Assignment2

July 21, 2025

Objective :

The goal is to analyze global pollution data and develop strategies for pollution reduction and converting pollutants into energy. The dataset will be used for both data preprocessing and building regression models to predict energy recovery from pollution levels

Phase 1Data Collection and Exploratory Data Analysis (EDA)

contains 3 steps

Step 1 - Data Import and Preprocessing

[1]:
```
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
 ↪accuracy_score, confusion_matrix, recall_score, precision_score, f1_score,␣
 ↪ConfusionMatrixDisplay, classification_report
from scipy import stats
```

[2]:
```
data=pd.read_csv('Global_Pollution_Analysis.csv')
d=data.copy()
d.head()
```

[2]:
```
        Country  Year  Air_Pollution_Index  Water_Pollution_Index  \
0       Hungary  2005               272.70                 124.27
1     Singapore  2001                86.72                  60.34
2       Romania  2016                91.59                  83.36
3  Cook Islands  2018               280.61                  67.16
4      Djibouti  2008               179.16                 127.53

   Soil_Pollution_Index  Industrial_Waste (in tons)  \
0                 51.95                    94802.83
1                117.22                    56283.92
2                121.72                    56256.02
```

```
3              93.58                   74864.73
4             121.55                   76862.06

   Energy_Recovered (in GWh)  CO2_Emissions (in MT)  Renewable_Energy (%)  \
0                     158.14                   5.30                 41.11
1                     498.04                   6.34                 36.44
2                     489.51                  49.69                  9.38
3                     145.18                   8.91                 18.97
4                      40.38                  14.93                 34.00

   Plastic_Waste_Produced (in tons)  Energy_Consumption_Per_Capita (in MWh)  \
0                          37078.88                                   12.56
1                          33128.20                                    5.23
2                          18803.46                                   13.15
3                           9182.27                                    0.78
4                          39235.12                                   12.84

   Population (in millions)  GDP_Per_Capita (in USD)
0                     42.22                 20972.96
1                    137.25                 34850.41
2                    124.47                 57773.15
3                     67.80                 21837.51
4                    186.52                 41379.37
```

[3]:

```
d.isnull().sum()
```

[3]:

```
Country                                   0
Year                                      0
Air_Pollution_Index                       0
Water_Pollution_Index                     0
Soil_Pollution_Index                      0
Industrial_Waste (in tons)                0
Energy_Recovered (in GWh)                 0
CO2_Emissions (in MT)                     0
Renewable_Energy (%)                      0
Plastic_Waste_Produced (in tons)          0
Energy_Consumption_Per_Capita (in MWh)    0
Population (in millions)                  0
GDP_Per_Capita (in USD)                   0
dtype: int64
```

Null values do not exist in any column Now checking for incorrect data

[4]:

```
if pd.api.types.is_float_dtype(d['Year']):
    d['Year'] = d['Year'].round().astype(int)

if pd.api.types.is_numeric_dtype(d['Air_Pollution_Index']):
    d['Air_Pollution_Index'] = d['Air_Pollution_Index'].astype(float)
```

```python
d.loc[d['Air_Pollution_Index'] < 0, 'Air_Pollution_Index'] = abs(d['Air_Pollution_Index'])

if pd.api.types.is_numeric_dtype(d['Water_Pollution_Index']):
    d['Water_Pollution_Index'] = d['Water_Pollution_Index'].astype(float)
d.loc[d['Water_Pollution_Index'] < 0, 'Water_Pollution_Index'] = abs(d['Water_Pollution_Index'])

if pd.api.types.is_numeric_dtype(d['Soil_Pollution_Index']):
    d['Soil_Pollution_Index'] = d['Soil_Pollution_Index'].astype(float)
d.loc[d['Soil_Pollution_Index'] < 0, 'Soil_Pollution_Index'] = abs(d['Soil_Pollution_Index'])

if pd.api.types.is_numeric_dtype(d['Industrial_Waste (in tons)']):
    d['Industrial_Waste (in tons)'] = d['Industrial_Waste (in tons)'].astype(float)
d.loc[d['Industrial_Waste (in tons)'] < 0, 'Industrial_Waste (in tons)'] = abs(d['Industrial_Waste (in tons)'])

if pd.api.types.is_numeric_dtype(d['Energy_Recovered (in GWh)']):
    d['Energy_Recovered (in GWh)'] = d['Energy_Recovered (in GWh)'].astype(float)
d.loc[d['Energy_Recovered (in GWh)'] < 0, 'Energy_Recovered (in GWh)'] = abs(d['Energy_Recovered (in GWh)'])

if pd.api.types.is_numeric_dtype(d['CO2_Emissions (in MT)']):
    d['CO2_Emissions (in MT)'] = d['CO2_Emissions (in MT)'].astype(float)
d.loc[d['CO2_Emissions (in MT)'] < 0, 'CO2_Emissions (in MT)'] = abs(d['CO2_Emissions (in MT)'])

if pd.api.types.is_numeric_dtype(d['Renewable_Energy (%)']):
    d['Renewable_Energy (%)'] = d['Renewable_Energy (%)'].astype(float)
d.loc[d['Renewable_Energy (%)']<0, 'Renewable_Energy (%)'] = 0
d.loc[d['Renewable_Energy (%)']>100, 'Renewable_Energy (%)'] = 100

if pd.api.types.is_numeric_dtype(d['Plastic_Waste_Produced (in tons)']):
    d['Plastic_Waste_Produced (in tons)'] = d['Plastic_Waste_Produced (in tons)'].astype(float)
d.loc[d['Plastic_Waste_Produced (in tons)'] < 0, 'Plastic_Waste_Produced (in tons)'] = abs(d['Plastic_Waste_Produced (in tons)'])

if pd.api.types.is_numeric_dtype(d['Energy_Consumption_Per_Capita (in MWh)']):
    d['Energy_Consumption_Per_Capita (in MWh)'] = d['Energy_Consumption_Per_Capita (in MWh)'].astype(float)
```

```
d.loc[d['Energy_Consumption_Per_Capita (in MWh)'] < 0,␣
↪'Energy_Consumption_Per_Capita (in MWh)'] =␣
↪abs(d['Energy_Consumption_Per_Capita (in MWh)'])

if pd.api.types.is_numeric_dtype(d['Population (in millions)']):
    d['Population (in millions)'] = d['Population (in millions)'].astype(float)
d.loc[d['Population (in millions)'] < 0, 'Population (in millions)'] =␣
↪abs(d['Population (in millions)'])

if pd.api.types.is_numeric_dtype(d['GDP_Per_Capita (in USD)']):
    d['GDP_Per_Capita (in USD)'] = d['GDP_Per_Capita (in USD)'].astype(float)
d.loc[d['GDP_Per_Capita (in USD)'] < 0, 'GDP_Per_Capita (in USD)'] =␣
↪abs(d['GDP_Per_Capita (in USD)'])
```

[5]:

```
d
```

[5]:

```
           Country  Year  Air_Pollution_Index  Water_Pollution_Index  \
0          Hungary  2005               272.70                 124.27
1        Singapore  2001                86.72                  60.34
2          Romania  2016                91.59                  83.36
3     Cook Islands  2018               280.61                  67.16
4         Djibouti  2008               179.16                 127.53
..             …    …                    …                      …
195         Latvia  2004               115.84                  78.75
196     Bangladesh  2002               121.82                 120.97
197          Korea  2011               149.73                 146.92
198        Vanuatu  2002               237.20                 113.63
199        Croatia  2010               135.50                 158.43

     Soil_Pollution_Index  Industrial_Waste (in tons)  \
0                   51.95                    94802.83
1                  117.22                    56283.92
2                  121.72                    56256.02
3                   93.58                    74864.73
4                  121.55                    76862.06
..                    …                           …
195                 42.34                    49503.35
196                 63.95                    74694.68
197                 37.04                     2818.85
198                101.96                    68746.82
199                 89.80                    36182.44

     Energy_Recovered (in GWh)  CO2_Emissions (in MT)  Renewable_Energy (%)  \
0                       158.14                   5.30                 41.11
1                       498.04                   6.34                 36.44
2                       489.51                  49.69                  9.38
3                       145.18                   8.91                 18.97
```

```
4                   40.38                 14.93                  34.00
..                    …                    …                     …
195                 81.23                  4.85                  17.38
196                 25.89                 46.22                  16.56
197                293.27                 38.46                  38.36
198                305.61                 28.82                  32.17
199                172.24                  5.55                  45.96

     Plastic_Waste_Produced (in tons)  Energy_Consumption_Per_Capita (in MWh)  \
0                            37078.88                                   12.56
1                            33128.20                                    5.23
2                            18803.46                                   13.15
3                             9182.27                                    0.78
4                            39235.12                                   12.84
..                                …                                      …
195                           4065.66                                    6.28
196                          36905.26                                   15.18
197                          24700.29                                   14.11
198                           1443.62                                   12.44
199                          45405.35                                   11.72

     Population (in millions)  GDP_Per_Capita (in USD)
0                       42.22                 20972.96
1                      137.25                 34850.41
2                      124.47                 57773.15
3                       67.80                 21837.51
4                      186.52                 41379.37
..                        …                        …
195                     92.96                 14818.18
196                    114.02                 59238.04
197                    183.06                 28895.94
198                     40.65                 17068.01
199                    166.62                 30304.59

[200 rows x 13 columns]
```

[6]:
```python
s=StandardScaler()
d['Air_Pollution_Index_Scaled'] = s.fit_transform(d[['Air_Pollution_Index']])
d['Water_Pollution_Index_Scaled'] = s.
 ↪fit_transform(d[['Water_Pollution_Index']])
d['Soil_Pollution_Index_Scaled'] = s.fit_transform(d[['Soil_Pollution_Index']])
```

[7]:
```python
d
```

[7]:
```
        Country  Year  Air_Pollution_Index  Water_Pollution_Index  \
0       Hungary  2005               272.70                 124.27
1     Singapore  2001                86.72                  60.34
```

```
2        Romania  2016              91.59             83.36
3   Cook Islands  2018             280.61             67.16
4       Djibouti  2008             179.16            127.53
..           …     …                  …                 …
195       Latvia  2004             115.84             78.75
196   Bangladesh  2002             121.82            120.97
197        Korea  2011             149.73            146.92
198      Vanuatu  2002             237.20            113.63
199      Croatia  2010             135.50            158.43

     Soil_Pollution_Index  Industrial_Waste (in tons)  \
0                   51.95                    94802.83
1                  117.22                    56283.92
2                  121.72                    56256.02
3                   93.58                    74864.73
4                  121.55                    76862.06
..                    …                          …
195                 42.34                    49503.35
196                 63.95                    74694.68
197                 37.04                     2818.85
198                101.96                    68746.82
199                 89.80                    36182.44

     Energy_Recovered (in GWh)  CO2_Emissions (in MT)  Renewable_Energy (%)  \
0                       158.14                   5.30                 41.11
1                       498.04                   6.34                 36.44
2                       489.51                  49.69                  9.38
3                       145.18                   8.91                 18.97
4                        40.38                  14.93                 34.00
..                         …                      …                    …
195                      81.23                   4.85                 17.38
196                      25.89                  46.22                 16.56
197                     293.27                  38.46                 38.36
198                     305.61                  28.82                 32.17
199                     172.24                   5.55                 45.96

     Plastic_Waste_Produced (in tons)  Energy_Consumption_Per_Capita (in MWh)  \
0                            37078.88                                   12.56
1                            33128.20                                    5.23
2                            18803.46                                   13.15
3                             9182.27                                    0.78
4                            39235.12                                   12.84
..                                …                                       …
195                           4065.66                                    6.28
196                          36905.26                                   15.18
197                          24700.29                                   14.11
198                           1443.62                                   12.44
```

```
199                           45405.35                                11.72

     Population (in millions)  GDP_Per_Capita (in USD)  \
0                       42.22                 20972.96
1                      137.25                 34850.41
2                      124.47                 57773.15
3                       67.80                 21837.51
4                      186.52                 41379.37
..                        …                      …
195                     92.96                 14818.18
196                    114.02                 59238.04
197                    183.06                 28895.94
198                     40.65                 17068.01
199                    166.62                 30304.59

     Air_Pollution_Index_Scaled  Water_Pollution_Index_Scaled  \
0                      1.376167                      0.193880
1                     -1.403578                     -1.153098
2                     -1.330788                     -0.668076
3                      1.494394                     -1.009403
4                     -0.021926                      0.262567
..                          …                            …
195                   -0.968336                     -0.765207
196                   -0.878956                      0.124351
197                   -0.461800                      0.671106
198                    0.845568                     -0.030300
199                   -0.674489                      0.913617

     Soil_Pollution_Index_Scaled
0                      -0.619764
1                       1.028744
2                       1.142400
3                       0.431675
4                       1.138106
..                           …
195                    -0.862482
196                    -0.316683
197                    -0.996342
198                     0.643326
199                     0.336204

[200 rows x 16 columns]
```

