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Agro-Food Sector Emissions

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Introduction

Climate change poses severe risks across various sectors, with the agri-food sector at a pivotal point due to its dual role as both a victim and a contributor to global warming. Agriculture relies heavily on stable climatic conditions, yet it is one of the largest emitters of greenhouse gases (GHGs), primarily CO_2, methane (CH_4), and nitrous oxide (N_2O). These emissions stem from activities such as livestock production, deforestation for farmland, fertilizer use, and energy consumption in food processing and transportation. This project focuses on quantifying and forecasting CO_2 emissions from this sector, which contributes approximately 62% of global emissions. By integrating historical data with advanced forecasting methods, such as Winter's method and exponential smoothing techniques, this study aims to shed light on the potential future trajectories of emissions and their associated climatic impacts. Accurately predicting these trends is crucial for developing effective mitigation strategies and policy interventions. The insights gained from this study will help inform policymakers, enabling targeted action to reduce emissions, enhance sustainability, and combat climate change while ensuring food security.

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.

Executive summary

The agri-food sector is crucial for global food security but also a significant source of CO_2 emissions, contributing to environmental degradation. This report applies advanced forecasting methods, including Winter's Method and exponential smoothing, to predict and analyze CO_2 emissions and temperature trends within the sector. Using a comprehensive dataset from sources such as the FAO and IPCC, the study focuses on key agricultural activities like livestock and crop production. Models were validated using metrics like MAE and MSE, with Winter's Method chosen for its ability to capture seasonal patterns in the data.

The forecasts reveal a steady rise in CO_2 emissions and temperature increases if current agricultural practices continue unchanged. A dynamic Tableau dashboard was developed to visualize these trends interactively, providing policymakers and stakeholders with insights into emission scenarios, trends over time, and regional variations. This study underscores the importance of accurate forecasting for environmental policy and management in the agri-food sector.

Data Description

The agricultural CO_2 emission dataset was constructed by merging and reprocessing around a dozen individual datasets from the Food and Agriculture Organization (FAO) and the Intergovernmental Panel on Climate Change (IPCC). These datasets were cleaned, preprocessed, and combined to form a cohesive dataset for analysis and forecasting.

The dataset focuses on emissions from the agri-food sector, which accounts for approximately 62% of global annual CO_2 emissions. It includes variables such as CO_2 emissions (in kilotons), methane (CH_4) and nitrous oxide (N_2O) emissions, fertilizer use, livestock populations, land use for agriculture, and average temperatures.

This dataset is crucial for understanding the agri-food sector's environmental impact, making it a valuable resource for developing strategies to mitigate climate change.

Forecasting Models Overview

In this study, several forecasting models were initially considered to predict CO2 emissions and temperature trends in the agri-food sector. After evaluating their suitability for the dataset, **Winter's Method** (Triple Exponential Smoothing) was chosen as the most appropriate due to its ability to handle both trend and seasonal components effectively. Below is an overview of the models considered and why Winter's Method was ultimately selected.

Models Considered

- **Moving Average and Simple Exponential Smoothing**:
  These models provide basic smoothing techniques to predict future data points by calculating averages or applying exponential decay to past observations. However, they fall short in accounting for trends and seasonality, both of which are crucial in the analysis of CO2 emissions data. Given the seasonal nature of agricultural emissions, these models were deemed insufficient.
- **Holt's Linear Trend Model**:
  Holt's method extends simple exponential smoothing by adding a trend component, making it suitable for data with a linear trend. While this model captures the upward or downward trends, it still lacks the ability to handle seasonal patterns, which are essential in the context of CO2 emissions from the agri-food sector, where emissions fluctuate with agricultural cycles. As a result, this model was also not suitable for this analysis.

Winter's Method (Chosen Method)

In this study, **both the additive and multiplicative forms of Winter's Method (Triple Exponential Smoothing)** were applied to forecast CO2 emissions and temperature trends. The decision to use both forms was driven by the specific characteristics of the data, which exhibited varying seasonal behaviors in different contexts. Below is an explanation of each form and why both were used.

1. Additive Form

The additive form of Winter's Method is used when the seasonal fluctuations are relatively constant over time, regardless of the overall level of the series. In this model, the seasonal component is added to the level and trend components, making it suitable for datasets where the magnitude of the seasonality remains stable across different periods.

- **Why Additive Was Chosen**:
  The additive form was applied to datasets where the seasonal variations did not grow or shrink in proportion to the overall trend. For example, in cases where agricultural processes such as crop production showed consistent seasonal peaks and troughs (planting and harvesting seasons) without significant variation in magnitude, the additive model was a better fit. This allowed the model to effectively capture the regular, cyclical changes in Average Temperature that occur year after year, without overestimating seasonal effects.
- **Mathematical Representation (Additive)**:

Alpha:
Lt = alpha * (Yt - St-p) + (1 - alpha) * (Lt-1 + Tt-1)

Beta:

Tt = beta * (Lt - Lt-1) + (1 - beta) * Tt-1

Gamma:

St = gamma * (Yt - Lt) + (1 - gamma) * St-p

Where:

- Alpha is the smoothing parameter for the level,
- Yt represents the actual observation at time t,
- St-p is the seasonal component from p periods prior,
- Lt-1 is the level from the previous period,
- Tt-1 is the trend from the previous period.

2. Multiplicative Form

The multiplicative form of Winter's Method is used when the seasonal fluctuations increase or decrease proportionally with the overall level of the series. This means that as the trend grows, the seasonal variations also grow in magnitude. In this model, the seasonal component is multiplied by the level, making it suitable for datasets where seasonality scales with the overall trend.

