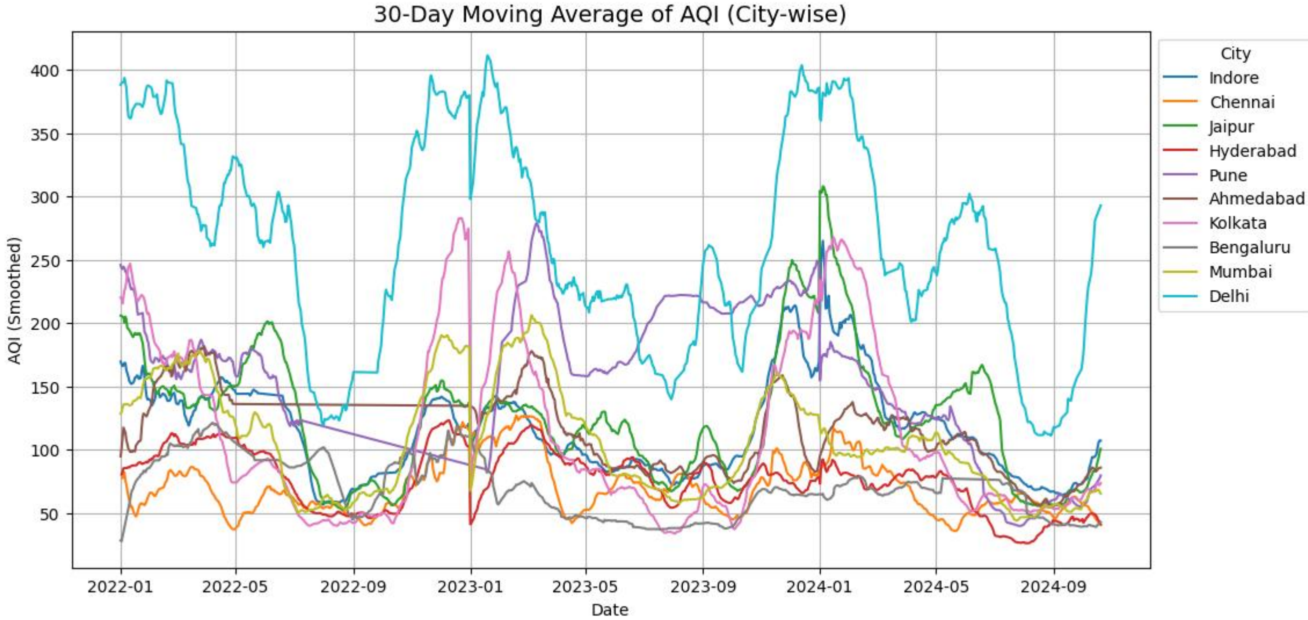
Observation: AQI fluctuates over time, with some cities showing a clear increasing trend, especially during winter months.

Insight: This indicates seasonal pollution variations, possibly due to weather conditions and human activities.

Moving Averages (Seasonality)

```
# Calculate 30-day moving average for AQI
df['AQI_MA'] = df.groupby('City')['AQI'].transform(lambda x: x.rolling(30,
min_periods=1).mean())

plt.figure(figsize=(12, 6))
sns.lineplot(x='Date', y='AQI_MA', hue='City', data=df, palette="tab10")
plt.title("30-Day Moving Average of AQI (City-wise)", fontsize=14)
plt.xlabel("Date")
plt.ylabel("AQI (Smoothed)")
plt.legend(title="City", bbox_to_anchor=(1,1))
plt.grid()
plt.show()
```



Observation: The 30-day moving average smooths out fluctuations, revealing periodic AQI increases.

Insight: There are seasonal cycles where AQI spikes, likely linked to weather, industrial activities, and vehicular pollution.

