CELEBAL TECHNOLOGIES

PROJECT: Air Quality Prediction for Urban Areas

GROUP: 1

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In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import chart_studio.plotly as py
import plotly.graph_objs as go
from plotly.offline import iplot, init_notebook_mode
import cufflinks
cufflinks.go_offline()
cufflinks.set_config_file(world_readable=True, theme='pearl')
from sklearn.model_selection import train_test_split
from sklearn import metrics
from math import sqrt
import requests
from sklearn.metrics import mean_squared_error, r2_score
```

In [2]:
```
df=pd.read_csv('Air_Quality.csv',parse_dates = ["Date"])
df
```

Out[2]:

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	AQI_Bucket
0	Ahmedabad	2015-01-01	NaN	NaN	0.92	18.22	17.15	NaN	0.92	27.64	133.36	0.00	0.02	0.00	NaN	NaN
1	Ahmedabad	2015-01-02	NaN	NaN	0.97	15.69	16.46	NaN	0.97	24.55	34.06	3.68	5.50	3.77	NaN	NaN
2	Ahmedabad	2015-01-03	NaN	NaN	17.40	19.30	29.70	NaN	17.40	29.07	30.70	6.80	16.40	2.25	NaN	NaN
3	Ahmedabad	2015-01-04	NaN	NaN	1.70	18.48	17.97	NaN	1.70	18.59	36.08	4.43	10.14	1.00	NaN	NaN
4	Ahmedabad	2015-01-05	NaN	NaN	22.10	21.42	37.76	NaN	22.10	39.33	39.31	7.01	18.89	2.78	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29526	Visakhapatnam	2020-06-27	15.02	50.94	7.68	25.06	19.54	12.47	0.47	8.55	23.30	2.24	12.07	0.73	41.0	Good
29527	Visakhapatnam	2020-06-28	24.38	74.09	3.42	26.06	16.53	11.99	0.52	12.72	30.14	0.74	2.21	0.38	70.0	Satisfactory
29528	Visakhapatnam	2020-06-29	22.91	65.73	3.45	29.53	18.33	10.71	0.48	8.42	30.96	0.01	0.01	0.00	68.0	Satisfactory
29529	Visakhapatnam	2020-06-30	16.64	49.97	4.05	29.26	18.80	10.03	0.52	9.84	28.30	0.00	0.00	0.00	54.0	Satisfactory
29530	Visakhapatnam	2020-07-01	15.00	66.00	0.40	26.85	14.05	5.20	0.59	2.10	17.05	NaN	NaN	NaN	50.0	Good

29531 rows × 16 columns

In [3]:
```
print(df.isnull().sum())
```

```
City              0
Date              0
PM2.5          4598
PM10          11140
NO             3582
NO2            3585
NOx            4185
NH3           10328
CO             2059
SO2            3854
O3             4022
Benzene        5623
Toluene        8041
Xylene        18109
AQI            4681
AQI_Bucket     4681
dtype: int64
```

In [4]:
```
(df.isnull().sum()/df.shape[0]*100).sort_values(ascending=False)
```

Out[4]:
```
Xylene        61.322001
PM10          37.723071
NH3           34.973418
Toluene       27.229014
Benzene       19.041008
AQI           15.851139
AQI_Bucket    15.851139
PM2.5         15.570079
NOx           14.171549
O3            13.619586
SO2           13.050692
NO2           12.139785
NO            12.129626
CO             6.972334
City           0.000000
Date           0.000000
dtype: float64
```

In [5]:
```
df.describe()
```

Out[5]:

	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI
count	24933.000000	18391.000000	25949.000000	25946.000000	25346.000000	19203.000000	27472.000000	25677.000000	25509.000000	23908.000000	21490.000000	11422.000000	24850.000000
mean	67.450578	118.127103	17.574730	28.560659	32.309123	23.483476	2.248598	14.531977	34.491430	3.280840	8.700972	3.070128	166.463581
std	64.661449	90.605110	22.785846	24.474746	31.646011	25.684275	6.962884	18.133775	21.694928	15.811136	19.969164	6.323247	140.696585
min	0.040000	0.010000	0.020000	0.010000	0.000000	0.010000	0.000000	0.010000	0.010000	0.000000	0.000000	0.000000	13.000000
25%	28.820000	56.255000	5.630000	11.750000	12.820000	8.580000	0.510000	5.670000	18.860000	0.120000	0.600000	0.140000	81.000000
50%	48.570000	95.680000	9.890000	21.690000	23.520000	15.850000	0.890000	9.160000	30.840000	1.070000	2.970000	0.980000	118.000000
75%	80.590000	149.745000	19.950000	37.620000	40.127500	30.020000	1.450000	15.220000	45.570000	3.080000	9.150000	3.350000	208.000000
max	949.990000	1000.000000	390.680000	362.210000	467.630000	352.890000	175.810000	193.860000	257.730000	455.030000	454.850000	170.370000	2049.000000

In [6]:
```
df['Date'] = pd.to_datetime(df['Date'])
df.rename(columns = {'AQI_Bucket':'Air_quality'}, inplace = True)
df.head()
```

Out[6]:

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	Air_quality
0	Ahmedabad	2015-01-01	NaN	NaN	0.92	18.22	17.15	NaN	0.92	27.64	133.36	0.00	0.02	0.00	NaN	NaN
1	Ahmedabad	2015-01-02	NaN	NaN	0.97	15.69	16.46	NaN	0.97	24.55	34.06	3.68	5.50	3.77	NaN	NaN
2	Ahmedabad	2015-01-03	NaN	NaN	17.40	19.30	29.70	NaN	17.40	29.07	30.70	6.80	16.40	2.25	NaN	NaN
3	Ahmedabad	2015-01-04	NaN	NaN	1.70	18.48	17.97	NaN	1.70	18.59	36.08	4.43	10.14	1.00	NaN	NaN
4	Ahmedabad	2015-01-05	NaN	NaN	22.10	21.42	37.76	NaN	22.10	39.33	39.31	7.01	18.89	2.78	NaN	NaN

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29531 entries, 0 to 29530
Data columns (total 16 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   City         29531 non-null  object
 1   Date         29531 non-null  datetime64[ns]
 2   PM2.5        24933 non-null  float64
 3   PM10         18391 non-null  float64
 4   NO           25949 non-null  float64
 5   NO2          25946 non-null  float64
 6   NOx          25346 non-null  float64
 7   NH3          19203 non-null  float64
 8   CO           27472 non-null  float64
 9   SO2          25677 non-null  float64
 10  O3           25509 non-null  float64
 11  Benzene      23908 non-null  float64
 12  Toluene      21490 non-null  float64
 13  Xylene       11422 non-null  float64
 14  AQI          24850 non-null  float64
 15  Air_quality  24850 non-null  object
dtypes: datetime64[ns](1), float64(13), object(2)
memory usage: 3.6+ MB
```

Feature Enginnering

In [8]:
```
# identify duplicate rows
duplicate_rows = df[df.duplicated()]
print(duplicate_rows)
```

```
Empty DataFrame
Columns: [City, Date, PM2.5, PM10, NO, NO2, NOx, NH3, CO, SO2, O3, Benzene, Toluene, Xylene, AQI, Air_quality]
Index: []
```

In [9]:
```
# count the number of duplicates
num_duplicates = df.duplicated().sum()
print(num_duplicates)
```

```
0
```

In [10]:
```
# For calculating the AQI we will replace all the NaN values of columns PM2.5, PM10, NO, NO2, NOx,
# NH3, CO, SO2, O3, Benzene, Toluene, Xylene with the mean values

df.iloc[:, 0:14]=df.fillna(df.mean())
df
```

```
C:\Users\Pranav Chouhan\AppData\Local\Temp\ipykernel_2876\1298381857.py:4: FutureWarning:

DataFrame.mean and DataFrame.median with numeric_only=None will include datetime64 and datetime64tz columns in a future version.

C:\Users\Pranav Chouhan\AppData\Local\Temp\ipykernel_2876\1298381857.py:4: FutureWarning:

Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
```

Out[10]:

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	Air_quality
0	Ahmedabad	2015-01-01	67.450578	118.127103	0.92	18.22	17.15	23.483476	0.92	27.64	133.36	0.00000	0.020000	0.000000	NaN	NaN
1	Ahmedabad	2015-01-02	67.450578	118.127103	0.97	15.69	16.46	23.483476	0.97	24.55	34.06	3.68000	5.500000	3.770000	NaN	NaN
2	Ahmedabad	2015-01-03	67.450578	118.127103	17.40	19.30	29.70	23.483476	17.40	29.07	30.70	6.80000	16.400000	2.250000	NaN	NaN
3	Ahmedabad	2015-01-04	67.450578	118.127103	1.70	18.48	17.97	23.483476	1.70	18.59	36.08	4.43000	10.140000	1.000000	NaN	NaN
4	Ahmedabad	2015-01-05	67.450578	118.127103	22.10	21.42	37.76	23.483476	22.10	39.33	39.31	7.01000	18.890000	2.780000	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29526	Visakhapatnam	2020-06-27	15.020000	50.940000	7.68	25.06	19.54	12.470000	0.47	8.55	23.30	2.24000	12.070000	0.730000	41.0	Good
29527	Visakhapatnam	2020-06-28	24.380000	74.090000	3.42	26.06	16.53	11.990000	0.52	12.72	30.14	0.74000	2.210000	0.380000	70.0	Satisfactory
29528	Visakhapatnam	2020-06-29	22.910000	65.730000	3.45	29.53	18.33	10.710000	0.48	8.42	30.96	0.01000	0.010000	0.000000	68.0	Satisfactory
29529	Visakhapatnam	2020-06-30	16.640000	49.970000	4.05	29.26	18.80	10.030000	0.52	9.84	28.30	0.00000	0.000000	0.000000	54.0	Satisfactory
29530	Visakhapatnam	2020-07-01	15.000000	66.000000	0.40	26.85	14.05	5.200000	0.59	2.10	17.05	3.28084	8.700972	3.070128	50.0	Good

29531 rows × 16 columns

We cannot fill null values of AQI with mean or mode nor we can delete it, So, we will calculate AQI from all 7 measures:

The AQI calculation uses 7 measures: PM2.5, PM10, SO2, NOx, NH3, CO and O3.

