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Major: Data Science

Course: Data Visualization

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Project : **"Visualization of Climate Change Impact on Agriculture"**

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Data Visualization Report

1. Introduction

This project involves the analysis of climate change impacts on agriculture, specifically focusing on several factors such as crop yield, CO2 emissions, temperature, and precipitation. The objective of this project is to visualize and analyze how different variables interact with one another and to uncover any patterns or correlations that could offer insights into how climate change is affecting agriculture. The visualizations generated in this project provide a comprehensive overview of the data from multiple perspectives and allow for in-depth analysis through various forms of plots.

2. Description of the Project

The dataset used in this project consists of information on agricultural production across different countries and regions, spanning several years. The dataset includes variables such as crop yield, average temperature, total precipitation, CO2 emissions, pesticide and fertilizer use, and soil health index, among others. The data covers a variety of crops and adaptation strategies, with the goal of understanding how these variables are interrelated and how they might evolve over time because of climate change. The project utilizes multiple Python libraries to generate visualizations and insights from the data, including heatmaps, bar charts, line graphs, scatter plots, and more.

3. List of Python Libraries Used

The following Python libraries were used in the project:

1. pandas - For data manipulation and processing.
2. matplotlib - For static data visualizations.
3. seaborn - For creating statistical visualizations.
4. numpy - For numerical operations.

4. Analysis of the Visualizations Obtained

Heatmap: Correlation Matrix Between Numerical Variables

1. Strong Positive Correlations:

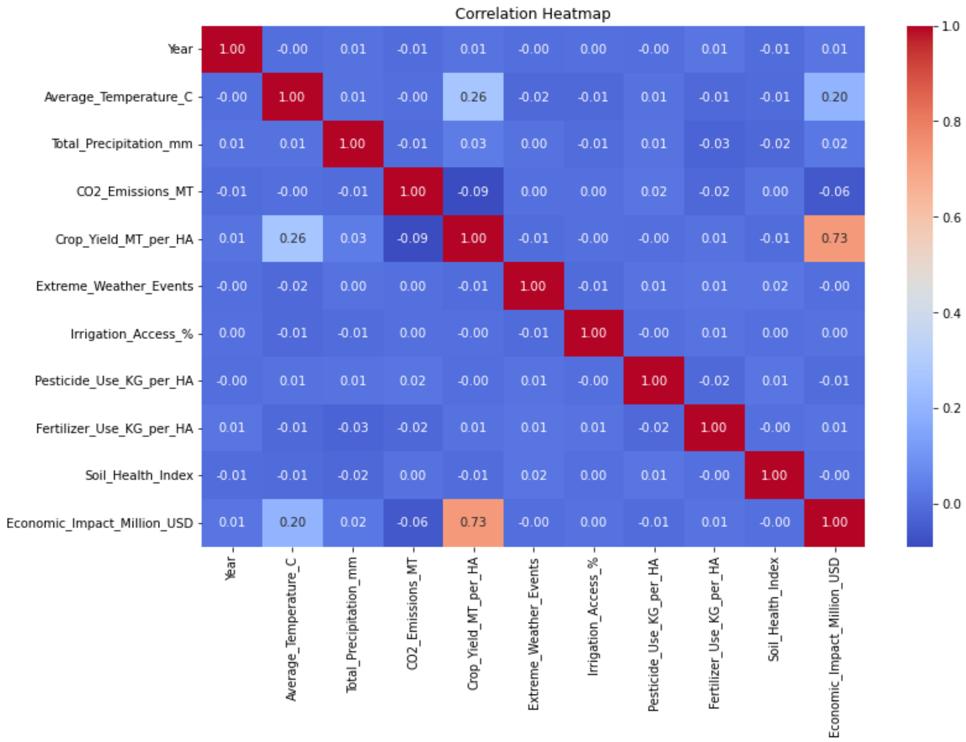
- **Crop Yield (MT/HA) vs. Economic Impact (Million USD)**:
  Correlation = **0.73**
  This indicates that higher crop yields tend to have a significant positive impact on economic outcomes. This relationship highlights the importance of improving agricultural productivity for economic growth.

2. Weak to Negligible Correlations:

- **CO2 Emissions (MT) vs. Crop Yield (MT/HA)**:
  Correlation = **-0.09**
  There is little to no significant relationship between CO2 emissions and crop yield, suggesting that other environmental or technological factors may be influencing crop productivity more directly.

- **Average Temperature (°C) vs. Crop Yield (MT/HA))**:
  Correlation = **0.26**
  A **correlation of 0.26** between **Average Temperature** and **Crop Yield** indicates a weak positive relationship, meaning slight temperature increases might slightly benefit yields. However, the weak strength suggests other factors like soil health or precipitation have a more significant impact.

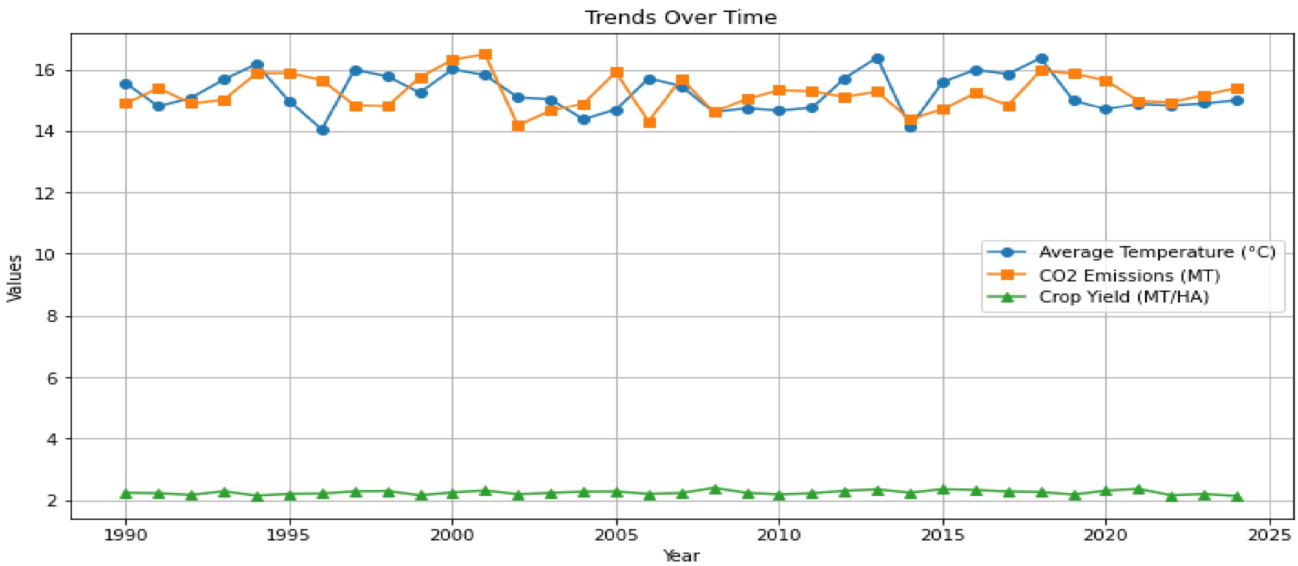
- **Average Temperature (°C) vs. Economic Impact (Million USD)**:
  Correlation = **0.20**
  A correlation of **0.20** between **Average Temperature (°C)** and **Economic Impact (Million USD)** indicates a **weak positive relationship**, suggesting that higher temperatures might slightly contribute to increased economic impact.



Line Charts:

Trends Over Time

- The line charts illustrate the trends of crop yield, CO2 emissions, and temperature over time. These visualizations show how each of these variables has changed over the years, providing insight into long-term patterns. Analyzing such trends can help identify areas where agricultural practices may need to be adapted in response to changing climate conditions.

