

# Sahan Chowdhury Data Science project -

Investigating historical trends and future projections of UK GHG emissions

In [408]...

```
#Importing required Libraries
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
import numpy as np
import matplotlib.cm as cm
import seaborn as sns
from scipy.stats import zscore
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [409]...

```
#Dataset Link
#Reference[1]: www.ons.gov.uk, n.d.
#https://www.ons.gov.uk/economy/environmentalaccounts/datasets/ukenvironmentalaccountsatmosphericemissionsgreen
```

In [410]...

```
#Importing the xlsx dataset and the correct sheet

dataset1 = 'provisionalatmosphericemissionsghg.xlsx'
sheet_name = 2
#Sheet 2 refers to sheet 3 in the excel sheet
```

In [411]...

```
#The sheet contains 2 tables
#First importing the first table from rows 7 to 42 and columns A to Y
#Reference[2]: Suma Katabattuni, 2024
table1 = pd.read_excel(dataset1,sheet_name,header=0, usecols="A:Y", skiprows=6, nrows=36 )

# Display the full table
table1
```

Out[411]:

	SIC code	A	B	C	D	E	F	G	H	I ...	C
0	Industry name	Agriculture, forestry and fishing	Mining and quarrying	Manufacturing	Electricity, gas, steam and air conditioning s...	Water supply; sewerage, waste management and r...	Construction	Wholesale and retail trade; repair of motor ve...	Transport and storage	Accommodation and food services	... administration and defence compulsory ..
1	1990	55690.3	50452.8	175212.7	217602.2	75316.3	8201.2	11560.8	66985.3	3015.3 ...	12058.4
2	1991	55492.6	50608.3	176254.4	214317.5	76852.7	8072	11984.1	67438.6	3453.5 ...	11381.2
3	1992	55149	51199.3	169388.2	202469.2	76959.1	8188.3	11789.9	68438.5	3163.4 ...	11523.4
4	1993	54319.9	50807.1	164365	184997.2	77275.6	8275.1	12032.9	69735.2	3371.4 ...	11710.9
5	1994	55129.7	44588.4	167285.9	180721.6	77637.9	8633.8	12403.1	70659.2	3342.3 ...	11071.3
6	1995	55061.9	46451.4	165344.1	178162.0	78712	8695.3	12560.6	73508.2	3450.7 ...	11079.5
7	1996	56343.6	46633.6	166622.3	177960.6	79209.4	8923.8	12825.8	79135.4	3636.1 ...	10890.1
8	1997	55810	45761.2	165258.4	164554.2	77982.7	9263.6	12631.7	88159.2	3237.9 ...	10462.7
9	1998	55950.8	44399.3	155653.0	170815.5	78691.1	9207.7	12926.4	93464.0	3581 ...	10028.0
10	1999	56176.1	40501.6	140696.8	163207.5	73742.9	9246.5	13464.5	91941.5	3819.3 ...	10260.4
11	2000	54133.6	38335.6	135627.4	176005.8	71060.5	9440.5	13774.1	94607.7	3913.4 ...	10046.3
12	2001	51955.6	38210.6	128931.3	186969.6	69110.6	9566.7	13738.1	98397.8	4077.2 ...	9921.5
13	2002	51495.5	36722.5	121456.3	182100.7	67450.9	9608.6	13544.7	95135.4	3457.7 ...	9629.5
14	2003	51950.4	34092.4	124723.3	191163.6	63375.2	9791.5	14202.6	95101.3	3705 ...	9518.5
15	2004	52813.4	32909.3	122868.9	191097.4	58712.5	10170.6	14461.8	97343.8	3673 ...	9605.4
16	2005	52934	30738.2	121871.7	192574.6	56104.9	10152	14753.1	99137.9	3694.7 ...	8493.2
17	2006	51899.8	28291.7	117269.7	200397.5	52739.5	10309.7	15013	90909.2	3518.8 ...	8486.5
18	2007	51473.1	27770.4	116409.3	195947.3	49262.6	10785.7	15656.8	94883.2	3433.4 ...	8360.2
19	2008	51240.7	27088.3	108134.2	191548.8	43934.9	10784.4	16297.4	90840.5	4178.1 ...	7647
20	2009	50442.8	27056.8	90639.6	169738.9	39631	9504.6	16483.2	84039.5	3525.6 ...	6938.5
21	2010	50502.1	26661.9	93988	177018.4	34835.1	9682.6	17024.2	84360.1	3773.8 ...	6907.7
22	2011	49647.4	24205.7	90258	164156.6	32853.5	9235.3	16767.9	87918.1	3403.6 ...	6299.3
23	2012	50368.8	22379.2	86759.9	178480.3	31469.9	9426.8	16946	84115	3794.9 ...	6217.2
24	2013	49299.1	21096.9	89442.9	169292	28566.7	9033.9	16508.8	80876.9	3896.3 ...	5696.7
25	2014	51149.2	21086.9	88797.2	148347.2	26627.8	9236	15865.5	85705.9	3444 ...	5057
26	2015	51774.5	22402.3	86036.2	131922.4	26416.7	9971.5	15912.8	87193.9	4289.6 ...	4693.1
27	2016	51397.4	21347.1	80201.2	109990	26154.7	10417.8	15949.4	89850.6	4486.3 ...	4674.1
28	2017	51685.1	21287.7	80871.8	100019.5	27149.1	10474.8	15320.7	83486.7	4484.6 ...	4685.5
29	2018	51227.2	21606.2	80321.5	95782.4	27404.6	10903.5	14993.8	88349.5	4685.3 ...	4865.3
30	2019	50889.8	21858.1	80113	89388.3	26787.1	10734.7	14592.1	86998.4	4618 ...	4739.5
31	2020	49836	20321.3	77060.3	80736.3	25434.7	9941	12705.2	63020.4	4213 ...	4038.4
32	2021	50909.4	18346.2	77092.3	86311	25252.1	11180.6	13471.4	57961.1	4446.4 ...	4494.4
33	2022	49682.9	17433.4	75449.5	82854.7	25109.3	10990.5	13084.3	80891	4203.9 ...	4233.5
34	2023	49176.8	16415.6	73496.8	70134.5	24868.4	11243.8	12855.7	83875.1	4122.1 ...	4380.0

35 rows × 25 columns

```
In [ ]:
```

```
In [412]: #table 2
dataset2 = 'provisionalatmosphericemissionsghg.xlsx'
sheet_name = 2

#The second table starts from row 45 to row 80 (36 rows) and columns A up to EC
table2 = pd.read_excel(dataset2, sheet_name=sheet_name, header=44, usecols="A:EC", nrows=36)

# Print the second table
table2
```

Out[412]:

	SIC code	A	A.1	A.2	B	B.1	B.2	B.3	B.4	C ...	R.1	R.2	R.3
0	SIC(07) group	1	2	3	5	6	7	8	9	10.1 ...	91	92	93
1	Industry name	Products of agriculture, hunting and related serv...	Products of forestry, logging and related serv...	Fish and other fishing products; aquaculture p...	Mining of coal and lignite	Crude petroleum and natural gas	Mining of metal ores	Other mining and quarrying products	Mining support services	Processing and preserving of meat and producti...	Library, archive, museum and other cultural se...	Gambling and betting services	Sporting services and amusement and recreation...
2	1990	54715.1	27	948.2	25423.1	22983.5	9	1237.2	800.1	1033.2 ...	182.8	267.8	1005.2
3	1991	54494.1	27.2	971.3	26059.1	22534.4	9	1244.9	760.8	1140 ...	184.3	281.1	1078.9
4	1992	54119.9	28	1001	25814.5	23477.2	9.1	1203	695.5	1169.5 ...	160.3	253.1	985.6
5	1993	53228.2	34.7	1057	23889.6	25204.8	9.2	1057.9	645.7	1180.2 ...	164.2	262.3	1032.9
6	1994	54010.2	42.7	1076.8	15998.5	26873	9.6	997.5	709.8	1257.4 ...	149.2	246.5	1003
7	1995	53906.4	33.2	1122.4	17362.9	27368.2	9.6	905	805.7	1391.4 ...	144.6	242.3	1011.2
8	1996	55225.1	29.9	1088.6	16060	28798.2	7.5	913.2	854.5	1334.6 ...	144	244.9	1057.6
9	1997	54706.5	36.4	1067.2	15418	28618.5	7.8	872.5	844.3	1316.3 ...	127.5	220.2	964.7
10	1998	54809.8	33.7	1107.3	13103.9	29552.3	7.9	875.8	859.2	1264.2 ...	157	255.2	1116.9
11	1999	55136.1	34.4	1005.6	10898.9	28494	7.2	806.2	295.3	1036.1 ...	166.2	270.4	1200.7
12	2000	53193.8	34.5	905.3	9444.8	27420	7.6	1271.9	191.4	1297.3 ...	170.6	282.5	1250.8
13	2001	51030	33.1	892.7	8478.8	28339.9	7.4	1230.5	154	1186.2 ...	191.1	298.8	1326
14	2002	50626	32.7	836.8	8318.6	27352.9	7.3	837.5	206.2	1107 ...	179.6	259.3	1212.5
15	2003	51128	32.8	789.6	6954.1	26056.7	7.4	879.6	194.7	1356.5 ...	182.5	264.7	1266.4
16	2004	51972.8	32.6	807.9	6296.6	25590.8	8.2	826.4	187.3	1105.4 ...	203.1	273.3	1310.1
17	2005	52096.1	37	801	4729.5	24878.7	8	949.9	172	1157.5 ...	202.8	266.5	1316.6
18	2006	51117.5	35.7	746.6	4327.5	23023.6	8.3	815.6	116.7	1058.4 ...	107.1	166.3	953.2
19	2007	50668.4	49	755.7	3616.2	23073.1	9	953.8	118.2	1055.3 ...	95.9	152.3	911.5
20	2008	50477.6	32.9	730.2	3625.8	21982.8	7.3	1373.6	98.8	917.9 ...	98.7	161.3	1020.6
21	2009	49706.2	30.6	706	3462.8	21993.5	5.7	1357.6	237.3	862.5 ...	87.2	131	908
22	2010	49728.8	28.9	744.4	3291.8	21719.6	6.4	1519	125	905.8 ...	85.1	133.4	918.6
23	2011	48891	29.1	727.3	3151.7	19873.4	6.5	1059.1	115.1	908.8 ...	71	113.7	827.2
24	2012	49575.2	28.9	764.7	3100.7	18294.3	6.1	772.3	205.7	865.9 ...	72.7	117.5	880.9
25	2013	48513.1	27.6	758.4	2226.9	17923.1	5.8	731.7	209.3	855.1 ...	69.5	114.3	892.7
26	2014	50211.8	28.7	908.7	2231.7	17529.6	6.3	985.9	333.5	900.7 ...	63.4	100.4	815.3
27	2015	50886.2	29.1	859.2	1890.2	19274.2	6.4	1061.2	170.4	880.7 ...	42.5	80.5	862.2
28	2016	50522.8	30.4	844.2	939	18852.3	6.8	1234.1	314.8	818.1 ...	44.9	81.7	902.5
29	2017	50792.9	29.6	862.7	918.6	18865.3	7.1	1392.3	104.3	854 ...	46	81.8	913
30	2018	50378.6	28.7	819.9	890.7	18856.6	7.1	1744.1	107.7	912.8 ...	48.1	83.8	930.3
31	2019	50136.5	28.8	724.6	870.3	18903.6	6.9	1952.6	124.7	959.1 ...	46.8	81.3	915.7
32	2020	49101	23.5	711.6	858.1	17269.6	7.4	2164.8	21.4	937.7 ...	38.8	74.1	856.5
33	2021	50147.1	26.1	736.1	806.9	15153.9	6.9	2312	66.4	915 ...	44.5	77.1	893.2
34	2022	48951	27.3	704.6	766.1	14313.3	6.9	2314.2	32.8	896.2 ...	41.4	71.9	855.3

35 rows × 133 columns

In [413...]

```
# Check for missing values in each table
print(table1.isnull().sum())
print(table2.isnull().sum())
```

```

SIC code      0
A             0
B             0
C             0
D             0
E             0
F             0
G             0
H             0
I             0
J             0
K             0
L             0
M             0
N             0
O             0
P             0
Q             0
R             0
S             0
T             0
-             0
Unnamed: 22   0
Unnamed: 23   0
Unnamed: 24   0
dtype: int64
SIC code      0
A             0
A.1            0
A.2            0
B             0
..
S.2            0
T             0
Unnamed: 130   0
Unnamed: 131   0
Unnamed: 132   1
Length: 133, dtype: int64

```

In [ ]:

In [ ]:

In [ ]:

In [414]: *##Reference:(Naveen Nelamali, 2022)*

```

# Selecting the numerical data for the years skipping the first column and first row
numerical_data_table1 = table1.iloc[1:, 1:].apply(pd.to_numeric, errors='coerce')

#make industry names as headings
numerical_data_table1.columns = industry_names_table1

```

In [415]:

```

#descriptive statistics
numerical_data_table1.describe()

```

Out[415]:

	Agriculture, forestry and fishing	Mining and quarrying	Manufacturing	Electricity, gas, steam and air conditioning supply	Water supply; sewerage, waste management and remediation activities	Construction	Wholesale and retail trade; repair of motor vehicles and motorcycles	Transport and storage	Accommodation and food services
<b>count</b>	34.000000	34.000000	34.000000	34.000000	34.000000	34.000000	34.000000	34.000000	34.000000
<b>mean</b>	52441.426471	32031.391176	117467.679412	159317.214706	50961.529412	9685.129412	14238.305882	83954.826471	3797.341176
<b>std</b>	2267.946845	11445.279839	35606.752905	42995.422940	22023.914957	901.871906	1673.486214	10880.706396	443.929933
<b>min</b>	49176.800000	16415.600000	73496.800000	70134.500000	24868.400000	8072.000000	11560.800000	57961.100000	3015.300000
<b>25%</b>	50894.700000	21669.175000	86217.125000	136028.600000	27212.975000	9214.600000	12833.275000	79570.775000	3451.400000
<b>50%</b>	51729.800000	28031.050000	116839.500000	176512.100000	51001.050000	9587.650000	13988.350000	86352.150000	3699.850000
<b>75%</b>	54876.400000	43424.875000	151913.950000	190065.450000	74922.950000	10390.775000	15813.325000	91683.425000	4164.100000
<b>max</b>	56343.600000	51199.300000	176254.400000	217602.200000	79209.400000	11243.800000	17024.200000	99137.900000	4685.300000

8 rows × 24 columns

In [ ]:

In [ ]:

```

In [416]: #Line graph

# Extracting the years (first column starting from row 1)
years = table1.iloc[1:, 0].astype(int)

# Extracting the 'Total greenhouse gas emissions' column (last column)
total_ghg_emissions = table1.iloc[1:, -1].apply(pd.to_numeric, errors='coerce')

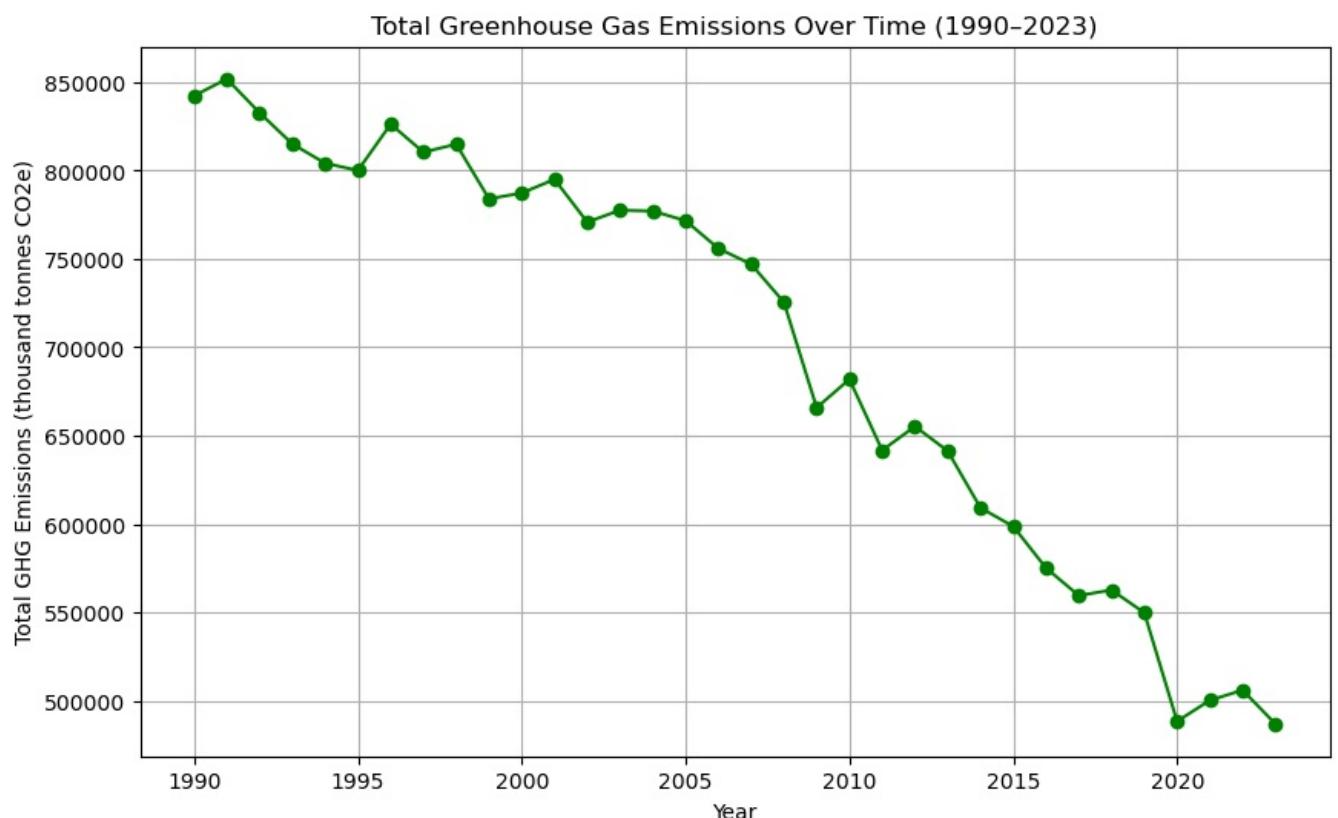
#sorting the df
emissions_data = pd.DataFrame({'Year': years, 'Total GHG Emissions': total_ghg_emissions})
emissions_data = emissions_data.sort_values(by='Year')

# Plot total greenhouse gas emissions over time
plt.figure(figsize=(10, 6))
plt.plot(emissions_data['Year'], emissions_data['Total GHG Emissions'], marker='o', linestyle='-', color='green')

#labels
plt.xlabel("Year")
plt.ylabel("Total GHG Emissions (thousand tonnes CO2e)")
plt.title("Total Greenhouse Gas Emissions Over Time (1990–2023)")
plt.grid(True)

# Show the plot
plt.show()

```



```

In [ ]:
In [417]: #Line graph for each sector

# Extracting years (from column 1, starting from row 1 going down)
years = table1.iloc[1:, 0].values

# Extract the industry names (from column 2 onwards in row 0)
industry_names = table1.iloc[0, 1:].values

# Loop through each industry to plot the data
for industry_index, industry in enumerate(industry_names):
    # Extract emissions data for the current industry in the loop
    emissions_data = table1.iloc[1:, industry_index + 1].values

```

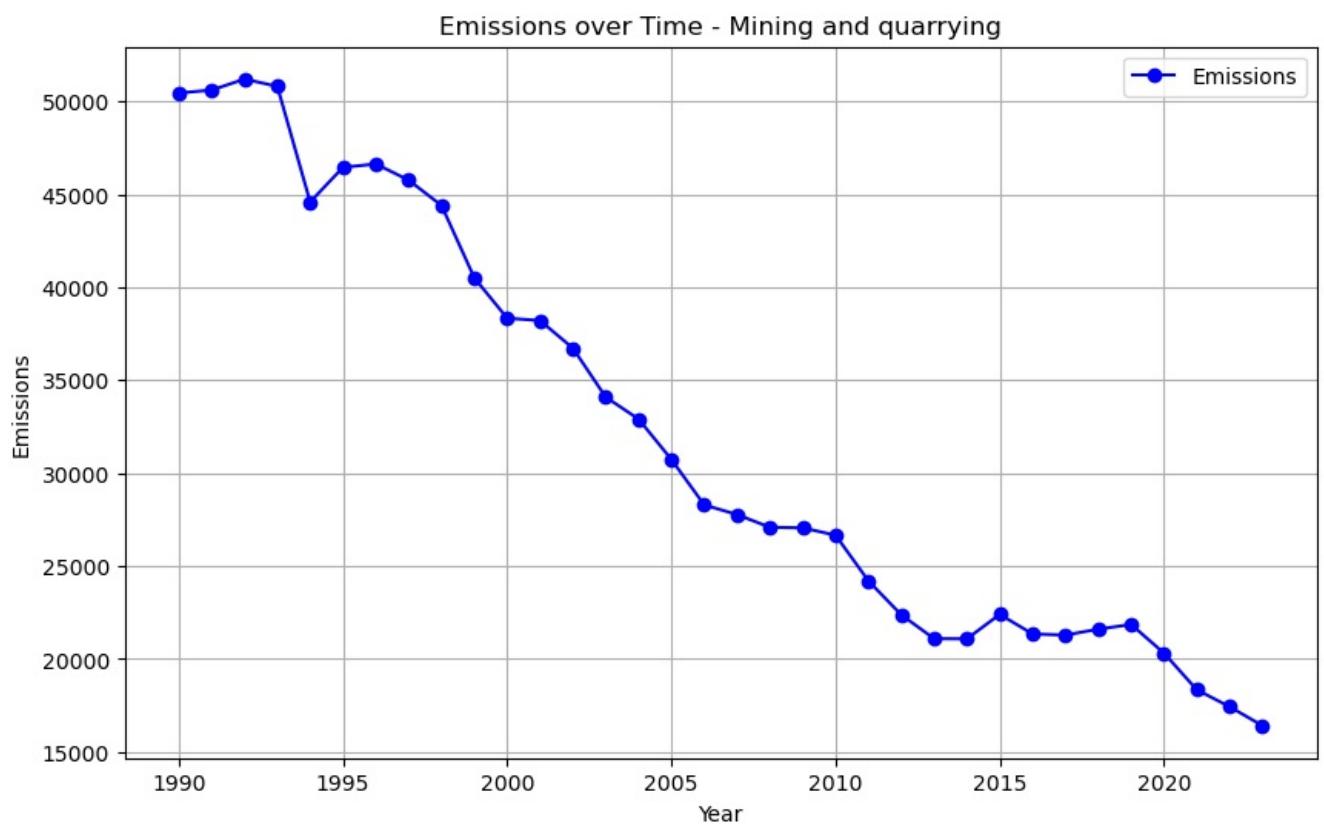
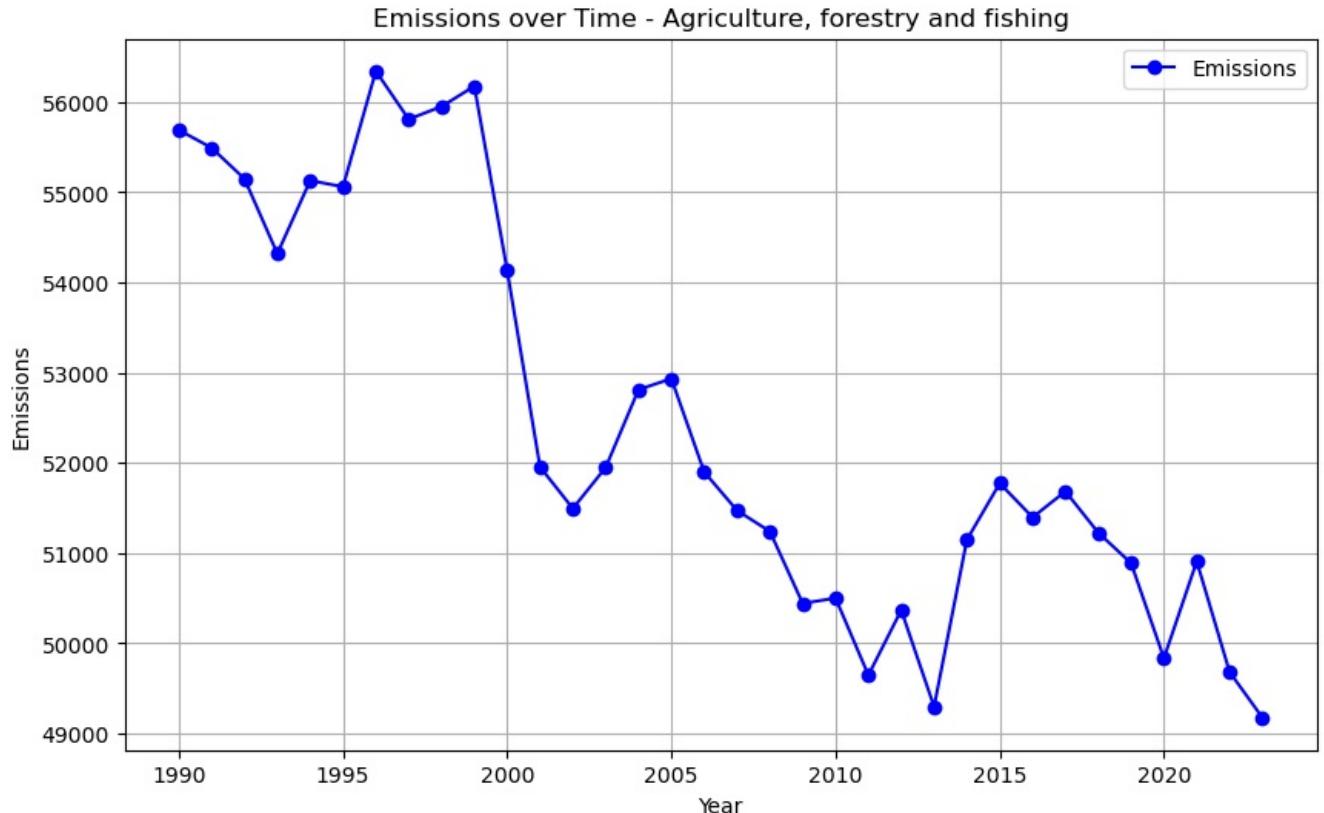
```

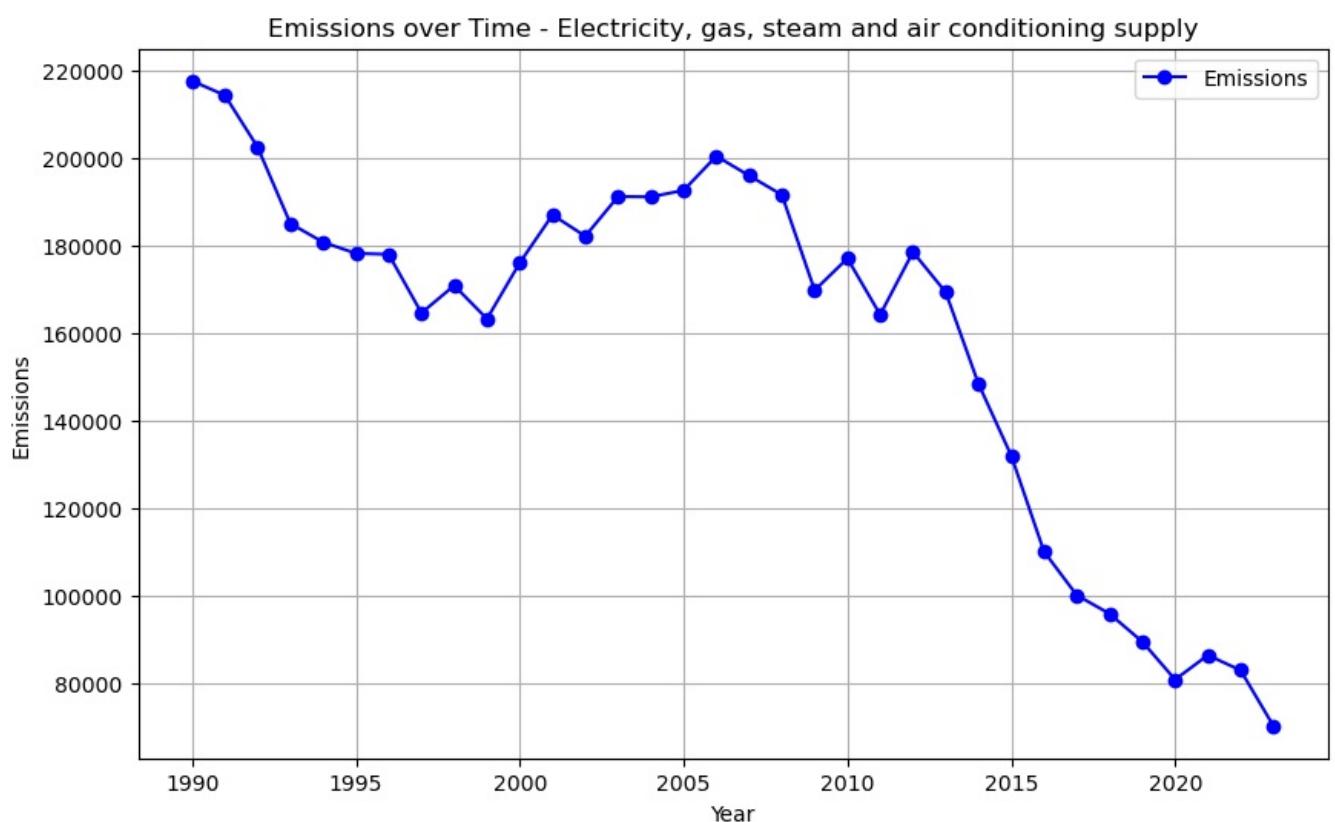
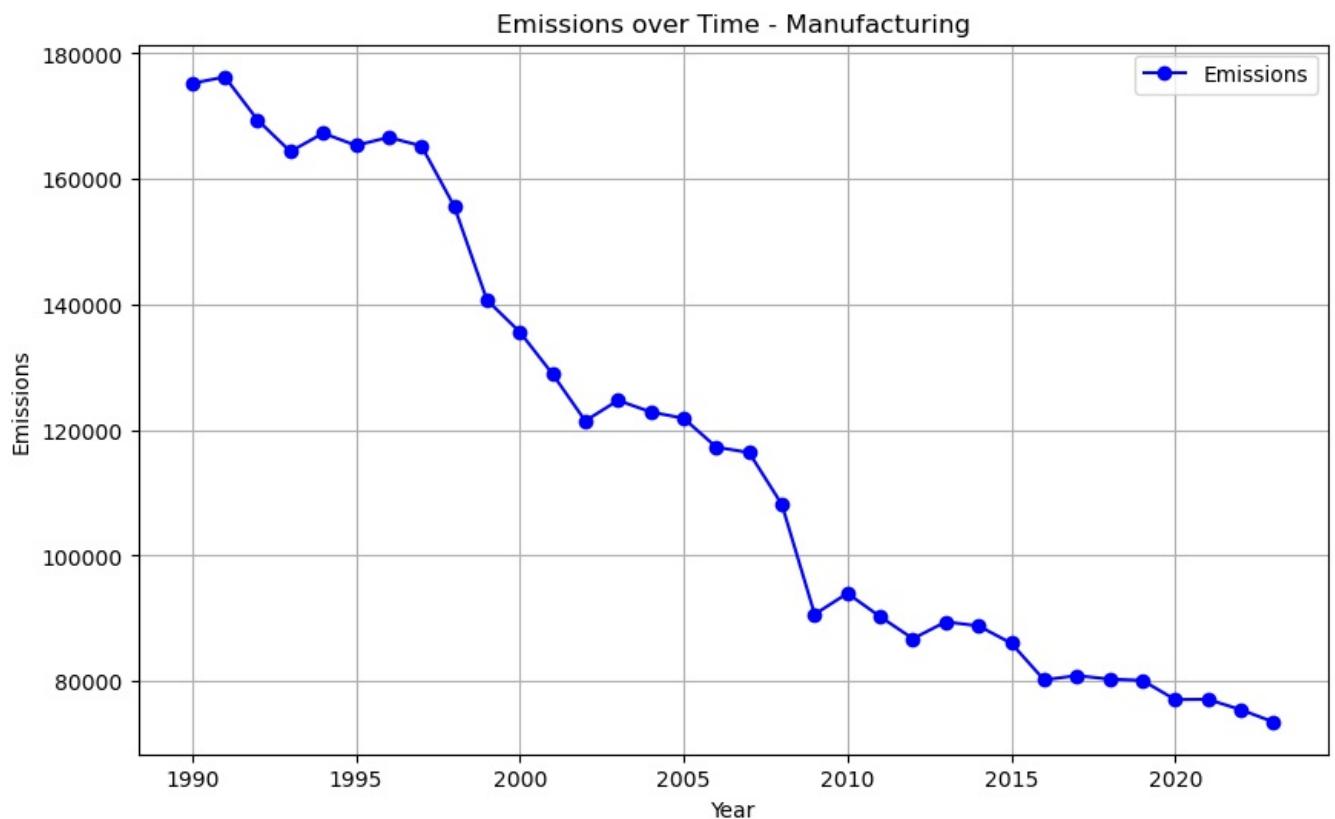
# Creating a figure and axis for each plot
plt.figure(figsize=(10, 6))
plt.plot(years, emissions_data, label='Emissions', marker='o', color='b')

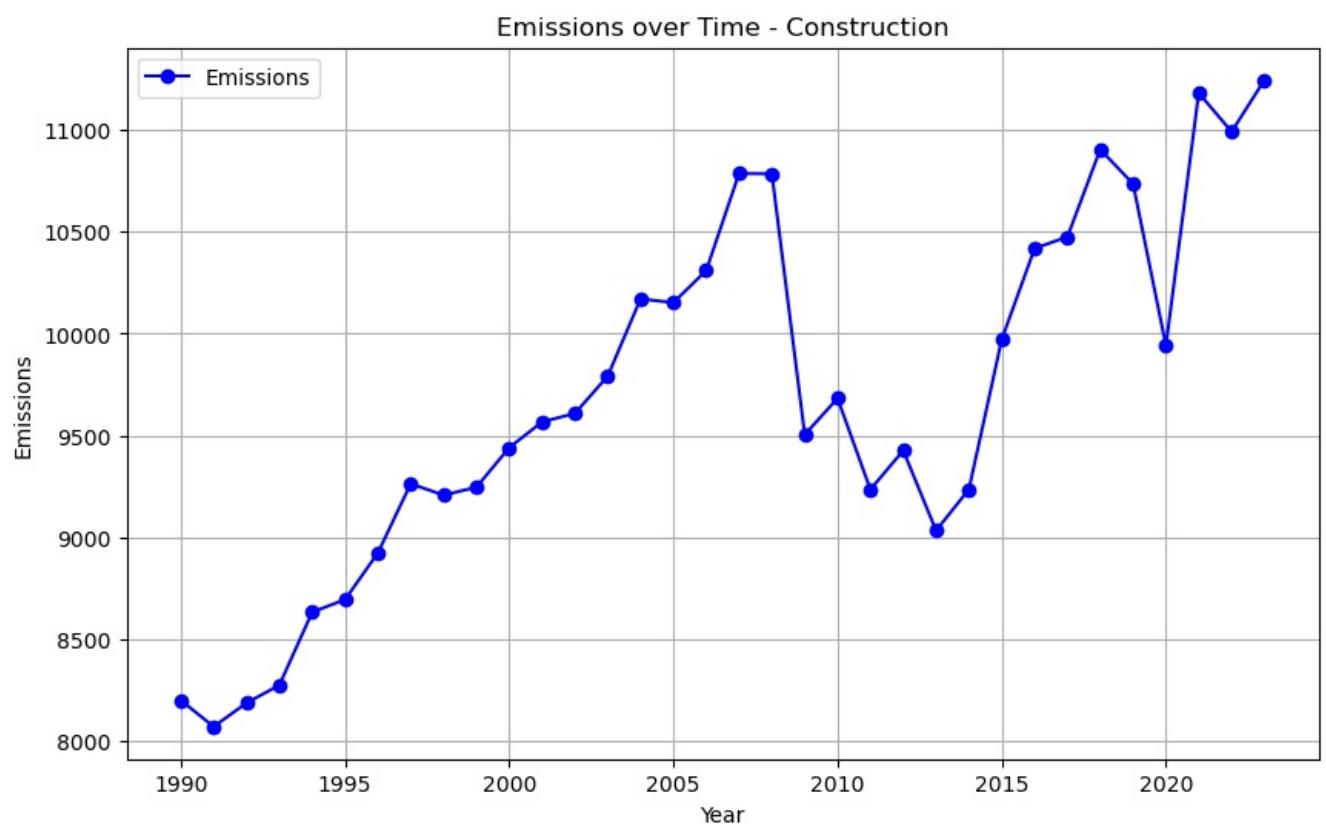
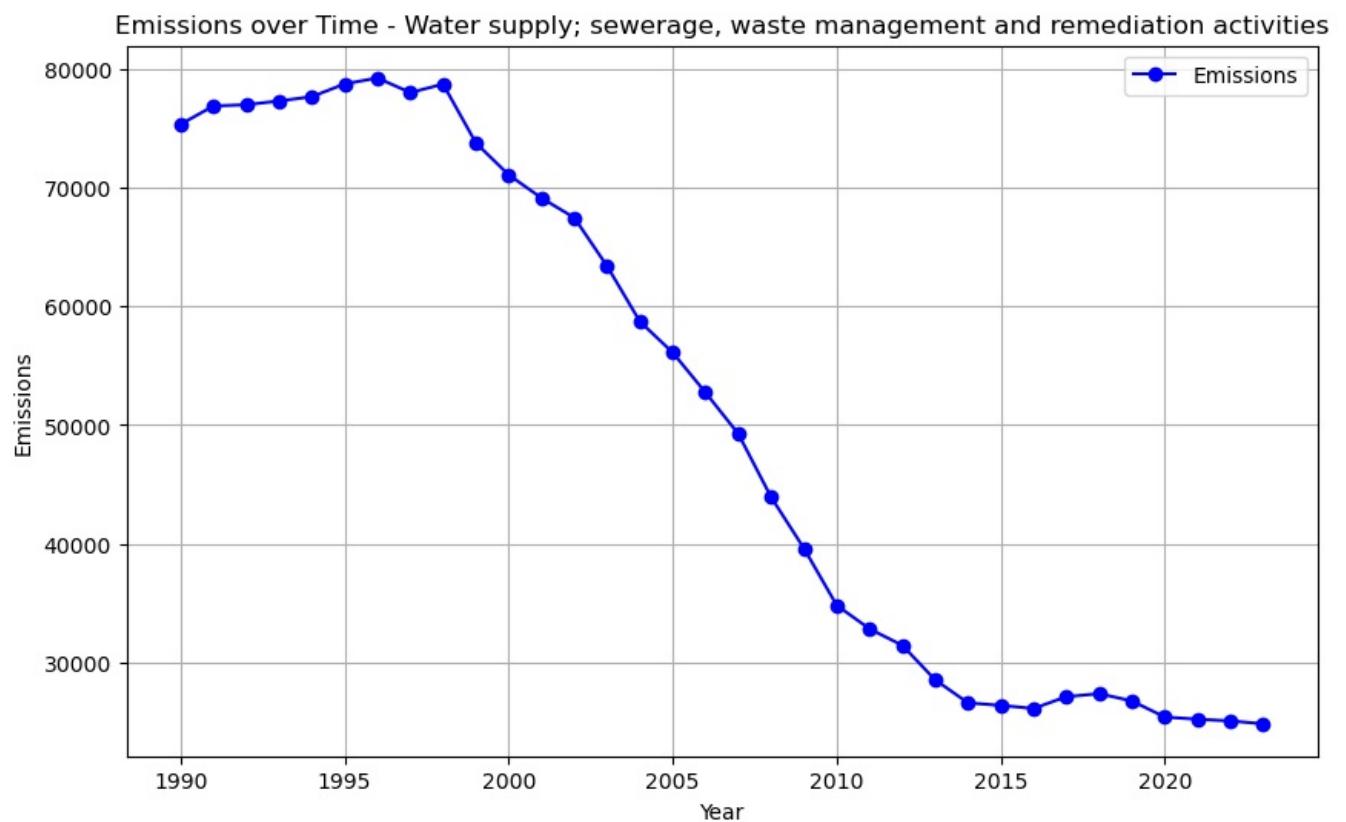
#plot labels
plt.title(f'Emissions over Time - {industry}')
plt.xlabel('Year')
plt.ylabel('Emissions')
plt.legend()
plt.grid(True)