> For PM2.5, PM10, SO2, NOx and NH3 the average value in last 24-hrs is used with the condition of having at least 16 values.
>
> For CO and O3 the maximum value in last 8-hrs is used.
>
> Each measure is converted into a Sub-Index based on pre-defined groups.
>
> Sometimes measures are not available due to lack of measuring or lack of required data points.
>
> Final AQI is the maximum Sub-Index with the condition that at least one of PM2.5 and PM10 should be available and at least three out of the seven should be available.

calculating Sub-Index

In [11]:
```
# PM10 Sub-Index calculation
def get_PM10_subindex(x):
    if x <= 50:
        return x
    elif x > 50 and x <= 100:
        return x
    elif x > 100 and x <= 250:
        return 100 + (x - 100) * 100 / 150
    elif x > 250 and x <= 350:
        return 200 + (x - 250)
    elif x > 350 and x <= 430:
        return 300 + (x - 350) * 100 / 80
    elif x > 430:
        return 400 + (x - 430) * 100 / 80
    else:
        return 0

df["PM10_SubIndex"] = df["PM10"].astype(int).apply(lambda x: get_PM10_subindex(x))

# PM2.5 Sub-Index calculation
def get_PM25_subindex(x):
    if x <= 30:
        return x * 50 / 30
```

```python
    elif x > 30 and x <= 60:
        return 50 + (x - 30) * 50 / 30
    elif x > 60 and x <= 90:
        return 100 + (x - 60) * 100 / 30
    elif x > 90 and x <= 120:
        return 200 + (x - 90) * 100 / 30
    elif x > 120 and x <= 250:
        return 300 + (x - 120) * 100 / 130
    elif x > 250:
        return 400 + (x - 250) * 100 / 130
    else:
        return 0

df["PM2.5_SubIndex"] = df["PM2.5"].astype(int).apply(lambda x: get_PM25_subindex(x))


# SO2 Sub-Index calculation
def get_SO2_subindex(x):
    if x <= 40:
        return x * 50 / 40
    elif x > 40 and x <= 80:
        return 50 + (x - 40) * 50 / 40
    elif x > 80 and x <= 380:
        return 100 + (x - 80) * 100 / 300
    elif x > 380 and x <= 800:
        return 200 + (x - 380) * 100 / 420
    elif x > 800 and x <= 1600:
        return 300 + (x - 800) * 100 / 800
    elif x > 1600:
        return 400 + (x - 1600) * 100 / 800
    else:
        return 0

df["SO2_SubIndex"] = df["SO2"].astype(int).apply(lambda x: get_SO2_subindex(x))

# NOx Sub-Index calculation
def get_NOx_subindex(x):
    if x <= 40:
        return x * 50 / 40
    elif x > 40 and x <= 80:
        return 50 + (x - 40) * 50 / 40
    elif x > 80 and x <= 180:
        return 100 + (x - 80) * 100 / 100
    elif x > 180 and x <= 280:
        return 200 + (x - 180) * 100 / 100
    elif x > 280 and x <= 400:
        return 300 + (x - 280) * 100 / 120
    elif x > 400:
        return 400 + (x - 400) * 100 / 120
    else:
        return 0

df["NOx_SubIndex"] = df["NOx"].astype(int).apply(lambda x: get_NOx_subindex(x))

# NH3 Sub-Index calculation
def get_NH3_subindex(x):
    if x <= 200:
        return x * 50 / 200
    elif x > 200 and x <= 400:
        return 50 + (x - 200) * 50 / 200
    elif x > 400 and x <= 800:
        return 100 + (x - 400) * 100 / 400
    elif x > 800 and x <= 1200:
        return 200 + (x - 800) * 100 / 400
    elif x > 1200 and x <= 1800:
        return 300 + (x - 1200) * 100 / 600
    elif x > 1800:
        return 400 + (x - 1800) * 100 / 600
    else:
        return 0

df["NH3_SubIndex"] = df["NH3"].astype(int).apply(lambda x: get_NH3_subindex(x))

# CO Sub-Index calculation
def get_CO_subindex(x):
    if x <= 1:
        return x * 50 / 1
    elif x > 1 and x <= 2:
        return 50 + (x - 1) * 50 / 1
    elif x > 2 and x <= 10:
        return 100 + (x - 2) * 100 / 8
    elif x > 10 and x <= 17:
        return 200 + (x - 10) * 100 / 7
    elif x > 17 and x <= 34:
        return 300 + (x - 17) * 100 / 17
    elif x > 34:
        return 400 + (x - 34) * 100 / 17
    else:
        return 0

df["CO_SubIndex"] = df["CO"].astype(int).apply(lambda x: get_CO_subindex(x))

# O3 Sub-Index calculation
def get_O3_subindex(x):
    if x <= 50:
        return x * 50 / 50
    elif x > 50 and x <= 100:
        return 50 + (x - 50) * 50 / 50
    elif x > 100 and x <= 168:
        return 100 + (x - 100) * 100 / 68
    elif x > 168 and x <= 208:
        return 200 + (x - 168) * 100 / 40
    elif x > 208 and x <= 748:
        return 300 + (x - 208) * 100 / 539
    elif x > 748:
        return 400 + (x - 400) * 100 / 539
    else:
        return 0

df["O3_SubIndex"] = df["O3"].astype(int).apply(lambda x: get_O3_subindex(x))
```

In [12]:

```python
if pd.isna(df["AQI"]).any():
        df["AQI"] = df["AQI"].fillna(round(df[["PM2.5_SubIndex", "PM10_SubIndex", "SO2_SubIndex", "NOx_SubIndex","NH3_SubIndex", "CO_SubIndex", "O3_SubIndex"]].max(axis = 1)))
df
```

Out[12]:

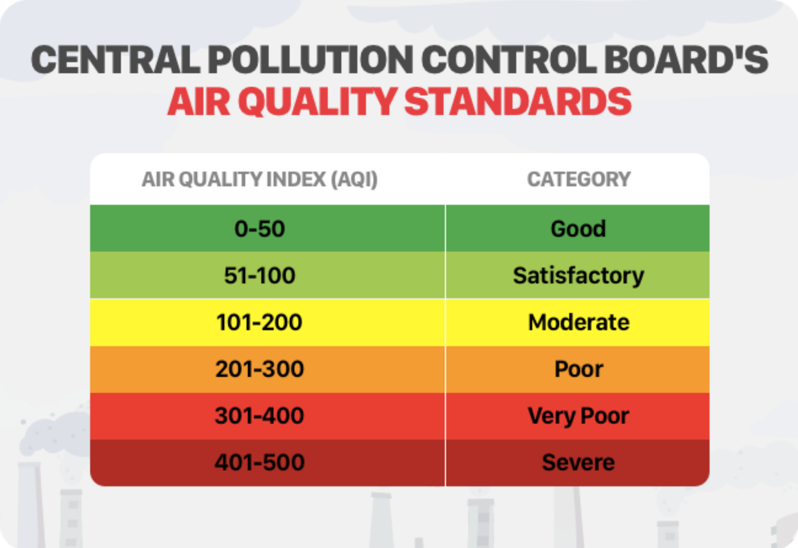
	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	...	Xylene	AQI	Air_quality	PM10_SubIndex	PM2.5_SubIndex	SO2_SubIndex	NOx_SubIndex	NH3_SubIndex	CO_SubIndex	O3_SubIndex
0	Ahmedabad	2015-01-01	67.450578	118.127103	0.92	18.22	17.15	23.483476	0.92	27.64	...	0.000000	149.0	NaN	112.0	123.333333	33.75	21.25	5.75	0.000000	148.529412
1	Ahmedabad	2015-01-02	67.450578	118.127103	0.97	15.69	16.46	23.483476	0.97	24.55	...	3.770000	123.0	NaN	112.0	123.333333	30.00	20.00	5.75	0.000000	34.000000
2	Ahmedabad	2015-01-03	67.450578	118.127103	17.40	19.30	29.70	23.483476	17.40	29.07	...	2.250000	300.0	NaN	112.0	123.333333	36.25	36.25	5.75	300.000000	30.000000
3	Ahmedabad	2015-01-04	67.450578	118.127103	1.70	18.48	17.97	23.483476	1.70	18.59	...	1.000000	123.0	NaN	112.0	123.333333	22.50	21.25	5.75	50.000000	36.000000
4	Ahmedabad	2015-01-05	67.450578	118.127103	22.10	21.42	37.76	23.483476	22.10	39.33	...	2.780000	329.0	NaN	112.0	123.333333	48.75	46.25	5.75	329.411765	39.000000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29526	Visakhapatnam	2020-06-27	15.020000	50.940000	7.68	25.06	19.54	12.470000	0.47	8.55	...	0.730000	41.0	Good	50.0	25.000000	10.00	23.75	3.00	0.000000	23.000000
29527	Visakhapatnam	2020-06-28	24.380000	74.090000	3.42	26.06	16.53	11.990000	0.52	12.72	...	0.380000	70.0	Satisfactory	74.0	40.000000	15.00	20.00	2.75	0.000000	30.000000
29528	Visakhapatnam	2020-06-29	22.910000	65.730000	3.45	29.53	18.33	10.710000	0.48	8.42	...	0.000000	68.0	Satisfactory	65.0	36.666667	10.00	22.50	2.50	0.000000	30.000000
29529	Visakhapatnam	2020-06-30	16.640000	49.970000	4.05	29.26	18.80	10.030000	0.52	9.84	...	0.000000	54.0	Satisfactory	49.0	26.666667	11.25	22.50	2.50	0.000000	28.000000
29530	Visakhapatnam	2020-07-01	15.000000	66.000000	0.40	26.85	14.05	5.200000	0.59	2.10	...	3.070128	50.0	Good	66.0	25.000000	2.50	17.50	1.25	0.000000	17.000000

29531 rows × 23 columns

In [13]:

```
# Now for removing NaN values of Air_quality we use AQI category

from IPython import display
display.Image("https://w.ndtvimg.com/sites/3/2019/12/18122812/air_pollution_standards_cpcb.png",width = 400, height = 200)
```

Out[13]:



CENTRAL POLLUTION CONTROL BOARD'S
AIR QUALITY STANDARDS

AIR QUALITY INDEX (AQI)	CATEGORY
0-50	Good
51-100	Satisfactory
101-200	Moderate
201-300	Poor
301-400	Very Poor
401-500	Severe

In [14]:

```
if pd.isna(df["Air_quality"]).any():
        def get_Air_quality(x):
            if x <= 50:
                return "Good"
            elif x > 50 and x <= 100:
                return "Satisfactory"
            elif x > 100 and x <= 200:
                return "Moderate"
            elif x > 200 and x <= 300:
                return "Poor"
            elif x > 300 and x <= 400:
                return "Very Poor"
            elif x > 400:
                return "Severe"
            else:
                return '0'

        df["Air_quality"] = df["Air_quality"].fillna(df["AQI"].apply(lambda x: get_Air_quality(x)))

df
```

Out[14]:

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	...	Xylene	AQI	Air_quality	PM10_SubIndex	PM2.5_SubIndex	SO2_SubIndex	NOx_SubIndex	NH3_SubIndex	CO_SubIndex	O3_SubIndex
0	Ahmedabad	2015-01-01	67.450578	118.127103	0.92	18.22	17.15	23.483476	0.92	27.64	...	0.000000	149.0	Moderate	112.0	123.333333	33.75	21.25	5.75	0.000000	148.529412
1	Ahmedabad	2015-01-02	67.450578	118.127103	0.97	15.69	16.46	23.483476	0.97	24.55	...	3.770000	123.0	Moderate	112.0	123.333333	30.00	20.00	5.75	0.000000	34.000000
2	Ahmedabad	2015-01-03	67.450578	118.127103	17.40	19.30	29.70	23.483476	17.40	29.07	...	2.250000	300.0	Poor	112.0	123.333333	36.25	36.25	5.75	300.000000	30.000000
3	Ahmedabad	2015-01-04	67.450578	118.127103	1.70	18.48	17.97	23.483476	1.70	18.59	...	1.000000	123.0	Moderate	112.0	123.333333	22.50	21.25	5.75	50.000000	36.000000
4	Ahmedabad	2015-01-05	67.450578	118.127103	22.10	21.42	37.76	23.483476	22.10	39.33	...	2.780000	329.0	Very Poor	112.0	123.333333	48.75	46.25	5.75	329.411765	39.000000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29526	Visakhapatnam	2020-06-27	15.020000	50.940000	7.68	25.06	19.54	12.470000	0.47	8.55	...	0.730000	41.0	Good	50.0	25.000000	10.00	23.75	3.00	0.000000	23.000000
29527	Visakhapatnam	2020-06-28	24.380000	74.090000	3.42	26.06	16.53	11.990000	0.52	12.72	...	0.380000	70.0	Satisfactory	74.0	40.000000	15.00	20.00	2.75	0.000000	30.000000
29528	Visakhapatnam	2020-06-29	22.910000	65.730000	3.45	29.53	18.33	10.710000	0.48	8.42	...	0.000000	68.0	Satisfactory	65.0	36.666667	10.00	22.50	2.50	0.000000	30.000000
29529	Visakhapatnam	2020-06-30	16.640000	49.970000	4.05	29.26	18.80	10.030000	0.52	9.84	...	0.000000	54.0	Satisfactory	49.0	26.666667	11.25	22.50	2.50	0.000000	28.000000
29530	Visakhapatnam	2020-07-01	15.000000	66.000000	0.40	26.85	14.05	5.200000	0.59	2.10	...	3.070128	50.0	Good	66.0	25.000000	2.50	17.50	1.25	0.000000	17.000000