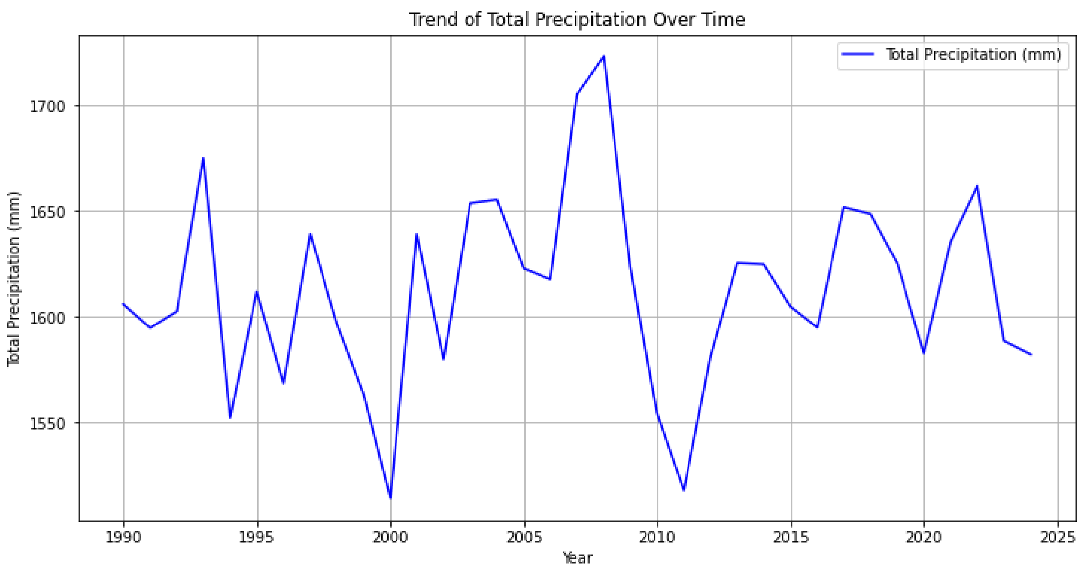


Total Precipitation Over Time

This chart visualizes how total precipitation (in mm) has changed over the years. Precipitation is a critical factor for agriculture, and observing its trends helps in understanding potential impacts on crop yields and water availability for farming.

Insights:

- Analyzing this trend can reveal whether regions are experiencing increasing or decreasing rainfall patterns over time.
- If precipitation levels are declining, this could signal risks of drought, which would require better water management strategies like 2000 and 2011.

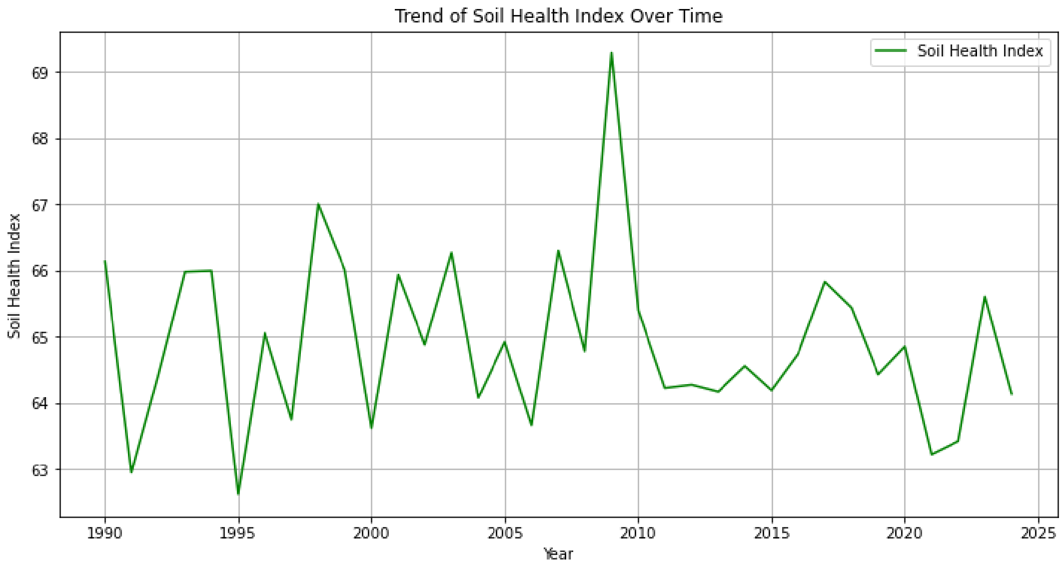


Soil Health Index Over Time

This chart tracks the changes in soil health index over the years. Soil health directly impacts crop yields, as healthier soil ensures better nutrient availability and water retention for crops.

Insights:

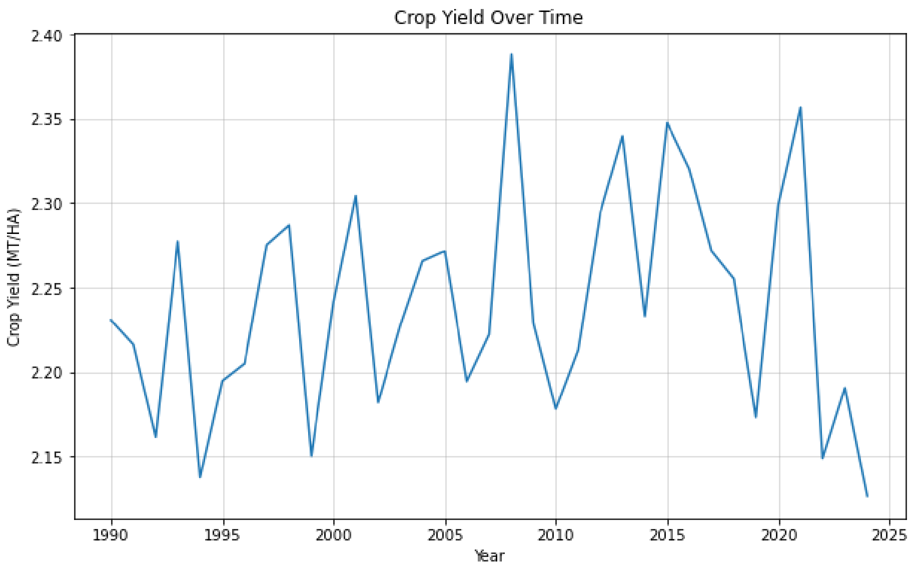
- A downward trend in the soil health index may indicate soil degradation, possibly caused by over-farming, deforestation, or lack of crop rotation.
- Identifying declining soil health regions early can help in implementing measures like reforestation, reduced pesticide use, and sustainable farming practices like 1991, 1995.



Crop Yield Over Time

This chart tracks the changes in crop yields over the years.

- **Insights**: The variability in crop yield might be influenced by factors such as changing weather patterns, agricultural practices, or economic policies. Identifying periods of low yields, like 1992 and 2024, can guide targeted interventions to stabilize production.