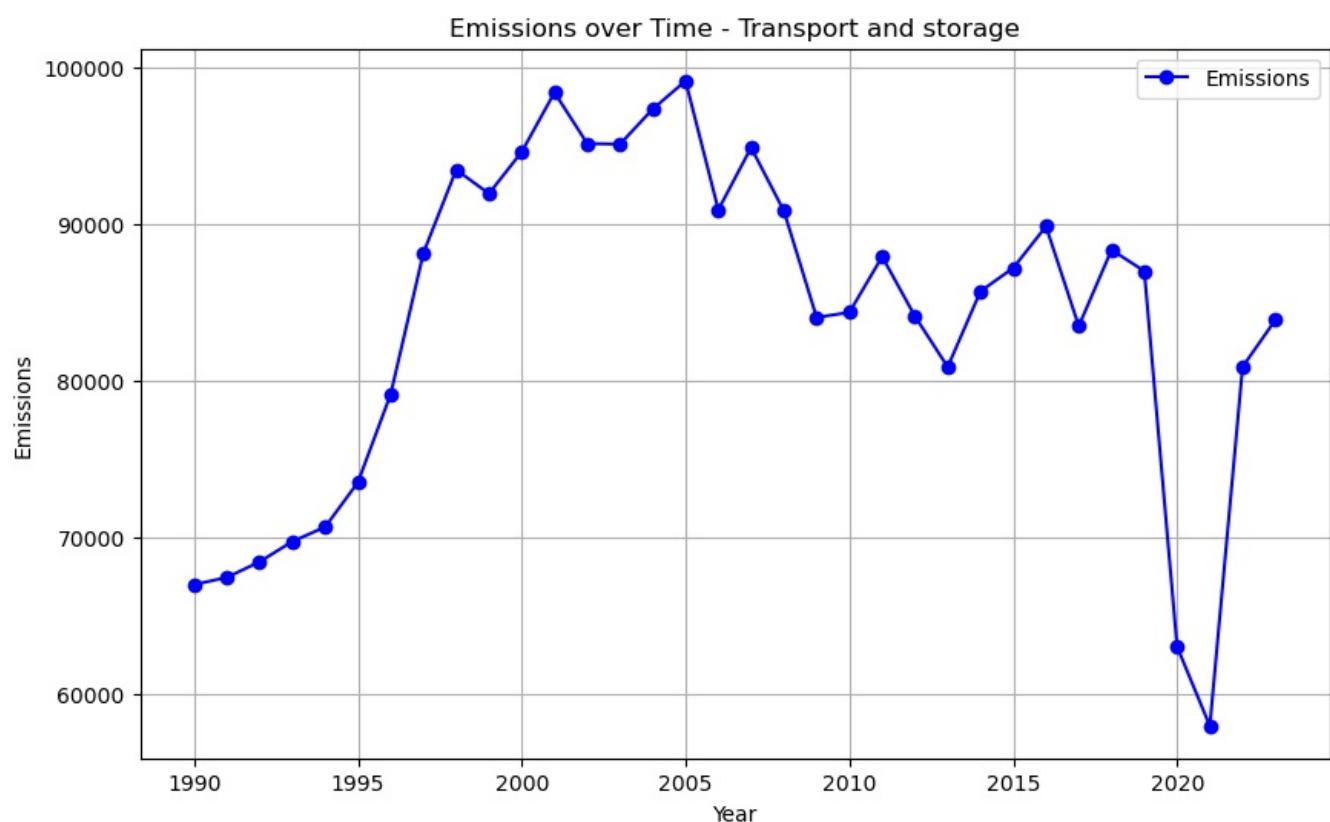
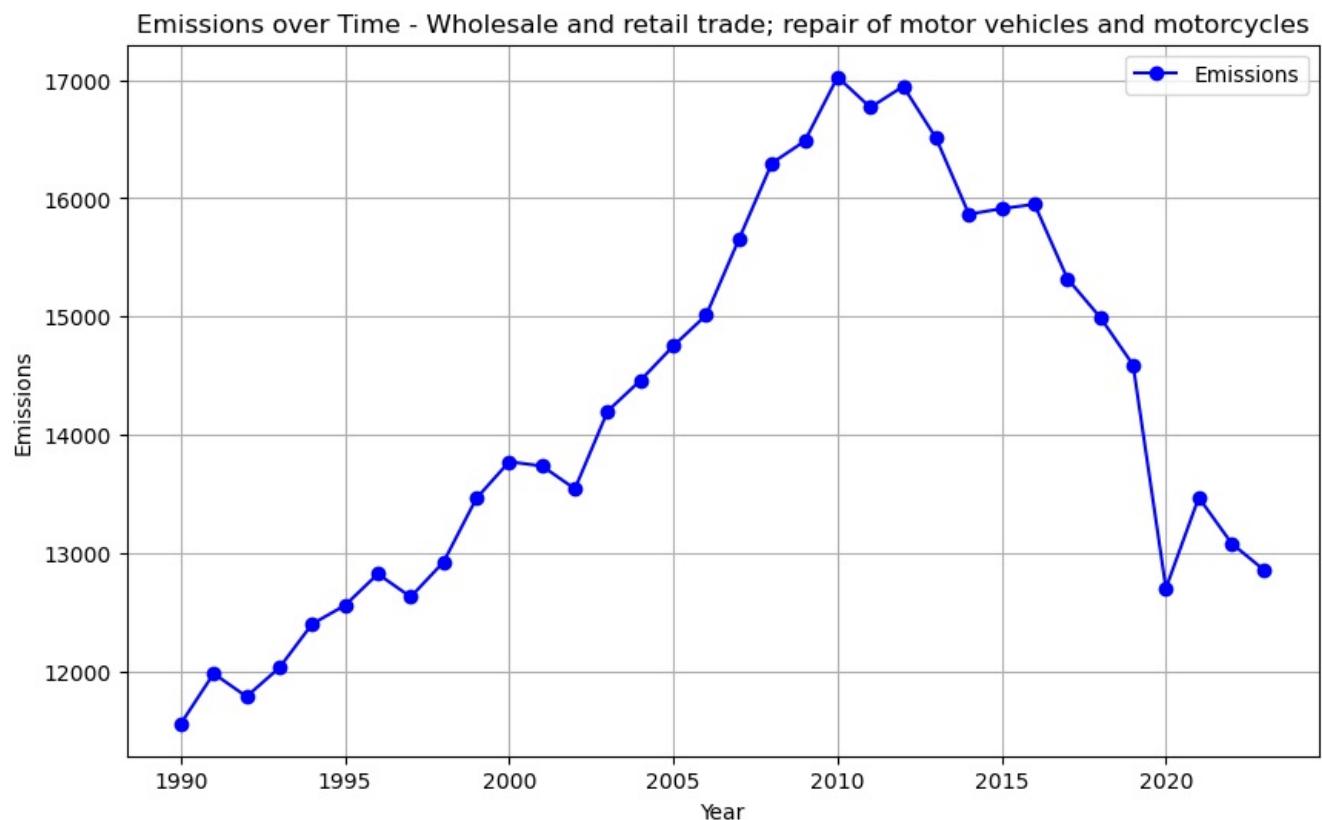
# Show the plot
plt.show()

```

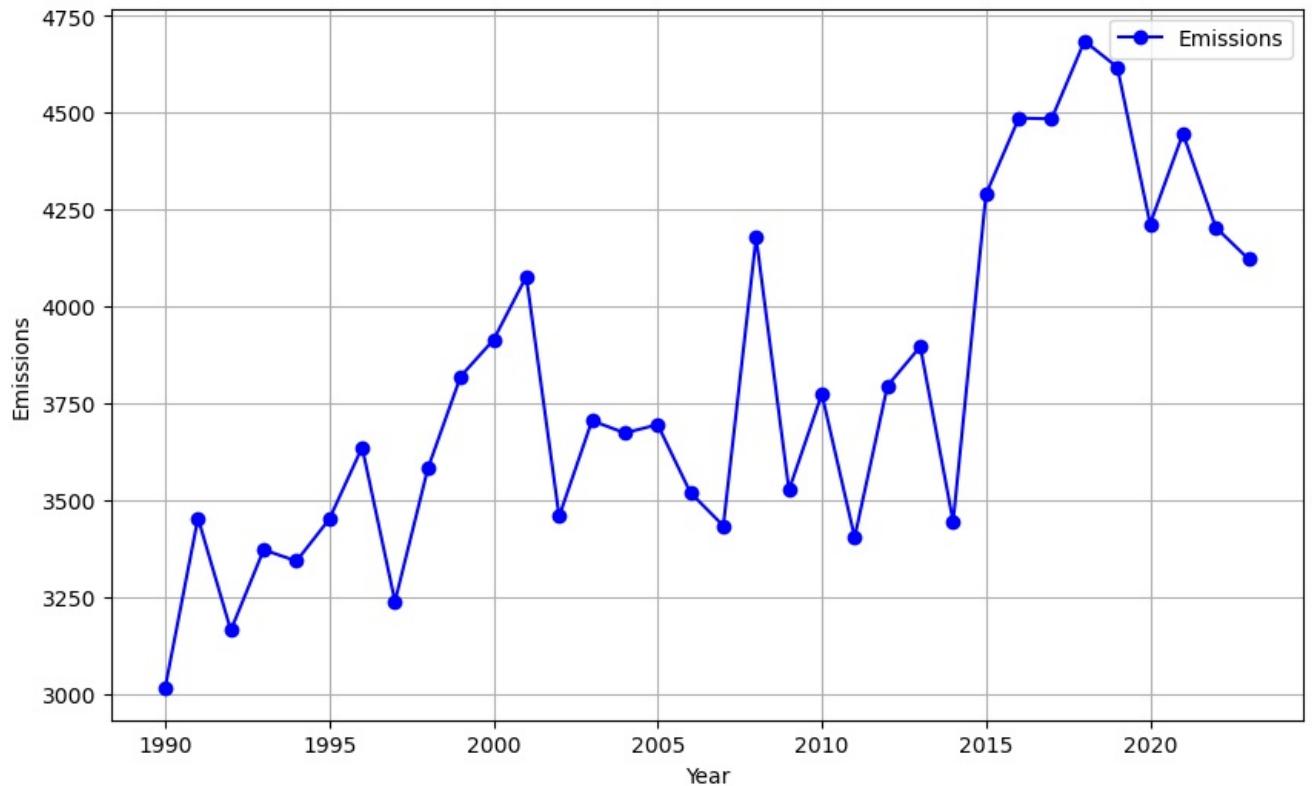




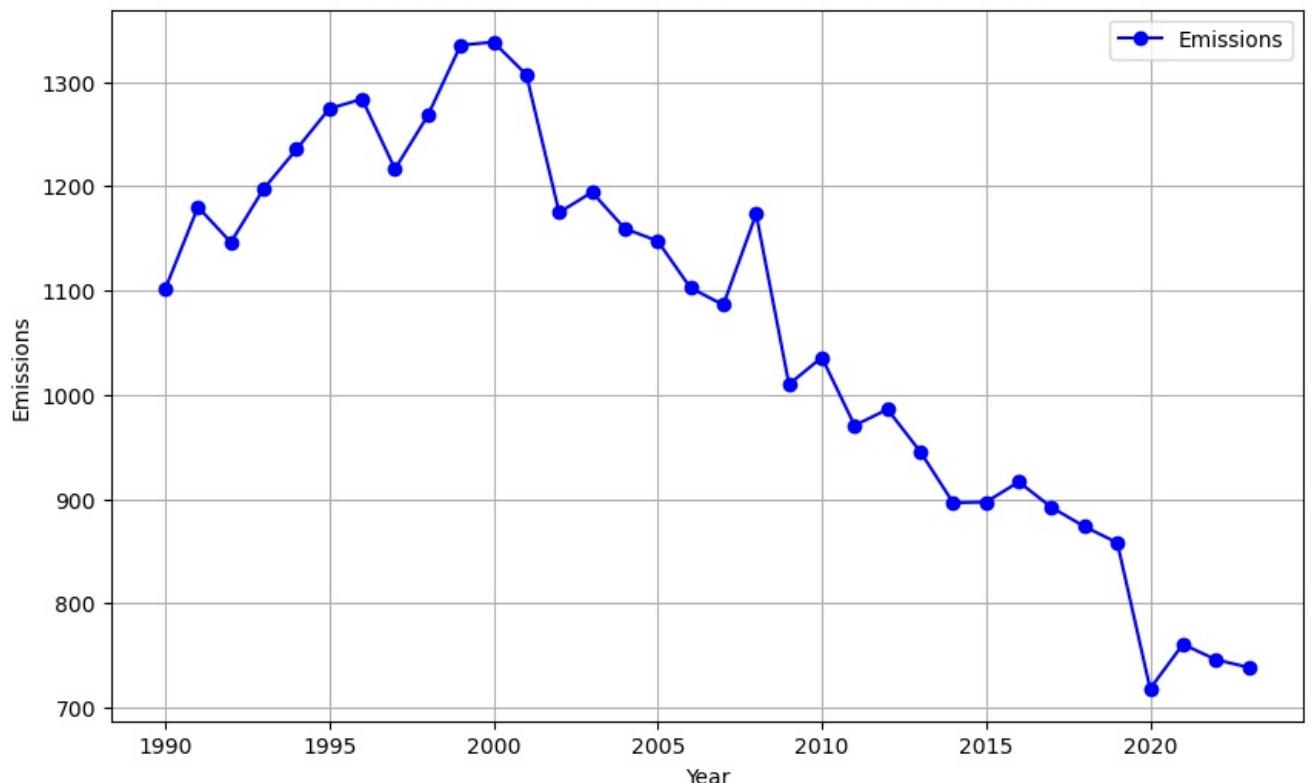




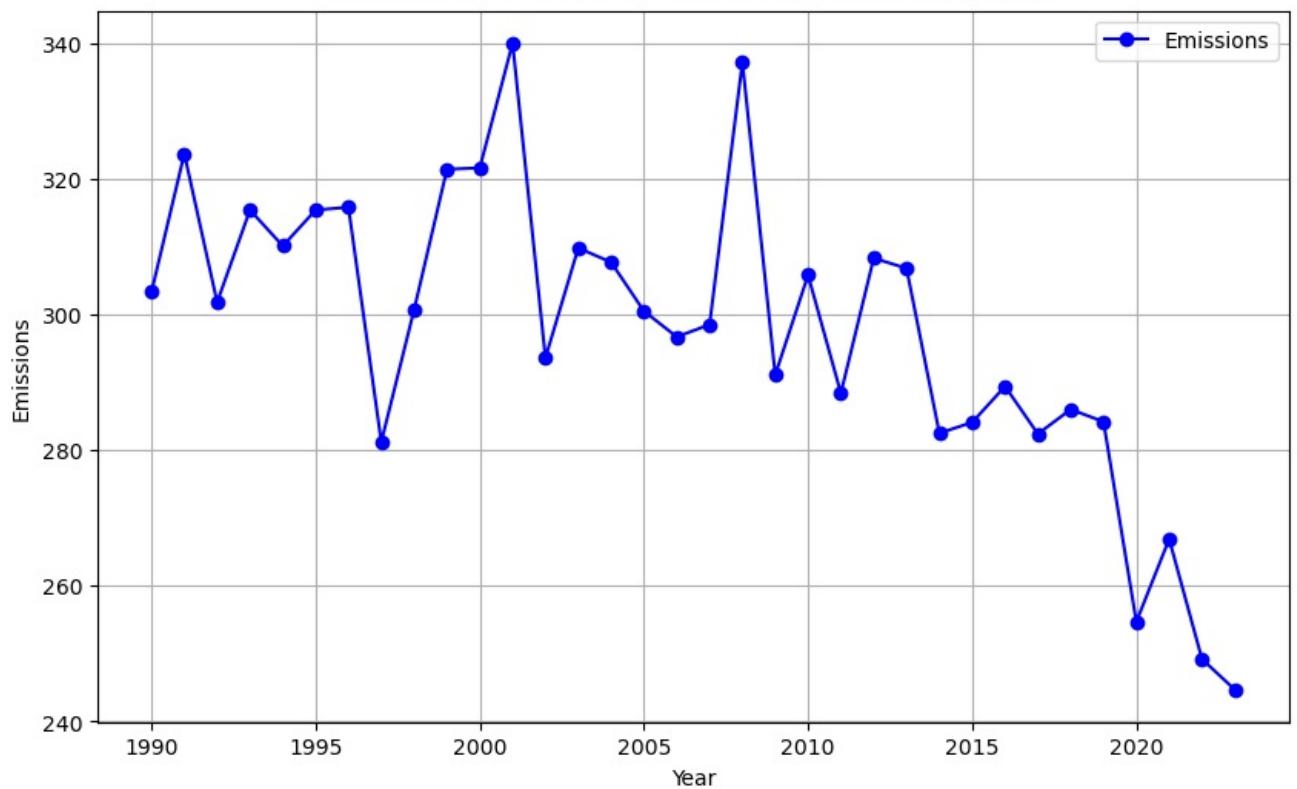
Emissions over Time - Accommodation and food services



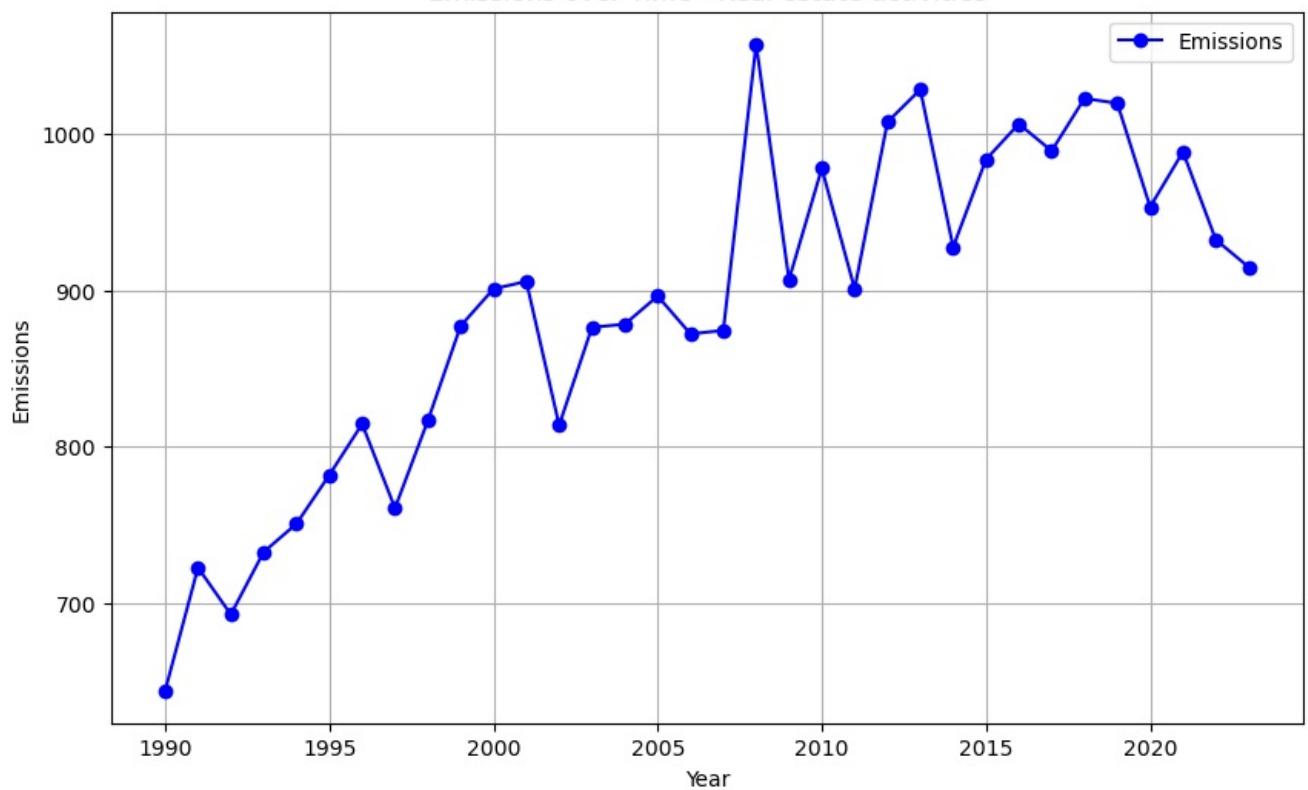
Emissions over Time - Information and communication



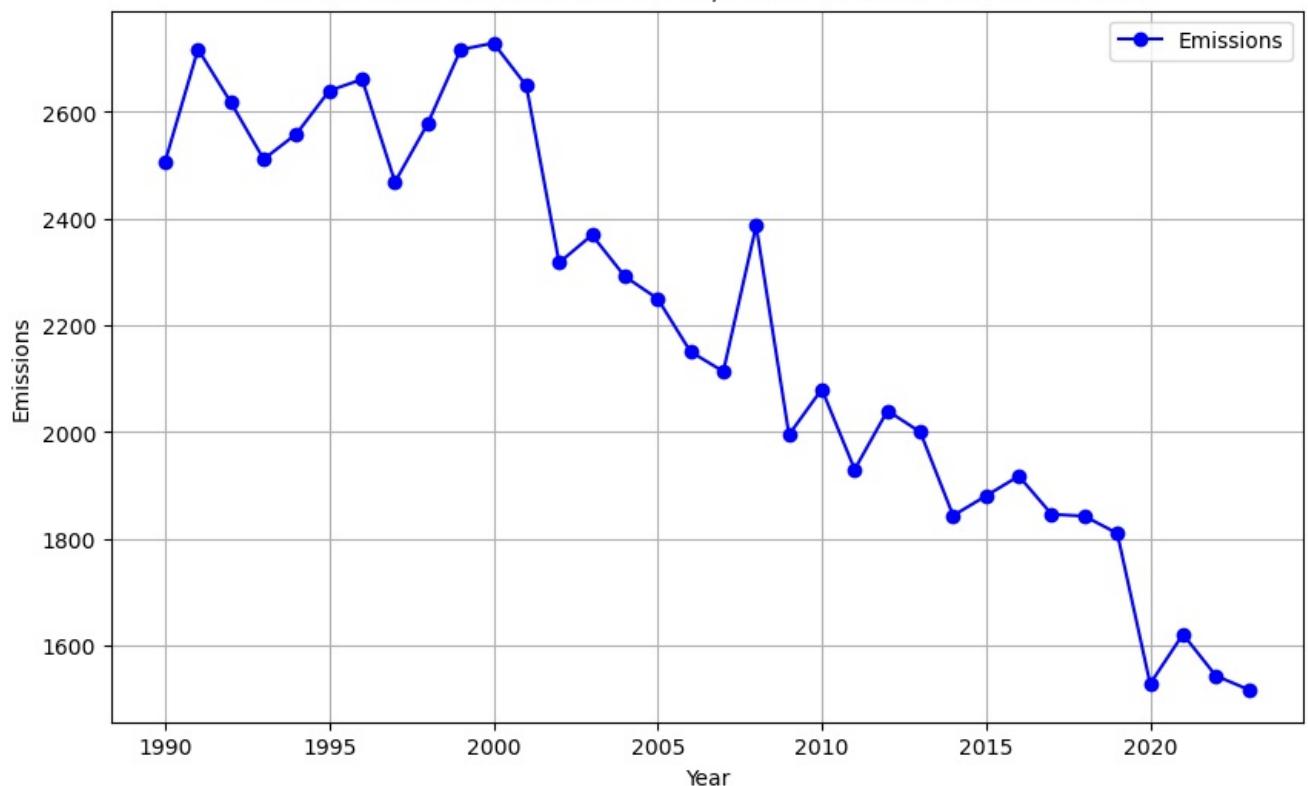
Emissions over Time - Financial and insurance activities



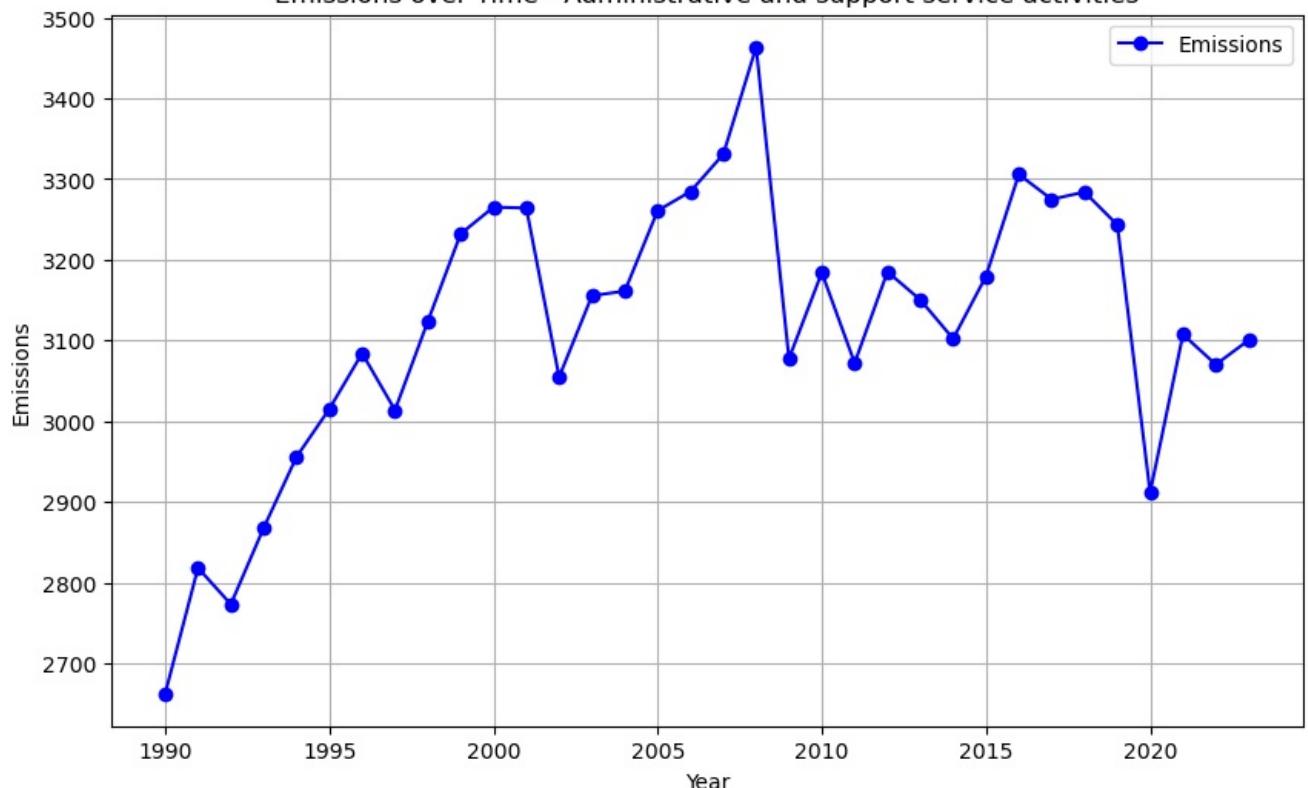
Emissions over Time - Real estate activities



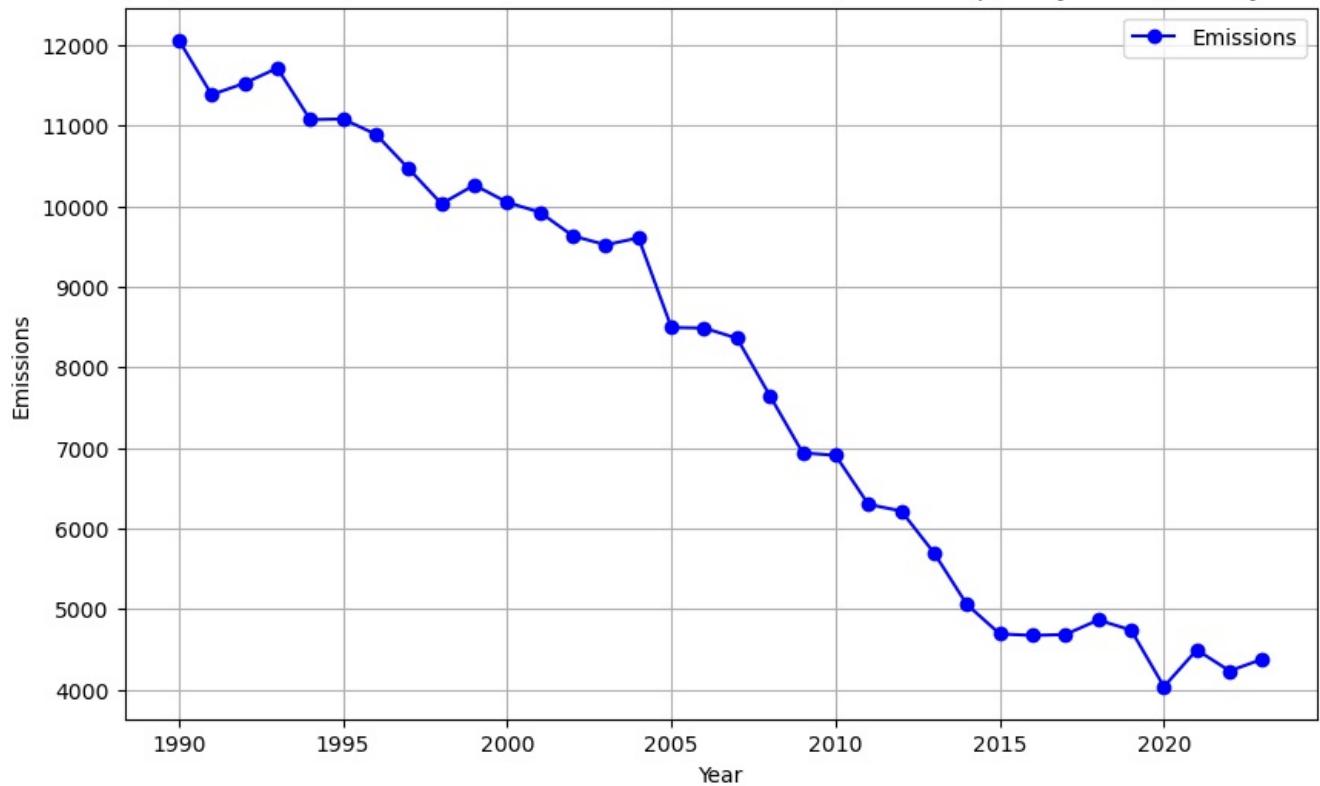
Emissions over Time - Professional, scientific and technical activities



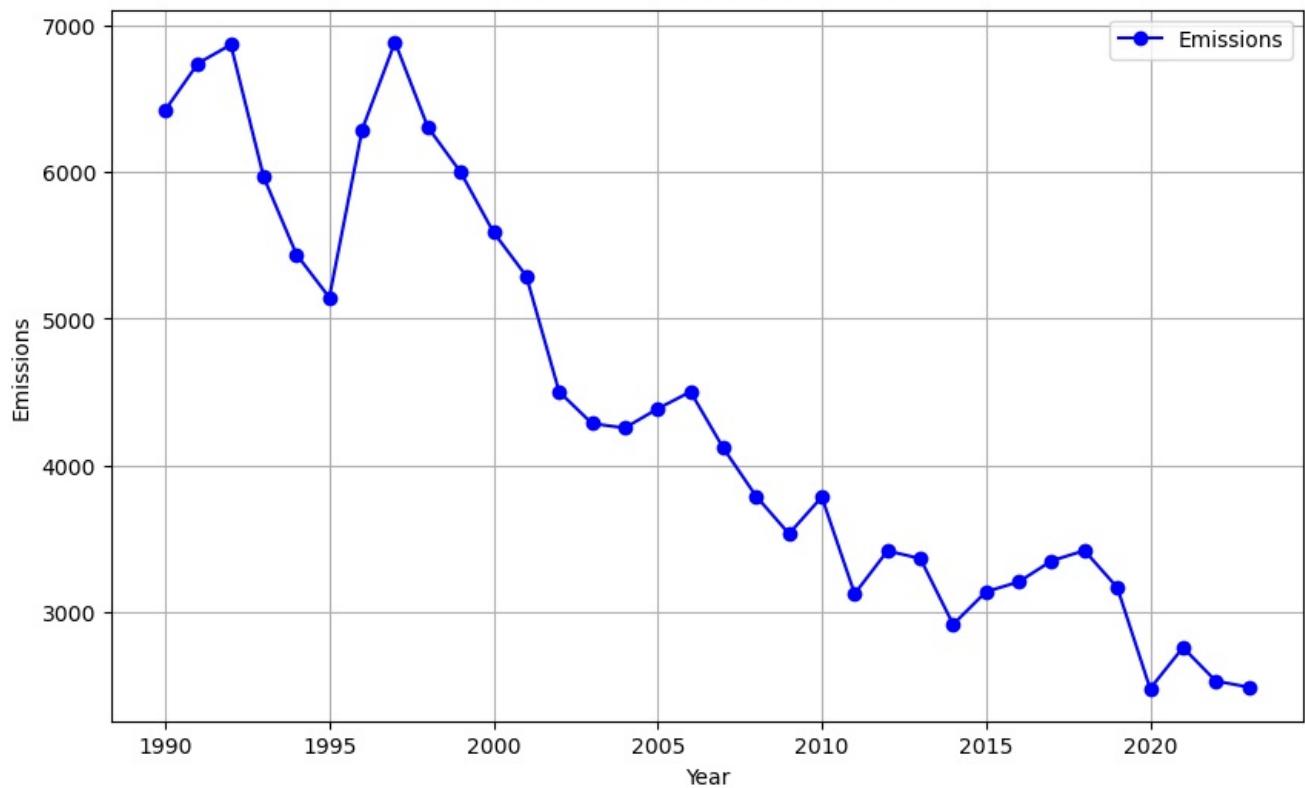
Emissions over Time - Administrative and support service activities



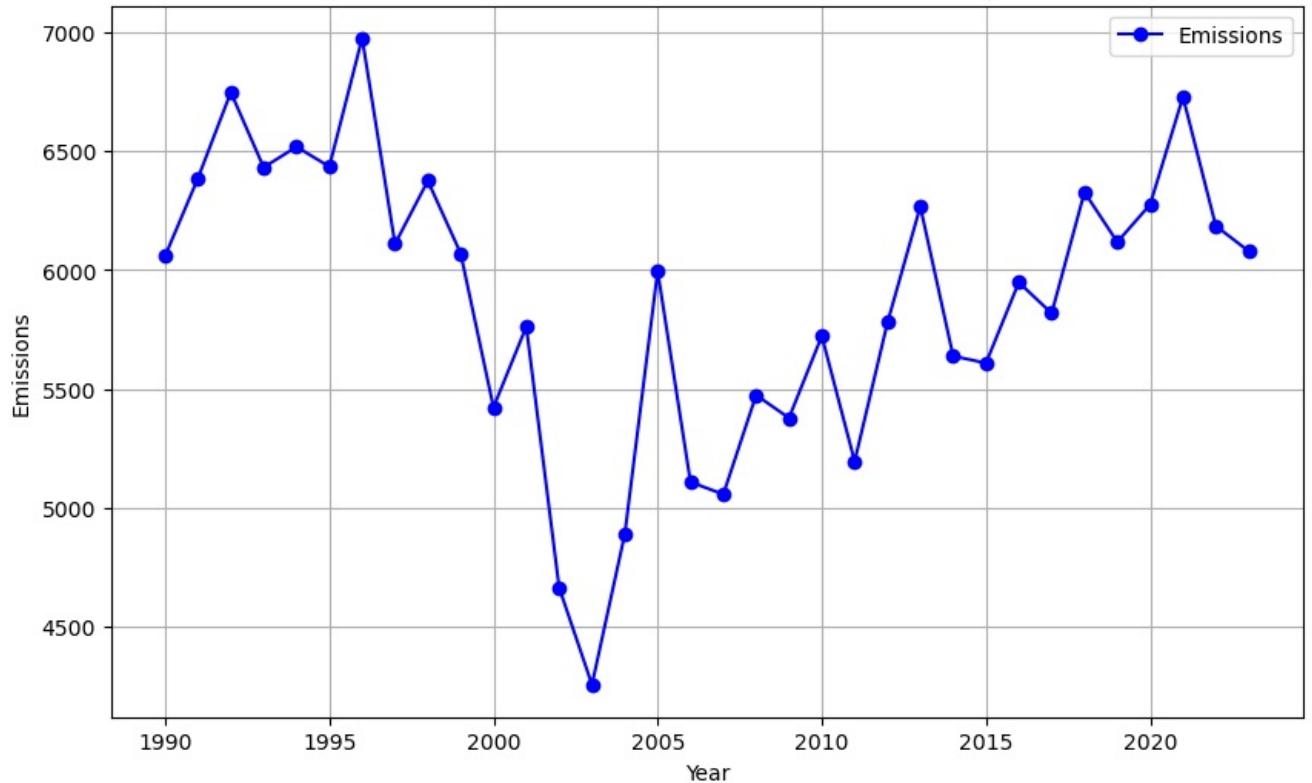
Emissions over Time - Public administration and defence; compulsory social security



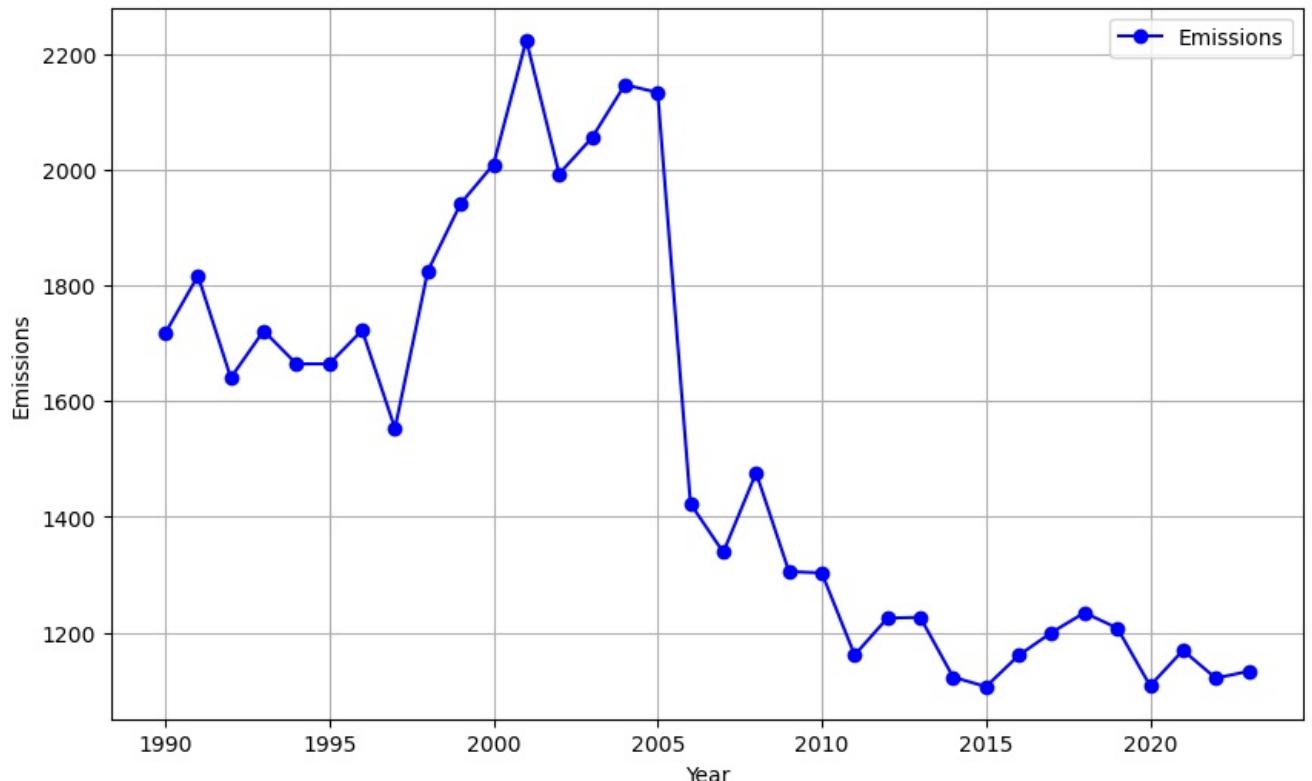
Emissions over Time - Education



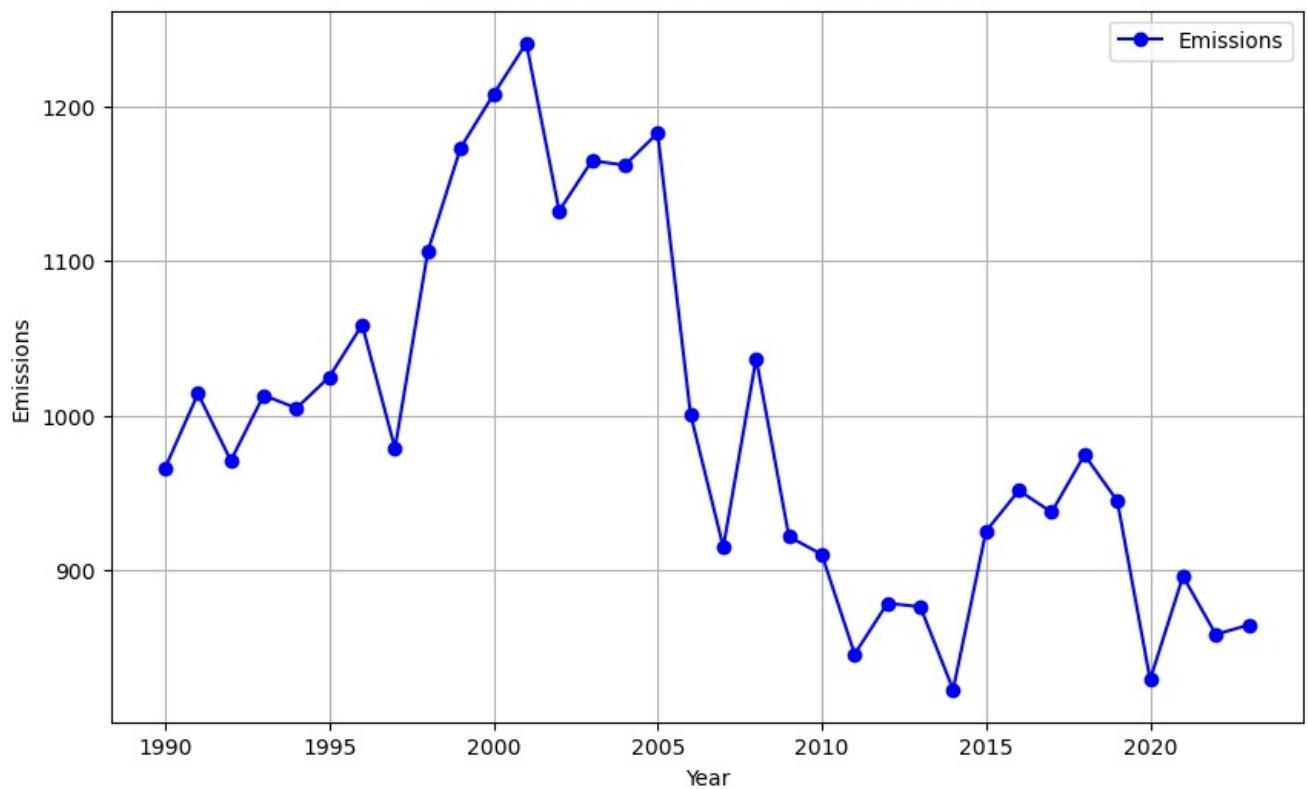
Emissions over Time - Human health and social work activities



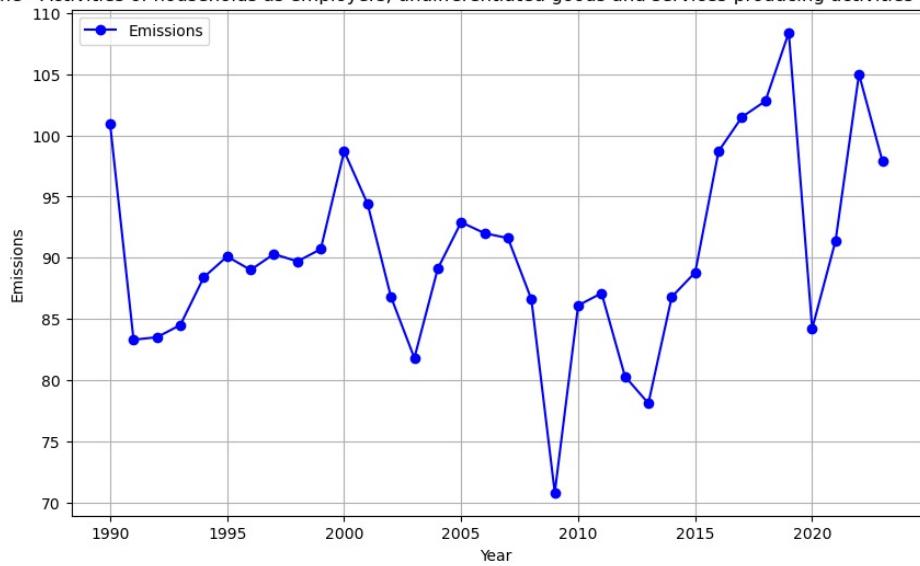
Emissions over Time - Arts, entertainment and recreation



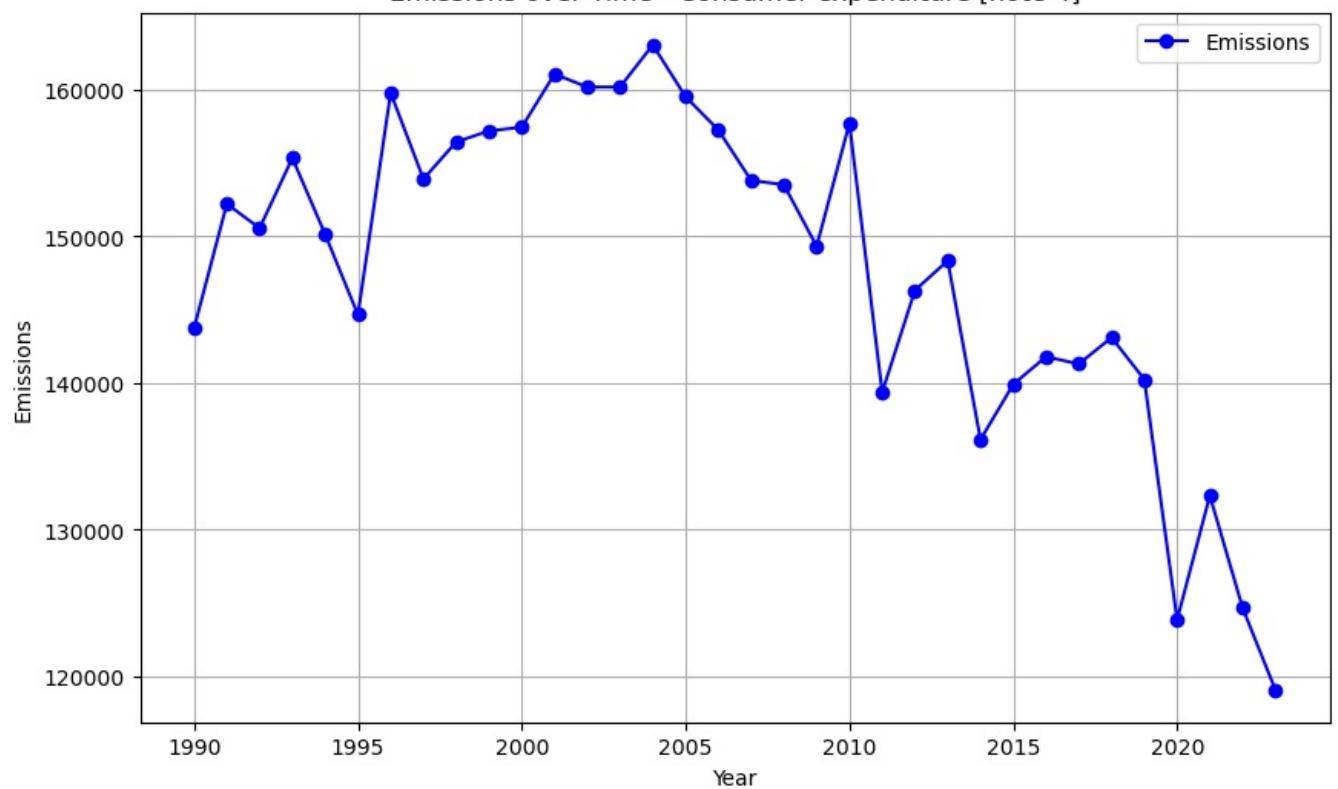
Emissions over Time - Other service activities



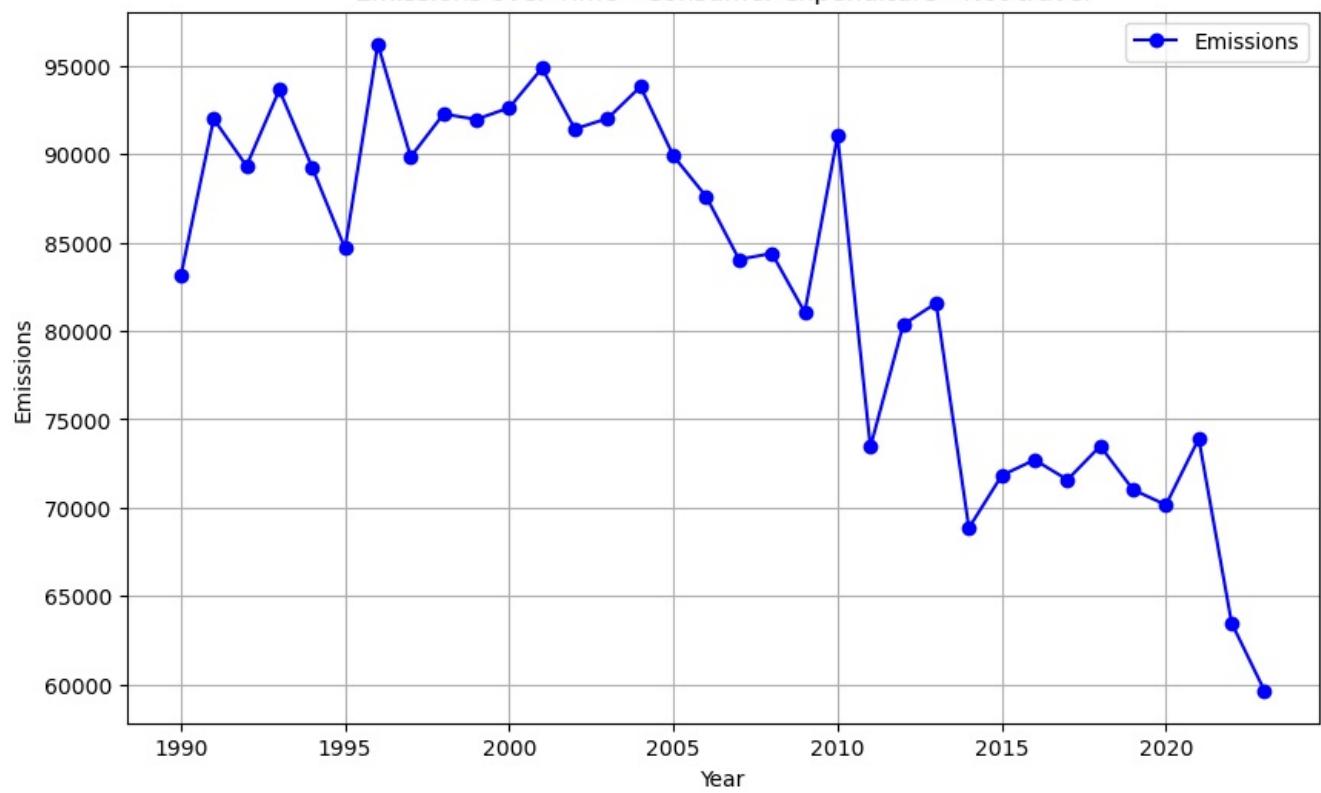
Emissions over Time - Activities of households as employers; undifferentiated goods and services-producing activities of households for own use



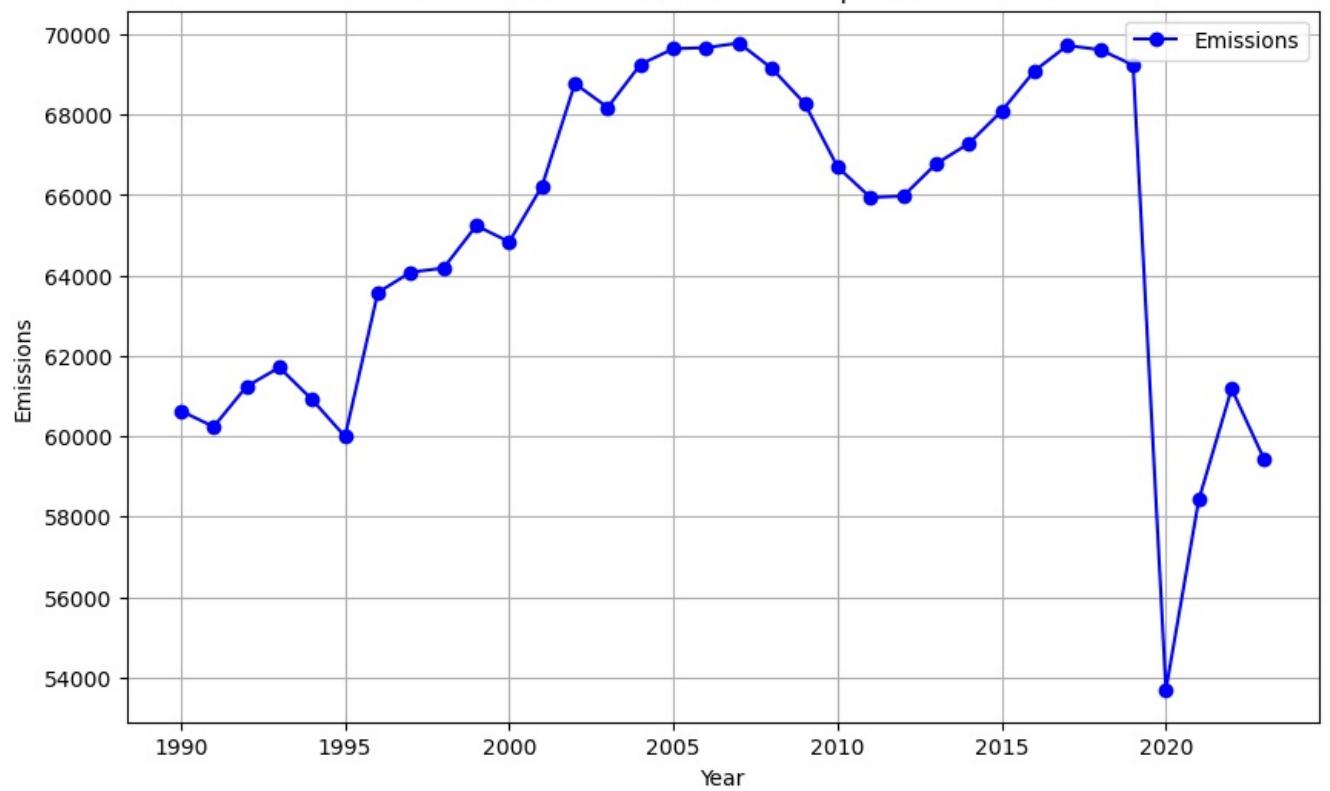
Emissions over Time - Consumer expenditure [note 4]

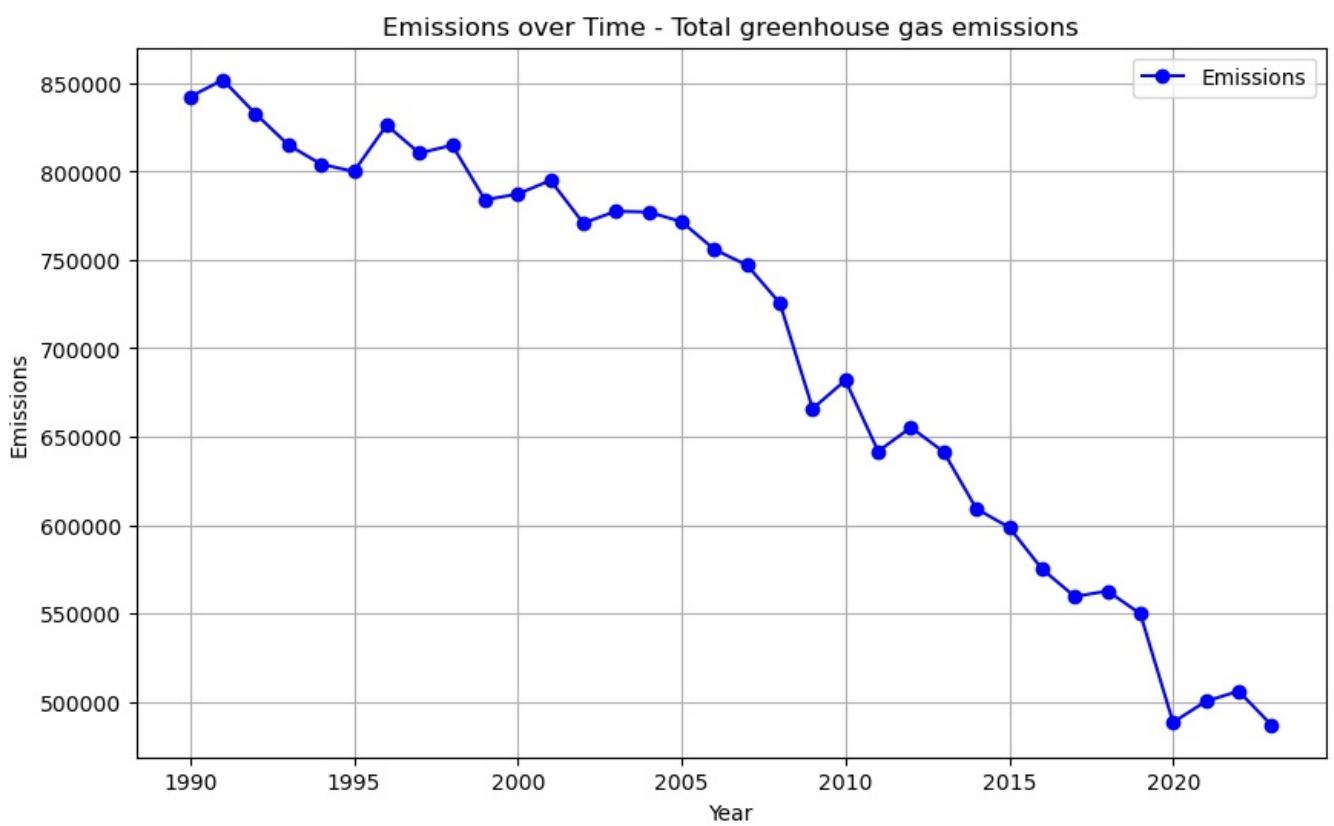


Emissions over Time - Consumer expenditure - Not travel



Emissions over Time - Consumer expenditure - Travel





In [418]: #Log line graph

