CARBON EMISSIONS ANALYSIS

NumPy pandas Matplotlib seaborn SciPy

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STEPS FOR ANALYZING CARBON FOOTPRINT EMISSIONS DATA

1. Importing Necessary Python Libraries.

2. Load the carbon footprint emissions dataset.

3. Data Exploration.

4. Identify and remove outliers using the Scipy library to ensure the data is clean and accurate.

5. Create visualizations to illustrate key trends and comparisons within the dataset.

6. Conclude and Summarize key findings and insights from the analysis.
Provide recommendations based on the data-driven insights.

Importing Necessary Python Libraries

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Load the carbon footprint emissions dataset

```python
df = pd.read_csv("emissions_high_granularity.csv")
df.head()
```

Output

year	parent_entity	parent_type	reporting_entity	commodity	production_value	production_unit	product_emissions_MtCO2	flaring_emissions_MtCO2	venting_emissions_MtCO2	own_fuel_use_emissions_MtCO2	fugitive_methane_emissions_MtCO2e	fugitive_methane_emissions_MtCH4	fugitive_methane_emissions_MtCH4	total_operational_emissions_MtCO2e	total_emissions_MtCO2e	source
1962	Abu Dhabi National Oil Company	State-owned Entity	Abu Dhabi	Oil & NGL	0.9125	Million bbl/yr	0.338928	0.005404	0.001299	0.0	0.018254	0.000652	0.000652	0.024957	0.363885	Abu Dhabi National Oil Company Annual Report 1975, pp. 35-37
1963	Abu Dhabi National Oil Company	State-owned Entity	Abu Dhabi	Oil & NGL	1.8250	Million bbl/yr	0.677855	0.010808	0.002598	0.0	0.036508	0.001304	0.001304	0.049914	0.727770	Abu Dhabi National Oil Company Annual Report 1975, pp. 35-38
1964	Abu Dhabi National Oil Company	State-owned Entity	Abu Dhabi	Oil & NGL	7.3000	Million bbl/yr	2.711422	0.043233	0.010392	0.0	0.146033	0.005215	0.005215	0.199657	2.911079	Abu Dhabi National Oil Company Annual Report 1975, pp. 35-39
1965	Abu Dhabi National Oil Company	State-owned Entity	Abu Dhabi	Oil & NGL	10.9500	Million bbl/yr	4.067132	0.064849	0.015588	0.0	0.219049	0.007823	0.007823	0.299486	4.366618	Abu Dhabi National Oil Company Annual Report 1975, pp. 35-40
1966	Abu Dhabi National Oil Company	State-owned Entity	Abu Dhabi	Oil & NGL	13.5050	Million bbl/yr	5.016130	0.079980	0.019225	0.0	0.270160	0.009649	0.009649	0.369366	5.385495	Abu Dhabi National Oil Company Annual Report 1975, pp. 35-41

Data Exploration

```
df.shape
```

```
(15797, 16)
```

```
# handel duplicate
df.duplicated().sum() #
```

```
0
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15797 entries, 0 to 15796
Data columns (total 16 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   year                             15797 non-null  int64
 1   parent_entity                    15797 non-null  object
 2   parent_type                      15797 non-null  object
 3   reporting_entity                 15797 non-null  object
 4   commodity                        15797 non-null  object
 5   production_value                 15797 non-null  float64
 6   production_unit                  15797 non-null  object
 7   product_emissions_MtCO2          15797 non-null  float64
 8   flaring_emissions_MtCO2          15797 non-null  float64
 9   venting_emissions_MtCO2          15797 non-null  float64
 10  own_fuel_use_emissions_MtCO2     15797 non-null  float64
 11  fugitive_methane_emissions_MtCO2e 15797 non-null  float64
 12  fugitive_methane_emissions_MtCH4 15797 non-null  float64
 13  total_operational_emissions_MtCO2e 15797 non-null  float64
 14  total_emissions_MtCO2e           15797 non-null  float64
 15  source                           15797 non-null  object
dtypes: float64(9), int64(1), object(6)
memory usage: 1.9+ MB
```

```
df.isnull().sum()
```

```
year                                 0
parent_entity                        0
parent_type                          0
reporting_entity                     0
commodity                            0
production_value                     0
production_unit                      0
product_emissions_MtCO2              0
flaring_emissions_MtCO2              0
venting_emissions_MtCO2              0
own_fuel_use_emissions_MtCO2         0
fugitive_methane_emissions_MtCO2e    0
fugitive_methane_emissions_MtCH4     0
total_operational_emissions_MtCO2e   0
total_emissions_MtCO2e               0
source                               0
dtype: int64
```

```
df.describe()
```

	year	production_value	product_emissions_MtCO2	flaring_emissions_MtCO2	venting_emissions_MtCO2	own_fuel_use_emissions_MtCO2
count	15797.000000	15797.000000	15797.000000	15797.000000	15797.000000	15797.000000
mean	1985.827942	327.879634	79.391514	0.517226	0.462462	0.688676
std	28.664256	1188.625001	261.984080	1.783744	1.804575	3.564171
min	1854.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1970.000000	11.800000	5.996490	0.000000	0.000000	0.000000
50%	1993.000000	59.970871	21.502409	0.015913	0.045247	0.000000
75%	2007.000000	246.375000	62.191954	0.197253	0.329719	0.162415
max	2022.000000	27192.000000	7769.222235	27.026872	41.458662	83.203465

Identify and remove outliers using the Scipy library to ensure the data is clean and accurate

```
In [4]: import scipy
        print(scipy.__version__)
```

```
1.11.1
```

```
In [5]: from scipy import stats
```

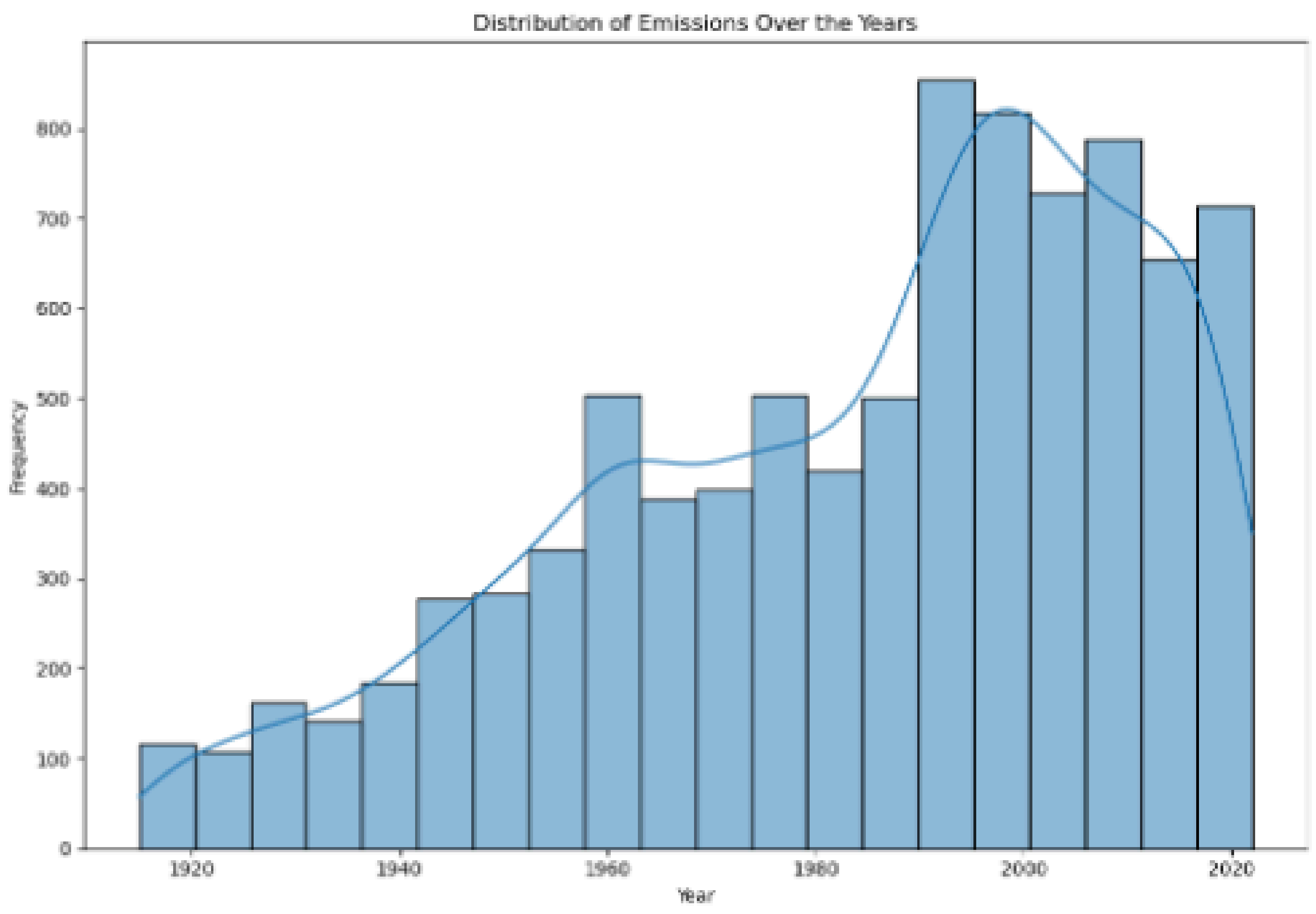
```
In [6]: # Select numerical columns
        numeric_columns = df.select_dtypes(include=[np.number]).columns

        # Calculate the IQR
        Q1 = df[numeric_columns].quantile(0.25)
        Q3 = df[numeric_columns].quantile(0.75)
        IQR = Q3 - Q1

        # Calculate bounds for outliers
        lower_bound = Q1 -  1.5* IQR
        upper_bound = Q3 + 1.5 * IQR

        # Create boolean DataFrames for outliers
        is_below_lower_bound = df[numeric_columns] < lower_bound
        is_above_upper_bound = df[numeric_columns] > upper_bound

        # Combine the boolean DataFrames
        is_outlier = is_below_lower_bound | is_above_upper_bound

        # Check for any outliers in each row
        has_outliers = is_outlier.any(axis=1)

        # Filter out rows with any outliers
        df = df[~has_outliers]
```