Time Series Analysis

The time series analysis shows trends in **economic impact** and **temperature** over the years:

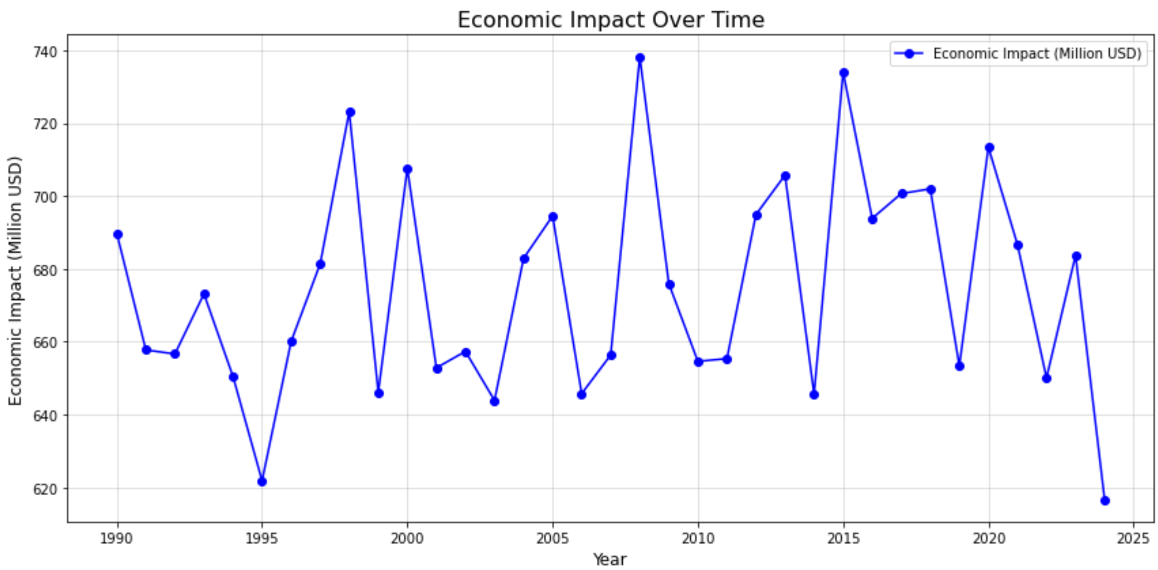
1. Economic Impact Over Time

The chart represents how the **economic impact (in million USD)** has changed from 1990 to 2025.

The line shows fluctuations, with significant peaks in the years around 1997, 2007, and 2015. However, there are dips, such as in 2002, 2008, and especially in 2024.

Insights:

- The economic impact does not follow a clear upward or downward trend, indicating that other factors, possibly related to external events (e.g., policy changes, extreme weather, or global market conditions), heavily influence the results.
- The peak in 1997 could be linked to favorable conditions, such as high agricultural output or effective adaptation strategies.
- The drop around 2024 indicates a possible economic shock, potentially due to increased environmental stress, reduced agricultural yield, or unfavorable climate changes.
- Policymakers could investigate the specific causes of the dips and spikes to better understand which interventions successful and which events were caused adverse impacts.



2. Average Temperature Over Time

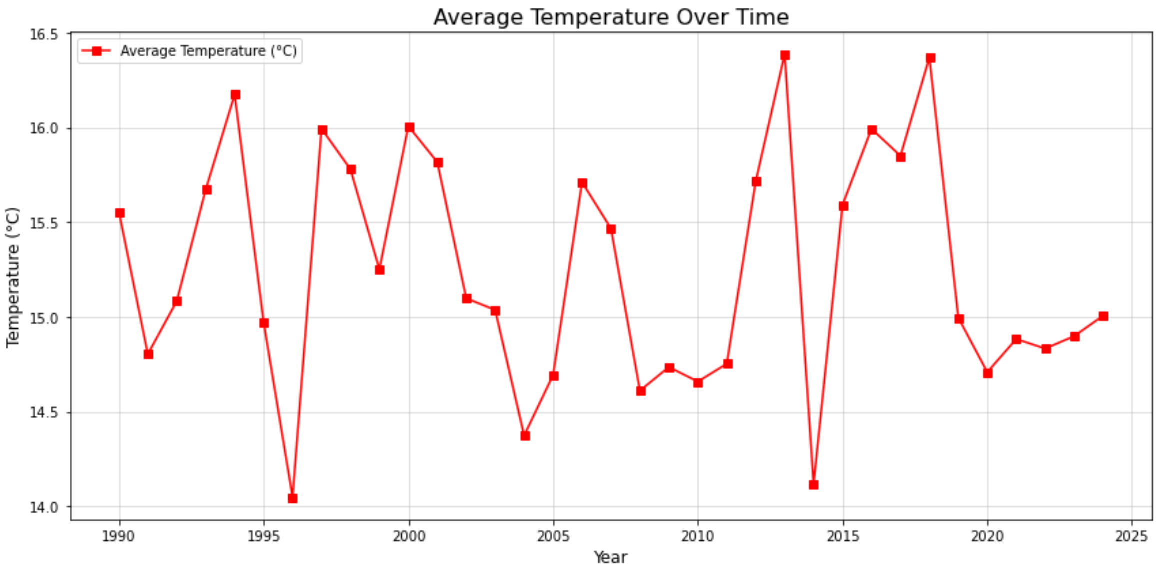
This chart shows how the **average temperature (°C)** has varied over the years.

There are sharp fluctuations, with significant peaks around 1994, 2006, and 2013, and noticeable dips in 1996 and 2014.

Insights:

- The lack of a steady increase or decrease suggests that temperatures are influenced by cyclical or irregular climate events, such as **El Niño**, **La Niña**, or regional climate anomalies.

- Peaks in temperature might correspond to heatwaves, droughts, or extreme weather conditions, which could have downstream effects on crop yields and economic impact.
- The consistent presence of high and low cycles suggests that climate variability needs to be a key factor in future planning and adaptation strategies for agricultural and economic sustainability.
- Comparing this with the **economic impact chart** could reveal whether higher or lower temperatures correlate with significant economic changes, helping prioritize temperature management in climate adaptation policies



These trends emphasize the growing economic importance of agriculture and the parallel challenges posed by climate change.

Bar Charts: Comparison of Categorical Values

Crop Yield by Economic Impact:

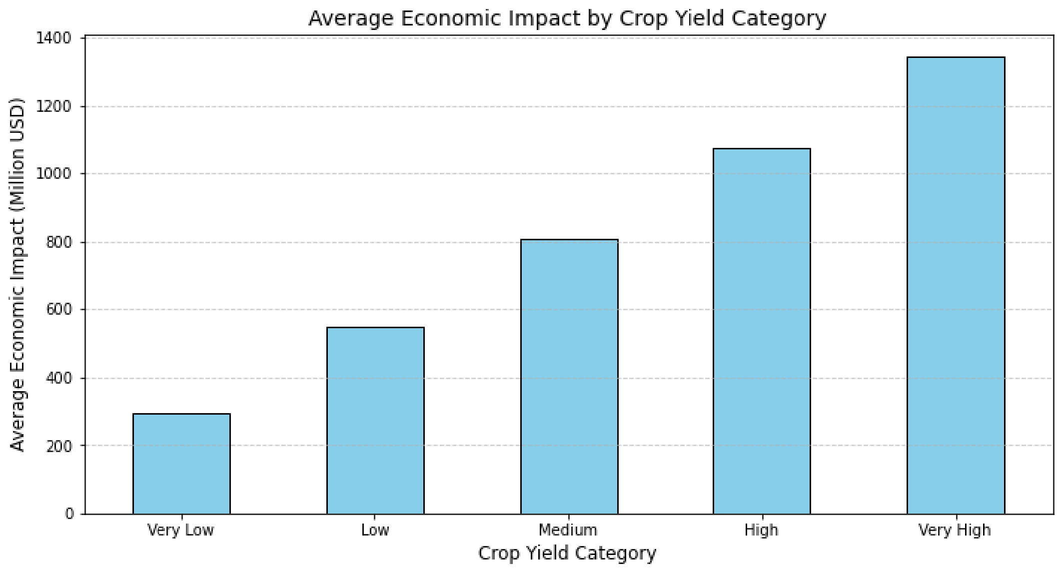
Economic Growth with Increased Yield:

Positive Relationship Between Crop Yield and Economic Impact:

- As crop yield increases from "Very Low" to "Very High," the average economic impact rises significantly.
- Regions or farms achieving "Very High" crop yield categories contribute over 5 times the economic impact of those in the "Very Low" category.

