```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr
from scipy.stats import ttest_ind
import statsmodels.api as sm
```

```
#load data set
df_co2 = pd.read_csv('/content/carbon_emmission.csv')
df_co2
```

	ObjectId	Country	Date	Value
0	1	World	1958M03	315.70
1	2	World	1958M04	317.45
2	3	World	1958M05	317.51
3	4	World	1958M06	317.24
4	5	World	1958M07	315.86
...	...	...	...	...
1565	1566	World	2023M11	0.72
1566	1567	World	2023M12	421.86
1567	1568	World	2023M12	0.68
1568	1569	World	2024M01	0.68
1569	1570	World	2024M01	0.68

1570 rows × 4 columns

Next steps: View recommended plots New interactive sheet

```
df_co2.isnull().sum()
```

	0
ObjectId	0
Country	0
Date	0
Value	0

dtype: int64

```
df_temp = pd.read_csv('/content/temperature.csv')
df_temp
```

	ObjectId	Country	ISO2	ISO3	F1961	F1962	F1963	F1964	F1965	F1966	...	F2013	F2014	F2015	F2016	F2017	F2018	F2019	F20
0	1	Afghanistan, Islamic Rep. of	AF	AFG	-0.113	-0.164	0.847	-0.764	-0.244	0.226	...	1.281	0.456	1.093	1.555	1.540	1.544	0.910	0.4
1	2	Albania	AL	ALB	0.627	0.326	0.075	-0.166	-0.388	0.559	...	1.333	1.198	1.569	1.464	1.121	2.028	1.675	1.4
2	3	Algeria	DZ	DZA	0.164	0.114	0.077	0.250	-0.100	0.433	...	1.192	1.690	1.121	1.757	1.512	1.210	1.115	1.9
3	4	American Samoa	AS	ASM	0.079	-0.042	0.169	-0.140	-0.562	0.181	...	1.257	1.170	1.009	1.539	1.435	1.189	1.539	1.4
4	5	Andorra, Principality of	AD	AND	0.736	0.112	-0.752	0.308	-0.490	0.415	...	0.831	1.946	1.690	1.990	1.925	1.919	1.964	2.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
220	221	Western Sahara	EH	ESH	0.632	0.576	0.333	0.819	-0.337	0.284	...	1.423	1.401	1.510	1.732	2.204	0.942	1.477	2.0
221	222	World	NaN	WLD	0.211	0.038	0.168	-0.246	-0.223	0.201	...	1.016	1.053	1.412	1.660	1.429	1.290	1.444	1.7
		Yemen, Rep.																	

```
df_temp.isnull().sum()
```

	0
ObjectId	0
Country	0
ISO2	2
ISO3	0
F1961	37
...	...
F2018	12
F2019	12
F2020	13
F2021	12
F2022	12

66 rows × 1 columns

dtype: int64

```
#check info
df_co2.describe().T
```

	count	mean	std	min	25%	50%	75%	max
ObjectId	1570.0	785.500000	453.364276	1.0	393.25	785.500	1177.7500	1570.0
Value	1570.0	180.716153	180.554706	-0.1	0.45	313.835	355.0725	424.0

```
df_temp.describe().T
```

	count	mean	std	min	25%	50%	75%	max
ObjectId	225.0	113.000000	65.096083	1.000	57.00000	113.0000	169.00000	225.000
F1961	188.0	0.163053	0.405080	-0.694	-0.09700	0.0645	0.31850	1.892
F1962	189.0	-0.013476	0.341812	-0.908	-0.16400	-0.0560	0.11400	0.998
F1963	188.0	-0.006043	0.387348	-1.270	-0.20550	-0.0030	0.23050	1.202
F1964	188.0	-0.070059	0.309305	-0.877	-0.23650	-0.0560	0.13250	1.097
...	...	...	...	...	...	...	...	...
F2018	213.0	1.302113	0.596786	0.238	0.86500	1.1250	1.83400	2.772
F2019	213.0	1.443061	0.467510	0.050	1.16900	1.4120	1.69800	2.689
F2020	212.0	1.552038	0.621930	0.229	1.16175	1.4770	1.82625	3.691
F2021	213.0	1.343531	0.484692	-0.425	1.01900	1.3270	1.62900	2.676
F2022	213.0	1.382113	0.669279	-1.305	0.87800	1.3150	1.91800	3.243

63 rows × 8 columns

Clean data

```
# Melt the dataframe from wide to long
df_temp_melted = df_temp.melt(
    id_vars=['Country', 'ISO2', 'ISO3'],
    value_vars=[col for col in df_temp.columns if col.startswith('F')],
    var_name='Year',
    value_name='Temperature'
)
```

```
df_temp_melted
```