29531 rows × 23 columns

In [15]:

```
# Remove the PM10_SubIndex, PM2.5_SubIndex, SO2_SubIndex, NOx_SubIndex, NH3_SubIndex, CO_SubIndex, and O3_SubIndex columns
# because now they are of no use for further process.
df = df.drop(columns=["PM10_SubIndex", "PM2.5_SubIndex", "SO2_SubIndex", "NOx_SubIndex", "NH3_SubIndex", "CO_SubIndex", "O3_SubIndex"])
df
```

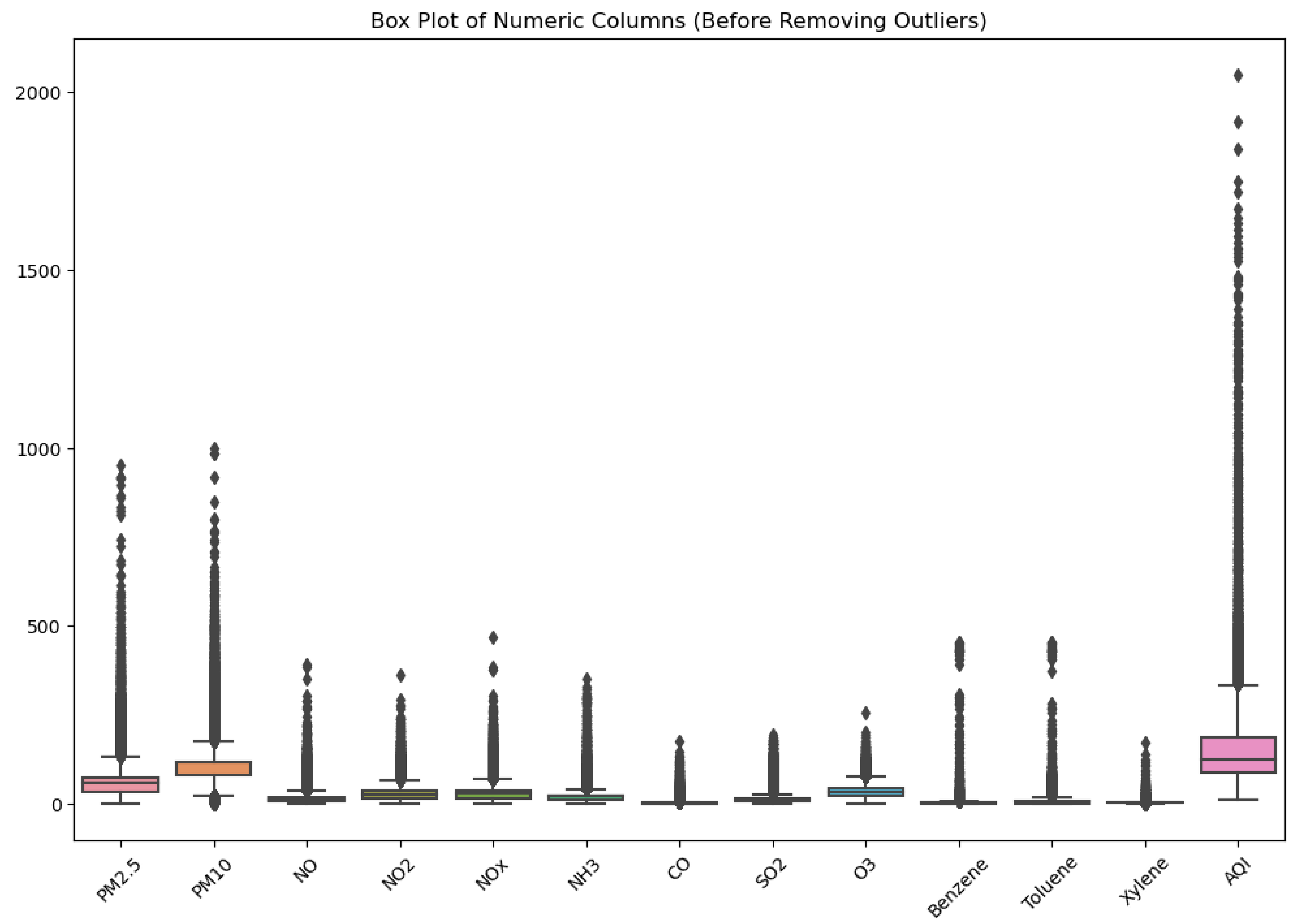
Out[15]:

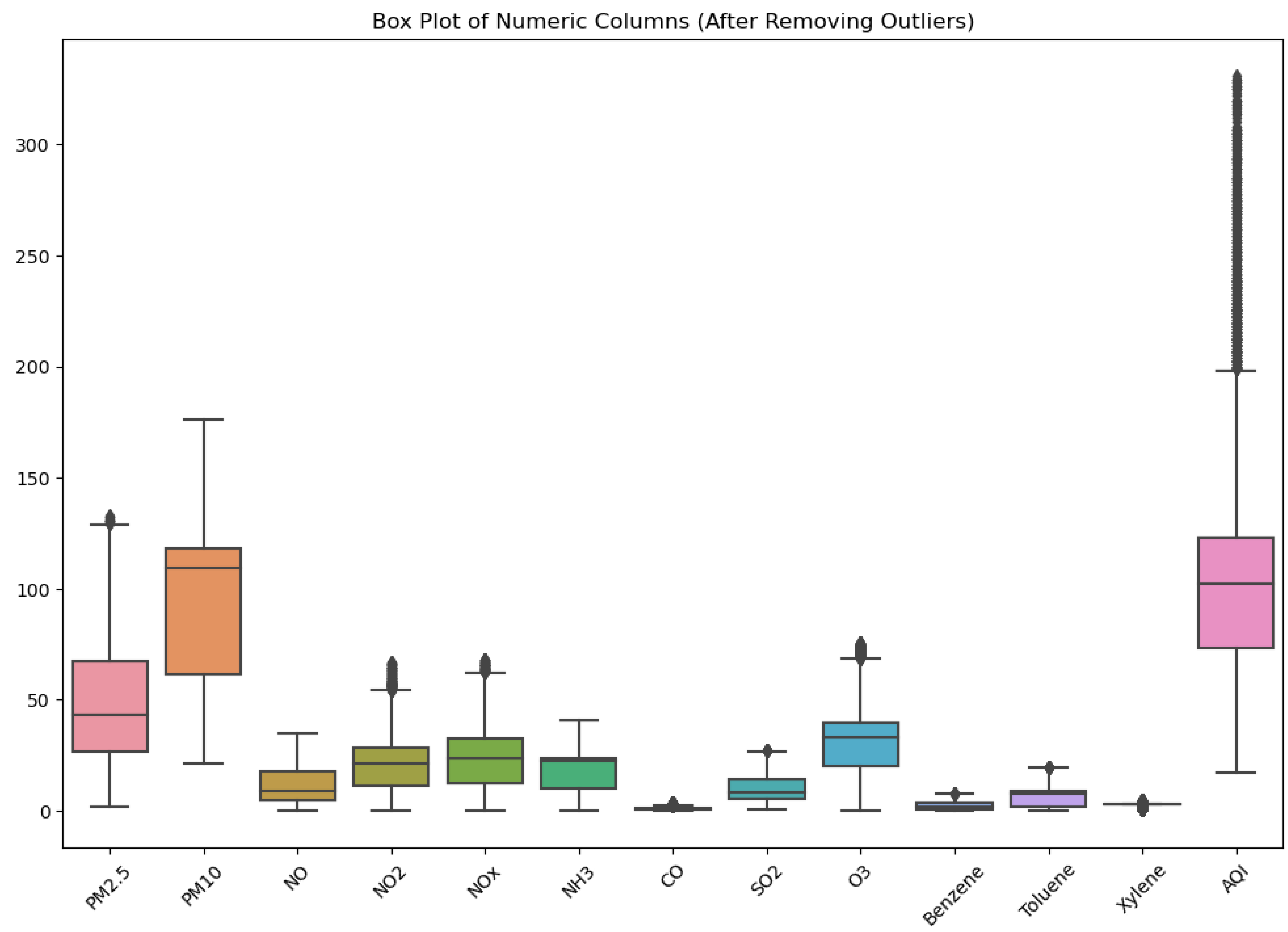
	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	Air_quality
0	Ahmedabad	2015-01-01	67.450578	118.127103	0.92	18.22	17.15	23.483476	0.92	27.64	133.36	0.00000	0.020000	0.000000	149.0	Moderate
1	Ahmedabad	2015-01-02	67.450578	118.127103	0.97	15.69	16.46	23.483476	0.97	24.55	34.06	3.68000	5.500000	3.770000	123.0	Moderate
2	Ahmedabad	2015-01-03	67.450578	118.127103	17.40	19.30	29.70	23.483476	17.40	29.07	30.70	6.80000	16.400000	2.250000	300.0	Poor
3	Ahmedabad	2015-01-04	67.450578	118.127103	1.70	18.48	17.97	23.483476	1.70	18.59	36.08	4.43000	10.140000	1.000000	123.0	Moderate
4	Ahmedabad	2015-01-05	67.450578	118.127103	22.10	21.42	37.76	23.483476	22.10	39.33	39.31	7.01000	18.890000	2.780000	329.0	Very Poor
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29526	Visakhapatnam	2020-06-27	15.020000	50.940000	7.68	25.06	19.54	12.470000	0.47	8.55	23.30	2.24000	12.070000	0.730000	41.0	Good
29527	Visakhapatnam	2020-06-28	24.380000	74.090000	3.42	26.06	16.53	11.990000	0.52	12.72	30.14	0.74000	2.210000	0.380000	70.0	Satisfactory
29528	Visakhapatnam	2020-06-29	22.910000	65.730000	3.45	29.53	18.33	10.710000	0.48	8.42	30.96	0.01000	0.010000	0.000000	68.0	Satisfactory
29529	Visakhapatnam	2020-06-30	16.640000	49.970000	4.05	29.26	18.80	10.030000	0.52	9.84	28.30	0.00000	0.000000	0.000000	54.0	Satisfactory
29530	Visakhapatnam	2020-07-01	15.000000	66.000000	0.40	26.85	14.05	5.200000	0.59	2.10	17.05	3.28084	8.700972	3.070128	50.0	Good