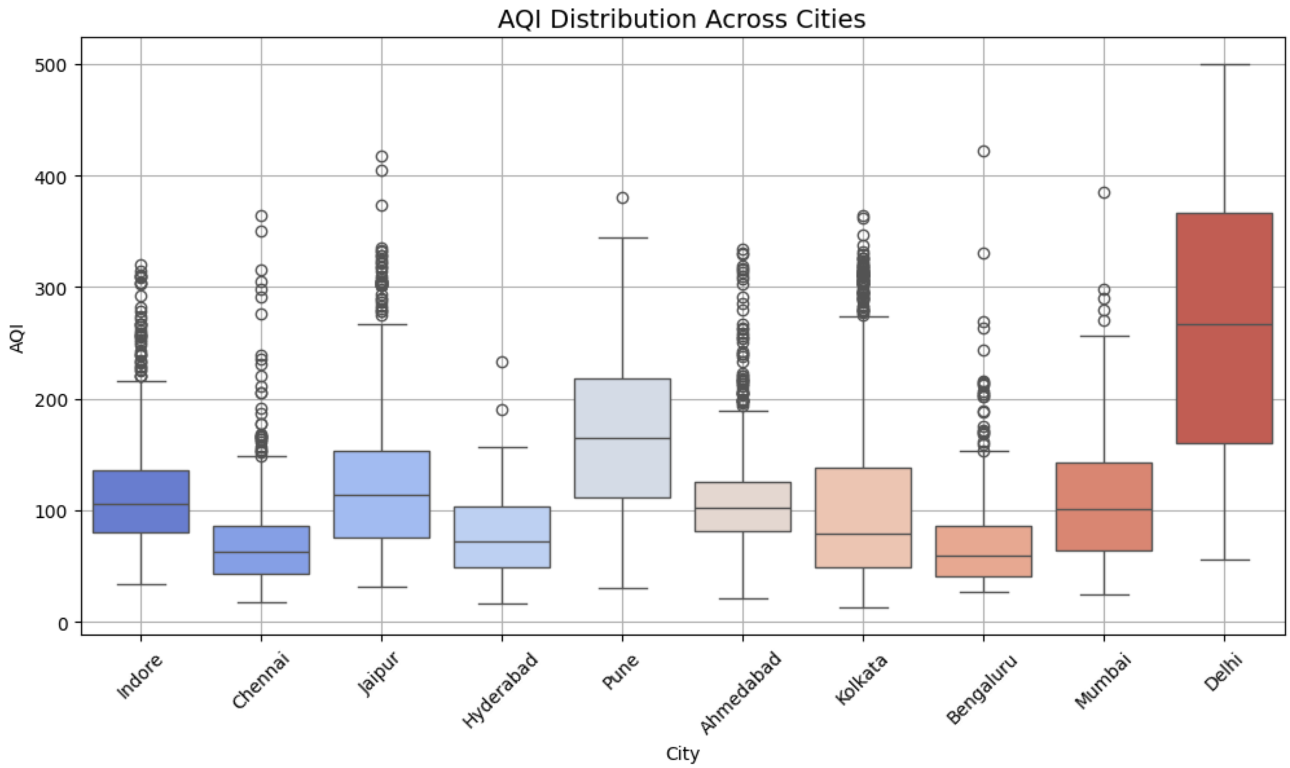
AQI Distribution (City-wise)

```
plt.figure(figsize=(12, 6))
sns.boxplot(x="City", y="AQI", data=df, palette="coolwarm")
plt.title("AQI Distribution Across Cities", fontsize=14)
plt.xticks(rotation=45)
plt.grid()
plt.show()
```

```
<ipython-input-30-816a593862b3>:2: FutureWarning:

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

  sns.boxplot(x="City", y="AQI", data=df, palette="coolwarm")
```



Observation: Some cities have consistently higher AQI values, while others show large variations.

Insight: Cities like Delhi and Mumbai show persistently high AQI, indicating chronic pollution problems, while others have occasional spikes.

Decomposing AQI (Trend, Seasonality, Residuals)