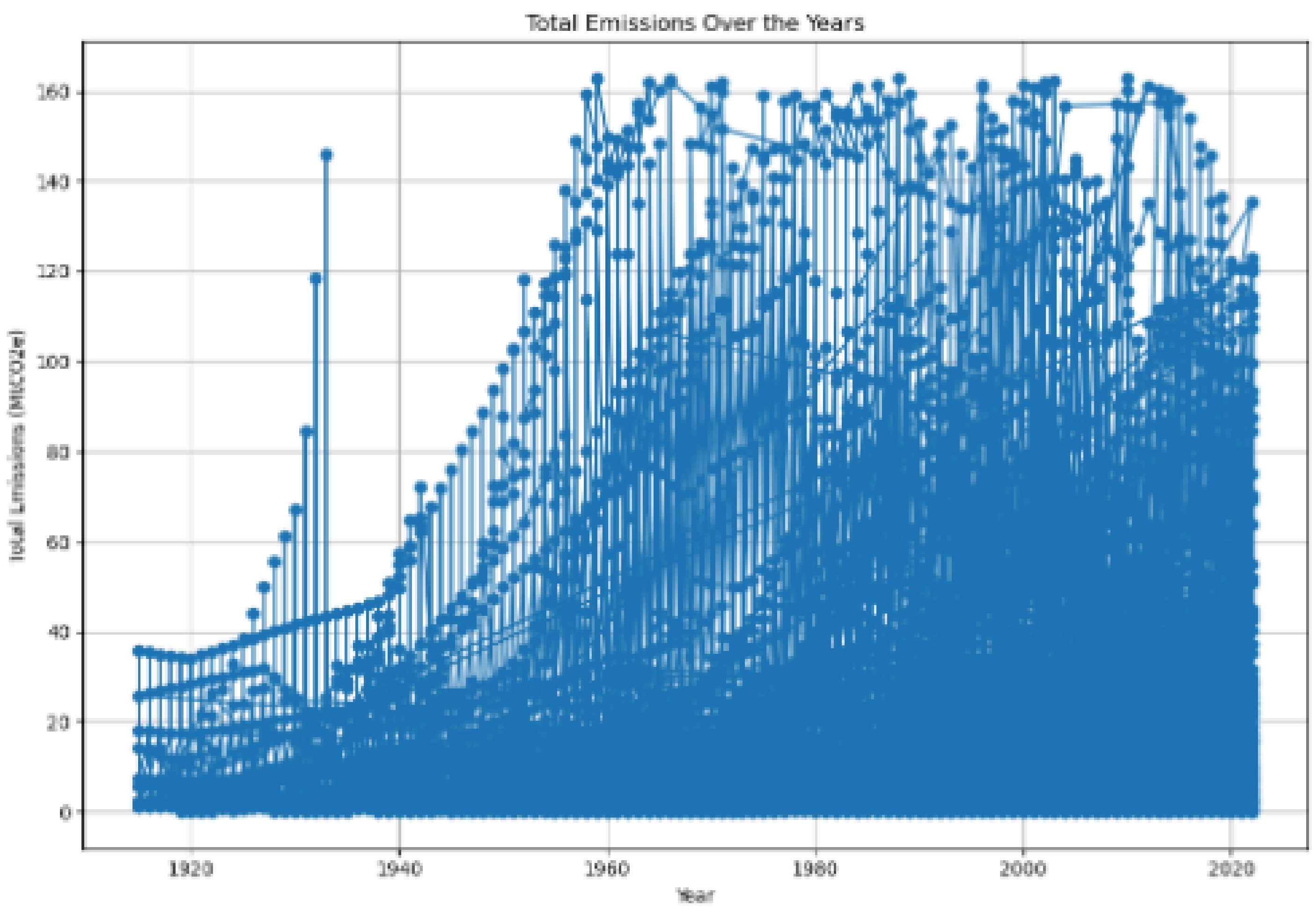
Plotting graph

1. Distribution of Emissions Over the Years

```
import matplotlib.pyplot as plt
import seaborn as sns

# Set up the figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(20, 7))

# First subplot: Histogram with KDE of 'year'
sns.histplot(df['year'], bins=20, kde=True, ax=axes[0])
axes[0].set_title('Distribution of Emissions Over the Years')
axes[0].set_xlabel('Year')
axes[0].set_ylabel('Frequency')

# Second subplot: Line plot of 'total_emissions_MtCO2e' over 'year'
axes[1].plot(df['year'], df['total_emissions_MtCO2e'], marker='o', linestyle='-')
axes[1].set_title('Total Emissions Over the Years')
axes[1].set_xlabel('Year')
axes[1].set_ylabel('Total Emissions (MtCO2e)')
axes[1].grid(True)

# Adjust layout and display the combined plot
plt.tight_layout()
plt.show()
```

Output





The line plot shows a clear upward trend in total emissions (MtCO2e) from the early 1900s to 2020.

Pre-1940s: Emissions were relatively low and infrequent.

1940s to 1980s: There was a steady increase in emissions, indicating industrial growth.