- **Why Multiplicative Was Chosen**:
  The multiplicative form was applied to CO_2 emissions data where seasonal effects intensified as the level of emissions increased. For example, emissions from livestock and industrial agriculture often show seasonal peaks that grow in magnitude as overall production increases. In such cases, where emissions patterns become more pronounced as agricultural activity grows, the multiplicative model provides a better fit, capturing the proportional relationship between the level of emissions and seasonal variations.
- **Mathematical Representation (Multiplicative)**:

  Alpha:
  Lt = alpha * (Yt / St-p) + (1 - alpha) * (Lt-1 + Tt-1)

  Beta:

  Tt = beta * (Lt - Lt-1) + (1 - beta) * Tt-1

  Gamma:

  St = gamma * (Yt / Lt) + (1 - gamma) * St-p

Where:

- Alpha is the smoothing parameter for the level,
- Yt represents the actual observation at time t,
- St-p is the seasonal component from p periods prior,
- Lt-1 is the level from the previous period,
- Tt-1 is the trend from the previous period.

- Here, the seasonal component is proportional to the level, meaning that higher levels of activity lead to larger seasonal variations.

Why Both Additive and Multiplicative Were Used

In this project, both the additive and multiplicative forms were necessary due to the nature of the dataset:

- **Additive Form**: Applied to emissions data that exhibited stable seasonal patterns, where the impact of seasonal fluctuations (e.g., planting or harvesting periods) remained constant over time.
- **Multiplicative Form**: Used where seasonal patterns grew in proportion to the overall level of emissions, such as in large-scale agricultural practices or livestock operations where seasonal variations became more significant with increased production.

By employing both forms, the study ensured that the forecasting model could accurately capture the complex patterns of CO_2 emissions & Average Temperature in different agricultural contexts. The combination of these two forms provided a comprehensive understanding of how seasonal effects interacted with long-term trends in the agri-food sector, allowing for more precise predictions of future emissions and temperature variations.

Code Implementation and Analysis

This section describes the implementation of the forecasting models using Python, focusing on the application of Winter's Method in both its additive and multiplicative forms. The models were coded using well-known Python libraries such as **Pandas**, **NumPy**, and **Matplotlib** for data handling, analysis, and visualization.

Code Explanation

To implement Winter's Method, two separate functions were written to handle the additive and multiplicative models. These functions were designed to adjust the level, trend, and seasonality based on the input data and forecast future values.

- Additive Winter's Method (winters): This function handles the additive model where the seasonal variations are constant over time.
- Multiplicative Winter's Method (winters_MULTI): This function is designed for the multiplicative model, where the seasonal variations change in proportion to the level of the series.

```python
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
```

Figure 1:Implementation Of Winters(Additive) In Python.

```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])
```

Figure 2:Implementation Of Winters(Multiplicative) In Python.

Key Operations:

- Each function iterates over the data, applying specified smoothing parameters (alpha, beta, gamma) to forecast future values.
- These parameters are crucial for fine-tuning the model's sensitivity to changes in the data.

Visualization:

- The results, including historical data and forecasts, are visualized using Matplotlib. This not only aids in validating the model's effectiveness but also illustrates the potential future trends based on the historical patterns.

```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()
```
Figure 3: Function For Visualising CO2 Emissions and Temperature Trends.

Mean Absolute Error (MAE) and Mean Squared Error (MSE):

MAE and **MSE** are fundamental metrics for evaluating the accuracy of forecasting models.

- MAE measures the average absolute difference between forecasted values and actual data, providing a direct indication of average error magnitude without direction. It is especially useful for comparing the error rates in the same units as the data.

- MSE calculates the average of the squares of the errors, accentuating larger errors more than smaller ones due to squaring each term. This makes MSE particularly effective at highlighting significant errors that are undesirable.

- Lower values of MAE and MSE suggest a more accurate model, critical for enhancing the reliability of forecasts.

```python
#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}")
```
Figure 4:MAE and MSE Calculations for CO2 Emissions and Average Temperature Forecasts.

Main Function Implementation:

The core of our analysis is encapsulated in the Main function, which orchestrates the loading of data, application of forecasting models, and visualization of results. This function is meticulously designed to execute several key processes:

- **Data Loading and Preprocessing**: The function begins by loading the CO2 emissions data from a CSV file. It then proceeds to format the 'Year' column for correct numerical analysis and filters the dataset to include only numeric data types, ensuring data consistency and usability.
- **Data Aggregation**: The data is grouped by 'Year' to calculate annual means for total emissions and average temperature, providing a clear basis for time-series forecasting.

- **Parameter Setting and Model Initialization**: Season length and forecast years are defined, along with alpha, beta, and gamma parameters for the Winter's method. These settings are crucial for tailoring the model to the specific seasonal and trend characteristics of the dataset.
- **Model Application**: The additive and multiplicative Winter's method models are applied to the aggregated data. This step involves calculating forecasts for future periods, demonstrating the model's capability to extend beyond the range of the actual data.
- **Visualization**: Using Matplotlib, the function plots both the actual data and the forecasts, visually comparing the historical emissions and temperature data against the projected future values.
- **Accuracy Assessment**: Finally, the function evaluates the accuracy of the forecasts using Mean Absolute Error (MAE) and Mean Squared Error (MSE), providing quantitative metrics to assess model performance.

```
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()
```

Figure 5: The Main Function.

Forecast Outputs and Model Evaluation

CO2 Emissions Forecast Overview:

The forecast generated by our model indicates a continued increase in CO_2 emissions from the agri-food sector, extending through the year 2030. This upward trend underscores the pressing need for implementing sustainable agricultural practices to mitigate emissions effectively. The graph illustrates this projection by comparing actual historical emissions data against the forecasted values, clearly depicting the trend's progression over time.