29531 rows × 16 columns

In [16]:

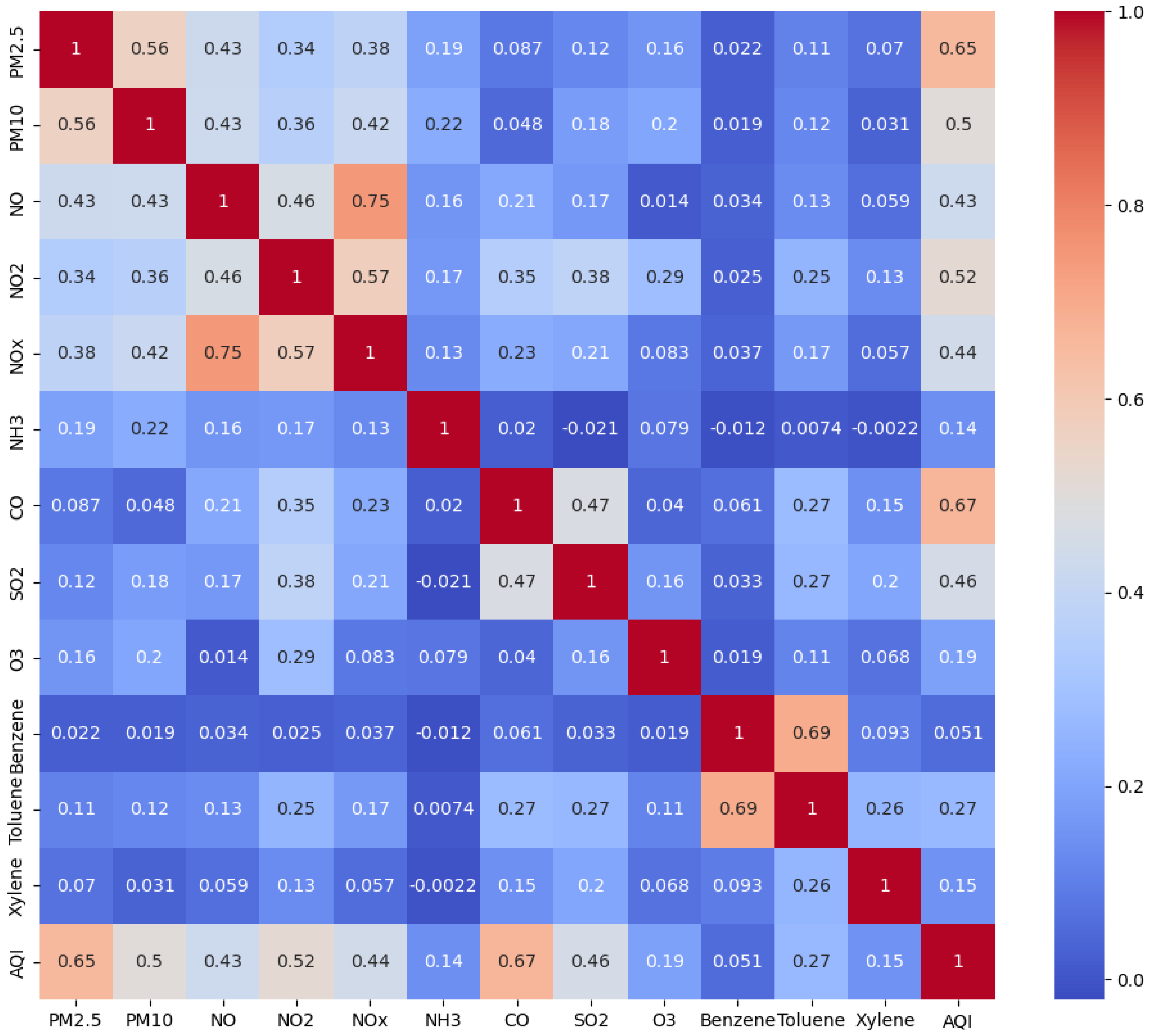
```
# Select numeric columns for outlier visualization
numeric_columns = ['PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2', 'O3', 'Benzene', 'Toluene', 'Xylene', 'AQI']

# Create a box plot for each numeric column before removing outliers
plt.figure(figsize=(12, 8))
sns.boxplot(data=df[numeric_columns])
plt.xticks(rotation=45)
plt.title('Box Plot of Numeric Columns (Before Removing Outliers)')
plt.show()

# Remove outliers from the dataset
Q1 = df[numeric_columns].quantile(0.25)
Q3 = df[numeric_columns].quantile(0.75)
IQR = Q3 - Q1
df_cleaned = df[~((df[numeric_columns] < (Q1 - 1.5 * IQR)) | (df[numeric_columns] > (Q3 + 1.5 * IQR))).any(axis=1)]

# Create a box plot for each numeric column after removing outliers
plt.figure(figsize=(12, 8))
sns.boxplot(data=df_cleaned[numeric_columns])
plt.xticks(rotation=45)
plt.title('Box Plot of Numeric Columns (After Removing Outliers)')
plt.show()
```





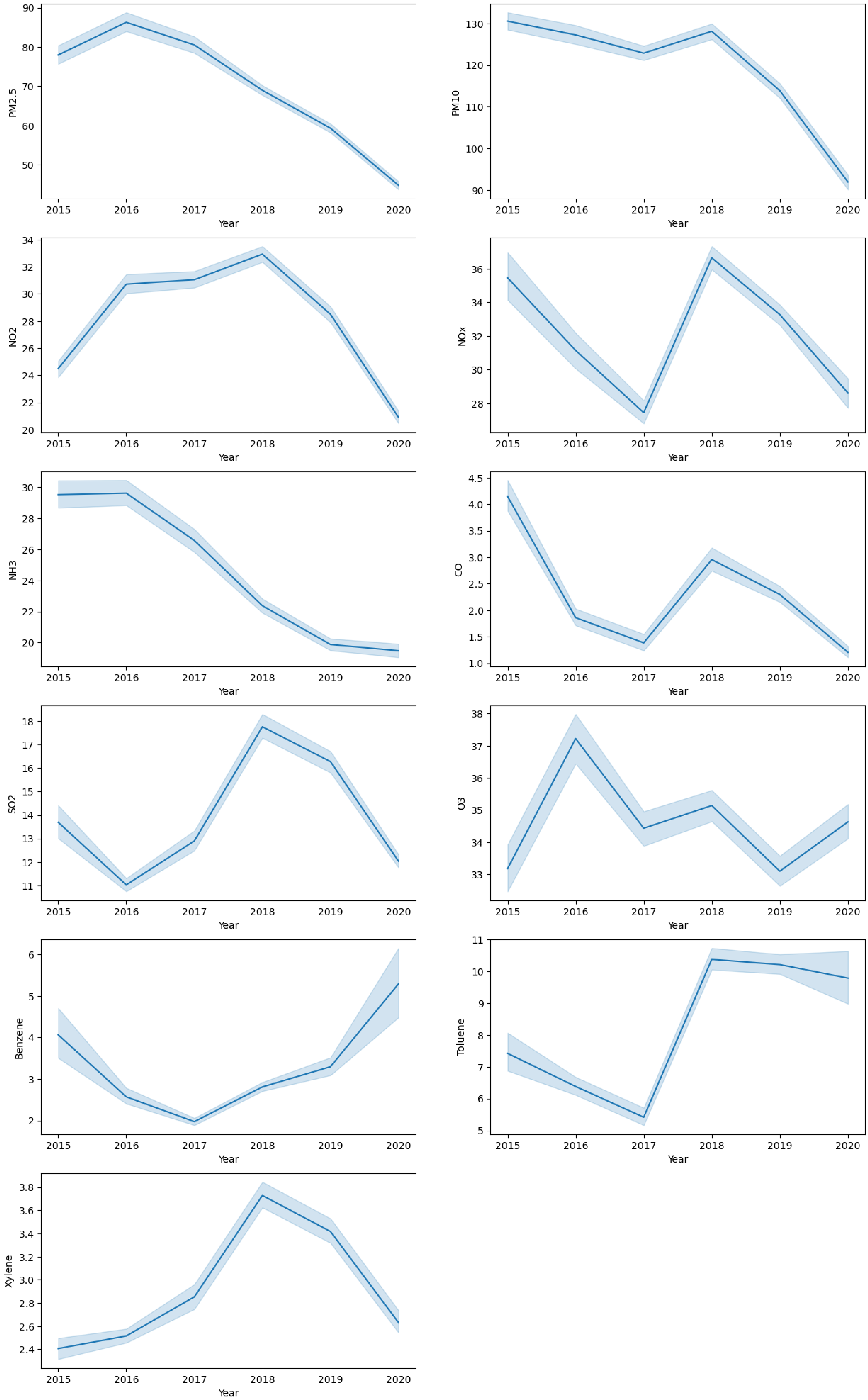
Exploratory Data Analysis

In [17]:
```
plt.figure(figsize=(12,10))
sns.heatmap(df.corr(),cmap='coolwarm',annot=True);
```



In [18]:
```
#segregating dates into months and years

df['Month']=df.Date.dt.month.astype(str)
df['Year']=df.Date.dt.year.astype(str)
```

In [19]:
```
#line plot analysis for amount of particulate matter and gases  over the years
cols=['PM2.5','PM10','NO2','NOx','NH3',
      'CO','SO2','O3','Benzene','Toluene','Xylene']

x=df.iloc[:,2:]
fig=plt.figure(figsize=(15,25))
for i,col  in enumerate(cols):
    fig.add_subplot(6,2,i+1)
    sns.lineplot(x='Year',y=col,data=x)
```