	Country	ISO2	ISO3	Year	Temperature
0	Afghanistan, Islamic Rep. of	AF	AFG	F1961	-0.113
1	Albania	AL	ALB	F1961	0.627
2	Algeria	DZ	DZA	F1961	0.164
3	American Samoa	AS	ASM	F1961	0.079
4	Andorra, Principality of	AD	AND	F1961	0.736
...	...	...	...	...	...
13945	Western Sahara	EH	ESH	F2022	1.970
13946	World	NaN	WLD	F2022	1.394
13947	Yemen, Rep. of	YE	YEM	F2022	NaN
13948	Zambia	ZM	ZMB	F2022	0.686
13949	Zimbabwe	ZW	ZWE	F2022	-0.490

13950 rows × 5 columns

```
# Remove 'F' from Year and convert to integer
df_temp_melted['Year'] = df_temp_melted['Year'].str.replace('F', '').astype(int)
```

```
#check df_temp
df_temp_melted
```

	Country	ISO2	ISO3	Year	Temperature
0	Afghanistan, Islamic Rep. of	AF	AFG	1961	-0.113
1	Albania	AL	ALB	1961	0.627
2	Algeria	DZ	DZA	1961	0.164
3	American Samoa	AS	ASM	1961	0.079
4	Andorra, Principality of	AD	AND	1961	0.736
...	...	...	...	...	...
13945	Western Sahara	EH	ESH	2022	1.970
13946	World	NaN	WLD	2022	1.394
13947	Yemen, Rep. of	YE	YEM	2022	NaN
13948	Zambia	ZM	ZMB	2022	0.686
13949	Zimbabwe	ZW	ZWE	2022	-0.490

13950 rows × 5 columns

```
#we have remove F from Year
```

```
# Filter only 'World' for global trend
df_temp_world = df_temp_melted[df_temp_melted['Country'] == 'World'].copy()
```

```
df_co2
```

	ObjectId	Country	Date	Value
0	1	World	1958M03	315.70
1	2	World	1958M04	317.45
2	3	World	1958M05	317.51
3	4	World	1958M06	317.24
4	5	World	1958M07	315.86
...	...	...	...	...
1565	1566	World	2023M11	0.72
1566	1567	World	2023M12	421.86
1567	1568	World	2023M12	0.68
1568	1569	World	2024M01	0.68
1569	1570	World	2024M01	0.68

1570 rows × 4 columns

```
#Clean & Transform df_co2
# Convert 'Date' to datetime format (YYYY-MM)
df_co2['Date'] = pd.to_datetime(df_co2['Date'].str.replace('M', '-'), format='%Y-%m')
```

```
df_co2
```

	ObjectId	Country	Date	Value
0	1	World	1958-03-01	315.70
1	2	World	1958-04-01	317.45
2	3	World	1958-05-01	317.51
3	4	World	1958-06-01	317.24
4	5	World	1958-07-01	315.86
...	...	...	...	...
1565	1566	World	2023-11-01	0.72
1566	1567	World	2023-12-01	421.86
1567	1568	World	2023-12-01	0.68
1568	1569	World	2024-01-01	0.68
1569	1570	World	2024-01-01	0.68

1570 rows × 4 columns

```
# Extract year
df_co2['Year'] = df_co2['Date'].dt.year
```

```
# Group by year and calculate average CO2 (ppm)
df_co2_yearly = df_co2.groupby('Year')['Value'].mean().reset_index()
df_co2_yearly.rename(columns={'Value': 'Avg_CO2_ppm'}, inplace=True)
```

```
df_temp_melted
```

	Country	ISO2	ISO3	Year	Temperature
0	Afghanistan, Islamic Rep. of	AF	AFG	1961	-0.113
1	Albania	AL	ALB	1961	0.627
2	Algeria	DZ	DZA	1961	0.164
3	American Samoa	AS	ASM	1961	0.079
4	Andorra, Principality of	AD	AND	1961	0.736
...	...	...	...	...	...
13945	Western Sahara	EH	ESH	2022	1.970
13946	World	NaN	WLD	2022	1.394
13947	Yemen, Rep. of	YE	YEM	2022	NaN
13948	Zambia	ZM	ZMB	2022	0.686
13949	Zimbabwe	ZW	ZWE	2022	-0.490

13950 rows × 5 columns

```
df_temp_melted.isnull().sum()
```

	0
Country	0
ISO2	124
ISO3	0
Year	0
Temperature	1490

dtype: int64

```
df_temp_melted.drop(columns=['ISO2'], inplace=True)
```

```
df_temp_melted['Temperature'] = df_temp_melted.groupby('Country')['Temperature'].transform(lambda x: x.fillna(x.mean()))
```

```
df_temp_melted.isnull().sum()
```