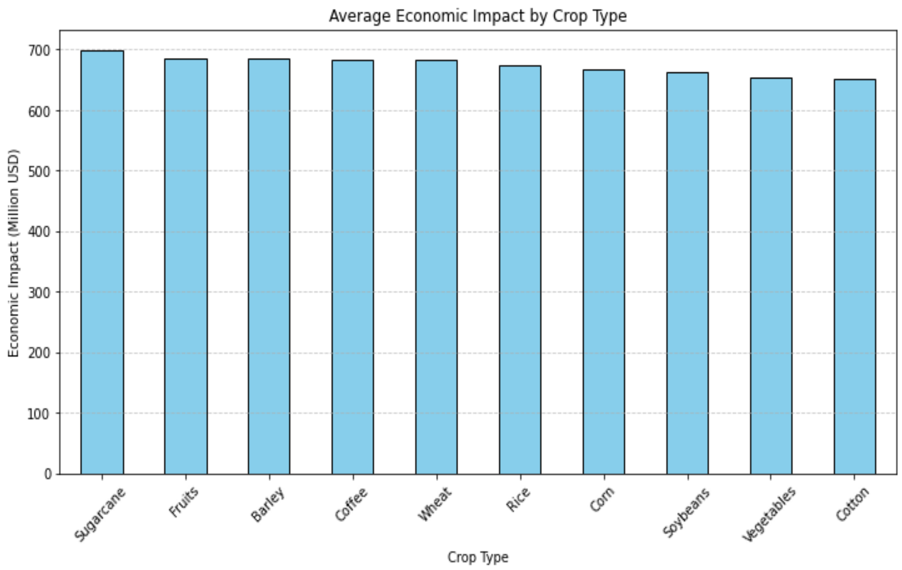
Significance of Yield Optimization:

- Improving crop yield, even slightly, can result in noticeable economic gains. For instance, moving from "Low" to "Medium" crop yield shows a significant increase in average economic impact.



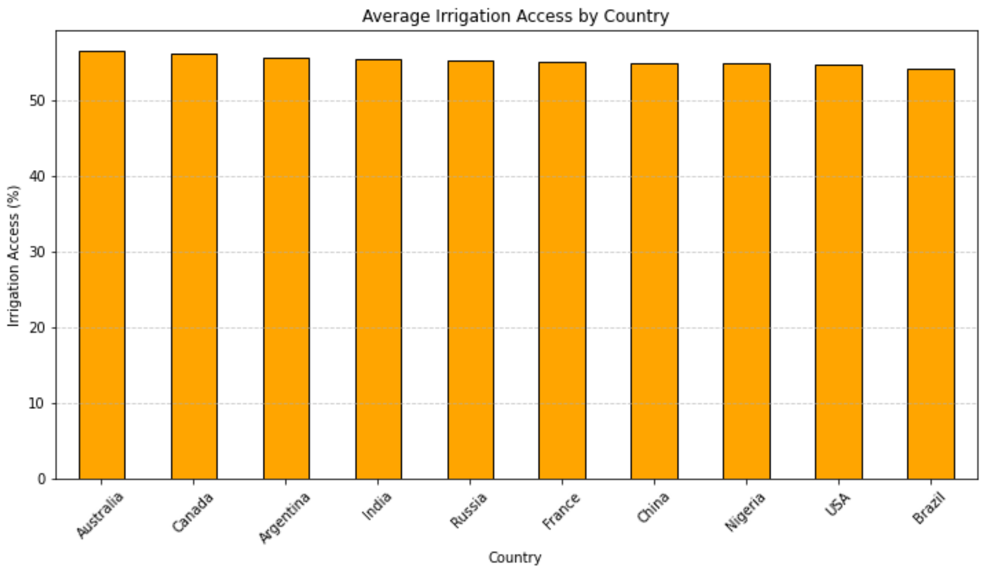
Crop Types by Economic Impact:

- The bar chart shows that the **average economic impact** across different crop types is relatively consistent, with no significant variation among them. This suggests that all crop types contribute similarly to the economic impact, emphasizing the importance of overall agricultural productivity rather than focusing on specific crops.



Irrigation Access by Country:

- The bar chart shows that **average irrigation access** is relatively consistent across the listed countries, with no major variations. This suggests a similar level of irrigation infrastructure, but further analysis may be needed to assess the quality and efficiency of irrigation systems.



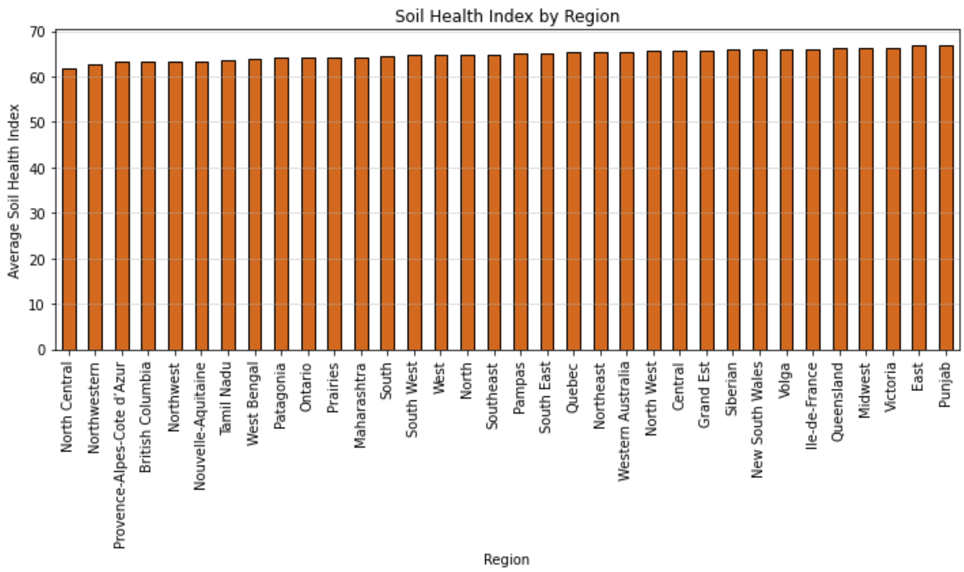
Soil Health Index by Region

This bar chart shows the average soil health index for each region, giving insights into the regional disparities in soil quality. Healthy soil is vital for sustainable agriculture, and this chart can help identify areas that may need improvement in soil management practices.

This chart highlights regional differences in soil health, helping policymakers and agricultural experts focus on areas needing improvement.

Insights:

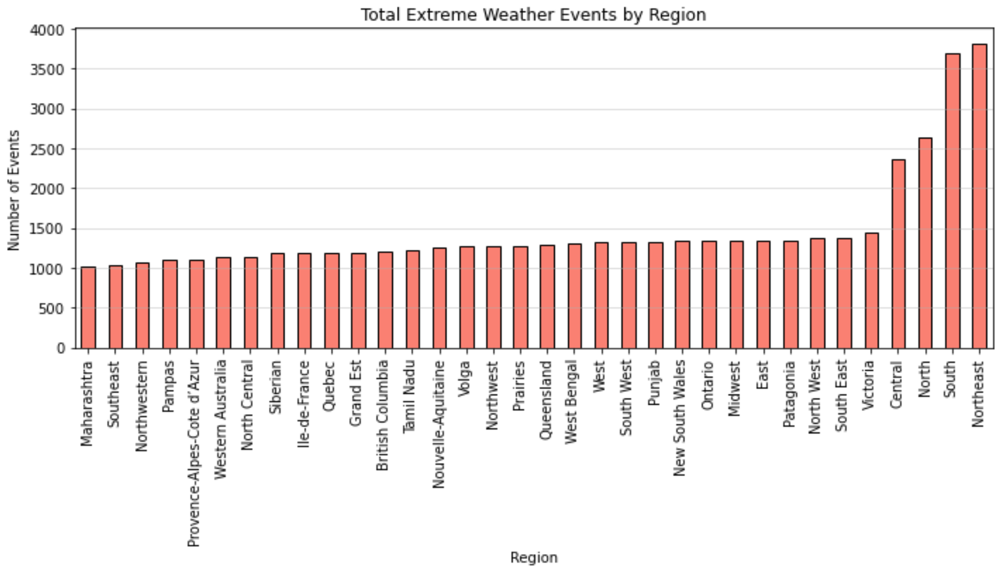
- Regions with higher soil health indices are likely to have more sustainable agricultural systems and higher crop yields.
- Regions with lower soil health indices may face challenges like reduced productivity and may require intervention measures such as soil amendments, better irrigation techniques, or crop rotation practices.