[8]:
```
le = LabelEncoder()
d['Country_Label'] = le.fit_transform(d['Country'])
d['Year_Label'] = le.fit_transform(d['Year'])
# Assigns each unique value in the column a unique integer
```

```
# so that machine learning models can use it effectively
```

[9]:
```
d
```

[9]:
```
          Country  Year  Air_Pollution_Index  Water_Pollution_Index  \
0         Hungary  2005               272.70                 124.27
1       Singapore  2001                86.72                  60.34
2         Romania  2016                91.59                  83.36
3    Cook Islands  2018               280.61                  67.16
4        Djibouti  2008               179.16                 127.53
..            …     …                    …                      …
195        Latvia  2004               115.84                  78.75
196    Bangladesh  2002               121.82                 120.97
197         Korea  2011               149.73                 146.92
198       Vanuatu  2002               237.20                 113.63
199       Croatia  2010               135.50                 158.43

     Soil_Pollution_Index  Industrial_Waste (in tons)  \
0                   51.95                    94802.83
1                  117.22                    56283.92
2                  121.72                    56256.02
3                   93.58                    74864.73
4                  121.55                    76862.06
..                    …                          …
195                 42.34                    49503.35
196                 63.95                    74694.68
197                 37.04                     2818.85
198                101.96                    68746.82
199                 89.80                    36182.44

     Energy_Recovered (in GWh)  CO2_Emissions (in MT)  Renewable_Energy (%)  \
0                       158.14                   5.30                 41.11
1                       498.04                   6.34                 36.44
2                       489.51                  49.69                  9.38
3                       145.18                   8.91                 18.97
4                        40.38                  14.93                 34.00
..                        …                      …                    …
195                      81.23                   4.85                 17.38
196                      25.89                  46.22                 16.56
197                     293.27                  38.46                 38.36
198                     305.61                  28.82                 32.17
199                     172.24                   5.55                 45.96

     Plastic_Waste_Produced (in tons)  Energy_Consumption_Per_Capita (in MWh)  \
0                            37078.88                                   12.56
1                            33128.20                                    5.23
2                            18803.46                                   13.15
```

```
3                    9182.27                             0.78
4                   39235.12                            12.84
..                       …                               …
195                  4065.66                             6.28
196                 36905.26                            15.18
197                 24700.29                            14.11
198                  1443.62                            12.44
199                 45405.35                            11.72

     Population (in millions)  GDP_Per_Capita (in USD)  \
0                       42.22                 20972.96
1                      137.25                 34850.41
2                      124.47                 57773.15
3                       67.80                 21837.51
4                      186.52                 41379.37
..                        …                       …
195                     92.96                 14818.18
196                    114.02                 59238.04
197                    183.06                 28895.94
198                     40.65                 17068.01
199                    166.62                 30304.59

     Air_Pollution_Index_Scaled  Water_Pollution_Index_Scaled  \
0                      1.376167                      0.193880
1                     -1.403578                     -1.153098
2                     -1.330788                     -0.668076
3                      1.494394                     -1.009403
4                     -0.021926                      0.262567
..                          …                             …
195                   -0.968336                     -0.765207
196                   -0.878956                      0.124351
197                   -0.461800                      0.671106
198                    0.845568                     -0.030300
199                   -0.674489                      0.913617

     Soil_Pollution_Index_Scaled  Country_Label  Year_Label
0                      -0.619764             77           5
1                       1.028744            147           1
2                       1.142400            136          16
3                       0.431675             38          18
4                       1.138106             46           8
..                           …             …          …
195                    -0.862482             92           4
196                    -0.316683             13           2
197                    -0.996342             88          11
198                     0.643326            170           2
199                     0.336204             41          10
```

```
[200 rows x 18 columns]
```

Step 2 - Exploratory Data Analysis (EDA)

```
[10]: # 'CO2_Emissions (in MT)' column
mean_co2 = d['CO2_Emissions (in MT)'].mean()
mode_co2 = stats.mode(d['CO2_Emissions (in MT)'], keepdims=True).mode[0]
median_co2 = d['CO2_Emissions (in MT)'].median()
std_co2 = d['CO2_Emissions (in MT)'].std()
var_co2 = d['CO2_Emissions (in MT)'].var()
min_co2 = d['CO2_Emissions (in MT)'].min()
max_co2 = d['CO2_Emissions (in MT)'].max()
count_co2 = d['CO2_Emissions (in MT)'].count()

# 'Industrial_Waste (in tons)' column
mean_waste = d['Industrial_Waste (in tons)'].mean()
mode_waste = stats.mode(d['Industrial_Waste (in tons)'], keepdims=True).mode[0]
median_waste = d['Industrial_Waste (in tons)'].median()
std_waste = d['Industrial_Waste (in tons)'].std()
var_waste = d['Industrial_Waste (in tons)'].var()
min_waste = d['Industrial_Waste (in tons)'].min()
max_waste = d['Industrial_Waste (in tons)'].max()
count_waste = d['Industrial_Waste (in tons)'].count()

# 'Energy_Recovered (in GWh)' column
mean_energy = d['Energy_Recovered (in GWh)'].mean()
mode_energy = stats.mode(d['Energy_Recovered (in GWh)'], keepdims=True).mode[0]
median_energy = d['Energy_Recovered (in GWh)'].median()
std_energy = d['Energy_Recovered (in GWh)'].std()
var_energy = d['Energy_Recovered (in GWh)'].var()
min_energy = d['Energy_Recovered (in GWh)'].min()
max_energy = d['Energy_Recovered (in GWh)'].max()
count_energy = d['Energy_Recovered (in GWh)'].count()

# 'Renewable_Energy (%)' column
mean_renewable = d['Renewable_Energy (%)'].mean()
mode_renewable = stats.mode(d['Renewable_Energy (%)'], keepdims=True).mode[0]
median_renewable = d['Renewable_Energy (%)'].median()
std_renewable = d['Renewable_Energy (%)'].std()
var_renewable = d['Renewable_Energy (%)'].var()
min_renewable = d['Renewable_Energy (%)'].min()
max_renewable = d['Renewable_Energy (%)'].max()
count_renewable = d['Renewable_Energy (%)'].count()

# 'Plastic_Waste_Produced (in tons)' column
mean_plastic = d['Plastic_Waste_Produced (in tons)'].mean()
```

```
mode_plastic = stats.mode(d['Plastic_Waste_Produced (in tons)'], keepdims=True).
 ↪mode[0]
median_plastic = d['Plastic_Waste_Produced (in tons)'].median()
std_plastic = d['Plastic_Waste_Produced (in tons)'].std()
var_plastic = d['Plastic_Waste_Produced (in tons)'].var()
min_plastic = d['Plastic_Waste_Produced (in tons)'].min()
max_plastic = d['Plastic_Waste_Produced (in tons)'].max()
count_plastic = d['Plastic_Waste_Produced (in tons)'].count()

# 'Energy_Consumption_Per_Capita (in MWh)' column
mean_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].mean()
mode_Consumption = stats.mode(d['Energy_Consumption_Per_Capita (in MWh)'],␣
 ↪keepdims=True).mode[0]
median_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].median()
std_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].std()
var_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].var()
min_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].min()
max_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].max()
count_Consumption = d['Energy_Consumption_Per_Capita (in MWh)'].count()

# 'Population (in millions)' column
mean_population = d['Population (in millions)'].mean()
mode_population = stats.mode(d['Population (in millions)'], keepdims=True).
 ↪mode[0]
median_population = d['Energy_Consumption_Per_Capita (in MWh)'].median()
std_population = d['Population (in millions)'].std()
var_population = d['Population (in millions)'].var()
min_population = d['Population (in millions)'].min()
max_population = d['Population (in millions)'].max()
count_population = d['Population (in millions)'].count()

# 'GDP_Per_Capita (in USD)' column
mean_gdp = d['GDP_Per_Capita (in USD)'].mean()
mode_gdp = stats.mode(d['GDP_Per_Capita (in USD)'], keepdims=True).mode[0]
median_gdp = d['GDP_Per_Capita (in USD)'].median()
std_gdp = d['GDP_Per_Capita (in USD)'].std()
var_gdp = d['GDP_Per_Capita (in USD)'].var()
min_gdp = d['GDP_Per_Capita (in USD)'].min()
max_gdp = d['GDP_Per_Capita (in USD)'].max()
count_gdp = d['GDP_Per_Capita (in USD)'].count()
```

[11]:
```
print(f"CO2 Emissions - \nMean: {mean_co2}, \nMode: {mode_co2}, \nMedian:␣
 ↪{median_co2}, \nStd: {std_co2}, \nVar: {var_co2}, \nMin: {min_co2}, \nMax:␣
 ↪{max_co2}, \nCount: {count_co2}")
```

```
print(f"\nIndustrial Waste - \nMean: {mean_renewable}, \nMode: 
 ↪{mode_renewable}, \nMedian: {median_renewable}, \nStd: {std_renewable}, 
 ↪\nVar: {var_renewable}, \nMin: {min_renewable}, \nMax: {max_renewable}, 
 ↪\nCount: {count_renewable}")
print(f"\nEnergy Recovered - \nMean: {mean_energy}, \nMode: {mode_energy}, 
 ↪\nMedian: {median_energy}, \nStd: {std_energy}, \nVar: {var_energy}, \nMin: 
 ↪{min_energy}, \nMax: {max_energy}, \nCount: {count_energy}")
print(f"\nRenewable Energy - \nMean: {mean_renewable}, \nMode: 
 ↪{mode_renewable}, \nMedian: {median_renewable}, \nStd: {std_renewable}, 
 ↪\nVar: {var_renewable}, \nMin: {min_renewable}, \nMax: {max_renewable}, 
 ↪\nCount: {count_renewable}")
print(f"\nPlastic Waste - \nMean: {mean_plastic}, \nMode: {mode_plastic}, 
 ↪\nMedian: {median_plastic}, \nStd: {std_plastic}, \nVar: {var_plastic}, 
 ↪\nMin: {min_plastic}, \nMax: {max_plastic}, \nCount: {count_plastic}")
print(f"\nEnergy Consumption Per Capita - \nMean: {mean_Consumption}, \nMode: 
 ↪{mode_Consumption}, \nMedian: {median_Consumption}, \nStd: 
 ↪{std_Consumption}, \nVar: {var_Consumption}, \nMin: {min_Consumption}, \nMax:
 ↪ {max_Consumption}, \nCount: {count_Consumption}")
print(f"\nPopulation - \nMean: {mean_population}, \nMode: {mode_population}, 
 ↪\nMedian: {median_population}, \nStd: {std_population}, \nVar: 
 ↪{var_population}, \nMin: {min_population}, \nMax: {max_population}, \nCount: 
 ↪{count_population}")
print(f"\nGDP Per Capita - \nMean: {mean_gdp}, \nMode: {mode_gdp}, \nMedian: 
 ↪{median_gdp}, \nStd: {std_gdp}, \nVar: {var_gdp}, \nMin: {min_gdp}, \nMax: 
 ↪{max_gdp}, \nCount: {count_gdp}")
```