	0
Country	0
ISO3	0
Year	0
Temperature	0

dtype: int64

```
df_temp_world
```

	Country	ISO2	ISO3	Year	Temperature
221	World	NaN	WLD	1961	0.211
446	World	NaN	WLD	1962	0.038
671	World	NaN	WLD	1963	0.168
896	World	NaN	WLD	1964	-0.246
1121	World	NaN	WLD	1965	-0.223
...	...	...	...	...	...
13046	World	NaN	WLD	2018	1.290
13271	World	NaN	WLD	2019	1.444
13496	World	NaN	WLD	2020	1.711
13721	World	NaN	WLD	2021	1.447
13946	World	NaN	WLD	2022	1.394

62 rows × 5 columns

```
df_temp_world.drop(columns=['ISO2','ISO3'], inplace=True)
```

```
df_co2_yearly
```

	Year	Avg_CO2_ppm
0	1958	315.232000
1	1959	172.460455
2	1960	158.601667
3	1961	158.938333
4	1962	159.355000
...	...	...
62	2020	207.416667
63	2021	208.472083
64	2022	209.518333
65	2023	210.844167
66	2024	0.680000

67 rows × 2 columns

```
#cehck for null in df_co2_yearly
df_co2_yearly.isnull().sum()
```

	0
Year	0
Avg_CO2_ppm	0

dtype: int64

```
#cehck for null in df_temp_world
df_temp_world.isnull().sum()

df_temp_world.columns
```

```
Index(['Country', 'Year', 'Temperature', 'Period'], dtype='object')
```

```
#downlaod df_co2_yearly final data as csv
df_co2_yearly.to_csv('df_co2_yearly.csv', index=False)
df_co2_yearly.columns
```

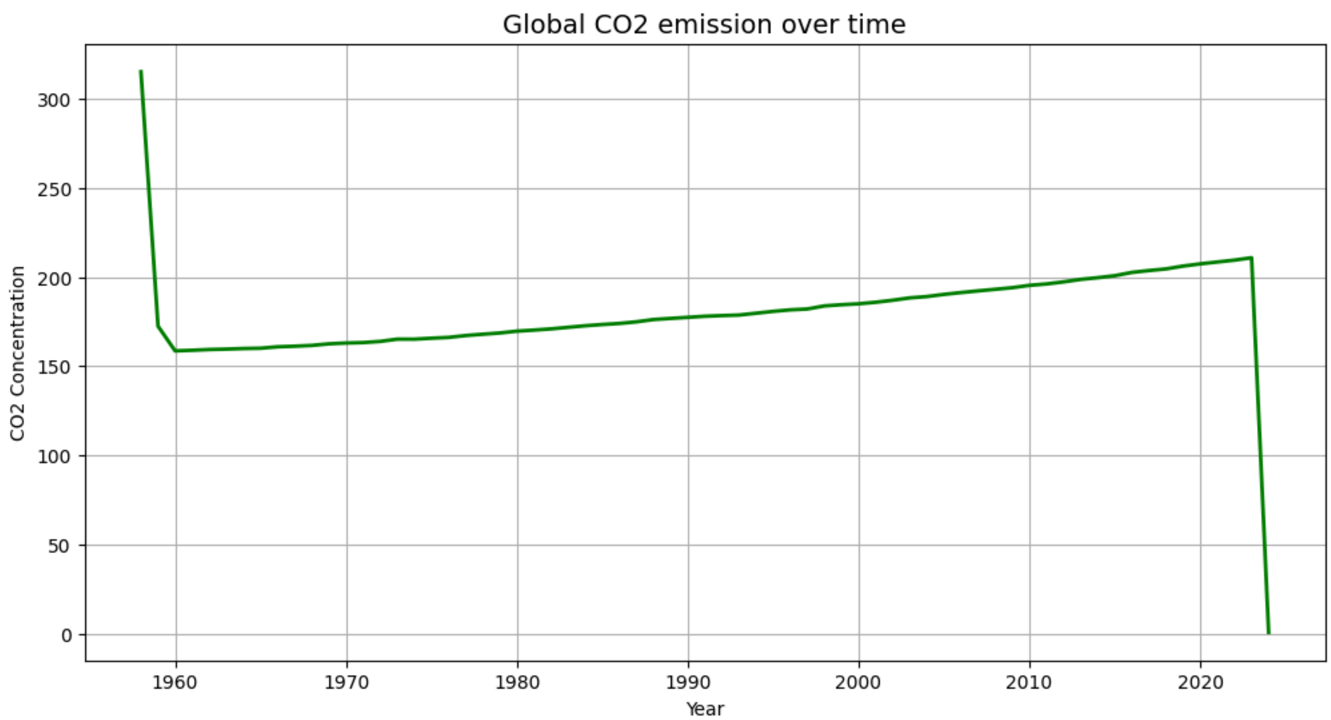
```
Index(['Year', 'Avg_CO2_ppm'], dtype='object')
```

```
#download data as csv
df_temp_melted.to_csv('df_temp_melted.csv', index=False)
df_temp_world.to_csv('df_temp_world.csv', index=False)
```

Exploratory Data Analysis (EDA)