Graphical Analysis:

The visual representation (Figure 6) shows two data trajectories:

- **Actual Emissions**: Represented by the blue line, plots the historical data points of CO_2 emissions from 1990 through the present.

- **Forecasted Emissions**: Indicated by the red dashed line, extends from the current data point into future projections up to 2030. This forecast suggests that without significant changes in current practices, emissions will continue to rise, reflecting the model's ability to capture both the ongoing trends and the immediate impacts of seasonal and cyclic variations within the sector.

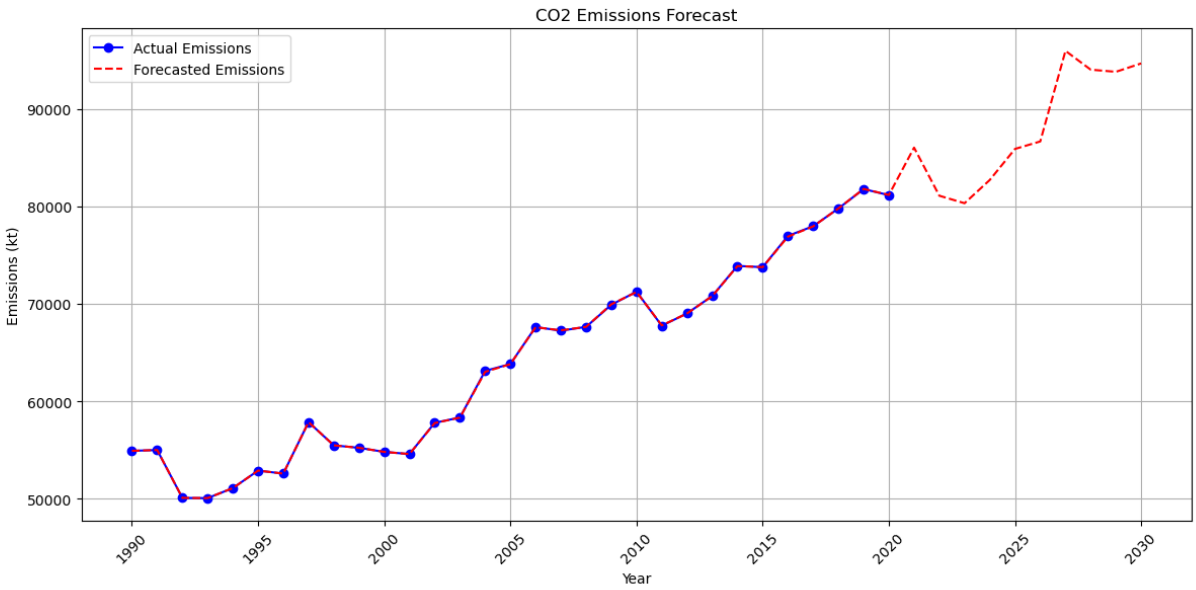

Figure 6: Forecasted Co2 Emissions.

Accuracy Metrics:

The model's accuracy was quantitatively assessed using two standard metrics:

- **Mean Absolute Error (MAE)**: The MAE for the total emissions forecast was calculated to be 16.57 kt. This low value indicates a high level of precision in the forecasts, with the model demonstrating minimal average deviation from the actual data.
- **Mean Squared Error (MSE)**: The MSE was computed as 816.90 kt^2, suggesting that while the model is generally accurate, there are instances where the squared errors (likely from outlier years or unexpected emissions spikes) contribute to a higher average error squared.

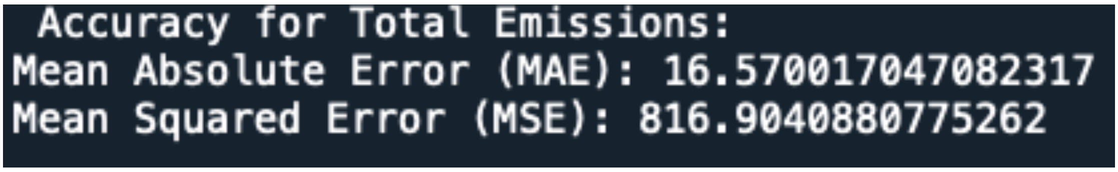
Accuracy for Total Emissions:
Mean Absolute Error (MAE): 16.570017047082317
Mean Squared Error (MSE): 816.9040880775262

Figure 7: MAE & MSE Values For Total Emissions

Temperature Forecast Overview:

The forecast model provides a predictive look at the average temperature trends up to the year 2030, based on historical data extending back to 1990. As depicted in the graph, the forecasted temperatures show a clear upward trend, indicating a potential increase in average temperatures over the next decade. This trend aligns with the global patterns observed in climate change studies, suggesting an ongoing rise in temperatures if current environmental conditions persist.

Graphical Analysis:

Visual Representation the graph (Figure 8) clearly illustrates two distinct data trajectories, helping to visualize the trends in CO2 emissions over time:

- **Actual Emissions**: The blue line represents actual historical CO2 emissions data collected from 1990 to the present. This line shows the real values as recorded annually, providing a baseline against which the forecasted data can be compared.
- **Forecasted Emissions**: Indicated by the red dashed line, extends from the current data point into future projections up to 2030. The forecast underscores a progressive increase in average temperatures, suggesting that, in the absence of mitigative environmental measures, we can expect a continuation of this warming trend. The forecast underscores a progressive increase in average temperatures, suggesting that, in the absence of mitigative environmental measures, we can expect a continuation of this warming trend.