```

years = table1.iloc[1:, 0].values
industry_names = table1.iloc[0, 1:-1].values

plt.figure(figsize=(15, 10))

#tab20 for distinct colours
colormap = cm.get_cmap('tab20', len(industry_names))

# Loop through each industry to plot the data
for industry_index, industry in enumerate(industry_names):
    emissions_data = table1.iloc[1:, industry_index + 1].values

    # Plot the emissions data for the industry with a log scale on the y-axis
    plt.plot(years, emissions_data, label=industry, marker='o', linestyle='-', markersize=5, color=colormap(industry_index))

#log scale for y-axis
plt.yscale('log')

plt.title('Annual GHG Emissions for Various Industries (Log Scale)', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Emissions (Log Scale)', fontsize=14)
plt.grid(True, which="both", linestyle='--', linewidth=0.5)

```

```

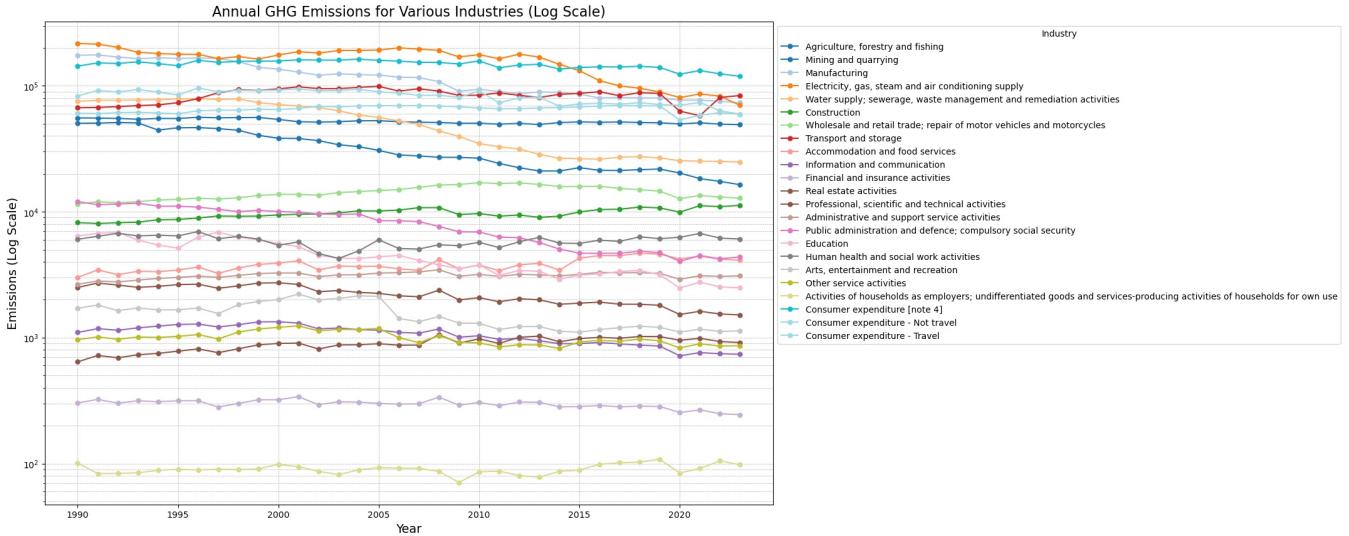
plt.legend(loc='upper left', bbox_to_anchor=(1, 1), title="Industry", fontsize=10)

# Show the plot
plt.show()

```

/var/folders/qx/yygks\_tn4\_32lm3xlq53x1pc0000gn/T/ipykernel\_38548/2882286533.py:10: MatplotlibDeprecationWarning : The get\_cmap function was deprecated in Matplotlib 3.7 and will be removed two minor releases later. Use ``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get\_cmap(obj)`` instead.

```
    colormap = cm.get_cmap('tab20', len(industry_names))
```



In [ ]:

In [419]: table1

Out[419]:

	SIC code	A	B	C	D	E	F	G	H	I ...	C
0	Industry name	Agriculture, forestry and fishing	Mining and quarrying	Manufacturing	Electricity, gas, steam and air conditioning s...	Water supply; sewerage, waste management and r...	Construction	Wholesale and retail trade; repair of motor ve...	Transport and storage	Accommodation and food services	... administration and defence compulsory ..
1	1990	55690.3	50452.8	175212.7	217602.2	75316.3	8201.2	11560.8	66985.3	3015.3 ...	12058.4
2	1991	55492.6	50608.3	176254.4	214317.5	76852.7	8072	11984.1	67438.6	3453.5 ...	11381.2
3	1992	55149	51199.3	169388.2	202469.2	76959.1	8188.3	11789.9	68438.5	3163.4 ...	11523.4
4	1993	54319.9	50807.1	164365	184997.2	77275.6	8275.1	12032.9	69735.2	3371.4 ...	11710.9
5	1994	55129.7	44588.4	167285.9	180721.6	77637.9	8633.8	12403.1	70659.2	3342.3 ...	11071.3
6	1995	55061.9	46451.4	165344.1	178162.0	78712	8695.3	12560.6	73508.2	3450.7 ...	11079.5
7	1996	56343.6	46633.6	166622.3	177960.6	79209.4	8923.8	12825.8	79135.4	3636.1 ...	10890.1
8	1997	55810	45761.2	165258.4	164554.2	77982.7	9263.6	12631.7	88159.2	3237.9 ...	10462.7
9	1998	55950.8	44399.3	155653.0	170815.5	78691.1	9207.7	12926.4	93464.0	3581 ...	10028.0
10	1999	56176.1	40501.6	140696.8	163207.5	73742.9	9246.5	13464.5	91941.5	3819.3 ...	10260.4
11	2000	54133.6	38335.6	135627.4	176005.8	71060.5	9440.5	13774.1	94607.7	3913.4 ...	10046.3
12	2001	51955.6	38210.6	128931.3	186969.6	69110.6	9566.7	13738.1	98397.8	4077.2 ...	9921.5
13	2002	51495.5	36722.5	121456.3	182100.7	67450.9	9608.6	13544.7	95135.4	3457.7 ...	9629.5
14	2003	51950.4	34092.4	124723.3	191163.6	63375.2	9791.5	14202.6	95101.3	3705 ...	9518.5
15	2004	52813.4	32909.3	122868.9	191097.4	58712.5	10170.6	14461.8	97343.8	3673 ...	9605.4
16	2005	52934	30738.2	121871.7	192574.6	56104.9	10152	14753.1	99137.9	3694.7 ...	8493.2
17	2006	51899.8	28291.7	117269.7	200397.5	52739.5	10309.7	15013	90909.2	3518.8 ...	8486.5
18	2007	51473.1	27770.4	116409.3	195947.3	49262.6	10785.7	15656.8	94883.2	3433.4 ...	8360.2
19	2008	51240.7	27088.3	108134.2	191548.8	43934.9	10784.4	16297.4	90840.5	4178.1 ...	7647
20	2009	50442.8	27056.8	90639.6	169738.9	39631	9504.6	16483.2	84039.5	3525.6 ...	6938.5
21	2010	50502.1	26661.9	93988	177018.4	34835.1	9682.6	17024.2	84360.1	3773.8 ...	6907.7
22	2011	49647.4	24205.7	90258	164156.6	32853.5	9235.3	16767.9	87918.1	3403.6 ...	6299.3
23	2012	50368.8	22379.2	86759.9	178480.3	31469.9	9426.8	16946	84115	3794.9 ...	6217.2
24	2013	49299.1	21096.9	89442.9	169292	28566.7	9033.9	16508.8	80876.9	3896.3 ...	5696.7
25	2014	51149.2	21086.9	88797.2	148347.2	26627.8	9236	15865.5	85705.9	3444 ...	5057
26	2015	51774.5	22402.3	86036.2	131922.4	26416.7	9971.5	15912.8	87193.9	4289.6 ...	4693.1
27	2016	51397.4	21347.1	80201.2	109990	26154.7	10417.8	15949.4	89850.6	4486.3 ...	4674.1
28	2017	51685.1	21287.7	80871.8	100019.5	27149.1	10474.8	15320.7	83486.7	4484.6 ...	4685.5
29	2018	51227.2	21606.2	80321.5	95782.4	27404.6	10903.5	14993.8	88349.5	4685.3 ...	4865.3
30	2019	50889.8	21858.1	80113	89388.3	26787.1	10734.7	14592.1	86998.4	4618 ...	4739.5
31	2020	49836	20321.3	77060.3	80736.3	25434.7	9941	12705.2	63020.4	4213 ...	4038.4
32	2021	50909.4	18346.2	77092.3	86311	25252.1	11180.6	13471.4	57961.1	4446.4 ...	4494.4
33	2022	49682.9	17433.4	75449.5	82854.7	25109.3	10990.5	13084.3	80891	4203.9 ...	4233.5
34	2023	49176.8	16415.6	73496.8	70134.5	24868.4	11243.8	12855.7	83875.1	4122.1 ...	4380.0

35 rows × 25 columns

```
In [ ]:
```

```
In [420]: #Boxplots
#Reference: (Mondal, 2024)
years = table1.iloc[1:, 0]

# Setting a threshold for outliers = 2
outlier_threshold = 2

# Loop through all industries
for col in table1.columns[1:]:
    industry_name = table1.iloc[0, table1.columns.get_loc(col)]
    emissions_data = table1.iloc[1:, table1.columns.get_loc(col)].astype(float)

    # Calculating Z-scores for the emissions data
    z_scores = zscore(emissions_data)

    # Finding outliers based on Z-scores
    outliers = []
    for i in range(1, len(emissions_data)):
        if abs(z_scores[i]) > outlier_threshold:
            outliers.append(i)
```

```

for year, emission, z in zip(years, emissions_data, z_scores):
    if abs(z) > outlier_threshold:
        outliers.append((year, emission, z))

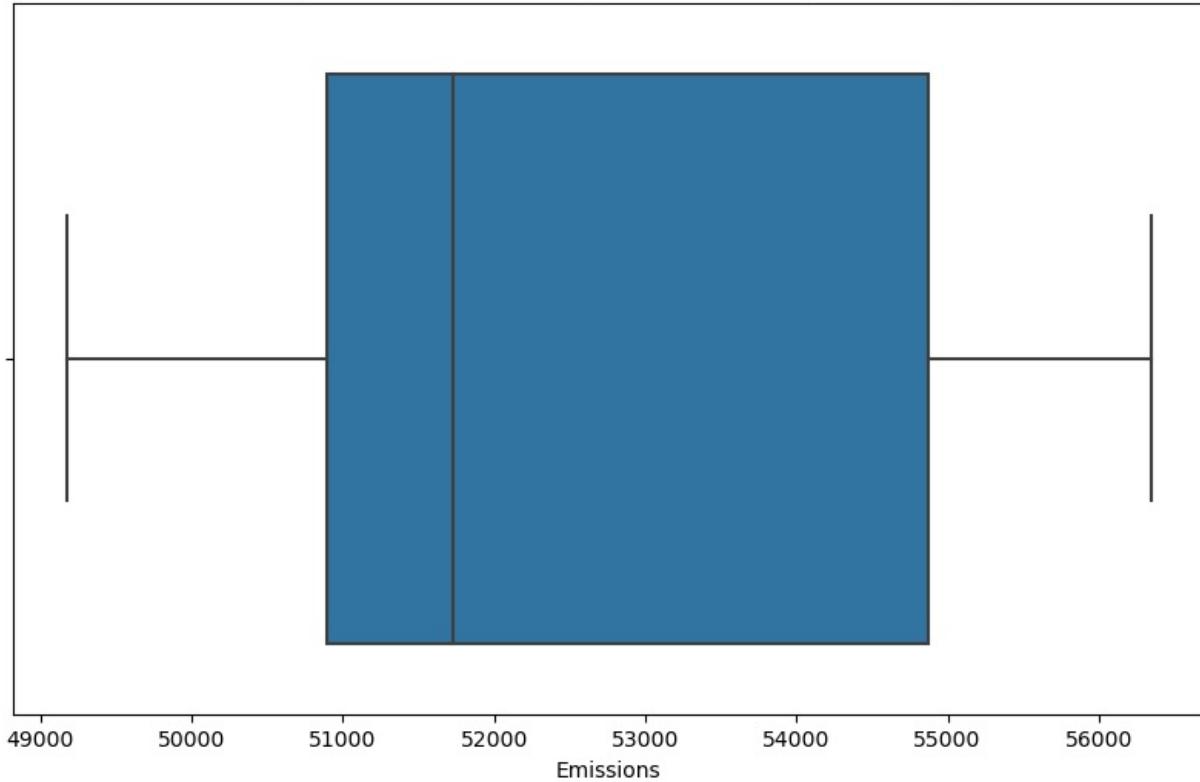
# Displaying outliers
if outliers:
    print(f"Outliers in {industry_name}:")
    for year, emission, z in outliers:
        print(f"Year: {year}, Emissions: {emission}, Z-score: {z:.2f}")
else:
    print(f"No outliers found for {industry_name}.")