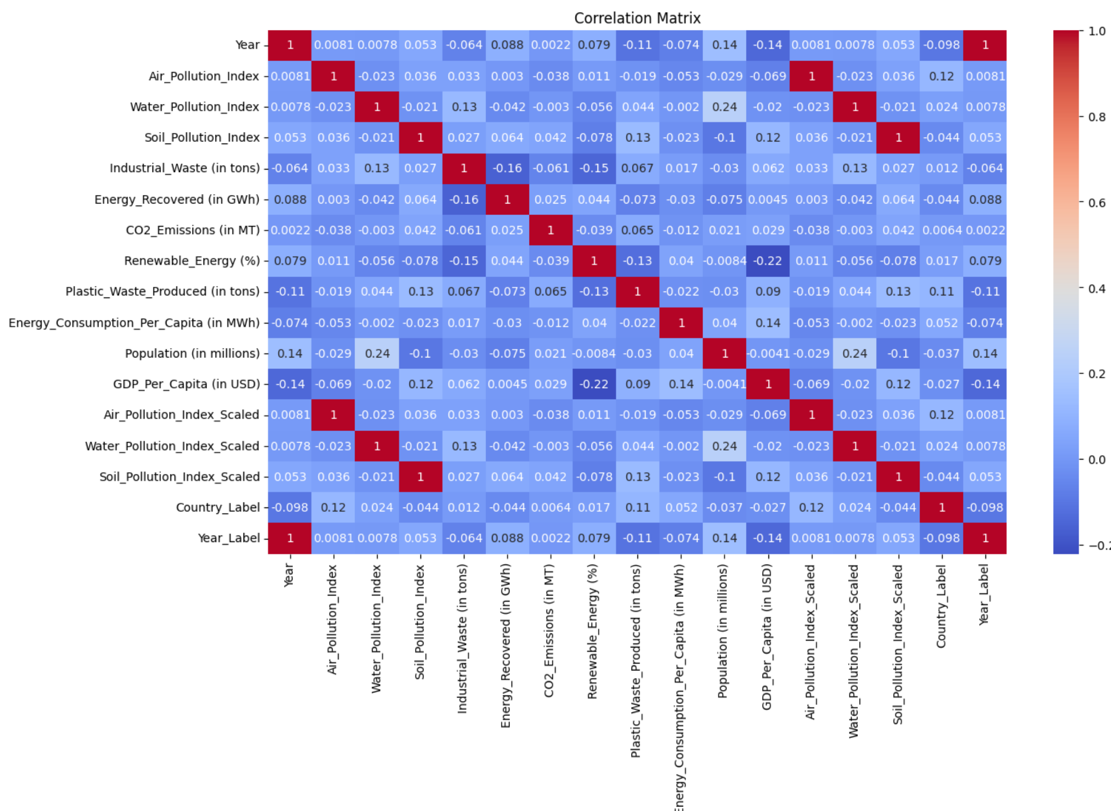
```
CO2 Emissions -
Mean: 24.8781,
Mode: 5.3,
Median: 25.355,
Std: 14.470891919808325,
Var: 209.4067129547739,
Min: 1.92,
Max: 49.69,
Count: 200

Industrial Waste -
Mean: 27.799699999999998,
Mode: 17.7,
Median: 29.17,
Std: 12.361878543149414,
Var: 152.8160411155779,
Min: 5.04,
Max: 49.56,
Count: 200

Energy Recovered -
```

```
Mean: 260.44870000000003,
Mode: 440.11,
Median: 273.14,
Std: 147.1419229340628,
Var: 21650.74548473367,
Min: 11.73,
Max: 499.98,
Count: 200

Renewable Energy -
Mean: 27.799699999999998,
Mode: 17.7,
Median: 29.17,
Std: 12.361878543149414,
Var: 152.8160411155779,
Min: 5.04,
Max: 49.56,
Count: 200

Plastic Waste -
Mean: 24492.89355,
Mode: 542.95,
Median: 24121.54,
Std: 14421.356002211007,
Var: 207975508.94250745,
Min: 542.95,
Max: 49852.28,
Count: 200

Energy Consumption Per Capita -
Mean: 9.43575,
Mode: 0.78,
Median: 9.225,
Std: 5.575670087272968,
Var: 31.08809692211055,
Min: 0.53,
Max: 19.98,
Count: 200

Population -
Mean: 104.27130000000001,
Mode: 30.44,
Median: 9.225,
Std: 56.90657395332747,
Var: 3238.3581591055276,
Min: 2.32,
Max: 198.82,
Count: 200
```

```
GDP Per Capita -
Mean: 35307.6024,
Mode: 1298.7,
Median: 35043.325,
Std: 19481.71445523607,
Var: 379537198.115354,
Min: 1298.7,
Max: 69143.14,
Count: 200
```

[12]:

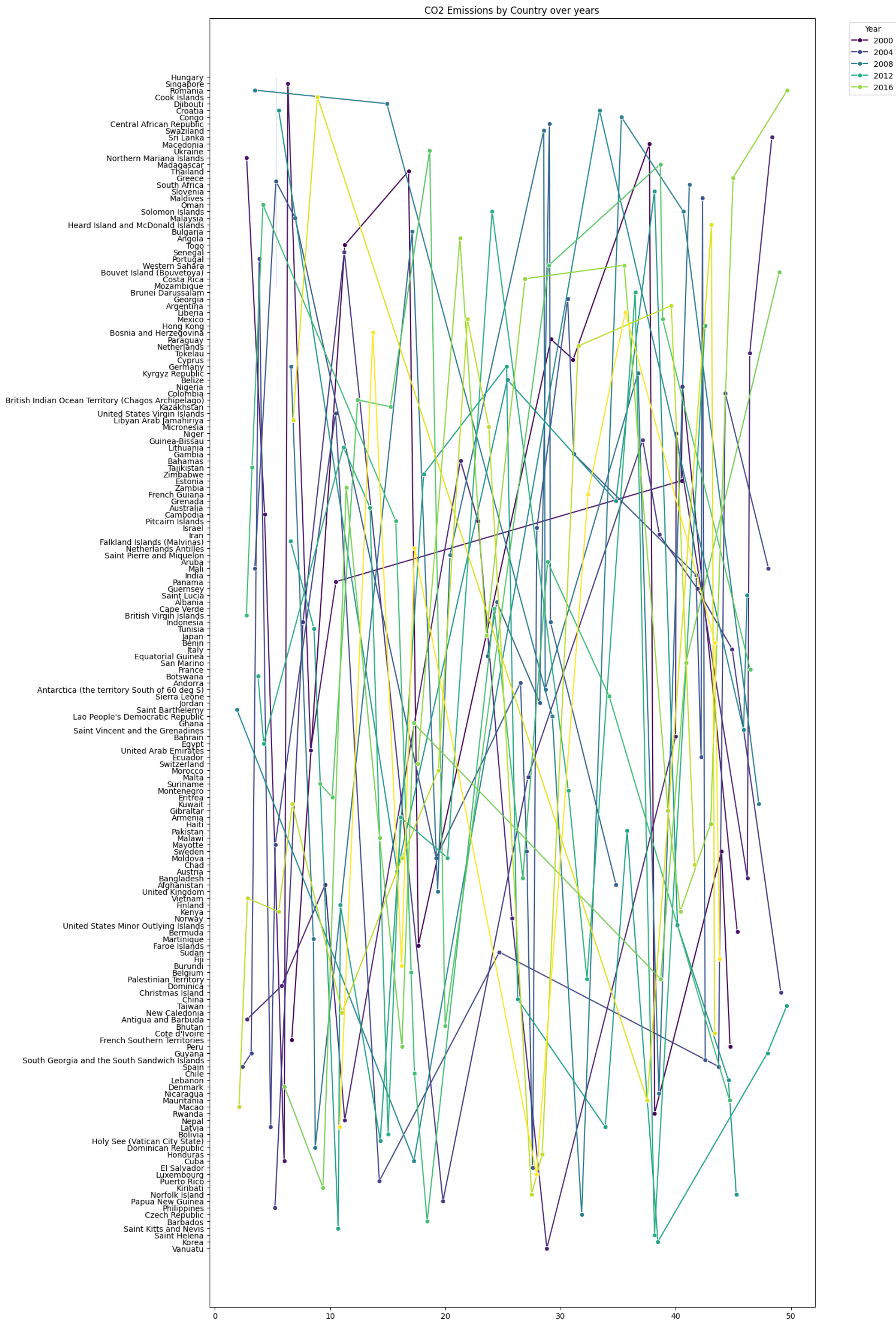
```python
correlation_matrix = d.corr(numeric_only=True)
plt.figure(figsize=(14, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

correlation_with_target = d.corr(numeric_only=True)['CO2_Emissions (in MT)'].
    ↪sort_values(ascending=False)
print("Correlation with CO2 Emissions (in MT):")
print(correlation_with_target)
```



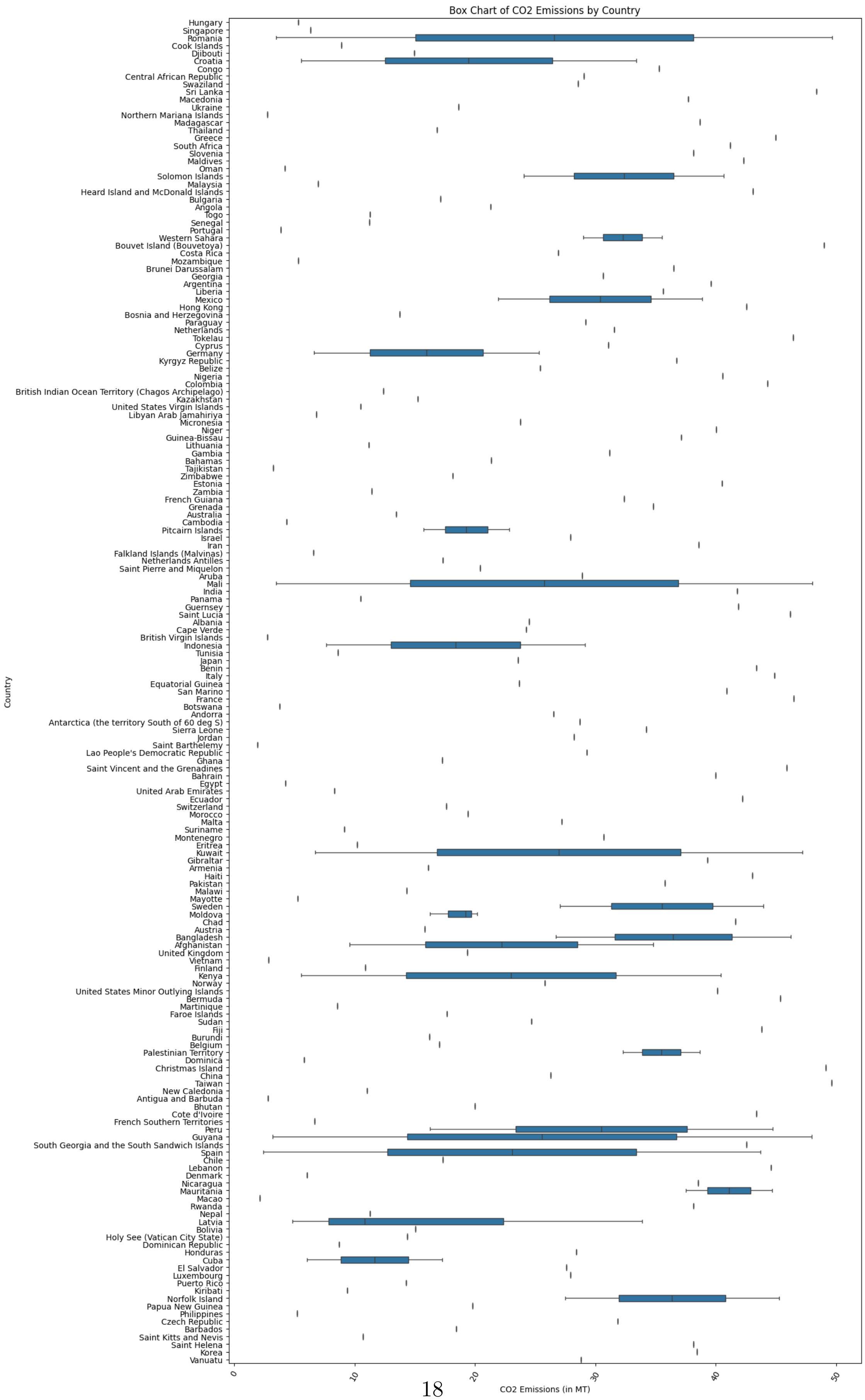
```
Correlation with CO2 Emissions (in MT):
CO2_Emissions (in MT)                    1.000000
Plastic_Waste_Produced (in tons)         0.065154
Soil_Pollution_Index_Scaled              0.041913
Soil_Pollution_Index                     0.041913
GDP_Per_Capita (in USD)                  0.029267
Energy_Recovered (in GWh)                0.024758
Population (in millions)                 0.020784
Country_Label                            0.006350
Year_Label                               0.002163
Year                                     0.002163
Water_Pollution_Index_Scaled            -0.002979
Water_Pollution_Index                   -0.002979
Energy_Consumption_Per_Capita (in MWh)  -0.011750
Air_Pollution_Index                     -0.038179
Air_Pollution_Index_Scaled              -0.038179
Renewable_Energy (%)                    -0.038888
Industrial_Waste (in tons)              -0.060737
Name: CO2_Emissions (in MT), dtype: float64
```