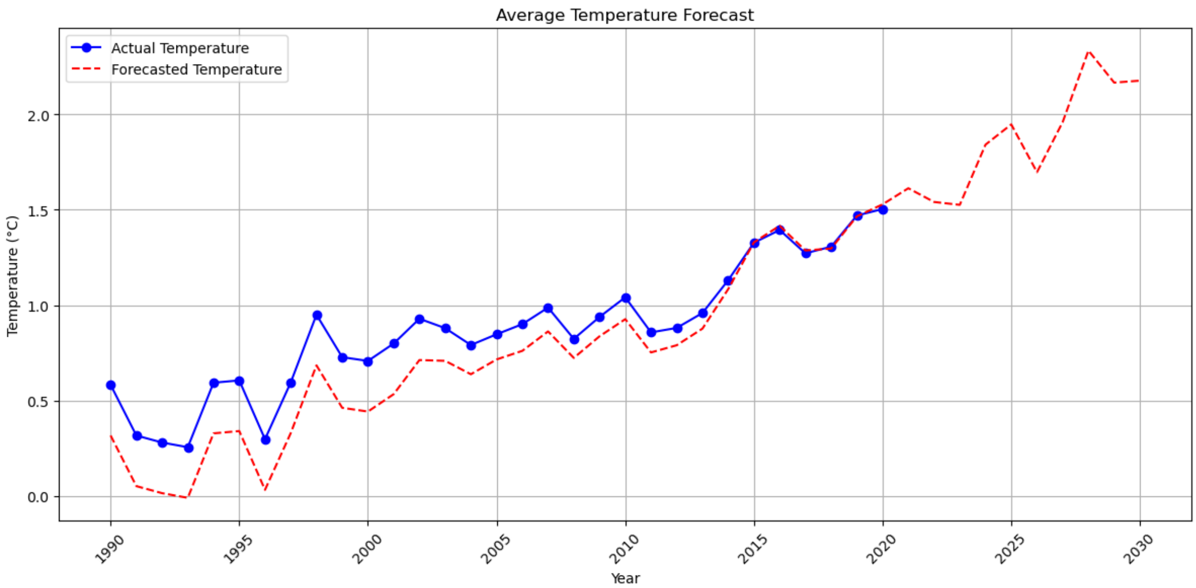

Figure 8: Forecasted Average Temperature.

Accuracy Metrics:

- Mean Absolute Error (MAE): The MAE for the temperature forecast is exceptionally low at 0.1559°C, indicating that the model's average prediction error is minimal, suggesting a high degree of accuracy in the temperature forecasts.
- Mean Squared Error (MSE): Similarly, the MSE value is 0.0341°C², reinforcing the model's precision. The low MSE value highlights that significant deviations from actual temperature values are rare, emphasizing the model's reliability in forecasting temperature changes.

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

Figure 9: MAE & MSE Values For Average Temperature

Insights from Code Outputs

Upon implementation and validation of our forecasting models for CO2 emissions and average temperature, utilizing Mean Absolute Error (MAE) and Mean Squared Error (MSE) as primary accuracy metrics, several critical insights have emerged.

Increasing Trends:

The analysis reveals a clear upward trend in both CO2 emissions and average temperatures, as indicated by the forecasting models. This pattern suggests that if existing practices within the agri-food sector persist without significant modification, the sector will continue to exert considerable environmental impacts. The consistent rise depicted in the forecast models underscores the potential for severe consequences if no corrective measures are taken, such as intensified global warming and an increase in extreme weather events.

High Accuracy:

The forecasts demonstrate high accuracy, evidenced by the low values of MAE and MSE. This high degree of accuracy affirms the reliability of the forecasting models and suggests they are robust against various fluctuations and potential data inconsistencies.

Need for Intervention:

The projected increase in emissions and temperature highlights an urgent need for sustainable interventions within the agri-food sector. This insight is pivotal, as it not only signals the necessity for immediate action to mitigate adverse environmental trends but also serves as a quantitative basis for advocating for policy changes and innovative practices. Implementing sustainable methods is crucial not only for reducing the sector's environmental footprint but also for aligning with global sustainability targets and improving resilience to climate change.

Dashboard Analysis and Insights

Overview of the Dashboard:

This comprehensive dashboard presents a multi-faceted view of the environmental impacts associated with the agri-food sector, particularly focusing on CO2 emissions and global temperature trends. It allows users to interactively explore how different factors contribute to these environmental issues.

Detailed Breakdown of Each Graph:

- **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.

Functionality:
This graph combines historical temperature data with advanced predictive analytics to extend the trend line into the future, offering a visual representation of annual global temperature trends. The use of actual historical data points provides a solid foundation for the model, while the forecast section anticipates future temperature increases based on current trends.

Impact:
The visualization is crucial for understanding the dynamics of global temperature changes and their potential implications. By clearly delineating past trends and future projections, this graph serves as a valuable tool for climate scientists, policymakers, and environmental planners to assess the pace of climate change. It aids in evaluating the effectiveness of existing climate policies and in formulating strategic responses to anticipated environmental conditions. The forecast section particularly helps in preparing for future challenges by indicating potential temperature rises, thus supporting proactive climate adaptation and mitigation strategies.