1. Global CO_2 Emission Trend (1958–2023)

```
plt.figure(figsize=(12,6))
sns.lineplot(data=df_co2_yearly, x='Year', y = 'Avg_CO2_ppm', color='green', linewidth=2)
plt.title("Global CO2 emission over time", fontsize=14)
plt.xlabel('Year')
plt.ylabel('CO2 Concentration')
plt.grid(True)
plt.show()
```

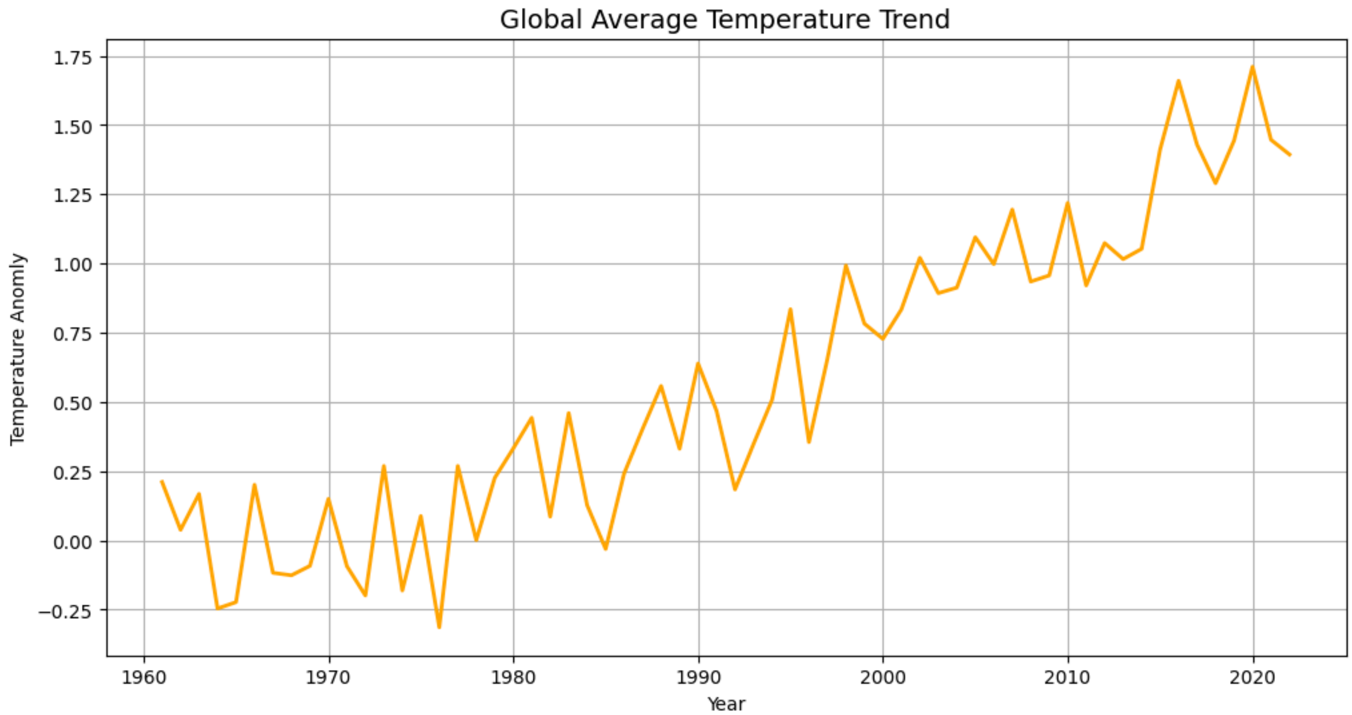


The green line shows that CO_2 levels have gone up steadily from 1960 to 2023. There was a small dip around 2020–2021, likely because of COVID-19 lockdowns, but emissions went back up afterward.

2. Global Temperature Trend (1961–2022)

```
plt.figure(figsize=(12,6))
sns.lineplot(data=df_temp_world, x='Year', y='Temperature', color = 'orange', linewidth=2)
plt.title('Global Average Temperature Trend', fontsize=14)
```

```
plt.xlabel('Year')
plt.ylabel('Temperature Anomly')
plt.grid(True)
plt.show()
```



The orange line shows that the Earth is getting hotter over time. Even though there are ups and downs in some years, the overall trend is clearly rising, especially after the year 2000.