Total Extreme Weather Events by Region

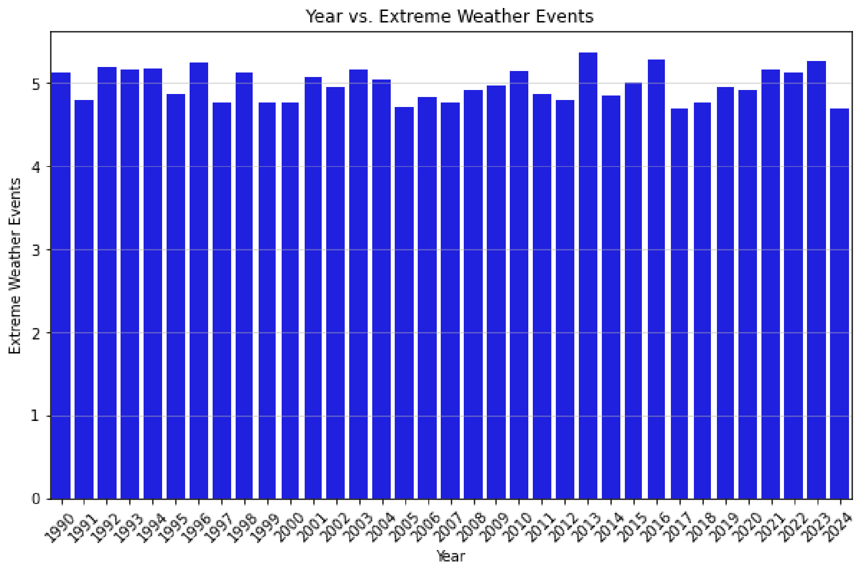
Insights:

The bar chart reveals that while most regions experience a similar frequency of extreme weather events, the Northeast, North, and South regions face disproportionately higher occurrences. This emphasizes the urgency of prioritizing disaster preparedness and mitigation strategies in these high-risk areas.



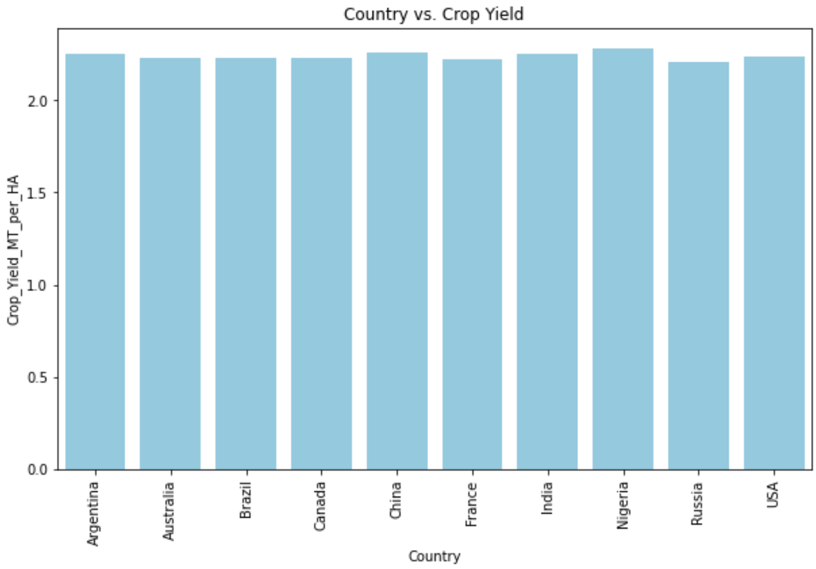
Year vs. Extreme Weather Events

The bar chart indicates that the frequency of extreme weather events has remained relatively stable over the years, with minor fluctuations. This suggests that while climate extremes persist, there has not been a significant upward or downward trend during the observed period, and which can be the reason why this dataset needs to be deeper and more studied.



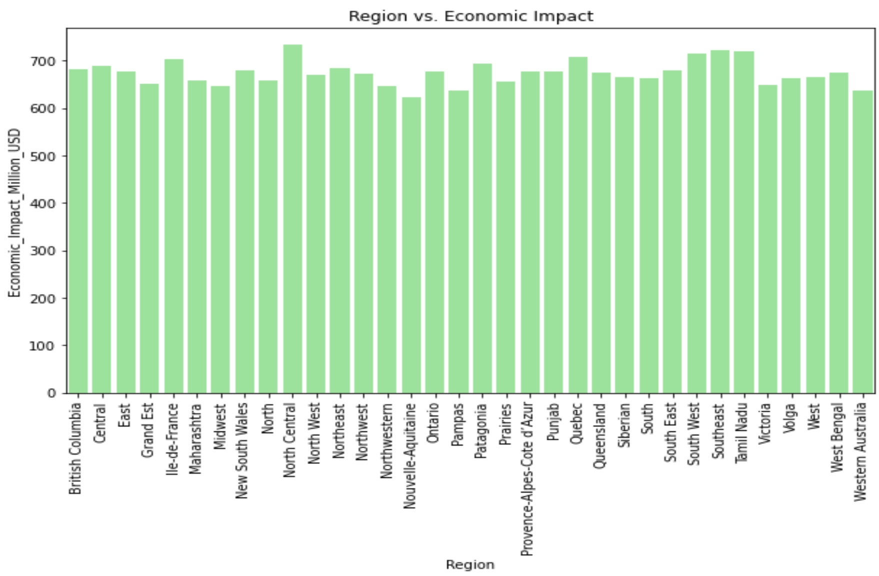
Country vs. Crop Yield

The bar chart shows that **crop yield (MT/HA)** is relatively consistent across the listed countries, with minimal variation. This suggests that agricultural productivity per hectare is uniform globally, potentially influenced by similar farming techniques or crop types.



Region vs. Economic Impact

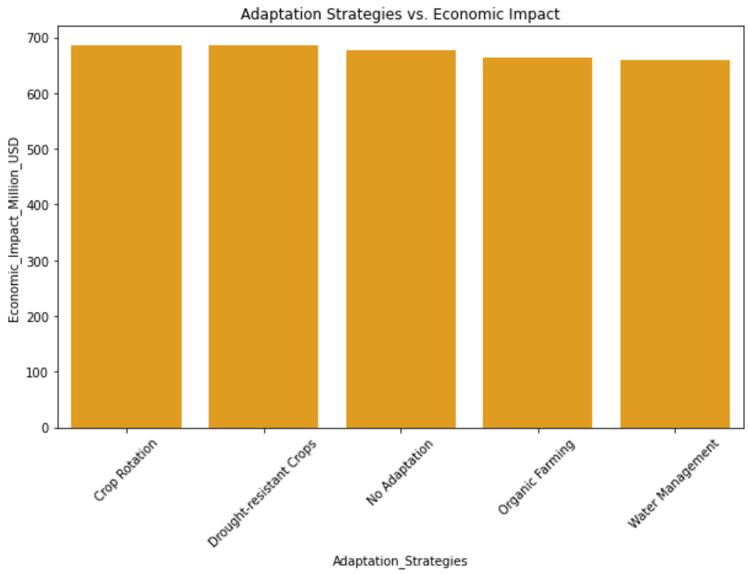
The bar chart illustrates that the economic impact (Million USD) is consistent across regions, with only minor variations. This indicates that economic contributions from agriculture are relatively balanced, regardless of regional differences in farming practices or environmental conditions.