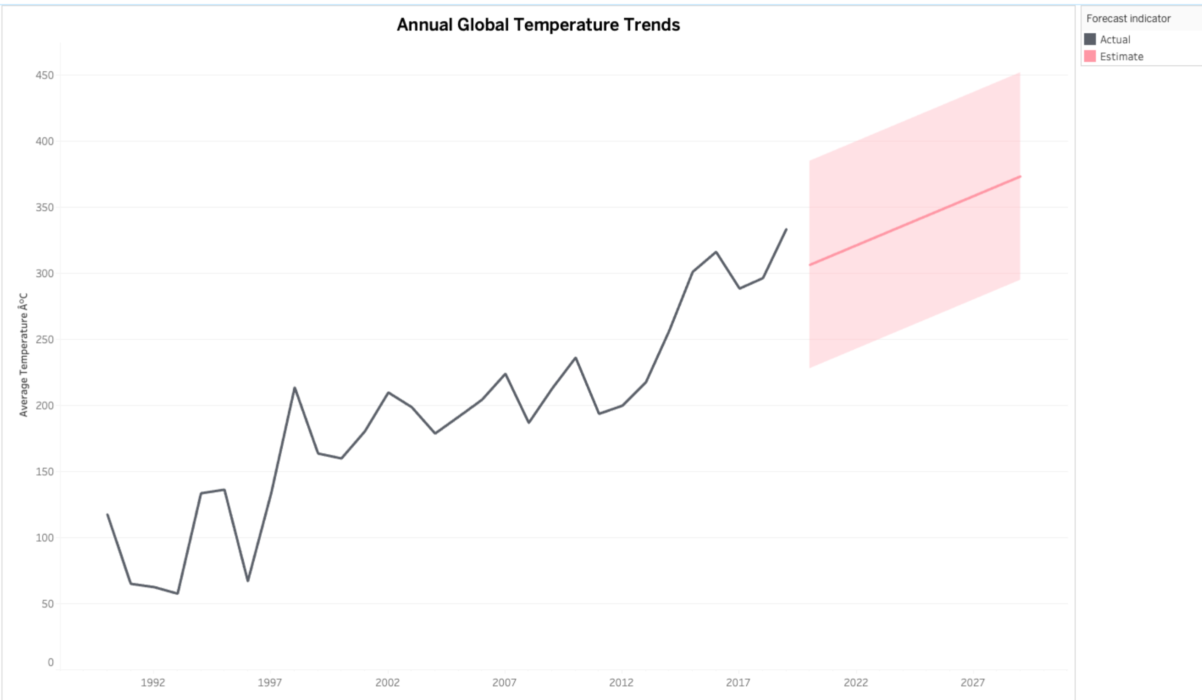

Figure 10:Annual Global Temperature Trends

- **Historical CO2 Emissions Trend:**

Purpose:
To present a comprehensive historical perspective of CO2 emissions trends over the years and to forecast future trajectories based on current and past data.

Functionality:
This graph merges historical CO2 emissions data with predictive modeling to extend the trend into future years, offering a clear visualization of past trends and potential future scenarios. The actual data provides a solid foundation for predictions, while the forecast highlights expected trends based on current environmental and industrial practices.

Impact:
Crucial for assessing the effectiveness of past environmental policies and interventions, this graph also aids in strategic planning for future emissions management. By forecasting future emissions, it allows policymakers, businesses, and environmental groups to see the potential impact of continuing current practices. It serves as a vital tool in the strategic planning process, helping to model various scenarios and plan interventions that could alter these projected outcomes.

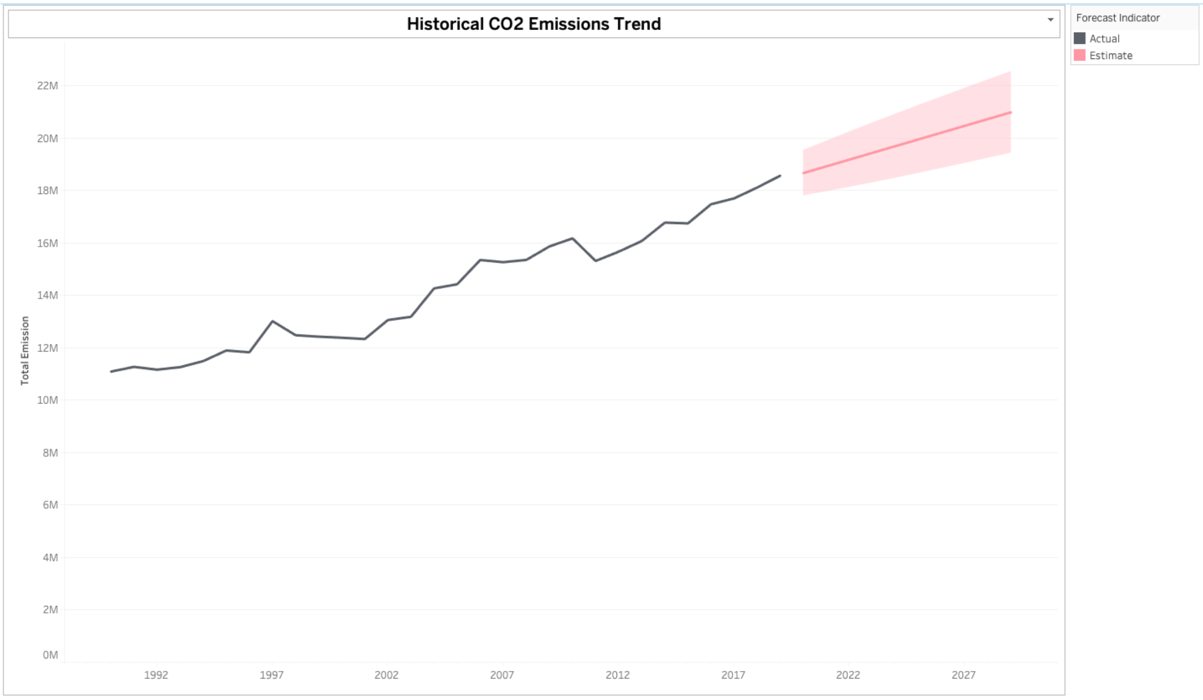

Figure 11: Historical CO2 Emissions Trend.

- **Metric- over the years**

  Purpose:
  To provide a dynamic and interactive way to explore different environmental trends over the years.

  Functionality:
  This suite of visualizations allows users to select from multiple metrics, such as Average Temperature, Drained Organic Soils (CO2), Rural Population, and Urban Population, using a slicer. Each selection updates the line chart to display relevant data, A calculated field is utilized within the visualization software to dynamically alter the display based on user selection, ensuring that the line chart reflects the most current data according to the chosen metric.