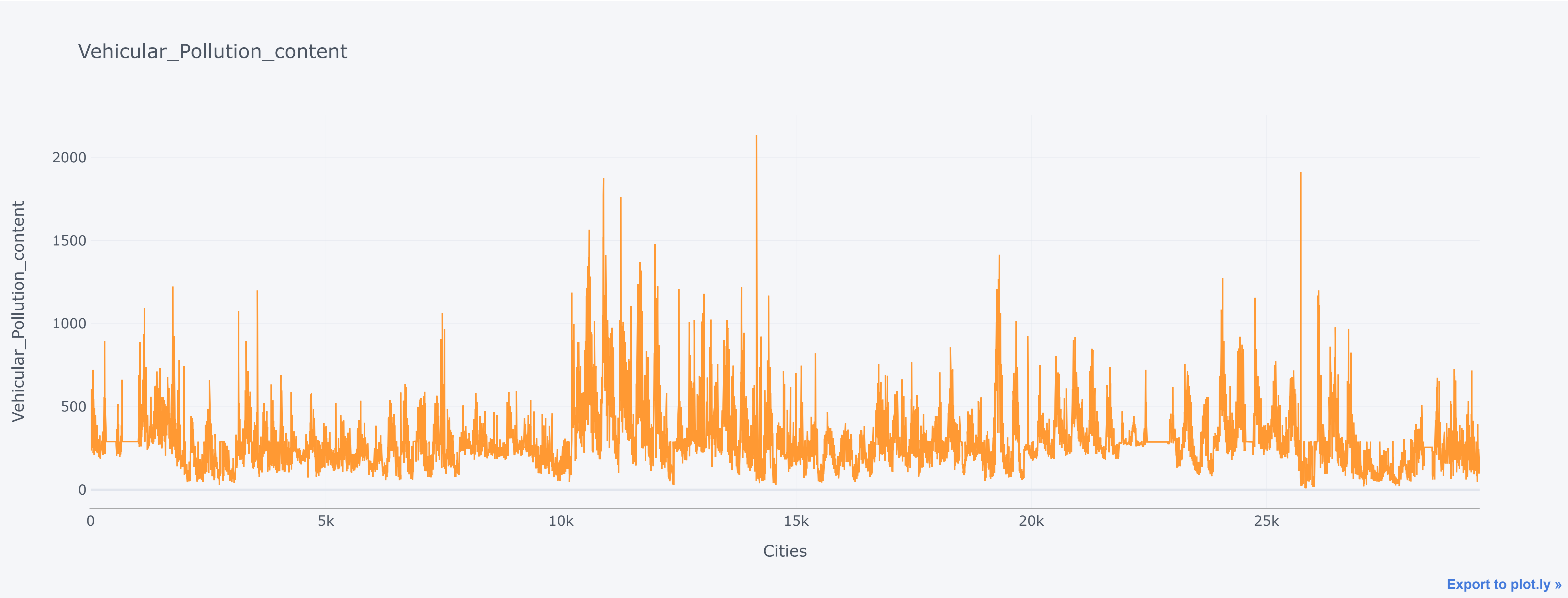
Here I divide the data set into two part namely Vehicular Pollution content (PM2.5, PM10, NO2, NH3, CO,) and Industrial Pollution content (CO, SO2, O3, Benzene, Toluene, Xylene) and find how these contents correlated with AQI (air quality index)

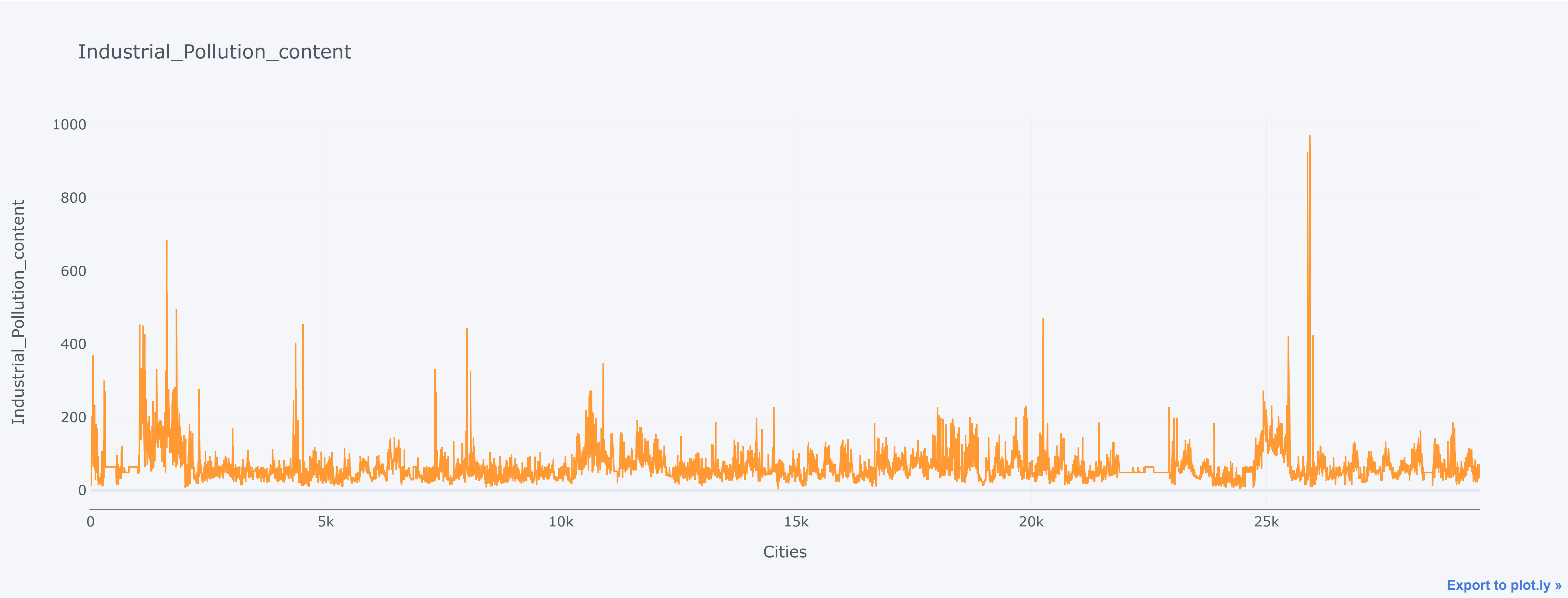
In [20]:
```
df2 = df.copy()
df2['Vehicular_Pollution_content'] = df2['PM2.5']+df2['PM10']+df2['NO']+df2['NO2']+df2['NOx']+df2['NH3']+df2['CO']
df2['Industrial_Pollution_content'] = df2['SO2']+df2['O3']+df2['Benzene']+df2['Toluene']+df2['Xylene']
df2 = df2.drop(['PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2',
       'O3','Benzene','Toluene','Xylene'],axis=1)
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29531 entries, 0 to 29530
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype         
---  ------                       --------------  -----         
 0   City                         29531 non-null  object        
 1   Date                         29531 non-null  datetime64[ns]
 2   AQI                          29531 non-null  float64       
 3   Air_quality                  29531 non-null  object        
 4   Month                        29531 non-null  object        
 5   Year                         29531 non-null  object        
 6   Vehicular_Pollution_content  29531 non-null  float64       
 7   Industrial_Pollution_content  29531 non-null  float64       
dtypes: datetime64[ns](1), float64(3), object(4)
memory usage: 1.8+ MB
```

In [21]:

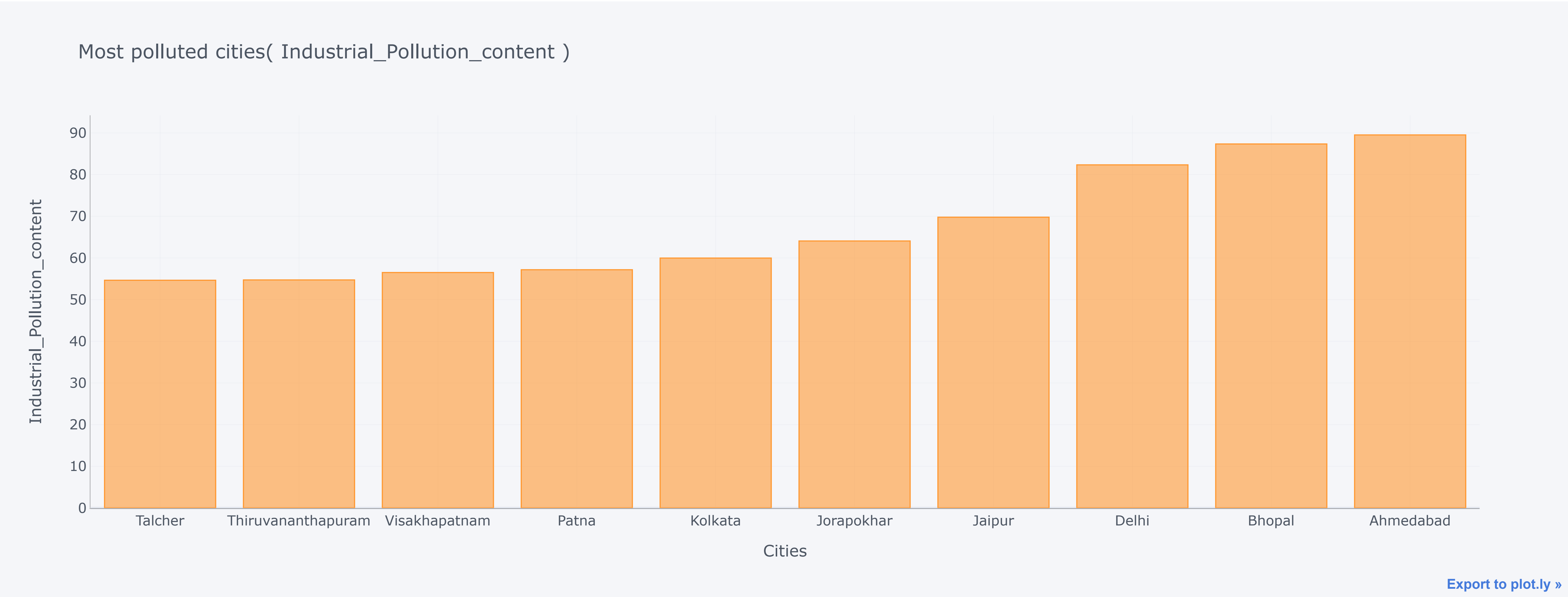
```python
def ploting(var):
    df2[var].iplot(title=var,xTitle='Cities',yTitle=var, linecolor='black',)
    plt.show()
ploting('Vehicular_Pollution_content')
ploting('Industrial_Pollution_content')
```