Adaptation Strategies vs. Economic Impact

A bar chart comparing the average economic impact across different adaptation strategies.

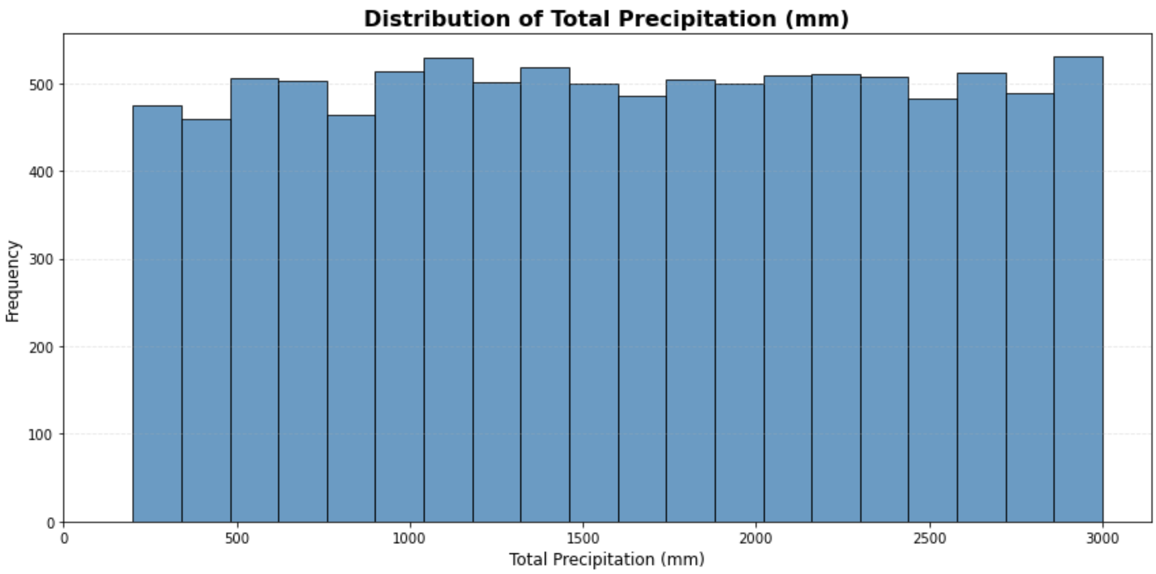
- **Insights**: The bar chart shows that the **economic impact (Million USD)** is nearly the same across all adaptation strategies, including crop rotation, organic farming, and water management. However**, s**trategies like water management and crop rotation tend to minimize economic losses.



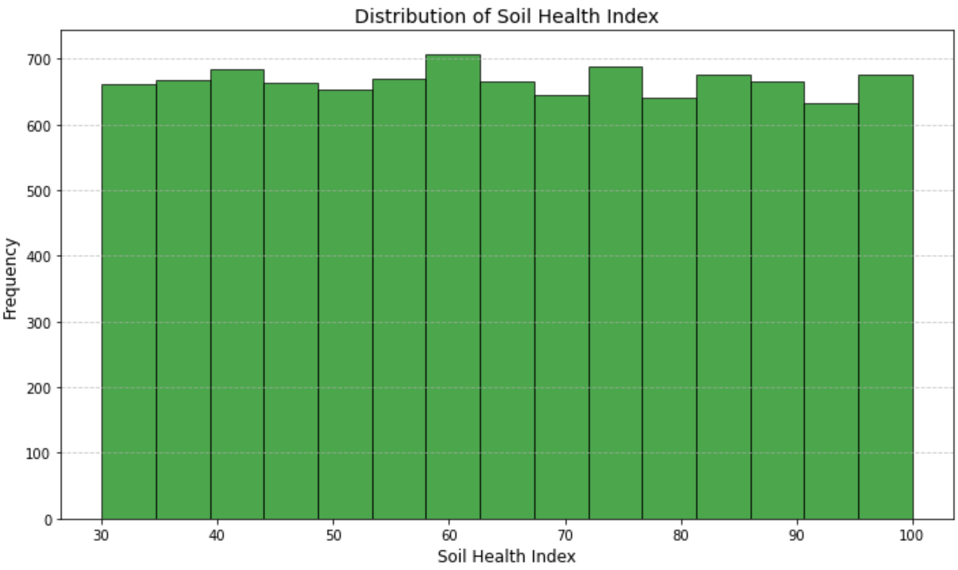
Histograms: Distribution of Numeric Variables

The histograms demonstrate the **distribution** of **precipitation** and the **soil health index** across the dataset:

- Most regions show moderate to high levels of precipitation, with a few areas experiencing extreme rainfall. This variability could affect crop growth and yield, as consistent rainfall is often ideal for agricultural productivity.



- Soil health shows a wide distribution, with most regions having moderate soil health scores. This suggests that soil quality is an important factor influencing agricultural productivity but may need further improvement in some areas.

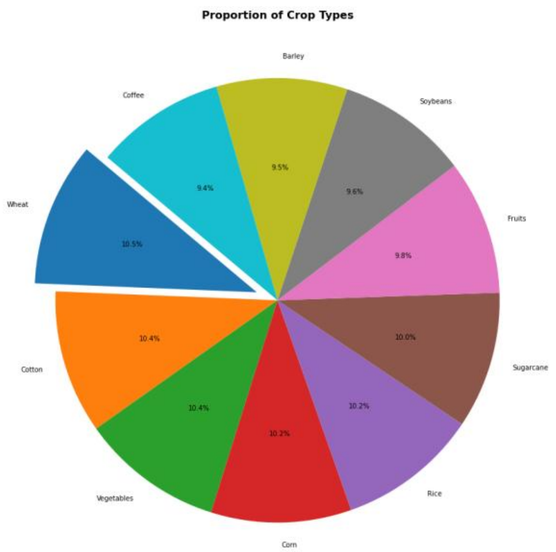


Pie Charts: Proportion of Crop Types, Adaptation Strategies, Regions

The pie charts show the distribution of **crop types**, **adaptation strategies**, and **regions**:

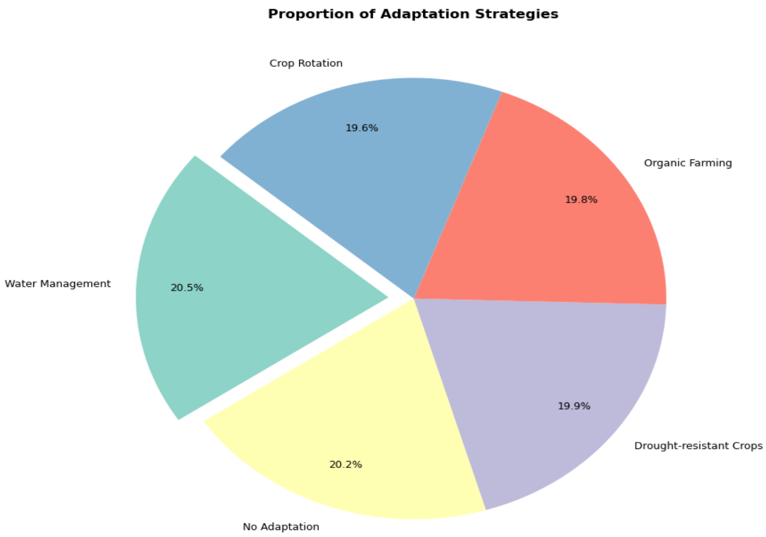
Crop Types:

- The chart reveals that certain crops, such as wheat, cotton, and vegetables, dominate agricultural practices worldwide, contributing to a large portion of global agricultural output.



