CO2 and Temperature Forecasts: Agri-food Sector Insights

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Course:CSDS(311)

Executive Summary

- Application of advanced forecasting methods to CO_2 emissions and temperature changes.
- Focus on agri-food sector, contributing 62% to global emissions.
- Reliable forecasts to support environmental policy planning.
- Insights for targeted interventions in agricultural practices.
- Outcomes aimed at reducing emissions and improving climate resilience.

Problem Statement

As global CO_2 emissions continue to rise, predicting their impact on climate change becomes crucial for effective environmental management. This study addresses the need for precise forecasting of emissions and temperature variations, which are critical for devising proactive environmental strategies and policies.

Proposed Solution

- Strategic approach using advanced statistical techniques.
- Focus on forecasting CO2 emissions and temperature variations.
- Enhancing predictive capabilities to address environmental challenges.
- Reliable forecasts to inform environmental policies.

Data Description

- Dataset sourced from Kaggle, combining FAO and IPCC data on agri-food sector emissions.
- Cleaned, preprocessed, and merged into a cohesive dataset for accurate analysis and forecasting.
- Represents 62% of global annual CO_2 emissions attributed to agricultural activities.
- Includes additional features like population growth and temperature variations.
- Aims to provide insights into the impact of agricultural practices on climate change.

Data Description

Area The geografical Area	# Year The year the emissions were recorded	# Savanna fires Emissions from fires in savanna ecosystems.	# Forest fires Emissions from fires in forested areas.	# Crop Residues Emissions from burning or decomposing leftover plant material after crop harvesting.	# Rice Cultivation Emissions from methane released during rice cultivation.	# Drained organic ... Drained organic soils (CO2)	# Pesticides Manu... Emissions from the production of pesticides.
# Food Transport Emissions from transporting food products.	# Forestland Land covered by forests.	# Net Forest conve...	# Food Household ...	# Food Retail	# On-farm Electric...	# Food Packaging	# Agrifood System...
# Food Processing	# Fertilizers Manuf...	# IPPU	# Manure applied t...	# Manure left on P...	# Manure Manage...	# Fires in organic s...	# Fires in humid tr...
# Fires in humid tr...	# On-farm energy ...	# Rural population	# Urban population	# Total Population ...	# Total Population ...	# total_emission	# Average Temper...

Forecasting Models Overview

Our evaluation included several forecasting models, each with unique strengths but varying suitability for our dataset characterized by pronounced seasonal patterns. The models reviewed included the Moving Average Method, Simple Exponential Smoothing, Holt's Method, and Simple Linear Regression:

- **Moving Average** and **Simple Exponential Smoothing** are straightforward but fail to capture the seasonal trends crucial for our analysis.
- **Holt's Method** addresses trends but lacks the ability to model seasonality, which is essential for our dataset.
- **Simple Linear Regression** provides initial insights but cannot accommodate the non-linear dynamics present in environmental data.

Forecasting Methodology

Winter's Method

Winter's Method, or **Triple Exponential Smoothing**, can be applied in both additive and multiplicative forms. The additive model handles level, trend, and seasonal variations in a linear manner, while the multiplicative model is more suited for cases where seasonal and trend effects grow or decay exponentially.

1. Level:

$$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

- L_t: Level at time t
- α: Smoothing factor for the level ($0 < \alpha < 1$)
- y_t: Actual value at time t
- S_{t-s}: Seasonal component at time $t - s$, where s is the length of the season
- L_{t-1}: Previous level
- T_{t-1}: Previous trend

Forecasting Methodology

Winter’s Method

2. Trend:

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

- T_t: Trend at time t
- β: Smoothing factor for the trend ($0 < \beta < 1$)
- L_t: Current level
- L_{t-1}: Previous level
- T_{t-1}: Previous trend

3. Seasonality:

$$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-s}$$

- S_t: Seasonal component at time t
- γ: Smoothing factor for the seasonality ($0 < \gamma < 1$)
- y_t: Actual value at time t
- L_t: Current level
- S_{t-s}: Previous seasonal component at time $t - s$

Winter’s Method

Why Winter's Method Was Selected?

- **Seasonality in Data:** Our dataset exhibits strong seasonal patterns.
- **Handling Trend and Seasonality Simultaneously:** Unlike simpler methods.
- **Flexibility with Additive and Multiplicative Models:** Linear and exponential trends.
- **Forecasting Accuracy:** Ability to update level, trend, and seasonality.

Application of Winter's Method

Winter’s (Additive)

```
def winters(data, alpha, beta, gamma, seasonlength, fp):
    level = data[0]
    trend = data[1] - data[0]
    seasonals = [data[i] - data[0] for i in range(seasonlength)]
    forecast = []

    for t in range(len(data)):
        if t >= seasonlength:
            lastlevel = level
            lasttrend = trend
            level = alpha * (data[t] - seasonals[t % seasonlength]) + (1 - alpha) * (lastlevel + lasttrend)
            trend = beta * (level - lastlevel) + (1 - beta) * lasttrend
            seasonals[t % seasonlength] = gamma * (data[t] - level) + (1 - gamma) * seasonals[t % seasonlength]
        forecast.append(level + trend + seasonals[t % seasonlength])

    # future Forecats
    for t in range(fp):
        last_level = level
        last_trend = trend
        level = alpha * (level + trend) + (1 - alpha) * (last_level + last_trend)
        trend = beta * (level - last_level) + (1 - beta) * last_trend
        seasonals.append(seasonals[-seasonlength])
        forecast.append(level + trend + seasonals[-seasonlength])

    return forecast
```

Detailed Code Walkthrough

- Initialization of basic variables and seasonal adjustments.
- Recursive calculations to update level, trend, and seasonality.
- Extending the model to forecast future periods.
- Final preparation of the forecast output.

Application of Winter's Method

Winter’s (Multiplicative)

```python
def winters_MULTI(data, alpha, beta, gamma, seasonlength, fp):
    level = data[0]
    trend = data[1] / data[0]  # Trend is now multiplicative
    seasonals = [data[i] / data[0] for i in range(seasonlength)]  # Seasonal factors are multiplicative
    forecast = []

    for t in range(len(data)):
        if t >= seasonlength:
            lastlevel = level
            lasttrend = trend
            level = alpha * (data[t] / seasonals[t % seasonlength]) + (1 - alpha) * (lastlevel * lasttrend)
            trend = beta * (level / lastlevel) + (1 - beta) * lasttrend
            seasonals[t % seasonlength] = gamma * (data[t] / level) + (1 - gamma) * seasonals[t % seasonlength]
        forecast.append((level + trend) * seasonals[t % seasonlength])

    # Future forecasts
    for t in range(fp):
        last_level = level
        last_trend = trend
        level = alpha * (level * trend) + (1 - alpha) * (last_level * last_trend)
        trend = beta * (level / last_level) + (1 - beta) * last_trend
        seasonals.append(seasonals[-seasonlength])
        forecast.append((level + trend) * seasonals[-seasonlength])
```

Detailed Code Walkthrough

- Initialization of basic variables and seasonal adjustments.
- Recursive calculations to update level, trend, and seasonality.
- Extending the model to forecast future periods.
- Final preparation of the forecast output.

Visualizing Forecasts

CO2 Emissions & Average Temperature

```python
def plot_forecast(years, actual_data, forecast_data, label_actual, label_forecast, title, ylabel, forecast_years):
    plt.figure(figsize=(12, 6))


    future_years = np.arange(years[-1] + 1, years[-1] + 1 + forecast_years)
    extended_years = np.concatenate([years, future_years])

    # Plotting actual and forecast data
    plt.plot(years, actual_data, label=label_actual, color='blue', marker='o', linestyle='-')
    plt.plot(extended_years, forecast_data, label=label_forecast, color='red', linestyle='--')

    plt.title(title)
    plt.xlabel("Year")
    plt.ylabel(ylabel)
    plt.legend()
    plt.grid(True)
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

Detailed Code Walkthrough

- Function Definition.
- Calculating Future Year.
- Plotting Data.
- Enhancing the Plot.

Calculating Accuracy: MAE and MSE Metrics

CO2 Emissions & Average Temperature

Formula:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

- n is the number of data points.
- y_i is the actual value of the i-th data point.
- $\hat{y}_i$ is the predicted value of the i-th data point.
- $|y_i - \hat{y}_i|$ is the absolute error between the predicted and actual value for the i-th data point.
- $(y_i - \hat{y}_i)^2$ is the squared error between the predicted and actual value for the i-th data point.

