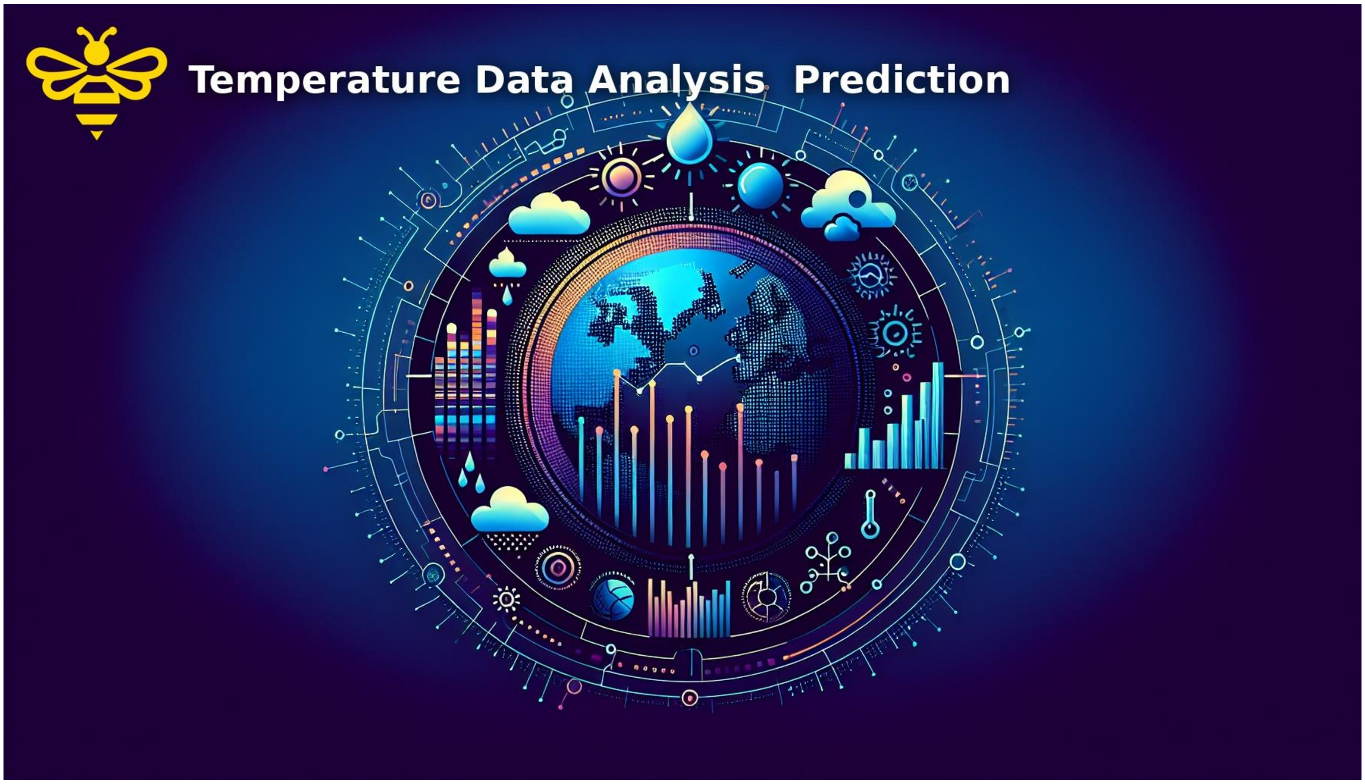


Temperature Data Analysis Notebook

This notebook was created with the help of [Devra AI]

Few may presume that climate change statistics are dry; our dataset will show that the numbers tell a story full of surprises and predictions. If you find this notebook useful, please upvote it.

linkcode

Table of Contents¶

In [1]:

```
# Import and setup libraries

import warnings
```

```python
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib
matplotlib.use('Agg')  # Necessary backend setting
import matplotlib.pyplot as plt
plt.switch_backend('Agg')  # switch backend if only plt imported

import seaborn as sns
sns.set(style='whitegrid', palette='muted', color_codes=True)

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error

# Ensure inline plotting (Kaggle specific)
%matplotlib inline

# Set a random seed for reproducibility
RANDOM_STATE = 42

print('Libraries imported and backend configured.')
```

Libraries imported and backend configured.

Data Loading

In this section we load the temperature dataset. The data contains yearly records per country and features such as average temperature, CO2 emissions, sea level rise, rainfall, and more. Although the year is an integer, it represents a time component so it can be treated as a date-type feature when necessary.