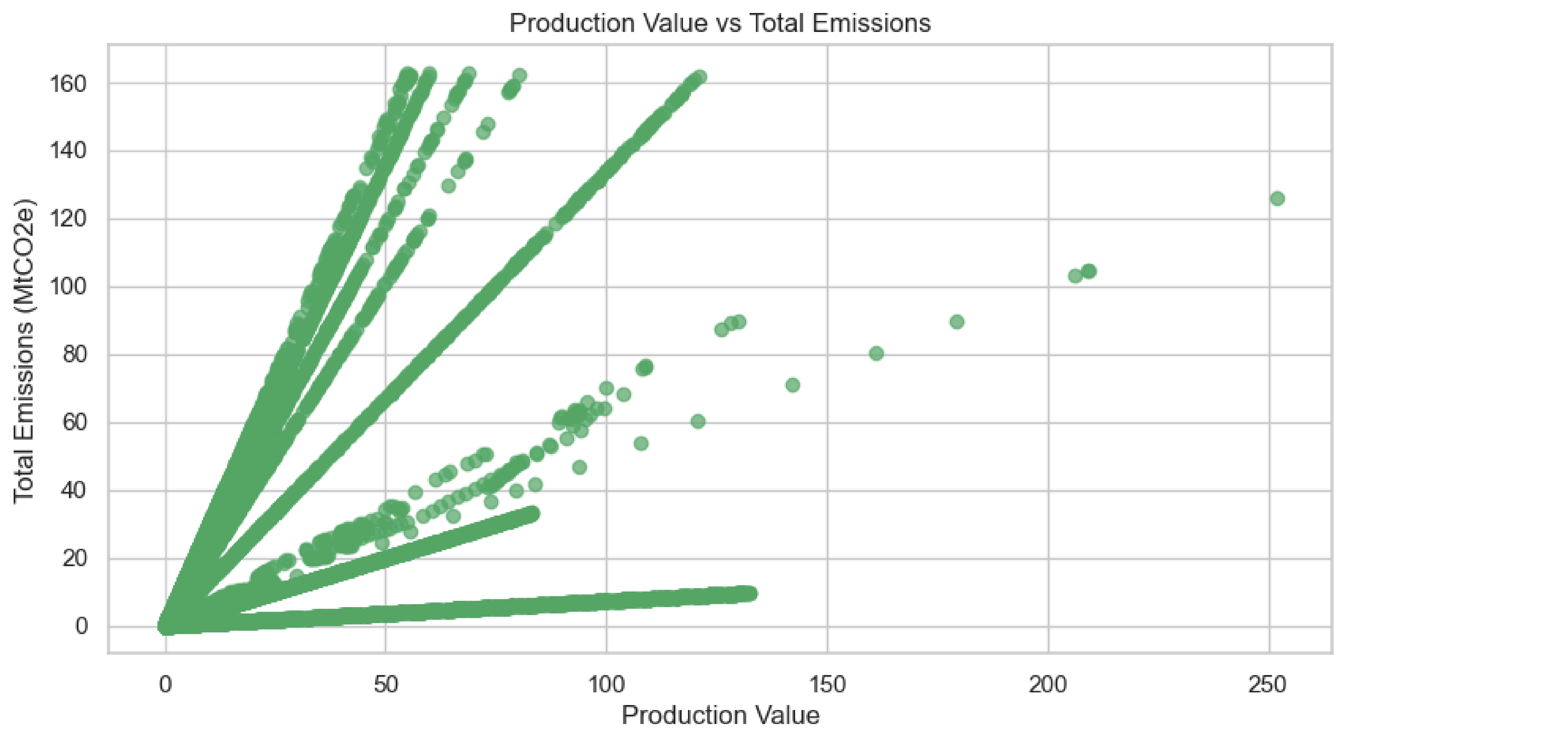
1980s to 2020: Emissions continued to rise significantly, with higher and more frequent spikes, reflecting rapid industrialization and economic growth globally.

Plotting graph

2.Production Value vs Total Emissions

```
# Set up the figure size
plt.figure(figsize=(10, 5))

# Create a scatter plot
plt.scatter(df['production_value'], df['total_emissions_MtCO2e'], alpha=0.7, color='g')

# Set the title and labels
plt.title('Production Value vs Total Emissions')
plt.xlabel('Production Value')
plt.ylabel('Total Emissions (MtCO2e)')

# Show the plot
plt.show()
```

Output



Positive Correlation: The scatter plot suggests a positive correlation between production value and total emissions, implying that as production increases, emissions also tend to increase.

Emission Variability: The variability in total emissions grows with higher production values, indicating that some production activities are more emission-intensive than others.

Clusters: The vertical clustering at specific production values may indicate consistent production levels across multiple observations, possibly due to standardized production processes or reporting practices.

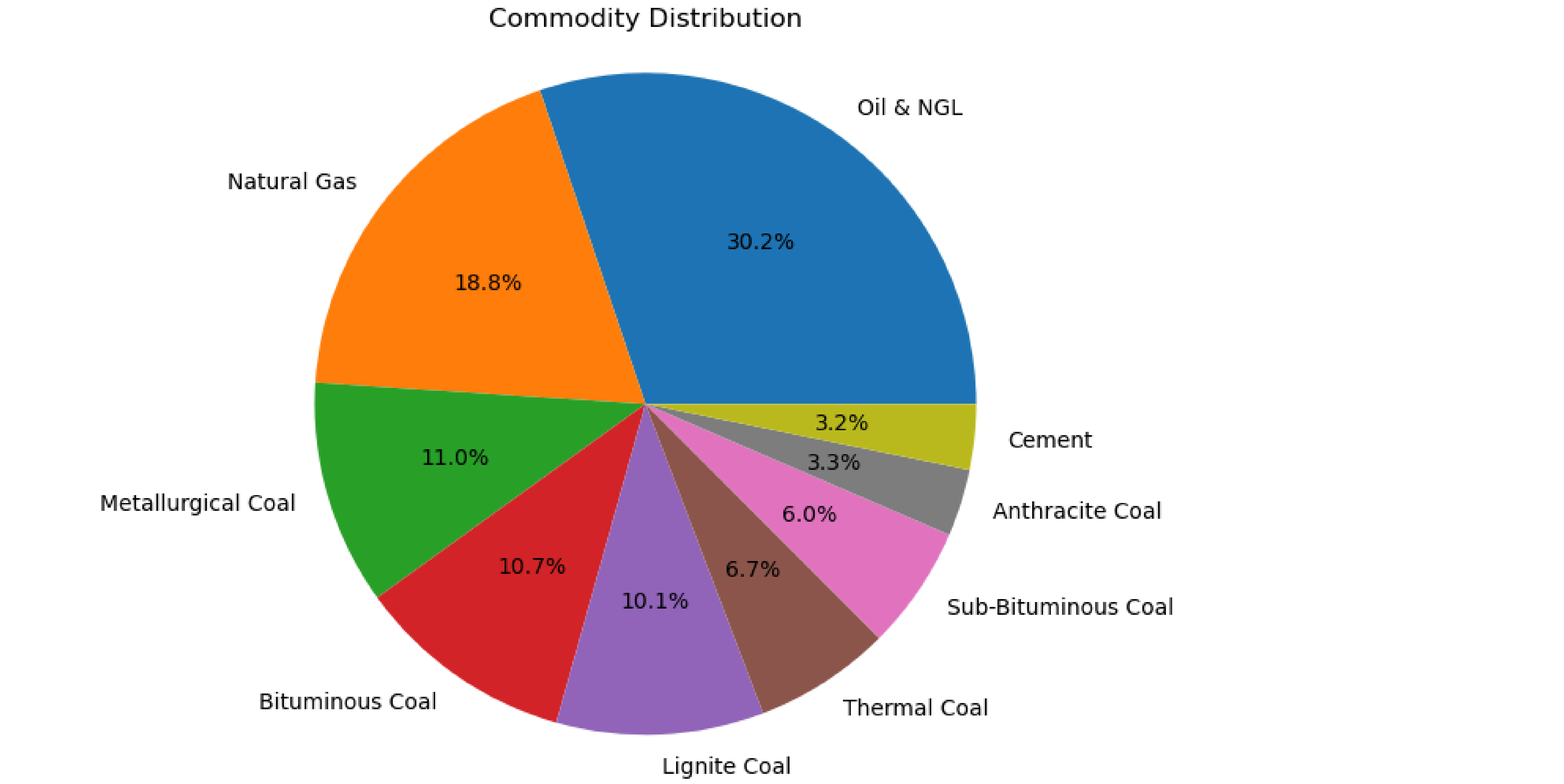
High Emission Outliers: The presence of high emission outliers emphasizes the need to manage and reduce emissions, especially for high-capacity production units.