```
#calculate MAE and MSE
def calculate_accuracy_metrics(actual, forecast):
    mae = np.mean(np.abs(actual - forecast[:len(actual)]))
    mse = np.mean((actual - forecast[:len(actual)])**2)
    print(f"Mean Absolute Error (MAE): {mae}")
    print(f"Mean Squared Error (MSE): {mse}")
```

Detailed Code Walkthrough

- Function Definition.
- Calculating Mean Absolute Error (MAE).
- Calculating Mean Squared Error (MSE).
- Printing the Results.

Calling Functions in the main

Calling all Functions

```
def main():
    df = pd.read_csv('/Users/soham/Downloads/Agrofood_co2_emission.csv')

    df['Year'] = pd.to_numeric(df['Year'], errors='coerce')
    numericcols = df.select_dtypes(include=[np.number])
    df_aggregated = numericcols.groupby('Year').mean().reset_index()
    years = df_aggregated['Year'].values

    total_emission = df_aggregated.get('total_emission', np.array([])).values
    at = df_aggregated.get('Average Temperature °C', np.array([])).values

    season_length = 12
    alpha1, beta1, gamma1 = 0.9, 0.03, 0.9
    alpha,beta,gamma=0.9,0.1,0.9
    forecastyears = 10

    forecast_total_emission = winters_MULTI(total_emission, alpha1, beta1, gamma1, season_length, forecastyears)
    ft = winters(at, alpha, beta, gamma, season_length, forecastyears)


    plot_forecast(years, total_emission, forecast_total_emission, "Actual Emissions", "Forecasted Emissions", "CO2 Emissions Forecast", "Emissions (kt)", forecastyears)


    plot_forecast(years, at, ft, "Actual Temperature", "Forecasted Temperature", "Average Temperature Forecast", "Temperature (°C)", forecastyears)


    print("Accuracy for Total Emissions:")
    calculate_accuracy_metrics(total_emission, forecast_total_emission)

    print("\nAccuracy for Average Temperature:")
    calculate_accuracy_metrics(at, ft)

if __name__ == "__main__":
    main()
```

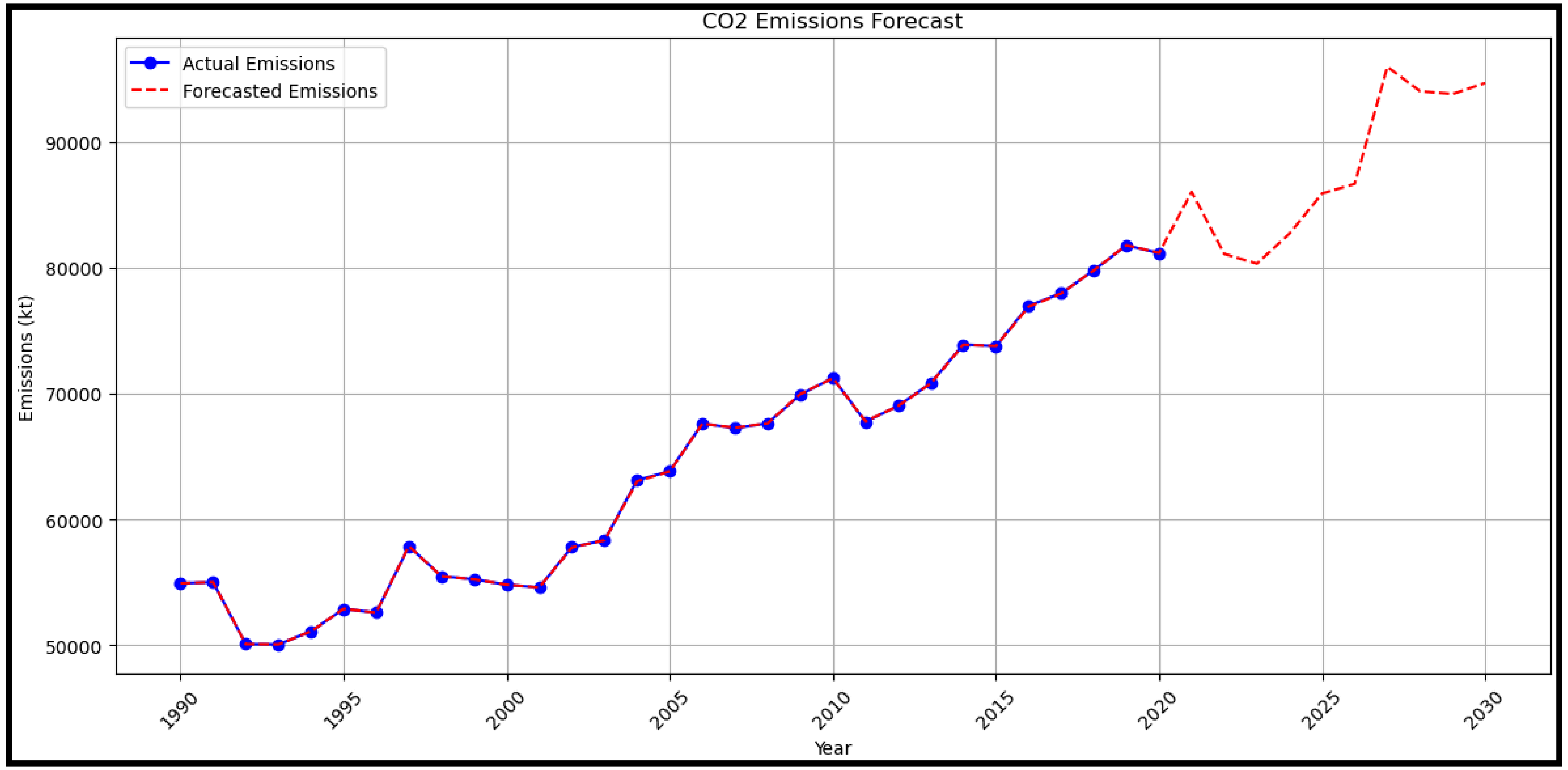
Detailed Code Walkthrough

- Data Loading and Initial Processing.
- Extracting Data for Forecasting.
- Setting Forecasting Parameters.
- Performing & Visualizing the Forecasts.
- Calculating Accuracy Metrics.

Model Predictions: Environmental Impact Forecasts

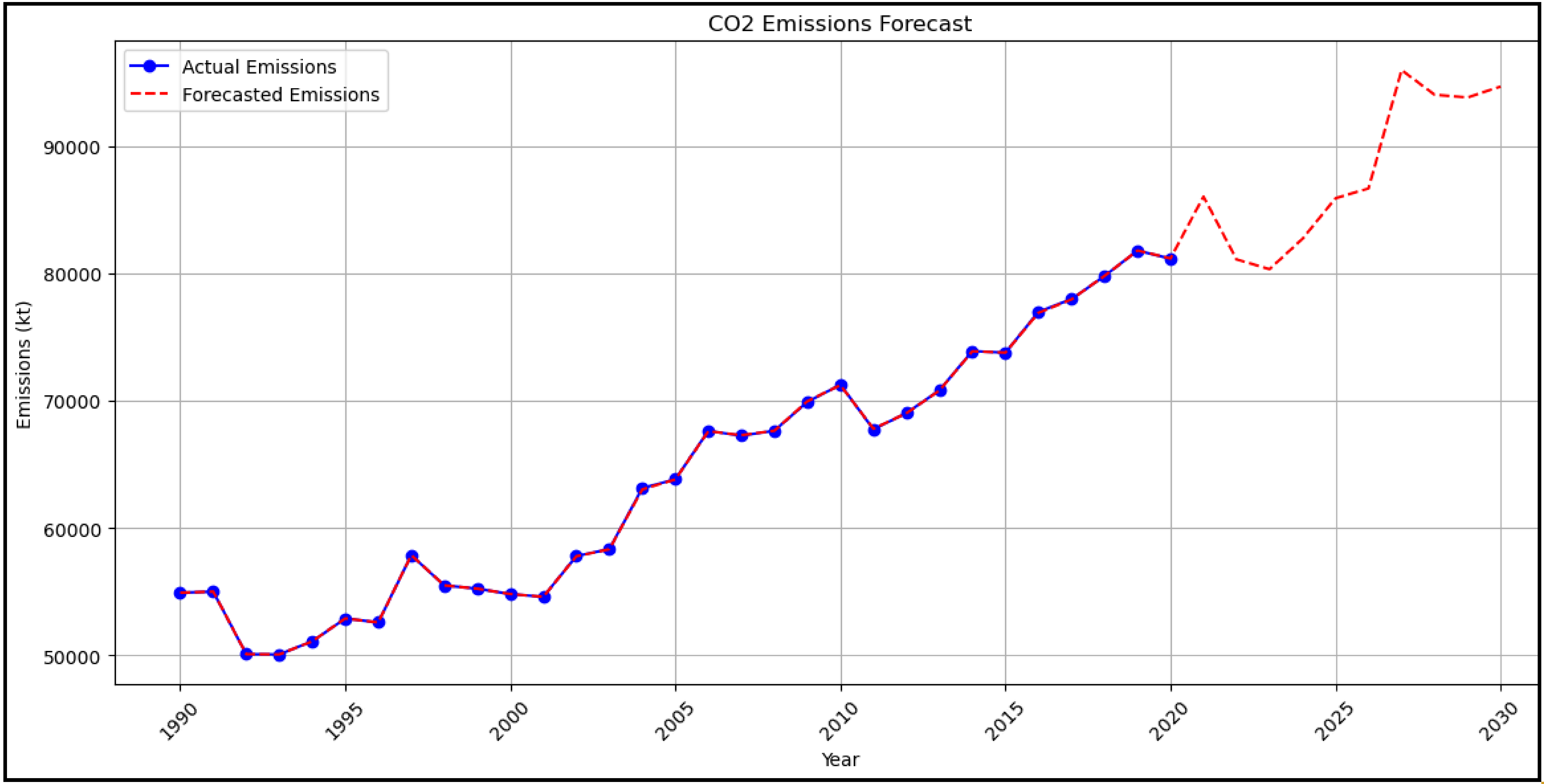
CO2 Emissions Forecast

- Forecast predicts a continued rise in CO_2 emissions from the agri-food sector.
- Insights suggest the need for sustainable practices to mitigate emissions.
- Accuracy metrics: MAE = 16.57 kt, MSE = 816.90 kt^2.
- Model demonstrates effective forecasting for long-term planning.
- The graph shows the actual versus forecasted emissions, trends up to 2030.