In [2]:

```
# Load the dataset
file_path = '/kaggle/input/temperature/temperature.csv'
try:
    df = pd.read_csv(file_path, encoding='ascii', delimiter=',')
    print('Data loaded successfully, sample records below:')
    display(df.head())
except Exception as error:
    print('Error loading the dataset. Check file path or encoding settings.')
    print(error)
```

Data loaded successfully, sample records below:

	Year	Country	Avg_Temperature_degC	CO2_Emissions_tons_per_capita	Sea_Level_Rise_mm	Rainfall_mm	Population	Renewable_Energy_pct	Extreme_Weather_Events	Forest_Area_pct
0	2006	UK	8.9	9.3	3.1	1441	530911230	20.4	14	59.8
1	2019	USA	31.0	4.8	4.2	2407	107364344	49.2	8	31.0
2	2014	France	33.9	2.8	2.2	1241	441101758	33.3	9	35.5
3	2010	Argentina	5.9	1.8	3.2	1892	1069669579	23.7	7	17.7
4	20	Germany	26.9	5.6	2.4	1743	124079175	12.5	4	17.4

	Year	Country	Avg_Temperature_degC	CO2_Emissions_tons_per_capita	Sea_Level_Rise_mm	Rainfall_mm	Population	Renewable_Energy_pct	Extreme_Weather_Events	Forest_Area_pct
	07									

Data Cleaning and Preprocessing

We start by checking for missing values and potential data type issues. It is common for datasets to have imperfections and while the schema here is defined, errors may occur during the realization. Any necessary type conversions are done in this step. Enjoy the beauty of clean data.

In [3]:

```
# Basic data exploration
print('Dataset shape:', df.shape)
print('\nDataset info:')
df.info()

# Check for missing values
print('\nMissing values per column:')
print(df.isnull().sum())

# Handle missing values if any (using median imputation for numeric columns as an example)
numeric_cols = df.select_dtypes(include=[np.number]).columns
for col in numeric_cols:
    if df[col].isnull().sum() > 0:
        median_val = df[col].median()
        df[col].fillna(median_val, inplace=True)
        print(f'Filled missing values in {col} with median value {median_val}')

# A quick check of data types
print('\nData types after cleaning:')
print(df.dtypes)
```

```
Dataset shape: (1000, 10)

Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Year                          1000 non-null   int64
 1   Country                       1000 non-null   object
 2   Avg_Temperature_degC          1000 non-null   float64
 3   CO2_Emissions_tons_per_capita 1000 non-null   float64
 4   Sea_Level_Rise_mm             1000 non-null   float64
 5   Rainfall_mm                   1000 non-null   int64
 6   Population                    1000 non-null   int64
 7   Renewable_Energy_pct          1000 non-null   float64
 8   Extreme_Weather_Events        1000 non-null   int64
 9   Forest_Area_pct               1000 non-null   float64
dtypes: float64(5), int64(4), object(1)
memory usage: 78.2+ KB

Missing values per column:
Year                             0
Country                          0
Avg_Temperature_degC             0
CO2_Emissions_tons_per_capita    0
Sea_Level_Rise_mm                0
Rainfall_mm                      0
```

```
Population                 0
Renewable_Energy_pct       0
Extreme_Weather_Events     0
Forest_Area_pct            0
dtype: int64


Data types after cleaning:
Year                            int64
Country                        object
Avg_Temperature_degC          float64
CO2_Emissions_tons_per_capita float64
Sea_Level_Rise_mm             float64
Rainfall_mm                     int64
Population                      int64
Renewable_Energy_pct          float64
Extreme_Weather_Events          int64
Forest_Area_pct               float64
dtype: object
```

Exploratory Data Analysis

Let us now dive into the numerical trends, distributions, and correlations present in our dataset. Notice how several features interact with one another: understanding these relationships will help us in building an effective predictor.

In [4]:

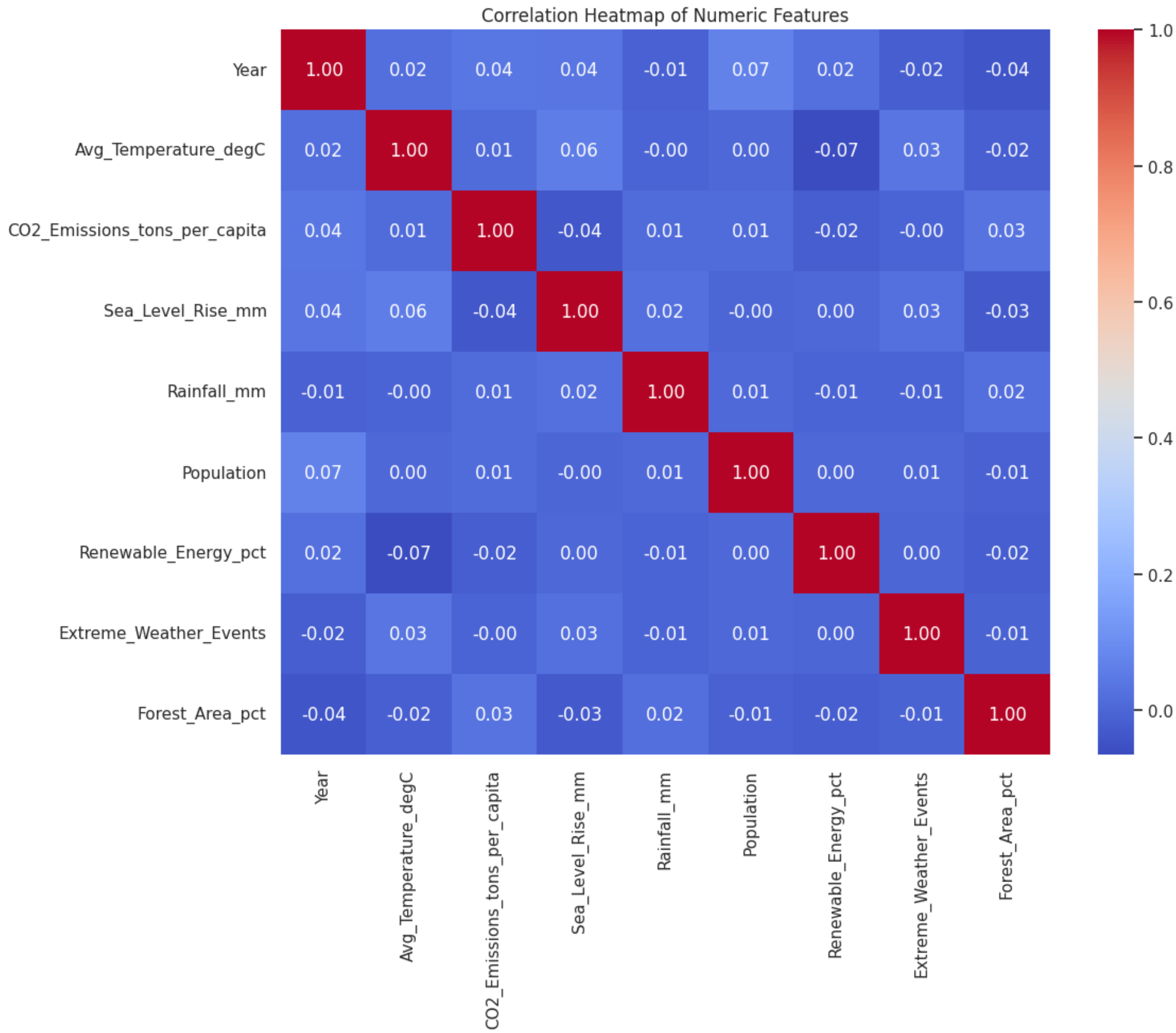
```
# Descriptive statistics
print('Descriptive statistics for numerical features:')
display(df.describe())


# Correlation analysis on numeric data
numeric_df = df.select_dtypes(include=[np.number])
```

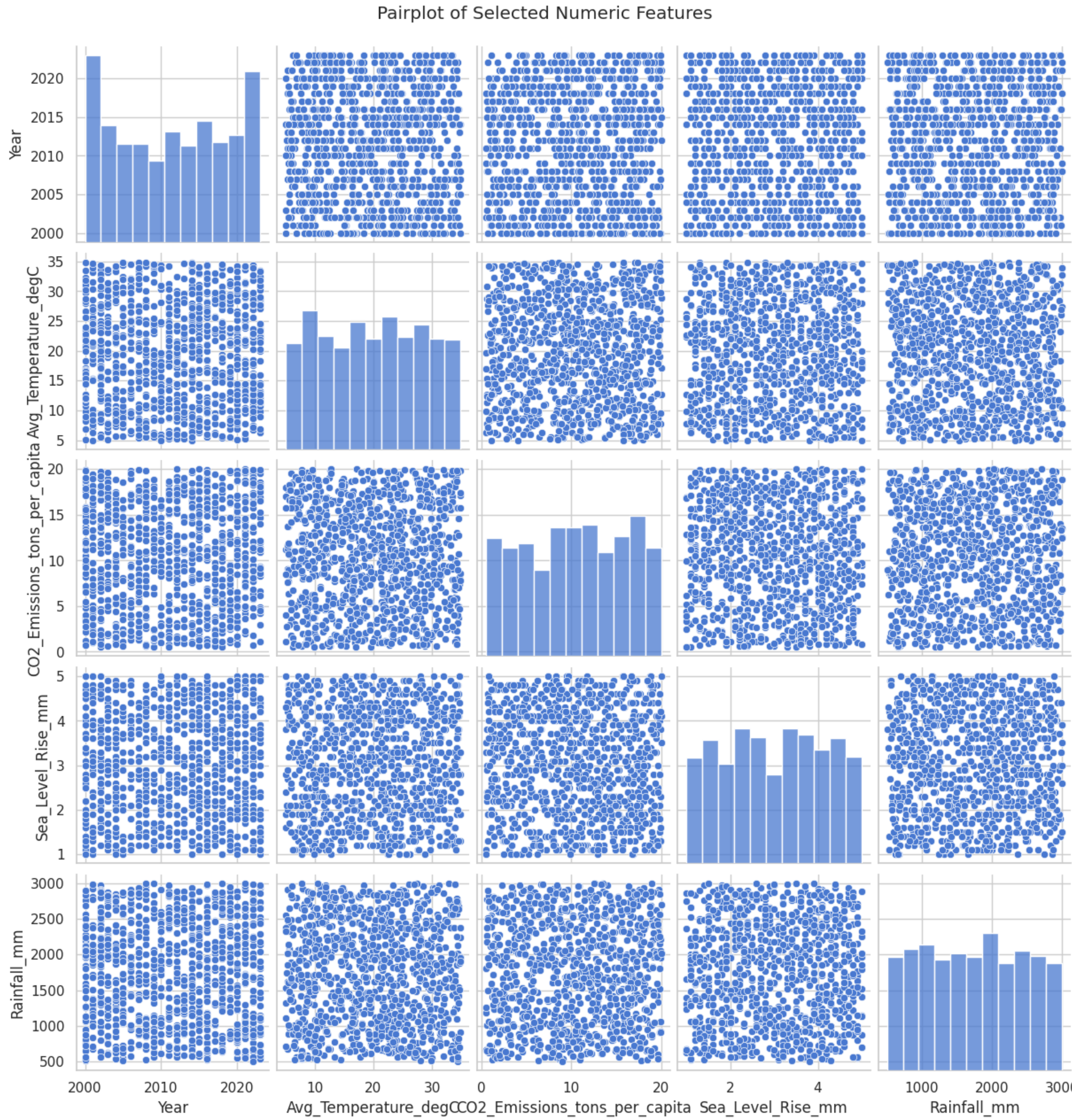
```python
if numeric_df.shape[1] >= 4:
    plt.figure(figsize=(12, 10))
    corr = numeric_df.corr()
    sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
    plt.title('Correlation Heatmap of Numeric Features')
    plt.tight_layout()
    plt.show()
else:
    print('Not enough numeric columns for a correlation heatmap.')


# Pairplot for a subset of numeric columns to inspect bivariate relationships
sample_cols = [col for col in ['Year', 'Avg_Temperature_degC', 'CO2_Emissions_tons_per_capita',
                               'Sea_Level_Rise_mm', 'Rainfall_mm'] if col in numeric_df.columns]
if len(sample_cols) >= 2:
    sns.pairplot(df[sample_cols].dropna())
    plt.suptitle('Pairplot of Selected Numeric Features', y=1.02)
    plt.show()
else:
    print('Not enough variables for a meaningful pairplot.')
```