# Plotting a box plot for emissions data of the industry
plt.figure(figsize=(10, 6))
sns.boxplot(x=emissions_data)
plt.title(f"Boxplot of Emissions for {industry_name}")
plt.xlabel("Emissions")
plt.show()

```

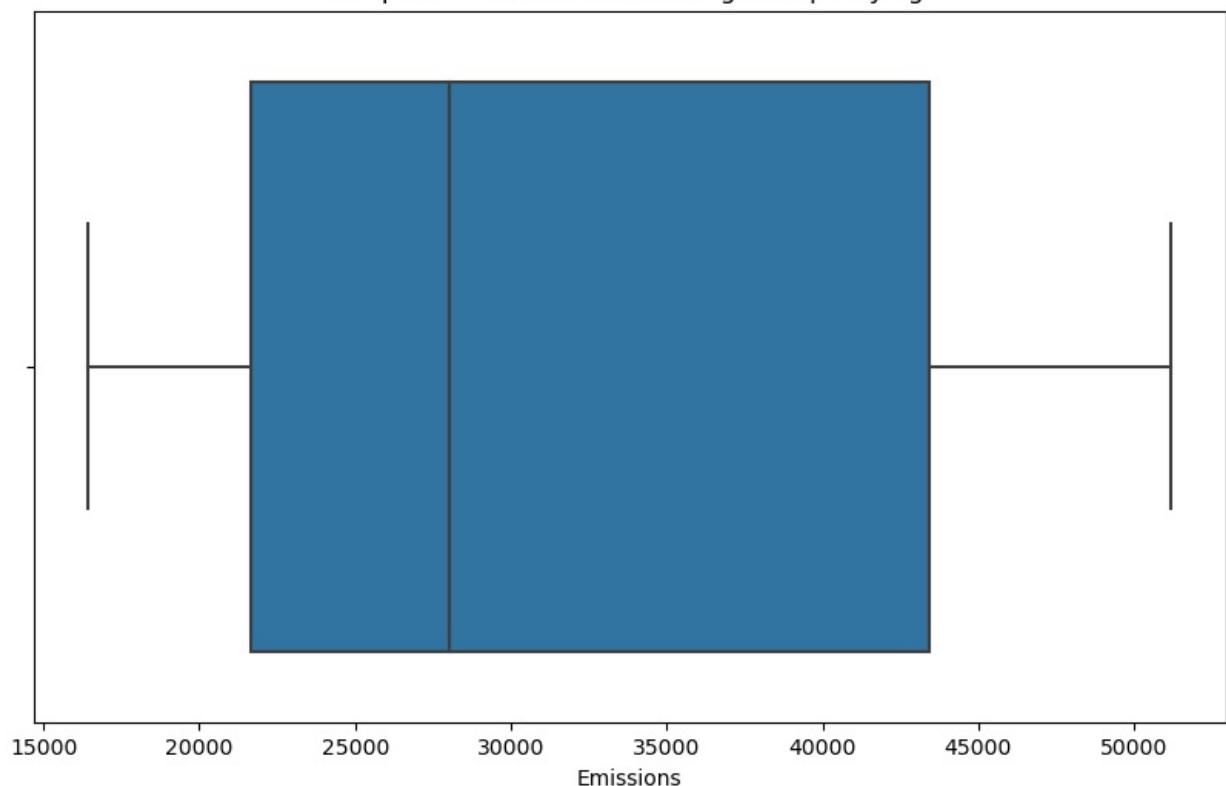
No outliers found for Agriculture, forestry and fishing.

Boxplot of Emissions for Agriculture, forestry and fishing



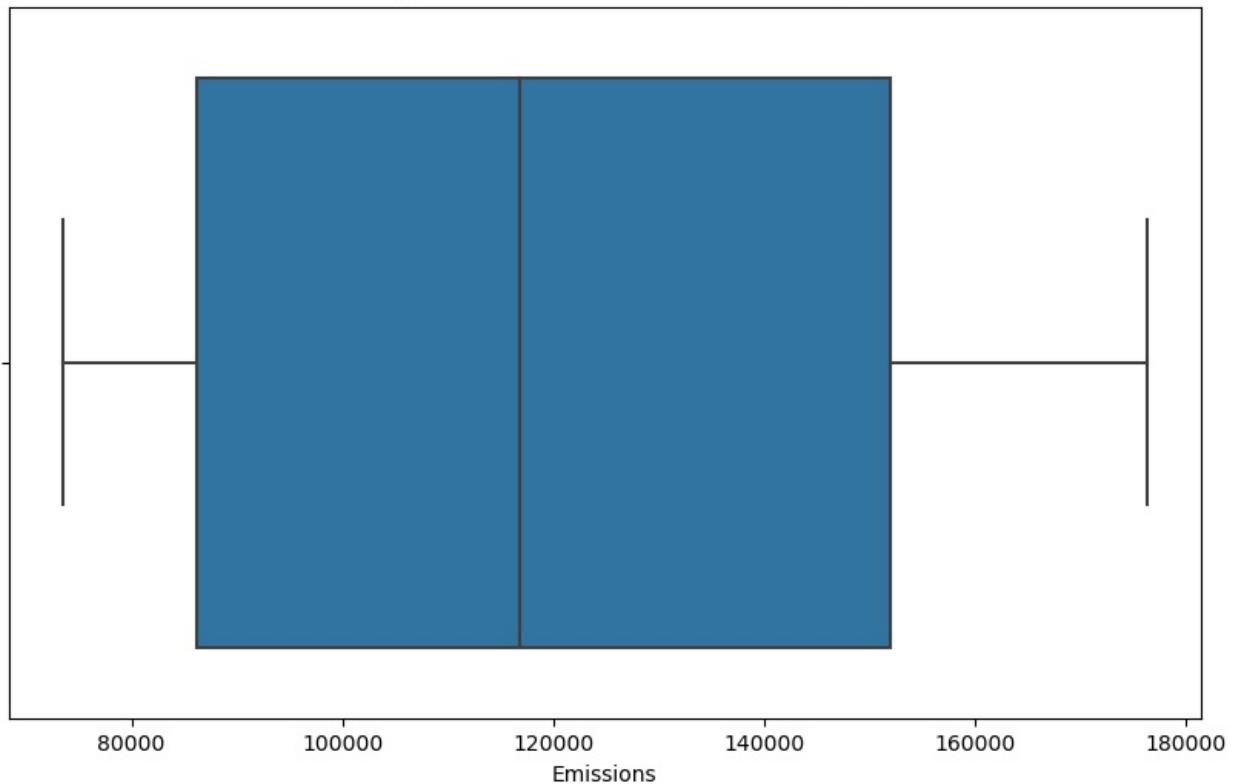
No outliers found for Mining and quarrying.

Boxplot of Emissions for Mining and quarrying



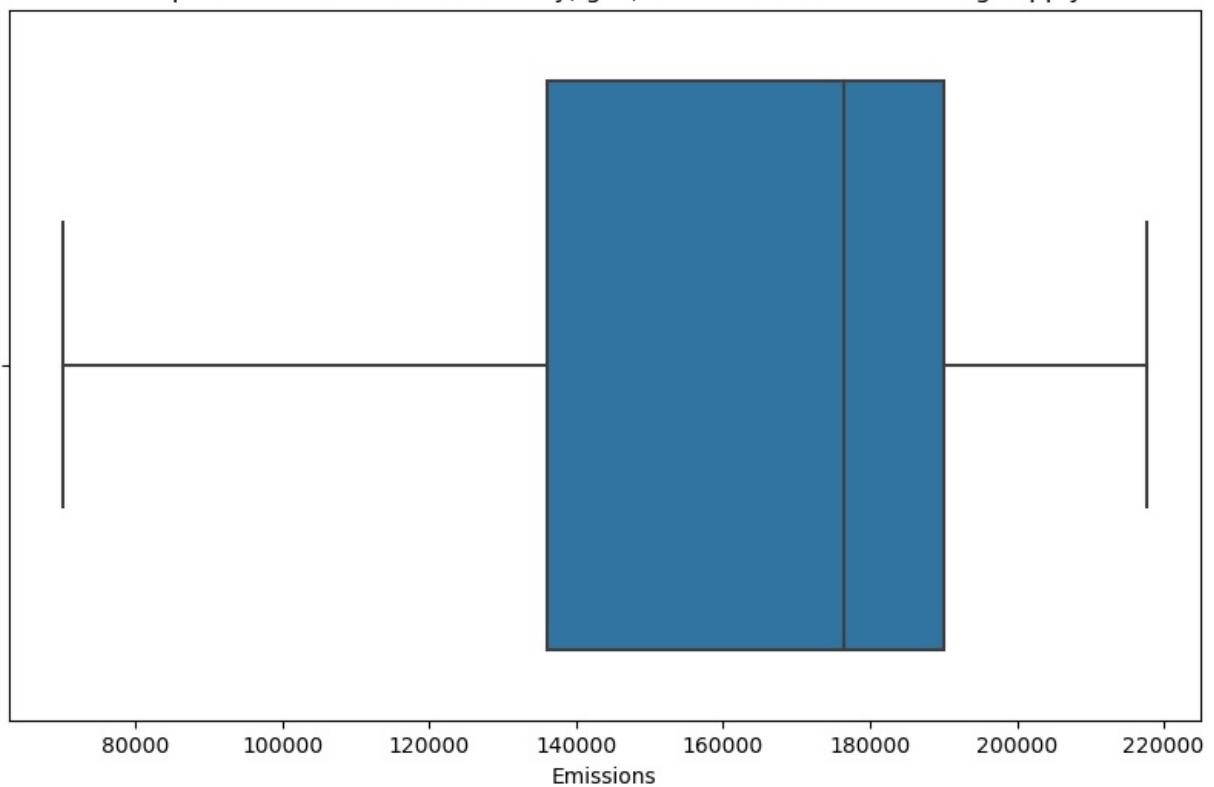
No outliers found for Manufacturing.

Boxplot of Emissions for Manufacturing



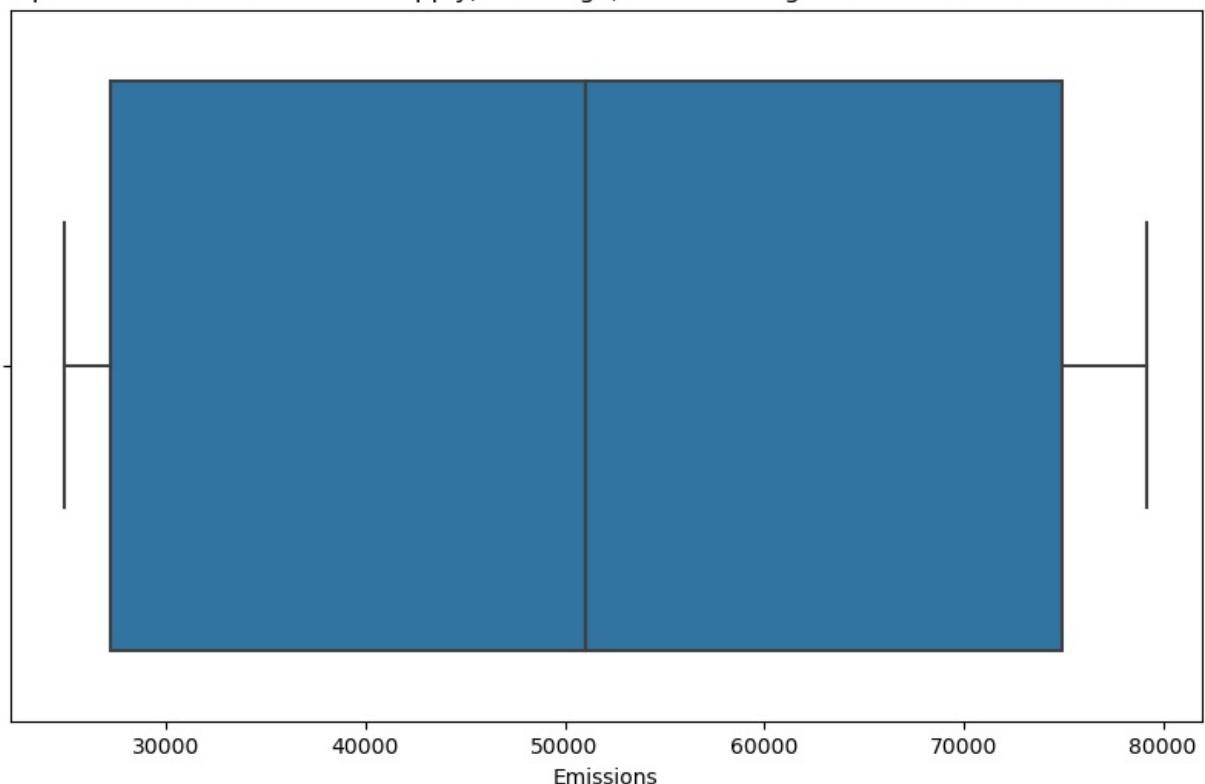
Outliers in Electricity, gas, steam and air conditioning supply:  
Year: 2023, Emissions: 70134.5, Z-score: -2.11

Boxplot of Emissions for Electricity, gas, steam and air conditioning supply



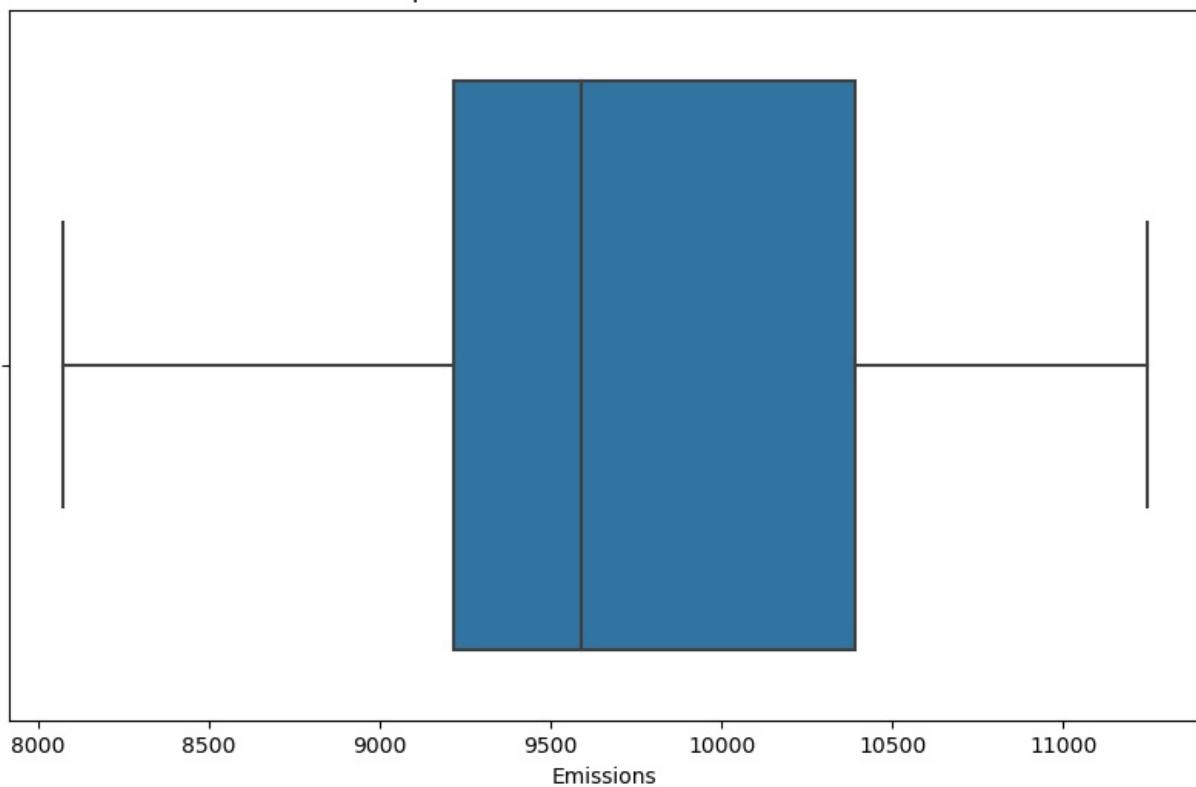
No outliers found for Water supply; sewerage, waste management and remediation activities.

Boxplot of Emissions for Water supply; sewerage, waste management and remediation activities



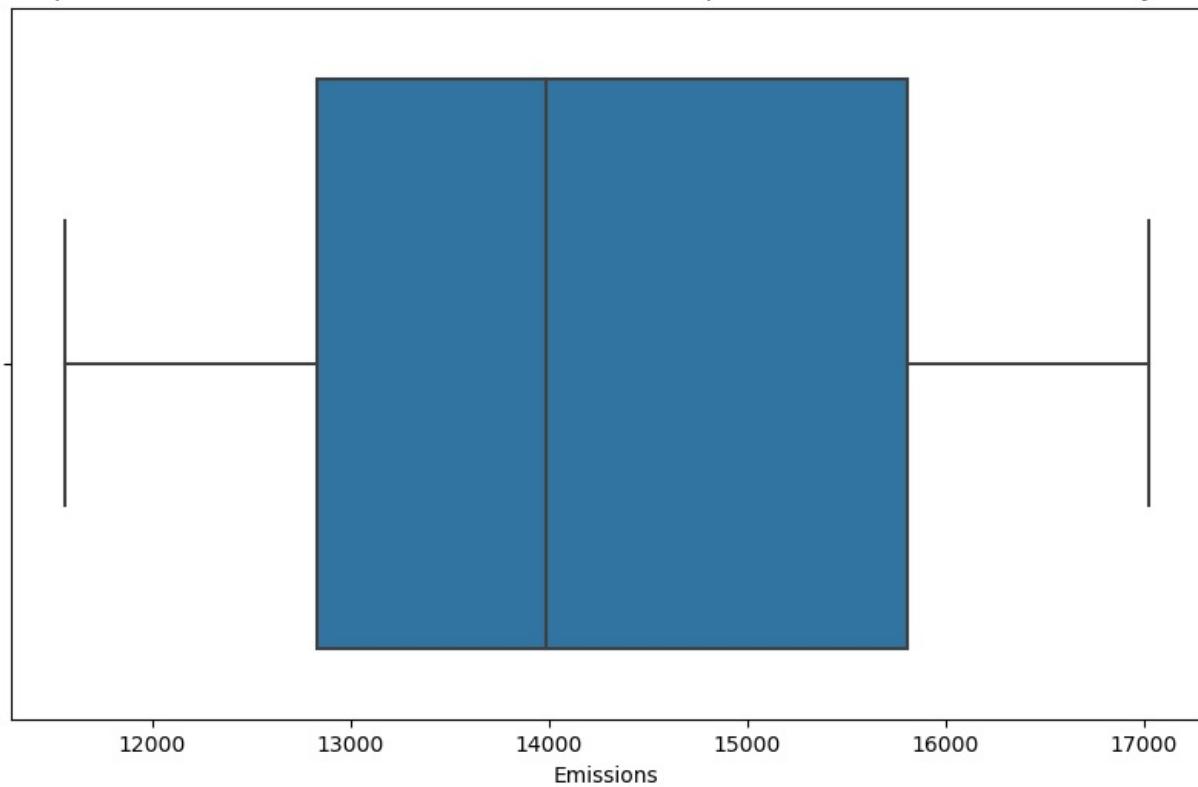
No outliers found for Construction.

Boxplot of Emissions for Construction



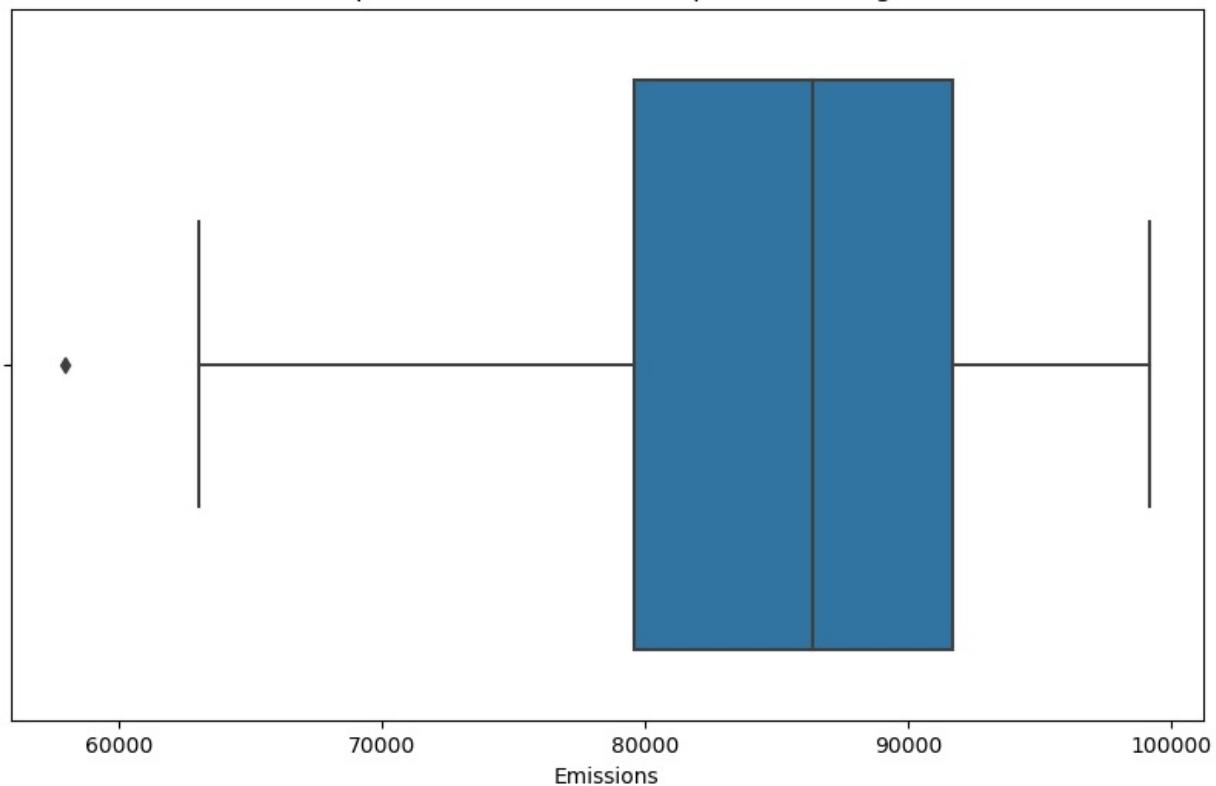
No outliers found for Wholesale and retail trade; repair of motor vehicles and motorcycles.

Boxplot of Emissions for Wholesale and retail trade; repair of motor vehicles and motorcycles



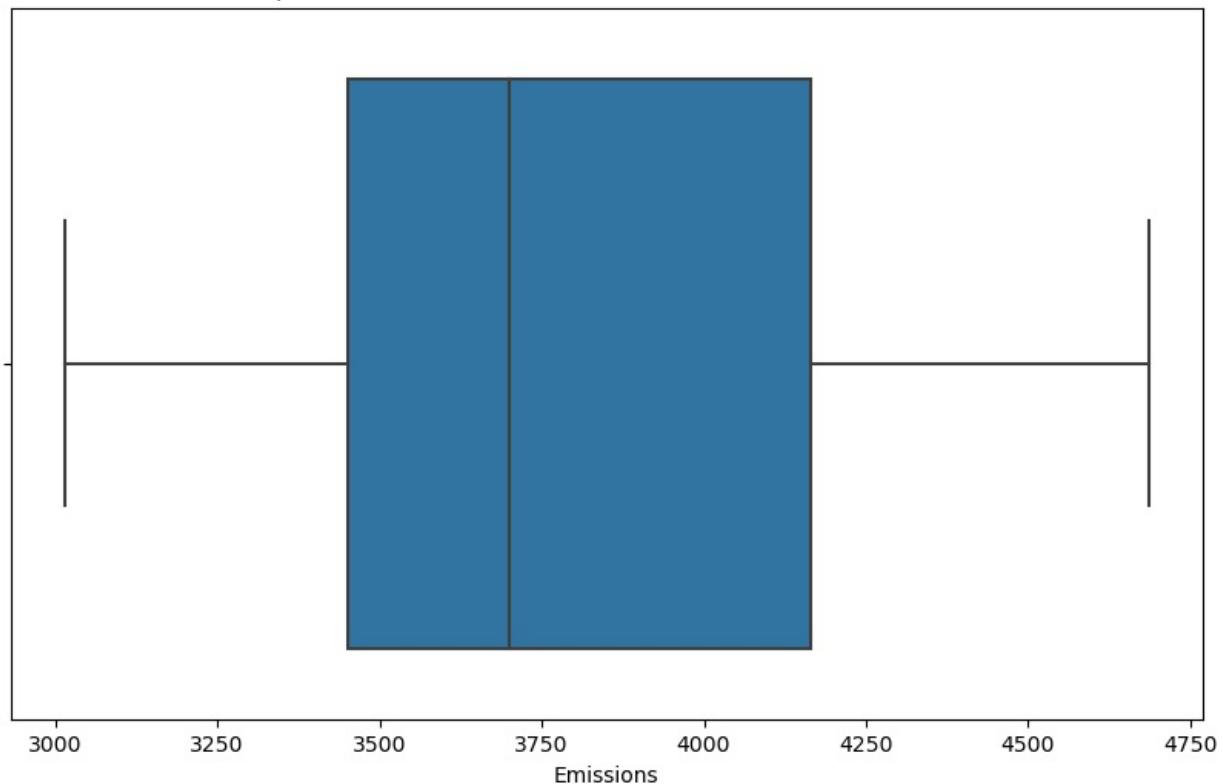
Outliers in Transport and storage:  
Year: 2021, Emissions: 57961.09999999999, Z-score: -2.42

Boxplot of Emissions for Transport and storage



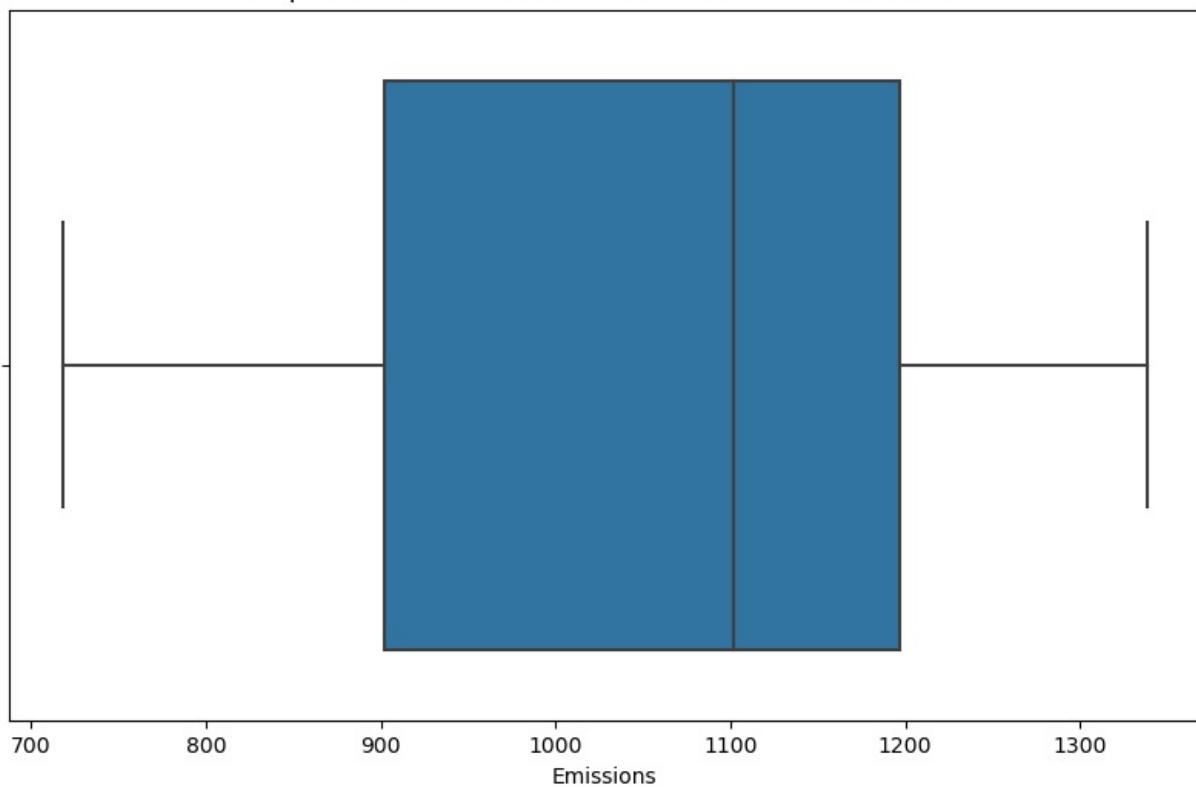
Outliers in Accommodation and food services:  
Year: 2018, Emissions: 4685.300000000001, Z-score: 2.03

Boxplot of Emissions for Accommodation and food services



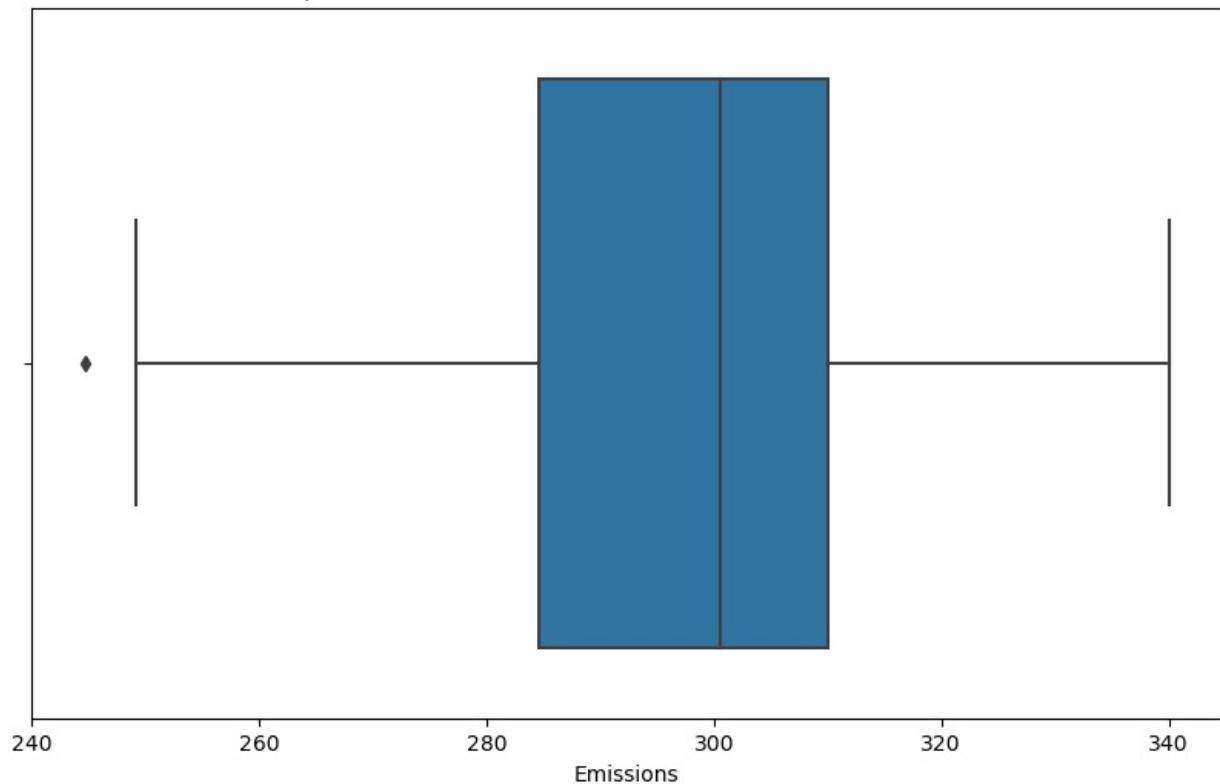
No outliers found for Information and communication.

Boxplot of Emissions for Information and communication



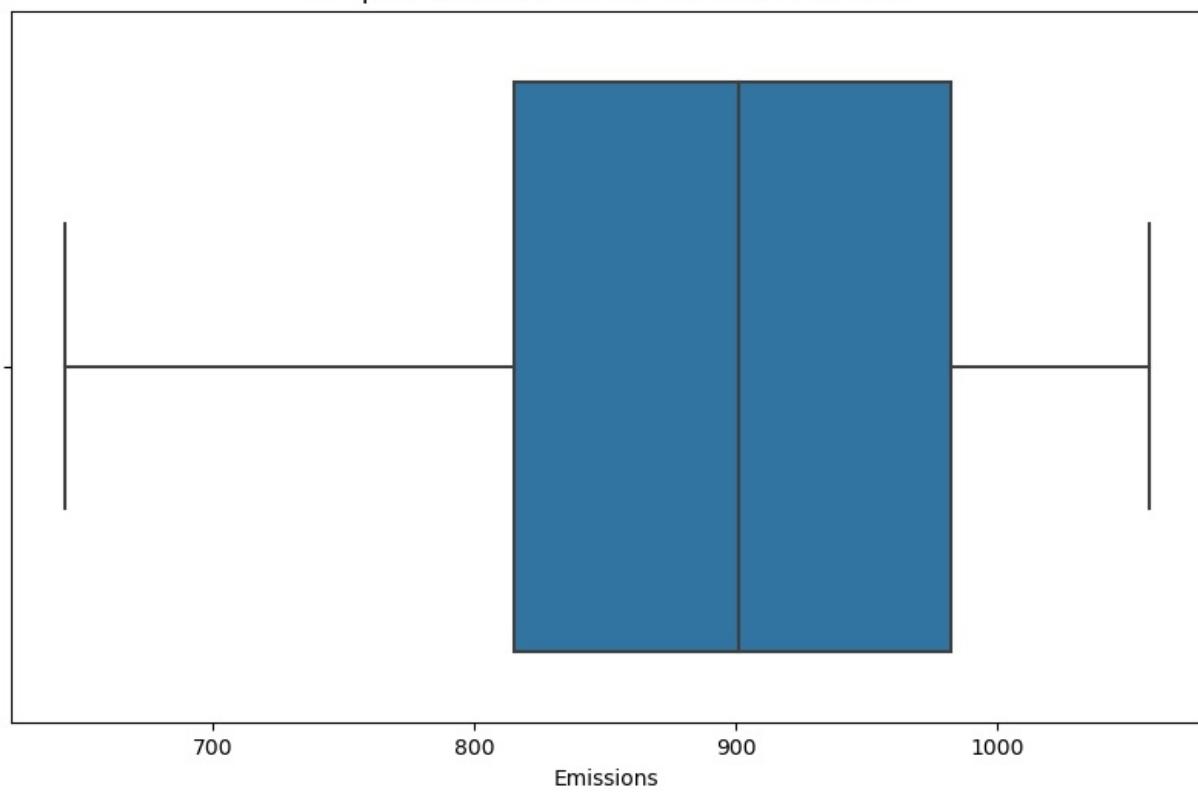
Outliers in Financial and insurance activities:  
Year: 2022, Emissions: 249.2000000000002, Z-score: -2.21  
Year: 2023, Emissions: 244.7000000000002, Z-score: -2.42

Boxplot of Emissions for Financial and insurance activities



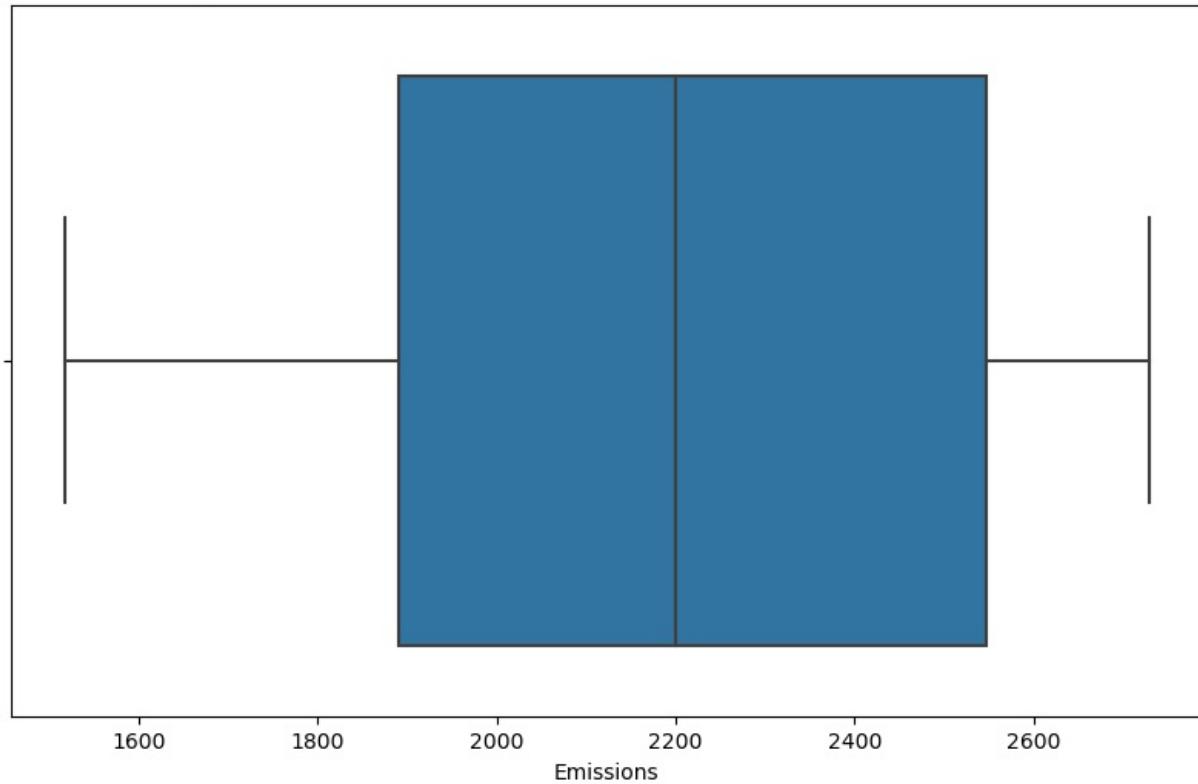
Outliers in Real estate activities:  
Year: 1990, Emissions: 643.7, Z-score: -2.34

Boxplot of Emissions for Real estate activities



No outliers found for Professional, scientific and technical activities.

Boxplot of Emissions for Professional, scientific and technical activities



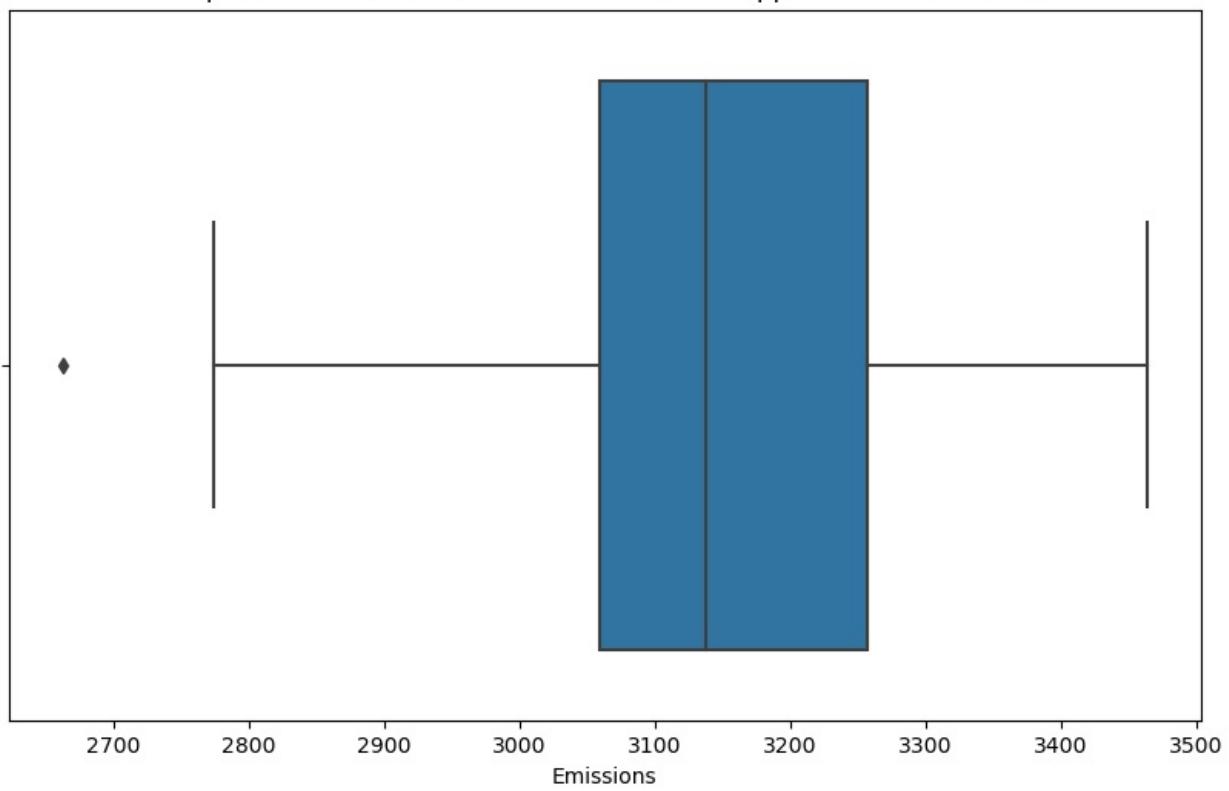
Outliers in Administrative and support service activities:

Year: 1990, Emissions: 2662.3, Z-score: -2.70

Year: 1992, Emissions: 2773.1, Z-score: -2.05

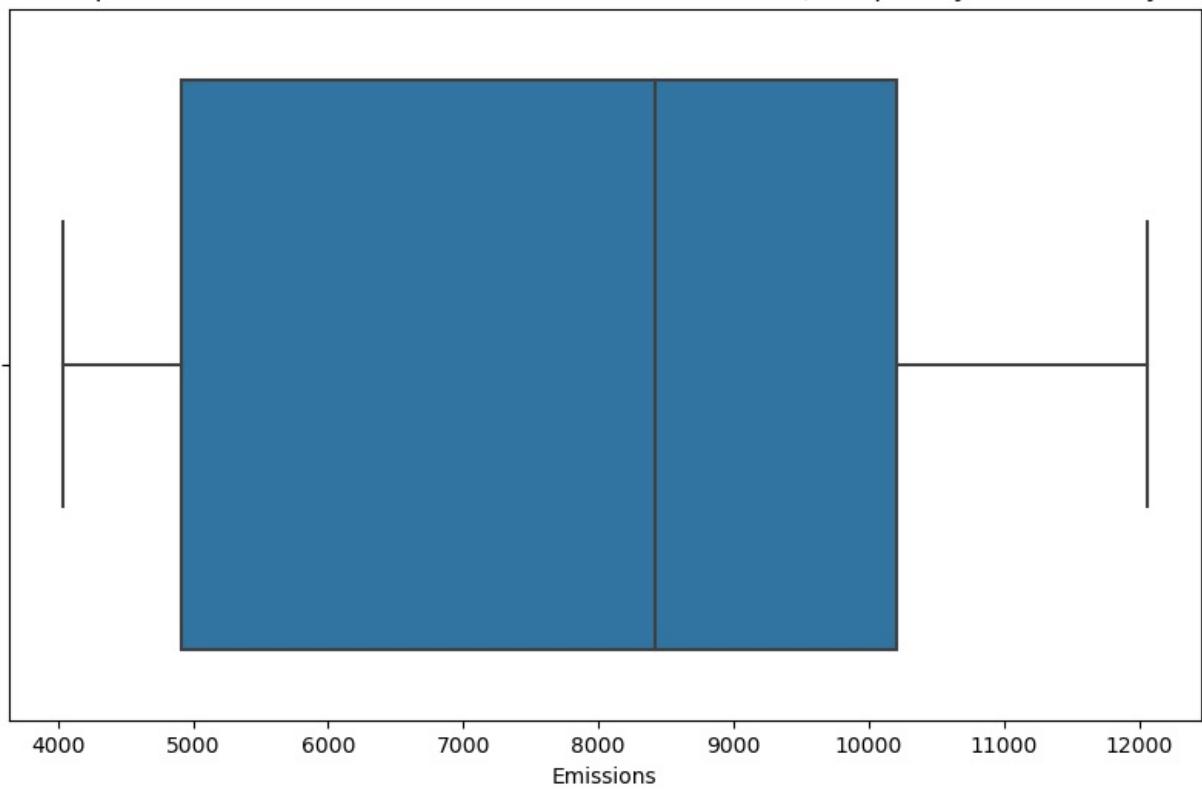
Year: 2008, Emissions: 3463.6, Z-score: 2.04

Boxplot of Emissions for Administrative and support service activities



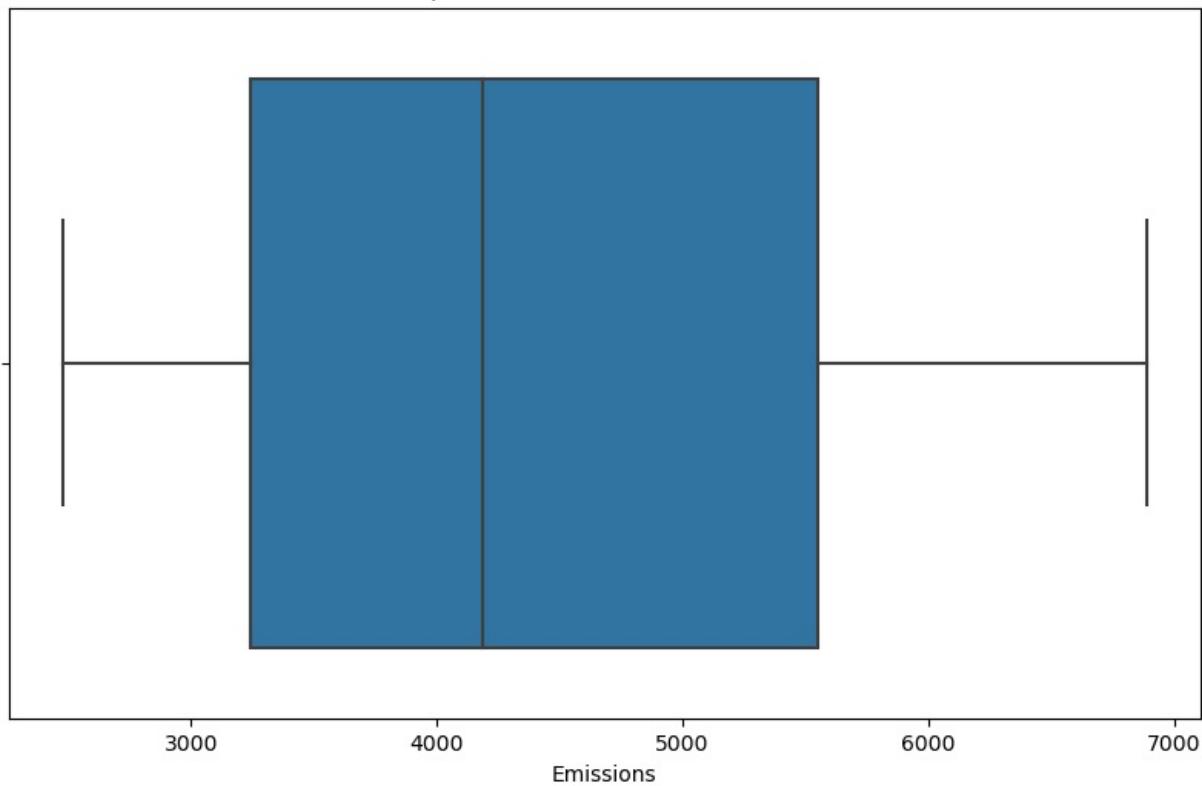
No outliers found for Public administration and defence; compulsory social security.

Boxplot of Emissions for Public administration and defence; compulsory social security



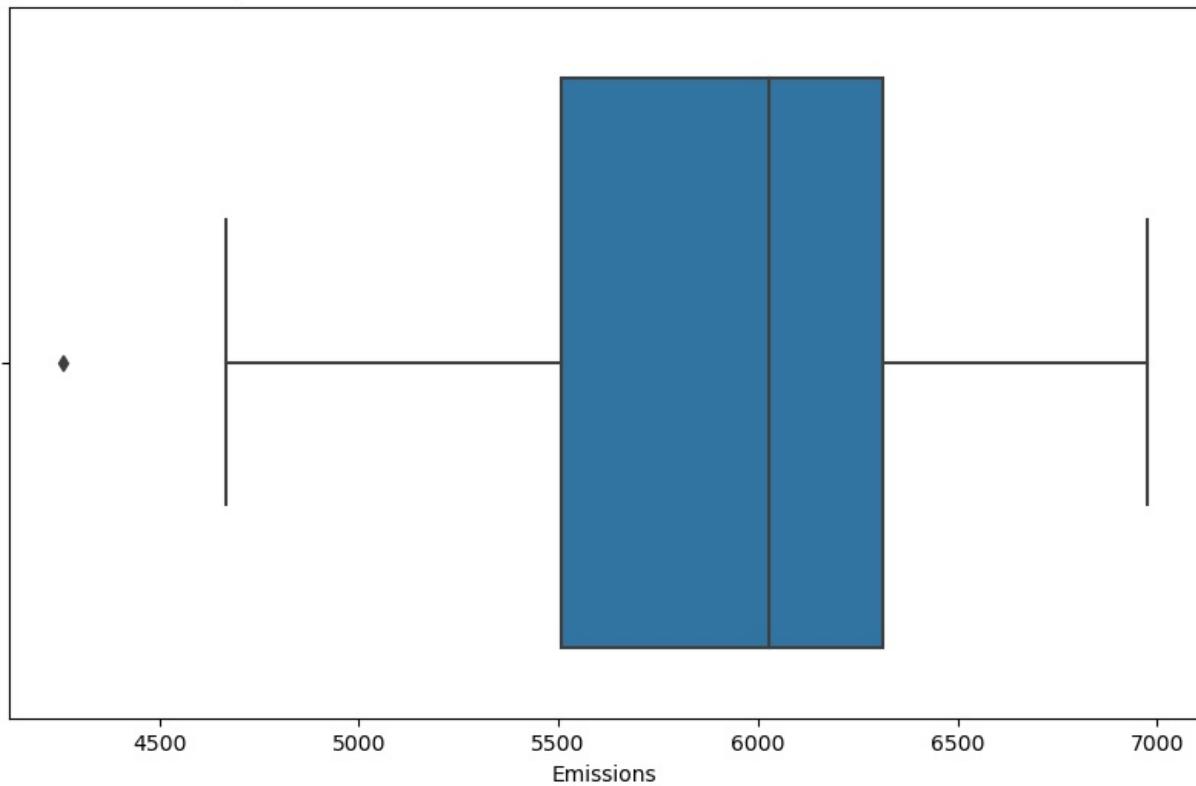
No outliers found for Education.

Boxplot of Emissions for Education



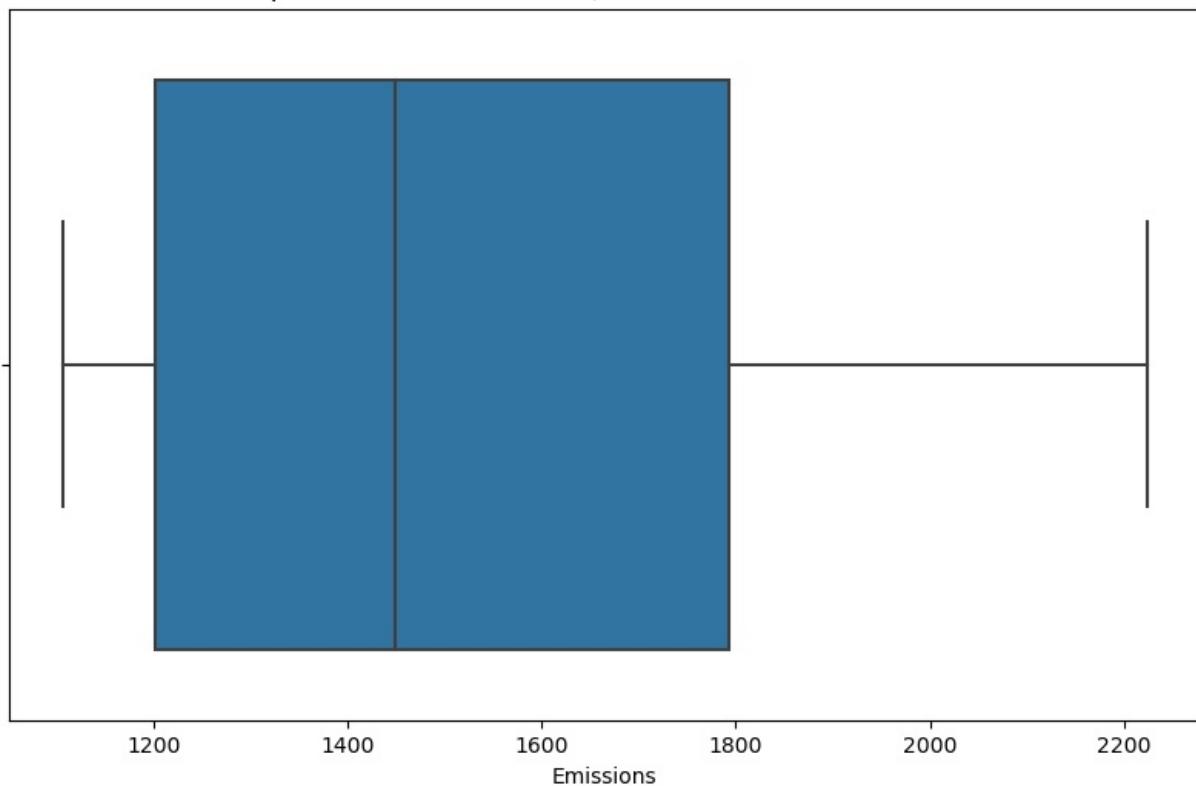
Outliers in Human health and social work activities:  
Year: 2003, Emissions: 4258.400000000001, Z-score: -2.65

Boxplot of Emissions for Human health and social work activities



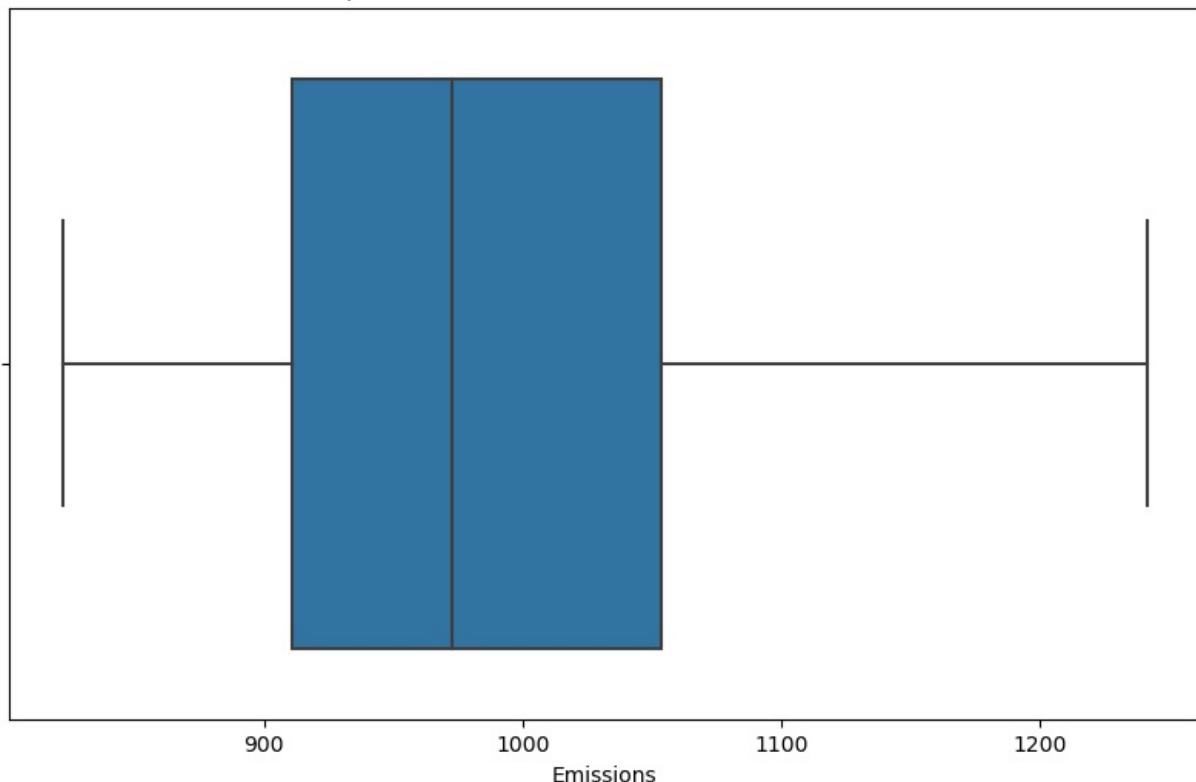
No outliers found for Arts, entertainment and recreation.

Boxplot of Emissions for Arts, entertainment and recreation



Outliers in Other service activities:  
Year: 2001, Emissions: 1241.2, Z-score: 2.14

Boxplot of Emissions for Other service activities

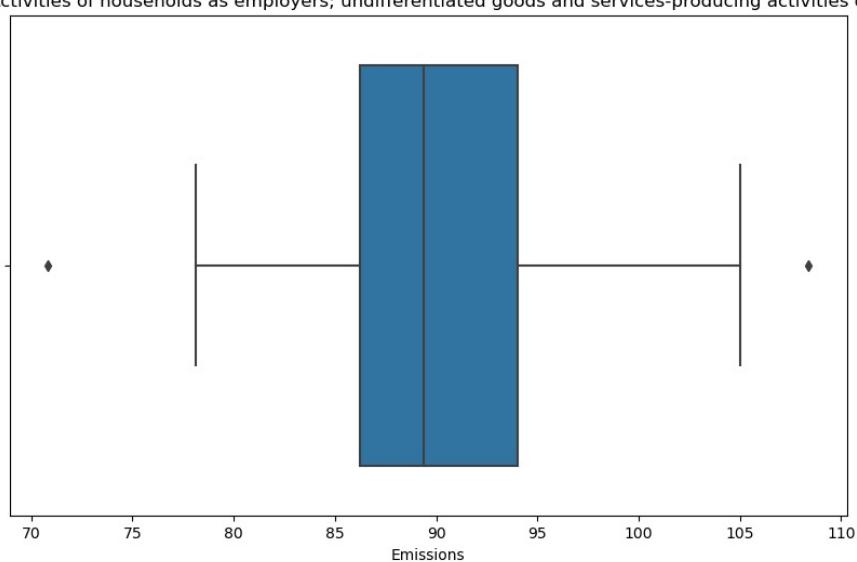


Outliers in Activities of households as employers; undifferentiated goods and services-producing activities of households for own use:

Year: 2009, Emissions: 70.8, Z-score: -2.48

Year: 2019, Emissions: 108.4, Z-score: 2.29

Boxplot of Emissions for Activities of households as employers; undifferentiated goods and services-producing activities of households for own use



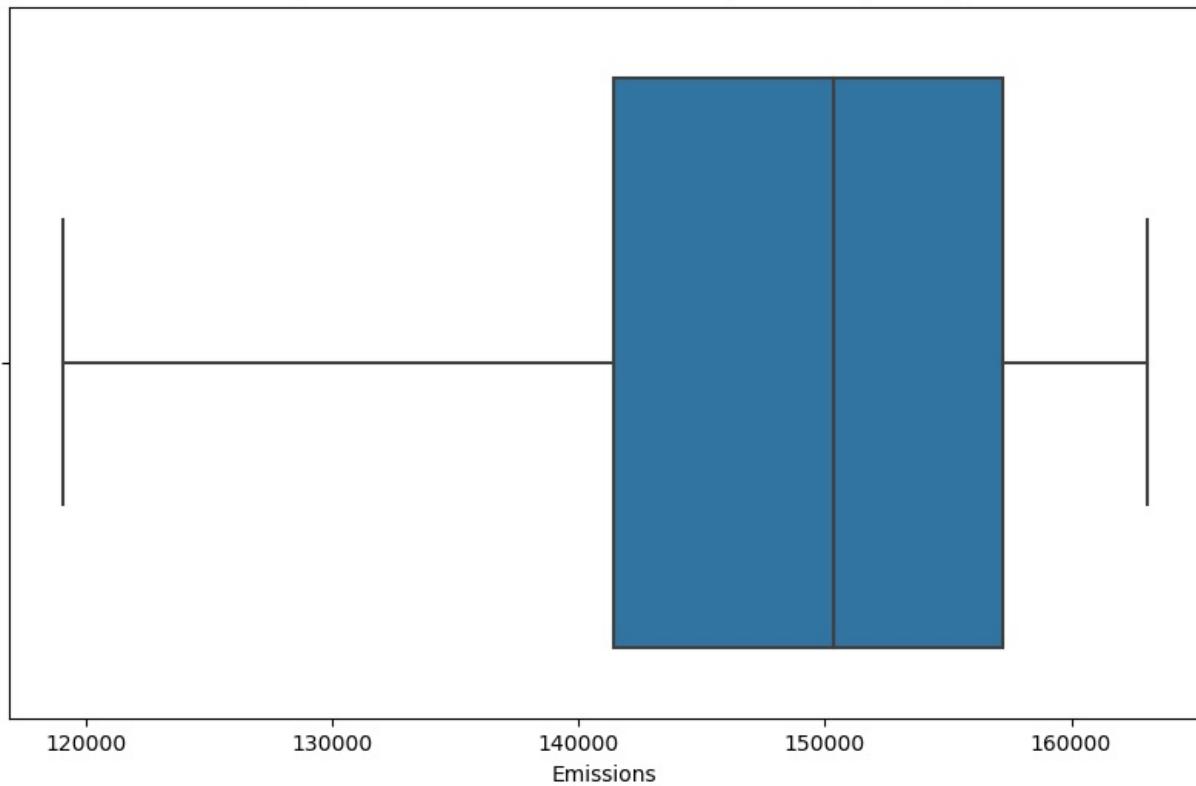
Outliers in Consumer expenditure [note 4]:

Year: 2020, Emissions: 123858.1000000002, Z-score: -2.16

Year: 2022, Emissions: 124667.7, Z-score: -2.09

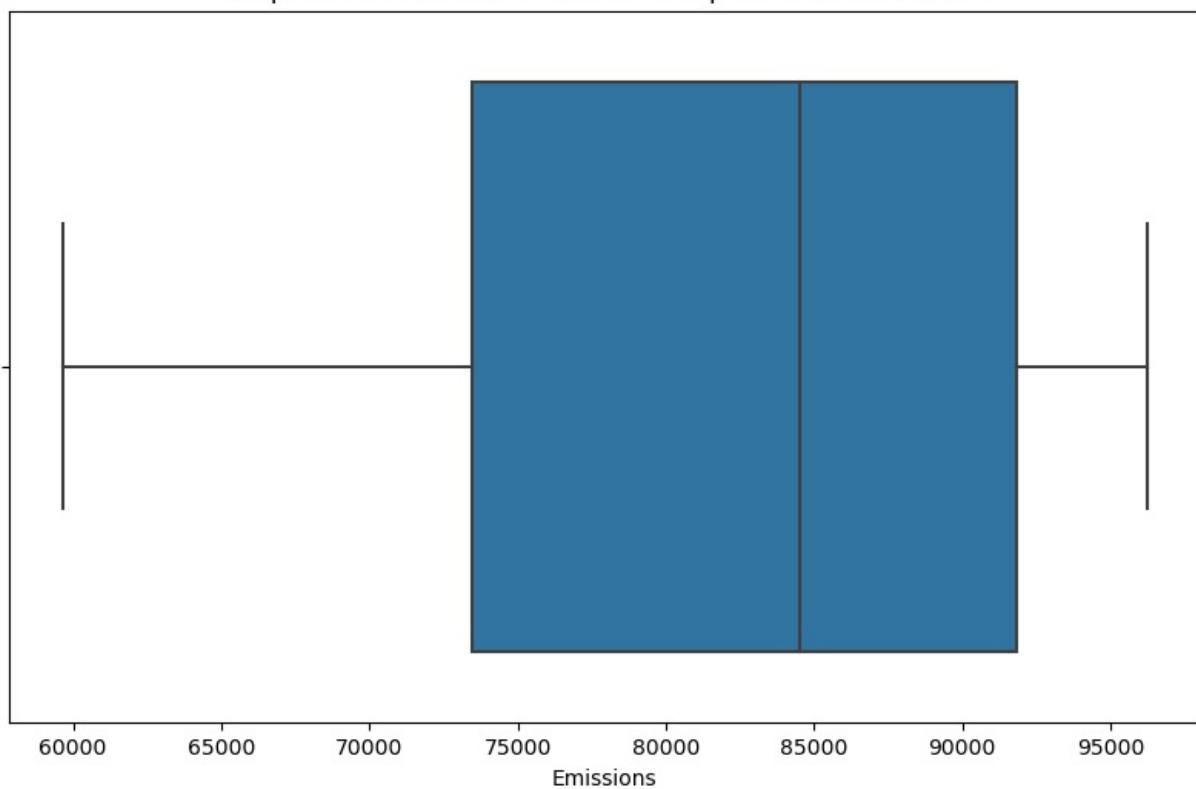
Year: 2023, Emissions: 119071.5, Z-score: -2.59

Boxplot of Emissions for Consumer expenditure [note 4]



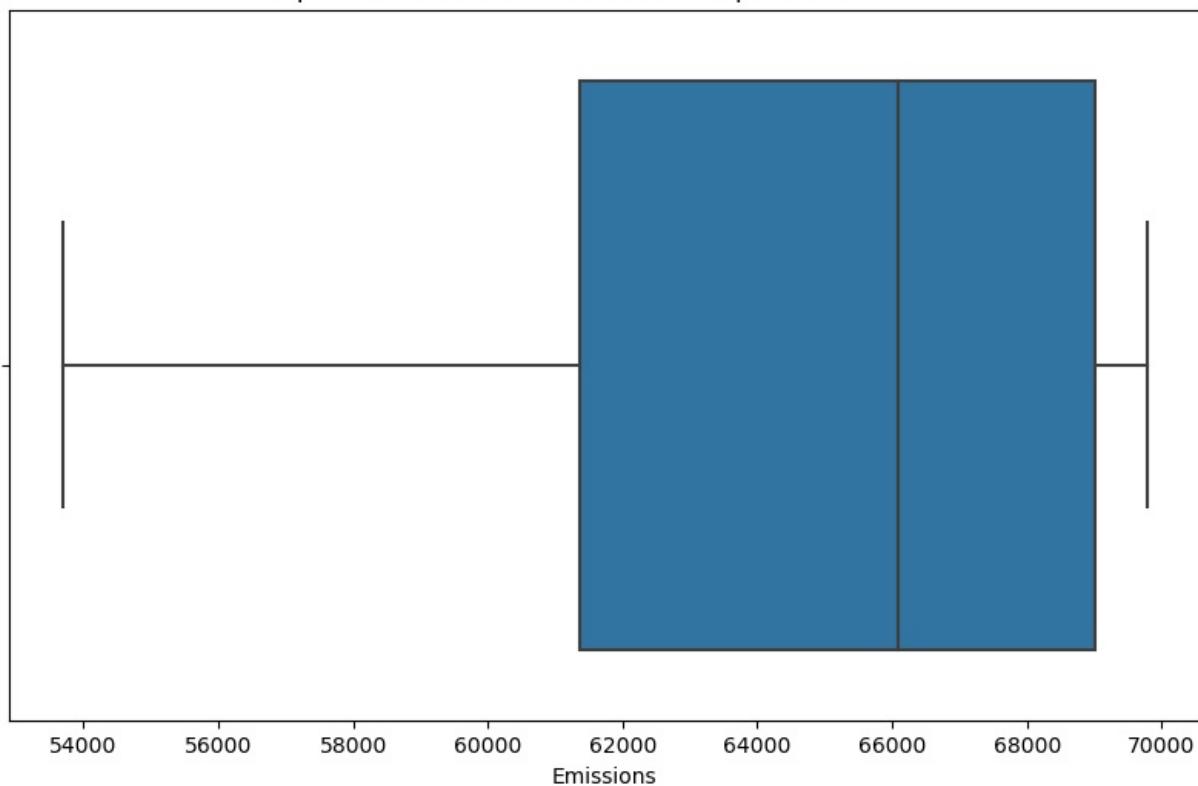
Outliers in Consumer expenditure - Not travel:  
Year: 2023, Emissions: 59659.7, Z-score: -2.33

Boxplot of Emissions for Consumer expenditure - Not travel



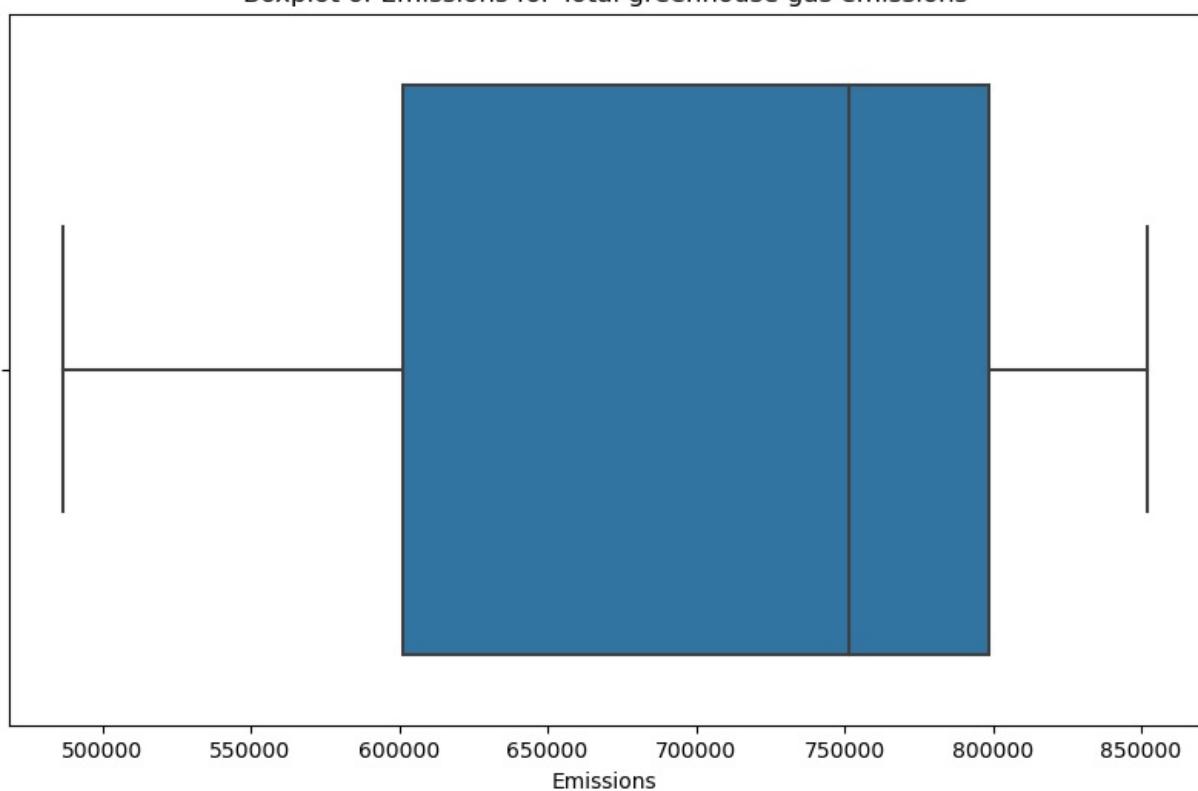
Outliers in Consumer expenditure - Travel:  
Year: 2020, Emissions: 53696.3, Z-score: -2.82

Boxplot of Emissions for Consumer expenditure - Travel



No outliers found for Total greenhouse gas emissions.

Boxplot of Emissions for Total greenhouse gas emissions



In [42]: table2

Out[421]:

35 rows × 133 columns

In [1]:

In [ ]

In [ ]:

In [ ]:

In [ ]:

In 1923

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```
In [422]: #Formatting table 2
# Drop the first row (index 0), which contains the 'SIC(07) group'
table2 = table2.drop(0).reset_index(drop=True)

# Set the second row (index 1) as the column names and drop that row
table2.columns = table2.iloc[0]
table2 = table2.drop(1).reset_index(drop=True)

# Check the dataframe to ensure the changes were applied
table2.head()
```

Out[422]:

	Industry name	Products of agriculture, hunting and related services	Products of forestry, logging and related services	Fish and other fishing products; aquaculture products; support services to fishing	Mining of coal and lignite	Crude petroleum and natural gas	Mining of metal ores	Other mining and quarrying products	Mining support services	Processing and preserving of meat and production of meat products	... Library, archive, museum and other cultural services	Gambling and betting services	S... sp... se... amus... recre...
0	Industry name	Products of agriculture, hunting and related s...	Products of forestry, logging and related serv...	Fish and other fishing products; aquaculture p...	Mining of coal and lignite	Crude petroleum and natural gas	Mining of metal ores	Other mining and quarrying products	Mining support services	Processing and preserving of meat and producti...	... Library, archive, museum and other cultural se...	Gambling and betting services	S... sp... se... amus... recre...
1	1991	54494.1	27.2	971.3	26059.1	22534.4	9	1244.9	760.8	1140	...	184.3	281.1
2	1992	54119.9	28	1001	25814.5	23477.2	9.1	1203	695.5	1169.5	...	160.3	253.1
3	1993	53228.2	34.7	1057	23889.6	25204.8	9.2	1057.9	645.7	1180.2	...	164.2	262.3
4	1994	54010.2	42.7	1076.8	15998.5	26873	9.6	997.5	709.8	1257.4	...	149.2	246.5