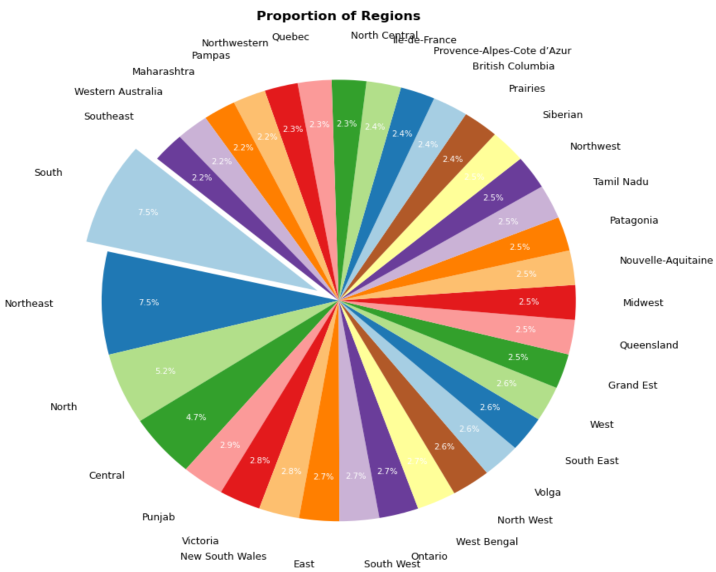
Adaptation Strategies:

- Most countries employ "Water Management" strategies, suggesting that managing water resources is critical for sustaining agricultural production under changing climate conditions.



Regions:

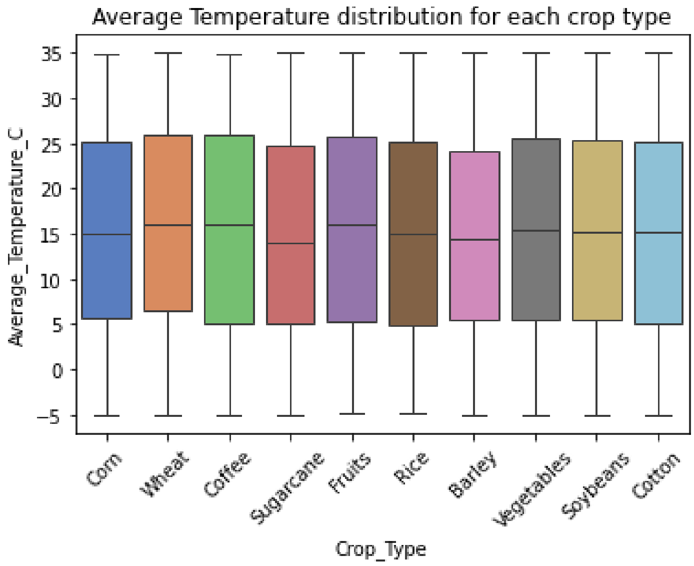
- The distribution of regions highlights how agriculture is concentrated in specific geographic locations, with some regions like South and North East showing more diverse crop types and greater agricultural output.



Box Plots:

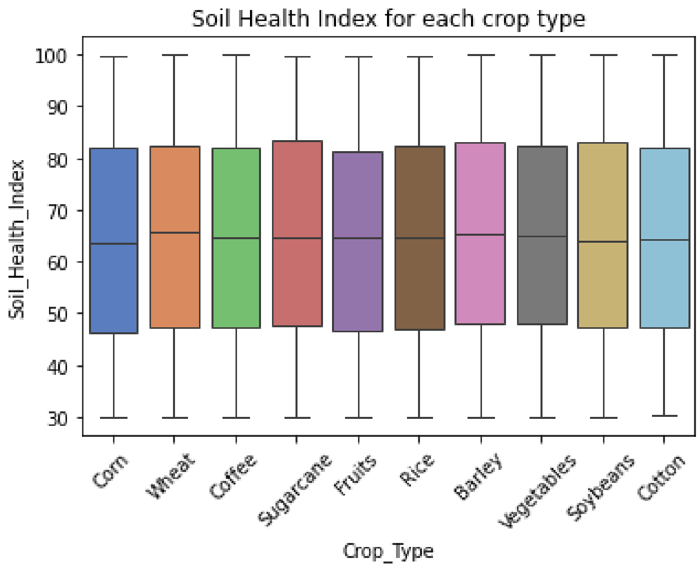
Average Temperature distribution for each crop type

The average temperature varies across crop types, with most crops thriving between 10°C and 25°C, indicating a preference for moderate climates.



Soil Health Index for each crop type

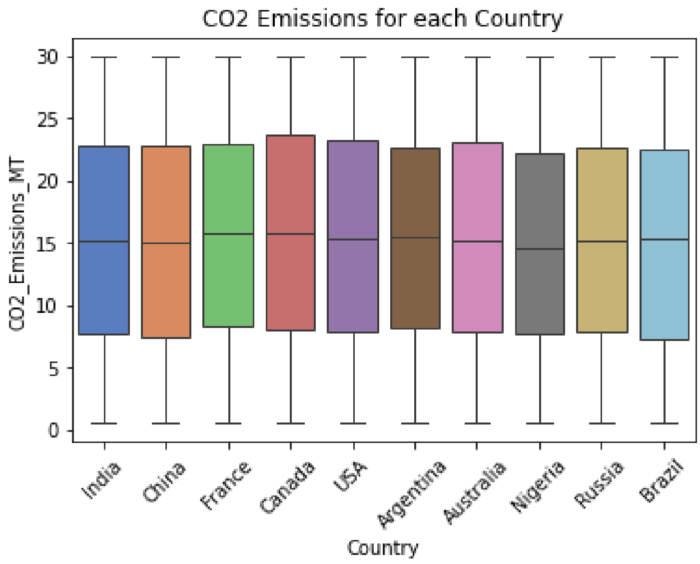
- The Soil Health Index is relatively consistent across crop types, generally ranging between 45 and 80, suggesting that most crops perform well within this soil quality range.
- Some crops show a wider distribution of soil health, indicating a higher sensitivity to soil conditions.



CO2 Emissions for each Country

- CO2 emissions vary significantly by country, with most countries falling within 7 to 25 MT, but a few exhibiting higher emissions.

- This variability may reflect differences in agricultural practices and industrialization levels among countries.