Plotting graph

3.Commodity Distribution

```
commodity_counts = df['commodity'].value_counts()  # Count occurrences of each commodity

plt.figure(figsize=(10, 6))  # Set the size of the figure (width=10 inches, height=6 inches)

# Create a pie chart with the counts of each commodity
plt.pie(commodity_counts, labels=commodity_counts.index, autopct='%1.1f%%')

plt.title('Commodity Distribution')  # Set the title of the plot
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle

plt.show()  # Display the plot
```

Output



Oil & NGL: Represents the largest share at 30.2% of the total commodity distribution.

Natural Gas: Accounts for 18.8%, making it the second largest commodity.

Metallurgical Coal: Holds 11.0% of the distribution.

Bituminous Coal: Comprises 10.7% of the commodities.

Lignite Coal: Makes up 10.1% of the distribution.

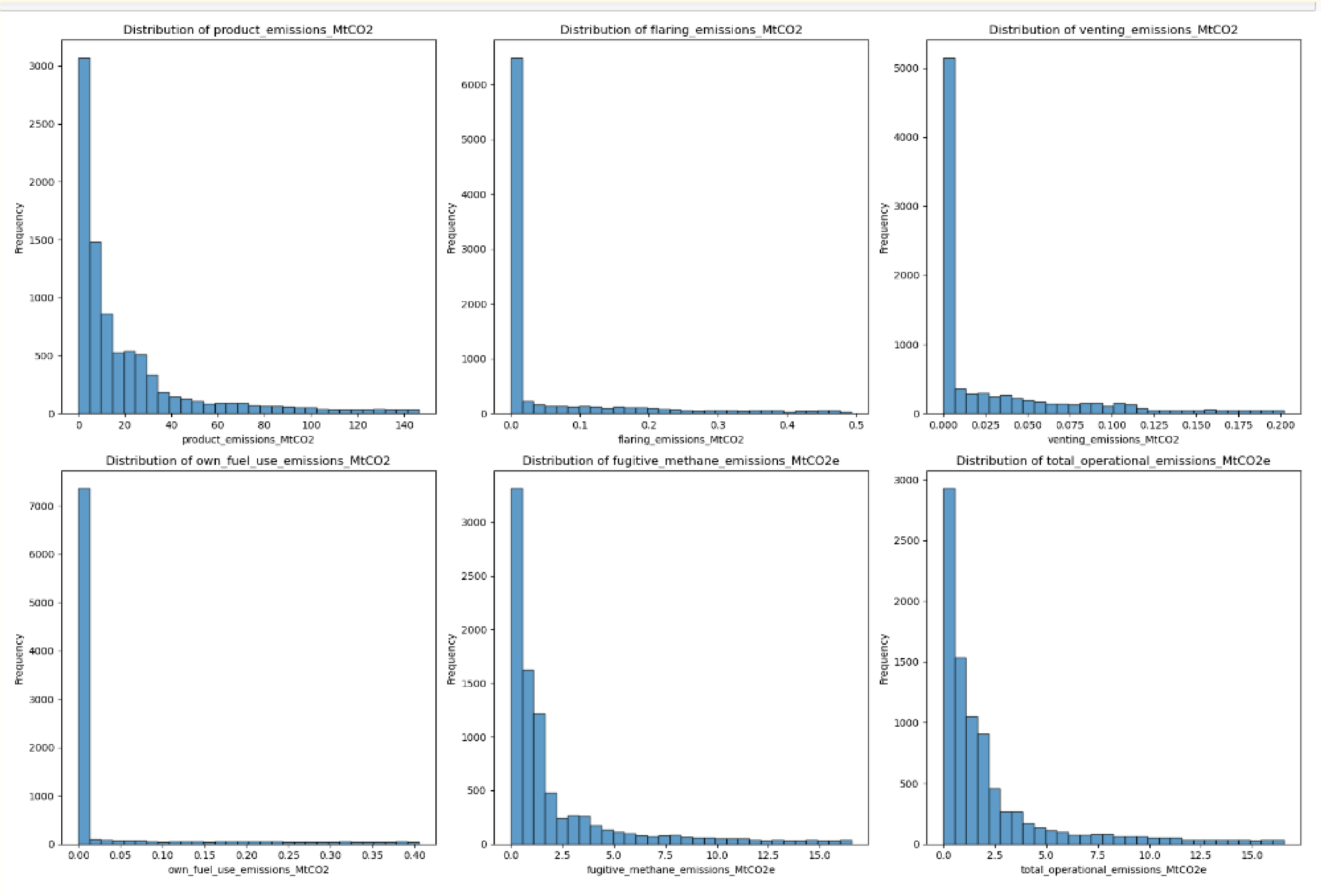
Other Commodities: Include Thermal Coal, Sub-Bituminous Coal, Anthracite Coal, and Cement, each with smaller shares ranging from 3.2% to 6.7%. Overall, the chart highlights that Oil & NGL and Natural Gas are the predominant commodities in the distribution.

Plotting graph

4.Distribution of Various type of Emissions

```
# Histograms for Emission Types in Subplots
emissions_columns = ['product_emissions_MtCO2', 'flaring_emissions_MtCO2', 'venting_emissions_MtCO2',
                     'own_fuel_use_emissions_MtCO2', 'fugitive_methane_emissions_MtCO2e', 'total_operational_emissions_MtCO2e']

fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 12))
axes = axes.flatten()

for i, col in enumerate(emissions_columns):
    axes[i].hist(df[col], bins=30, edgecolor='k', alpha=0.7)
    axes[i].set_title(f'Distribution of {col}')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Frequency')

plt.tight_layout()
plt.show()
```

Output



Key Observations from Emission Types Distributions

Product Emissions (MtCO2) Distribution: Predominantly between 0 and 20 MtCO2, with a few outliers extending up to 140 MtCO2. Impact: Directly increases the carbon footprint, contributing significantly to greenhouse gas emissions.

Flaring Emissions (MtCO2) Distribution: Mainly concentrated around 0 MtCO2, with very few values exceeding 0.1 MtCO2. Impact: Flaring results in the release of CO2 and other pollutants, contributing to air pollution and climate change.

Venting Emissions (MtCO2) Distribution: Mostly close to 0 MtCO2, with rare occurrences above 0.05 MtCO2. Impact: Venting releases methane, a potent greenhouse gas, directly into the atmosphere, exacerbating global warming.

Own Fuel Use Emissions (MtCO2) Distribution: Almost all values are near 0 MtCO2, indicating minimal emissions from own fuel use. Impact: Low emissions suggest good energy efficiency, but there's always room for improvement to achieve near-zero emissions.

Fugitive Methane Emissions (MtCO2e) Distribution: Most values are below 2.5 MtCO2e, with some extending up to 15 MtCO2e. Impact: Fugitive emissions are significant due to methane's high global warming potential, leading to a notable impact on climate change . Total Operational Emissions (MtCO2e) Distribution: Skewed towards lower values, with most emissions below 2.5 MtCO2e and some reaching up to 15 MtCO2e. Impact: Represents the overall carbon footprint of operations, encompassing all emission sources.

Overall, the histograms reveal that emissions are generally low for most types, with a few high-emission outliers.