Delhi

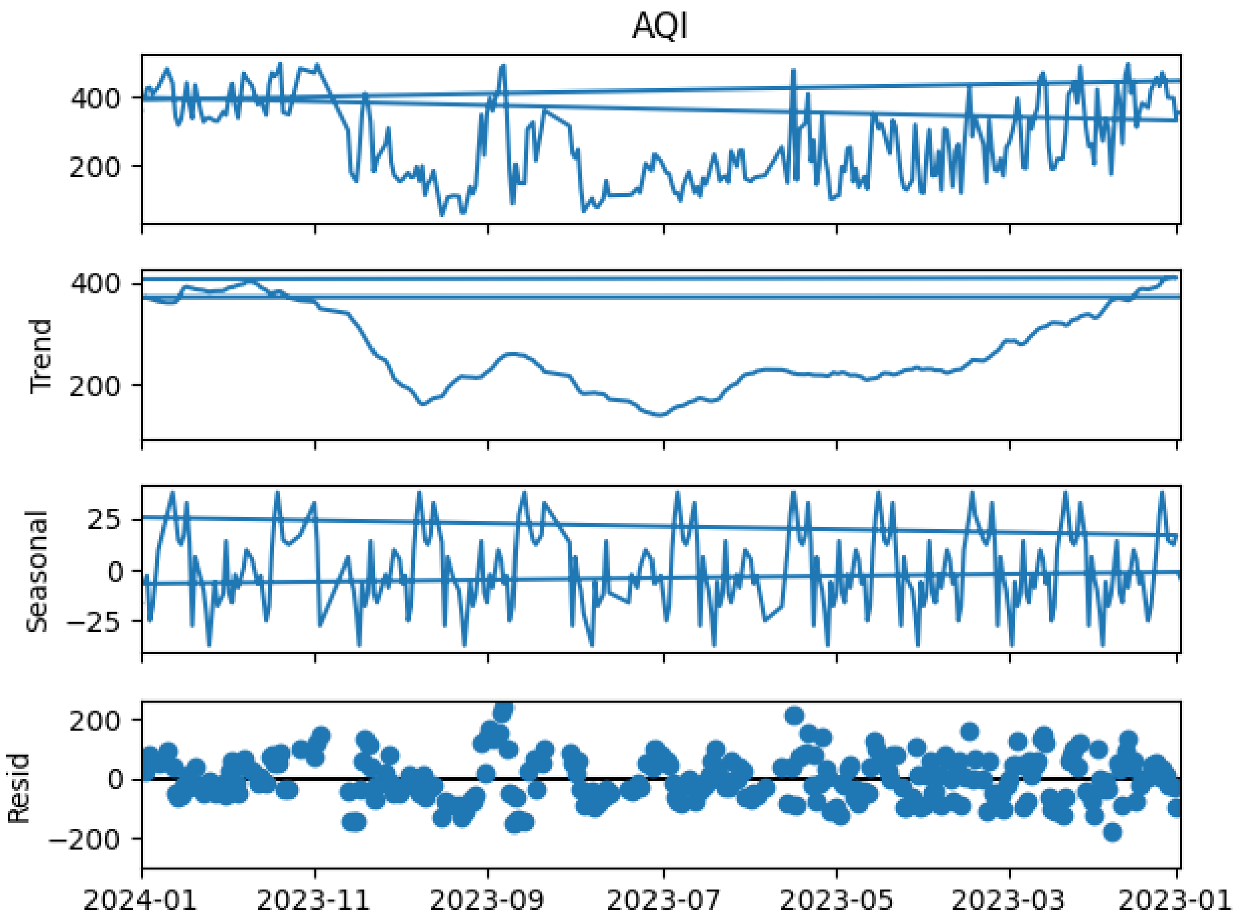
```
city = "Delhi"  # Choose a city
city_df = df[df["City"] == city].set_index("Date")  # Filter city data

decomposition = seasonal_decompose(city_df['AQI'], model='additive',