```
 Accuracy for Total Emissions:
Mean Absolute Error (MAE): 16.570017047082317
Mean Squared Error (MSE): 816.9040880775262
```

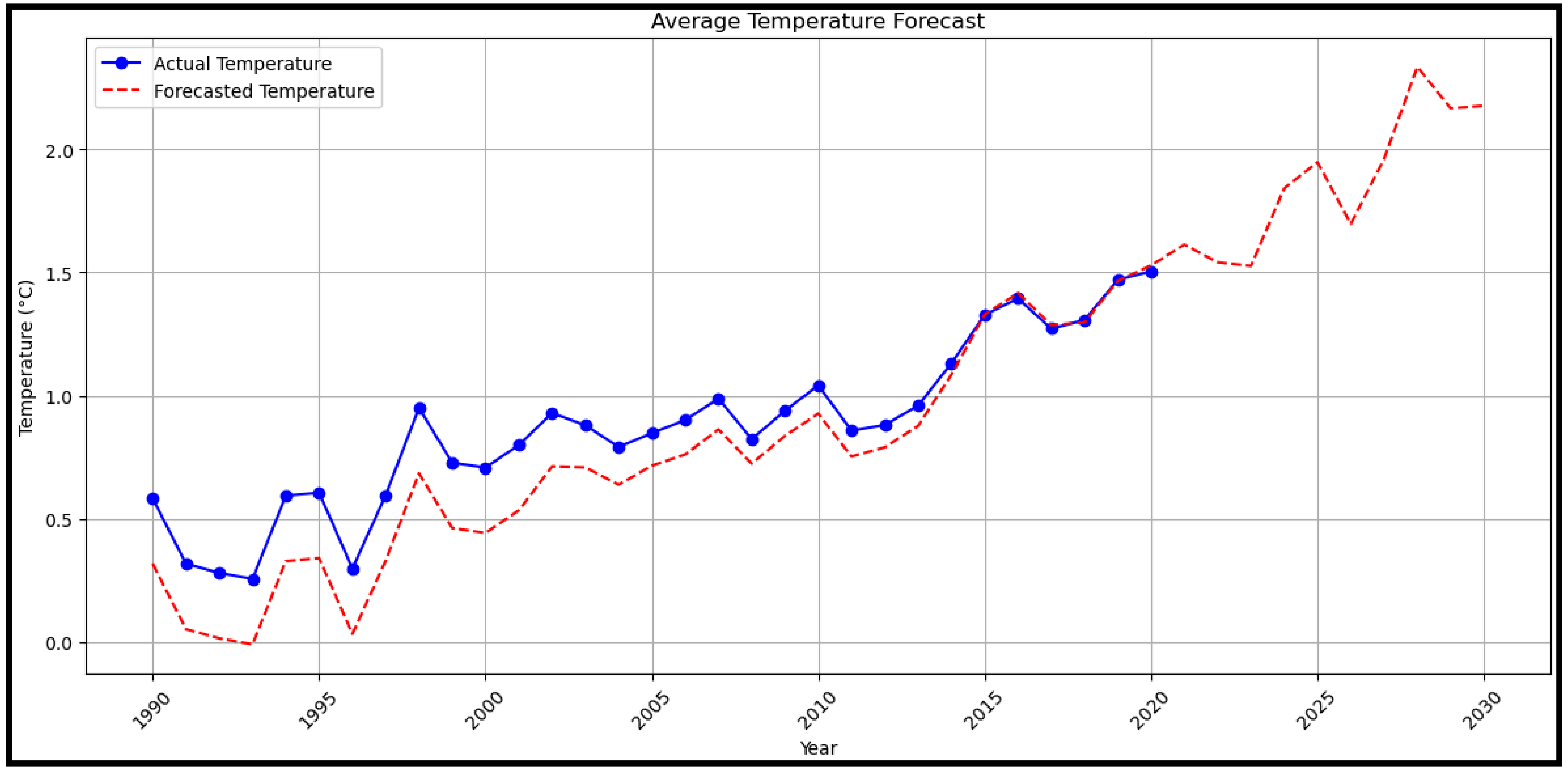
CO2 Emissions Forecast



Model Predictions: Environmental Impact Forecasts

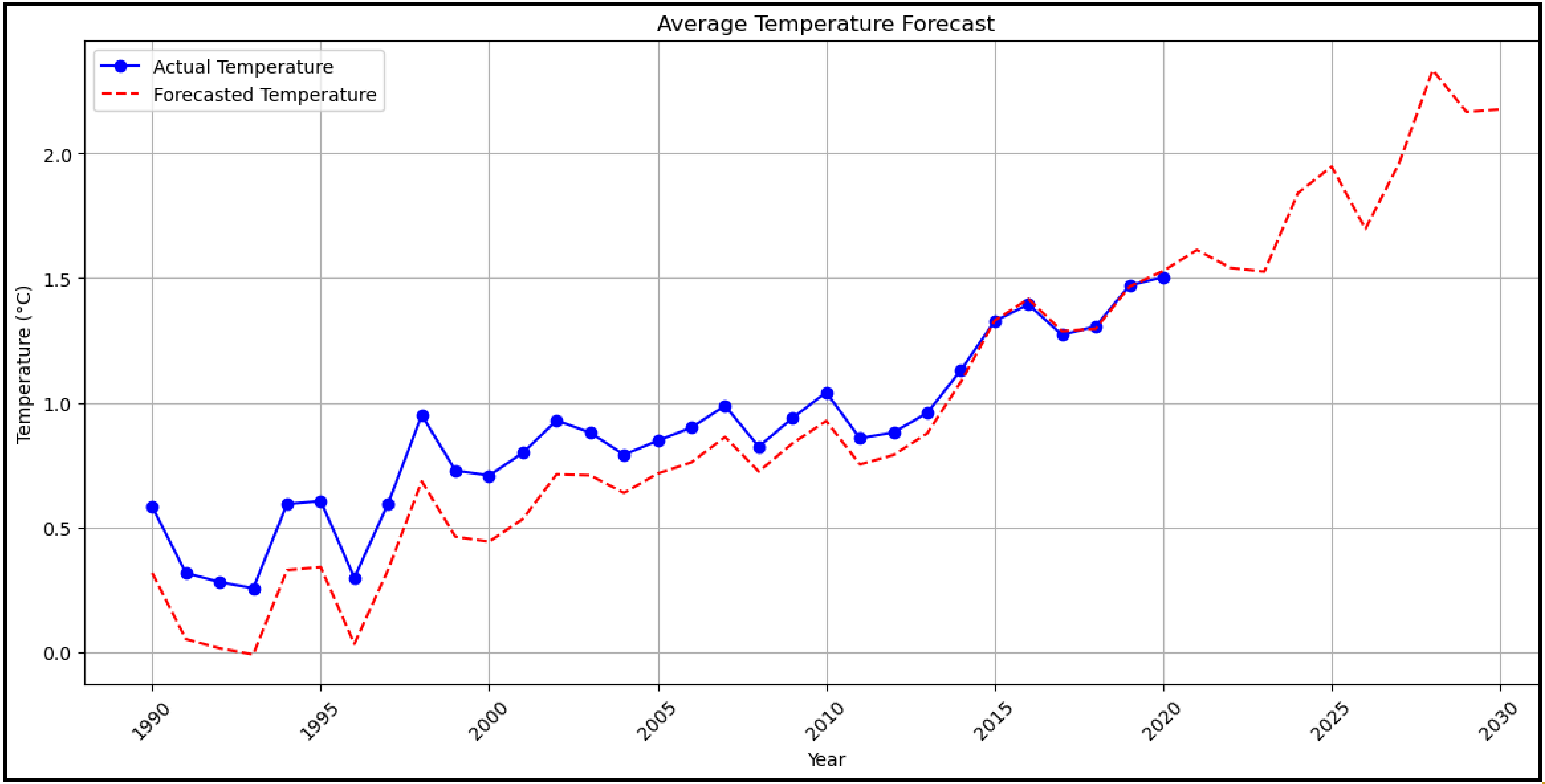
Average Temperature

- Temperature forecast indicates a general rise in global temperatures.
- Aligns with expectations of global warming due to increased emissions.
- Provides insight into the potential impacts on agriculture and climate patterns.