Plotting graph

5.Correlation Matrix Heatmap

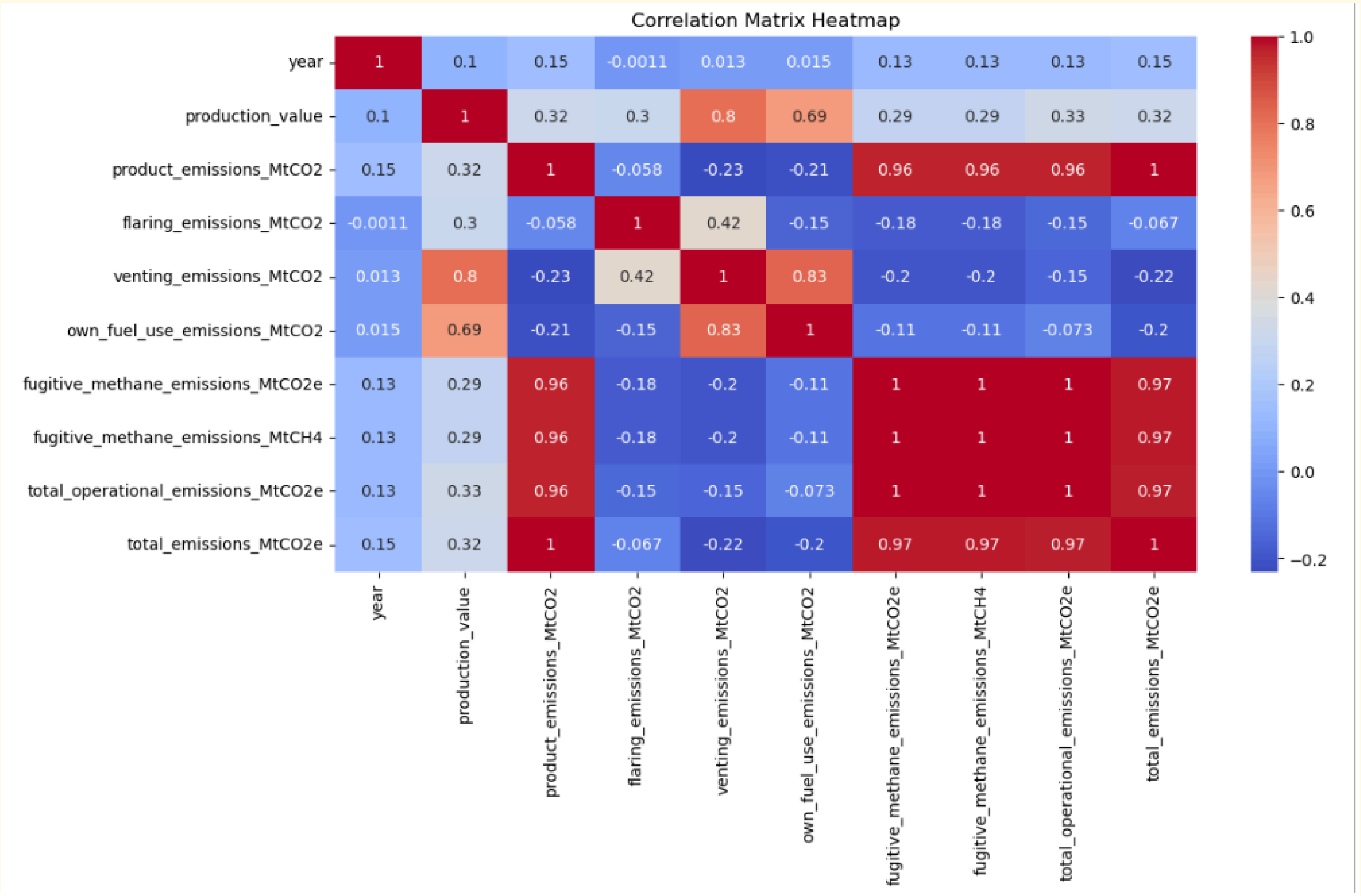
```
In [19]: numeric_cols = df.select_dtypes(include=[np.number])
         numeric_cols.head()
```

Out[19]:

	year	production_value	product_emissions_MtCO2	flaring_emissions_MtCO2	venting_emissions_MtCO2	own_fuel_use_emissions_MtCO2	fugitive_methane_em
0	1962	0.9125	0.338928	0.005404	0.001299	0.0	
1	1963	1.8250	0.677855	0.010808	0.002598	0.0	
2	1964	7.3000	2.711422	0.043233	0.010392	0.0	
3	1965	10.9500	4.067132	0.064849	0.015588	0.0	
4	1966	13.5050	5.016130	0.079980	0.019225	0.0	

```
# plotting a heat map
corr_matrix = numeric_cols.corr()
plt.figure(figsize=(12,6))
sns.heatmap(corr_matrix,annot=True,cmap="coolwarm")
plt.title('Correlation Matrix Heatmap')
plt.show()
```

Output



Valuable Insights from the Correlation Matrix Heatmap

1. High Correlation: Product Emissions and Fugitive Methane Emissions: The correlation between product_emissions_MtCO2 and fugitive_methane_emissions_MtCH4 is extremely high (0.96), indicating that as product emissions increase, fugitive methane emissions also increase.

Fugitive Methane Emissions and Fugitive Methane Emissions (CO2e): There is a perfect correlation (1.00) between fugitive_methane_emissions_MtCH4 and fugitive_methane_emissions_MtCO2e, which is expected since these metrics likely measure the same phenomenon in different units or contexts.

Fugitive Methane Emissions (CO2e) and Total Operational Emissions (CO2e): Another perfect correlation (1.00), suggesting that fugitive methane emissions are a significant component of total operational emissions.

2. Moderate Correlation: Production Value and Venting Emissions: The correlation between production_value and venting_emissions_MtCO2 is moderately high (0.8), implying that higher production values are associated with higher venting emissions.

Production Value and Own Fuel Use Emissions: There is a notable correlation (0.69) between production_value and own_fuel_use_emissions_MtCO2, suggesting that as production increases, emissions from own fuel use also increase.

3. Low or Negative Correlation: Flaring Emissions and Product Emissions: A weak negative correlation (-0.058) between flaring_emissions_MtCO2 and product_emissions_MtCO2, indicating that these emissions types do not have a significant linear relationship.

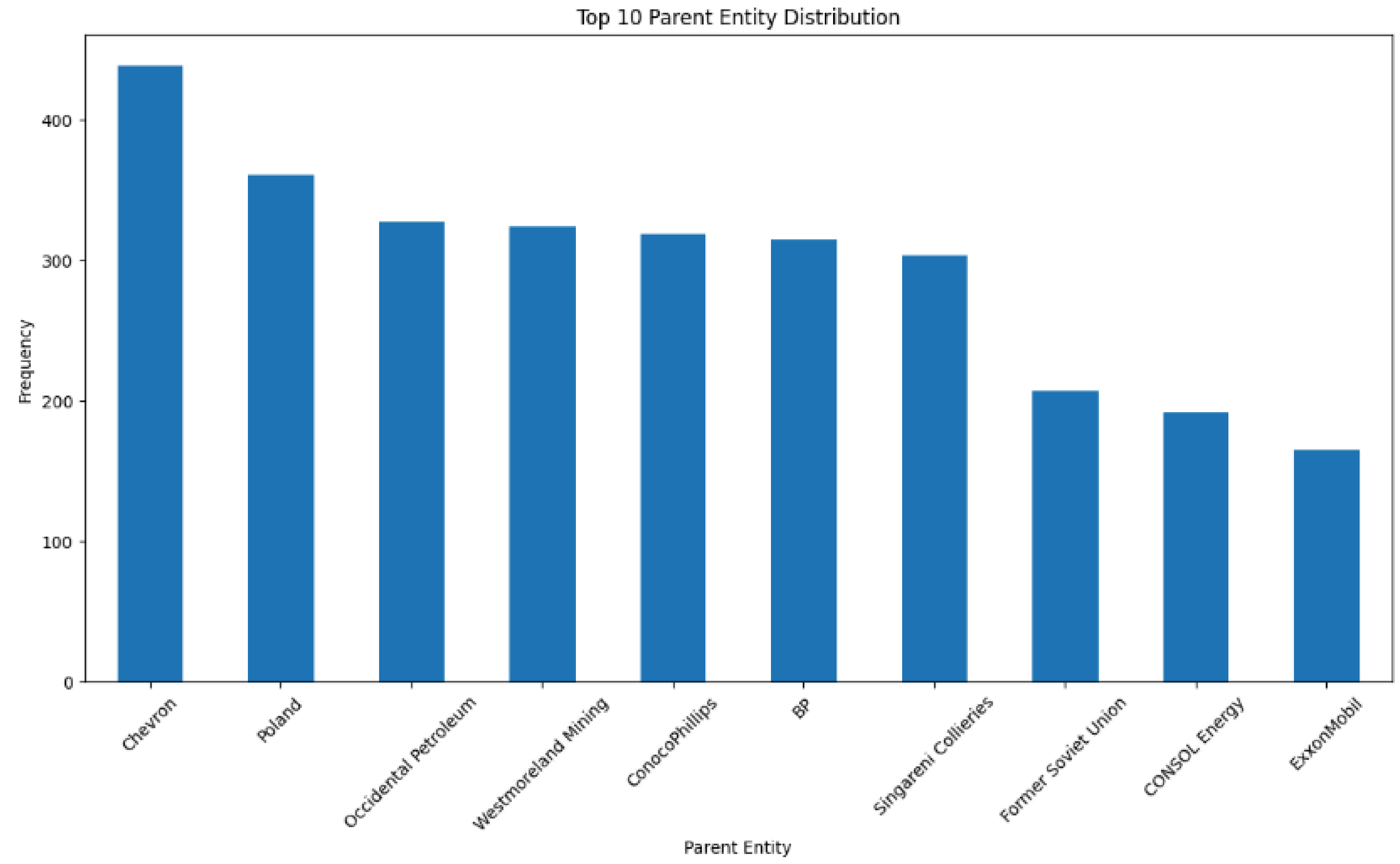
Venting Emissions and Total Emissions: The correlation between venting_emissions_MtCO2 and total_emissions_MtCO2e is low (-0.22), suggesting that venting emissions do not strongly predict total emissions.