[13]:

```
plt.figure(figsize=(14, 30))
sns.lineplot(data=d, y=d['Country'], x=d['CO2_Emissions (in␣
 ↪MT)'],hue=d['Year'], marker="o", palette='viridis')
plt.title("CO2 Emissions by Country over years")
plt.xlabel("CO2 Emissions (in MT)")
plt.ylabel("Year")
plt.legend(title='Year', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

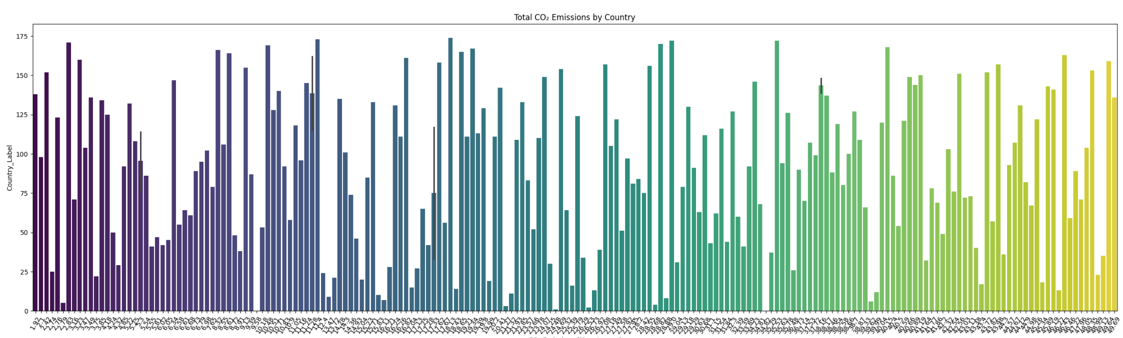

CO2 Emissions by Country over years
Year
2000
2004
2008
2012
2016
Hungary
Singapore
Romania
Cook Islands
Djibouti
Croatia
Congo
Central African Republic
Swaziland
Sri Lanka
Macedonia
Ukraine
Northern Mariana Islands
Madagascar
Thailand
Greece
South Africa
Slovenia
Maldives
Oman
Solomon Islands
Malaysia
Heard Island and McDonald Islands
Bulgaria
Angola
Togo
Senegal
Portugal
Western Sahara
Bouvet Island (Bouvetoya)
Costa Rica
Mozambique
Brunei Darussalam
Georgia
Argentina
Liberia
Mexico
Hong Kong
Bosnia and Herzegovina
Paraguay
Netherlands
Tokelau
Cyprus
Germany
Kyrgyz Republic
Belize
Nigeria
Colombia
British Indian Ocean Territory (Chagos Archipelago)
Kazakhstan
United States Virgin Islands
Libyan Arab Jamahiriya
Micronesia
Niger
Guinea-Bissau
Lithuania
Gambia
Bahamas
Tajikistan
Zimbabwe
Estonia
Zambia
French Guiana
Grenada
Australia
Cambodia
Pitcairn Islands
Israel
Iran
Falkland Islands (Malvinas)
Netherlands Antilles
Saint Pierre and Miquelon
Aruba
Mali
India
Panama
Guernsey
Saint Lucia
Albania
Cape Verde
British Virgin Islands
Indonesia
Tunisia
Japan
Benin
Italy
Equatorial Guinea
San Marino
France
Botswana
Andorra
Antarctica (the territory South of 60 deg S)
Sierra Leone
Jordan
Saint Barthelemy
Lao People's Democratic Republic
Ghana
Saint Vincent and the Grenadines
Bahrain
Egypt
United Arab Emirates
Ecuador
Switzerland
Morocco
Malta
Suriname
Montenegro
Eritrea
Kuwait
Gibraltar
Armenia
Haiti
Pakistan
Malawi
Mayotte
Sweden
Moldova
Chad
Austria
Bangladesh
Afghanistan
United Kingdom
Vietnam
Finland
Kenya
Norway
United States Minor Outlying Islands
Bermuda
Martinique
Faroe Islands
Sudan
Fiji
Burundi
Belgium
Palestinian Territory
Dominica
Christmas Island
China
Taiwan
New Caledonia
Antigua and Barbuda
Bhutan
Cote d'Ivoire
French Southern Territories
Peru
Guyana
South Georgia and the South Sandwich Islands
Spain
Chile
Lebanon
Denmark
Nicaragua
Mauritania
Macao
Rwanda
Nepal
Latvia
Bolivia
Holy See (Vatican City State)
Dominican Republic
Honduras
Cuba
El Salvador
Luxembourg
Puerto Rico
Kiribati
Norfolk Island
Papua New Guinea
Philippines
Czech Republic
Barbados
Saint Kitts and Nevis
Saint Helena
Korea
Vanuatu
0
10
20
30
40
50
CO2 Emissions (in MT)

[14]:
```
plt.figure(figsize=(14, 30))
sns.boxplot(data=d, y=d['Country'], x=d['CO2_Emissions (in MT)'])
plt.title("Box Chart of CO2 Emissions by Country")
plt.ylabel("Country")
plt.xlabel("CO2 Emissions (in MT)")
plt.xticks(rotation=60)
plt.show()
```


Box Chart of CO2 Emissions by Country
Country
Hungary
Singapore
Romania
Cook Islands
Djibouti
Croatia
Congo
Central African Republic
Swaziland
Sri Lanka
Macedonia
Ukraine
Northern Mariana Islands
Madagascar
Thailand
Greece
South Africa
Slovenia
Maldives
Oman
Solomon Islands
Malaysia
Heard Island and McDonald Islands
Bulgaria
Angola
Togo
Senegal
Portugal
Western Sahara
Bouvet Island (Bouvetoya)
Costa Rica
Mozambique
Brunei Darussalam
Georgia
Argentina
Liberia
Mexico
Hong Kong
Bosnia and Herzegovina
Paraguay
Netherlands
Tokelau
Cyprus
Germany
Kyrgyz Republic
Belize
Nigeria
Colombia
British Indian Ocean Territory (Chagos Archipelago)
Kazakhstan
United States Virgin Islands
Libyan Arab Jamahiriya
Micronesia
Niger
Guinea-Bissau
Lithuania
Gambia
Bahamas
Tajikistan
Zimbabwe
Estonia
Zambia
French Guiana
Grenada
Australia
Cambodia
Pitcairn Islands
Israel
Iran
Falkland Islands (Malvinas)
Netherlands Antilles
Saint Pierre and Miquelon
Aruba
Mali
India
Panama
Guernsey
Saint Lucia
Albania
Cape Verde
British Virgin Islands
Indonesia
Tunisia
Japan
Benin
Italy
Equatorial Guinea
San Marino
France
Botswana
Andorra
Antarctica (the territory South of 60 deg S)
Sierra Leone
Jordan
Saint Barthelemy
Lao People's Democratic Republic
Ghana
Saint Vincent and the Grenadines
Bahrain
Egypt
United Arab Emirates
Ecuador
Switzerland
Morocco
Malta
Suriname
Montenegro
Eritrea
Kuwait
Gibraltar
Armenia
Haiti
Pakistan
Malawi
Mayotte
Sweden
Moldova
Chad
Austria
Bangladesh
Afghanistan
United Kingdom
Vietnam
Finland
Kenya
Norway
United States Minor Outlying Islands
Bermuda
Martinique
Faroe Islands
Sudan
Fiji
Burundi
Belgium
Palestinian Territory
Dominica
Christmas Island
China
Taiwan
New Caledonia
Antigua and Barbuda
Bhutan
Cote d'Ivoire
French Southern Territories
Peru
Guyana
South Georgia and the South Sandwich Islands
Spain
Chile
Lebanon
Denmark
Nicaragua
Mauritania
Macao
Rwanda
Nepal
Latvia
Bolivia
Holy See (Vatican City State)
Dominican Republic
Honduras
Cuba
El Salvador
Luxembourg
Puerto Rico
Kiribati
Norfolk Island
Papua New Guinea
Philippines
Czech Republic
Barbados
Saint Kitts and Nevis
Saint Helena
Korea
Vanuatu
0
10
20
30
40
50
CO2 Emissions (in MT)

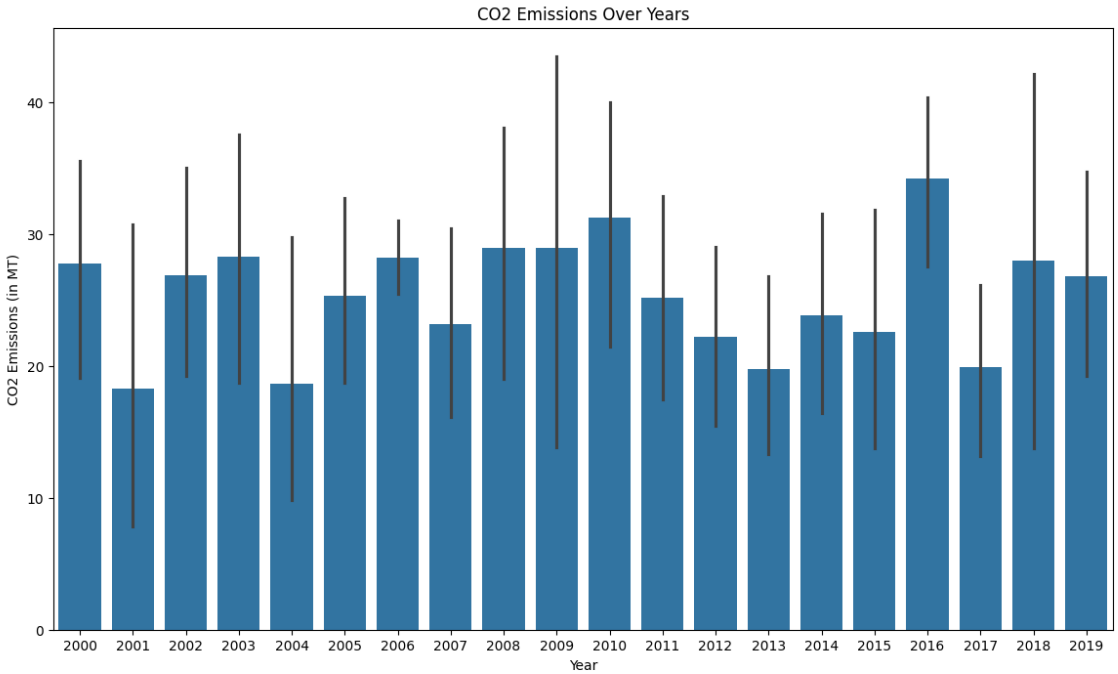
[15]:
```python
plt.figure(figsize=(30,8))
sns.barplot(data=d, y=d['Country_Label'], x=d['CO2_Emissions (in MT)'],␣
↪palette='viridis')
plt.title("Total CO  Emissions by Country")
plt.xlabel("CO  Emissions (Megatonnes)")
plt.ylabel("Country_Label")
plt.xticks(rotation=60)
plt.show()
```