```
Accuracy for Average Temperature:
Mean Absolute Error (MAE): 0.15598443453651492
Mean Squared Error (MSE): 0.034142207812937066
```

Average Temperature Forecast

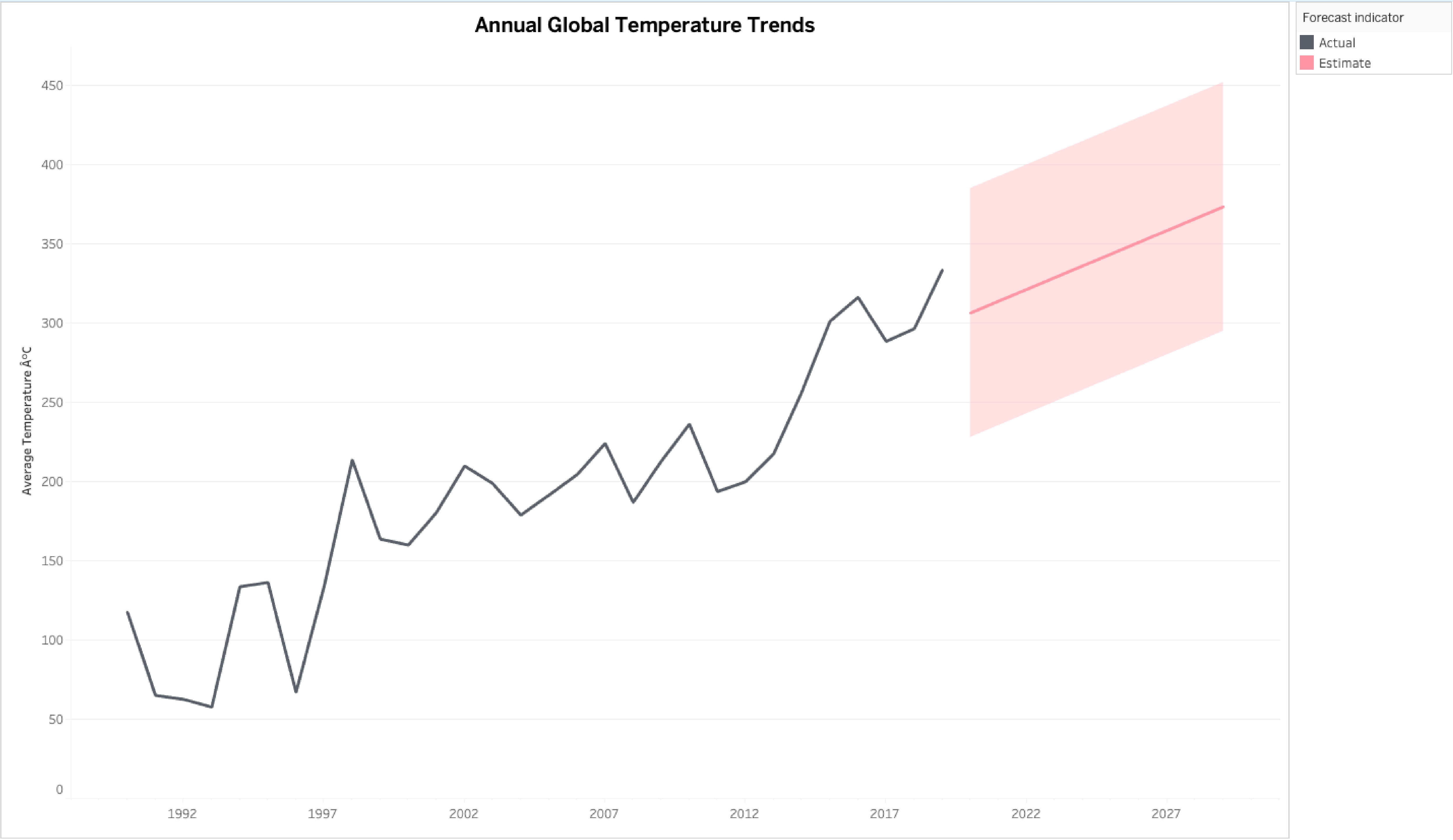


Agro-Food Sector Emissions

Introduction to the Dashboard:

- **This dashboard provides a comprehensive visualization of CO2 emissions and temperature trends in the agri-food sector. It enables stakeholders and policymakers to interactively explore key factors influencing climate change and assess the effectiveness of environmental policies.**

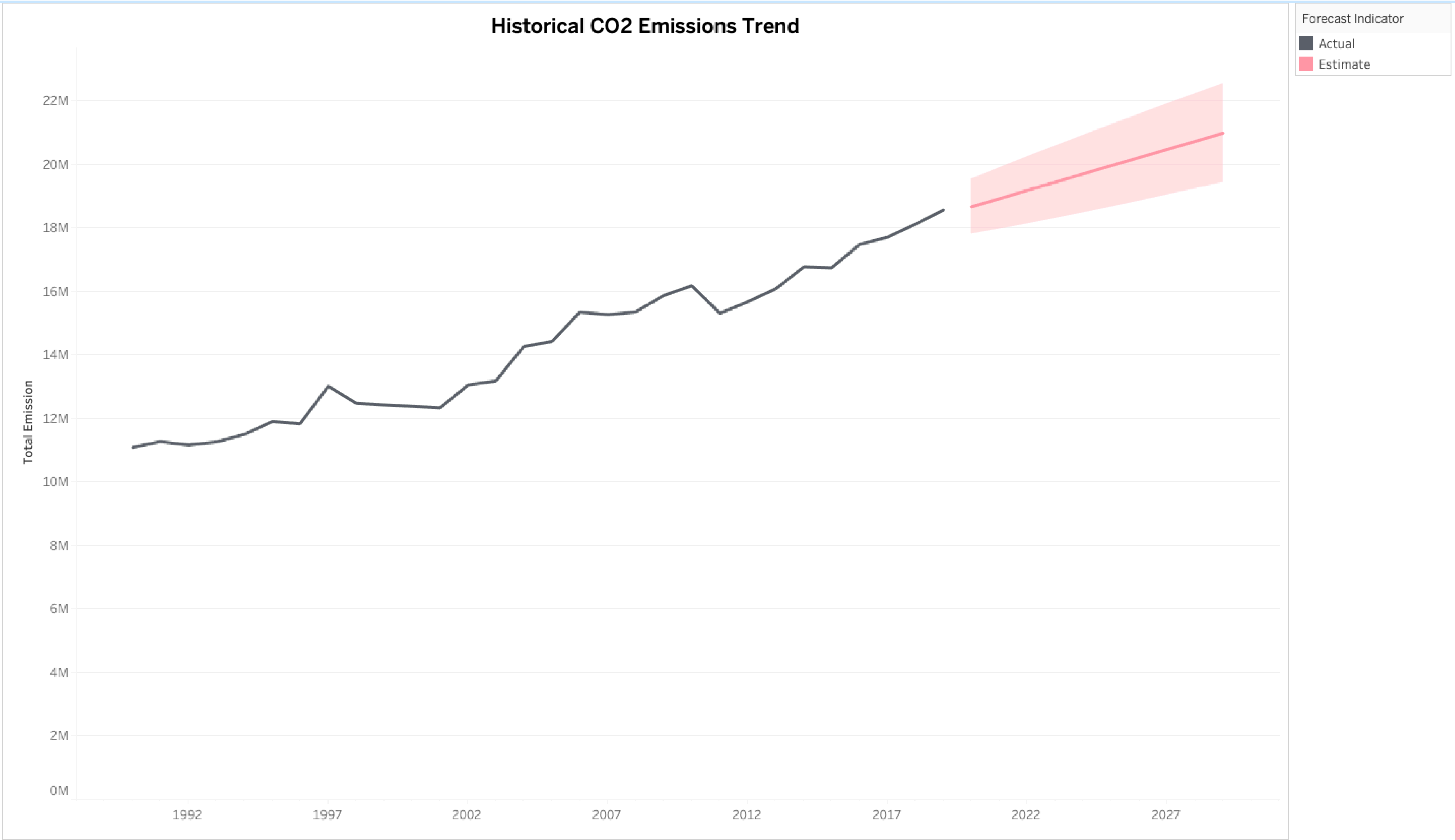
Annual Global Temperature Trends



Purpose

- To track and project the progression of global temperature changes over time, providing a clear visualization of past trends and future forecasts.

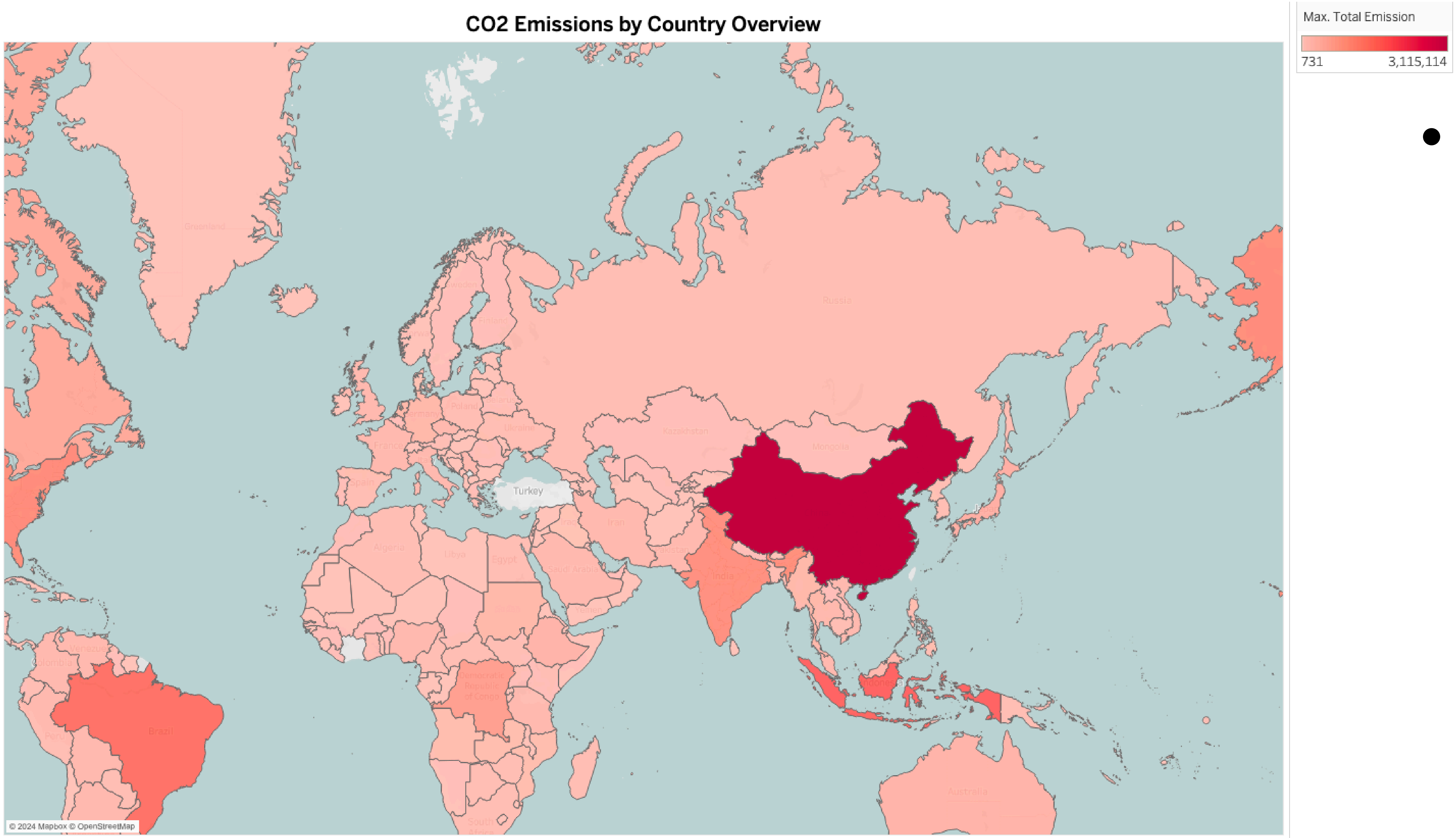
Historical CO2 Emissions Trend



Purpose

- To present a comprehensive historical perspective of CO_2 emissions trends over the years and to forecast future trajectories based on current and past data.

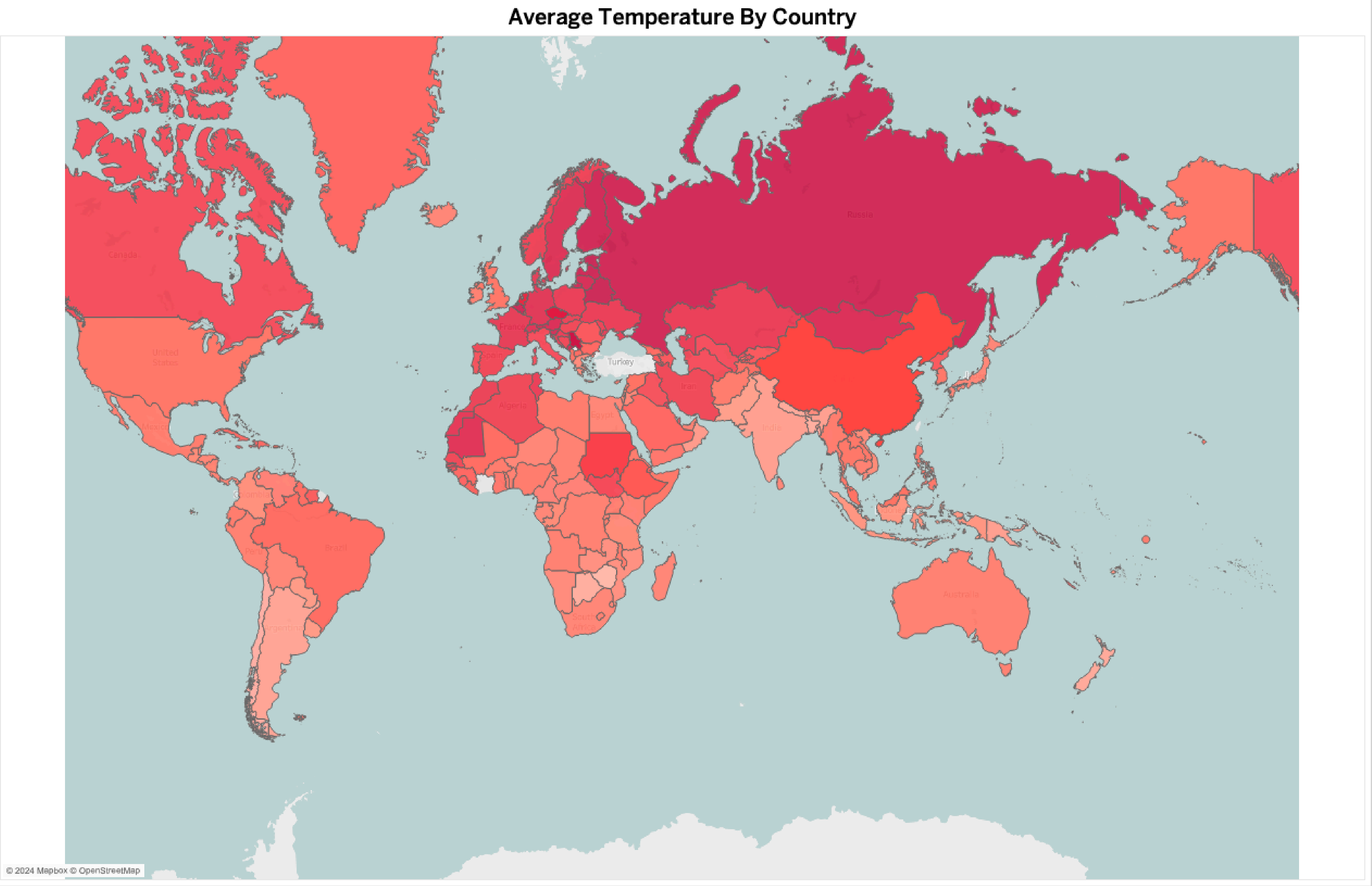
CO2 Emissions by Country Overview

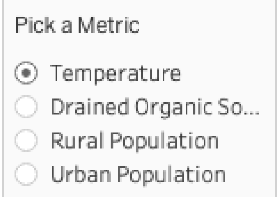


Purpose