3. Combined CO_2 and Temperature Line Plot (Dual Axis)

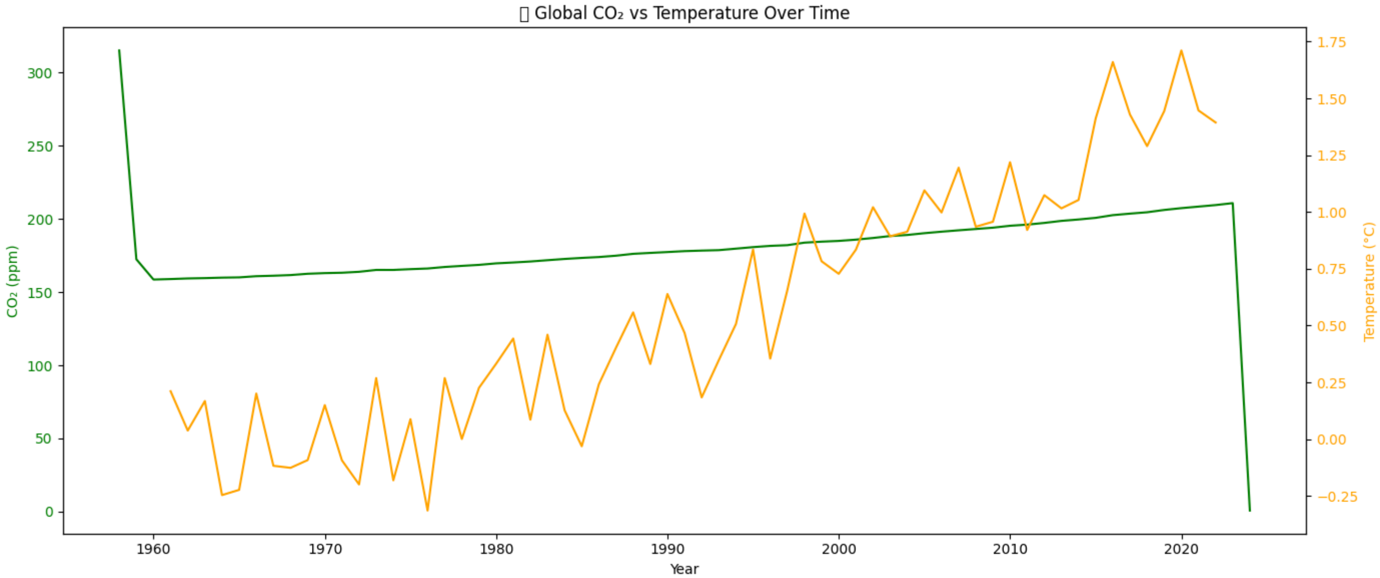
```
fig, ax1 = plt.subplots(figsize=(14, 6))

# CO2
ax1.set_xlabel('Year')
ax1.set_ylabel('CO₂ (ppm)', color='green')
ax1.plot(df_co2_yearly['Year'], df_co2_yearly['Avg_CO2_ppm'], color='green', label='CO₂ (ppm)')
ax1.tick_params(axis='y', labelcolor='green')

# Temperature
ax2 = ax1.twinx()
ax2.set_ylabel('Temperature (°C)', color='orange')
ax2.plot(df_temp_world['Year'], df_temp_world['Temperature'], color='orange', label='Temp (°C)')
ax2.tick_params(axis='y', labelcolor='orange')

plt.title('📈 Global CO₂ vs Temperature Over Time')
fig.tight_layout()
plt.show()
```

```
/tmp/ipython-input-27-1690362908.py:16: UserWarning: Glyph 128200 (\N{CHART WITH UPWARDS TREND}) missing from font(s) DejaVu Sans.
  fig.tight_layout()
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128200 (\N{CHART WITH UPWARDS TREND}) missing
  fig.canvas.print_figure(bytes_io, **kw)
```