```
C:\Users\Princy Pandya\AppData\Local\Temp\ipykernel_9172\1296014978.py: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.barplot(data=d, y=d['Country_Label'], x=d['CO2_Emissions (in MT)'],
palette='viridis')
```



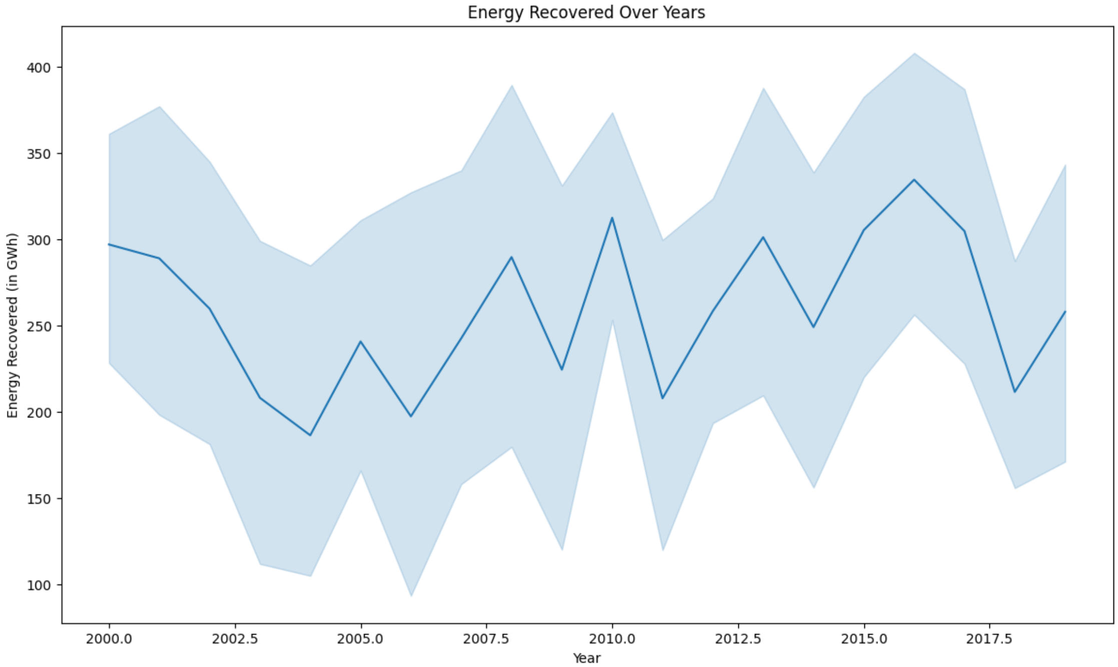
Step 3 - Feature Engineering

[16]:
```python
plt.figure(figsize=(14,8))
sns.barplot(data=d, y=d['CO2_Emissions (in MT)'], x=d['Year'])
plt.xlabel("Year")
plt.ylabel("CO2 Emissions (in MT)")
plt.title("CO2 Emissions Over Years")
plt.show()
```

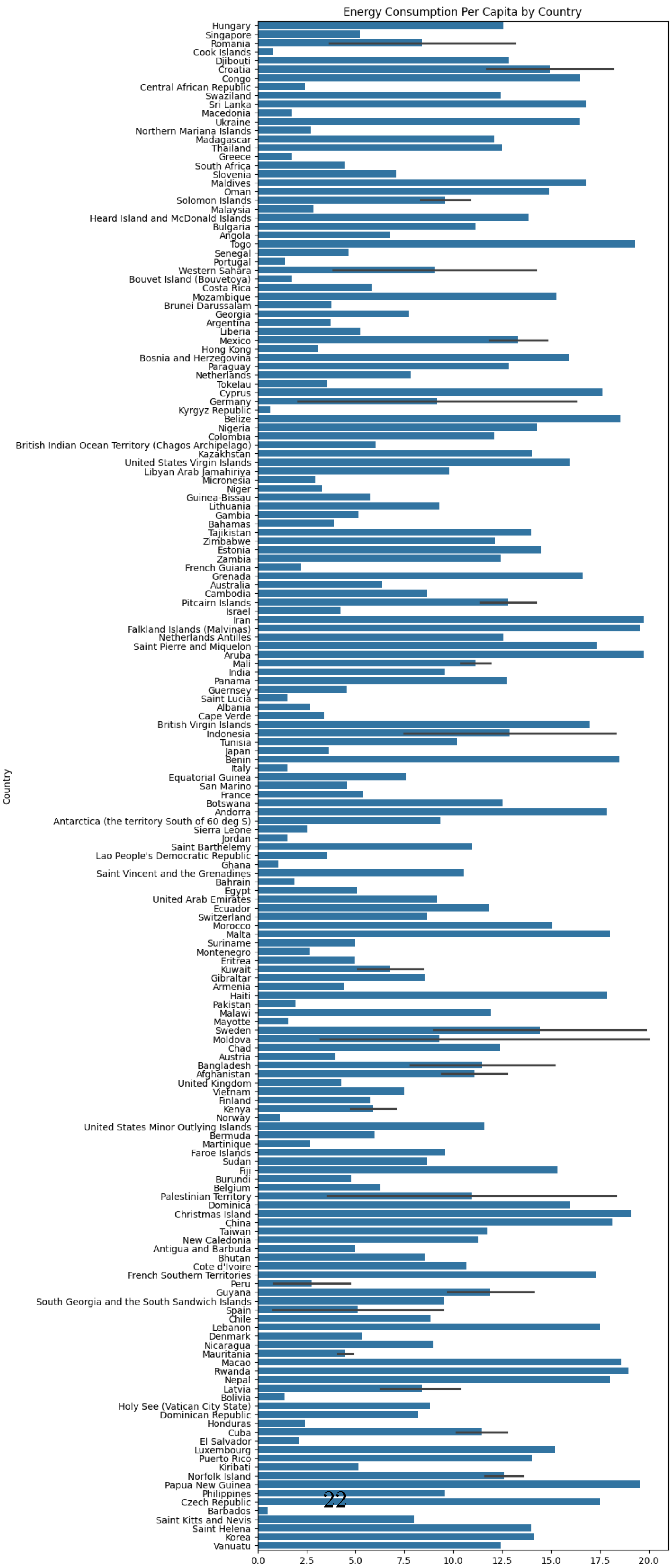


[17]:

```
plt.figure(figsize=(14,8))
sns.lineplot(data=d, x=d['Year'], y=d['Energy_Recovered (in GWh)'])
plt.title("Energy Recovered Over Years")
plt.xlabel("Year")
plt.ylabel("Energy Recovered (in GWh)")
plt.show()
```



[18]:
```
plt.figure(figsize=(8,30))
sns.barplot(data=d, y=d['Country'], x=d['Energy_Consumption_Per_Capita (in␣
↪MWh)'])
plt.title("Energy Consumption Per Capita by Country")
plt.xlabel("Energy Consumption Per Capita (in MWh)")
plt.ylabel("Country")
plt.title("Energy Consumption Per Capita by Country")
plt.show()
```

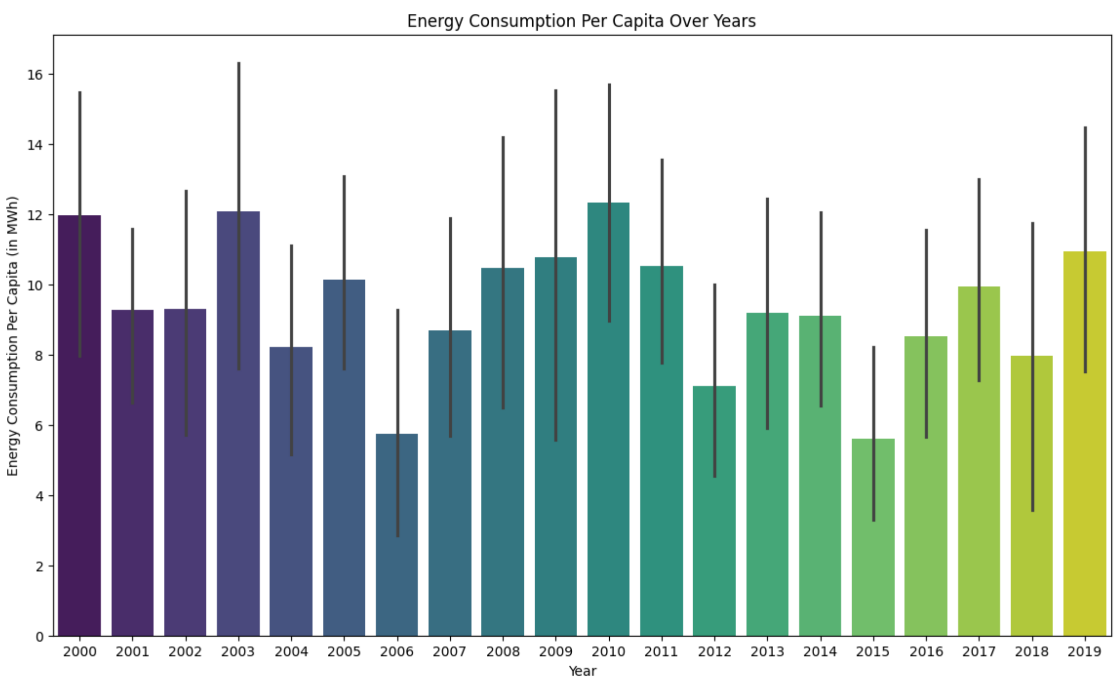

Energy Consumption Per Capita by Country
Hungary
Singapore
Romania
Cook Islands
Djibouti
Croatia
Congo
Central African Republic
Swaziland
Sri Lanka
Macedonia
Ukraine
Northern Mariana Islands
Madagascar
Thailand
Greece
South Africa
Slovenia
Maldives
Oman
Solomon Islands
Malaysia
Heard Island and McDonald Islands
Bulgaria
Angola
Togo
Senegal
Portugal
Western Sahara
Bouvet Island (Bouvetoya)
Costa Rica
Mozambique
Brunei Darussalam
Georgia
Argentina
Liberia
Mexico
Hong Kong
Bosnia and Herzegovina
Paraguay
Netherlands
Tokelau
Cyprus
Germany
Kyrgyz Republic
Belize
Nigeria
Colombia
British Indian Ocean Territory (Chagos Archipelago)
Kazakhstan
United States Virgin Islands
Libyan Arab Jamahiriya
Micronesia
Niger
Guinea-Bissau
Lithuania
Gambia
Bahamas
Tajikistan
Zimbabwe
Estonia
Zambia
French Guiana
Grenada
Australia
Cambodia
Pitcairn Islands
Israel
Iran
Falkland Islands (Malvinas)
Netherlands Antilles
Saint Pierre and Miquelon
Aruba
Mali
India
Panama
Guernsey
Saint Lucia
Albania
Cape Verde
British Virgin Islands
Indonesia
Tunisia
Japan
Benin
Italy
Equatorial Guinea
San Marino
France
Botswana
Andorra
Antarctica (the territory South of 60 deg S)
Sierra Leone
Jordan
Saint Barthelemy
Lao People's Democratic Republic
Ghana
Saint Vincent and the Grenadines
Bahrain
Egypt
United Arab Emirates
Ecuador
Switzerland
Morocco
Malta
Suriname
Montenegro
Eritrea
Kuwait
Gibraltar
Armenia
Haiti
Pakistan
Malawi
Mayotte
Sweden
Moldova
Chad
Austria
Bangladesh
Afghanistan
United Kingdom
Vietnam
Finland
Kenya
Norway
United States Minor Outlying Islands
Bermuda
Martinique
Faroe Islands
Sudan
Fiji
Burundi
Belgium
Palestinian Territory
Dominica
Christmas Island
China
Taiwan
New Caledonia
Antigua and Barbuda
Bhutan
Cote d'Ivoire
French Southern Territories
Peru
Guyana
South Georgia and the South Sandwich Islands
Spain
Chile
Lebanon
Denmark
Nicaragua
Mauritania
Macao
Rwanda
Nepal
Latvia
Bolivia
Holy See (Vatican City State)
Dominican Republic
Honduras
Cuba
El Salvador
Luxembourg
Puerto Rico
Kiribati
Norfolk Island
Papua New Guinea
Philippines
Czech Republic
Barbados
Saint Kitts and Nevis
Saint Helena
Korea
Vanuatu
Country
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Energy Consumption Per Capita (in MWh)

[19]:
```
plt.figure(figsize=(14,8))
sns.barplot(data=d, x=d['Year'], y=d['Energy_Consumption_Per_Capita (in MWh)'],␣
↪palette='viridis')
plt.xlabel("Year")
plt.ylabel("Energy Consumption Per Capita (in MWh)")
plt.title("Energy Consumption Per Capita Over Years")
plt.show()
```