Descriptive statistics for numerical features:

	Year	Avg_Temperature_degC	CO2_Emissions_tons_per_capita	Sea_Level_Rise_mm	Rainfall_mm	Population	Renewable_Energy_pct	Extreme_Weather_Events	Forest_Area_pct
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1.000000e+03	1000.000000	1000.000000	1000.000000
mean	2011.432000	19.883100	10.425800	3.009600	1738.761000	7.053830e+08	27.300500	7.291000	40.572000

	Year	Avg_Temperature_degC	CO2_Emissions_tons_per_capita	Sea_Level_Rise_mm	Rainfall_mm	Population	Renewable_Energy_pct	Extreme_Weather_Events	Forest_Area_pct
std	7.147199	8.542897	5.614665	1.146081	708.976616	4.093910e+08	12.970808	4.422655	17.398998
min	2000.000000	5.000000	0.500000	1.000000	501.000000	3.660891e+06	5.100000	0.000000	10.100000
25%	2005.000000	12.175000	5.575000	2.000000	1098.750000	3.436242e+08	16.100000	3.000000	25.600000
50%	2012.000000	20.100000	10.700000	3.000000	1726.000000	7.131166e+08	27.150000	8.000000	41.150000
75%	2018.000000	27.225000	15.400000	4.000000	2362.500000	1.073868e+09	38.925000	11.000000	55.800000
max	2023.000000	34.900000	20.000000	5.000000	2999.000000	1.397016e+09	50.000000	14.000000	70.000000


Correlation Heatmap of Numeric Features
Year
Avg_Temperature_degC
CO2_Emissions_tons_per_capita
Sea_Level_Rise_mm
Rainfall_mm
Population
Renewable_Energy_pct
Extreme_Weather_Events
Forest_Area_pct
1.00 0.02 0.04 0.04 -0.01 0.07 0.02 -0.02 -0.04
0.02 1.00 0.01 0.06 -0.00 0.00 -0.07 0.03 -0.02
0.04 0.01 1.00 -0.04 0.01 0.01 -0.02 -0.00 0.03
0.04 0.06 -0.04 1.00 0.02 -0.00 0.00 0.03 -0.03
-0.01 -0.00 0.01 0.02 1.00 0.01 -0.01 -0.01 0.02
0.07 0.00 0.01 -0.00 0.01 1.00 0.00 0.01 -0.01
0.02 -0.07 -0.02 0.00 -0.01 0.00 1.00 0.00 -0.02
-0.02 0.03 -0.00 0.03 -0.01 0.01 0.00 1.00 -0.01
-0.04 -0.02 0.03 -0.03 0.02 -0.01 -0.02 -0.01 1.00
1.0
0.8
0.6
0.4
0.2
0.0