Plotting graph

6.Top 10 Parent Entity Distribution

```
# Bar Plot for Parent Entity Distribution
parent_entity_counts = df['parent_entity'].value_counts().head(10)  # Top 10 entities
fig, ax = plt.subplots(figsize=(10, 5))

# Plotting the bar chart
parent_entity_counts.plot(kind='bar')

# Title and labels
ax.set_title('Top 10 Parent Entity Distribution')
ax.set_xlabel('Parent Entity')
ax.set_ylabel('Frequency')

# Adjust x-axis labels
ax.set_xticklabels(parent_entity_counts.index, rotation=45, ha='right', fontsize=10)

plt.show()
```

Output



The bar plot displays the distribution of the top 10 parent entities based on frequency. Here are the key observations:

Chevron: Has the highest frequency among the parent entities, indicating it is the most prominent entity in the dataset.

Poland, Occidental Petroleum, Westmoreland Mining, Conocophillips, BP, Singareni Collieries: These entities have similar frequencies, showcasing their significant presence.

Former Soviet Union, CONSOL Energy, ExxonMobil: These entities have relatively lower frequencies compared to the others but are still among the top 10.

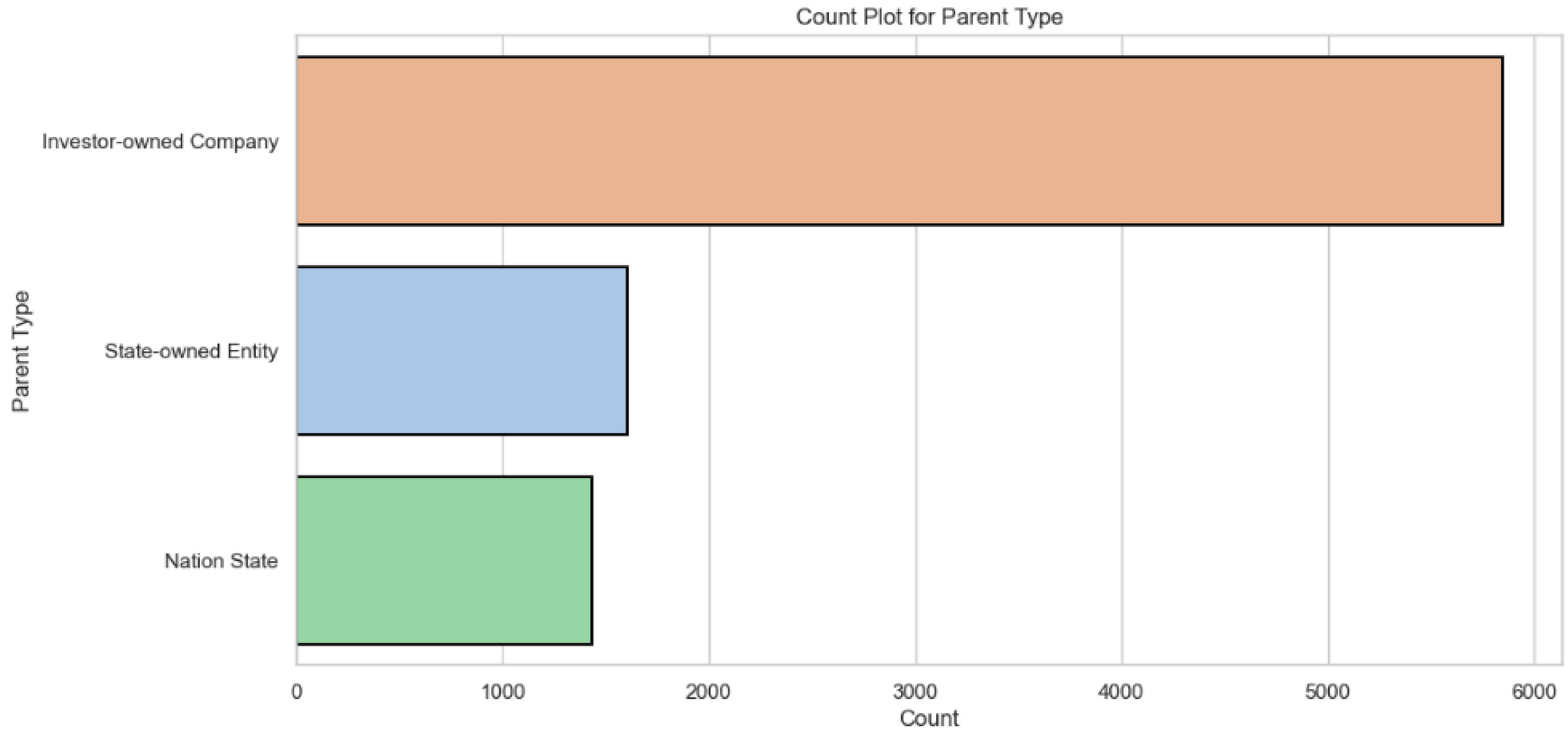
Overall, Chevron stands out as the most frequent parent entity, followed by a mix of international and national corporations.