5 rows × 133 columns

```
In [423]: table2 = table2.drop(0)
```

```
table2.columns = ['Year'] + list(table2.columns[1:])
```

```
table2['Year'] = table2['Year'].astype(int)
```

```
In [424]: #Manually assinging groups
```

```
group_1 = [
    'Products of agriculture, hunting and related services',
    'Products of forestry, logging and related services',
    'Fish and other fishing products; aquaculture products; support services to fishing'
]
group_2 = [
    'Mining of coal and lignite',
    'Crude petroleum and natural gas',
    'Mining of metal ores',
    'Other mining and quarrying products',
    'Mining support services'
]
group_3 = [
    'Processing and preserving of meat and production of meat products',
    'Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables',
    'Manufacture of vegetable and animal oils and fats',
    'Manufacture of dairy products',
    'Manufacture of grain mill products, starches and starch products',
    'Manufacture of bakery and farinaceous products',
    'Manufacture of other food products',
    'Manufacture of prepared animal feeds',
    'Manufacture of alcoholic beverages, including spirits, wine, cider, beer and malt',
    'Manufacture of soft drinks: production of mineral waters and other bottled waters',
    'Tobacco products',
    'Textiles',
    'Wearing apparel',
    'Leather and related products',
    'Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials',
    'Paper and paper products',
    'Printing and recording services',
    'Manufacture of coke oven products',
    'Manufacture of refined petroleum products',
    'Manufacture of industrial gases and non-nitrogen-based inorganic chemicals',
    'Fertilisers',
    'Other nitrogen compounds',
    'Manufacture of petrochemicals',
    'Manufacture of dyestuffs, agro-chemicals',
    'Manufacture of paints, varnishes & ink',
    'Manufacture of cleaning & toilet preparations',
    'Manufacture of other chemical products',
    'Basic pharmaceutical products and pharmaceutical preparations',
    'Rubber products',
    'Plastics products',
]
```

```
'Manufacture of glass, refractory, clay, other porcelain and ceramic products, Stone, & abrasive products',
'Manufacture of cement',
'Manufacture of lime',
'Manufacture of plaster',
'Manufacture of articles of concrete, cement and plaster',
'Manufacture of basic Iron & Steel',
'Manufacture of other basic metals & casting (excl. Nuclear fuel & Aluminium)',
'Aluminium production',
'Processing of nuclear fuel',
'Fabricated metal products, except machinery and equipment, excluding weapons and ammunition',
'Manufacture of weapons and ammunition',
'Computer, electronic, communication and optical products',
'Electrical equipment',
'Machinery and equipment n.e.c.',
'Motor vehicles, trailers and semi-trailers',
'Building of ships and boats',
'Manufacture of air and spacecraft and related machinery',
'Manufacture of other transport equipment, excluding ships, boats, air and spacecraft',
'Furniture',
'Other manufactured goods',
'Repair & maintenance of ships',
'Rest of repair; Installation'
]
group_4 = [
    'Electricity production - gas',
    'Electricity production - coal',
    'Electricity production - nuclear',
    'Electricity production - oil',
    'Electricity production - other',
    'Manufacture of gas; distribution of gaseous fuels through mains and steam and air conditioning supply'
]
group_5 = [
    'Natural water; water treatment and supply services',
    'Sewerage services; sewage sludge',
    'Waste collection, treatment and disposal services; materials recovery services',
    'Remediation services and other waste management services'
]
group_6 = [
    'Buildings and building construction works',
    'Constructions and construction works for civil engineering',
    'Specialised construction works'
]
group_7 = [
    'Wholesale and retail trade and repair services of motor vehicles and motorcycles',
    'Wholesale trade services, except of motor vehicles and motorcycles',
    'Retail trade services, except of motor vehicles and motorcycles'
]
group_8 = [
    'Rail transport',
    'Buses, coaches, trams and similar public urban transport n.e.c',
    'Underground, metro other non interurban rail services',
    'Taxis and other renting of private cars with driver',
    'Freight transport by road and removal services',
    'Transport via pipeline',
    'Water transport services',
    'Air transport services',
    'Warehousing and support services for transportation',
    'Postal and courier services'
]
group_9 = [
    'Accommodation services',
    'Food and beverage serving services'
]
group_10 = [
    'Publishing services',
    'Motion picture, video and television programme production services, sound recording and music publishing',
    'Programming and broadcasting services',
    'Telecommunications services',
    'Computer programming, consultancy and related services',
    'Information services'
]
group_11 = [
    'Financial services, except insurance and pension funding',
    'Insurance & Reinsurance',
    'Pension funding',
    'Services auxiliary to financial services and insurance services'
]
group_12 = [
    'Buying and selling of own real estate: renting and operating of own or leased real estate, excluding imput',
    'Real estate activities on a fee or contract basis'
]
group_13 = [
    'Legal activities',
    'Accounting, bookkeeping and auditing activities: tax consultancy',
    'Services of head offices; management consulting services',
    'Architectural and engineering services; technical testing and analysis services',
    'Scientific research and development services',
    'Advertising and market research services',
    'Other professional, scientific and technical services',
```

```

    'Veterinary services'
]
group_14 = [
    'Rental and leasing services',
    'Employment services',
    'Travel agency, tour operator and other reservation services and related services',
    'Security and investigation services',
    'Services to buildings and landscape',
    'Office administrative, office support and other business support services'
]
group_15 = [
    'Public administration; compulsory social security services',
    'Public defence services'
]
group_16 = [
    'Education services'
]
group_17 = [
    'Human health services',
    'Residential care services',
    'Social work services without accommodation'
]
group_18 = [
    'Creative, arts and entertainment services',
    'Library, archive, museum and other cultural services',
    'Gambling and betting services',
    'Sporting services and amusement and recreation services'
]
group_19 = [
    'Services furnished by membership organisations',
    'Repair services of computers and personal and household goods',
    'Other personal services'
]
group_20 = [
    'Services of households as employers of domestic personnel'
]
group_21 = [
    'Consumer expenditure - not travel',
    'Consumer expenditure - travel'
]

# Function to plot stacked bar chart for each group
def plot_stacked_bar_chart(group, group_name):
    # Select the relevant data for the group from the DataFrame
    data_group = table2[group]

    # Plot the stacked bar chart
    ax = data_group.plot(kind='bar', stacked=True, figsize=(12, 8), colormap='tab20', edgecolor='black')

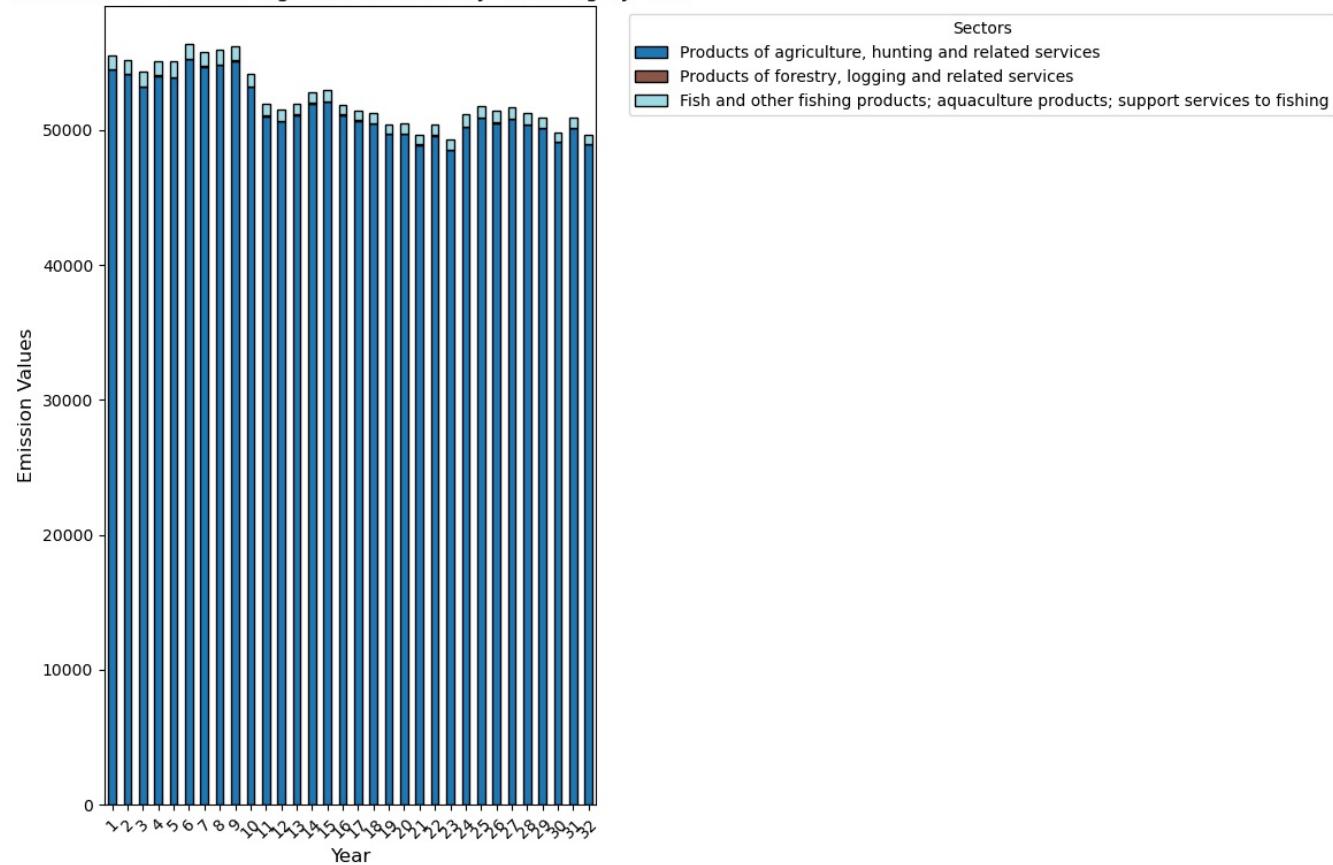
    # Title and axis labels
    ax.set_title(f'Stacked Bar Chart for {group_name} by Year', fontsize=14)
    ax.set_xlabel('Year', fontsize=12)
    ax.set_ylabel('Emission Values', fontsize=12)
    plt.xticks(rotation=45)

    # Adding legend and tight layout for neatness
    plt.legend(title='Sectors', bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.tight_layout()
    plt.show()

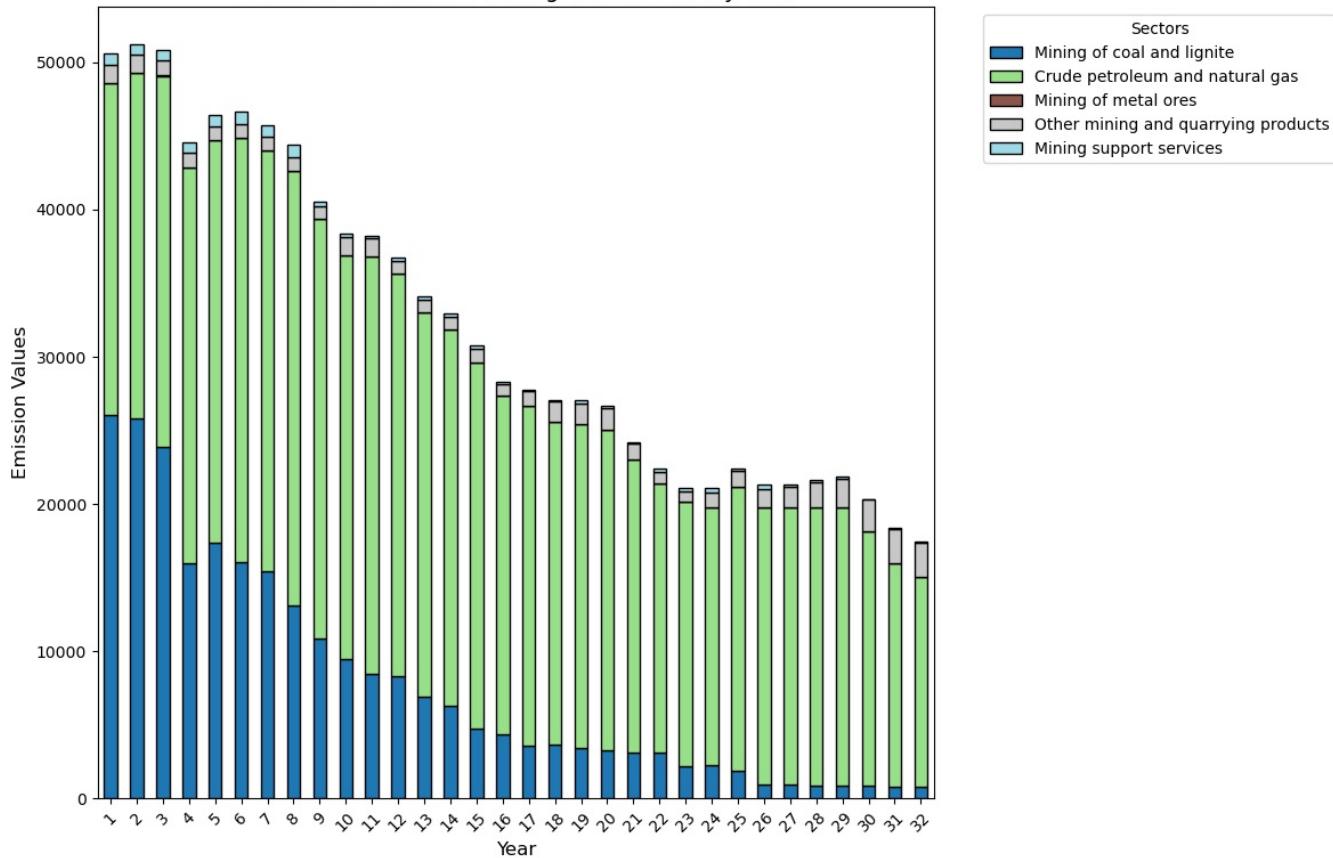
# Plot stacked bar charts for each group
plot_stacked_bar_chart(group_1, "Agriculture, Forestry & Fishing")
plot_stacked_bar_chart(group_2, "Mining & Petroleum")
plot_stacked_bar_chart(group_3, "Manufacturing & Other Products")
plot_stacked_bar_chart(group_4, "Electricity & Gas")
plot_stacked_bar_chart(group_5, "Water & Waste Services")
plot_stacked_bar_chart(group_6, "Construction")
plot_stacked_bar_chart(group_7, "Trade & Retail Services")
plot_stacked_bar_chart(group_8, "Transport & Postal Services")
plot_stacked_bar_chart(group_9, "Accommodation & Food Services")
plot_stacked_bar_chart(group_10, "Publishing & Telecom Services")
plot_stacked_bar_chart(group_11, "Financial & Insurance Services")
plot_stacked_bar_chart(group_12, "Real Estate Services")
plot_stacked_bar_chart(group_13, "Professional Services")
plot_stacked_bar_chart(group_14, "Business Support Services")
plot_stacked_bar_chart(group_15, "Public Services")
plot_stacked_bar_chart(group_16, "Education Services")
plot_stacked_bar_chart(group_17, "Health & Social Services")
plot_stacked_bar_chart(group_18, "Arts, Sports & Recreation")
plot_stacked_bar_chart(group_19, "Other Personal Services")
plot_stacked_bar_chart(group_20, "Domestic Personnel Services")
plot_stacked_bar_chart(group_21, "Consumer Expenditure")

```

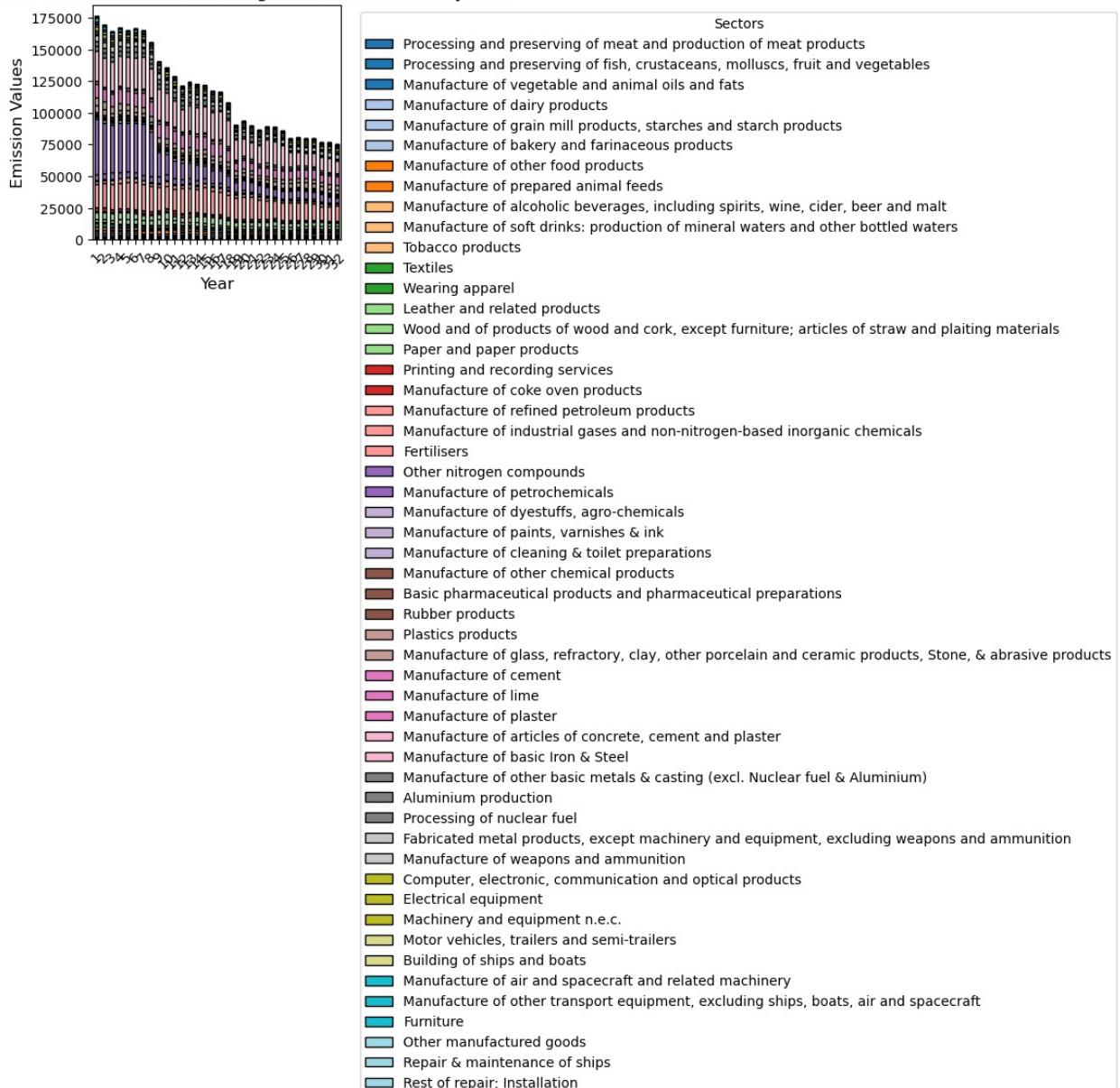
Stacked Bar Chart for Agriculture, Forestry & Fishing by Year



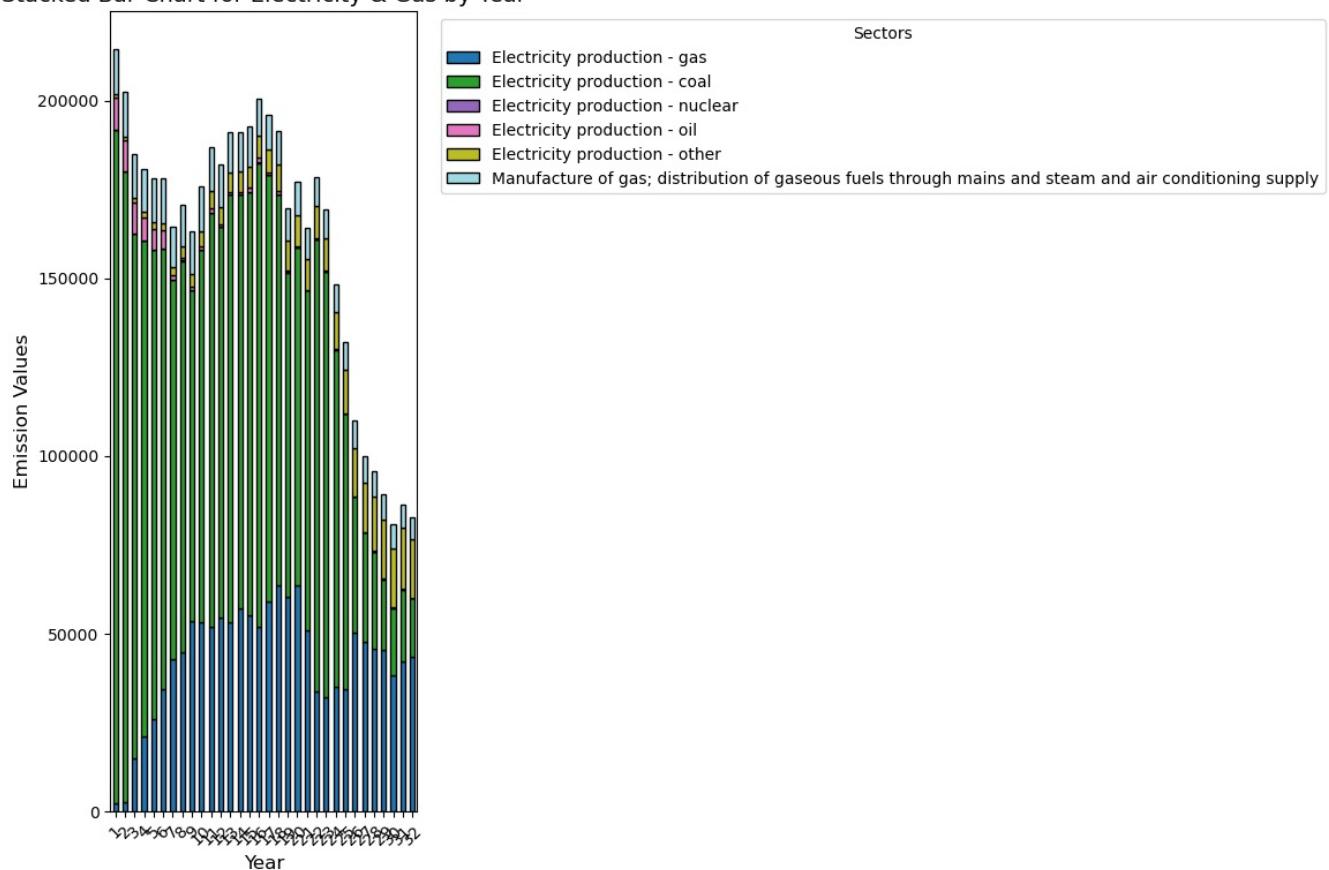
Stacked Bar Chart for Mining & Petroleum by Year



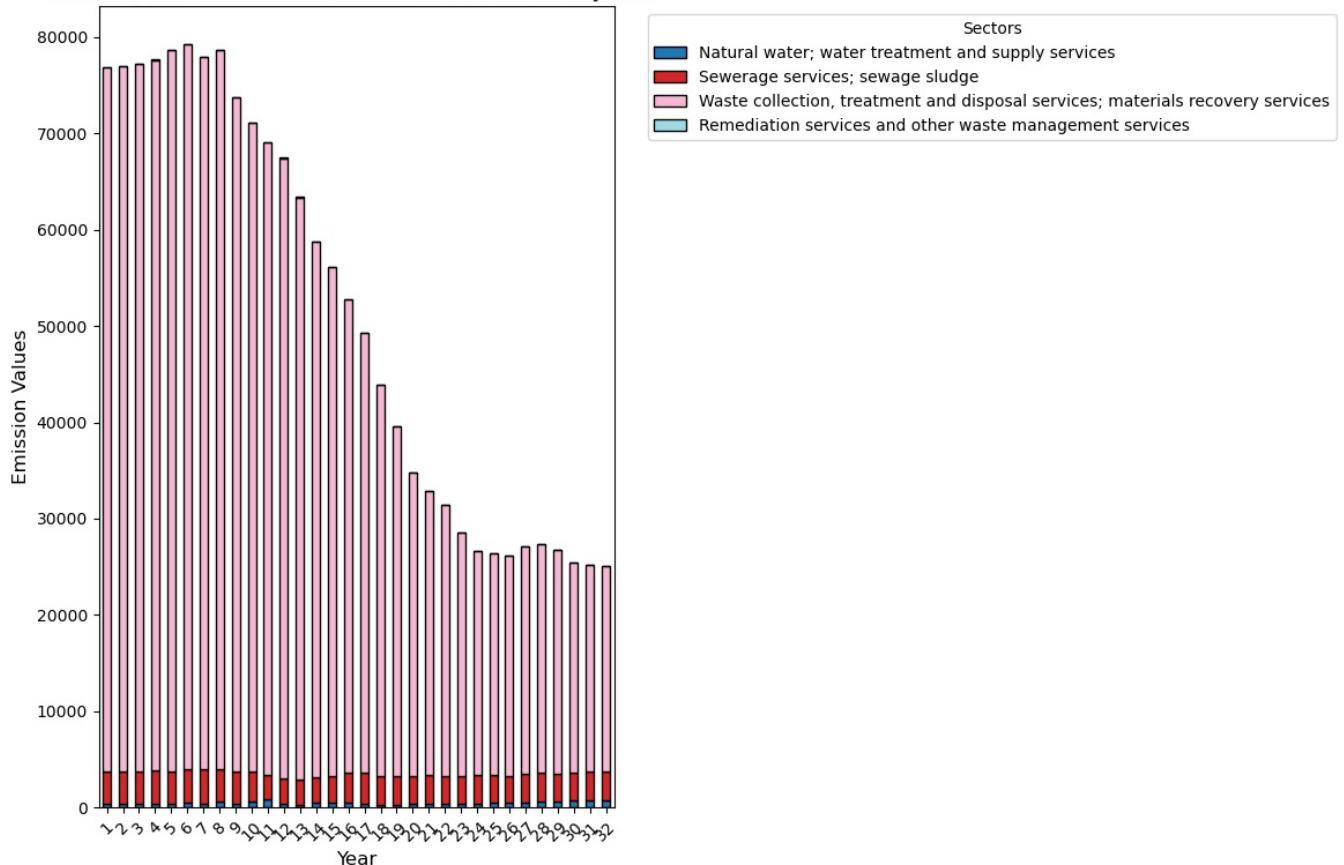
### Stacked Bar Chart for Manufacturing & Other Products by Year



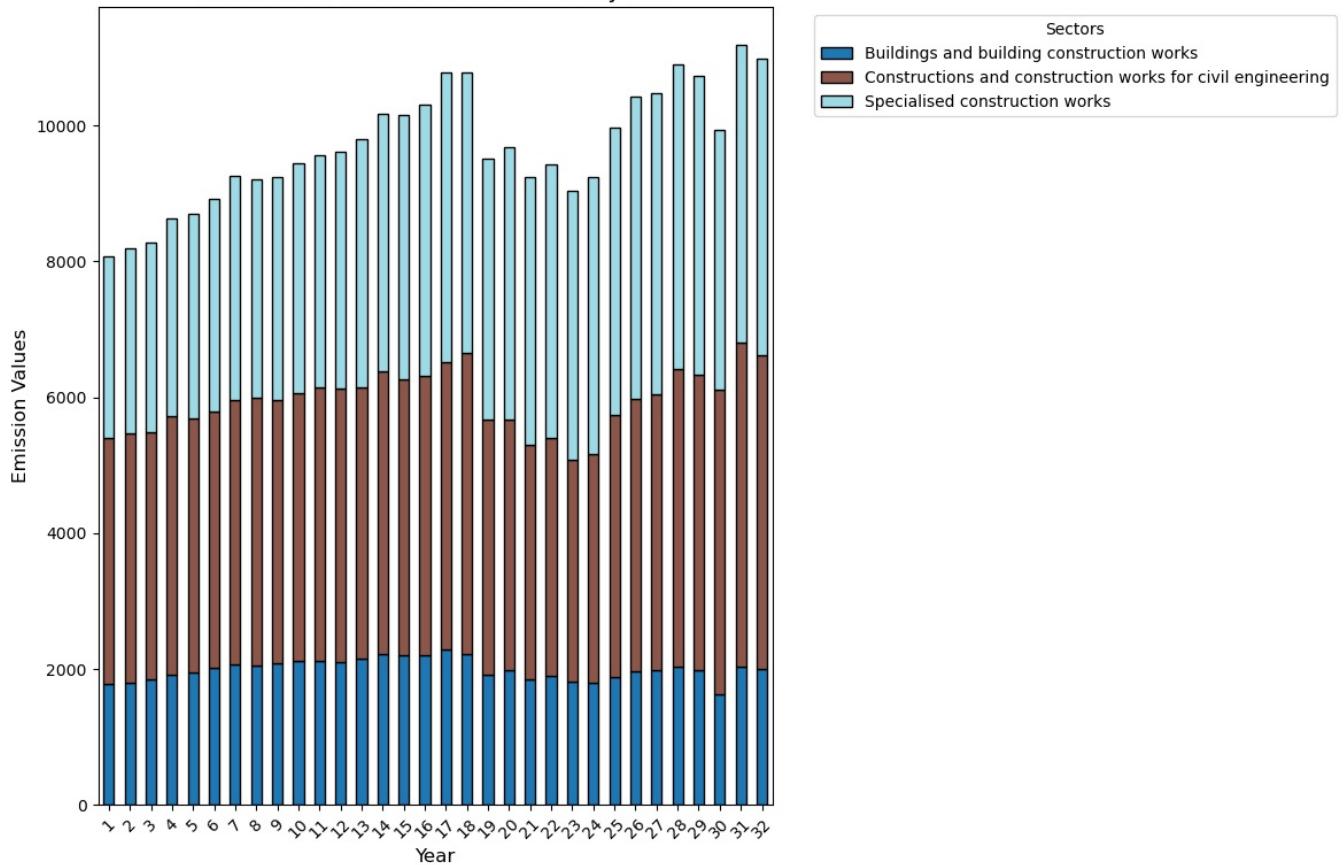
### Stacked Bar Chart for Electricity & Gas by Year



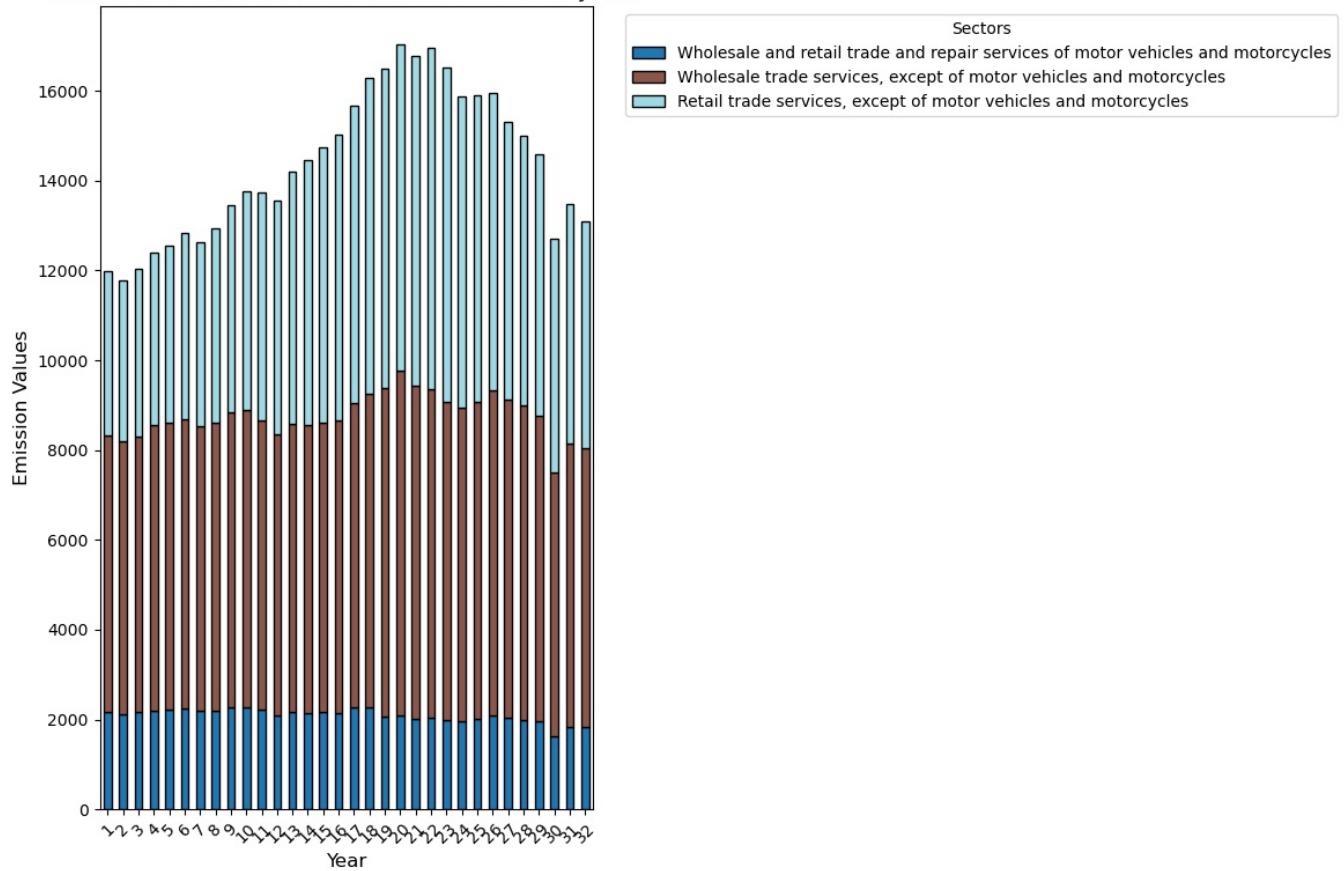
Stacked Bar Chart for Water & Waste Services by Year



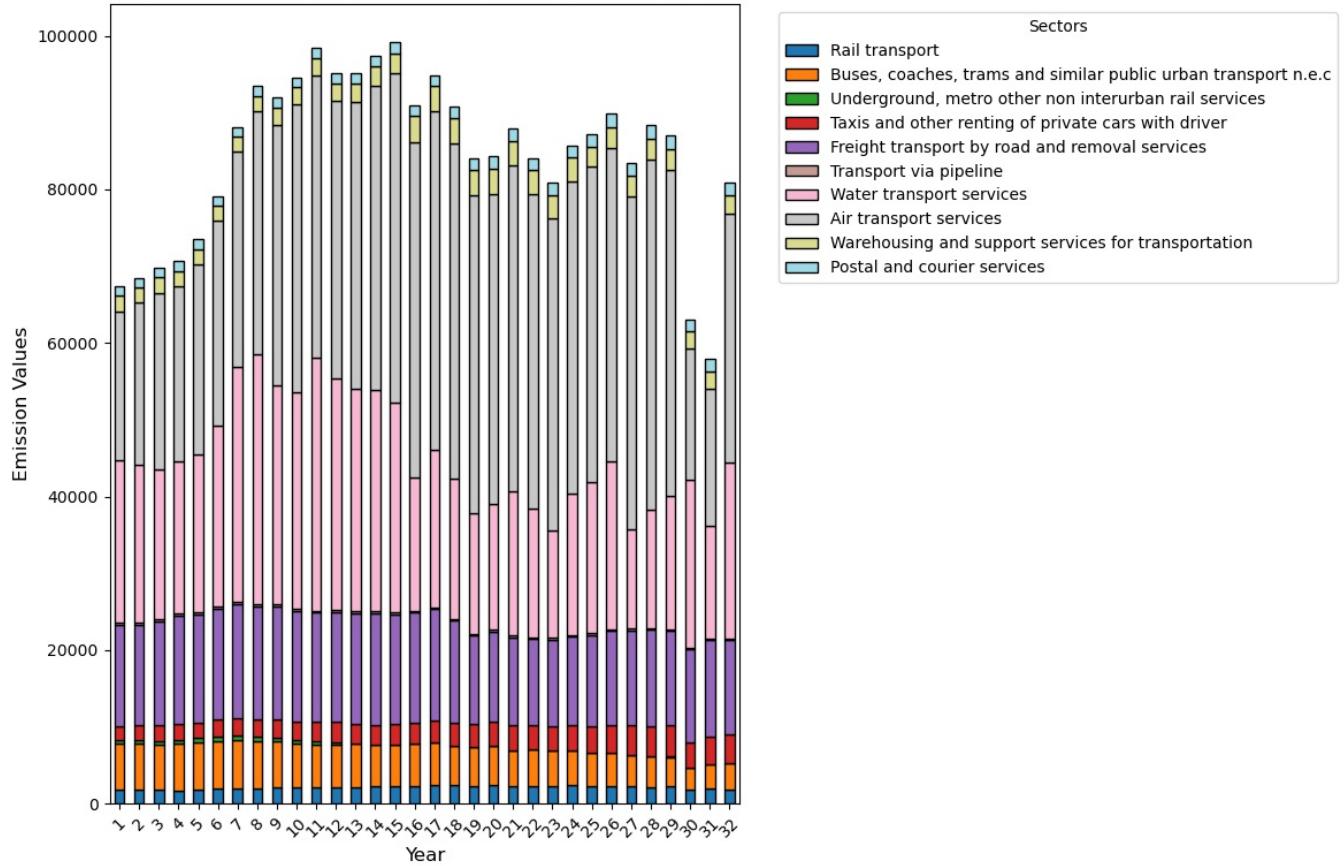
Stacked Bar Chart for Construction by Year



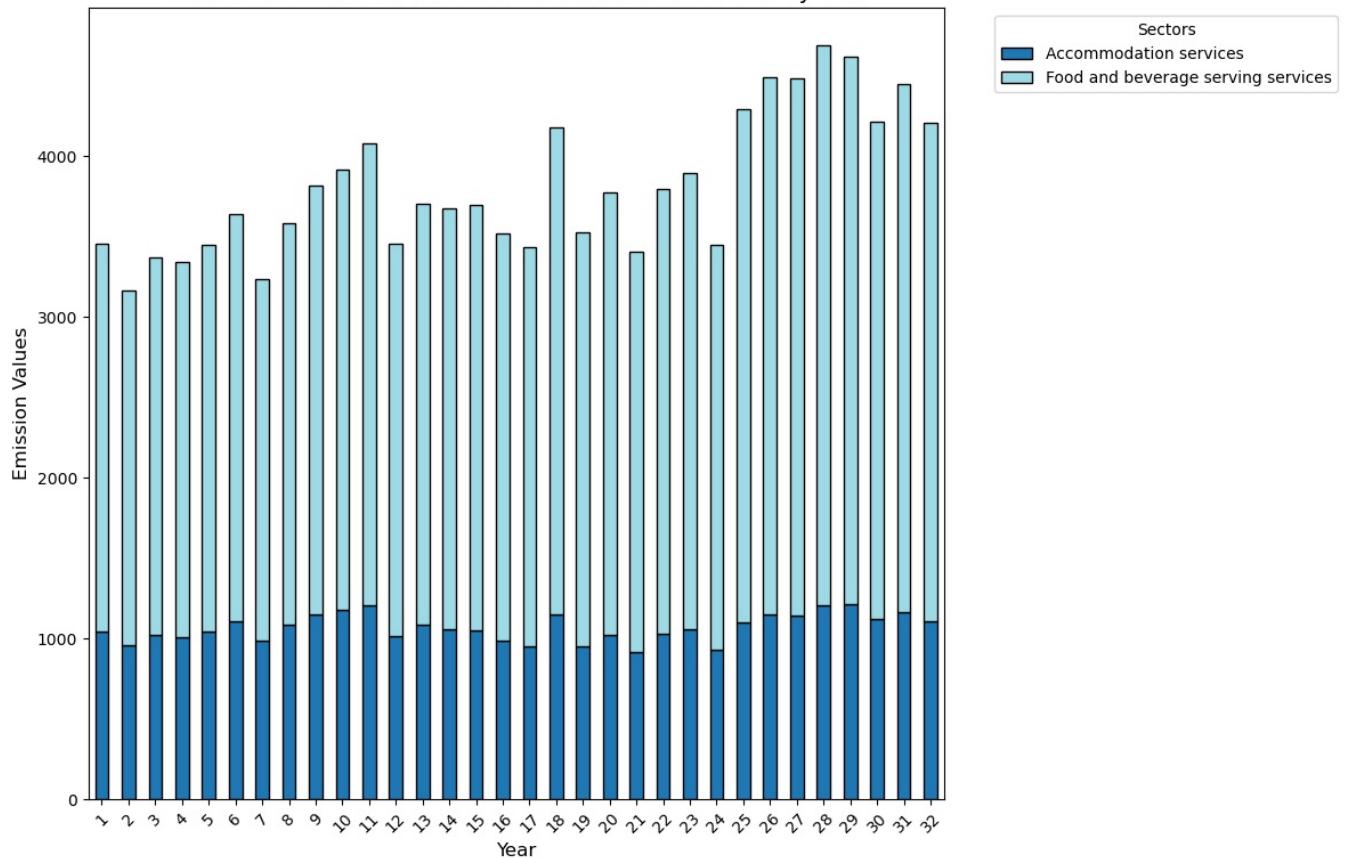
Stacked Bar Chart for Trade & Retail Services by Year



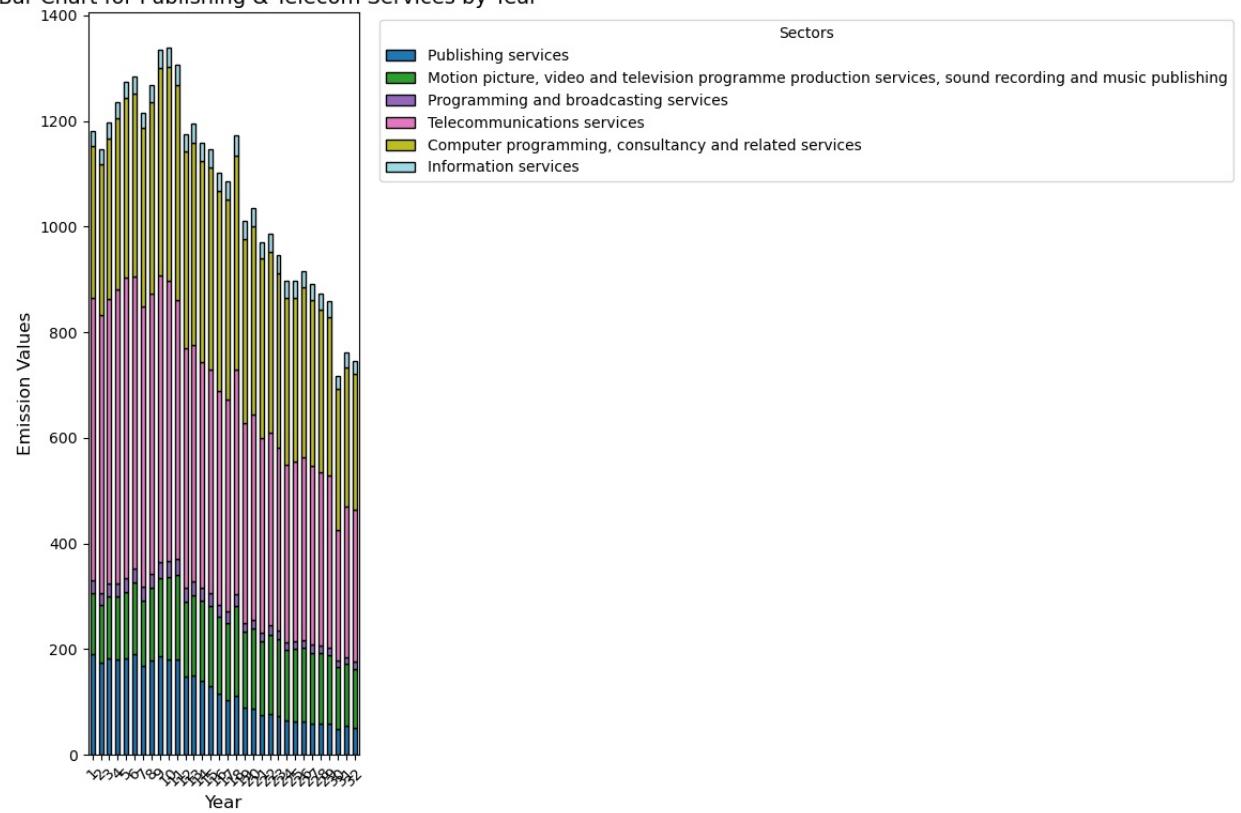
Stacked Bar Chart for Transport & Postal Services by Year