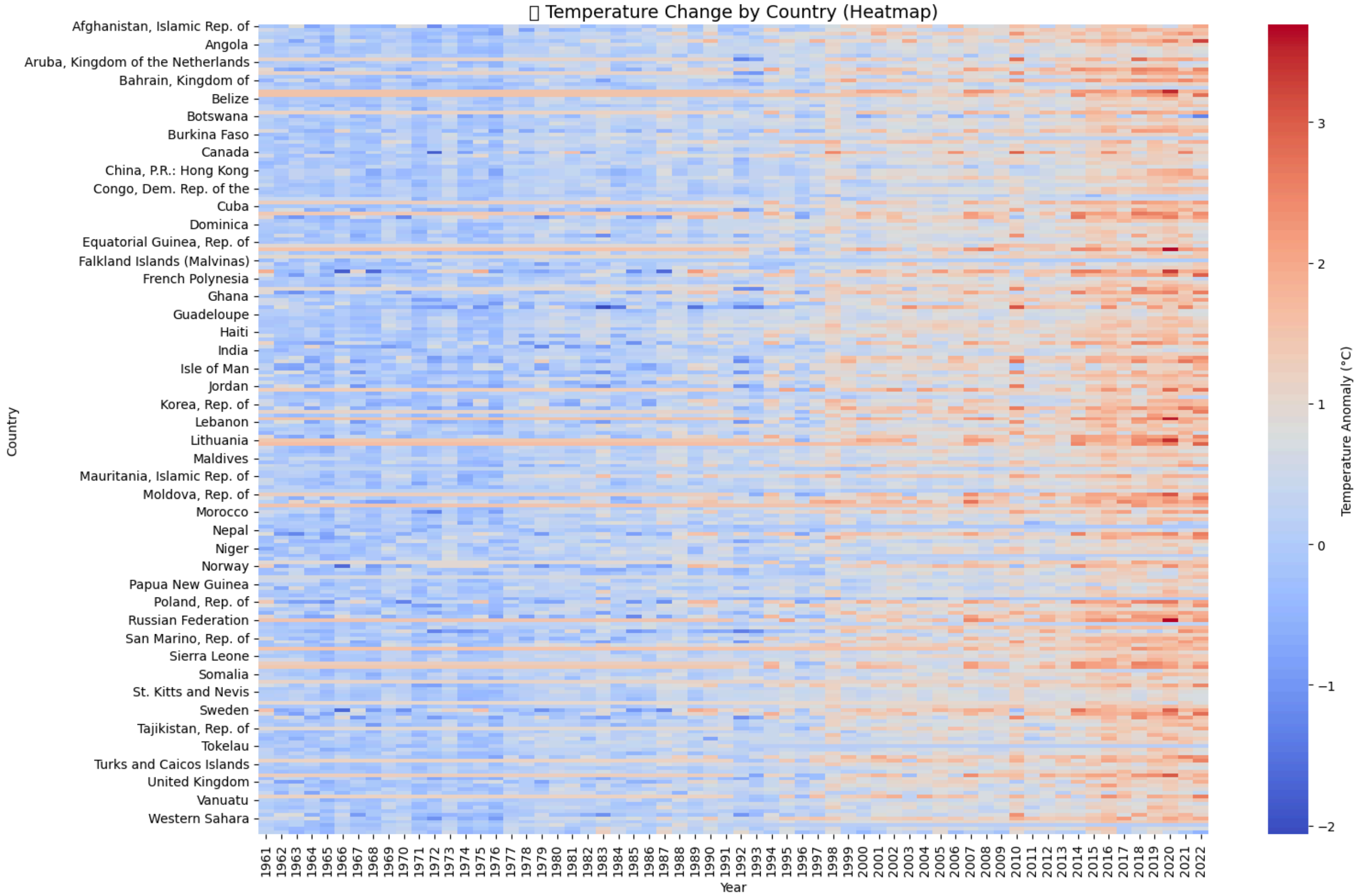
This combined chart shows both CO_2 and temperature rising together. It suggests that when CO_2 increases, the temperature also increases — meaning there may be a connection between them.

4. Heatmap of Temperature Change by Country

```
# Create pivot table for heatmap
temp_heatmap = df_temp_melted.pivot_table(index='Country', columns='Year', values='Temperature')

plt.figure(figsize=(16, 10))
sns.heatmap(temp_heatmap, cmap='coolwarm', cbar_kws={'label': 'Temperature Anomaly (°C)'})
plt.title('🔥 Temperature Change by Country (Heatmap)', fontsize=14)
plt.xlabel('Year')
plt.ylabel('Country')
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-28-3201790925.py:9: UserWarning: Glyph 128293 (\N{FIRE}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128293 (\N{FIRE}) missing from font(s) Deja
  fig.canvas.print_figure(bytes_io, **kw)
```



This heatmap shows how temperatures have changed in different countries from 1961 to 2022.