  Impact:

  The dynamic nature of this graph enhances its utility in multi-faceted climate studies, allowing for simultaneous analysis of temperature trends alongside other variables such as CO2 emissions, population growth, or land use changes. This integration provides a comprehensive tool for researchers and policymakers to visualize the interdependencies of climate factors and human activities, which can inform more targeted and effective environmental policies and actions.

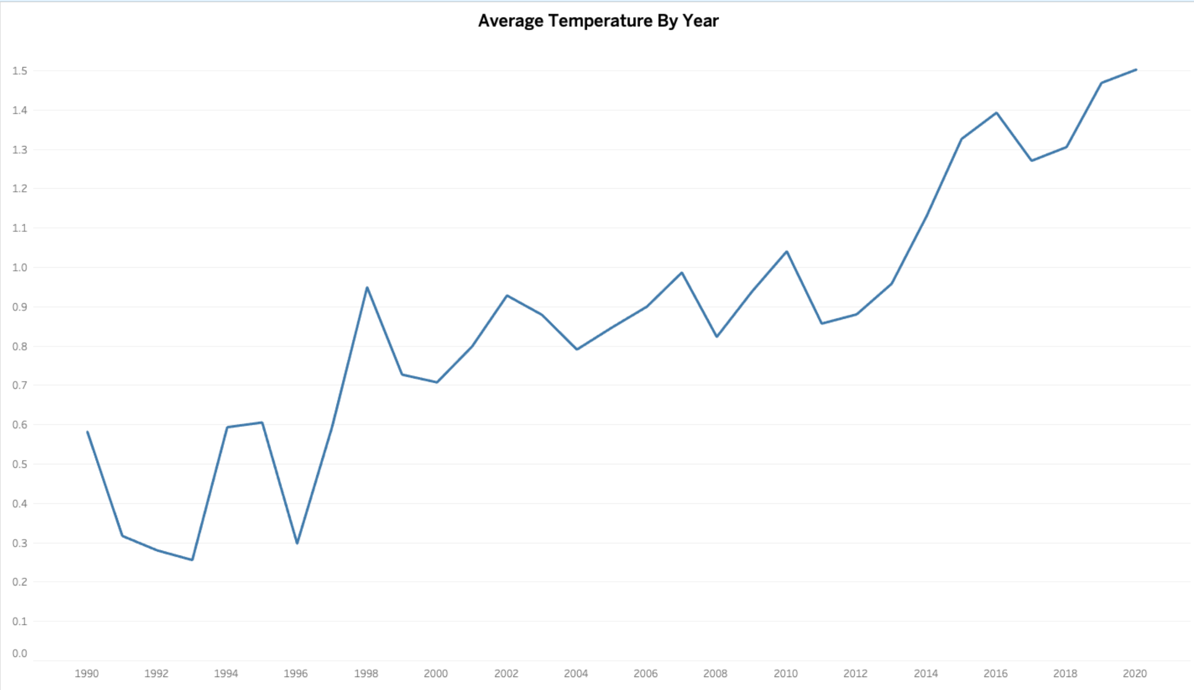

Figure 12:Chosen Metric Vs Time.

- **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.

  Functionality:
  This interactive map allows users to view CO2 emissions data for each country, color-coded to reflect the intensity of emissions. The map includes tools for zooming and selecting specific regions, enabling a more detailed examination of emissions data. It also features a sidebar that displays the maximum total emissions, allowing comparisons between countries at a glance.

  Impact:
  Essential for understanding the global distribution of CO2 emissions, this map serves as a critical tool for international policy makers, environmental researchers, and activists. By identifying countries with the highest emissions, it facilitates targeted international collaborations and the formulation of region-specific strategies to reduce the global carbon footprint. Moreover, it helps in assessing the effectiveness of current environmental policies and in planning strategic interventions where they are most needed.