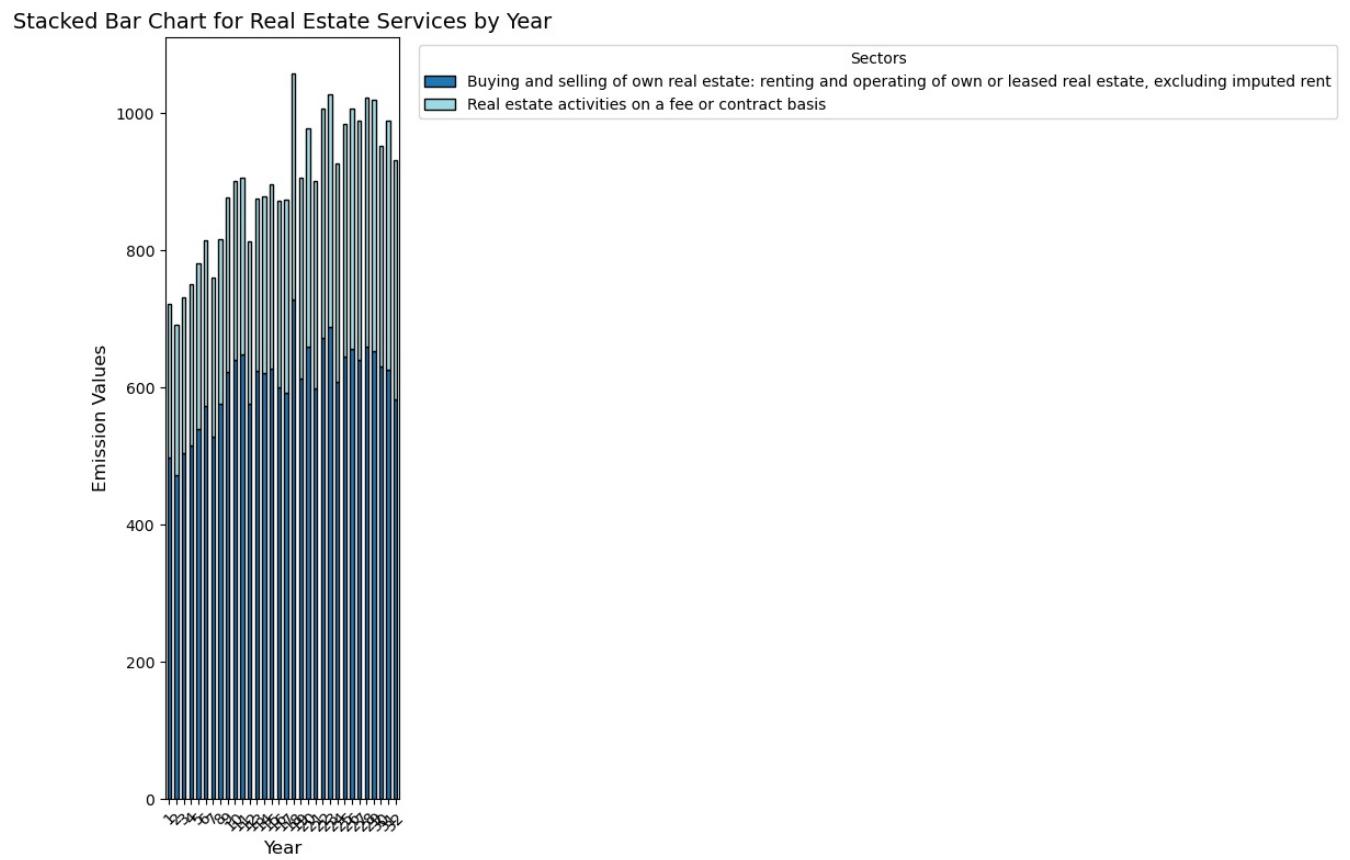
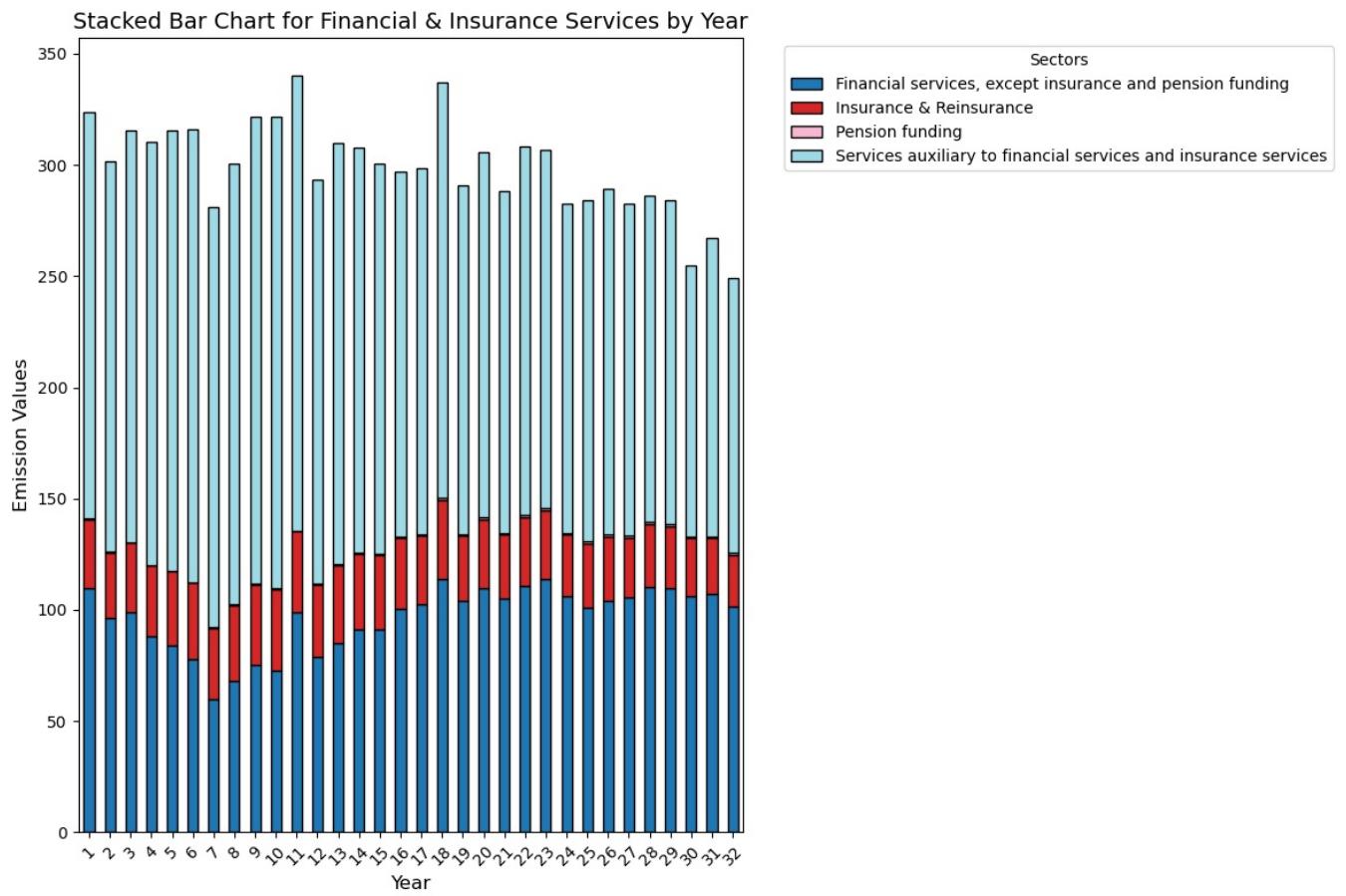


Stacked Bar Chart for Accommodation & Food Services by Year

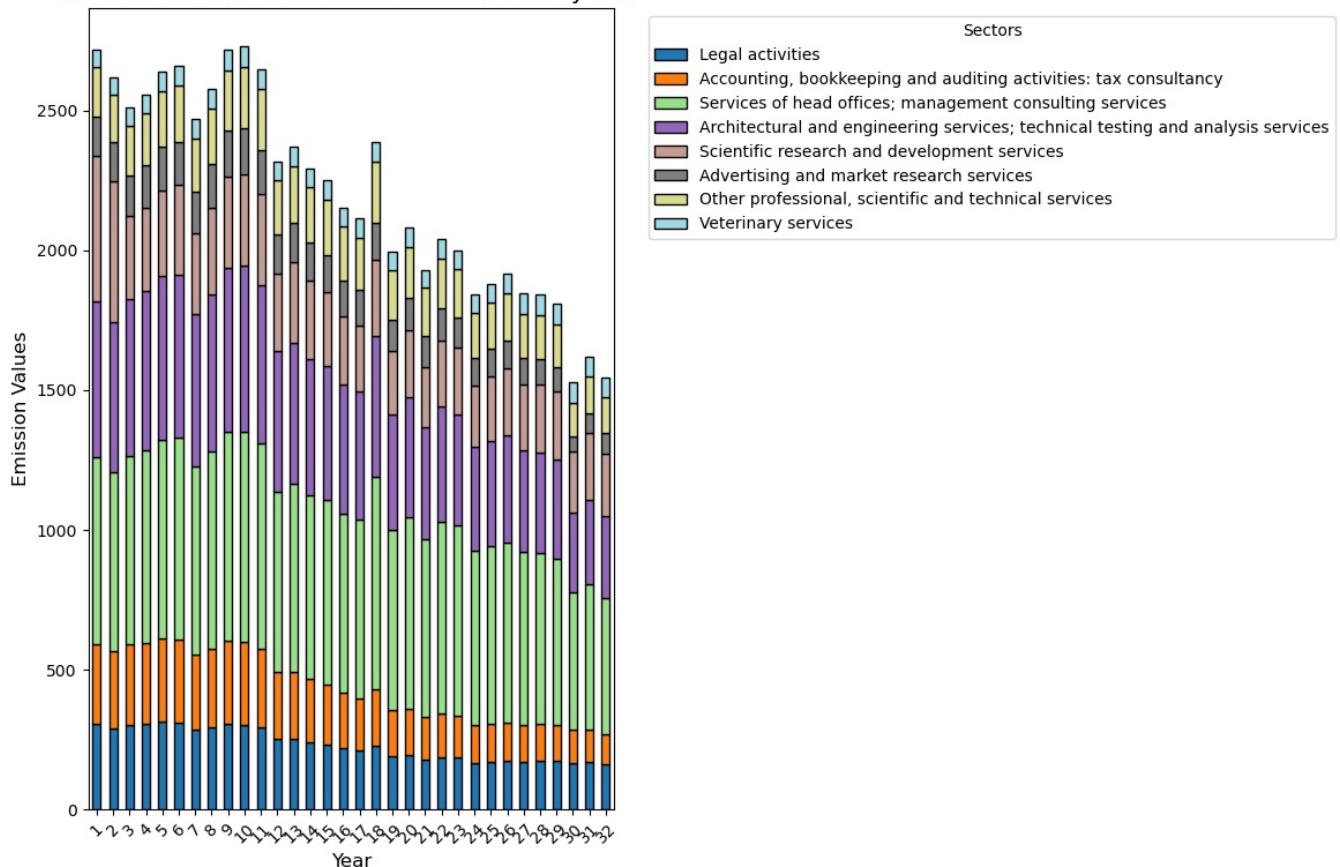


Stacked Bar Chart for Publishing & Telecom Services by Year

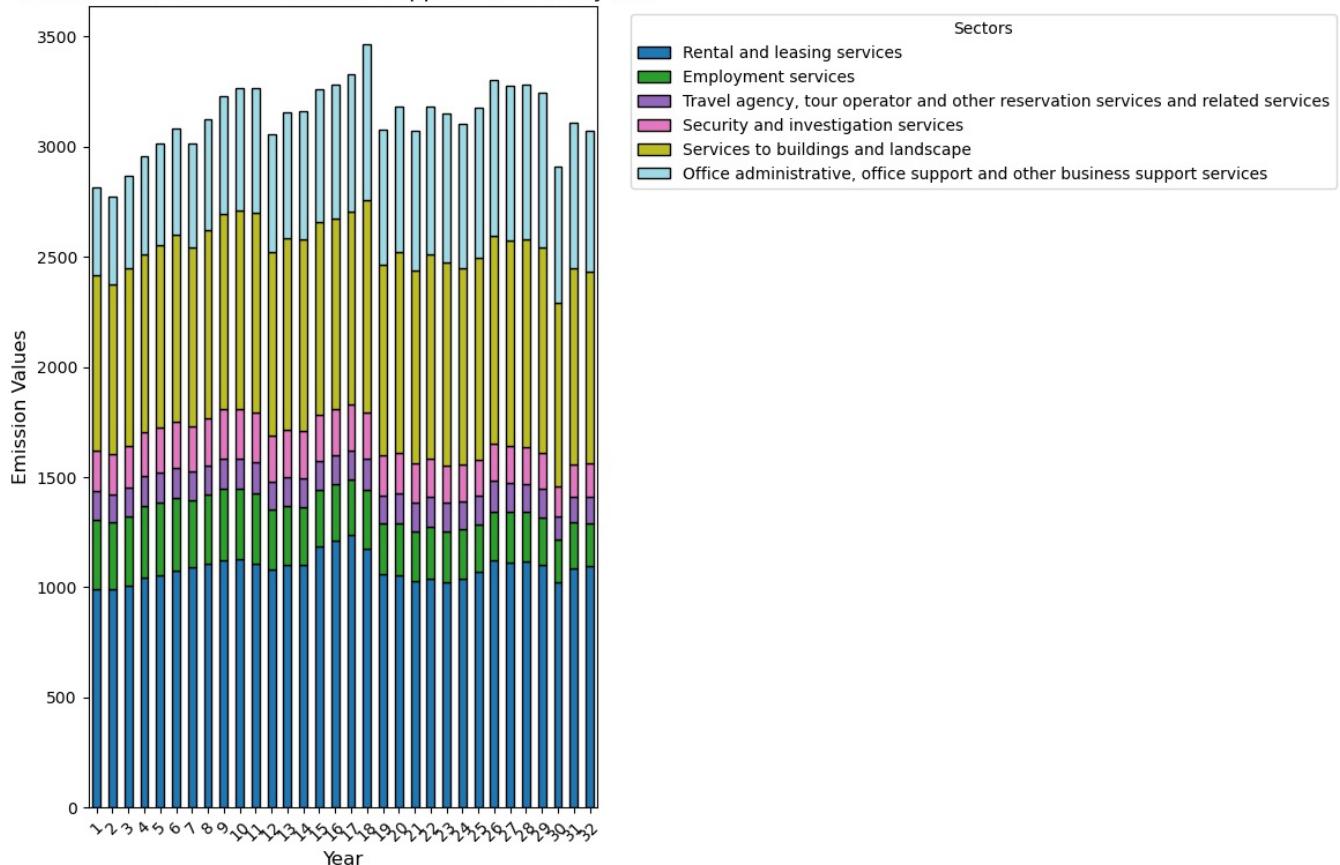


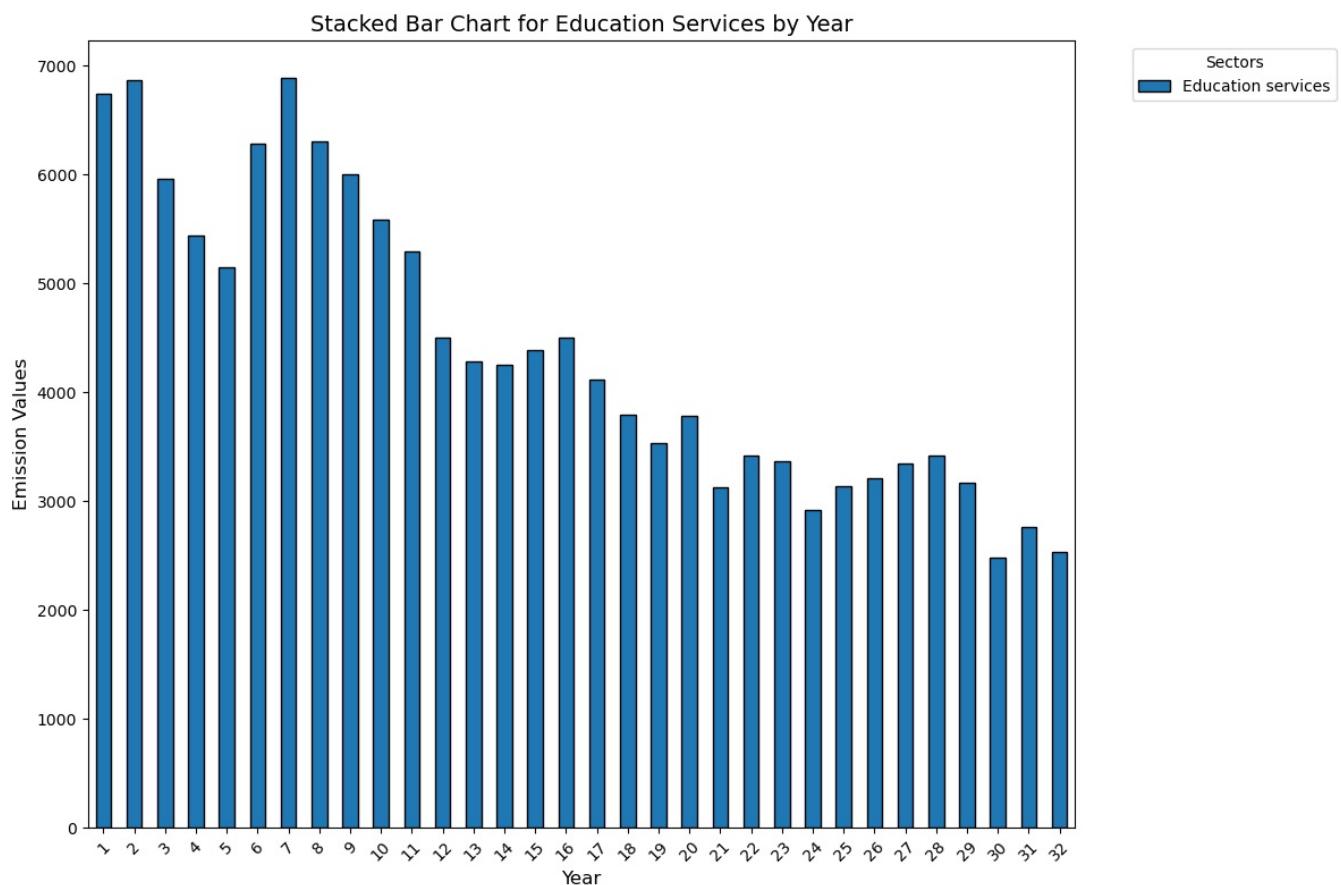
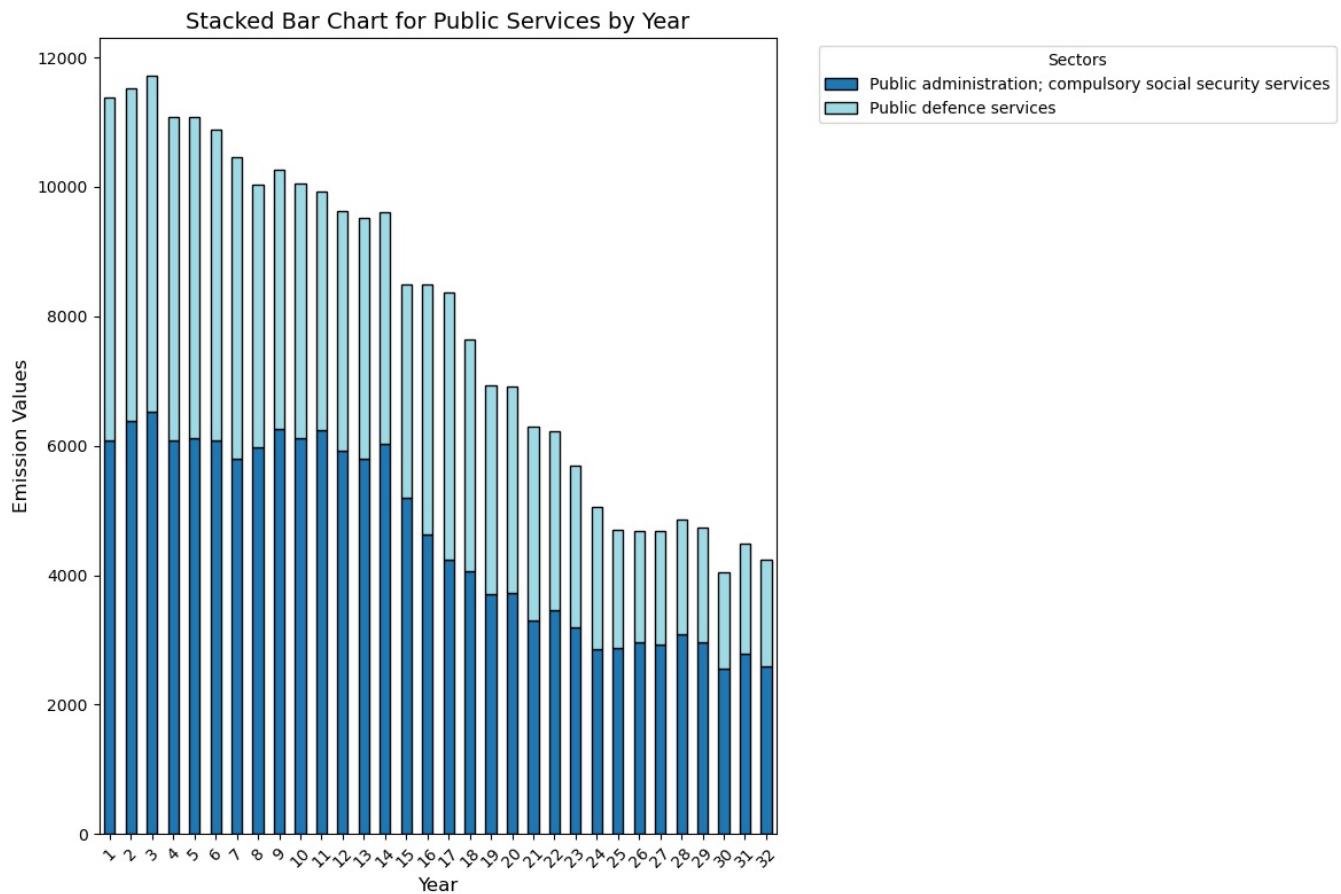


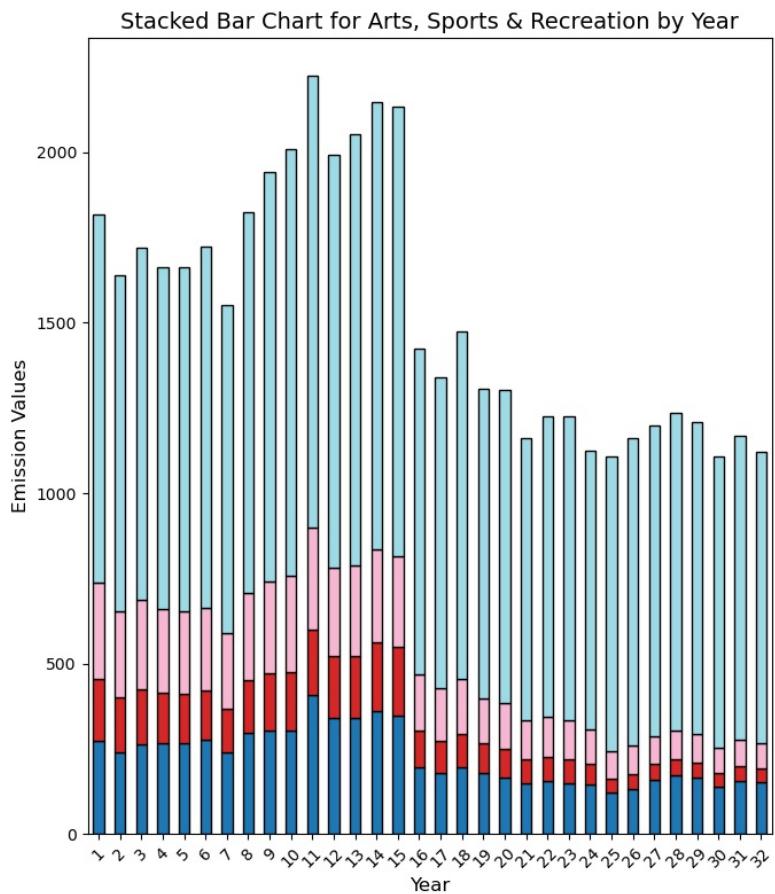
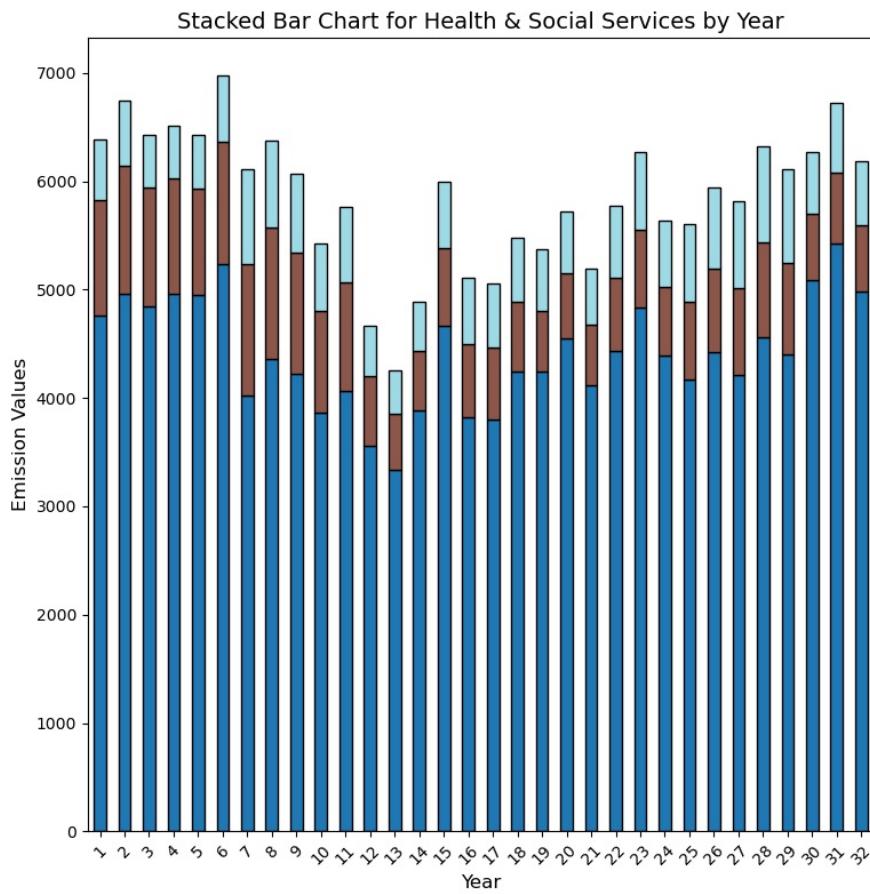
Stacked Bar Chart for Professional Services by Year



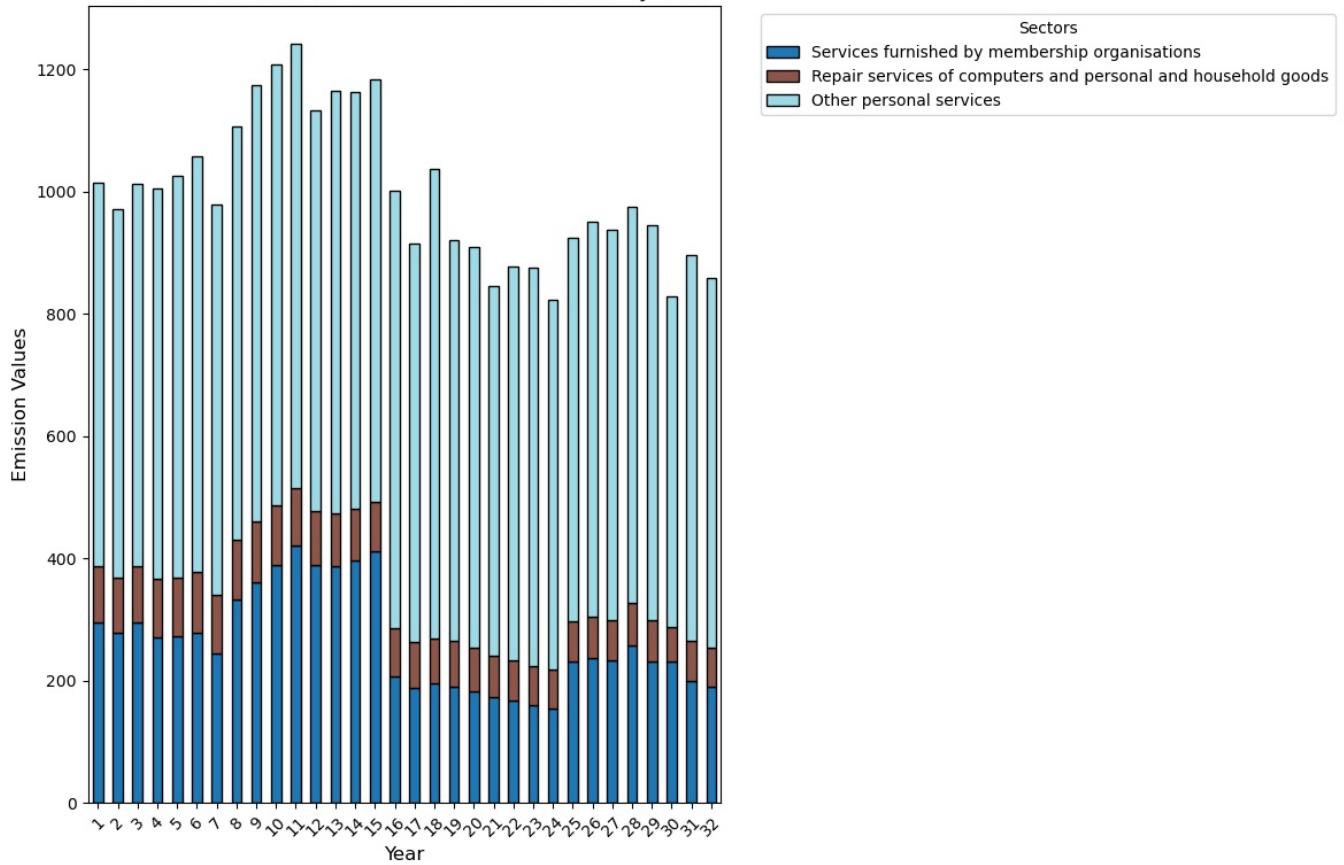
Stacked Bar Chart for Business Support Services by Year



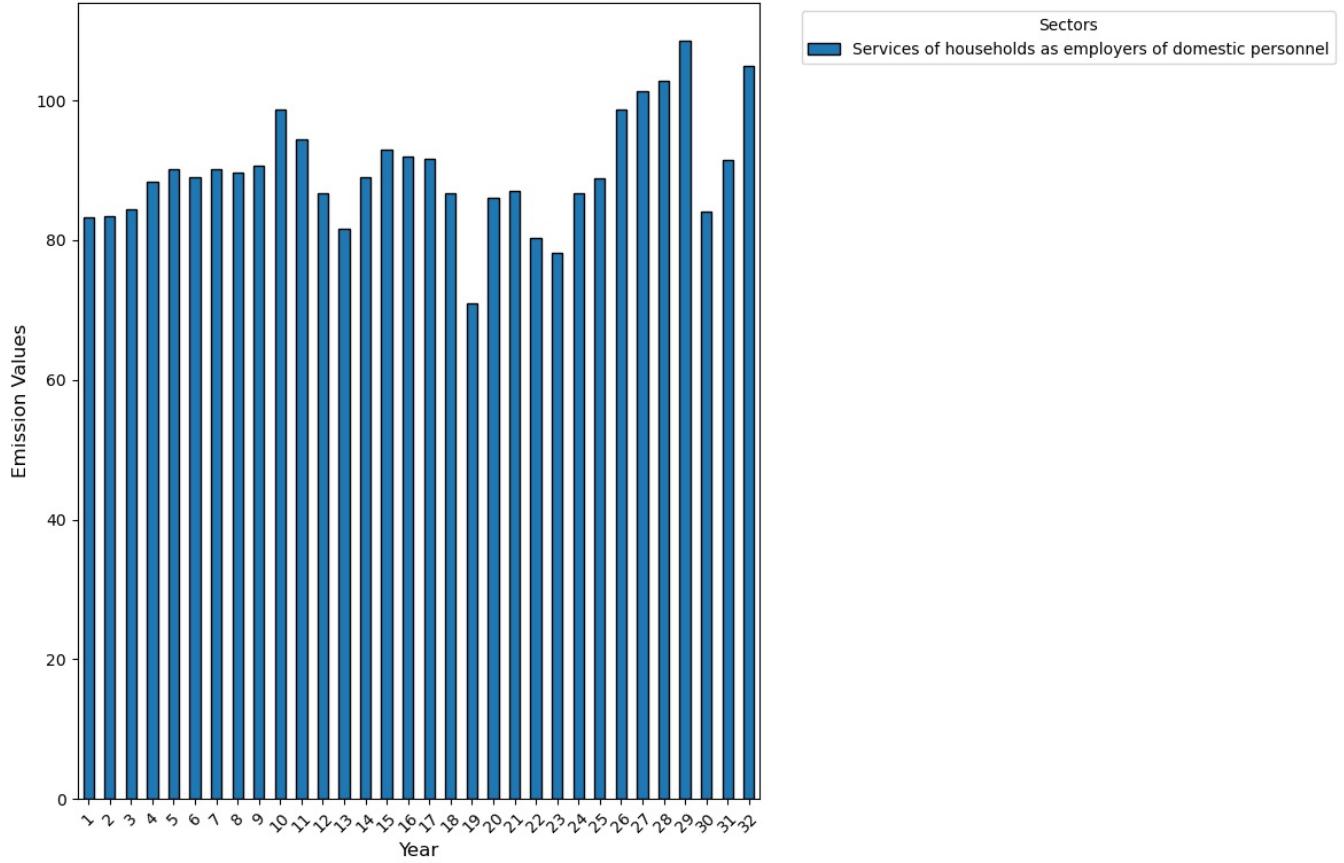


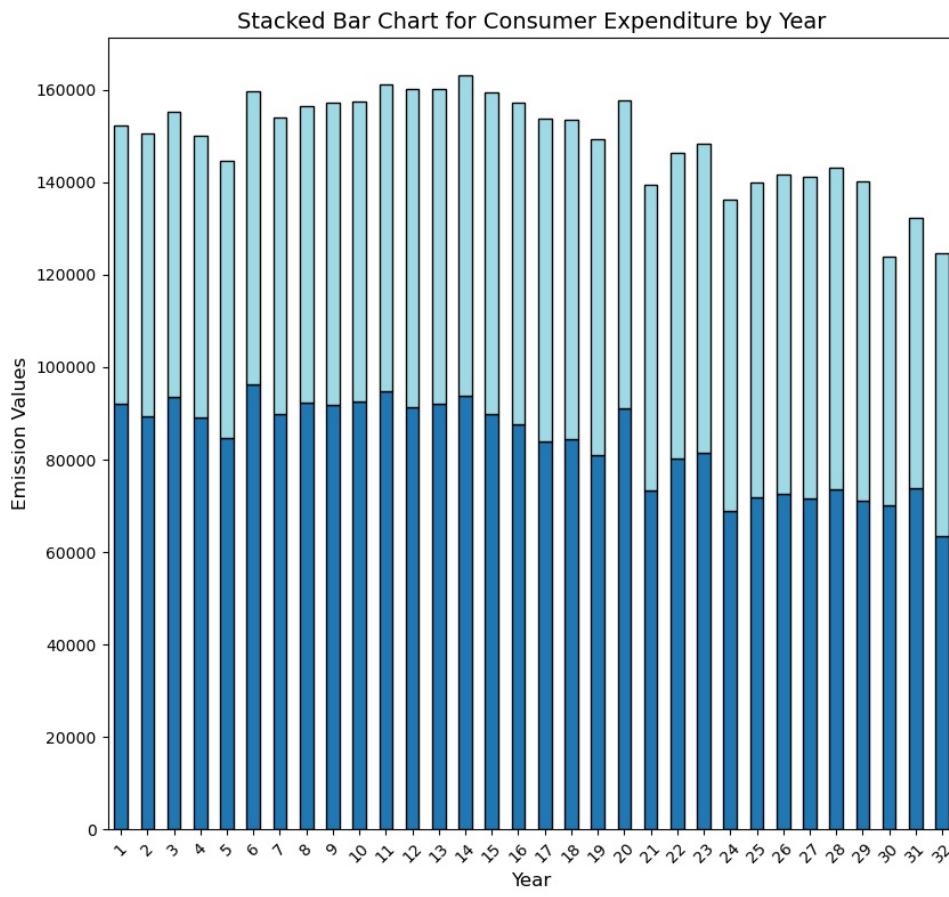


Stacked Bar Chart for Other Personal Services by Year



Stacked Bar Chart for Domestic Personnel Services by Year





In [ ]:

In [425]: table1

Out[425]:

	SIC code	A	B	C	D	E	F	G	H	I ...	C
0	Industry name	Agriculture, forestry and fishing	Mining and quarrying	Manufacturing	Electricity, gas, steam and air conditioning s...	Water supply; sewerage, waste management and r...	Construction	Wholesale and retail trade; repair of motor ve...	Transport and storage	Accommodation and food services	... administration and defence compulsory ..
1	1990	55690.3	50452.8	175212.7	217602.2	75316.3	8201.2	11560.8	66985.3	3015.3 ...	12058.4
2	1991	55492.6	50608.3	176254.4	214317.5	76852.7	8072	11984.1	67438.6	3453.5 ...	11381.2
3	1992	55149	51199.3	169388.2	202469.2	76959.1	8188.3	11789.9	68438.5	3163.4 ...	11523.4
4	1993	54319.9	50807.1	164365	184997.2	77275.6	8275.1	12032.9	69735.2	3371.4 ...	11710.9
5	1994	55129.7	44588.4	167285.9	180721.6	77637.9	8633.8	12403.1	70659.2	3342.3 ...	11071.3
6	1995	55061.9	46451.4	165344.1	178162.0	78712	8695.3	12560.6	73508.2	3450.7 ...	11079.5
7	1996	56343.6	46633.6	166622.3	177960.6	79209.4	8923.8	12825.8	79135.4	3636.1 ...	10890.1
8	1997	55810	45761.2	165258.4	164554.2	77982.7	9263.6	12631.7	88159.2	3237.9 ...	10462.7
9	1998	55950.8	44399.3	155653.0	170815.5	78691.1	9207.7	12926.4	93464.0	3581 ...	10028.0
10	1999	56176.1	40501.6	140696.8	163207.5	73742.9	9246.5	13464.5	91941.5	3819.3 ...	10260.4
11	2000	54133.6	38335.6	135627.4	176005.8	71060.5	9440.5	13774.1	94607.7	3913.4 ...	10046.3
12	2001	51955.6	38210.6	128931.3	186969.6	69110.6	9566.7	13738.1	98397.8	4077.2 ...	9921.5
13	2002	51495.5	36722.5	121456.3	182100.7	67450.9	9608.6	13544.7	95135.4	3457.7 ...	9629.5
14	2003	51950.4	34092.4	124723.3	191163.6	63375.2	9791.5	14202.6	95101.3	3705 ...	9518.5
15	2004	52813.4	32909.3	122868.9	191097.4	58712.5	10170.6	14461.8	97343.8	3673 ...	9605.4
16	2005	52934	30738.2	121871.7	192574.6	56104.9	10152	14753.1	99137.9	3694.7 ...	8493.2
17	2006	51899.8	28291.7	117269.7	200397.5	52739.5	10309.7	15013	90909.2	3518.8 ...	8486.5
18	2007	51473.1	27770.4	116409.3	195947.3	49262.6	10785.7	15656.8	94883.2	3433.4 ...	8360.2
19	2008	51240.7	27088.3	108134.2	191548.8	43934.9	10784.4	16297.4	90840.5	4178.1 ...	7647
20	2009	50442.8	27056.8	90639.6	169738.9	39631	9504.6	16483.2	84039.5	3525.6 ...	6938.5
21	2010	50502.1	26661.9	93988	177018.4	34835.1	9682.6	17024.2	84360.1	3773.8 ...	6907.7
22	2011	49647.4	24205.7	90258	164156.6	32853.5	9235.3	16767.9	87918.1	3403.6 ...	6299.3
23	2012	50368.8	22379.2	86759.9	178480.3	31469.9	9426.8	16946	84115	3794.9 ...	6217.2
24	2013	49299.1	21096.9	89442.9	169292	28566.7	9033.9	16508.8	80876.9	3896.3 ...	5696.7
25	2014	51149.2	21086.9	88797.2	148347.2	26627.8	9236	15865.5	85705.9	3444 ...	5057
26	2015	51774.5	22402.3	86036.2	131922.4	26416.7	9971.5	15912.8	87193.9	4289.6 ...	4693.1
27	2016	51397.4	21347.1	80201.2	109990	26154.7	10417.8	15949.4	89850.6	4486.3 ...	4674.1
28	2017	51685.1	21287.7	80871.8	100019.5	27149.1	10474.8	15320.7	83486.7	4484.6 ...	4685.5
29	2018	51227.2	21606.2	80321.5	95782.4	27404.6	10903.5	14993.8	88349.5	4685.3 ...	4865.3
30	2019	50889.8	21858.1	80113	89388.3	26787.1	10734.7	14592.1	86998.4	4618 ...	4739.5
31	2020	49836	20321.3	77060.3	80736.3	25434.7	9941	12705.2	63020.4	4213 ...	4038.4
32	2021	50909.4	18346.2	77092.3	86311	25252.1	11180.6	13471.4	57961.1	4446.4 ...	4494.4
33	2022	49682.9	17433.4	75449.5	82854.7	25109.3	10990.5	13084.3	80891	4203.9 ...	4233.5
34	2023	49176.8	16415.6	73496.8	70134.5	24868.4	11243.8	12855.7	83875.1	4122.1 ...	4380.0

35 rows × 25 columns

In [ ]:

```
#percentage increase calculator

years = table1.iloc[1:, 0].values
industry_names = table1.iloc[0, 1:-1].values

#empty array to store percentages
total_percentage_changes = {}

# Loop through each industry to calculate the total percentage change
for industry_index, industry in enumerate(industry_names):
    emissions_data = table1.iloc[1:, industry_index + 1].values

    #total percentage change from 1990 to 2023
    start_value = emissions_data[0] # Emissions in 1990
    end_value = emissions_data[-1] # Emissions in 2023
    total_percentage_change = ((end_value - start_value) / start_value) * 100

    total_percentage_changes[industry] = total_percentage_change
```

```

# Store the total percentage change in the dictionary
total_percentage_changes[industry] = total_percentage_change

# Display the results
print("Total percentage change in emissions from 1990 to 2023 for each industry:")
for industry, percentage_change in total_percentage_changes.items():
    print(f"{industry}: {percentage_change:.2f}%")

```

Total percentage change in emissions from 1990 to 2023 for each industry:

- Agriculture, forestry and fishing: -11.70%
- Mining and quarrying: -67.46%
- Manufacturing: -58.05%
- Electricity, gas, steam and air conditioning supply: -67.77%
- Water supply; sewerage, waste management and remediation activities: -66.98%
- Construction: 37.10%
- Wholesale and retail trade; repair of motor vehicles and motorcycles: 11.20%
- Transport and storage: 25.21%
- Accommodation and food services: 36.71%
- Information and communication: -32.93%
- Financial and insurance activities: -19.32%
- Real estate activities: 42.15%
- Professional, scientific and technical activities: -39.47%
- Administrative and support service activities: 16.46%
- Public administration and defence; compulsory social security: -63.68%
- Education: -61.21%
- Human health and social work activities: 0.33%
- Arts, entertainment and recreation: -34.00%
- Other service activities: -10.54%
- Activities of households as employers; undifferentiated goods and services-producing activities of households for own use: -2.97%
- Consumer expenditure [note 4]: -17.16%
- Consumer expenditure - Not travel: -28.22%
- Consumer expenditure - Travel: -2.01%

In [427...]

```

#Correlation matrix

emissions_data = table1.iloc[1:, 1:-1]

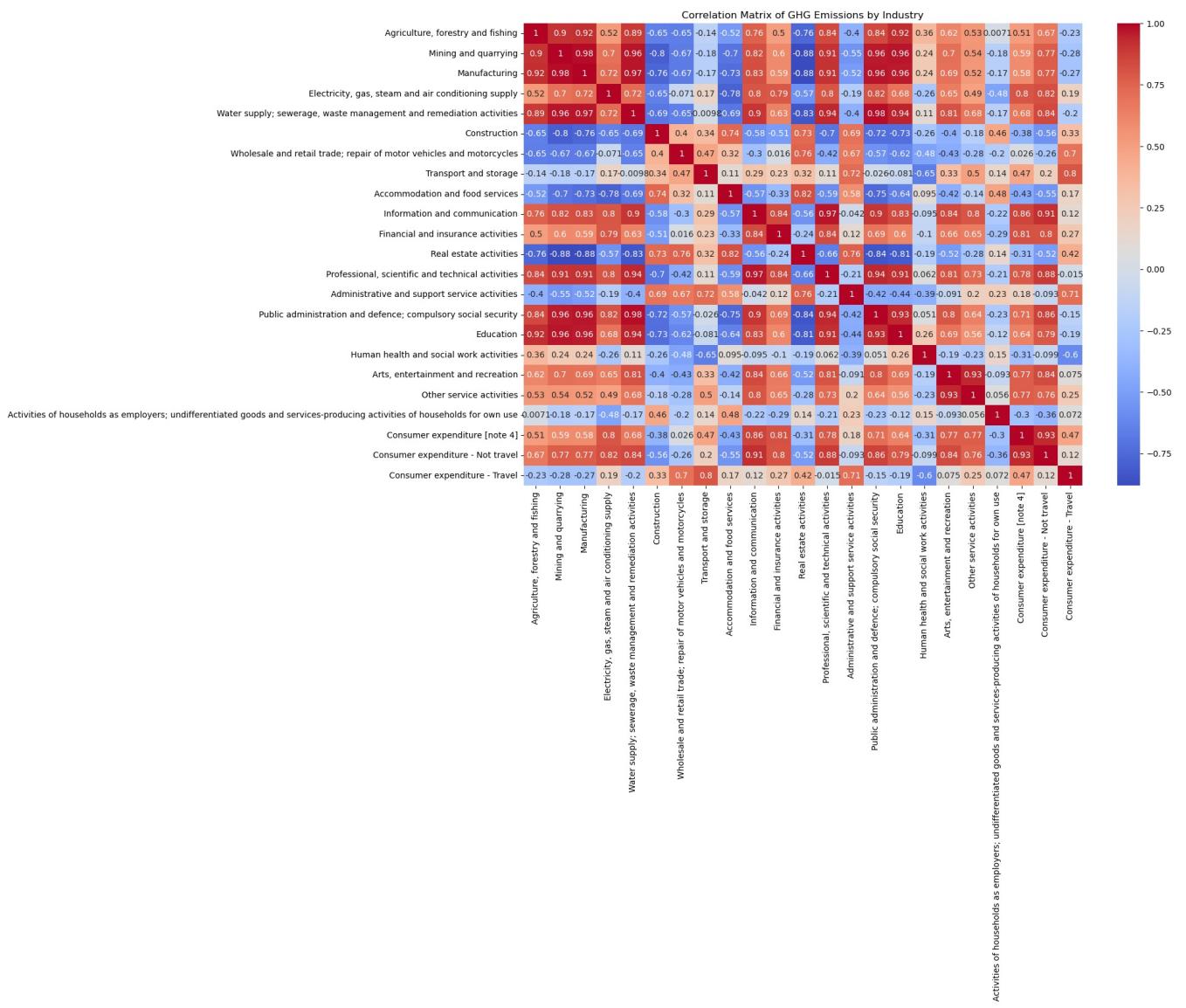
emissions_data = emissions_data.apply(pd.to_numeric, errors='coerce')

# Calculate the correlation matrix
correlation_matrix = np.corrcoef(emissions_data.T)

# Create the heatmap
plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', xticklabels=industry_names, yticklabels=industry_n
plt.title('Correlation Matrix of GHG Emissions by Industry')

plt.show()