- To provide a detailed geographical visualization of CO2 emissions across different countries, highlighting regions with higher emission rates and identifying global patterns in environmental impact.

Metric-Based Geographic Visualizations

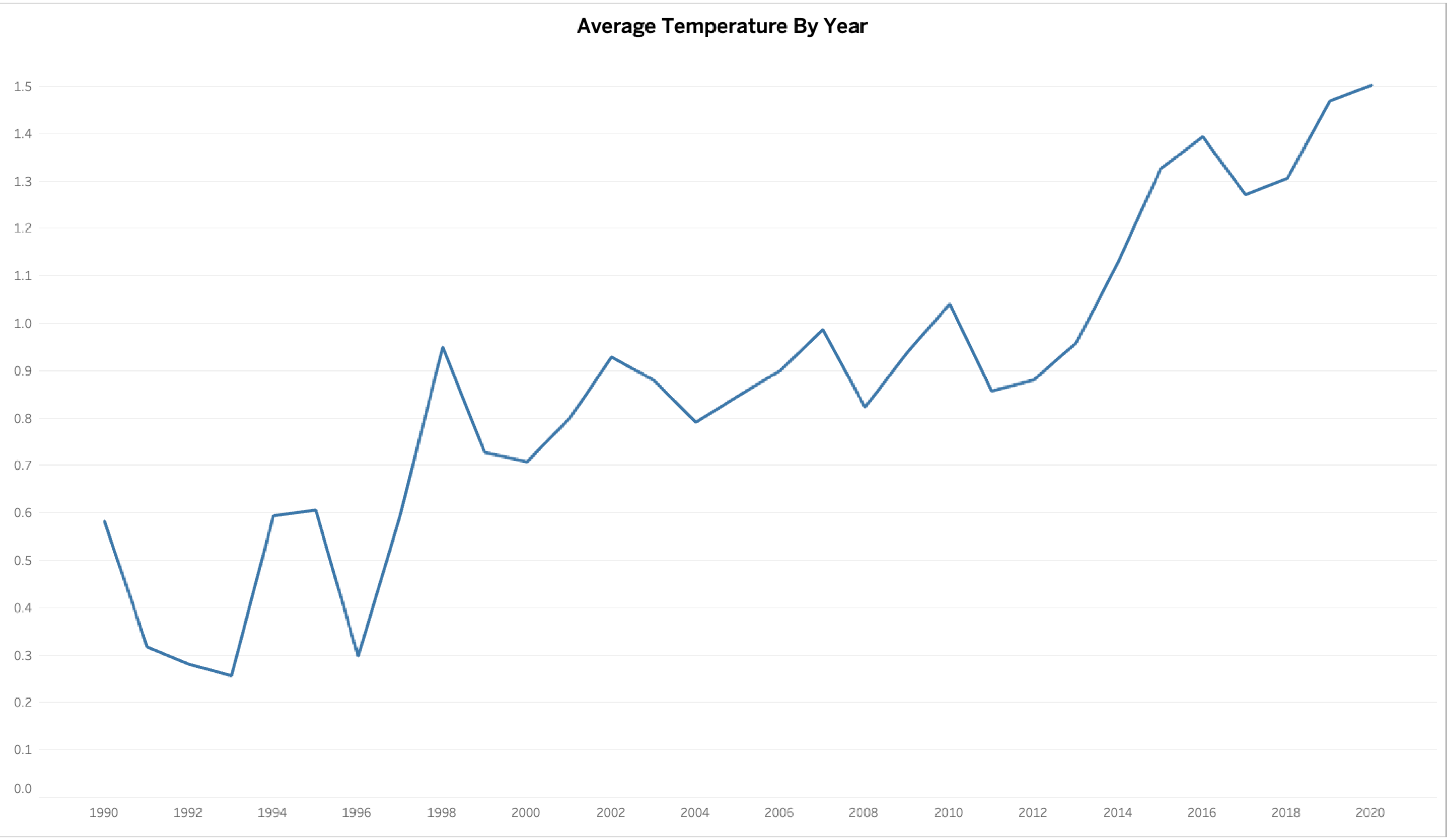




Purpose

- To provide a dynamic and interactive way to explore different environmental and demographic metrics across countries, enhancing understanding of global patterns and correlations between various factors.

Average Metric By Year



Purpose

- To provide a dynamic and interactive way to explore different environmental trends.

Summary KPI(Key Point Indicators)

Agro-Food Sector Emissions	64,091 Avg. Total Emission	6,018 Avg. Agrifood Systems Waste Disposal	3,503 Avg. Drained organic soils (CO2)	3,009 Avg. On-farm energy use	1,940 Avg. Food Transport	3,036 Avg. Fertilizers Manufacturing	999 Avg. Crop Residues

Purpose

- The KPI summary visualization aims to encapsulate the agro-food sector's emissions impact in a succinct and informative display

Agro-Food Sector Emissions

Agro-Food Sector Emissions

64,091
Avg. Total Emission

6,018
Avg. Agrifood Systems Waste Disposal

3,503
Avg. Drained organic soils (CO2)