period=30)

plt.figure(figsize=(12, 8))
```

```
decomposition.plot()
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



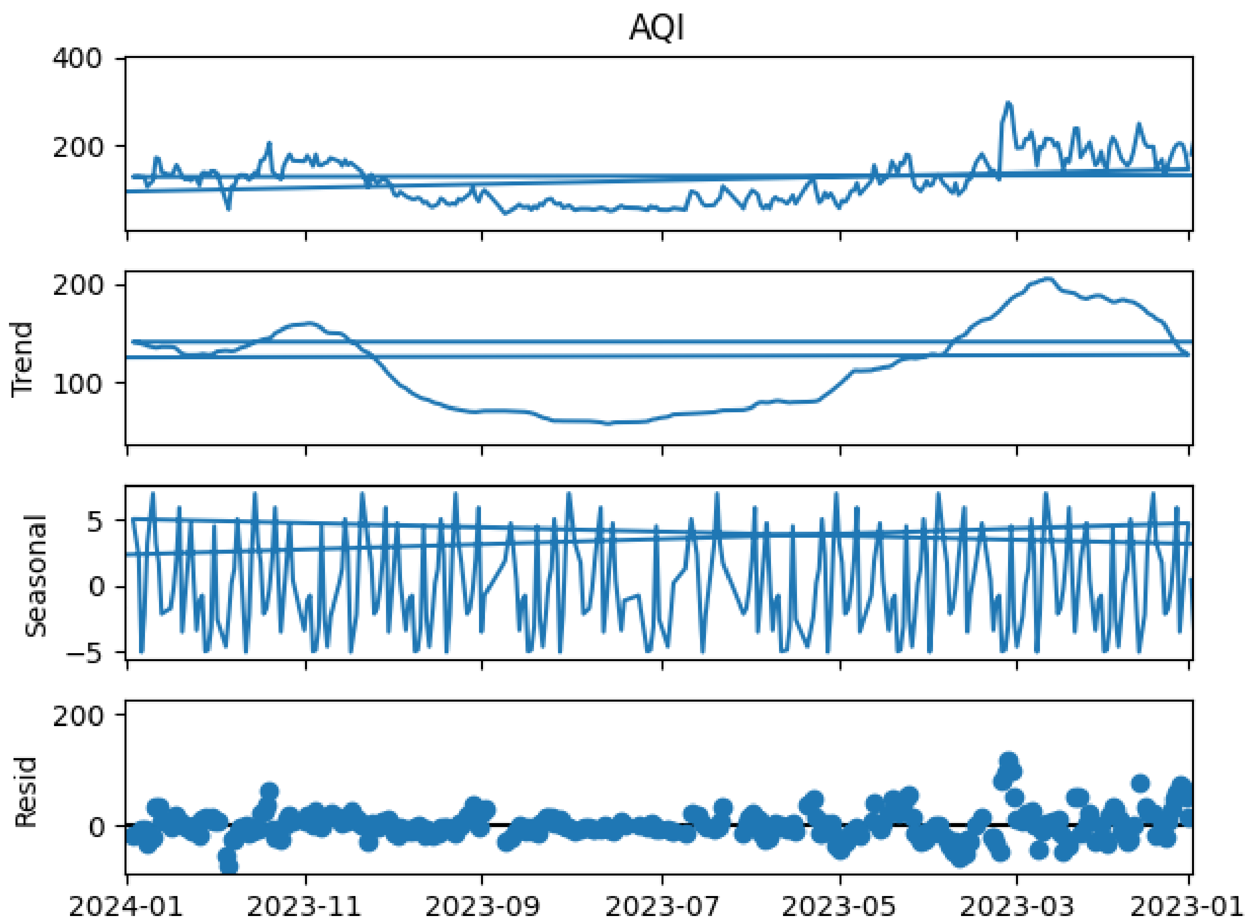
Mumbai