Blue means cooler years

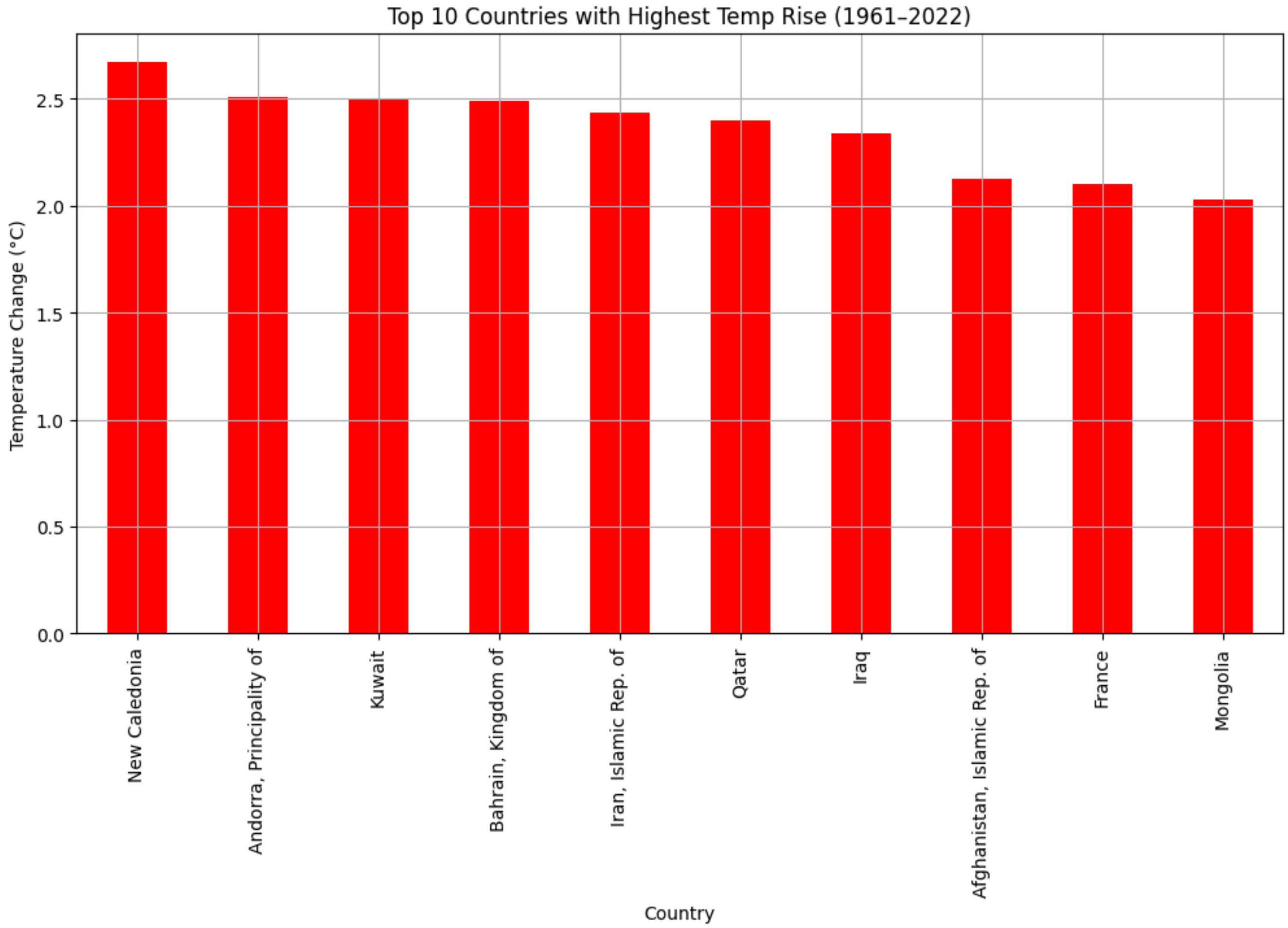
Red means hotter years Most countries are turning red over time, showing that global warming is affecting many parts of the world.

5. Top 10 Countries with Highest Temp Rise (1961 vs 2022)

```
# Pivot for start-end comparison
pivot_temp = df_temp_melted[df_temp_melted['Year'].isin([1961, 2022])]
pivot_diff = pivot_temp.pivot(index='Country', columns='Year', values='Temperature').dropna()
pivot_diff['Change'] = pivot_diff[2022] - pivot_diff[1961]
top10_countries = pivot_diff['Change'].sort_values(ascending=False).head(10)

top10_countries.plot(kind='bar', figsize=(12, 6), color='red')
plt.title('Top 10 Countries with Highest Temp Rise (1961–2022)')
plt.ylabel('Temperature Change (°C)')

plt.grid(True)
plt.show()
```



This heatmap shows how temperatures have changed in different countries from 1961 to 2022.

Blue means cooler years

Red means hotter years Most countries are turning red over time, showing that global warming is affecting many parts of the world.

- CO_2 is going up, temperatures are rising, and many countries are seeing real changes.
- The data shows clear signs of global warming, and understanding this can help make better climate decisions.

Statistical Analysis

Is CO_2 significantly correlated with Global Temperature?

We'll use the Pearson correlation coefficient to check the strength of the linear relationship.

```
# Merge global temperature and CO2 by year
df_merged = pd.merge(df_temp_world[['Year', 'Temperature']], df_co2_yearly, on='Year')
```

```
df_merged.isnull().sum()
```

	0
Year	0
Temperature	0
Avg_CO2_ppm	0

dtype: int64

Pearson Correlation

```
# Pearson Correlation
corr, p_value = pearsonr(df_merged['Avg_CO2_ppm'], df_merged['Temperature'])
print(f"Pearson Correlation: {corr:.4f}, P-value: {p_value:.4e}")
```

```
Pearson Correlation: 0.9430, P-value: 2.2883e-30
```

Pearson correlation coefficient between global CO_2 concentration and average temperature anomaly is 0.943, with a p-value < 0.001, indicating a strong and statistically significant positive relationship between CO_2 emissions and global warming.