Plotting graph

7.Count Plot for Parent Type

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6))
sns.countplot(y='parent_type', data=df, order=df['parent_type'].value_counts().index,hue = "parent_type",palette='pastel',
              linewidth=1.5,
              edgecolor='black',
              saturation=0.75)
plt.bar_width = 0.5
plt.title('Count Plot for Parent Type')
plt.xlabel('Count')
plt.ylabel('Parent Type')
plt.show()
```

Output



The count plot displays the distribution of different parent types in the dataset. Here are the key observations:

Investor-owned Company: This is the most common parent type, with a significantly higher count compared to other types.

State-owned Entity: The second most common parent type, though with considerably fewer instances than investor-owned companies.

Nation State: The least common parent type among the three, with the lowest count.

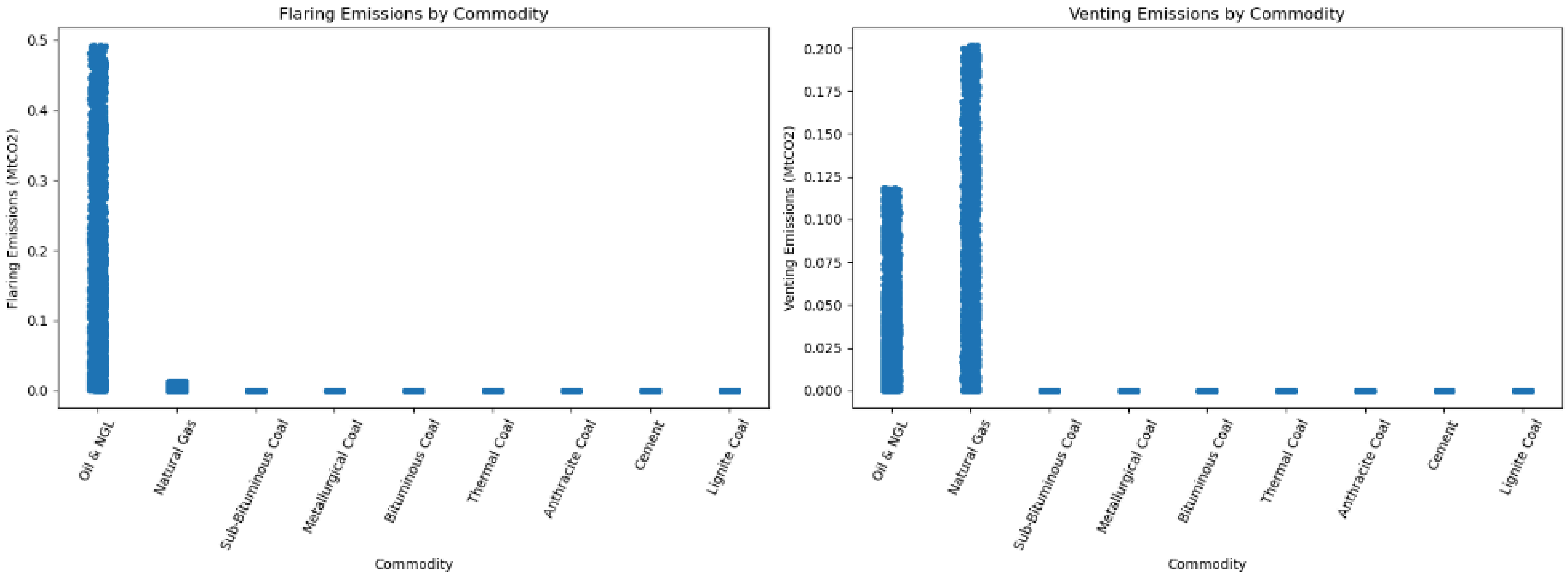
Overall, the plot highlights that investor-owned companies dominate the dataset, followed by state-owned entities and nation states.

Plotting graph

8.Comparision between Flaring and Venting Emission by Commodity

```python
# Create subplots
fig, axs = plt.subplots(1, 2, figsize=(16, 6))

# Strip plot for flaring emissions
sns.stripplot(x='commodity', y='flaring_emissions_MtCO2', data=df, ax=axs[0])
axs[0].set_title('Flaring Emissions by Commodity')
axs[0].set_xlabel('Commodity')
axs[0].set_ylabel('Flaring Emissions (MtCO2)')
axs[0].tick_params(axis='x', rotation=65)

# Strip plot for venting emissions
sns.stripplot(x='commodity', y='venting_emissions_MtCO2', data=df, ax=axs[1])
axs[1].set_title('Venting Emissions by Commodity')
axs[1].set_xlabel('Commodity')
axs[1].set_ylabel('Venting Emissions (MtCO2)')
axs[1].tick_params(axis='x', rotation=65)

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```

Output



The strip plot displays the distribution of flaring emissions (MtCO2) and venting emissions (MtCO2) by different commodities. Here are the key observations:

Oil & NGL: This commodity has the highest flaring emissions, with values ranging from 0 to 0.5 MtCO2, and moderate venting emissions, with values ranging from 0 to 0.125 MtCO2. The data points are densely packed, indicating frequent flaring emissions and notable venting emissions in this category.

Natural Gas: This commodity shows flaring emissions close to 0 MtCO2 but reaches a peak of 0.2 MtCO2 in venting emissions, which is the highest among all commodities.

Other Commodities: Sub-Bituminous Coal, Metallurgical Coal, Bituminous Coal, Thermal Coal, Anthracite Coal, Cement, and Lignite Coal all have minimal to no flaring and venting emissions, with values clustered around 0 MtCO2.

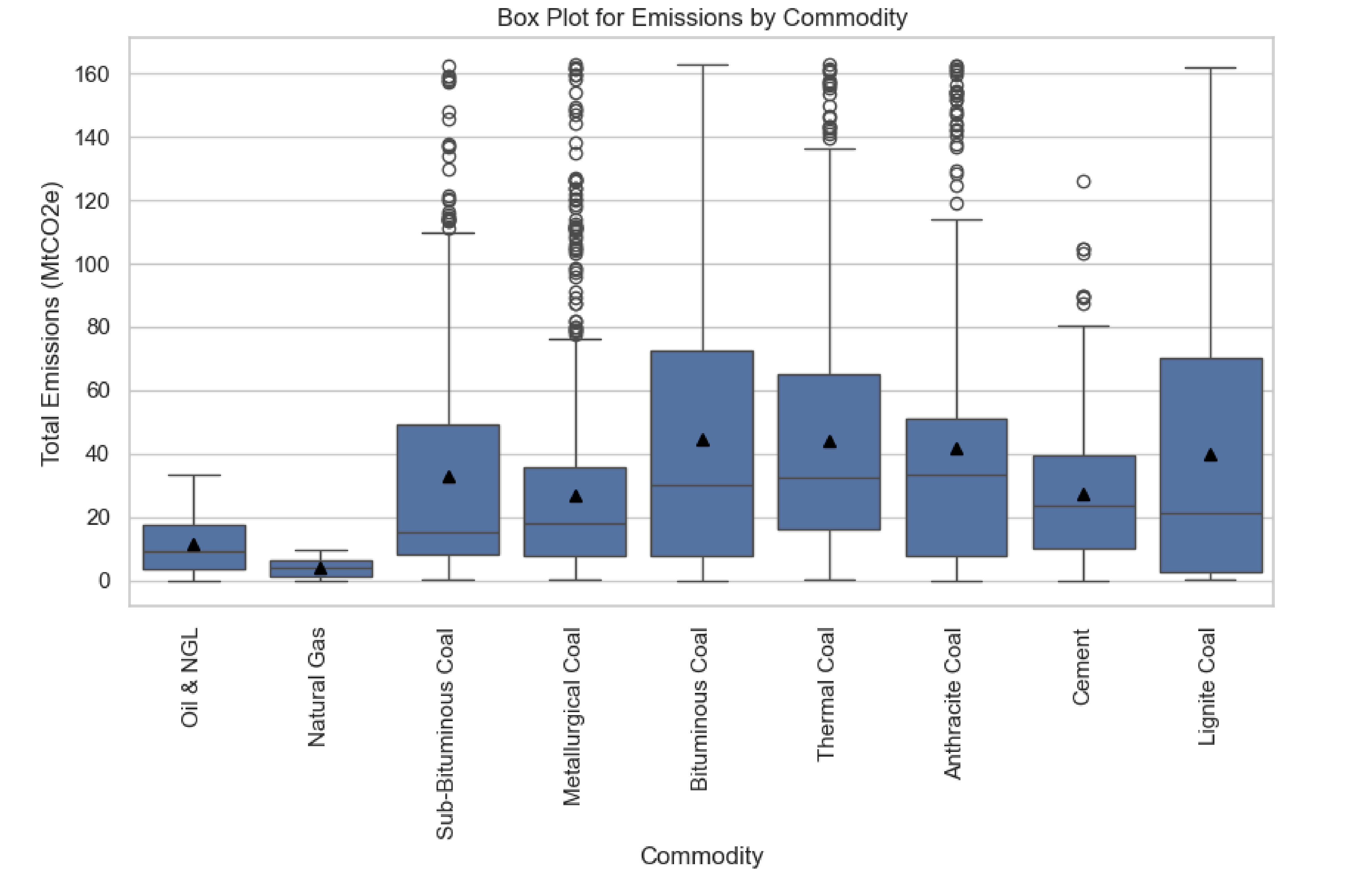
Overall, the plot highlights that Oil & NGL predominate in flaring emissions, while Natural Gas predominates in venting emissions, followed by a notable impact from Oil & NGL. Other commodities contribute negligibly to both flaring and venting emissions.