```



## Models

In [ ]:

```
#Linear regression model
#Reference[5]:(freshhotdata, 2023)

years = table1.iloc[1:, 0].values.reshape(-1, 1)
total_emissions = table1.iloc[1:, -1].values

# Train the linear regression model on available data
model = LinearRegression()
model.fit(years, total_emissions)

# Predict the emissions for the years 2024 to 2030
future_years = np.array([2024, 2025, 2026, 2027, 2028, 2029, 2030]).reshape(-1, 1)
predicted_emissions = model.predict(future_years)

# Create a line of best fit for the historical data (line of best fit for actual data)
line_of_best_fit = model.predict(years)

# Plotting the results
plt.figure(figsize=(10, 6))

# Plot actual emissions
plt.plot(years, total_emissions, label='Actual Emissions', color='blue', marker='o')

# Plot predicted emissions for 2024-2030 as a dotted line
plt.plot(future_years, predicted_emissions, label='Predicted Emissions (2024-2030)', color='red', linestyle='--')

# Plot the line of best fit for the historical data
plt.plot(years, line_of_best_fit, label='Line of Best Fit', color='green', linestyle='-', linewidth=2)

# Adding labels and title
plt.title('Actual and Predicted GHG Emissions- Linear Regression', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Total GHG Emissions', fontsize=12)
```

```

plt.legend(loc='upper left', fontsize=10)
plt.grid(True)

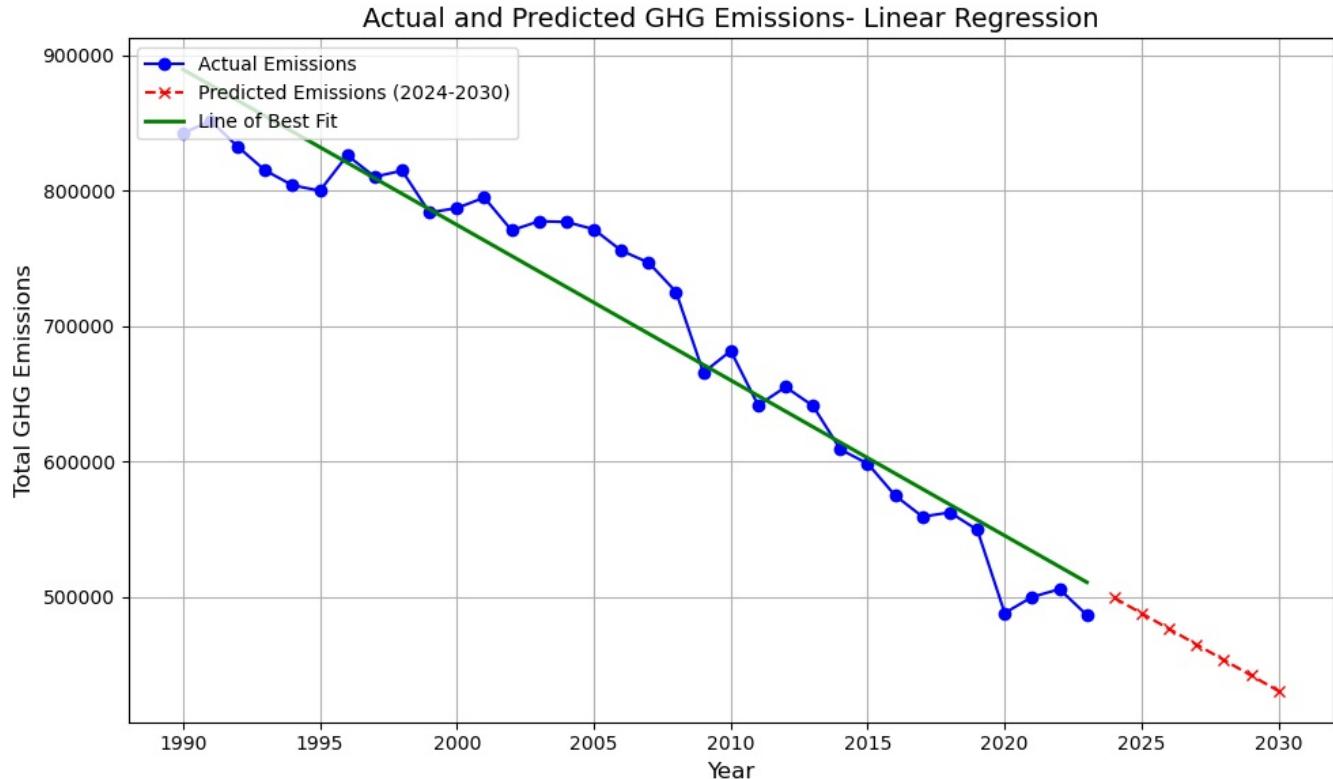
# Show plot
plt.tight_layout()
plt.show()

#statistical measures for the model's performance
r_squared = model.score(years, total_emissions)
mae = mean_absolute_error(total_emissions, line_of_best_fit)
mse = mean_squared_error(total_emissions, line_of_best_fit)

# Print the statistical measures
print(f'R-squared: {r_squared:.4f}')
print(f'Mean Absolute Error (MAE): {mae:.4f}')
print(f'Mean Squared Error (MSE): {mse:.4f}')

# Print predicted values for 2024-2030
for i, year in enumerate(future_years):
    print(f'Predicted Total GHG Emissions for {year[0]}: {predicted_emissions[i]:.2f}')

```



R-squared: 0.9329  
Mean Absolute Error (MAE): 25031.9173  
Mean Squared Error (MSE): 911108081.9840  
Predicted Total GHG Emissions for 2024: 499563.25  
Predicted Total GHG Emissions for 2025: 488090.44  
Predicted Total GHG Emissions for 2026: 476617.63  
Predicted Total GHG Emissions for 2027: 465144.82  
Predicted Total GHG Emissions for 2028: 453672.01  
Predicted Total GHG Emissions for 2029: 442199.20  
Predicted Total GHG Emissions for 2030: 430726.39

```

In [ ]: 
In [429]: #Support Vector Regression
#Reference[6]: (Muz, 2016)
years = table1.iloc[:, 0].values
total_emissions = table1.iloc[:, -1].values

years_reshaped = years.reshape(-1, 1)

#Using rbf kernel; and setting parameters
svr_model = SVR(kernel='rbf', C=100, gamma=0.1, epsilon=0.1)

# Train the SVR model

```

```

svr_model.fit(years_reshaped, total_emissions)

# Predict emissions for the next 5 years (2024 to 2028)
years_future = np.arange(2024, 2031).reshape(-1, 1)
svr_predictions = svr_model.predict(years_future)

#predictions
plt.figure(figsize=(10, 6))

# Plot the actual emissions data
plt.plot(years, total_emissions, label='Actual Emissions', color='black', linewidth=2)

# Plot Support Vector Regression predictions (with dotted line)
plt.plot(np.concatenate((years, years_future.flatten())), np.concatenate((total_emissions, svr_predictions)), label='SVR Prediction', color='green', linestyle='dotted')
plt.title('GHG Emissions Predictions (2024-2028)- Support Vector Regression', fontsize=16)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Emissions (Total)', fontsize=12)
plt.legend()
plt.grid(True)

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

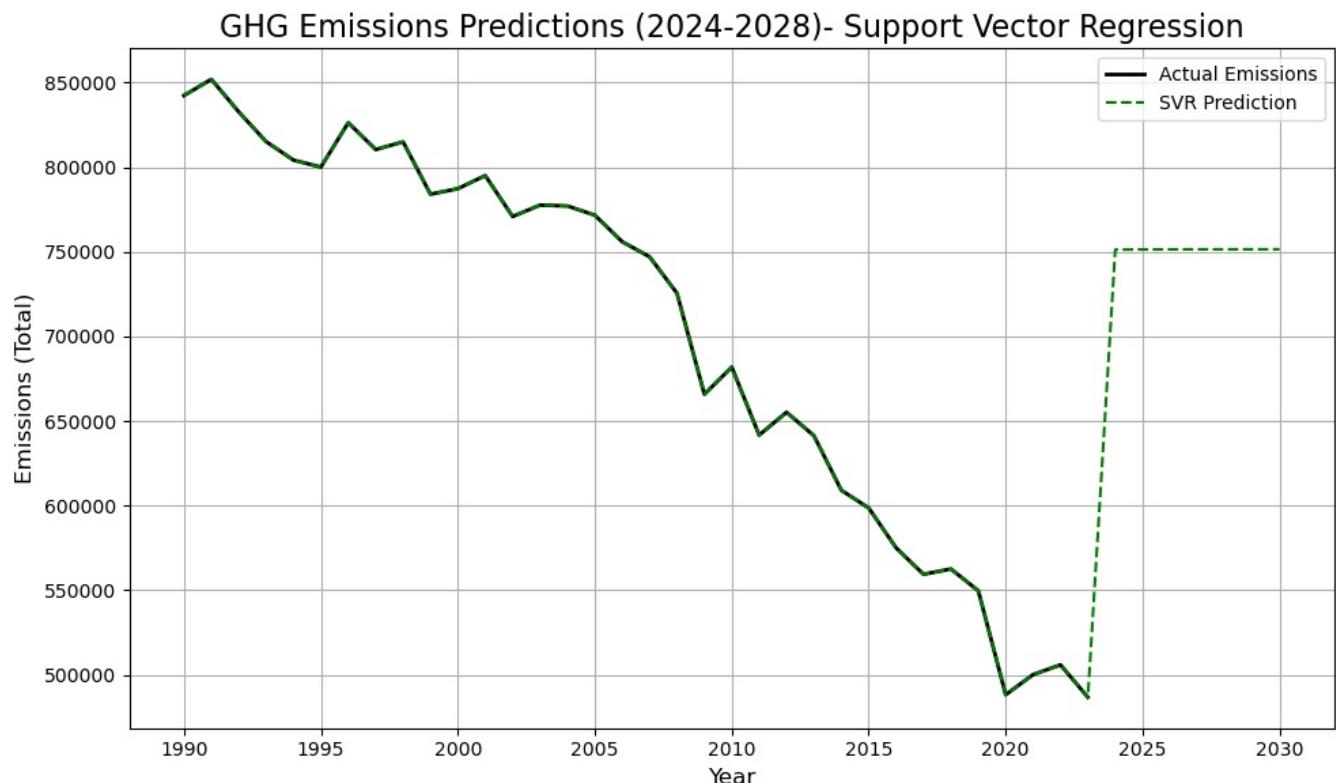
# ---Evaluation Metrics
svr_r2 = r2_score(total_emissions, svr_model.predict(years_reshaped))
svr_mae = mean_absolute_error(total_emissions, svr_model.predict(years_reshaped))
svr_mse = mean_squared_error(total_emissions, svr_model.predict(years_reshaped))

print("Support Vector Regression (SVR):")
print(f"R-squared: {svr_r2:.4f}")
print(f"Mean Absolute Error: {svr_mae:.4f}")
print(f"Mean Squared Error: {svr_mse:.4f}")

# Predict total emissions for the years 2024 to 2030
years_extended = np.arange(2024, 2031).reshape(-1, 1)
extended_predictions = svr_model.predict(years_extended)

#predictions for 2024-2030
print("\nPredictions for 2024 to 2030:")
for year, prediction in zip(years_extended.flatten(), extended_predictions):
    print(f"Year {year}: {prediction:.2f}")

```



Support Vector Regression (SVR):  
R-squared: -0.1853  
Mean Absolute Error: 100198.8564  
Mean Squared Error: 16095826593.6651

Predictions for 2024 to 2030:  
Year 2024: 751252.75  
Year 2025: 751343.23  
Year 2026: 751410.27  
Year 2027: 751450.92  
Year 2028: 751471.11  
Year 2029: 751479.32  
Year 2030: 751482.05

In [ ]:

In [430]:

```
#Linear regression on industries

years = table1.iloc[1:, 0].values.reshape(-1, 1)

# Loop through each industry and apply linear regression
industry_names = table1.columns[1:-1]

predictions = {} # Array to store predictions for each industry

for industry in industry_names:
    emissions = table1[industry].iloc[1:,:].values

    # Train the linear regression model
    model = LinearRegression()
    model.fit(years, emissions)

    # Predict the emissions for the years 2024 to 2030
    future_years = np.array([2024, 2025, 2026, 2027, 2028, 2029, 2030]).reshape(-1, 1)
    predicted_emissions = model.predict(future_years)

    # Store predictions
    predictions[industry] = predicted_emissions

# Plotting the results for current data
plt.figure(figsize=(10, 6))

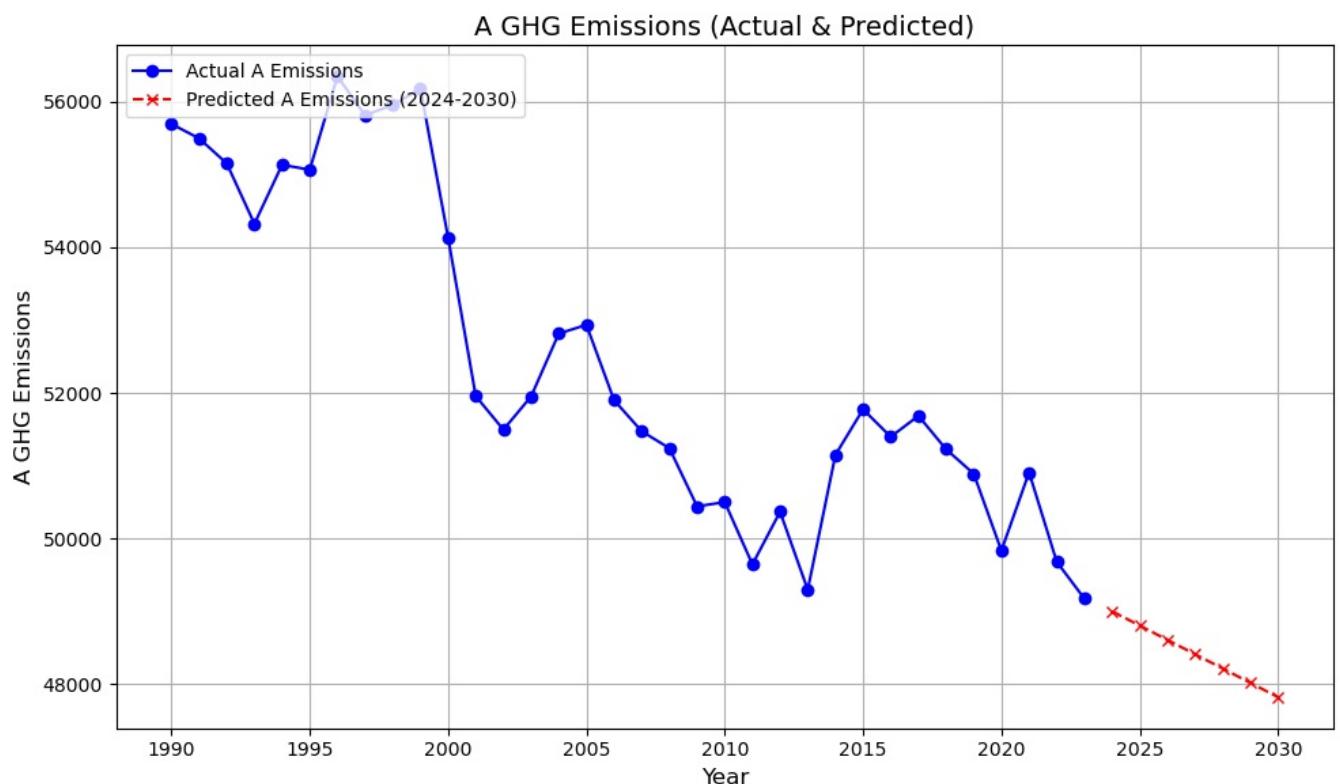
# Plot actual emissions
plt.plot(years, emissions, label=f'Actual {industry} Emissions', color='blue', marker='o')

# Plot predicted emissions for 2024–2030 as a dotted line
plt.plot(future_years, predicted_emissions, label=f'Predicted {industry} Emissions (2024-2030)', color='red', linestyle='dashed')

# Adding labels and title
plt.title(f'{industry} GHG Emissions (Actual & Predicted)', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel(f'{industry} GHG Emissions', fontsize=12)
plt.legend(loc='upper left', fontsize=10)
plt.grid(True)

# Show plot
plt.tight_layout()
plt.show()

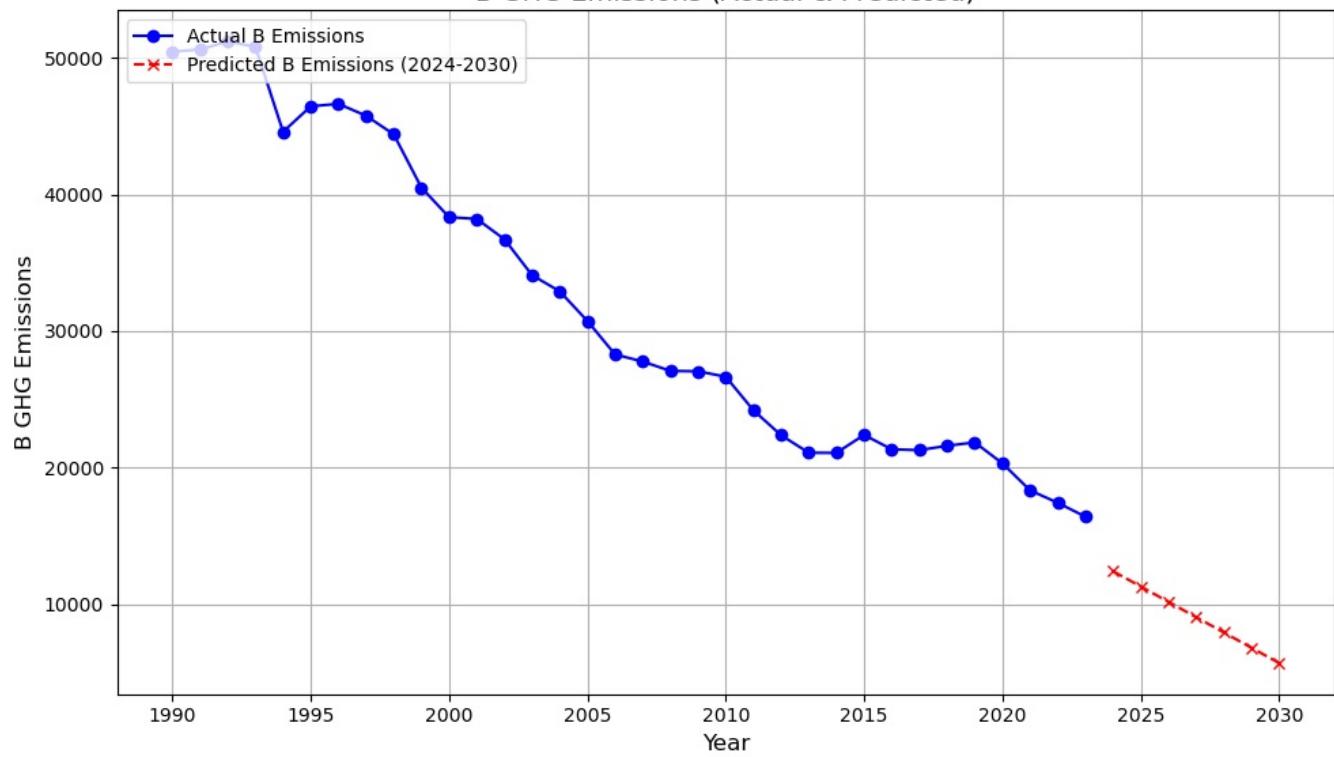
# Print predicted values for 2024-2030
print(f"Predicted {industry} GHG Emissions for 2024-2030:")
for i, year in enumerate(future_years):
    print(f" {year[0]}: {predicted_emissions[i]:.2f}")
```



Predicted A GHG Emissions for 2024-2030:

2024: 49003.57  
2025: 48807.12  
2026: 48610.67  
2027: 48414.22  
  
2028: 48217.78  
2029: 48021.33  
2030: 47824.88

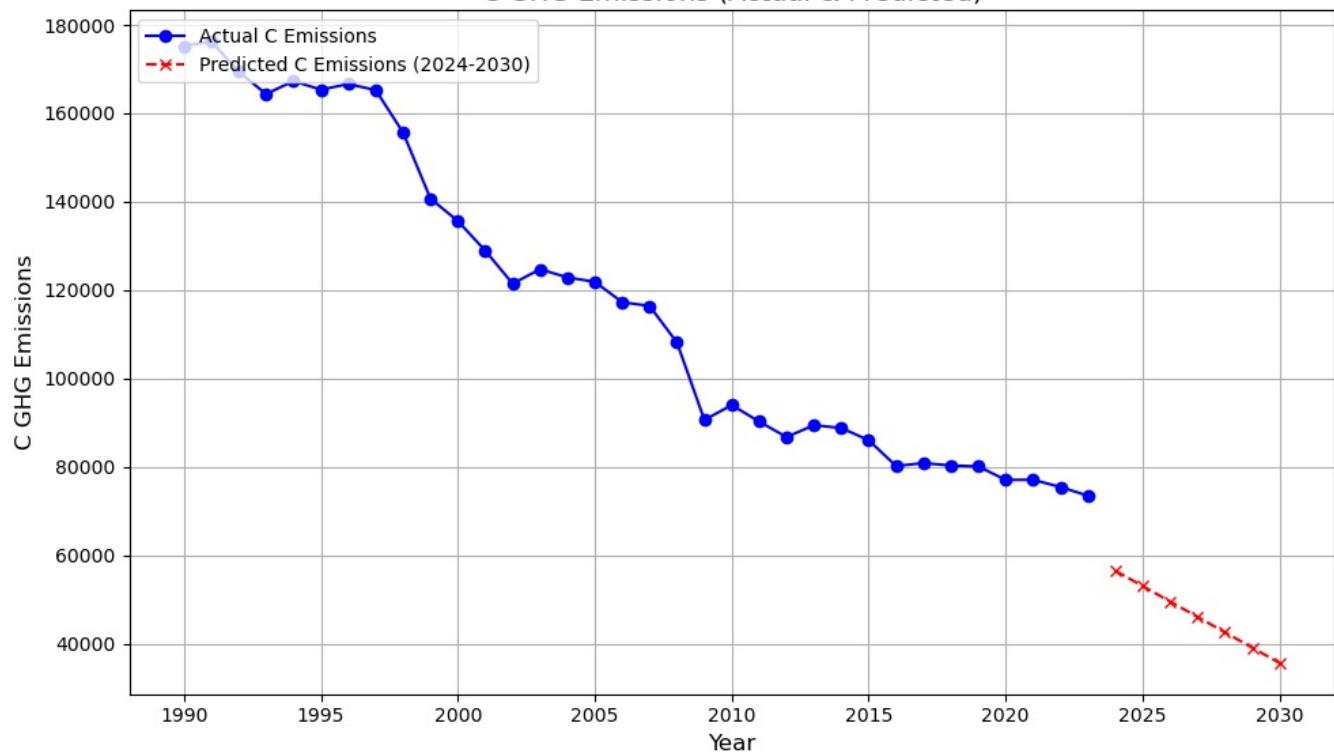
B GHG Emissions (Actual & Predicted)



Predicted B GHG Emissions for 2024-2030:

2024: 12426.71  
2025: 11306.44  
2026: 10186.17  
2027: 9065.91  
2028: 7945.64  
2029: 6825.37  
2030: 5705.10

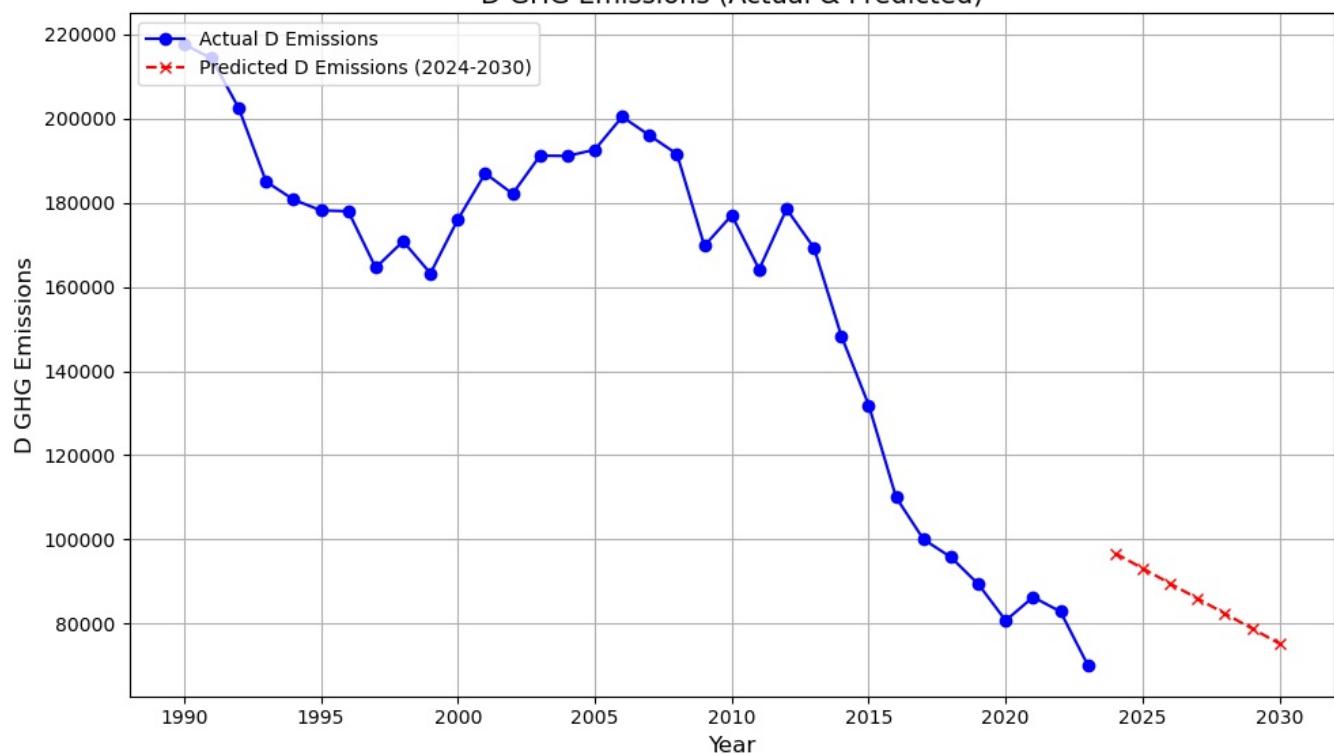
C GHG Emissions (Actual & Predicted)



Predicted C GHG Emissions for 2024-2030:

2024: 56525.20  
2025: 53042.77  
2026: 49560.34  
2027: 46077.91  
2028: 42595.49  
  
2029: 39113.06  
2030: 35630.63

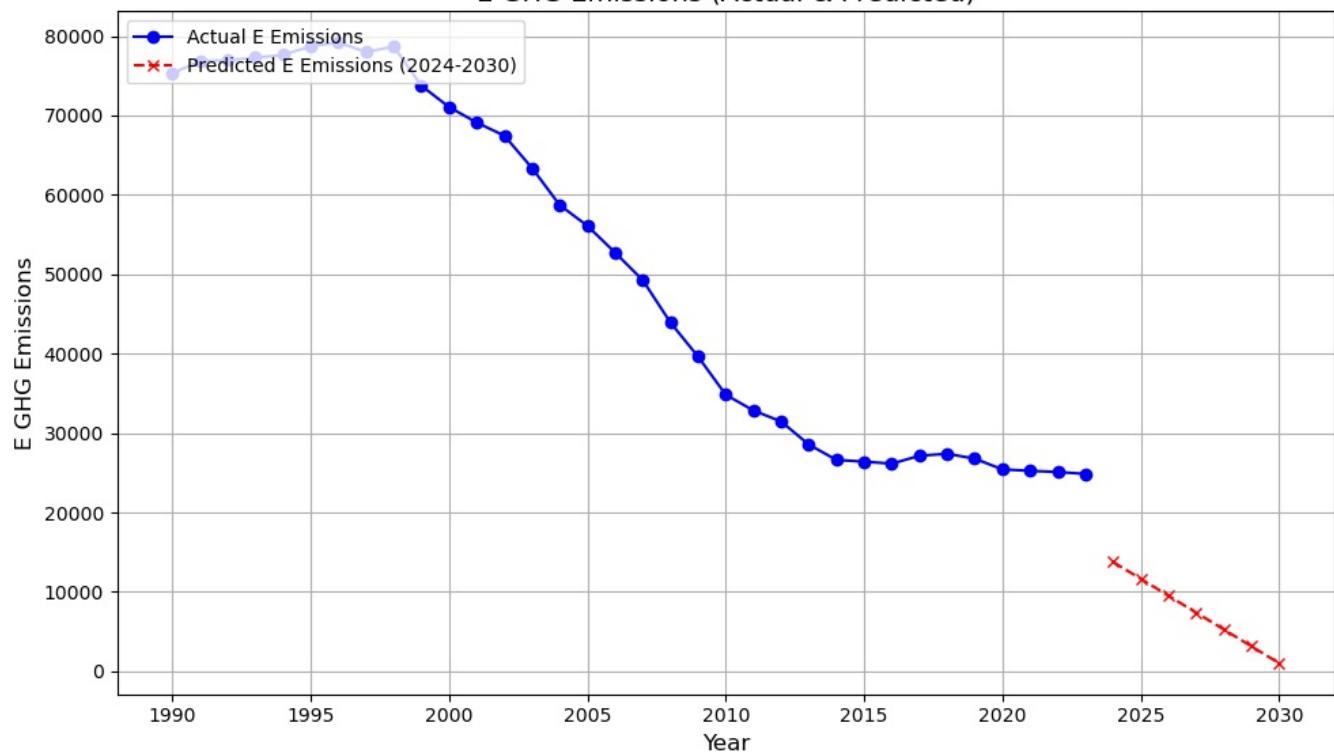
D GHG Emissions (Actual & Predicted)



Predicted D GHG Emissions for 2024-2030:

2024: 96706.14  
2025: 93128.37  
2026: 89550.59  
2027: 85972.81  
2028: 82395.04  
2029: 78817.26  
2030: 75239.49

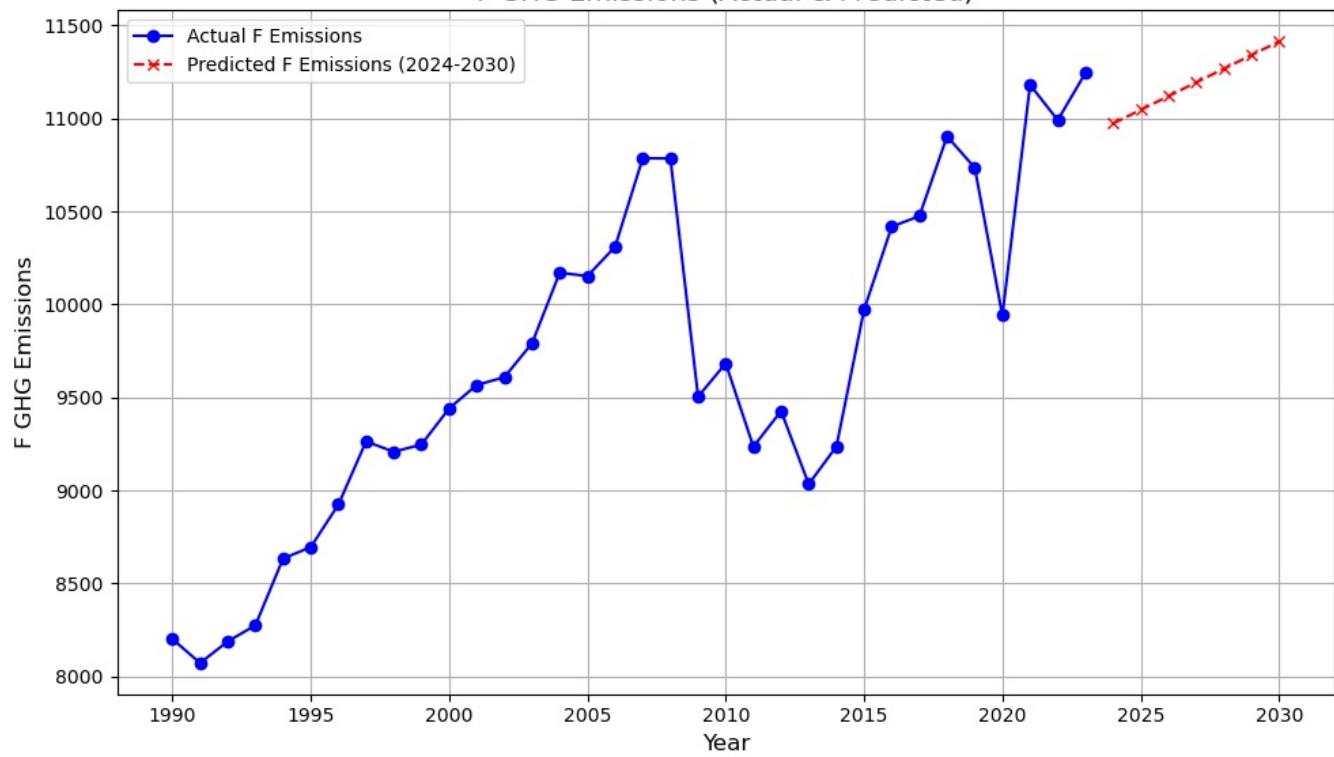
E GHG Emissions (Actual & Predicted)



Predicted E GHG Emissions for 2024-2030:

2024: 13780.29  
 2025: 11655.65  
 2026: 9531.01  
 2027: 7406.37  
 2028: 5281.73  
 2029: 3157.08  
 2030: 1032.44

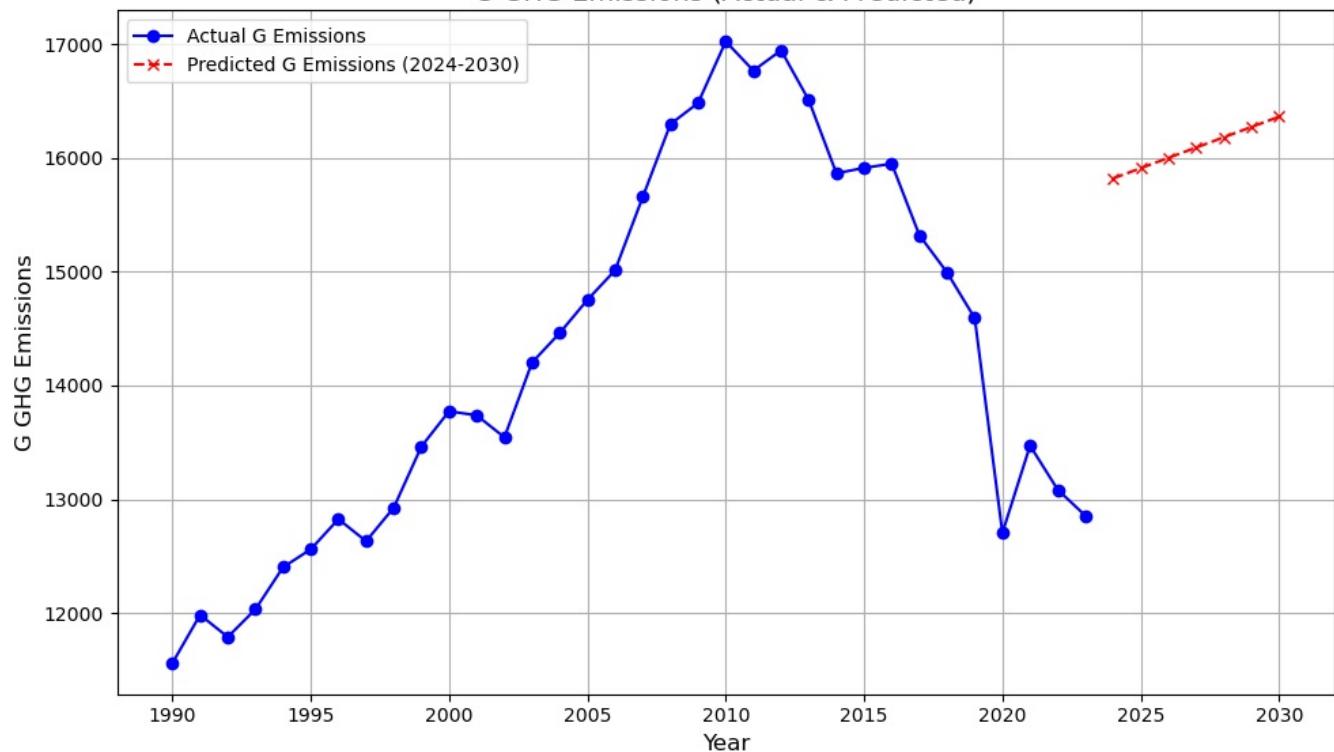
F GHG Emissions (Actual & Predicted)



Predicted F GHG Emissions for 2024-2030:

2024: 10972.22  
 2025: 11045.76  
 2026: 11119.31  
 2027: 11192.86  
 2028: 11266.41  
 2029: 11339.96  
 2030: 11413.50

G GHG Emissions (Actual & Predicted)



Predicted G GHG Emissions for 2024-2030:

2024: 15820.22

2025: 15910.62

2026: 16001.01

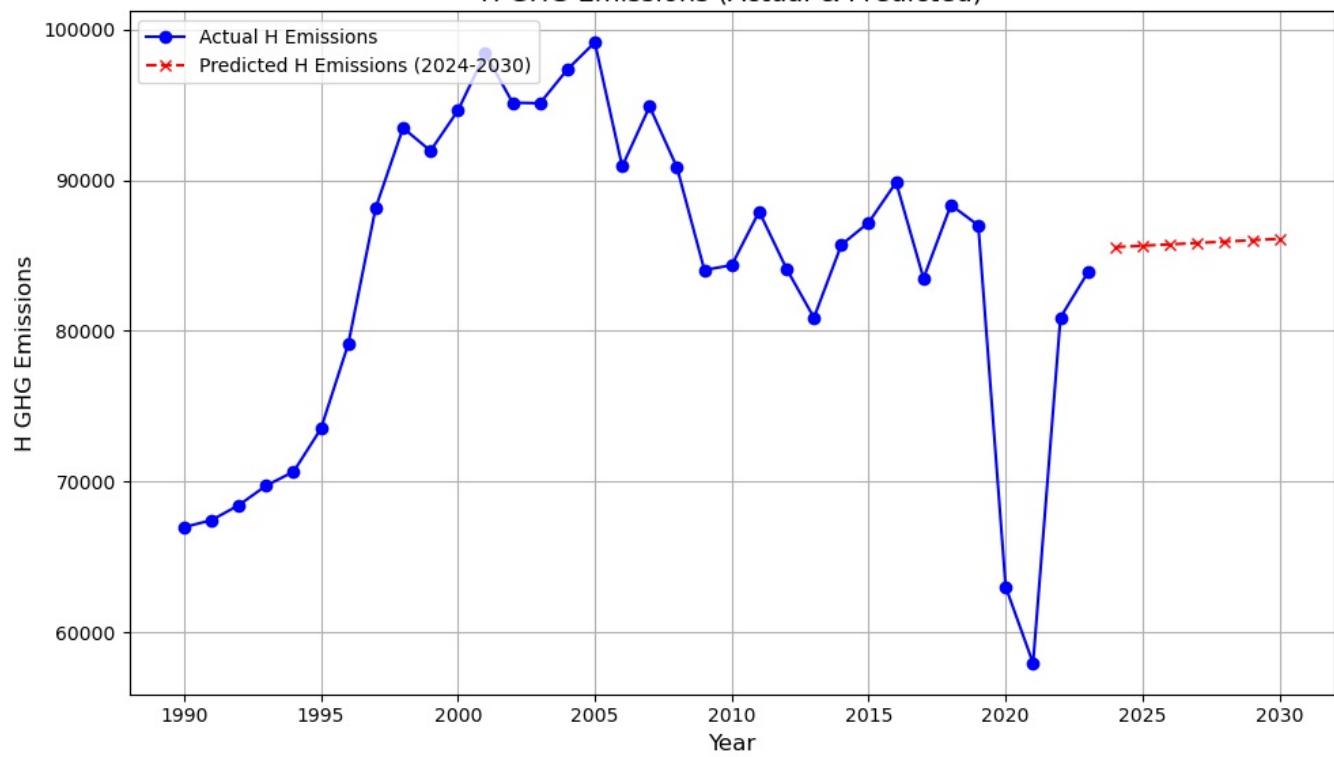
2027: 16091.41

2028: 16181.80

2029: 16272.20

2030: 16362.59

H GHG Emissions (Actual & Predicted)



Predicted H GHG Emissions for 2024-2030:

2024: 85557.14

2025: 85648.70

2026: 85740.27

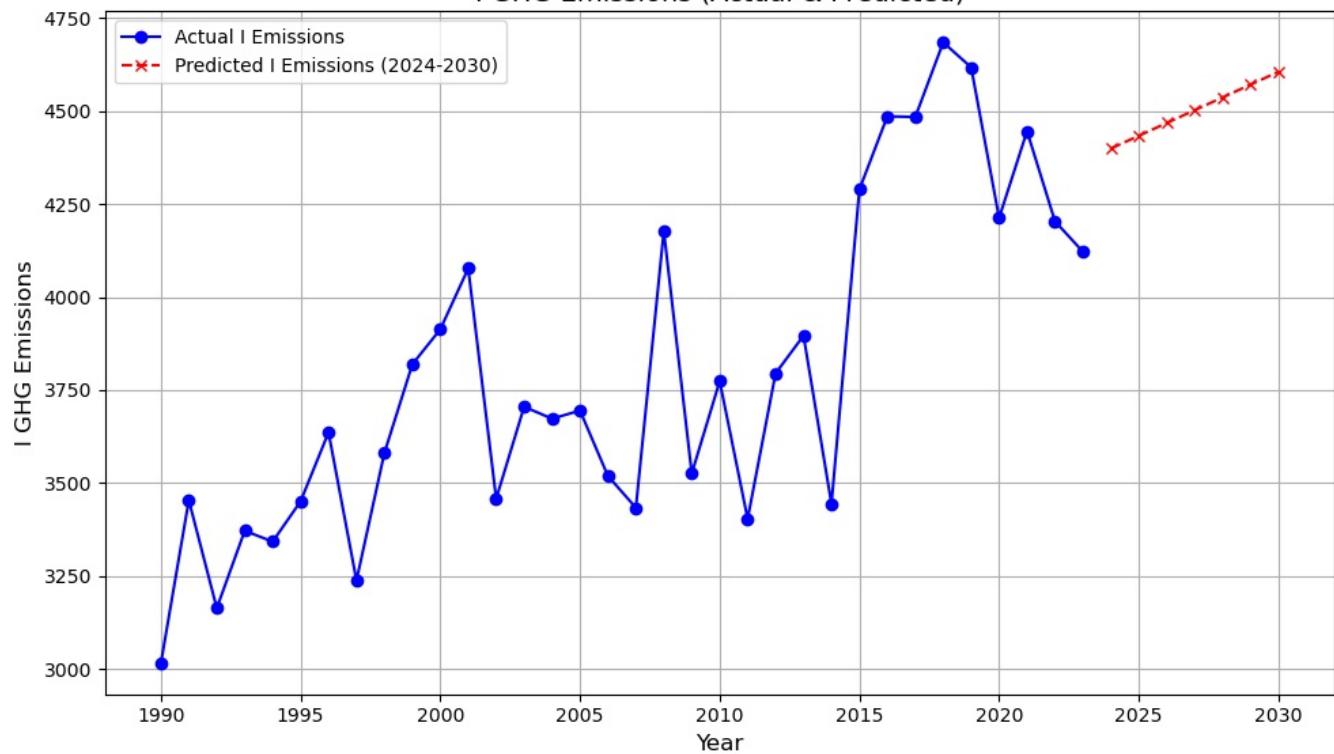
2027: 85831.83

2028: 85923.39

2029: 86014.95

2030: 86106.51

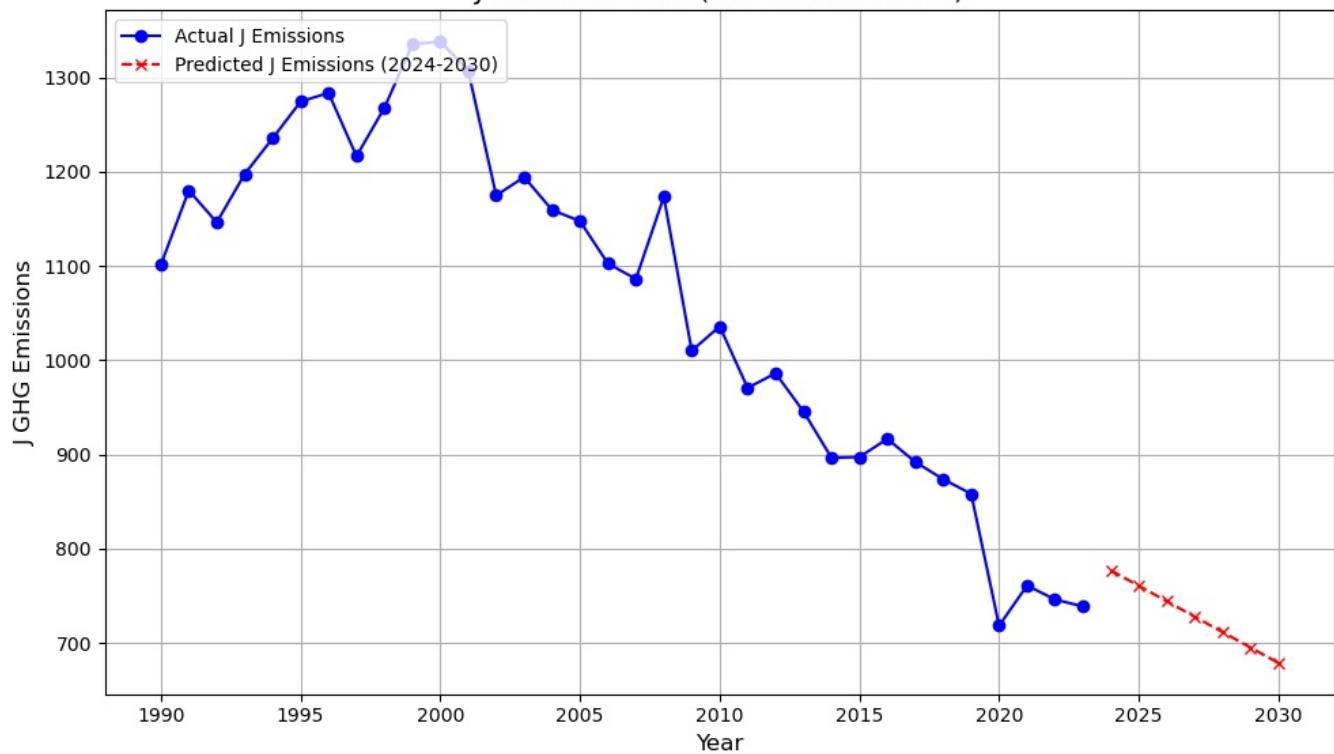
I GHG Emissions (Actual & Predicted)