```
C:\Users\Princy Pandya\AppData\Local\Temp\ipykernel_9172\4173994313.py: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.barplot(data=d, x=d['Year'], y=d['Energy_Consumption_Per_Capita (in
MWh)'], palette='viridis')
```



Phase 2:Predictive Modeling

Step 4 - Linear Regression Model (for Pollution Prediction)

[20]:
```
d
```

[20]:
```
          Country  Year  Air_Pollution_Index  Water_Pollution_Index  \
0         Hungary  2005               272.70                 124.27
1       Singapore  2001                86.72                  60.34
2         Romania  2016                91.59                  83.36
3    Cook Islands  2018               280.61                  67.16
4        Djibouti  2008               179.16                 127.53
..            …     …                   …                     …
195        Latvia  2004               115.84                  78.75
196    Bangladesh  2002               121.82                 120.97
197         Korea  2011               149.73                 146.92
198       Vanuatu  2002               237.20                 113.63
199       Croatia  2010               135.50                 158.43

     Soil_Pollution_Index  Industrial_Waste (in tons)  \
0                   51.95                    94802.83
1                  117.22                    56283.92
2                  121.72                    56256.02
3                   93.58                    74864.73
4                  121.55                    76862.06
..                    …                          …
195                 42.34                    49503.35
196                 63.95                    74694.68
197                 37.04                     2818.85
198                101.96                    68746.82
199                 89.80                    36182.44

     Energy_Recovered (in GWh)  CO2_Emissions (in MT)  Renewable_Energy (%)  \
0                       158.14                   5.30                 41.11
1                       498.04                   6.34                 36.44
2                       489.51                  49.69                  9.38
3                       145.18                   8.91                 18.97
4                        40.38                  14.93                 34.00
..                        …                      …                    …
195                      81.23                   4.85                 17.38
196                      25.89                  46.22                 16.56
197                     293.27                  38.46                 38.36
198                     305.61                  28.82                 32.17
199                     172.24                   5.55                 45.96

     Plastic_Waste_Produced (in tons)  Energy_Consumption_Per_Capita (in MWh)  \
0                            37078.88                                  12.56
1                            33128.20                                   5.23
2                            18803.46                                  13.15
3                             9182.27                                   0.78
4                            39235.12                                  12.84
..                               …                                      …
195                           4065.66                                   6.28
```

```
196                          36905.26                                    15.18
197                          24700.29                                    14.11
198                           1443.62                                    12.44
199                          45405.35                                    11.72

     Population (in millions)  GDP_Per_Capita (in USD)  \
0                       42.22                 20972.96
1                      137.25                 34850.41
2                      124.47                 57773.15
3                       67.80                 21837.51
4                      186.52                 41379.37
..                        …                       …
195                     92.96                 14818.18
196                    114.02                 59238.04
197                    183.06                 28895.94
198                     40.65                 17068.01
199                    166.62                 30304.59

     Air_Pollution_Index_Scaled  Water_Pollution_Index_Scaled  \
0                      1.376167                      0.193880
1                     -1.403578                     -1.153098
2                     -1.330788                     -0.668076
3                      1.494394                     -1.009403
4                     -0.021926                      0.262567
..                         …                           …
195                   -0.968336                     -0.765207
196                   -0.878956                      0.124351
197                   -0.461800                      0.671106
198                    0.845568                     -0.030300
199                   -0.674489                      0.913617

     Soil_Pollution_Index_Scaled  Country_Label  Year_Label
0                      -0.619764             77           5
1                       1.028744            147           1
2                       1.142400            136          16
3                       0.431675             38          18
4                       1.138106             46           8
..                          …             …          …
195                    -0.862482             92           4
196                    -0.316683             13           2
197                    -0.996342             88          11
198                     0.643326            170           2
199                     0.336204             41          10

[200 rows x 18 columns]
```

[21]:
```
features1 = ['Air_Pollution_Index_Scaled', 'Industrial_Waste (in tons)',
 ↪'CO2_Emissions (in MT)', 'Population (in millions)']
x1 = d[features1]
y1 = d['Energy_Recovered (in GWh)'].values.reshape(-1,1)
```

[22]:
```
x1_train, x1_test, y1_train, y1_test = train_test_split(x1,y1,test_size=0.3,
 ↪random_state=42)
```

[23]:
```
model1 = LinearRegression()
model1.fit(x1_train, y1_train)
```

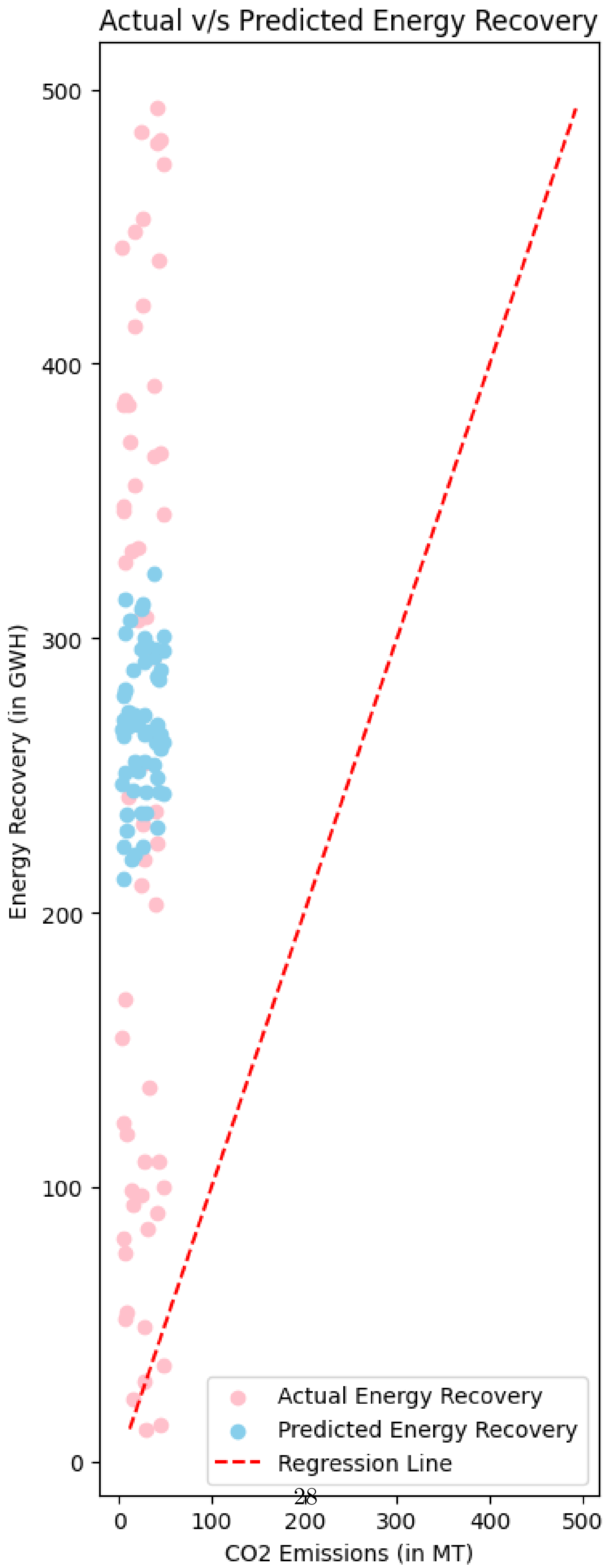
[23]:
```
LinearRegression()
```

[24]:
```
y1_pred = model1.predict(x1_test)
y1_pred
```

[24]:
```
array([[243.8095464 ],
       [259.85454974],
       [300.00975363],
       [244.42870374],
       [235.88074888],
       [288.29352918],
       [251.06617352],
       [268.83183434],
       [267.74366935],
       [224.28625127],
       [288.39015524],
       [251.55035009],
       [295.30699022],
       [236.10946311],
       [264.87839311],
       [291.41831989],
       [297.3572524 ],
       [254.00979102],
       [229.68624541],
       [323.81628421],
       [264.16337236],
       [231.04120893],
       [271.97021133],
       [271.93080839],
       [212.37753419],
       [286.21211717],
       [243.74104455],
       [255.10705757],
       [296.9007434 ],
       [221.36652128],
       [300.71186934],
```

```
       [285.14265891],
       [306.48171142],
       [273.18579305],
       [314.45039619],
       [265.20434332],
       [301.62912975],
       [312.41700131],
       [280.55183194],
       [249.2853279 ],
       [310.66019593],
       [293.0141232 ],
       [219.16162561],
       [268.45197474],
       [246.86164837],
       [279.07338577],
       [262.01352786],
       [224.08291744],
       [281.41779002],
       [296.1142626 ],
       [270.55180483],
       [236.08854432],
       [265.95965738],
       [261.99908013],
       [268.72220185],
       [243.16997378],
       [266.96436999],
       [296.00786676],
       [285.99794003],
       [255.2277686 ]])
```

[25]:
```
plt.figure(figsize=(4,10))
plt.scatter(x1_test['CO2_Emissions (in MT)'],y1_test,color='pink',␣
 ↪label='Actual Energy Recovery')
plt.scatter(x1_test['CO2_Emissions (in MT)'],y1_pred,color='skyblue',␣
 ↪label='Predicted Energy Recovery')
plt.plot([y1_test.min(),y1_test.max()],[y1_test.min(),y1_test.
 ↪max()],'r--',label='Regression Line')
plt.title('Actual v/s Predicted Energy Recovery')
plt.xlabel('CO2 Emissions (in MT)')
plt.ylabel('Energy Recovery (in GWH)')
plt.legend()
plt.tight_layout()
plt.show()
```


Actual v/s Predicted Energy Recovery
Energy Recovery (in GWH)
CO2 Emissions (in MT)
Actual Energy Recovery
Predicted Energy Recovery
Regression Line
0
100
200
300
400
500
0
100
200
300
400
500

[26]:
```
mse = mean_squared_error(y1_test,y1_pred)
mae = mean_absolute_error(y1_test,y1_pred)
rsquared = model1.score(x1_test,y1_test)

print('Mean squared error : ',mse)
print('Mean absolute error : ',mae)
print('r squared (accuracy) : ',rsquared)
```