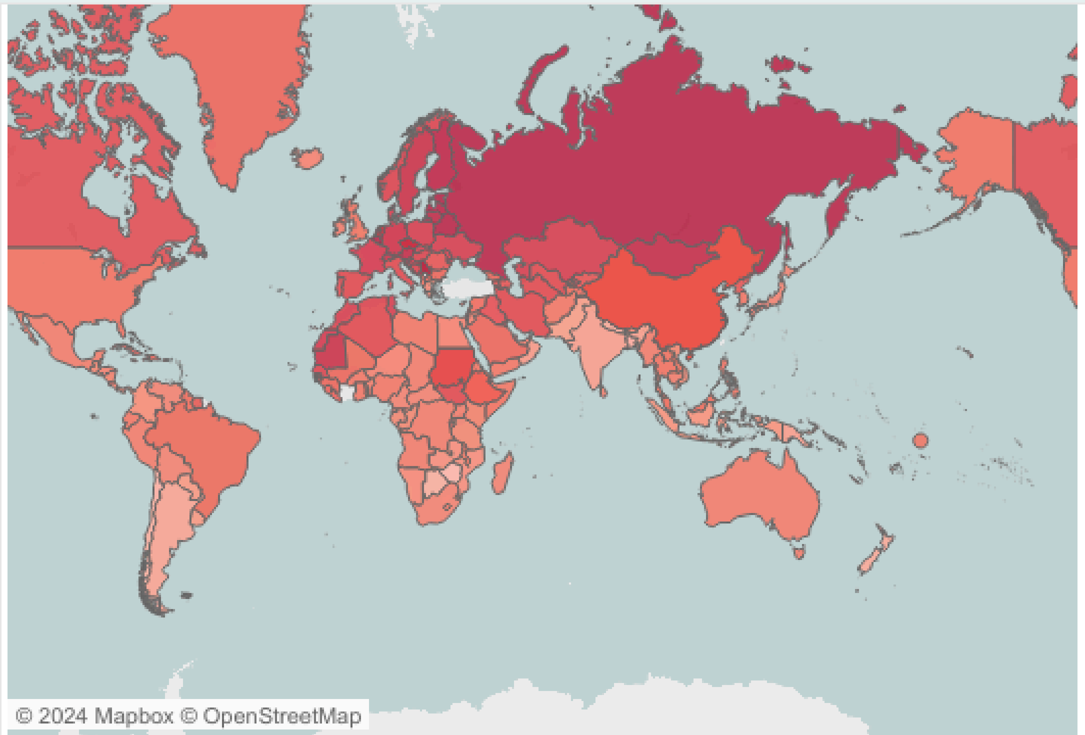
3,009
Avg. On-farm energy use

1,940
Avg. Food Transport

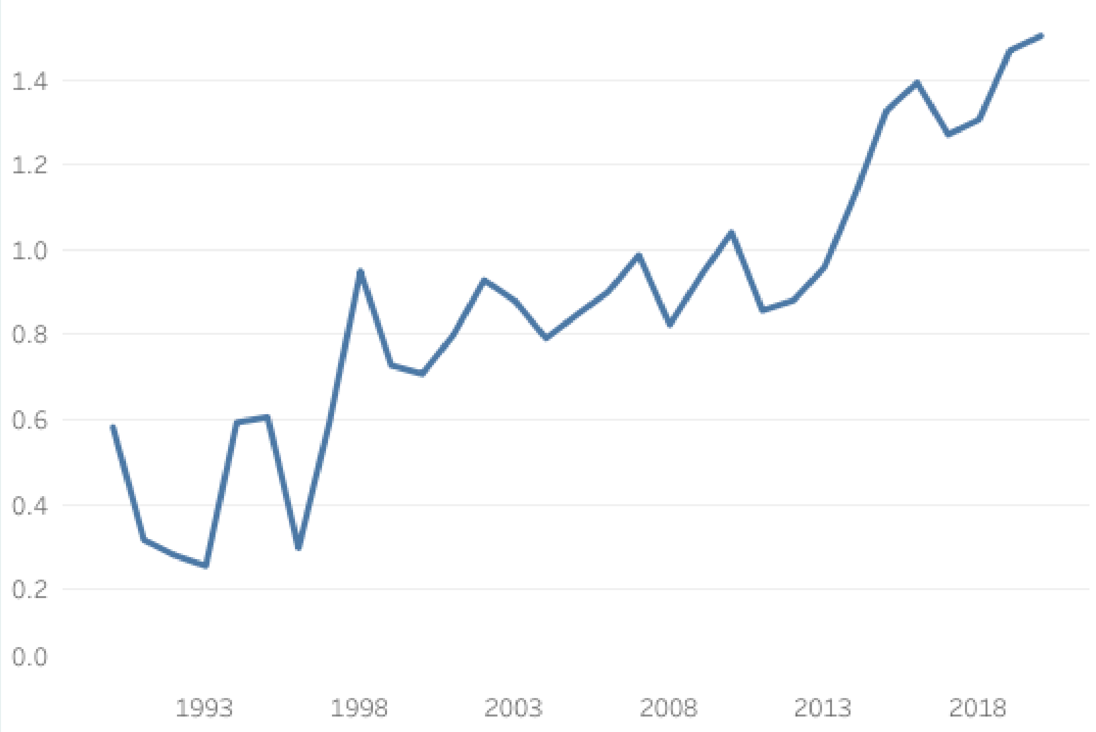
3,036
Avg. Fertilizers Manufacturing

999
Avg. Crop Residues

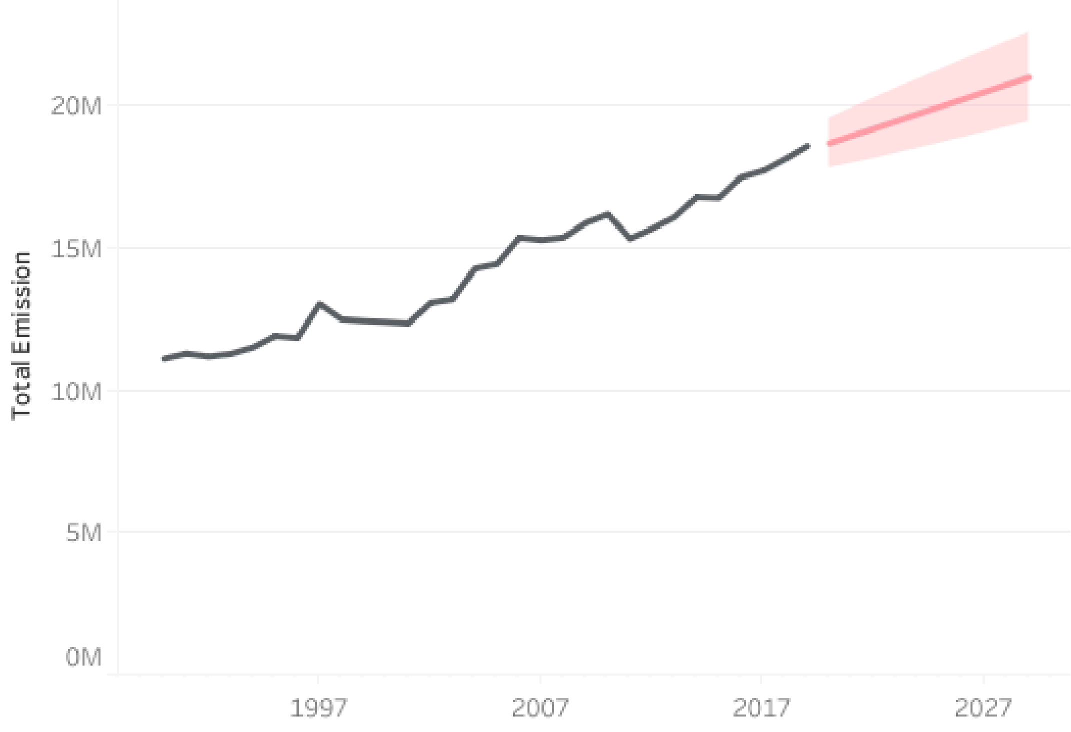
Average Average Temperature By Country



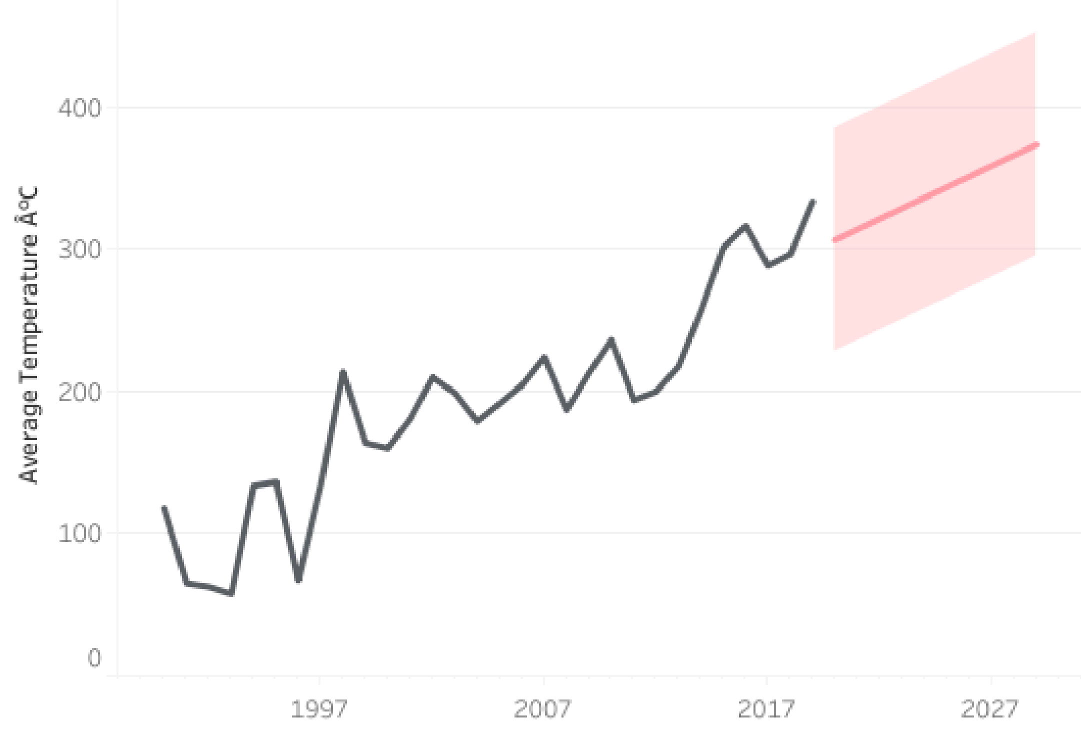
Average Average Temperature By Year



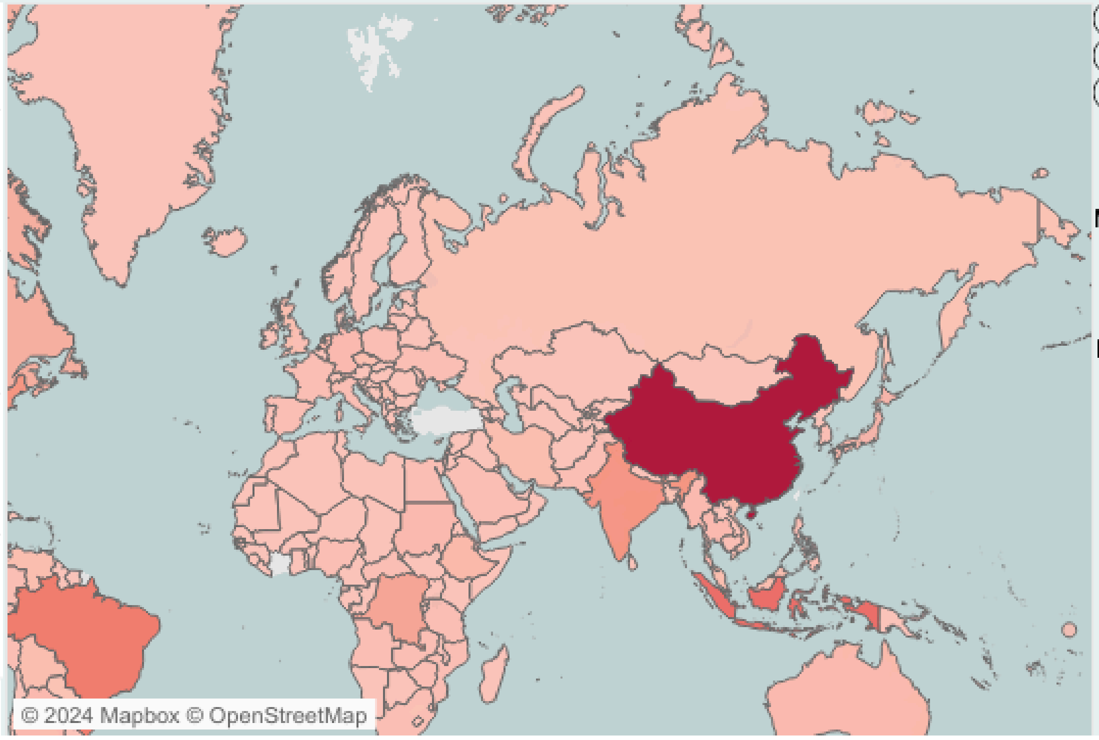
Historical CO2 Emissions Trend



Annual Global Temperature Trends



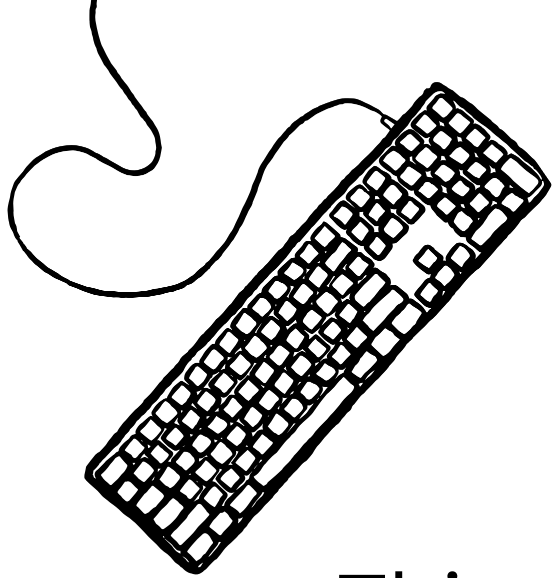
CO2 Emissions by Country Overview



Pick a Metric
- Average Temperature
- Drained Organic Soils (CO2)
- Rural Population
- Urban Population

Max. Total Emission
731 – 3,115,114

Forecast Indicator
- Actual
- Estimate

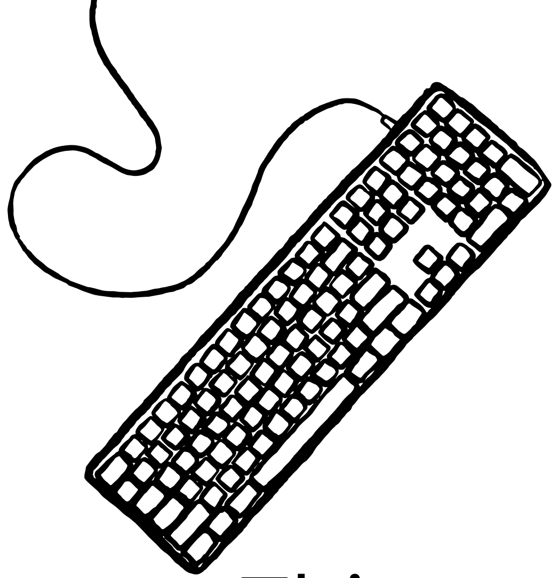


Dashboard Analysis

- This project leveraged advanced statistical methods to forecast CO2 emissions and temperature variations within the agri-food sector, revealing a concerning upward trend in both metrics. By utilizing Winter's Method and developing an interactive Tableau dashboard, the study provided a detailed visualization of future environmental impacts. These insights emphasize the urgency of implementing sustainable agricultural