```
city = "Mumbai"  # Choose a city
city_df = df[df["City"] == city].set_index("Date")  # Filter city data

decomposition = seasonal_decompose(city_df['AQI'], model='additive',
period=30)

plt.figure(figsize=(12, 8))
decomposition.plot()
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



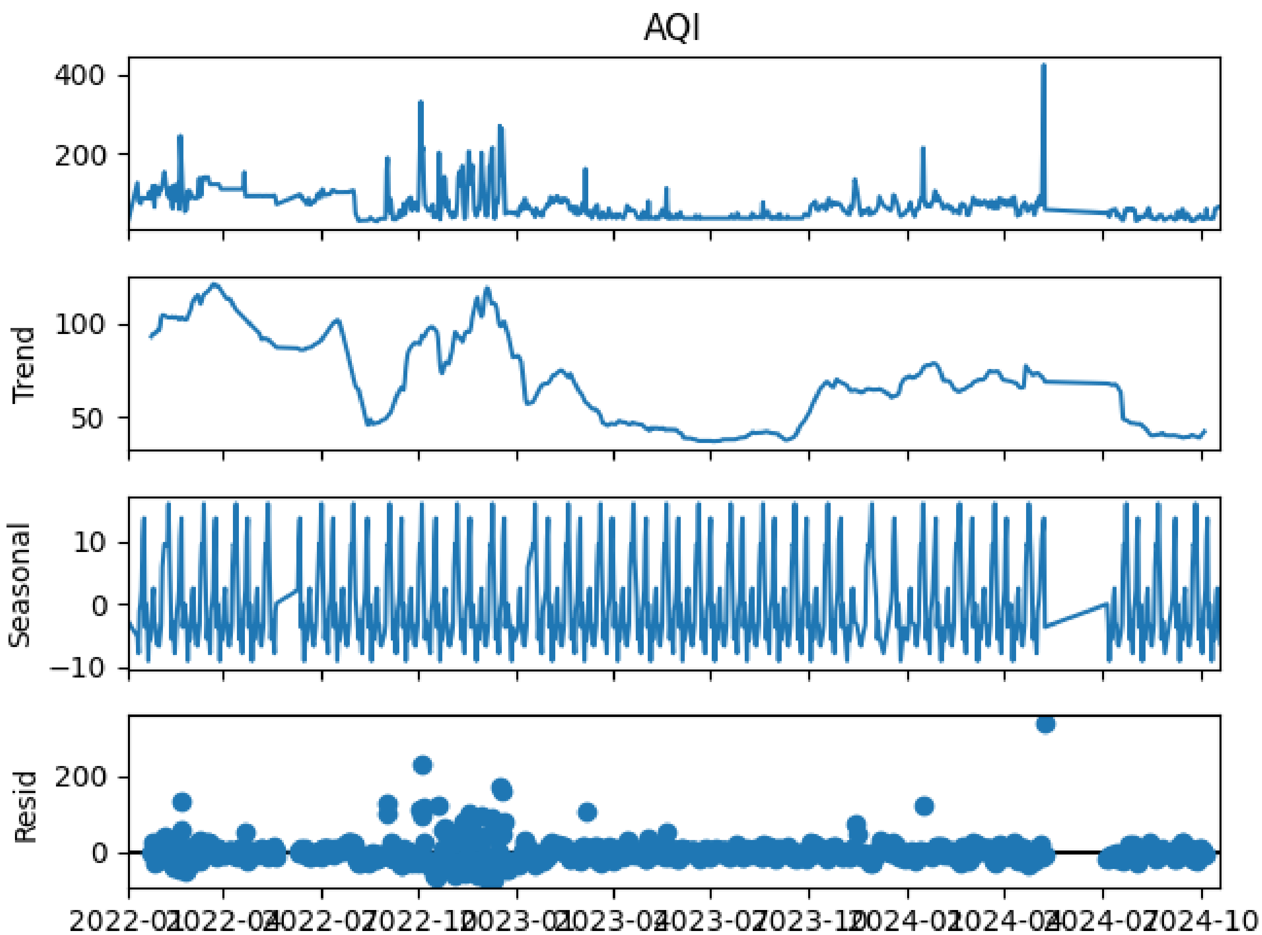
Bengaluru

```
city = "Bengaluru"  # Choose a city
city_df = df[df["City"] == city].set_index("Date")  # Filter city data

decomposition = seasonal_decompose(city_df['AQI'], model='additive',
period=30)

plt.figure(figsize=(12, 8))
decomposition.plot()
plt.show()

<Figure size 1200x800 with 0 Axes>
```