```
Mean squared error :  22548.84167404821
Mean absolute error :  133.57531391845018
r squared (accuracy) :  0.0012488528438489022
```

Step 5 - Logistic Regression Model (for Categorization of Pollution Levels)

[27]:
```
flag1_co2 = (min_co2+mean_co2)/2
flag2_co2 = (max_co2+mean_co2)/2
print(f"Flag 1 for CO2 Emissions: {flag1_co2}")
print(f"Flag 2 for CO2 Emissions: {flag2_co2}")
```

```
Flag 1 for CO2 Emissions: 13.399049999999999
Flag 2 for CO2 Emissions: 37.28405
```

[28]:
```
d.loc[d['CO2_Emissions (in MT)'] < flag1_co2, 'Pollution_severity'] = 'Low'
d.loc[(d['CO2_Emissions (in MT)'] >= flag1_co2) & (d['CO2_Emissions (in MT)'] <␣
↪flag2_co2), 'Pollution_severity'] = 'Medium'
d.loc[d['CO2_Emissions (in MT)'] >= flag2_co2, 'Pollution_severity'] = 'High'

d
```

[28]:
```
          Country  Year  Air_Pollution_Index  Water_Pollution_Index  \
0         Hungary  2005               272.70                 124.27
1       Singapore  2001                86.72                  60.34
2         Romania  2016                91.59                  83.36
3    Cook Islands  2018               280.61                  67.16
4        Djibouti  2008               179.16                 127.53
..            …     …                    …                      …
195        Latvia  2004               115.84                  78.75
196    Bangladesh  2002               121.82                 120.97
197         Korea  2011               149.73                 146.92
198       Vanuatu  2002               237.20                 113.63
199       Croatia  2010               135.50                 158.43

     Soil_Pollution_Index  Industrial_Waste (in tons)  \
0                   51.95                    94802.83
1                  117.22                    56283.92
2                  121.72                    56256.02
```

```
3                   93.58                       74864.73
4                  121.55                       76862.06
..                    …                            …
195                 42.34                       49503.35
196                 63.95                       74694.68
197                 37.04                        2818.85
198                101.96                       68746.82
199                 89.80                       36182.44

     Energy_Recovered (in GWh)  CO2_Emissions (in MT)  Renewable_Energy (%)  \
0                       158.14                   5.30                 41.11
1                       498.04                   6.34                 36.44
2                       489.51                  49.69                  9.38
3                       145.18                   8.91                 18.97
4                        40.38                  14.93                 34.00
..                        …                      …                    …
195                      81.23                   4.85                 17.38
196                      25.89                  46.22                 16.56
197                     293.27                  38.46                 38.36
198                     305.61                  28.82                 32.17
199                     172.24                   5.55                 45.96

     Plastic_Waste_Produced (in tons)  Energy_Consumption_Per_Capita (in MWh)  \
0                            37078.88                                   12.56
1                            33128.20                                    5.23
2                            18803.46                                   13.15
3                             9182.27                                    0.78
4                            39235.12                                   12.84
..                              …                                       …
195                           4065.66                                    6.28
196                          36905.26                                   15.18
197                          24700.29                                   14.11
198                           1443.62                                   12.44
199                          45405.35                                   11.72

     Population (in millions)  GDP_Per_Capita (in USD)  \
0                       42.22                 20972.96
1                      137.25                 34850.41
2                      124.47                 57773.15
3                       67.80                 21837.51
4                      186.52                 41379.37
..                       …                       …
195                     92.96                 14818.18
196                    114.02                 59238.04
197                    183.06                 28895.94
198                     40.65                 17068.01
199                    166.62                 30304.59
```

```
     Air_Pollution_Index_Scaled  Water_Pollution_Index_Scaled  \
0                      1.376167                      0.193880
1                     -1.403578                     -1.153098
2                     -1.330788                     -0.668076
3                      1.494394                     -1.009403
4                     -0.021926                      0.262567
..                          …                             …
195                   -0.968336                     -0.765207
196                   -0.878956                      0.124351
197                   -0.461800                      0.671106
198                    0.845568                     -0.030300
199                   -0.674489                      0.913617

     Soil_Pollution_Index_Scaled  Country_Label  Year_Label Pollution_severity
0                      -0.619764             77           5                Low
1                       1.028744            147           1                Low
2                       1.142400            136          16               High
3                       0.431675             38          18                Low
4                       1.138106             46           8             Medium
..                           …             …         …                  …
195                    -0.862482             92           4                Low
196                    -0.316683             13           2               High
197                    -0.996342             88          11               High
198                     0.643326            170           2             Medium
199                     0.336204             41          10                Low

[200 rows x 19 columns]
```

[29]:
```
d['Pollution_severity'].isnull().sum()
```

[29]:
```
np.int64(0)
```

[30]:
```
features2= ['Air_Pollution_Index_Scaled', 'Industrial_Waste (in tons)',
  'CO2_Emissions (in MT)', 'Population (in millions)']
x2=d[features2]
y2=d['Pollution_severity'].values.ravel()
```

[31]:
```
y2.reshape(-1,1)
```

[31]:
```
array([['Low'],
       ['Low'],
       ['High'],
       ['Low'],
       ['Medium'],
       ['Medium'],
       ['Medium'],
```

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```

```
       ['Low'],
       ['High'],
       ['High'],
       ['Medium'],
       ['Low']], dtype=object)
```

[32]:
```
x2_train, x2_test, y2_train, y2_test = train_test_split(x2, y2, test_size=0.3,␣
 ↪random_state=42)
```

[33]:
```
model2 = LogisticRegression()
model2.fit(x2_train, y2_train)
```

```
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\linear_model\_logistic.py:470: ConvergenceWarning: lbfgs failed
to converge after 100 iteration(s) (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=100).
You might also want to scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

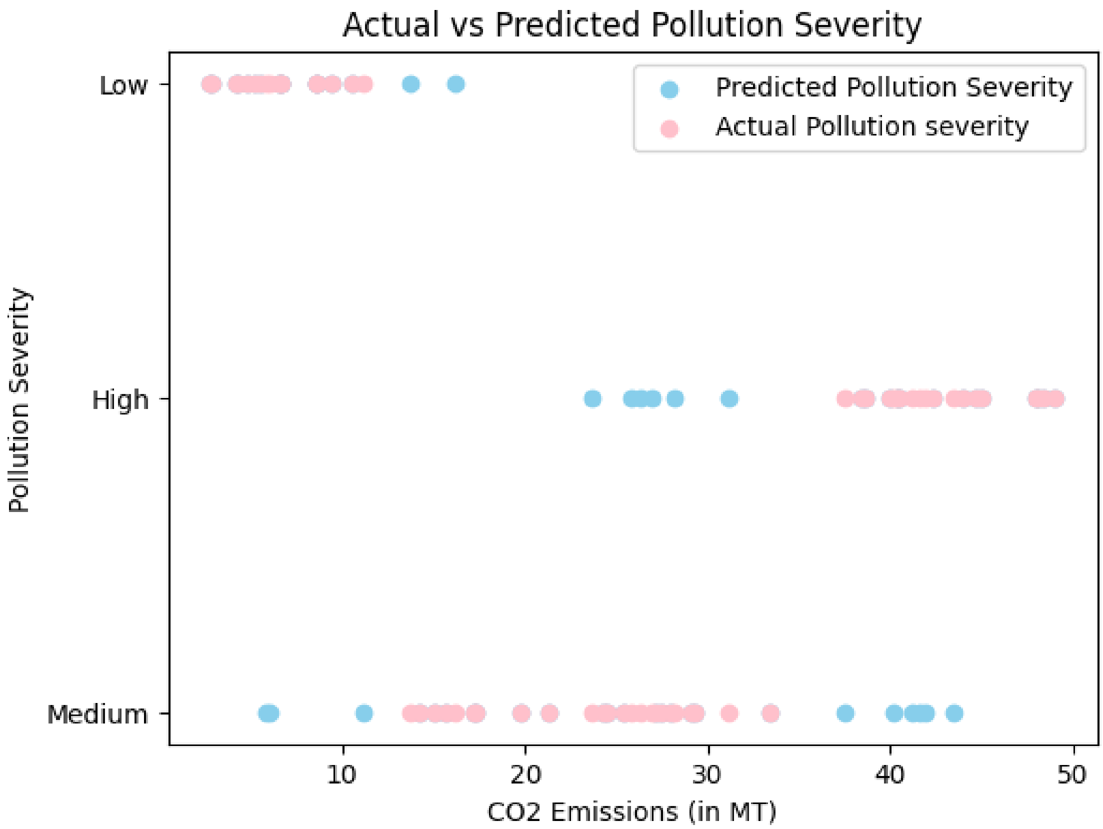
[33]:
```
LogisticRegression()
```

[34]:
```
y2_pred = model2.predict(x2_test)
y2_pred.ravel()
```

[34]:
```
array(['Medium', 'High', 'High', 'Medium', 'Low', 'High', 'Low', 'Medium',
       'Low', 'Medium', 'Medium', 'Medium', 'High', 'Medium', 'High',
       'Medium', 'High', 'Medium', 'Low', 'High', 'Low', 'Medium',
       'Medium', 'High', 'Low', 'High', 'Medium', 'Medium', 'High', 'Low',
       'High', 'High', 'Medium', 'Low', 'Medium', 'Medium', 'Medium',
       'High', 'Low', 'Medium', 'Medium', 'High', 'Low', 'Medium', 'Low',
       'Low', 'High', 'Low', 'Low', 'High', 'Low', 'Medium', 'Medium',
       'Medium', 'Medium', 'High', 'Low', 'High', 'High', 'Medium'],
      dtype=object)
```

[35]:
```
plt.Figure(figsize=(14,8))
plt.scatter(x2_test['CO2_Emissions (in MT)'], y2_pred, color='skyblue',␣
 ↪label='Predicted Pollution Severity')
plt.scatter(x2_test['CO2_Emissions (in MT)'], y2_test, color='pink',␣
 ↪label='Actual Pollution severity')
plt.title('Actual vs Predicted Pollution Severity')
plt.xlabel('CO2 Emissions (in MT)')
plt.ylabel('Pollution Severity')
```

```
plt.legend()
plt.show()
```



When you're calculating recall for multiple classes, there are several ways to combine the recall values of individual classes into a single number.That's what the average parameter controls.

Recall tells you : "Out of all the actual 'Low' (or 'Medium', or 'High') pollution samples, how many did the model correctly identify?" So if 100 samples are actually "High", and your model predicted 90 of them correctly, the recall for "High" is 90%.