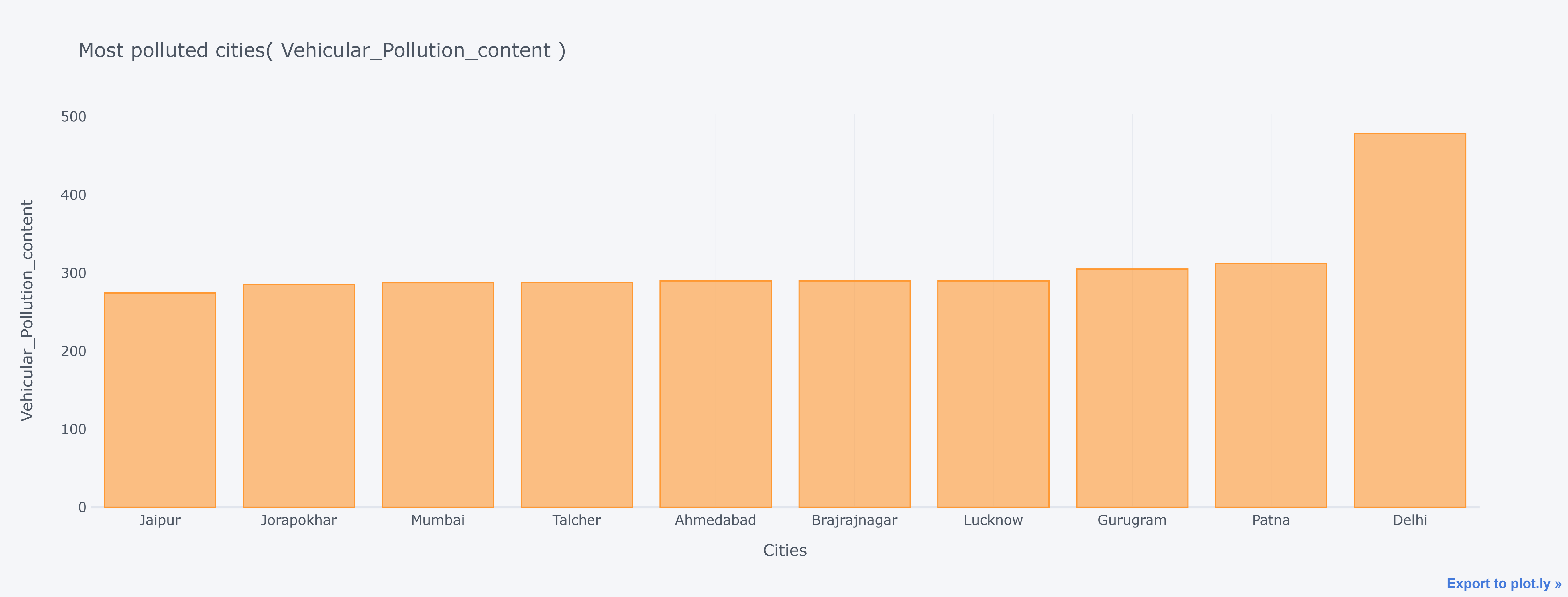




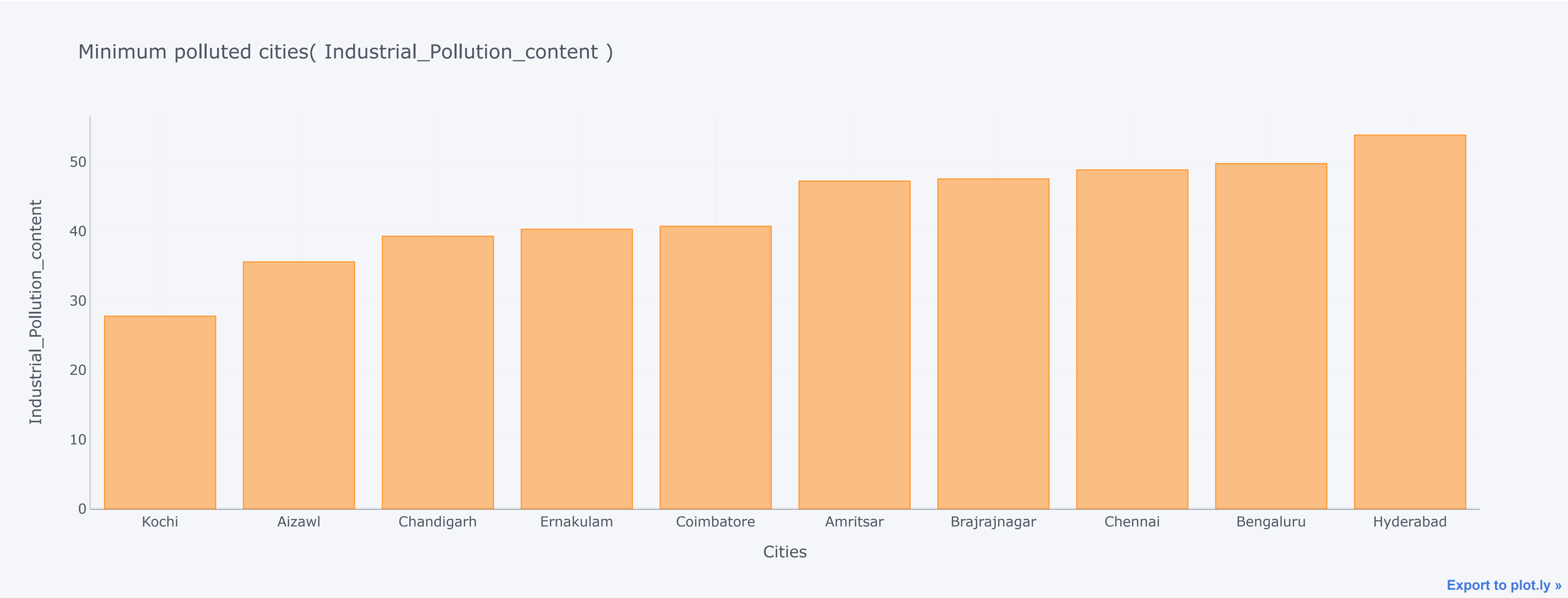
In [22]:

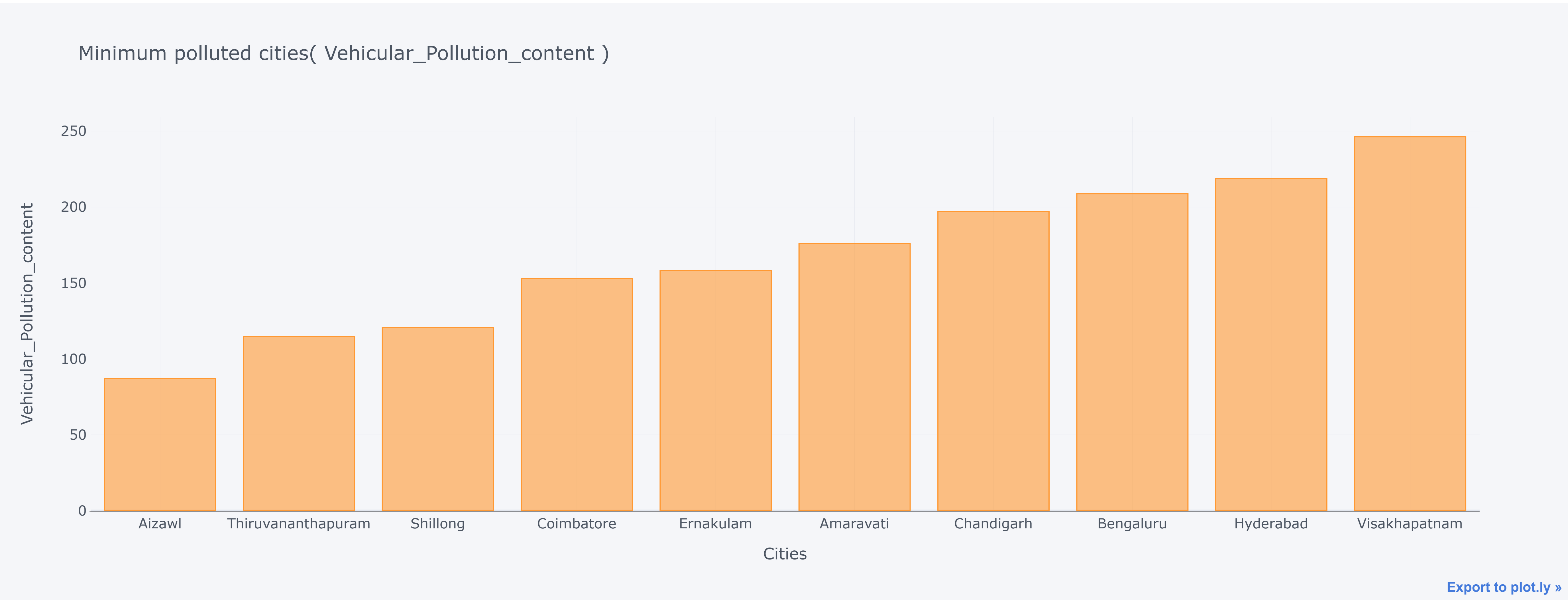
```python
def max_bar_plot(var):
    x1 = df2[['City',var]].groupby(["City"]).median().sort_values(by = var,
    ascending = True).tail(10).iplot(kind='bar', xTitle='Cities',yTitle=var,
                                 linecolor='black', title='{2} {1} {0}'.format(")",var,'Most polluted cities('))

p1 = max_bar_plot('Industrial_Pollution_content')
p2 = max_bar_plot('Vehicular_Pollution_content')
```



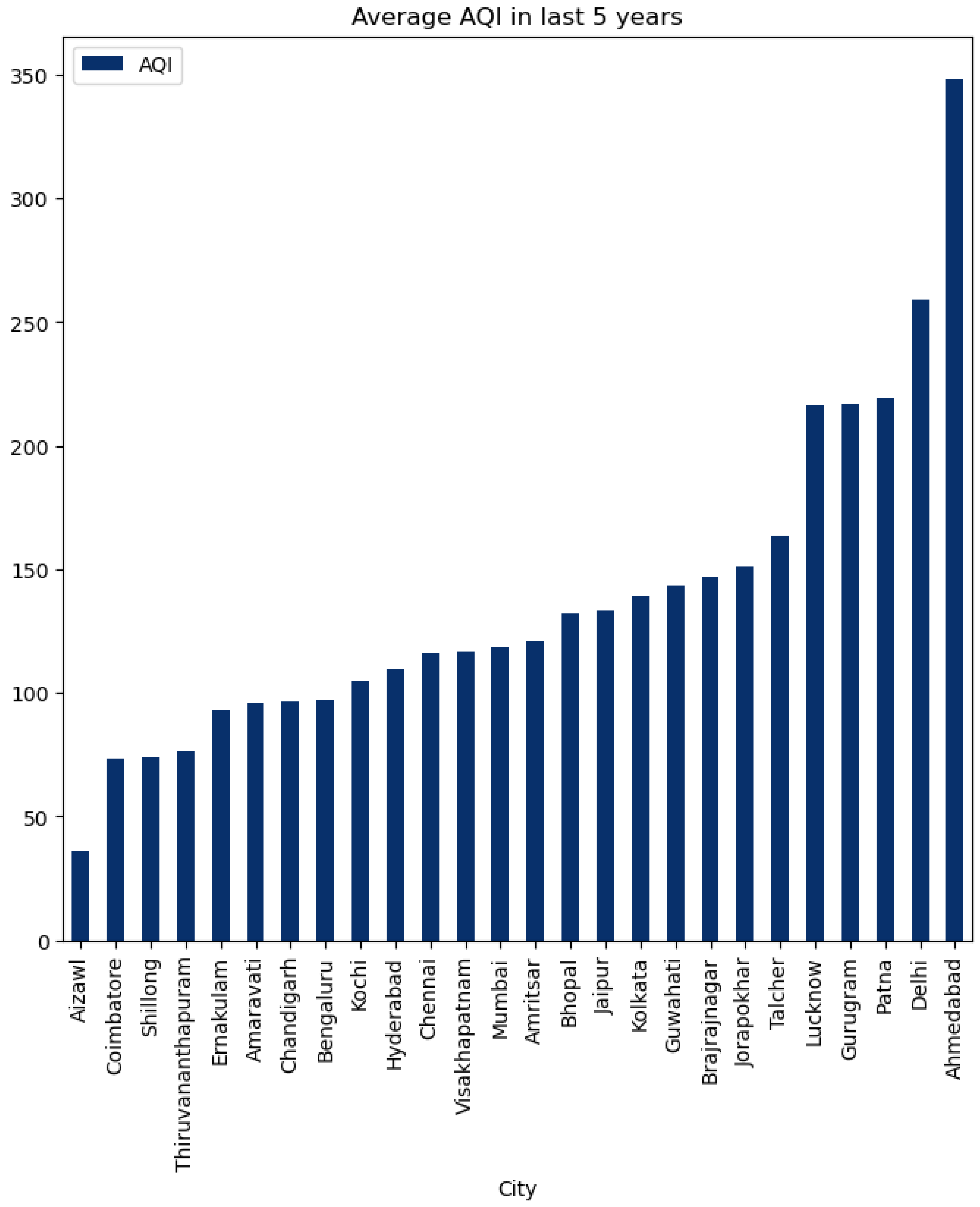


In [23]:
```
def min_bar_plot(var):
    x1 = df2[['City',var]].groupby(["City"]).mean().sort_values(by = var,
    ascending = True).head(10).iplot(kind='bar', xTitle='Cities',yTitle=var, linecolor='black',title='{2} {1} {0}'.format(")",var,' Minimum polluted cities('))
p1 = min_bar_plot('Industrial_Pollution_content')
p2 = min_bar_plot('Vehicular_Pollution_content')
```