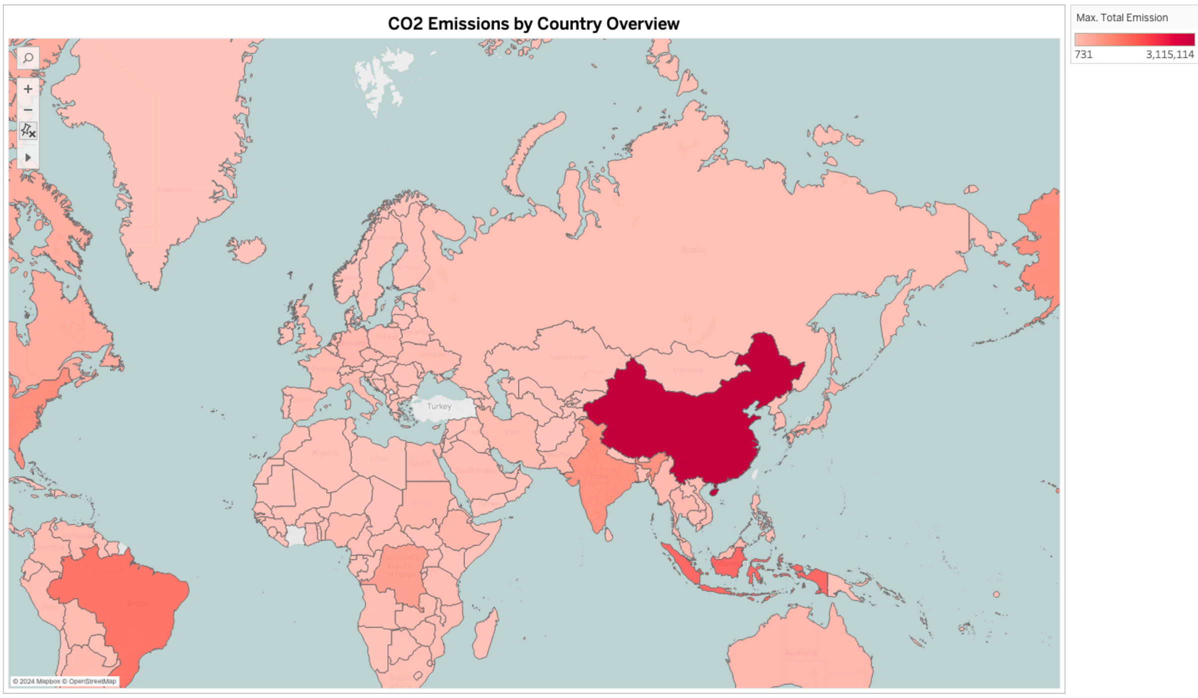

Figure 13: CO2 Emissions by Country

- **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.
- **Functionality:**
  This suite of visualizations allows users to select from multiple metrics, such as Average Temperature, Drained Organic Soils (CO2), Rural Population, and Urban Population, using a slicer. Each selection updates the map to display relevant data, color-coded according to the intensity of the metric. A calculated field is utilized within the visualization software to dynamically alter the display based on user selection, ensuring that the map reflects the most current data according to the chosen metric.
- **Impact:**
  By enabling interactive exploration of various metrics, these visualizations serve as powerful tools for analyzing global trends and disparities. For policymakers, researchers, and the general public, the ability to switch between different data views allows for a comprehensive analysis of how different factors influence or correlate with one another across regions. This can inform targeted interventions and policies, particularly in areas identified as having extreme values or notable trends. The interactive nature of these maps significantly enhances user engagement and comprehension, making complex datasets accessible and understandable.
- **Technical Implementation:**
  The functionality is powered by calculated fields in the visualization software, which dynamically adjust the data displayed based on user selection. This approach not only enhances interactivity but also ensures that users can personalize their analysis and view the data most relevant to their specific interests or research needs.

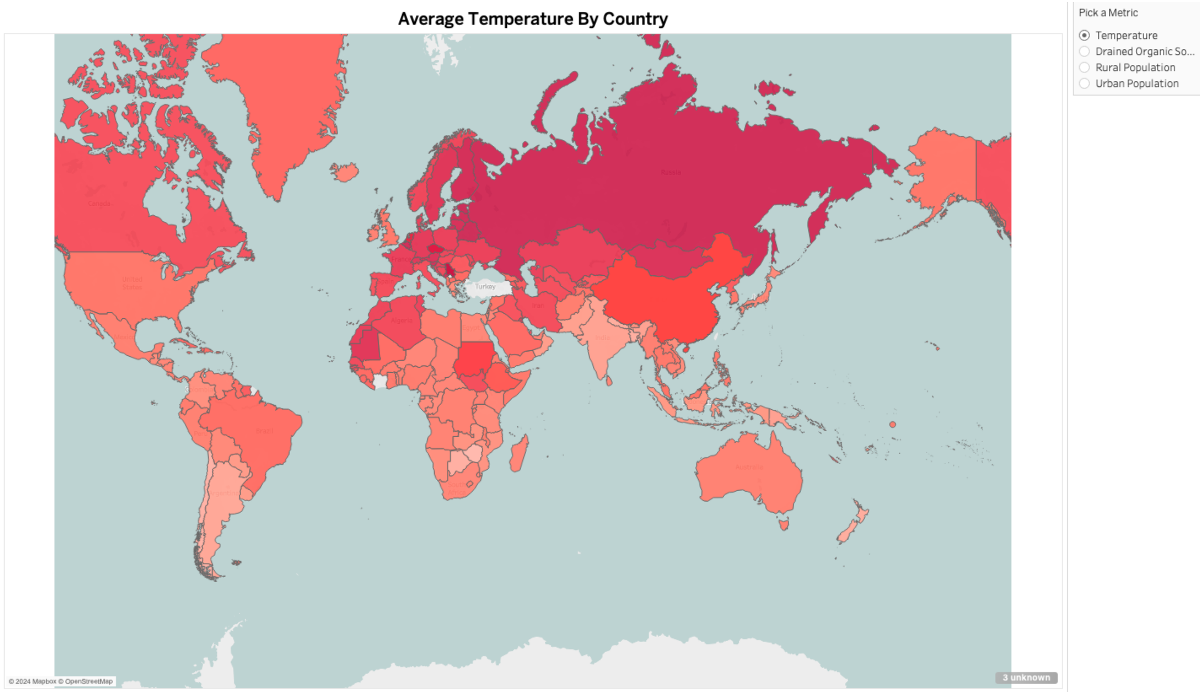

Figure 14:Chosen Metric Vs World

- **KPI Summary Visualization for Agro-Food Sector Emissions**
- **Purpose:**

  a. This visualization is designed to provide a snapshot of key emission metrics such as total emissions, and specific sources like agri-food systems waste disposal, drained organic soils, on-farm energy use, food transport, fertilizer manufacturing, and crop residues.

- **Functionality:**
  This summary visual presents aggregated data in a clear, easy-to-read format, enabling quick insights into significant emission contributors within the agro-food sector. Each metric is displayed alongside its average value, offering a comparative perspective that highlights the relative impact of different emission sources.
- **Impact:**
  The visualization serves as a crucial tool for stakeholders, including policymakers, researchers, and environmental strategists, by highlighting critical areas where interventions can be most effective. It aids in identifying the largest sources of emissions within the sector, facilitating targeted strategies to reduce environmental impact.