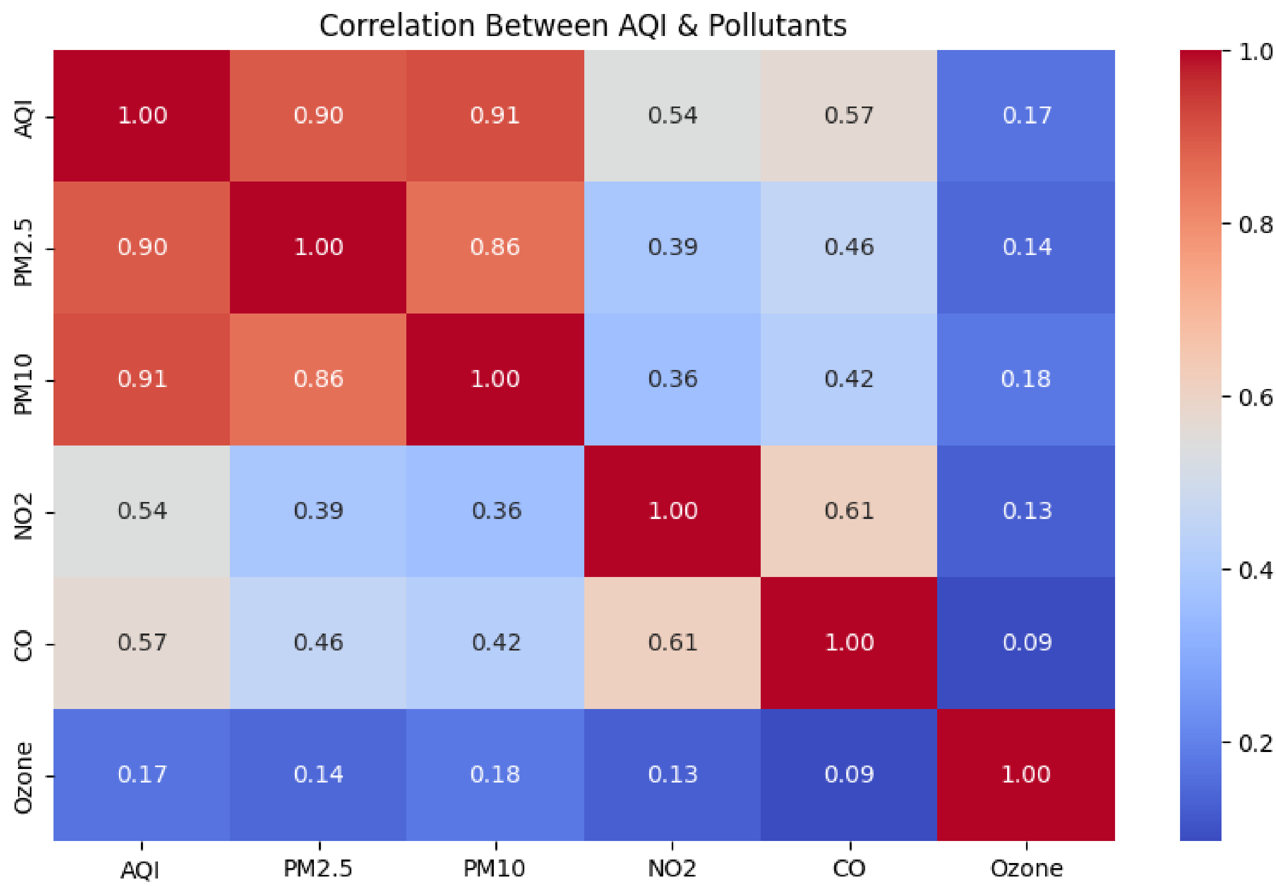


Observation: A strong upward trend is visible in some cities, and seasonal patterns are noticeable.

Insight: AQI prediction models should consider both long-term trends and seasonal effects for better accuracy.

Correlation Between AQI & Pollutants

```
plt.figure(figsize=(10,6))
sns.heatmap(df[['AQI', 'PM2.5', 'PM10', 'NO2', 'CO', 'Ozone']].corr(),
annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Between AQI & Pollutants")
plt.show()
```



Observation: PM2.5 and PM10 show the highest correlation with AQI, followed by NO_2. CO and Ozone have lower correlations.

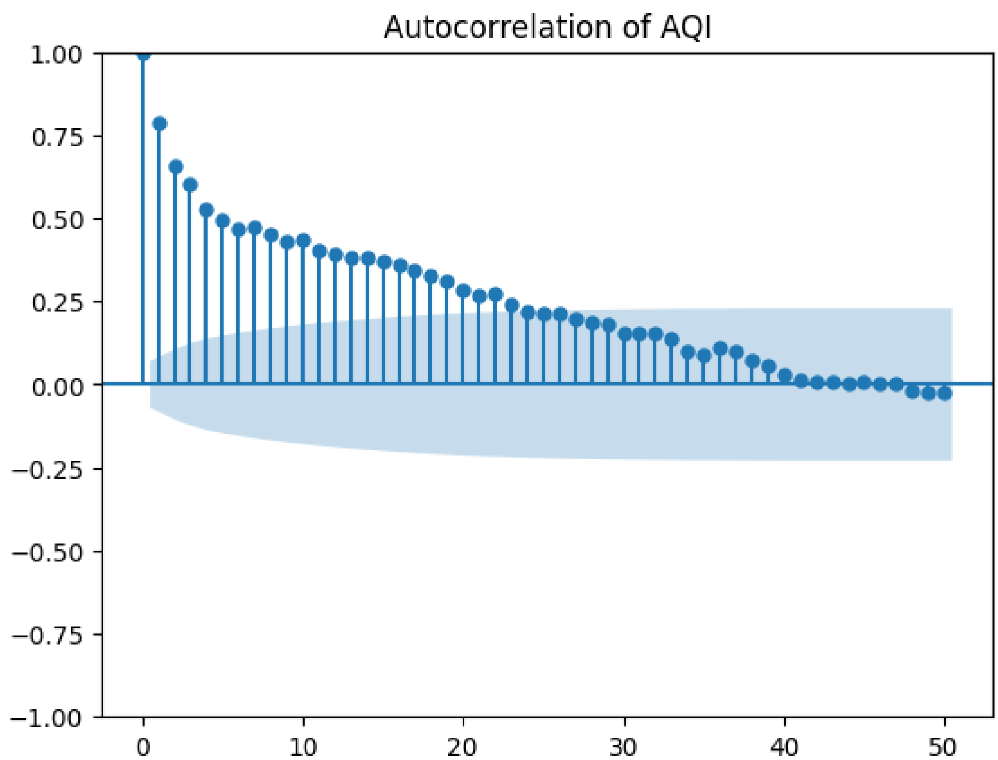
Insight: Fine particulate matter (PM2.5 & PM10) is the major contributor to air pollution, likely from vehicular emissions and construction dust.