Has warming accelerated after 1990?

```
# Split temp data pre and post 1990
pre_1990 = df_temp_world[df_temp_world['Year'] < 1990]['Temperature']
post_1990 = df_temp_world[df_temp_world['Year'] >= 1990]['Temperature']
```

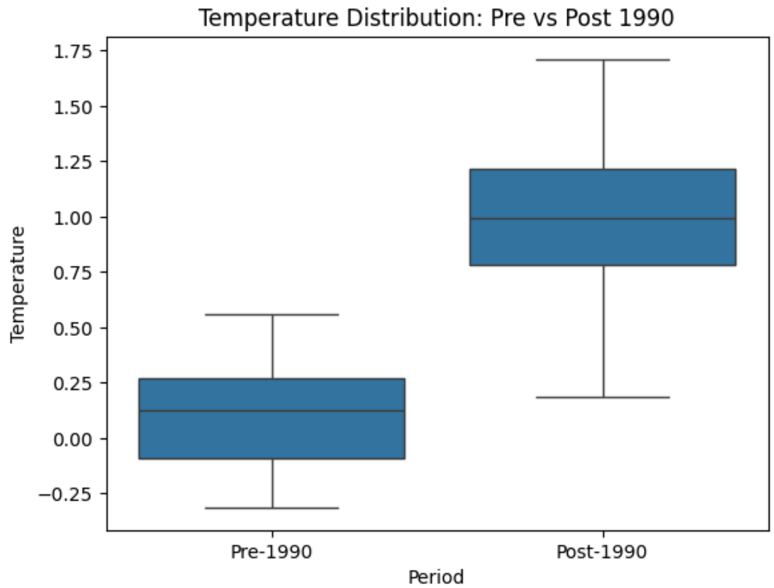
```
# Perform t-test
t_stat, p_val = ttest_ind(post_1990, pre_1990, equal_var=False)
print(f"T-Statistic: {t_stat:.4f}, P-value: {p_val:.4e}")
```

```
T-Statistic: 11.1855, P-value: 9.8266e-16
```

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

df_temp_world['Period'] = df_temp_world['Year'].apply(lambda x: 'Pre-1990' if x < 1990 else 'Post-1990')

sns.boxplot(x='Period', y='Temperature', data=df_temp_world)
plt.title('Temperature Distribution: Pre vs Post 1990')
plt.show()
```



A two-sample t-test was conducted to compare global temperatures before and after 1990.

- T-Statistic: 11.1855
- P-Value: 9.8266e-16

These results indicate a highly significant difference between the two periods. The extremely low p-value (much less than 0.05) strongly suggests that the observed increase in temperature after 1990 is not due to random chance, but reflects a real shift—likely due to climate change.

The boxplot visualization supports this finding, showing that:

Temperatures before 1990 were centered around 0 with low variation.

Post-1990 temperatures are consistently higher, with a clear upward shift in both the median and range.

Linear Regression: Temperature ~ CO_2

```
# Regression: Temperature ~ CO2
X = df_merged['Avg_CO2_ppm']
y = df_merged['Temperature']


X = sm.add_constant(X)  # add intercept
model = sm.OLS(y, X).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            Temperature   R-squared:                       0.889
Model:                            OLS   Adj. R-squared:                  0.887
Method:                 Least Squares   F-statistic:                     482.0
Date:                Fri, 25 Jul 2025   Prob (F-statistic):           2.29e-30
Time:                        17:07:58   Log-Likelihood:                 18.609
No. Observations:                  62   AIC:                            -33.22
Df Residuals:                      60   BIC:                            -28.96
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          -5.5339      0.279    -19.834      0.000      -6.092      -4.976
Avg_CO2_ppm     0.0339      0.002     21.955      0.000       0.031       0.037
==============================================================================
Omnibus:                        1.683   Durbin-Watson:                   1.937
Prob(Omnibus):                  0.431   Jarque-Bera (JB):                1.221
Skew:                          -0.065   Prob(JB):                        0.543
Kurtosis:                       2.325   Cond. No.                     2.18e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
[2] The condition number is large, 2.18e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

There is a very strong, statistically significant positive relationship between atmospheric CO_2 levels and global temperature. The model explains nearly 89% of the variation in temperature, and the probability of this result being due to chance is practically zero ($P < 0.0001$).

- This linear regression model analyzes the relationship between atmospheric CO_2 levels and global temperature. The model's R-squared value of 0.889 indicates that approximately 88.9% of the variation in global temperature can be explained by CO_2 concentration alone — reflecting a very strong relationship.
- The P-value for CO_2 is 0.000, confirming that the relationship is highly statistically significant and not due to random chance.
- The T-statistic of 21.955 for the CO_2 coefficient further supports the strong impact of CO_2 on temperature.
- Additionally, the model has a high F-statistic of 482.0, indicating that the regression as a whole is highly significant.
- The Durbin-Watson statistic is 1.937, suggesting that there is no autocorrelation in the residuals, which validates the model's reliability.
- The AIC (-33.22) and BIC (-28.96) scores show that this model performs well compared to alternative models.

What-If Simulation