Visualization and Analysis

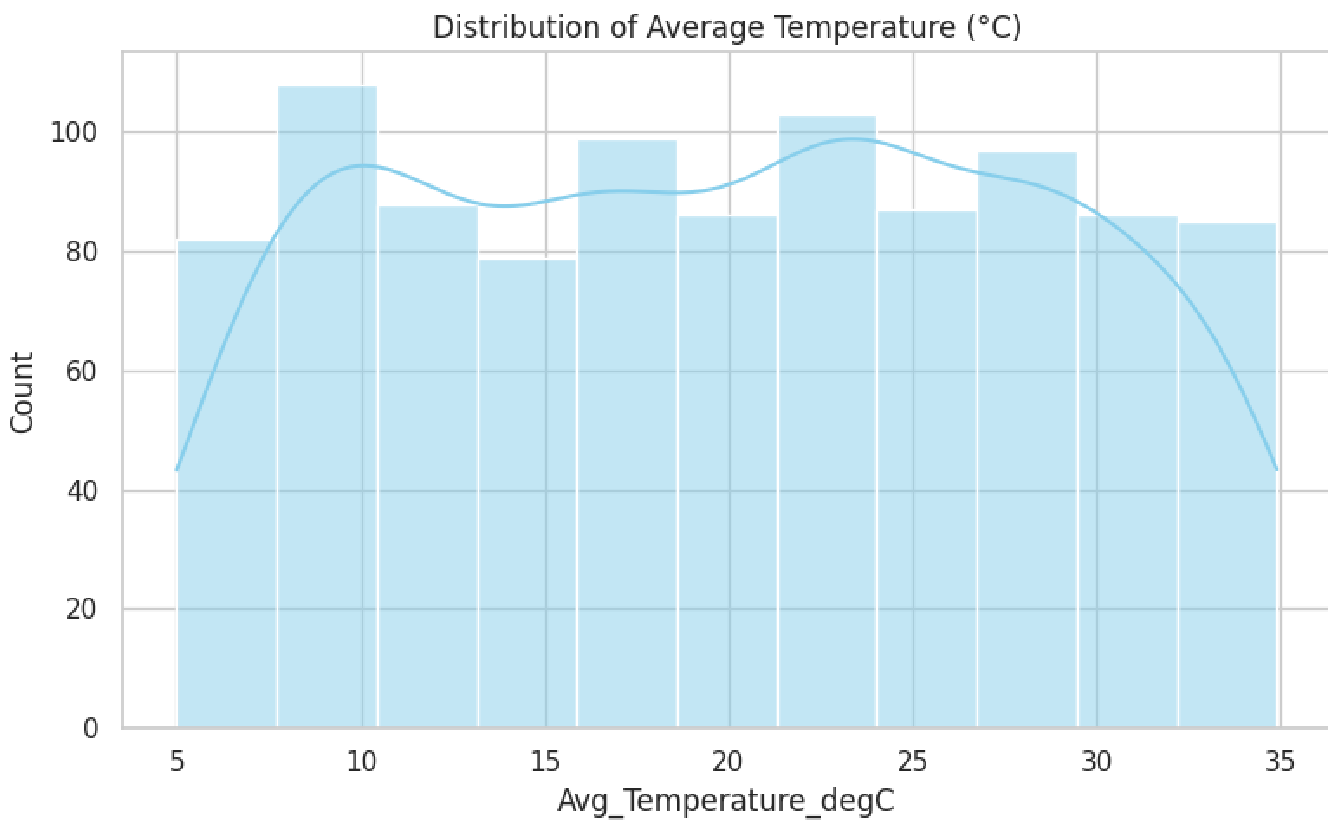
Time to visualize categorical trends and distribution shapes. We apply several plot types: histograms for distribution, box plots for outlier detection, and count plots for categorical frequencies.

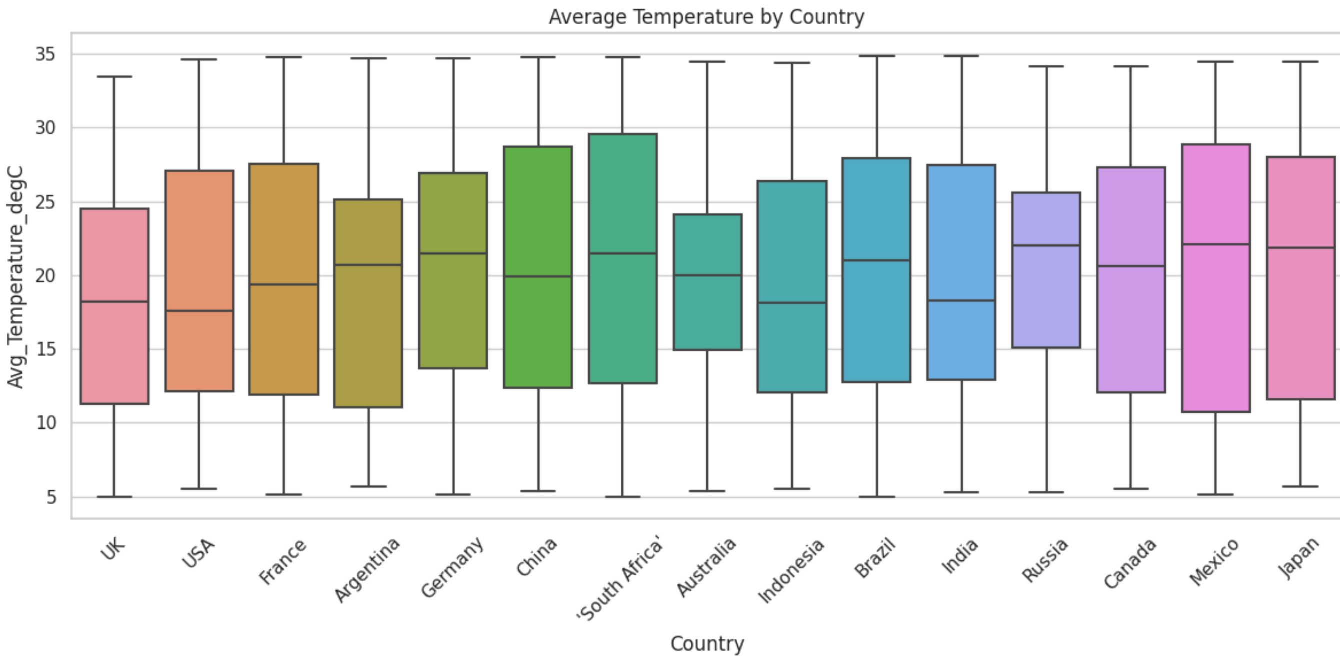
In [5]:

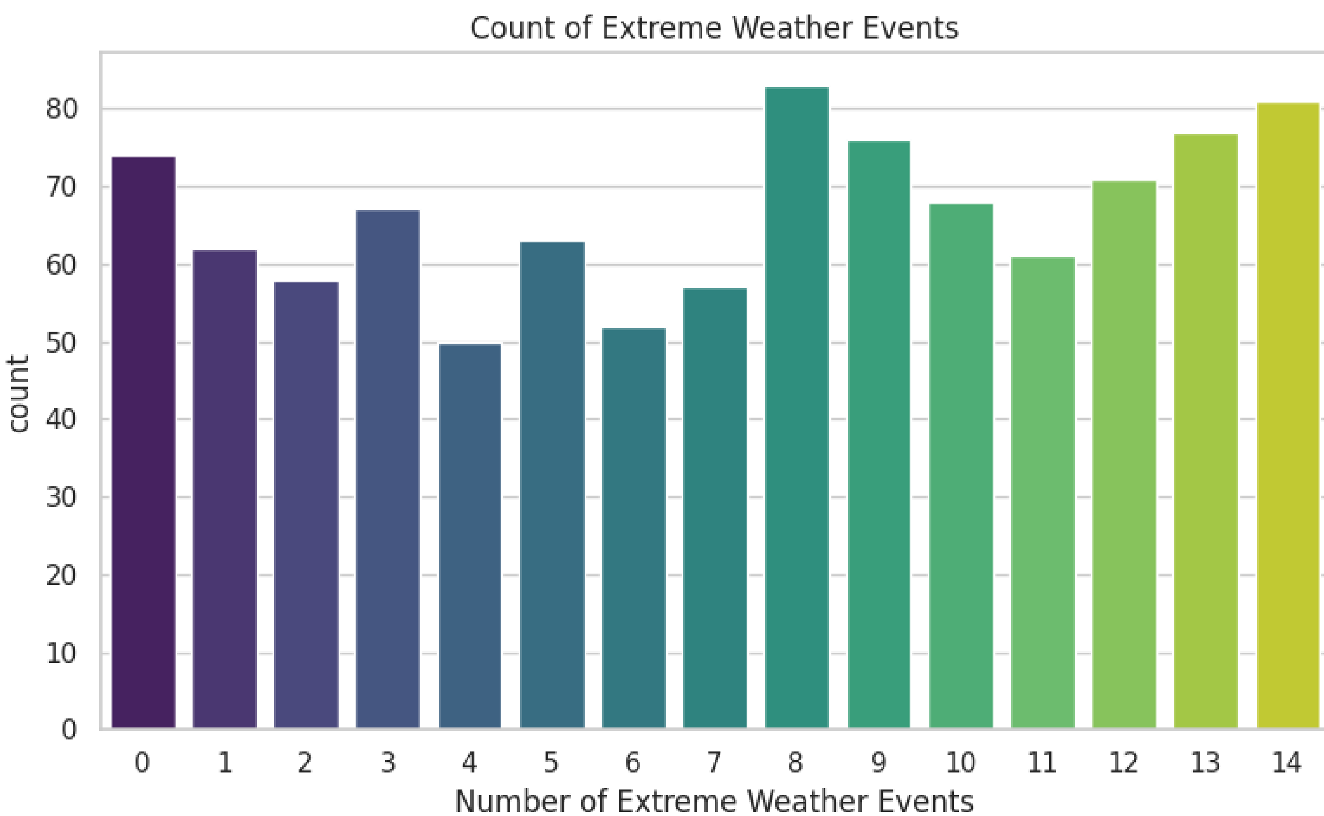
 # Histogram of Average Temperature

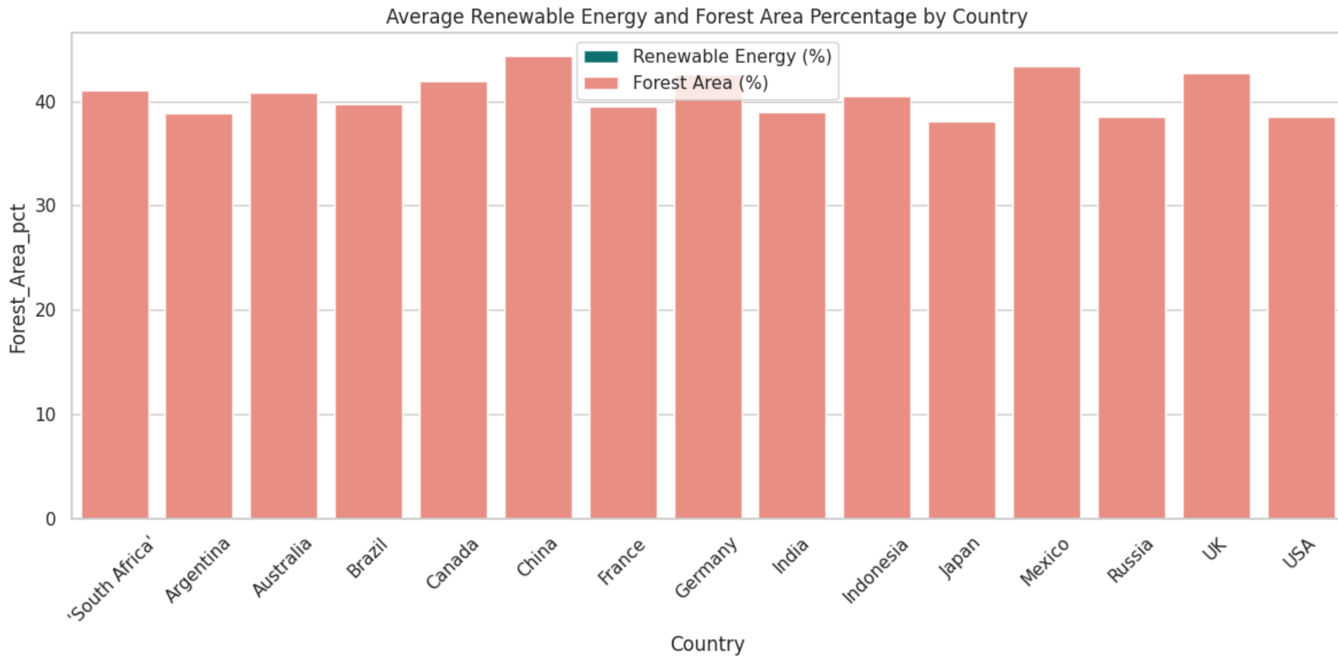
```python
plt.figure(figsize=(8, 5))
sns.histplot(df['Avg_Temperature_degC'].dropna(), kde=True, color='skyblue')
plt.title('Distribution of Average Temperature (°C)')
plt.xlabel('Avg_Temperature_degC')
plt.ylabel('Count')
plt.tight_layout()
plt.show()

# Box Plot for Avg Temperature by Country
plt.figure(figsize=(12, 6))
sns.boxplot(x='Country', y='Avg_Temperature_degC', data=df)
plt.title('Average Temperature by Country')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Count plot for Extreme Weather Events
plt.figure(figsize=(8, 5))
sns.countplot(x='Extreme_Weather_Events', data=df, palette='viridis')
plt.title('Count of Extreme Weather Events')
plt.xlabel('Number of Extreme Weather Events')
plt.tight_layout()
plt.show()

# Grouped Barplot: Renewable Energy vs. Forest Area by Country (aggregated)
agg_df = df.groupby('Country')[['Renewable_Energy_pct', 'Forest_Area_pct']].mean().reset_index()
plt.figure(figsize=(12, 6))
sns.barplot(x='Country', y='Renewable_Energy_pct', data=agg_df, color='teal', label='Renewable Energy (%)')
```

```
sns.barplot(x='Country', y='Forest_Area_pct', data=agg_df, color='salmon', label='Forest Area (%)')
plt.title('Average Renewable Energy and Forest Area Percentage by Country')
plt.xticks(rotation=45)
plt.legend()
plt.tight_layout()
plt.show()
```




Average Temperature by Country
Avg_Temperature_degC
35
30
25
20
15
10
5
UK
USA
France
Argentina
Germany
China
'South Africa'
Australia
Indonesia
Brazil
India
Russia
Canada
Mexico
Japan
Country


Count of Extreme Weather Events
count
80
70
60
50
40
30
20
10
0
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
Number of Extreme Weather Events



Prediction and Model Building

In this section we build a simple predictor. Feeling ambitious, we model the average temperature using a selection of available features. We use a Linear Regression model and evaluate the performance using the R^2 score and RMSE. Occasionally, modeling surprises us if the signal is weak. The predictor might be improved with further feature engineering in future work.