Autocorrelation & Partial Autocorrelation

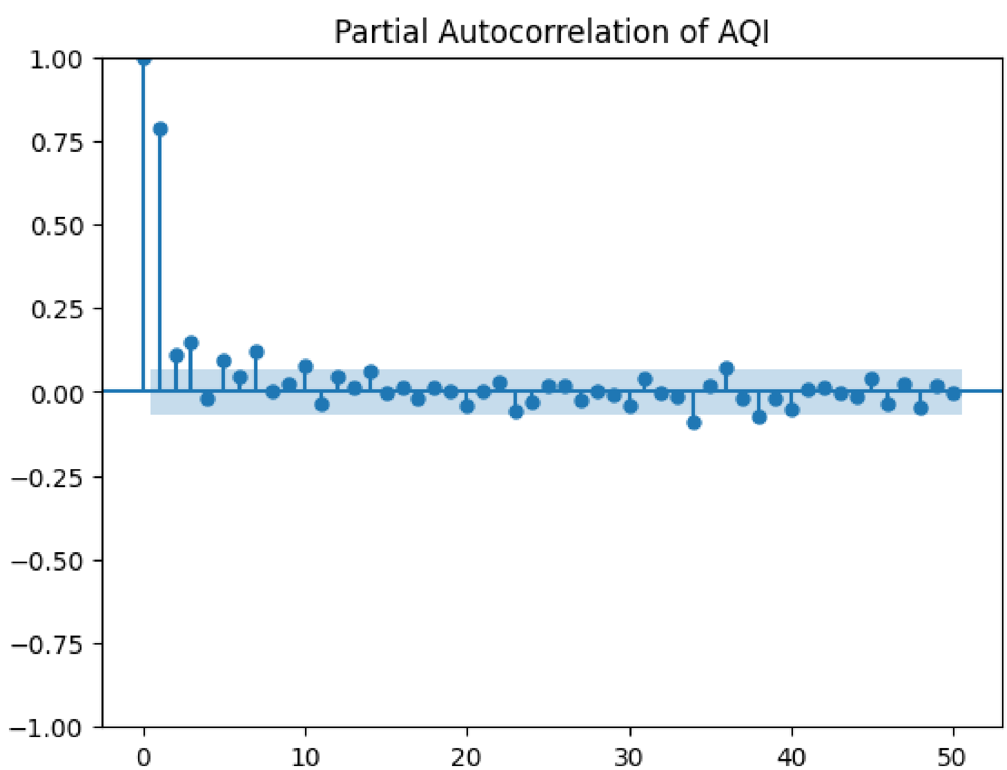
```
plt.figure(figsize=(12, 5))
plot_acf(city_df['AQI'], lags=50)
plt.title("Autocorrelation of AQI")
plt.show()

plt.figure(figsize=(12, 5))
plot_pacf(city_df['AQI'], lags=50)
plt.title("Partial Autocorrelation of AQI")
plt.show()
```

```
<Figure size 1200x500 with 0 Axes>
```



<Figure size 1200x500 with 0 Axes>



Observation: AQI values are highly correlated with past values, with a significant autocorrelation up to 30-50 days.