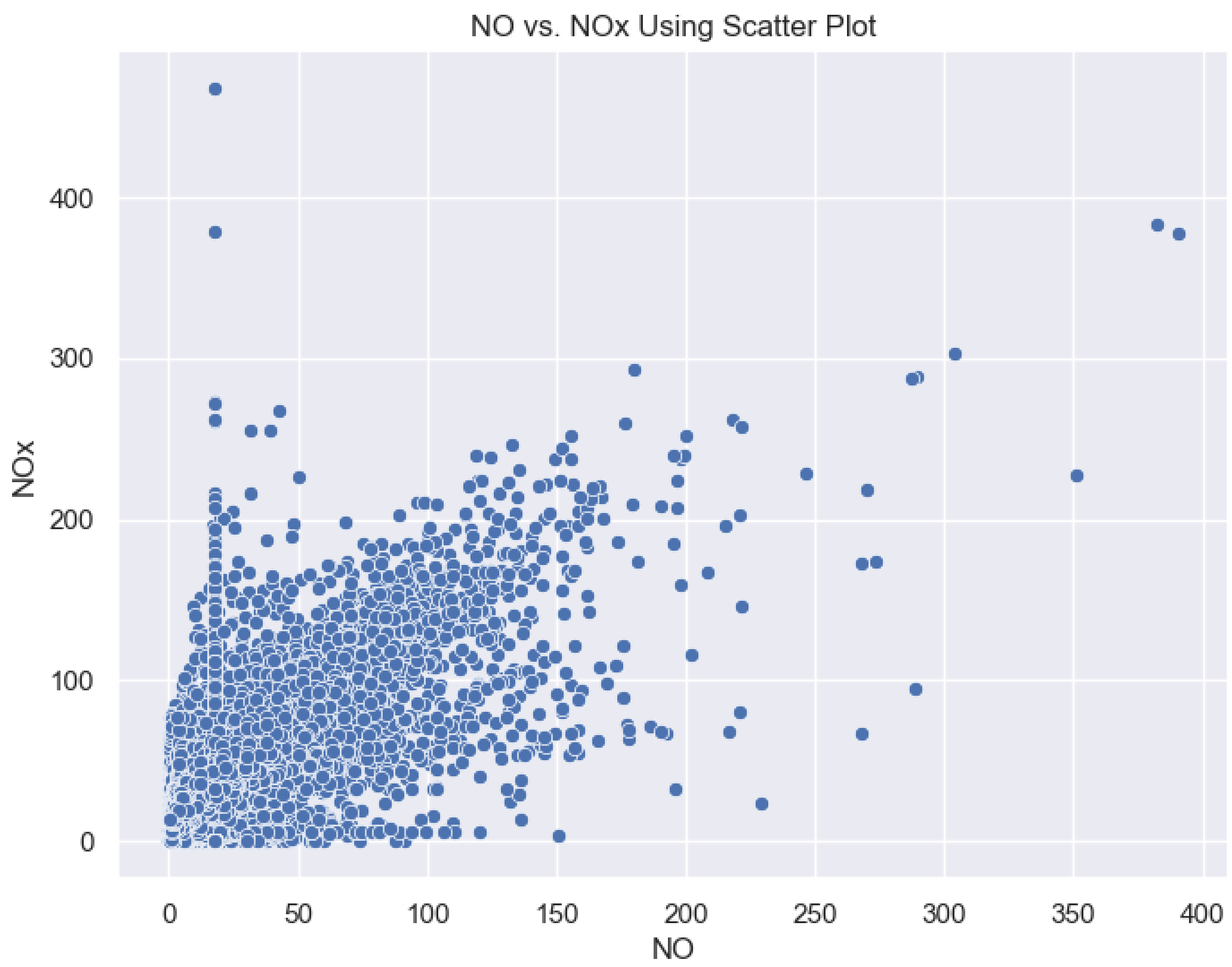
In [24]:
```
df[['City','AQI']].groupby('City').mean().sort_values('AQI').plot(kind='bar',cmap='Blues_r',figsize=(8,8))
plt.title('Average AQI in last 5 years');
```

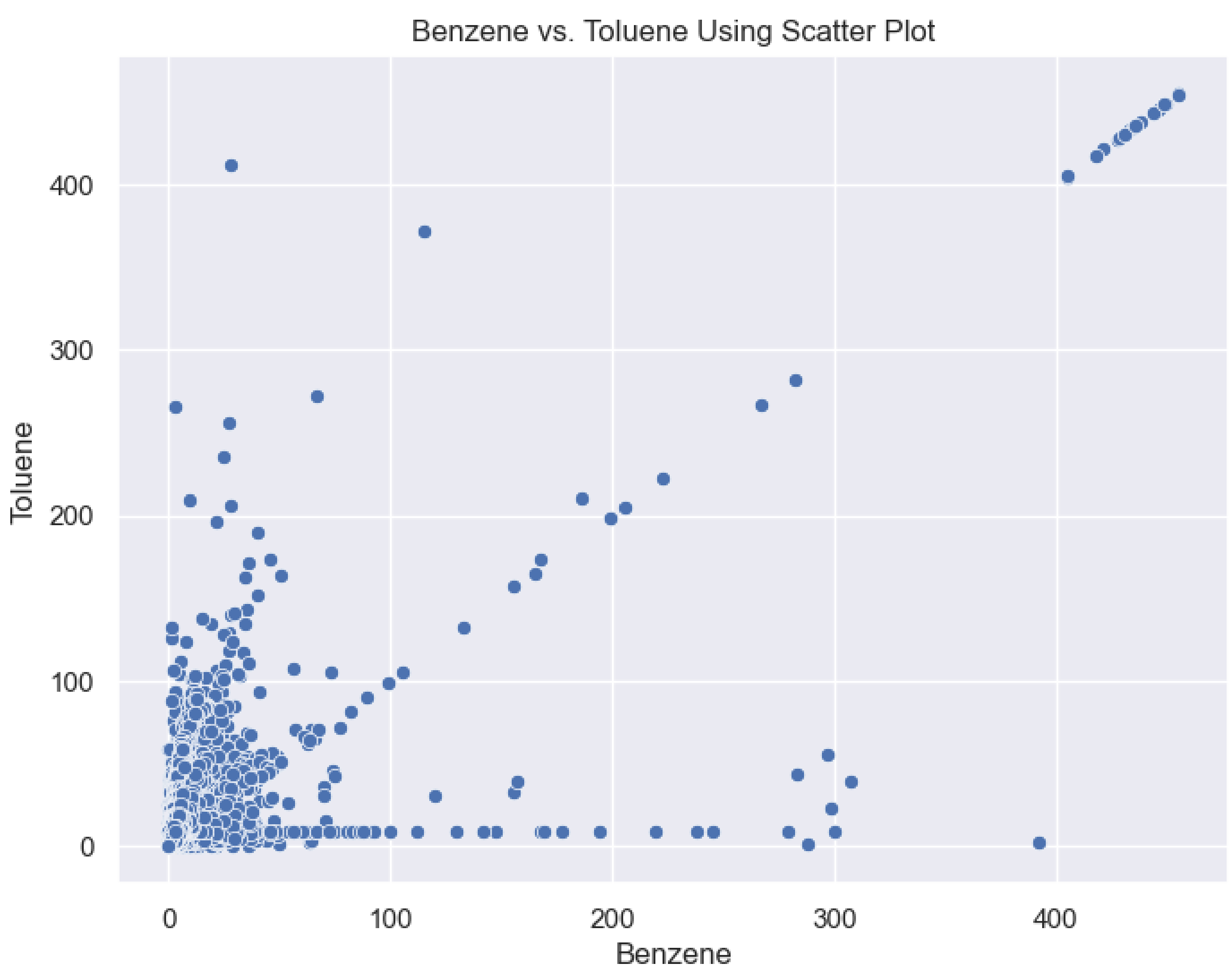


From above heatmap we observe a strong correlation of NO with NOx and of Benzene with Toluene so lets visualize them with the help of scatterplots¶

In [25]:

```
sns.set(rc={'figure.figsize': (8, 6)})
# plt.figure(figsize=(12, 6))
plt.figure(figsize=(8, 6))
sns.scatterplot(x='NO', y='NOx', data=df)
plt.title('NO vs. NOx Using Scatter Plot')
plt.show()

sns.scatterplot(x='Benzene', y='Toluene', data=df)
plt.title('Benzene vs. Toluene Using Scatter Plot')
plt.show()
```





MODEL TRAINING

In [26]:
```
df = df.drop(columns = ['Date', 'Month', 'Year', 'City'], axis=1)
df
```

Out[26]:

	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	Air_quality
0	67.450578	118.127103	0.92	18.22	17.15	23.483476	0.92	27.64	133.36	0.00000	0.020000	0.000000	149.0	Moderate
1	67.450578	118.127103	0.97	15.69	16.46	23.483476	0.97	24.55	34.06	3.68000	5.500000	3.770000	123.0	Moderate
2	67.450578	118.127103	17.40	19.30	29.70	23.483476	17.40	29.07	30.70	6.80000	16.400000	2.250000	300.0	Poor
3	67.450578	118.127103	1.70	18.48	17.97	23.483476	1.70	18.59	36.08	4.43000	10.140000	1.000000	123.0	Moderate
4	67.450578	118.127103	22.10	21.42	37.76	23.483476	22.10	39.33	39.31	7.01000	18.890000	2.780000	329.0	Very Poor
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29526	15.020000	50.940000	7.68	25.06	19.54	12.470000	0.47	8.55	23.30	2.24000	12.070000	0.730000	41.0	Good
29527	24.380000	74.090000	3.42	26.06	16.53	11.990000	0.52	12.72	30.14	0.74000	2.210000	0.380000	70.0	Satisfactory
29528	22.910000	65.730000	3.45	29.53	18.33	10.710000	0.48	8.42	30.96	0.01000	0.010000	0.000000	68.0	Satisfactory
29529	16.640000	49.970000	4.05	29.26	18.80	10.030000	0.52	9.84	28.30	0.00000	0.000000	0.000000	54.0	Satisfactory
29530	15.000000	66.000000	0.40	26.85	14.05	5.200000	0.59	2.10	17.05	3.28084	8.700972	3.070128	50.0	Good

29531 rows × 14 columns

Train-Test Split:

In [27]:
```
y = df["AQI"]
x = df[['PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2','O3', 'Benzene', 'Toluene', 'Xylene']]

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=0)
print(x_train.shape,x_test.shape,y_train.shape,y_test.shape)
```

```
(22148, 12) (7383, 12) (22148,) (7383,)
```

Supervised Learning:

In [28]:
```
# Importing all Models.
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
```