Class	Total Samples	Correct Predictions	Recall
Low	10	7	70%
Medium	20	14	70%
High	70	63	90%

if avereage='macro': averages all recalls equally. $(70 + 70 + 90) / 3 = 76.67\%$

if average='weighted': Gives more importance to bigger classes (like High with 70 samples) Recall $= (10\times0.7 + 20\times0.7 + 70\times0.9) / (10 + 20 + 70) = (7 + 14 + 63) / 100 = 84\%$

So 'weighted' gives a more realistic score when some classes are more frequent than others.

[36]:
```
accuracy = accuracy_score(y2_test, y2_pred)
precision = precision_score(y2_test, y2_pred, average='weighted')
f1score = f1_score(y2_test, y2_pred, average='weighted')
recall = recall_score(y2_test, y2_pred, average='weighted')

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"F1 Score: {f1score}")
print(f"Recall: {recall}")
```

```
Accuracy: 0.7166666666666667
Precision: 0.7205833333333334
F1 Score: 0.7182951968666255
Recall: 0.7166666666666667
```

[37]:
```
lb = LabelEncoder()
# converts y into numbers
# Low = 0, Medium = 1, High = 2
y = lb.fit_transform(y2)
y=y.ravel()
x = x2
```

[38]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[39]:
```
model1.fit(x_train, y_train)
y_pred = model1.predict(x_test)
y_pred
```

[39]:
```
array([0.94291452, 0.67026742, 1.04277004, 1.44295433, 1.63690987,
       0.55098226, 1.65106133, 1.42973758, 1.47644102, 1.23081222,
       1.19843383, 1.33807059, 0.56875222, 1.14070402, 0.65927932,
       1.16603962, 0.94004205, 0.98310214, 1.61804287, 0.71065523,
       1.68212928, 0.78049005, 1.41043422, 0.9690681 , 1.73695778,
       0.79151141, 0.77659423, 0.98650112, 1.06063102, 1.44211337,
       0.58589629, 0.6454287 , 1.40170179, 1.57618693, 1.4938707 ,
       1.03089977, 1.4873944 , 1.00628838, 1.54708282, 0.68777692])
```

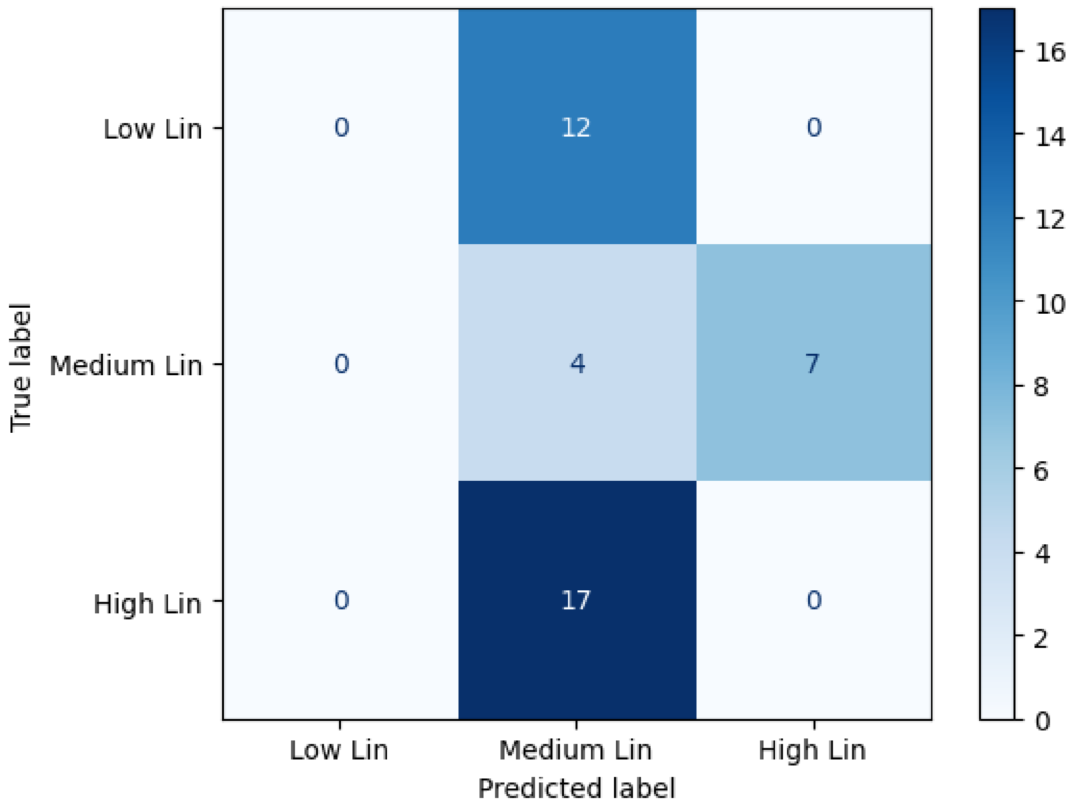
[40]:
```
y_pred_class = y_pred.round().astype(int).clip(0,2)
y_pred_class
```

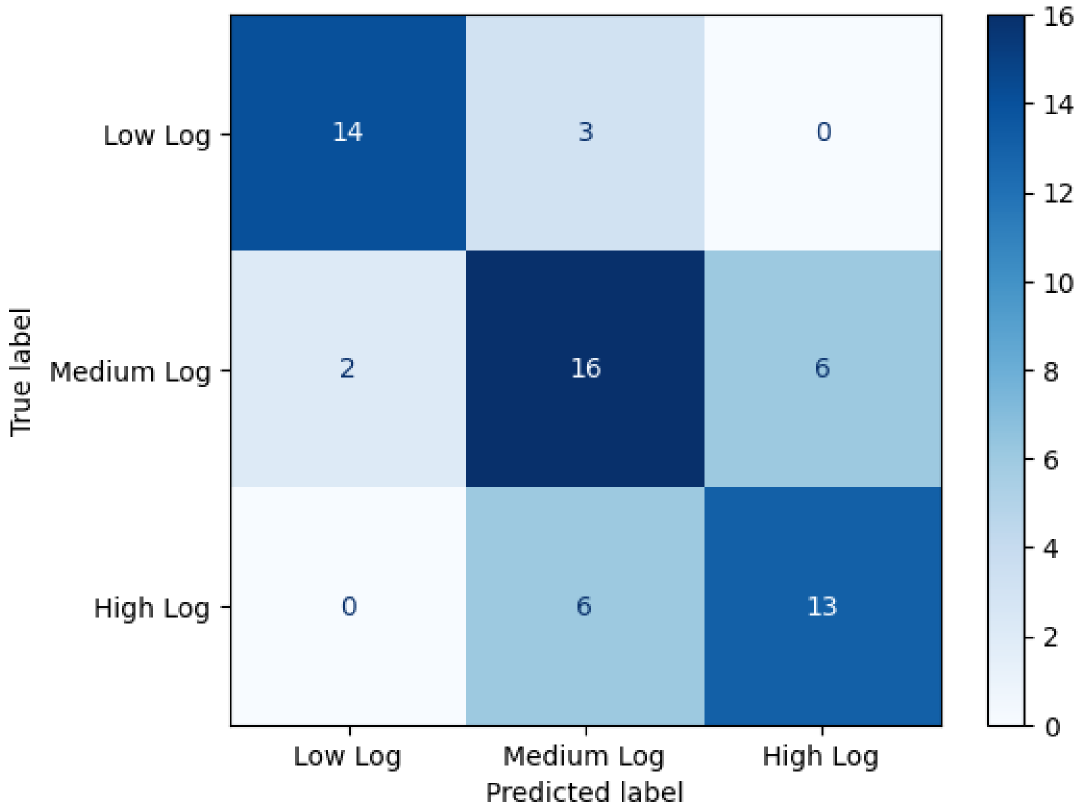
[40]:
```
array([1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1,
       1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 2, 1])
```

[41]:
```
# Confusion Matrices
cm_lin = confusion_matrix(y_test, y_pred_class)
ConfusionMatrixDisplay(confusion_matrix=cm_lin, display_labels=['Low Lin',␣
↪'Medium Lin', 'High Lin']).plot(cmap='Blues')
```

```
cm_log = confusion_matrix(y2_test, y2_pred, labels=['Low', 'Medium', 'High'])
ConfusionMatrixDisplay(confusion_matrix=cm_log, display_labels=['Low Log',␣
↪'Medium Log', 'High Log']).plot(cmap='Blues')
```

[41]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x195bcd4a560>





[42]:

```
# Classification Reports
cr_lin = classification_report(y_test, y_pred_class, target_names=['Low',␣
↪'Medium', 'High'])
cr_log = classification_report(y2_test, y2_pred, target_names=['Low', 'Medium',␣
↪'High'])

# Print Classification Reports
print("Linear Regression Classification Report:\n", cr_lin)
print("Logistic Regression Classification Report:\n", cr_log)
```

```
Linear Regression Classification Report:
               precision    recall  f1-score   support

         Low       0.00      0.00      0.00        12
      Medium       0.12      0.36      0.18        11
        High       0.00      0.00      0.00        17

    accuracy                           0.10        40
   macro avg       0.04      0.12      0.06        40
weighted avg       0.03      0.10      0.05        40
```

```
Logistic Regression Classification Report:
              precision    recall  f1-score   support

         Low       0.68      0.68      0.68        19
      Medium       0.88      0.82      0.85        17
        High       0.64      0.67      0.65        24

    accuracy                           0.72        60
   macro avg       0.73      0.72      0.73        60
weighted avg       0.72      0.72      0.72        60
```

```
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\metrics\_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\metrics\_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\metrics\_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
```

Logistic Regression : Features may not separate classes well Or the model needs tuning (e.g., better feature scaling, regularization, or hyperparameters)

Linear Regression performed better overall on this dataset: Higher accuracy, More balanced precision, recall, and f1-score

Step 7 - Actionable Insights

Higher pollution levels correlate with greater energy recovery potential from industrial waste. Countries with high pollution severity and moderate infrastructure may benefit most from energy recovery initiatives. Invest in technologies that convert pollutants into energy (e.g., waste-to-energy plants). Strengthen pollution control policies and monitoring systems. Encourage global cooperation for pollution reduction strategies and energy innovation.

0.0.1 Final Summary

This project aimed to analyze global pollution data and predict energy recovery using key environmental and demographic indicators. The workflow followed a structured pipeline across data preprocessing, statistical exploration, modeling, and insight generation.

- **Data Preparation:** The dataset was comprehensive, requiring minimal cleaning. All numerical features were scaled, and categorical variables like country and year were encoded.

Additional processing ensured consistency in pollution metrics and corrected outliers or invalid values.

- **Exploratory Data Analysis (EDA):** Descriptive statistics and visualizations revealed wide disparities in pollution levels and energy recovery among countries. However, correlation analysis showed weak relationships between CO emissions and features like population, industrial waste, or plastic waste — suggesting complex or non-linear patterns.
- **Model Building:**
  - A *Linear Regression* model was developed to predict continuous energy recovery, but it produced a very low **R^2 score of 0.0012**, with a high **mean absolute error of 133.57**, indicating poor predictive accuracy.
  - A *Logistic Regression* model was then used to classify pollution severity as *Low*, *Medium*, or *High* based on CO emission thresholds. This model yielded:
    * **Accuracy:** 71.67%
    * **Precision:** 72.06%
    * **Recall:** 71.67%
    * **F1-score:** 71.83%

    These results suggest that classification was significantly more effective than regression for this task.
- **Insights & Recommendations:**
  - Countries with higher pollution levels tend to have greater energy recovery potential.
  - The linear model's poor performance highlights the need for advanced modeling techniques or richer datasets.

To improve future outcomes, we recommend: 1. Leveraging *machine learning models like Random Forest or Gradient Boosting* for better accuracy. 2. Investing in *waste-to-energy infrastructure*, especially in high-pollution, mid-GDP countries. 3. Strengthening *pollution monitoring and data collection*, especially in regions with sparse environmental reporting.