Insight: LSTM models should use past 30-50 days of AQI data as input features for forecasting.

City-Wise Pollution Ranking

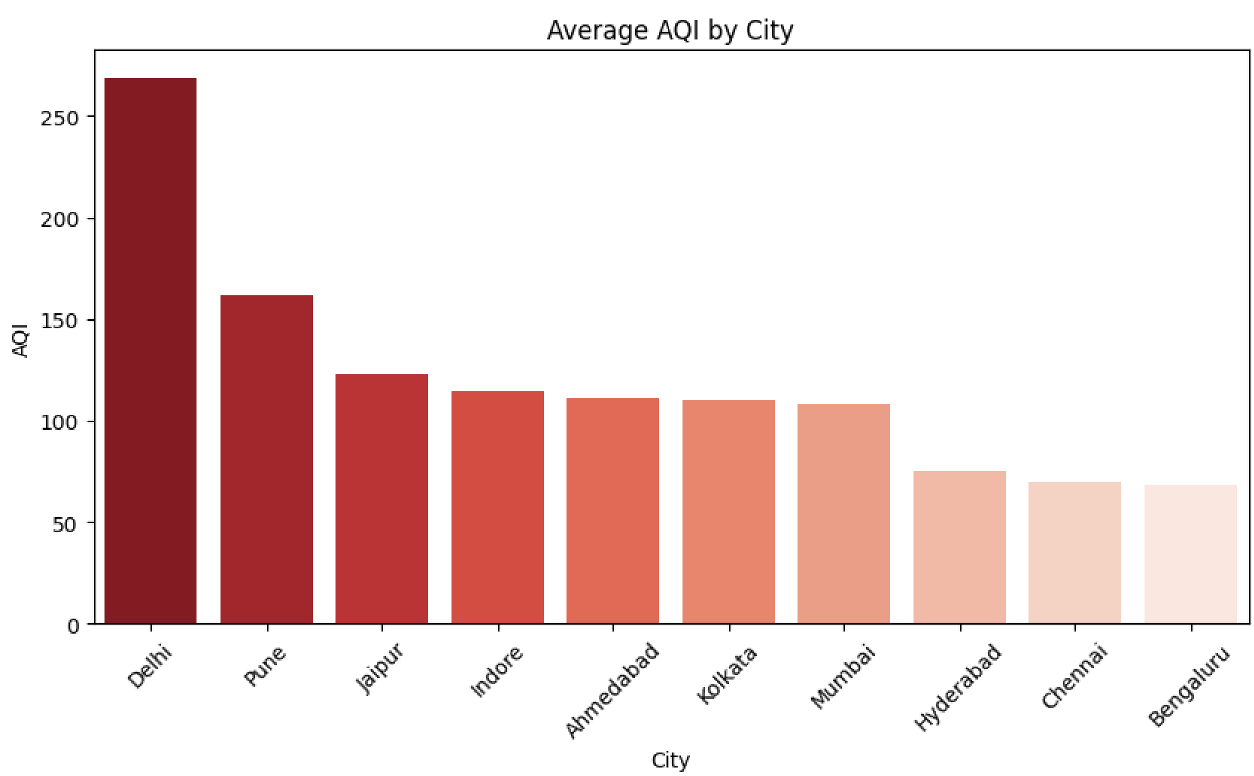
```
city_avg_aqi = df.groupby('City')['AQI'].mean().sort_values(ascending=False)

plt.figure(figsize=(10,5))
sns.barplot(x=city_avg_aqi.index, y=city_avg_aqi.values, palette="Reds_r")
plt.title("Average AQI by City")
plt.xticks(rotation=45)
plt.ylabel("AQI")
plt.show()
```

```
<ipython-input-34-a44a82e8bb66>:4: FutureWarning:

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

  sns.barplot(x=city_avg_aqi.index, y=city_avg_aqi.values, palette="Reds_r")
```



Observation: Cities like Delhi, Kolkata, and Mumbai have the highest AQI, while others like Bangalore are relatively cleaner.

Insight: Policy makers should focus on stricter pollution controls in highly polluted cities.

Conclusion

- AQI trends are highly seasonal, with winter months showing higher pollution.
- PM2.5 & PM10 are the biggest contributors to air pollution.
- Forecasting models should use at least 30-50 days of past data for accurate predictions.
- Policy actions should target high-pollution cities for effective air quality management.