1. Linear Regression:

In [29]:
```
# Linear Regression Model
mreg = LinearRegression()
mreg.fit(x_train,y_train)
mlr_y_predict = mreg.predict(x_test)
```

2. Polynomial Regression:

In [30]:
```
# Polynomial Regression Model:
# Degree = 2

poly_reg = PolynomialFeatures(degree = 2)
preg = LinearRegression()
pf = poly_reg.fit_transform(x_train)
preg.fit(pf,y_train)
pr_y_predict = preg.predict(poly_reg.fit_transform(x_test))
```

3. Decision Tree:

In [31]:
```
# Decision Tree Tegression Model:

dec_tree = DecisionTreeRegressor(random_state = 0)
dec_tree.fit(x_train,y_train)
dt_y_predict = dec_tree.predict(x_test)
```

4. Random Forest:

In [32]:
```
# Random Forest Regression Model
# Random Forest with 500 trees

rt_reg = RandomForestRegressor(n_estimators = 500, random_state = 0)
rt_reg.fit(x_train,y_train)
rt_y_predict = rt_reg.predict(x_test)
```

Model Evaluation: (Supervised Learning)

In [33]:
```
# Error Estimation Methods

# Test Data prediction

#----- Multiple Linear Regresion -------
rmse_mlr = sqrt(metrics.mean_squared_error(y_test, mlr_y_predict))
mae_mlr = metrics.mean_absolute_error(y_test, mlr_y_predict)
r2_mlr = metrics.r2_score(y_test,mlr_y_predict)

#----- Polynomial Regression ------------
rmse_pr = sqrt(metrics.mean_squared_error(y_test, pr_y_predict))
mae_pr = metrics.mean_absolute_error(y_test, pr_y_predict)
r2_pr = metrics.r2_score(y_test,pr_y_predict)

#----- Decision Tree Regression ---------
rmse_dt = sqrt(metrics.mean_squared_error(y_test, dt_y_predict))
mae_dt = metrics.mean_absolute_error(y_test, dt_y_predict)
r2_dt = metrics.r2_score(y_test,dt_y_predict)

#----- Random Forest Regression ---------
rmse_rt = sqrt(metrics.mean_squared_error(y_test, rt_y_predict))
mae_rt = metrics.mean_absolute_error(y_test, rt_y_predict)
r2_rt = metrics.r2_score(y_test,rt_y_predict)


# Training Data Prediction

#----- multiple linear regression -------
mlr_ytp_rmse = sqrt(metrics.mean_squared_error(y_train, mreg.predict(x_train)))
mlr_ytp_mae = metrics.mean_absolute_error(y_train, mreg.predict(x_train))
mlr_ytp_r2 = metrics.r2_score(y_train, mreg.predict(x_train))

#------ polynomial regression ---------
pr_ytp_rmse = sqrt(metrics.mean_squared_error(y_train, preg.predict(poly_reg.fit_transform(x_train))))
pr_ytp_mae = metrics.mean_absolute_error(y_train, preg.predict(poly_reg.fit_transform(x_train)))
pr_ytp_r2 = metrics.r2_score(y_train, preg.predict(poly_reg.fit_transform(x_train)))

#----- decision tree regression ---------
```

```
dt_ytp_rmse = sqrt(metrics.mean_squared_error(y_train, dec_tree.predict(x_train)))
dt_ytp_mae = metrics.mean_absolute_error(y_train, dec_tree.predict(x_train))
dt_ytp_r2 = metrics.r2_score(y_train, dec_tree.predict(x_train))

# ----- random forest regression -----
rf_ytp_rmse = sqrt(metrics.mean_squared_error(y_train, rt_reg.predict(x_train)))
rf_ytp_mae = metrics.mean_absolute_error(y_train, rt_reg.predict(x_train))
rf_ytp_r2 = metrics.r2_score(y_train, rt_reg.predict(x_train))


# RESULT

print("Evaluating on Training Data:")
print("Models                           \tR^2\tRMSE\tMAE")
print("Multiple Linear Regresion\t{0:.4f}\t{1:.4f}\t{2:.4f}".format(mlr_ytp_r2,mlr_ytp_rmse,mlr_ytp_mae))
print("Polynomial Regression    \t{0:.2f}\t{1:.2f}\t{2:.3f}".format(pr_ytp_r2,pr_ytp_rmse,pr_ytp_mae))
print("Decision Tree Regression \t{0:.4f}\t{1:.4f}\t{2:.4f}".format(dt_ytp_r2,dt_ytp_rmse,dt_ytp_mae))
print("Random Forest Regression \t{0:.4f}\t{1:.4f}\t{2:.4f}".format(rf_ytp_r2,rf_ytp_rmse,rf_ytp_mae))
print("\n")
print("Evaluating on Testing Data:")
print("Models                           \tR^2\tRMSE\tMAE")
print("Multiple Linear Regresion\t{0:.4f}\t{1:.4f}\t{2:.4f}".format(r2_mlr,rmse_mlr,mae_mlr))
print("Polynomial Regression    \t{0:.2f}\t{1:.2f}\t{2:.3f}".format(r2_pr,rmse_pr,mae_pr))
print("Decision Tree Regression \t{0:.4f}\t{1:.4f}\t{2:.4f}".format(r2_dt,rmse_dt,mae_dt))
print("Random Forest Regression \t{0:.4f}\t{1:.4f}\t{2:.4f}".format(r2_rt,rmse_rt,mae_rt))
```

```
Evaluating on Training Data:
Models                          R^2     RMSE    MAE
Multiple Linear Regresion       0.8417  52.6762 29.9116
Polynomial Regression           0.88    46.18   26.996
Decision Tree Regression        0.9996  2.5349  0.1274
Random Forest Regression        0.9860  15.6392 6.9710


Evaluating on Testing Data:
Models                          R^2     RMSE    MAE
Multiple Linear Regresion       0.8359  53.5959 30.7147
Polynomial Regression           0.86    49.11   27.993
Decision Tree Regression        0.8192  56.2576 26.1283
Random Forest Regression        0.9045  40.8925 18.5250
```

Based on the provided evaluation metrics for air quality prediction, the model with the highest R-squared (R^2) score and lowest Root Mean Squared Error (RMSE) on the testing data is often considered the best choice. In this case, the Random Forest Regression model outperforms the other models based on these metrics.

Predictions of all above Supervised models:

In [34]:
```
# Sample input data for prediction
sample_input = pd.DataFrame([[26, 50, 1, 19, 18, 23, 1, 3, 42, 2, 6, 1]],
                            columns=['PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2', 'O3', 'Benzene', 'Toluene', 'Xylene'])

# Predict AQI using the trained models
mlr_prediction = mreg.predict(sample_input)
pr_prediction = preg.predict(poly_reg.transform(sample_input))
dt_prediction = dec_tree.predict(sample_input)
rt_prediction = rt_reg.predict(sample_input)

# Define AQI quality labels
aqi_quality_labels = ['Good', 'Satisfactory', 'Moderate', 'Poor', 'Very Poor']

# Determine AQI quality based on AQI value
def get_aqi_quality(aqi):
    if aqi <= 50:
        return aqi_quality_labels[0]
    elif aqi <= 100:
        return aqi_quality_labels[1]
    elif aqi <= 200:
        return aqi_quality_labels[2]
    elif aqi <= 300:
        return aqi_quality_labels[3]
    else:
        return aqi_quality_labels[4]

# Get AQI quality for each prediction
mlr_aqi_quality = get_aqi_quality(mlr_prediction)
pr_aqi_quality = get_aqi_quality(pr_prediction)
dt_aqi_quality = get_aqi_quality(dt_prediction)
rt_aqi_quality = get_aqi_quality(rt_prediction)

# Print the predicted AQI and AQI quality
print("Multiple Linear Regression Prediction:")
print("AQI:", mlr_prediction)
print("AQI Quality:", mlr_aqi_quality)
print()
print("Polynomial Regression Prediction:")
print("AQI:", pr_prediction)
print("AQI Quality:", pr_aqi_quality)
print()
print("Decision Tree Regression Prediction:")
print("AQI:", dt_prediction)
print("AQI Quality:", dt_aqi_quality)
print()
print("Random Forest Regression Prediction:")
print("AQI:", rt_prediction)
print("AQI Quality:", rt_aqi_quality)
```

```
Multiple Linear Regression Prediction:
AQI: [74.03981208]
AQI Quality: Satisfactory

Polynomial Regression Prediction:
AQI: [75.08835171]
AQI Quality: Satisfactory

Decision Tree Regression Prediction:
AQI: [51.]
AQI Quality: Satisfactory

Random Forest Regression Prediction:
AQI: [77.038]
AQI Quality: Satisfactory
```

Hence, Random Forest is the best model with highest Accuracy. So, we will use Random Forest as the Regression Model.

Random Forest:

In [35]:
```
# Training the model:
Best_Model_RF = RandomForestRegressor(n_estimators = 500, random_state = 0)
Best_Model_RF.fit(x_train,y_train)
Best_Model_RF_predict = Best_Model_RF.predict(x_test)

# Model Evaluation:
# Error Estimation Methods

# Test Data prediction

rmse_r = sqrt(metrics.mean_squared_error(y_test, Best_Model_RF_predict))
mae_r = metrics.mean_absolute_error(y_test, Best_Model_RF_predict)
r2_r = metrics.r2_score(y_test,Best_Model_RF_predict)

# Training Data Prediction

# ----- random forest regression -----
```

```python
rf_ytp_rms = sqrt(metrics.mean_squared_error(y_train, Best_Model_RF.predict(x_train)))
rf_ytp_ma = metrics.mean_absolute_error(y_train, Best_Model_RF.predict(x_train))
rf_ytp_r = metrics.r2_score(y_train, Best_Model_RF.predict(x_train))


# RESULT

print("Evaluating on Training Data:")
print("Models                   \tR^2\tRMSE\tMAE")
print("Random Forest Regression \t{0:.4f}\t{1:.4f}\t{2:.4f}".format(rf_ytp_r,rf_ytp_rms,rf_ytp_ma))
print("\n")
print("Evaluating on Testing Data:")
print("Models                   \tR^2\tRMSE\tMAE")
print("Random Forest Regression \t{0:.4f}\t{1:.4f}\t{2:.4f}".format(r2_r,rmse_r,mae_r))
```

```
Evaluating on Training Data:
Models                          R^2     RMSE    MAE
Random Forest Regression        0.9860  15.6392 6.9710


Evaluating on Testing Data:
Models                          R^2     RMSE    MAE
Random Forest Regression        0.9045  40.8925 18.5250
```

Model Deployment:

In [36]:

```python
import pickle
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import pandas as pd

df = df
# Split the data into training and testing sets
y = df["AQI"]
x = df[['PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2','O3', 'Benzene', 'Toluene', 'Xylene']]

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=0)
print(x_train.shape,x_test.shape,y_train.shape,y_test.shape)

# Training the model:
best_model_rf = RandomForestRegressor(n_estimators=500, random_state=0)
best_model_rf.fit(x_train, y_train)

# Save the trained model to a pickle file
model_filename = 'random_forest_model.pkl'
with open(model_filename, 'wb') as file:
    pickle.dump(best_model_rf, file)
```

```
(22148, 12) (7383, 12) (22148,) (7383,)
```