Plotting graph

9.Box Plot for Emissions by Commodity

```
# Create subplots
fig, axs = plt.subplots(1, 2, figsize=(16, 6))

# Strip plot for flaring emissions
sns.stripplot(x='commodity', y='flaring_emissions_MtCO2', data=df, ax=axs[0])
axs[0].set_title('Flaring Emissions by Commodity')
axs[0].set_xlabel('Commodity')
axs[0].set_ylabel('Flaring Emissions (MtCO2)')
axs[0].tick_params(axis='x', rotation=65)

# Strip plot for venting emissions
sns.stripplot(x='commodity', y='venting_emissions_MtCO2', data=df, ax=axs[1])
axs[1].set_title('Venting Emissions by Commodity')
axs[1].set_xlabel('Commodity')
axs[1].set_ylabel('Venting Emissions (MtCO2)')
axs[1].tick_params(axis='x', rotation=65)

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```

Output



Predominant Emissions: Coal-related commodities, especially Sub-Bituminous Coal, Bituminous Coal, and Lignite Coal, show the highest emissions with a wide range and many outliers, indicating significant and variable emissions.

Moderate Emissions: Metallurgical Coal, Thermal Coal, and Anthracite Coal also have considerable emissions but generally lower than the highest-emitting categories.

Lower Emissions: Oil & NGL, Natural Gas, and Cement have lower and more consistent emissions compared to coal commodities.

Overall, the plot highlights that coal-related commodities are the predominant contributors to emissions, with significant variability and occasional very high emissions. In contrast, Oil & NGL, Natural Gas, and Cement have relatively minimal impact on total emissions.

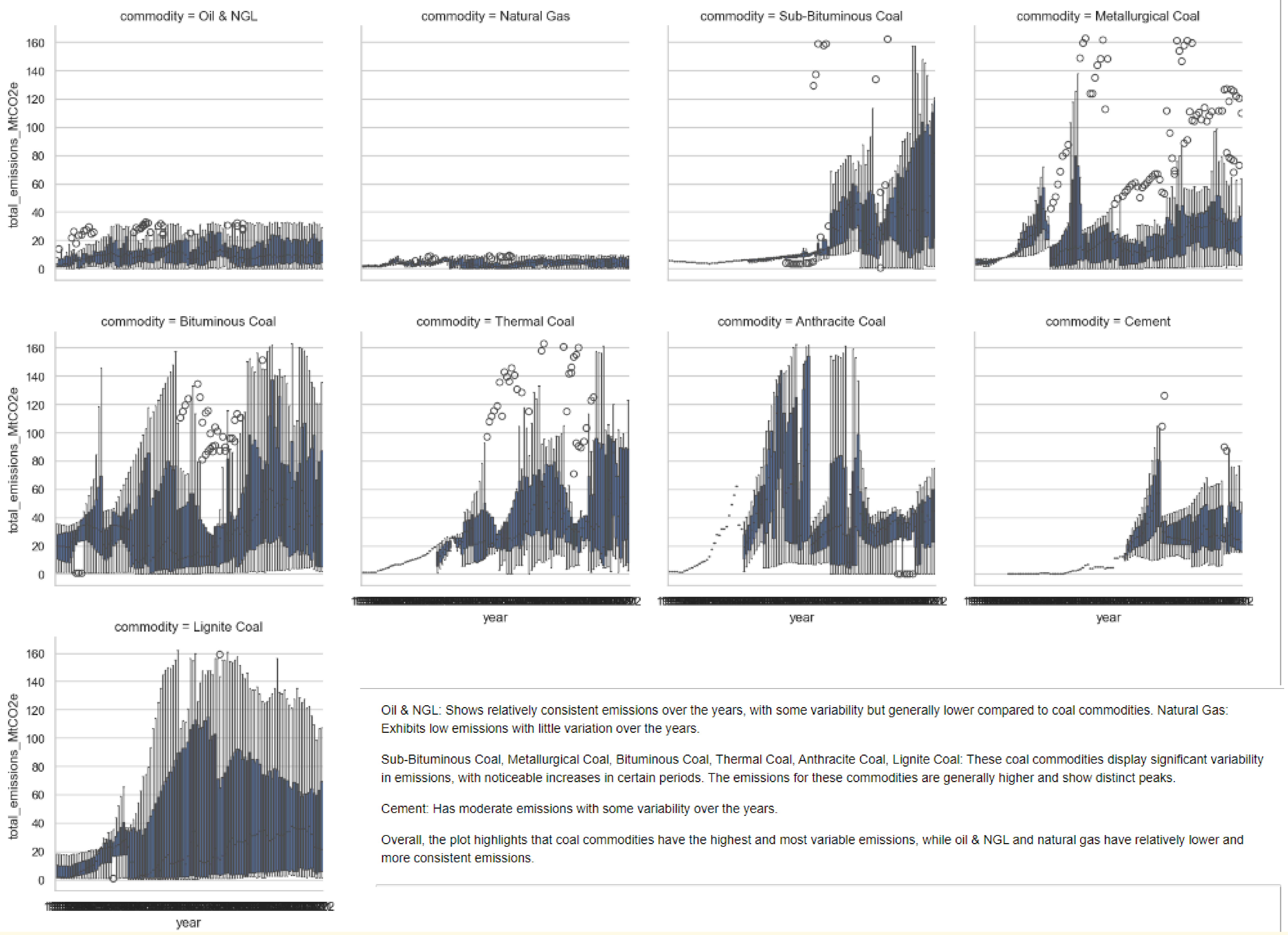
Plotting graph

10.Facet Grid for Emissions by Year and Commodity

```
# Facet Grid for Emissions by Year and Commodity
g = sns.FacetGrid(df, col='commodity', col_wrap=4, height=4)
g.map(sns.boxplot, 'year', 'total_emissions_MtCO2e')
g.add_legend()
plt.show()
```

```
C:\Users\UMA SHAW\anaconda3\Lib\site-packages\seaborn\axisgrid.py:718: UserWarning: Using the boxplot function without specifyi
ng `order` is likely to produce an incorrect plot.
  warnings.warn(warning)
C:\Users\UMA SHAW\anaconda3\Lib\site-packages\seaborn\axisgrid.py:123: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Output



Oil & NGL: Shows relatively consistent emissions over the years, with some variability but generally lower compared to coal commodities. Natural Gas: Exhibits low emissions with little variation over the years.

Sub-Bituminous Coal, Metallurgical Coal, Bituminous Coal, Thermal Coal, Anthracite Coal, Lignite Coal: These coal commodities display significant variability in emissions, with noticeable increases in certain periods. The emissions for these commodities are generally higher and show distinct peaks.

Cement: Has moderate emissions with some variability over the years.

Overall, the plot highlights that coal commodities have the highest and most variable emissions, while oil & NGL and natural gas have relatively lower and more consistent emissions.

SUMMARIZE KEY FINDINGS AND INSIGHTS FROM THE ANALYSIS.

From the 1980s to 2020, carbon emissions rose significantly due to increased production, contributing heavily to greenhouse gas emissions and climate change.

Product Emissions: Significant greenhouse gas contributor.
Flaring Emissions: Contributes to air pollution and climate change.
Venting Emissions: Releases methane, worsening global warming.
Fugitive Methane Emissions: Significant due to methane’s high warming potential.

Overall, oil & NGL, natural gas (flaring and venting), and coal-related commodities are key factors driving higher emissions.

PROVIDE RECOMMENDATIONS BASED ON THE DATA-DRIVEN INSIGHTS.

- Methane Management: Capture and convert methane to CO_2.
- Energy Efficiency: Invest in energy-efficient technologies and renewable energy.
- Carbon Offset Projects: Engage in reforestation and other carbon offset initiatives.
- Carbon Credits: Purchase to balance emissions and support global sustainability.
- Leak Detection: Use advanced technologies to detect and fix leaks.
- Sustainable Practices: Adopt and encourage voluntary emission-reduction efforts to earn carbon credits.
- Carbon Market: Establish a regulated market with transparency and incentives.

THANKS

HELP EARTH HEAL