practices to mitigate these effects. The comprehensive data analysis and the interactive dashboard enhance stakeholders' ability to make informed decisions, highlighting the crucial role of data-driven strategies in environmental management.

Key Findings

- The agri-food sector is a significant contributor to global emissions.
- Accurate forecasting can help policymakers devise better strategies to reduce emissions.
- Targeted interventions needed for key emission sources like livestock, rice paddies, and crop burning.
- Helps assess the effectiveness of current environmental policies and suggest improvements.

Conclusion

This project provided a detailed analysis of CO_2 emissions and temperature trends in the agricultural sector, using advanced forecasting methods to project future changes. The results highlight a steady increase in emissions and temperatures, underscoring the urgent need for sustainable practices. With accurate models evidenced by low MAE and MSE values, these forecasts offer reliable insights for shaping effective environmental policies and climate strategies. This study supports data-driven decision-making aimed at mitigating climate impacts, with future work focused on incorporating additional variables and exploring alternative models to enhance forecasting precision.

Future Work

- To enhance the precision and applicability of our forecasts, future research will incorporate a more comprehensive dataset that includes additional variables affecting CO_2 emissions and temperature changes.

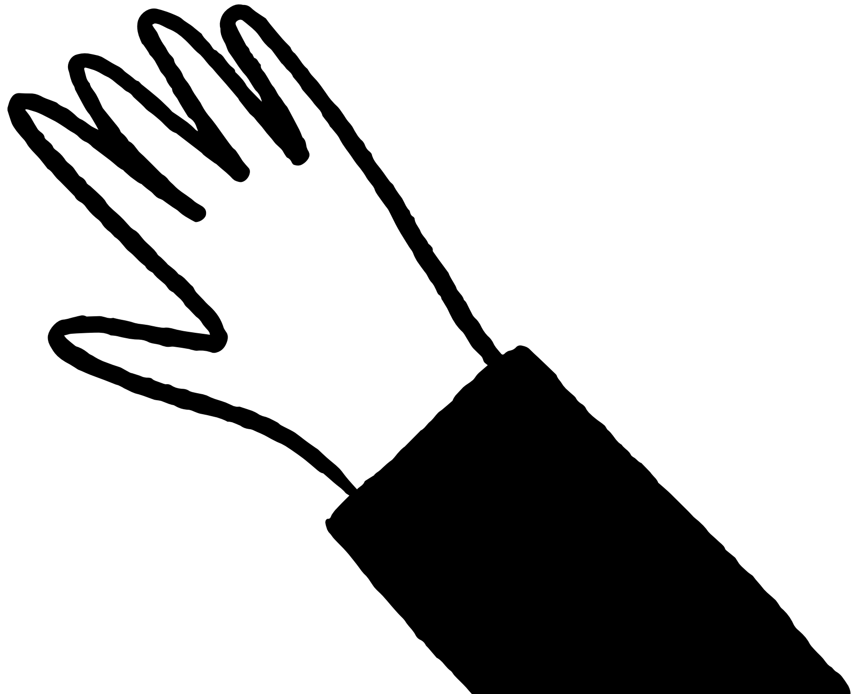
- Exploring alternative forecasting models will be a priority, particularly focusing on ARIMA (AutoRegressive Integrated Moving Average) models. ARIMA's capability to handle time series data with trends and seasonal patterns may provide deeper insights and more accurate forecasts compared to the Winter's Method used in this study.

- The incorporation of machine learning techniques to analyze complex interactions within the data will also be explored. These methods can help uncover non-linear relationships and interactions between variables that traditional models might not capture.

References

Kaggle Dataset:

- Title: Agri-food CO2 emission dataset - Forecasting ML.
- Source: Kaggle Datasets.
- URL: https://www.kaggle.com/datasets/alessandrolobello/agri-food-co2-emission-dataset-forecasting-ml



Thank You