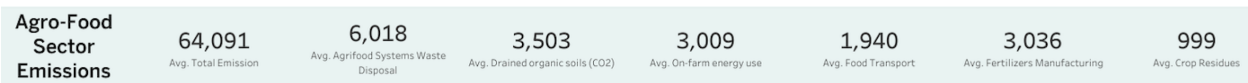

Figure 15: KPI (Key Point Indicators)

- **Dashboard:**

Displayed in Figure 16, the dashboard amalgamates various individual metrics such as CO2 emissions trends, average temperature fluctuations, and demographic statistics into one expansive visual interface. It incorporates interactive features like filters and selectors that allow users to customize the data display according to specific variables, geographical regions, or time periods. This functionality not only increases the dashboard's usability but also empowers users to conduct a tailored analysis that aligns with their unique research needs or policy objectives.

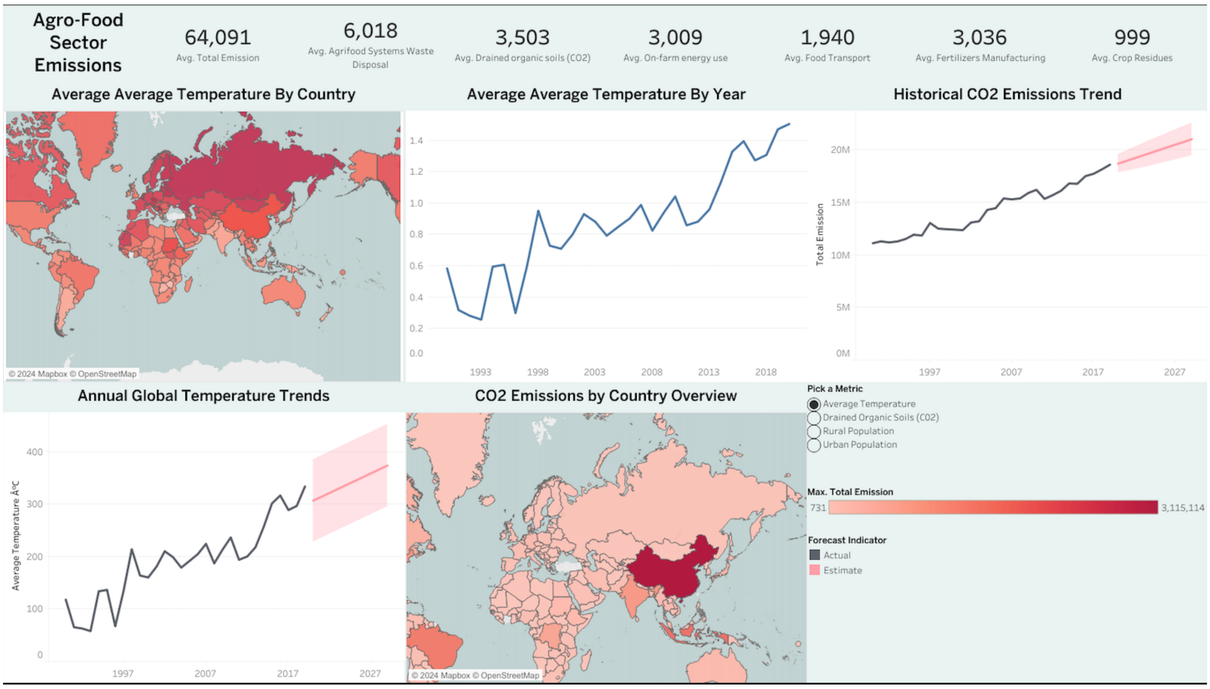

Figure 16:Complete Dashboard View of Agro-Food Sector Emissions

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.

Conclusion

This project has conducted a comprehensive analysis of CO_2 emissions and temperature fluctuations within the agricultural sector, a critical area given its substantial contribution of approximately 62% to global emissions. Through the application of advanced forecasting methods, specifically the additive and multiplicative forms of Winter's Method, this study has successfully projected future trends in emissions and temperature changes, highlighting both seasonal variations and long-term trajectories. The low Mean Absolute Error (MAE) and

Mean Squared Error (MSE) values for both CO_2 and temperature forecasts indicate a high level of model accuracy, underscoring the reliability of the results.

The findings underscore the urgent need for sustainable interventions in high-emission agricultural practices. By anticipating the impact of current trends, this study provides a quantitative foundation for policy development and proactive environmental strategies. The results emphasize that without significant changes, continued increases in emissions and temperatures may exacerbate the adverse effects of climate change, presenting a growing risk to ecosystems and global food security.

In conclusion, this project demonstrates the essential role of predictive analytics in environmental management. By offering data-driven insights into future emission scenarios, it contributes to the broader objective of supporting informed decision-making and fostering sustainable agricultural practices. Future work will aim to incorporate additional variables and alternative forecasting models, which will further enhance the precision and applicability of these findings for environmental policy and management.

Future Work

To enhance the precision and applicability of our forecasts, future research initiatives will focus on incorporating a more comprehensive dataset that includes additional variables affecting CO2 emissions and temperature changes. This expansion aims to provide a more nuanced understanding of the factors driving these environmental impacts.

A key area of focus will be the exploration of alternative forecasting models, with particular attention on ARIMA (AutoRegressive Integrated Moving Average) models. Given ARIMA's robust capability to handle time series data that exhibit trends and seasonal patterns, this approach is expected to yield deeper insights and produce forecasts of higher accuracy compared to those generated through Winter’s Method, which was primarily used in this study.

Furthermore, the incorporation of machine learning techniques to analyze complex interactions within the data will be pursued. These advanced analytical methods are anticipated to uncover non-linear relationships and interactions between variables that traditional statistical models might overlook, thereby enhancing the overall robustness and predictive power of our environmental forecasts.

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