Predicted I GHG Emissions for 2024-2030:

2024: 4399.63  
 2025: 4434.04  
 2026: 4468.46  
 2027: 4502.88  
 2028: 4537.29  
 2029: 4571.71  
 2030: 4606.13

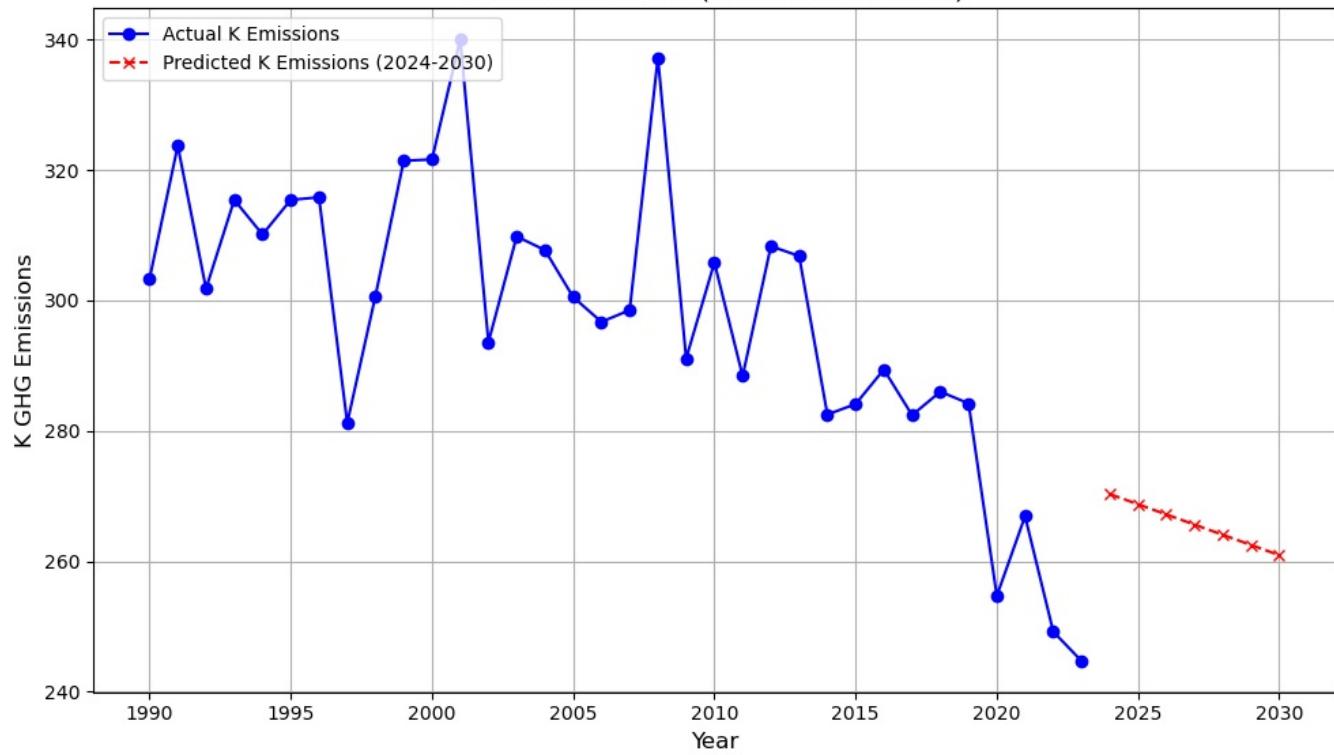
J GHG Emissions (Actual & Predicted)



Predicted J GHG Emissions for 2024-2030:

2024: 776.98  
 2025: 760.60  
 2026: 744.21  
 2027: 727.82  
 2028: 711.44  
 2029: 695.05  
 2030: 678.66

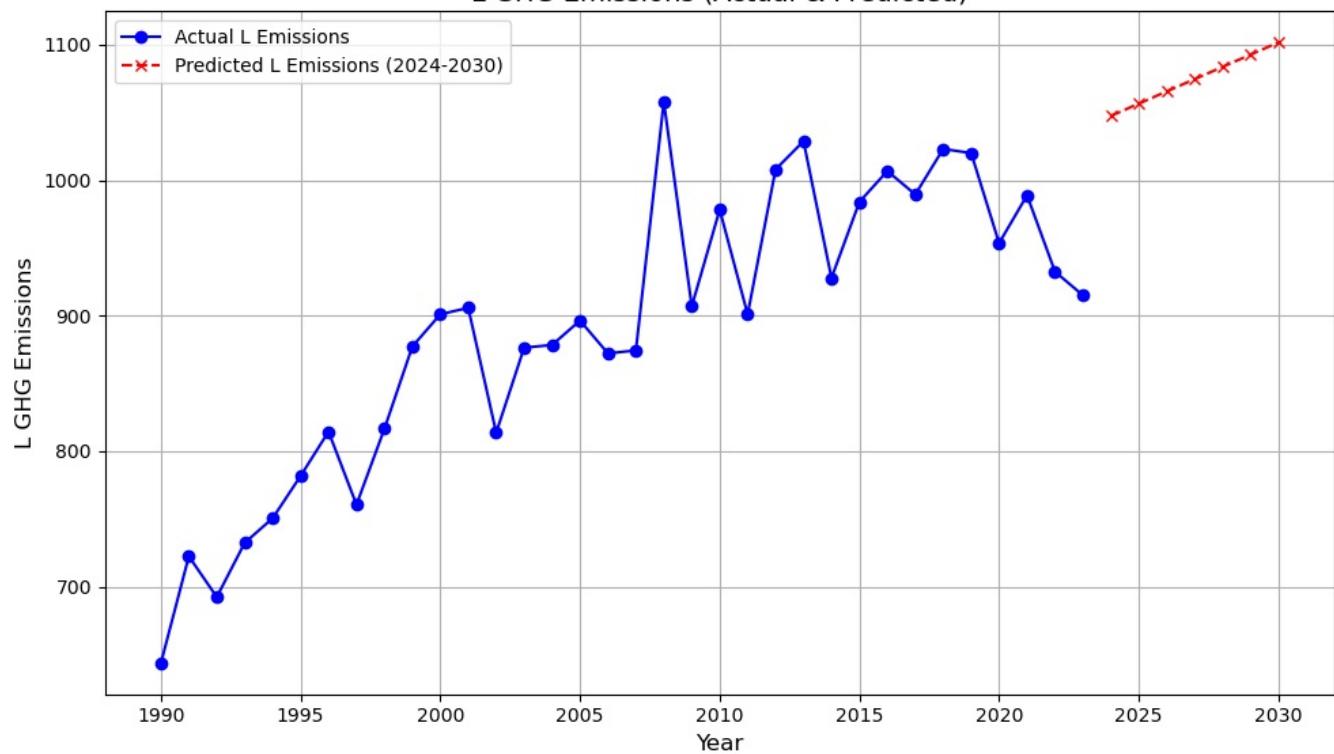
K GHG Emissions (Actual & Predicted)



Predicted K GHG Emissions for 2024-2030:

2024: 270.30  
 2025: 268.74  
 2026: 267.18  
 2027: 265.62  
 2028: 264.05  
 2029: 262.49  
 2030: 260.93

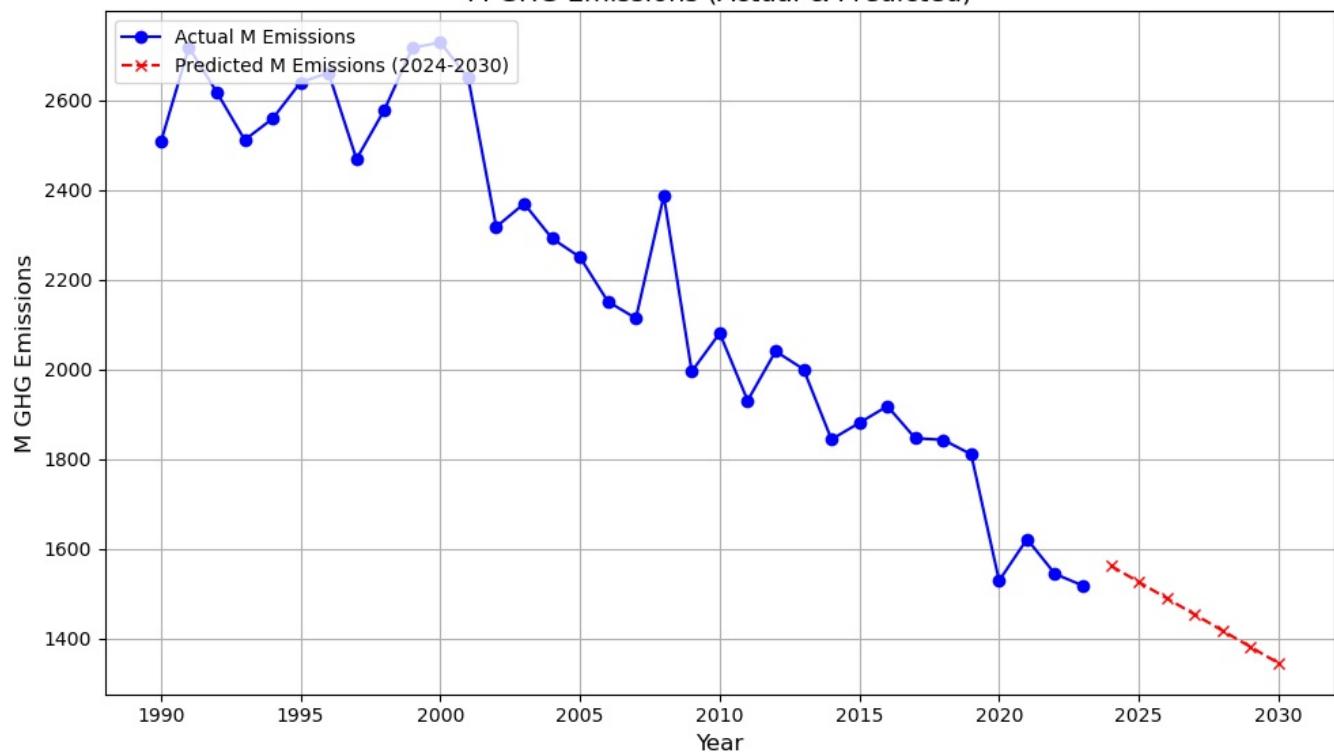
L GHG Emissions (Actual & Predicted)



Predicted L GHG Emissions for 2024-2030:

2024: 1047.36  
 2025: 1056.40  
 2026: 1065.44  
 2027: 1074.48  
 2028: 1083.52  
 2029: 1092.56  
 2030: 1101.60

M GHG Emissions (Actual & Predicted)



Predicted M GHG Emissions for 2024-2030:

2024: 1561.75

2025: 1525.56

2026: 1489.37

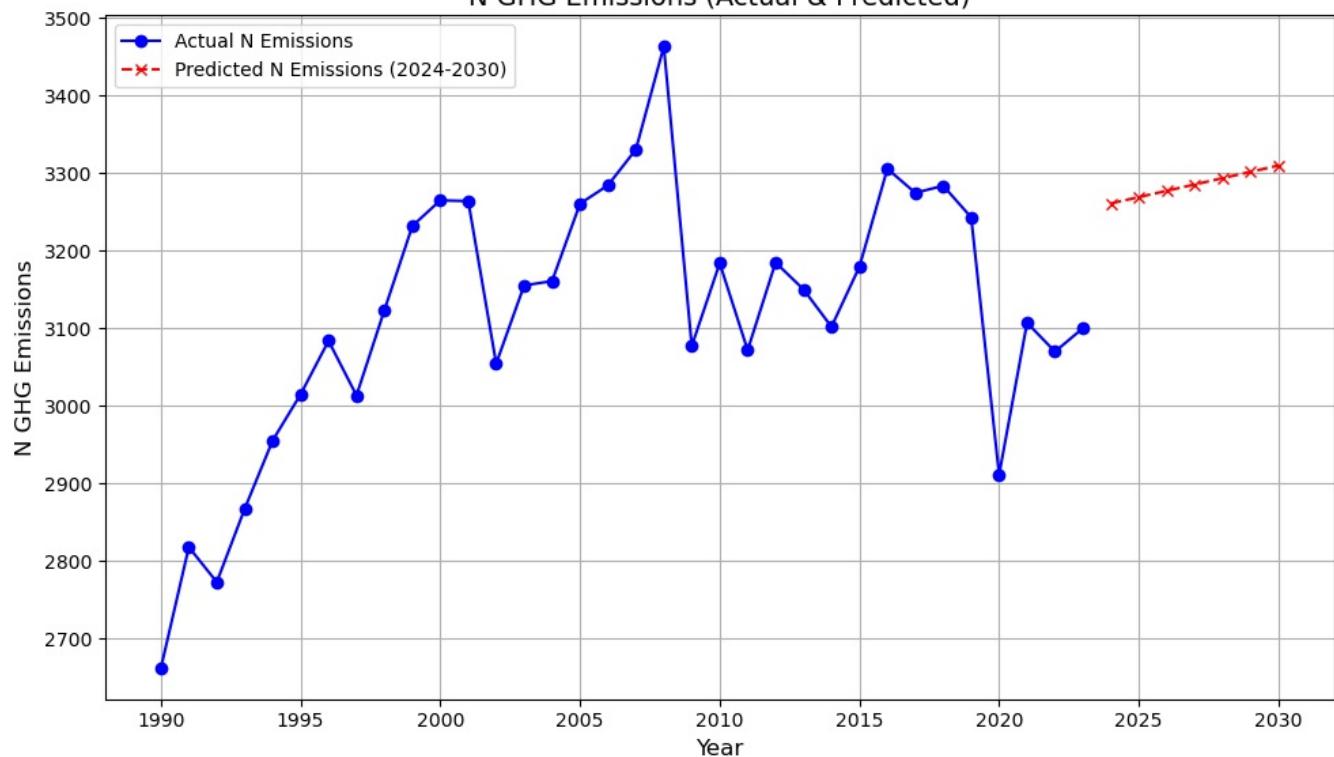
2027: 1453.18

2028: 1416.99

2029: 1380.80

2030: 1344.61

N GHG Emissions (Actual & Predicted)



Predicted N GHG Emissions for 2024-2030:

2024: 3261.24

2025: 3269.38

2026: 3277.53

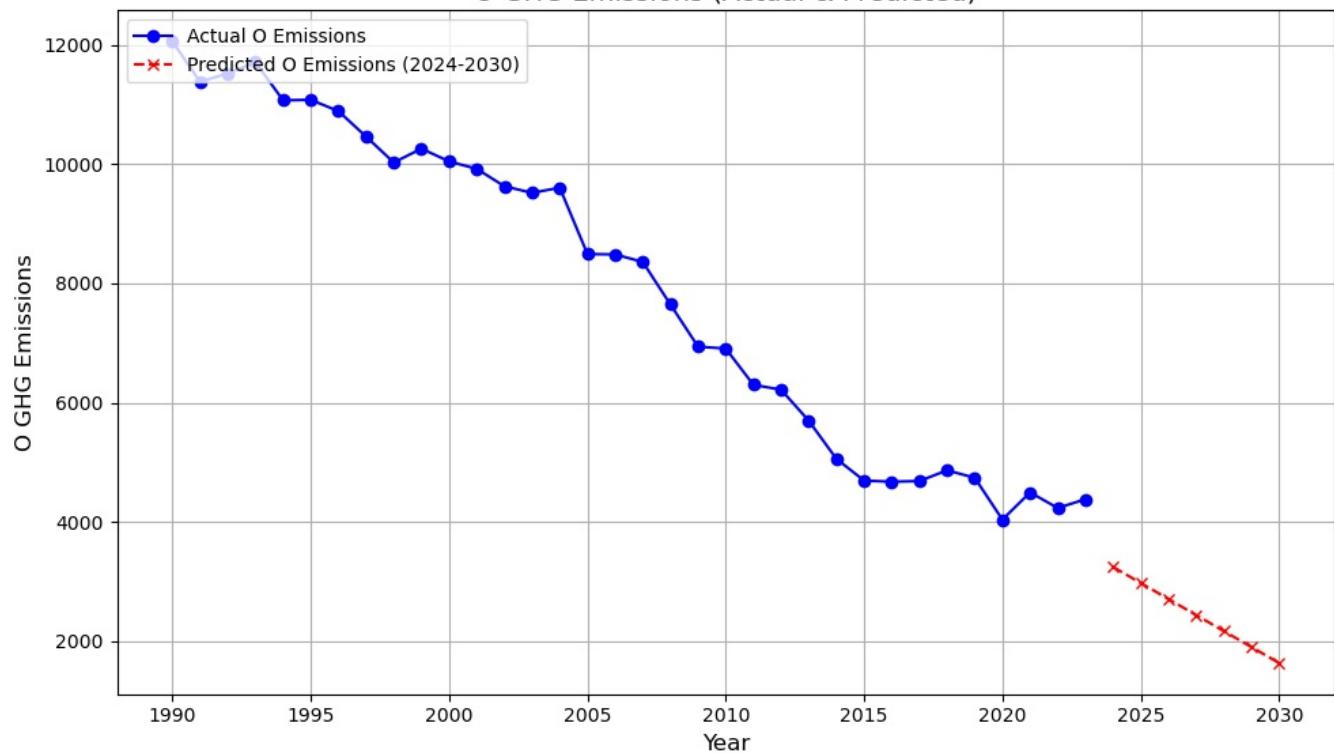
2027: 3285.67

2028: 3293.82

2029: 3301.96

2030: 3310.11

O GHG Emissions (Actual & Predicted)



Predicted 0 GHG Emissions for 2024-2030:

2024: 3244.08

2025: 2975.52

2026: 2706.96

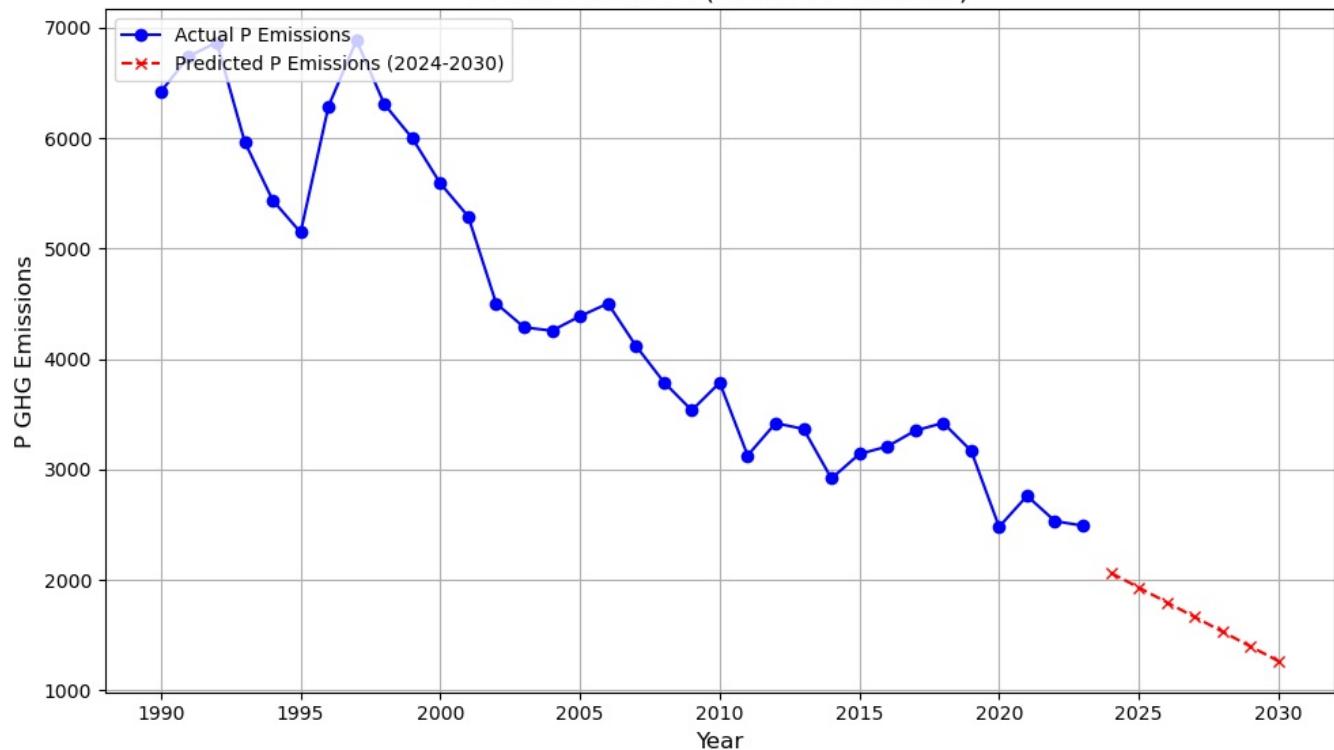
2027: 2438.39

2028: 2169.83

2029: 1901.26

2030: 1632.70

P GHG Emissions (Actual & Predicted)



Predicted P GHG Emissions for 2024-2030:

2024: 2063.89

2025: 1930.58

2026: 1797.26

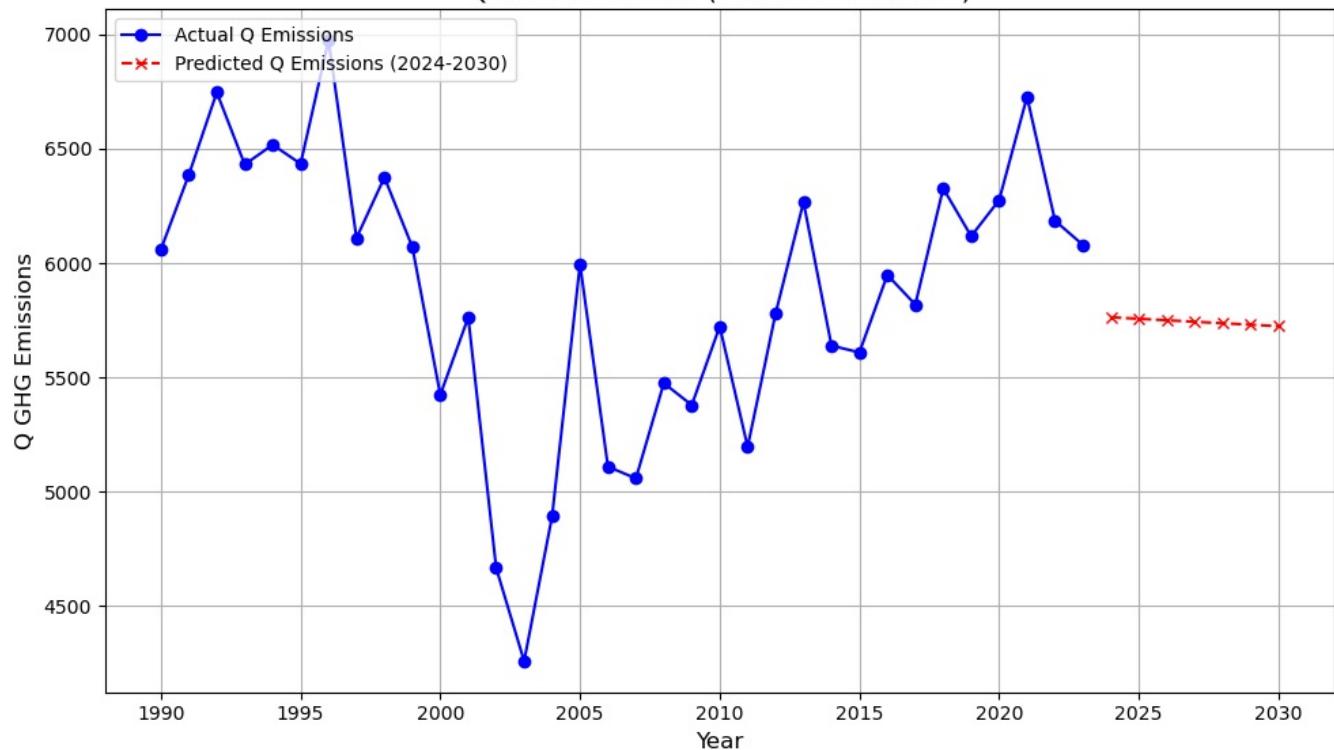
2027: 1663.94

2028: 1530.63

2029: 1397.31

2030: 1264.00

Q GHG Emissions (Actual & Predicted)



Predicted Q GHG Emissions for 2024-2030:

2024: 5762.97

2025: 5756.46

2026: 5749.94

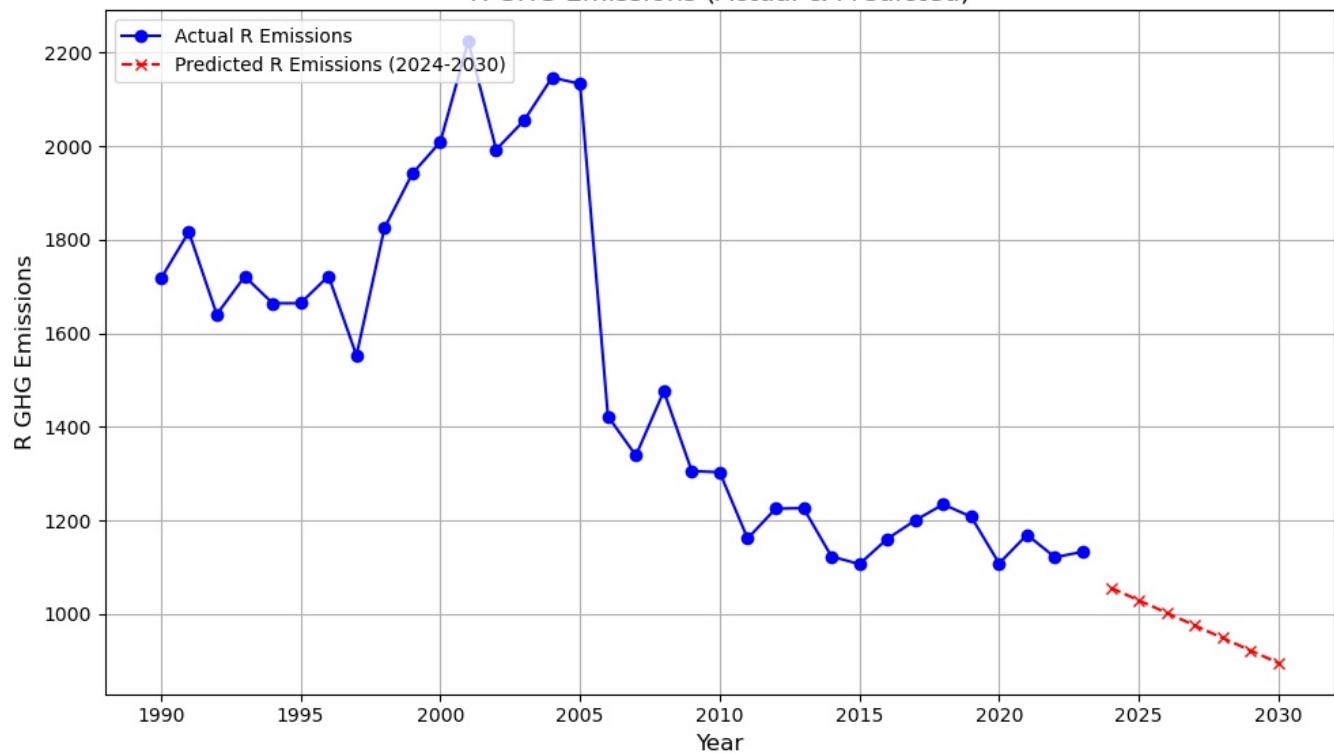
2027: 5743.42

2028: 5736.91

2029: 5730.39

2030: 5723.87

R GHG Emissions (Actual & Predicted)



Predicted R GHG Emissions for 2024-2030:

2024: 1056.09

2025: 1029.30

2026: 1002.51

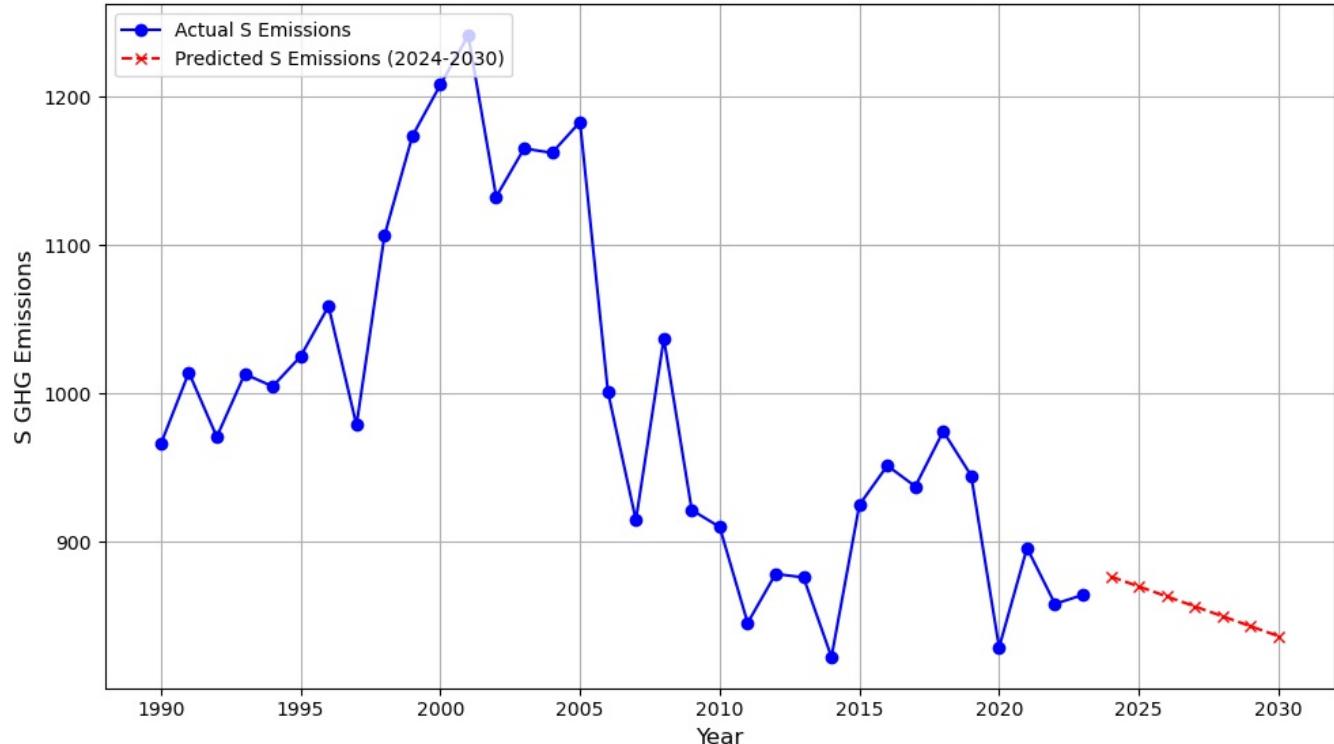
2027: 975.71

2028: 948.92

2029: 922.12

2030: 895.33

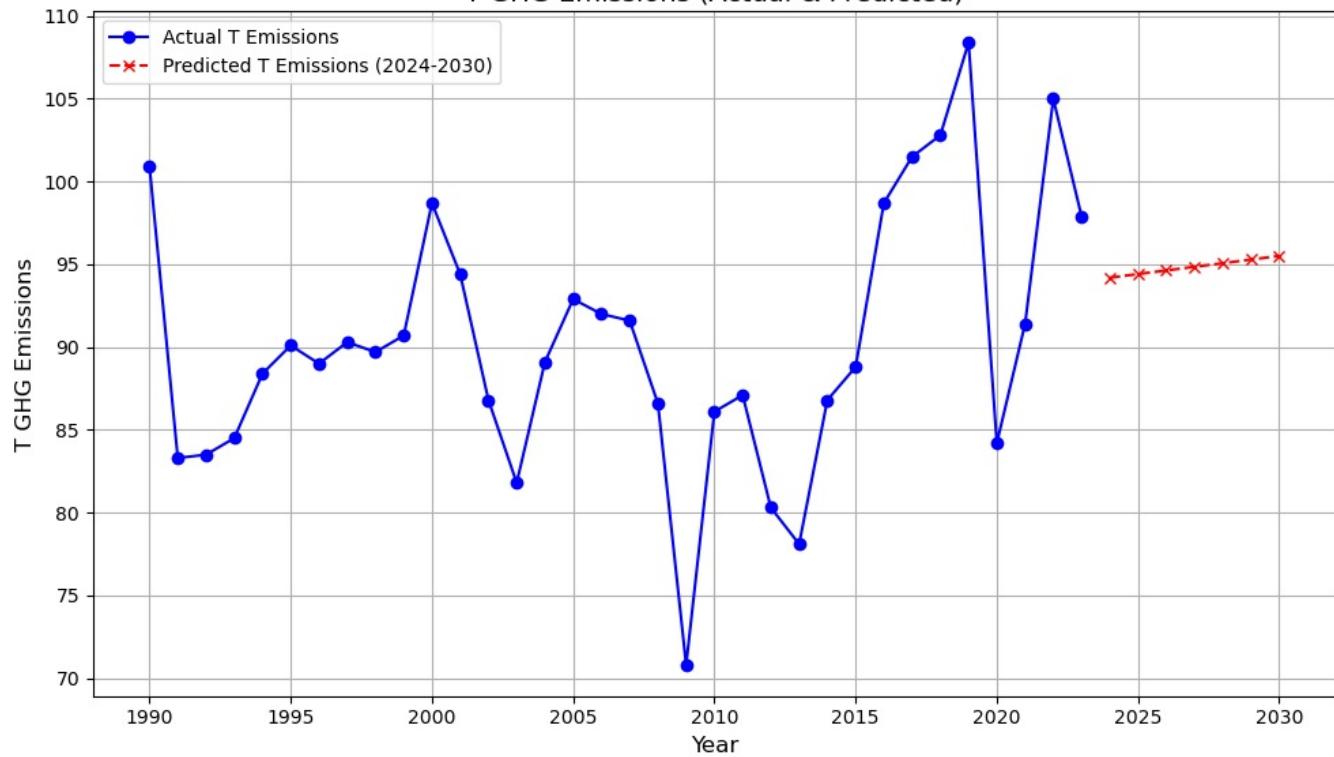
S GHG Emissions (Actual & Predicted)



Predicted S GHG Emissions for 2024-2030:

2024: 876.55  
 2025: 869.85  
 2026: 863.16  
 2027: 856.46  
 2028: 849.76  
 2029: 843.07  
 2030: 836.37

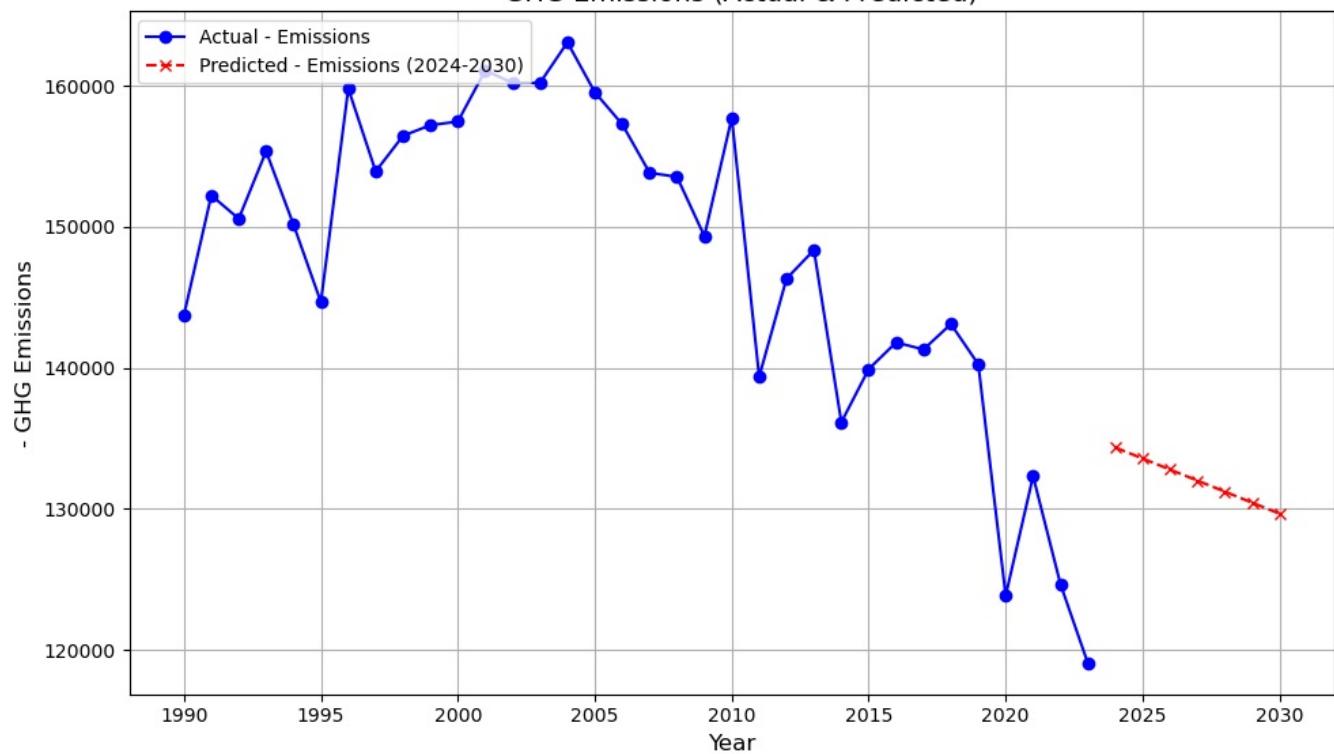
T GHG Emissions (Actual & Predicted)



Predicted T GHG Emissions for 2024-2030:

2024: 94.19  
 2025: 94.41  
 2026: 94.63  
 2027: 94.85  
 2028: 95.07  
 2029: 95.29  
 2030: 95.51

- GHG Emissions (Actual & Predicted)



Predicted - GHG Emissions for 2024-2030:

2024: 134356.72

2025: 133574.17

2026: 132791.63

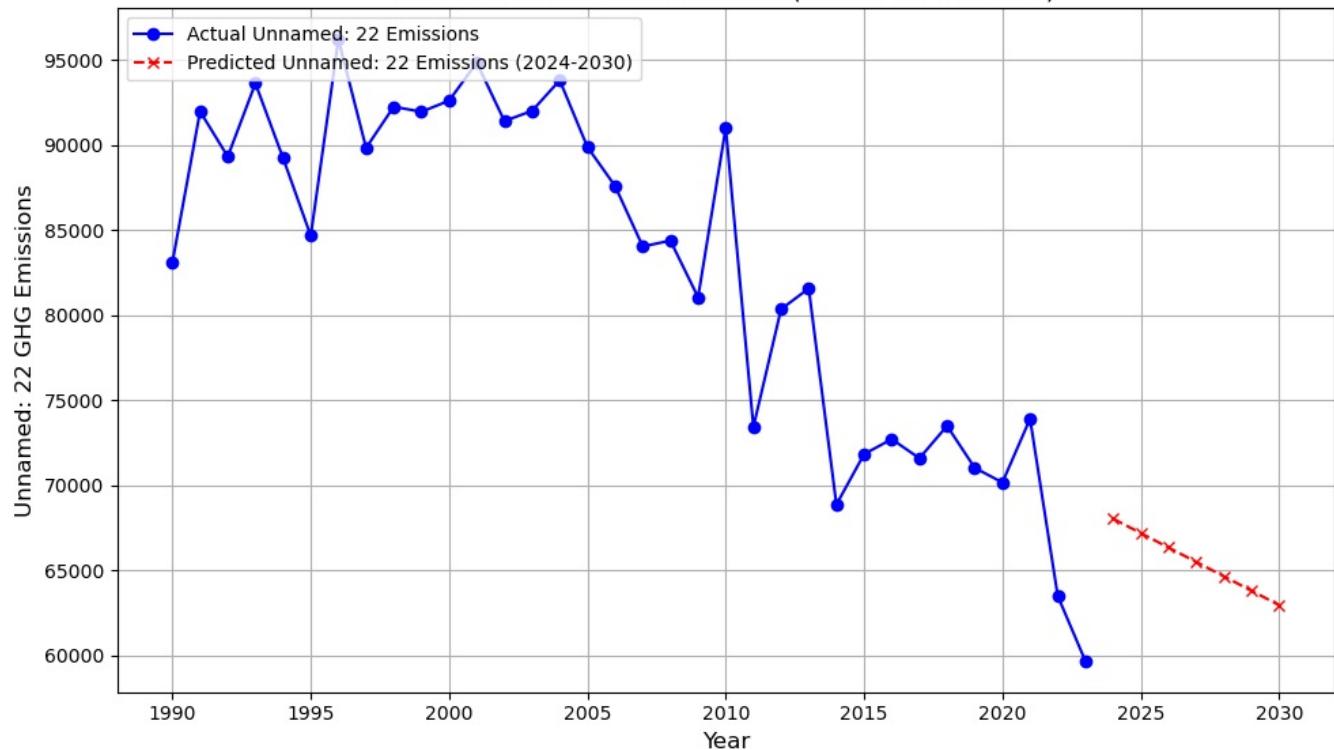
2027: 132009.08

2028: 131226.53

2029: 130443.99

2030: 129661.44

Unnamed: 22 GHG Emissions (Actual & Predicted)



Predicted Unnamed: 22 GHG Emissions for 2024-2030:

2024: 68032.63

2025: 67185.61

2026: 66338.59

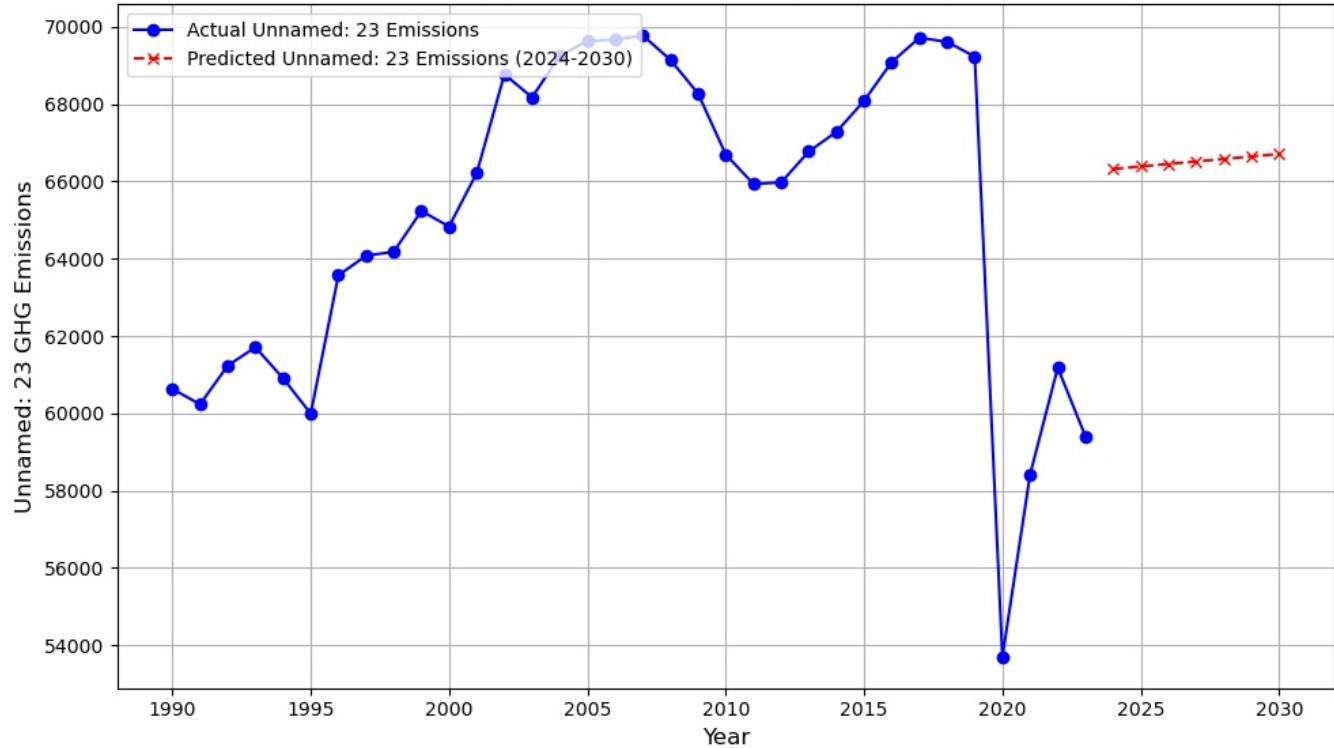
2027: 65491.57

2028: 64644.55

2029: 63797.53

2030: 62950.51

Unnamed: 23 GHG Emissions (Actual & Predicted)



Predicted Unnamed: 23 GHG Emissions for 2024-2030:

2024: 66324.13  
2025: 66388.61  
2026: 66453.08  
2027: 66517.56  
2028: 66582.04  
  
2029: 66646.51  
2030: 66710.99

In [ ]:

In [43]:

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#References
#[1]www.ons.gov.uk. (n.d.). Atmospheric emissions: greenhouse gases by industry and gas - Office for National Statistics.
#[2]Suma Katabattuni (2024). Simple pandas read_csv tricks to boost speed up to 250x. [online] Medium. Available at: https://medium.com/@sumakatabattuni/simple-pandas-read-csv-tricks-to-boost-speed-up-to-250x-2e0a2a2a2a2a
#[3]Naveen Nelamali (2022). Pandas iloc[] Usage with Examples. [online] Spark By Examples. Available at: http://sparkbyexamples.com/pandas/pandas-iloc-usage-with-examples/
#[4]Mondal, R. (2024). Z-Score to identify and remove outliers | Exploratory Data Analysis. [online] Medium. Available at: https://medium.com/@ratanmondal/z-score-to-identify-and-remove-outliers-exploratory-data-analysis-5a2a2a2a2a2a
#[5]freshhotdata (2023). Predicting Greenhouse Gas Emissions with Machine Learning. [online] Medium. Available at: https://medium.com/@freshhotdata/predicting-greenhouse-gas-emissions-with-machine-learning-5a2a2a2a2a2a
#[6]Muz (2016). I get a linear regression using the SVR by python scikit-learn when the data is not linear. [online] Medium. Available at: https://medium.com/@muz/linear-regression-with-svr-in-python-scikit-learn-when-the-data-is-not-linear-5a2a2a2a2a2a
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