In [6]:

```
# Prepare data for prediction
target = 'Avg_Temperature_degC'

# Choose features: excluding Country since it's categorical, although we could encode it
features = ['Year', 'CO2_Emissions_tons_per_capita', 'Sea_Level_Rise_mm',
            'Rainfall_mm', 'Population', 'Renewable_Energy_pct',
            'Extreme_Weather_Events', 'Forest_Area_pct']

# Drop rows with missing target or features
model_df = df[features + [target]].dropna()

# Define X and y
```

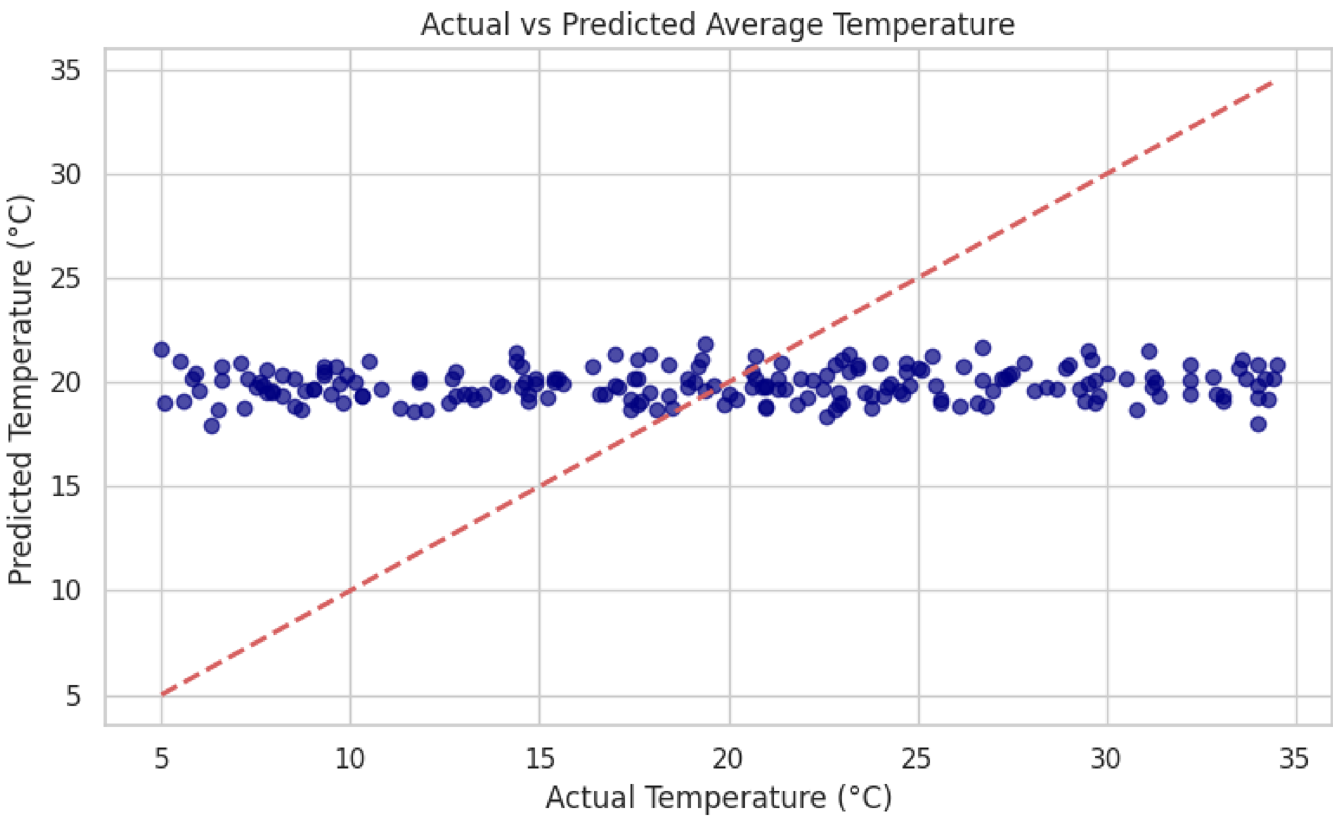
```
X = model_df[features]
y = model_df[target]

# Split into training and testing datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=RANDOM_STATE)
print('Data split into training and test sets.')

# Instantiate and train the Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = lr_model.predict(X_test)

# Evaluate model performance
r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f'Linear Regression R² score: {r2:.3f}')
print(f'Linear Regression RMSE: {rmse:.3f}')

# Plot actual vs predicted values
plt.figure(figsize=(8, 5))
plt.scatter(y_test, y_pred, alpha=0.7, color='navy')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title('Actual vs Predicted Average Temperature')
plt.xlabel('Actual Temperature (°C)')
plt.ylabel('Predicted Temperature (°C)')
plt.tight_layout()
```

plt.show()

Data split into training and test sets.

Linear Regression R^2 score: 0.006

Linear Regression RMSE: 8.298



Conclusion and Future Work

This notebook analyzed temperature data from multiple countries over the years. We explored data cleaning, performed several visualizations, and built a Linear Regression predictor to forecast average temperatures based on environmental indicators. Although the predictor provides a baseline performance, future work could include:

- More feature engineering (e.g., encoding country information, temporal trends analysis)
- Experimenting with advanced models such as Random Forests or Gradient Boosted Trees
- Incorporating more domain-specific metrics or external data sources

We hope you found this analysis engaging and insightful. Please upvote if you found it useful. Happy data exploring!