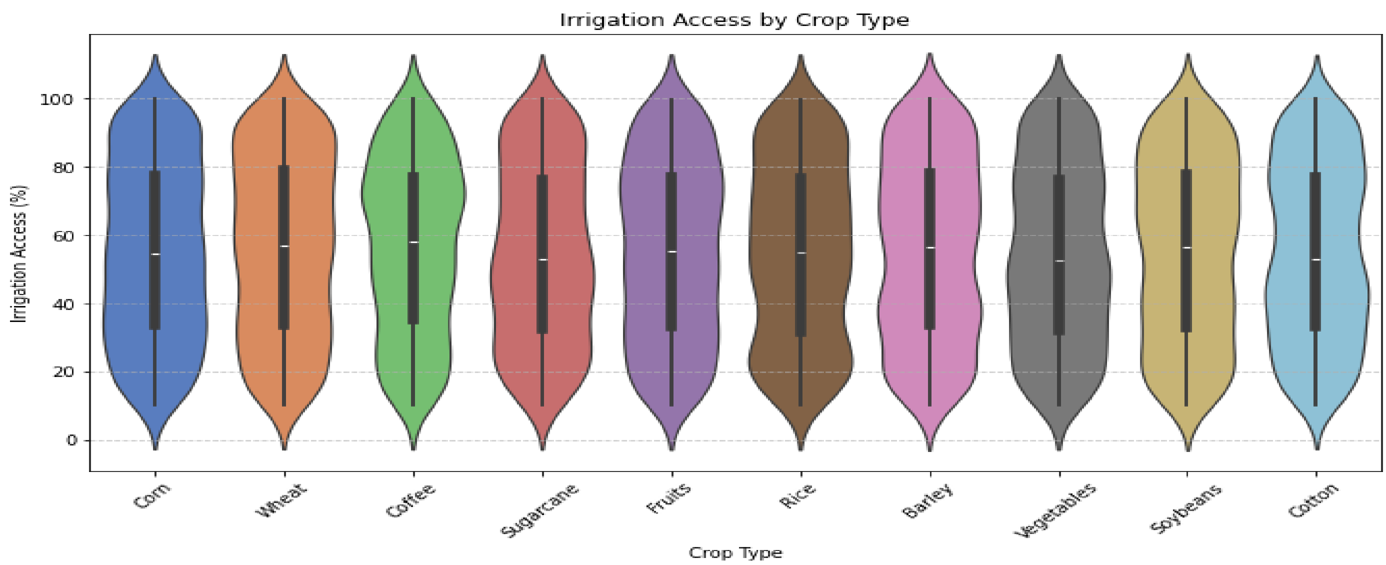


Violin Plots: Irrigation Access by Crop Type

The violin plot shows the distribution of **irrigation access** across various **crop types**:

The violin plot shows that irrigation access (%) varies significantly across crop types, with most distributions centered around 40-80%. Crops like Rice and Sugarcane show a broader range of irrigation access, suggesting variability in water requirements or availability across regions.

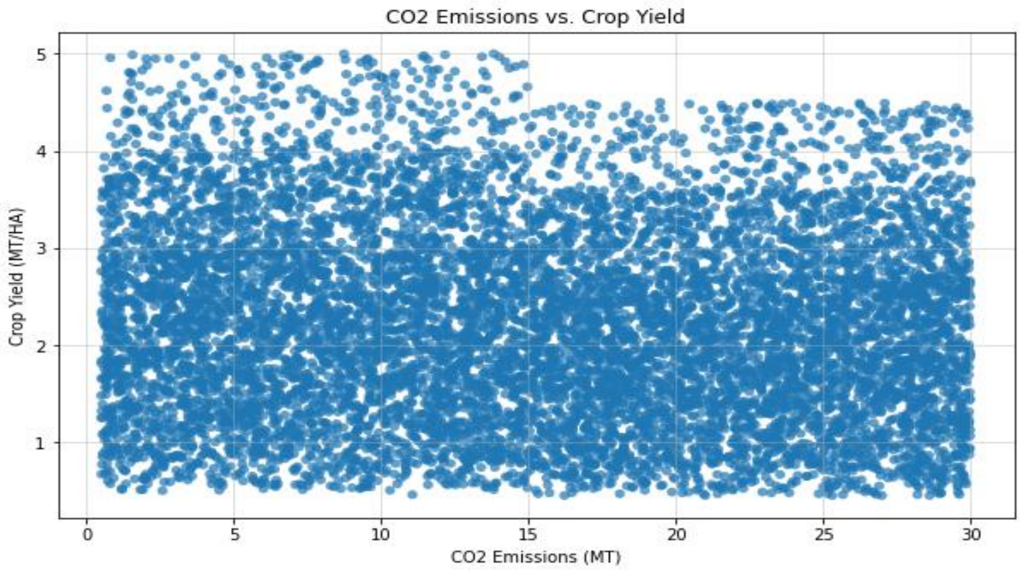
The violin plot provides a visual representation of how irrigation access varies by crop, helping us understand the influence of water availability on agricultural output.



Scatter Plots

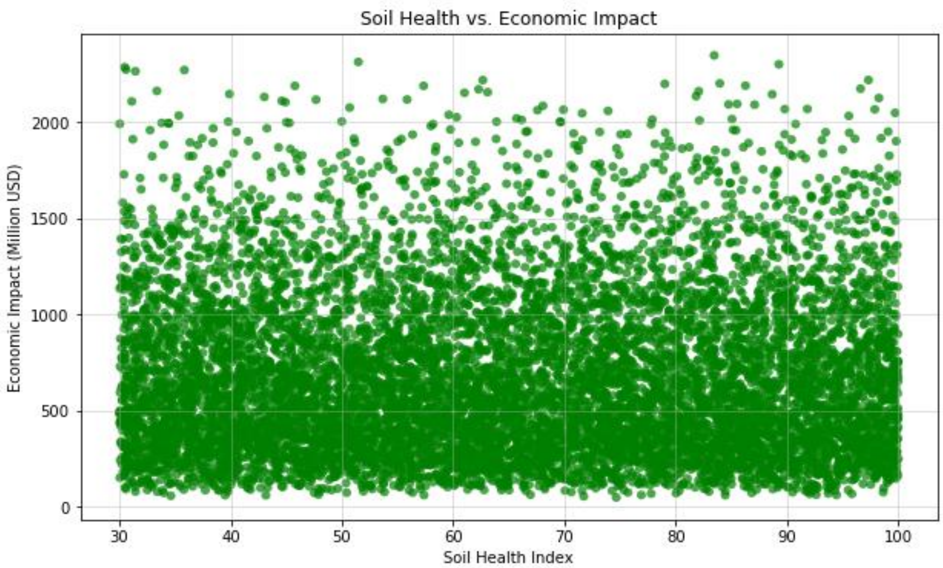
CO2 Emissions vs. Crop Yield

The scatter plot shows no clear relationship between **CO2 Emissions (MT)** and **Crop Yield (MT/HA)**, as the points are widely dispersed without a noticeable trend. This suggests that CO2 emissions alone do not significantly impact crop yield and that other factors may play a more critical role.



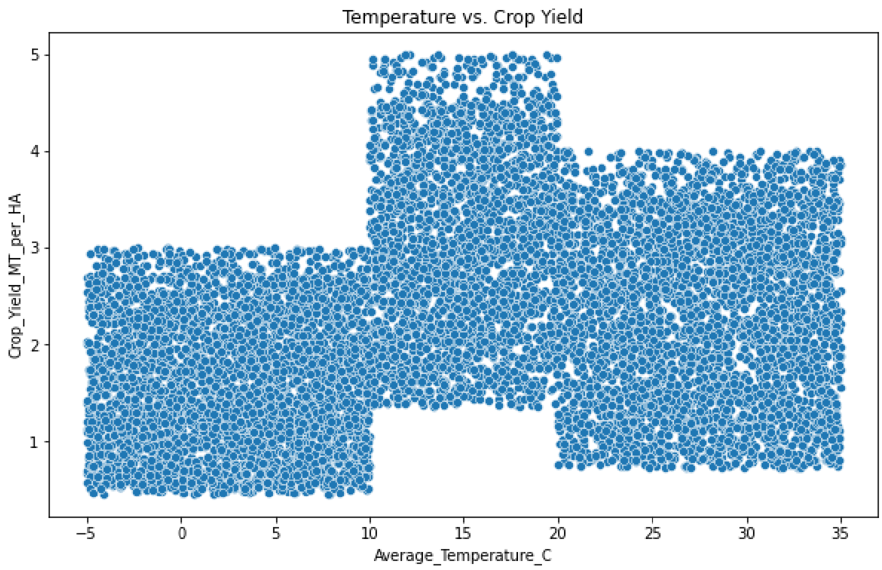
Soil Health vs. Economic Impact:

The scatter plot shows no clear trend between **Soil Health Index** and **Economic Impact (Million USD)**, with points widely scattered across the range. This indicates that while soil health is essential, its direct correlation with economic impact might be influenced by other factors, such as farming practices or regional conditions.



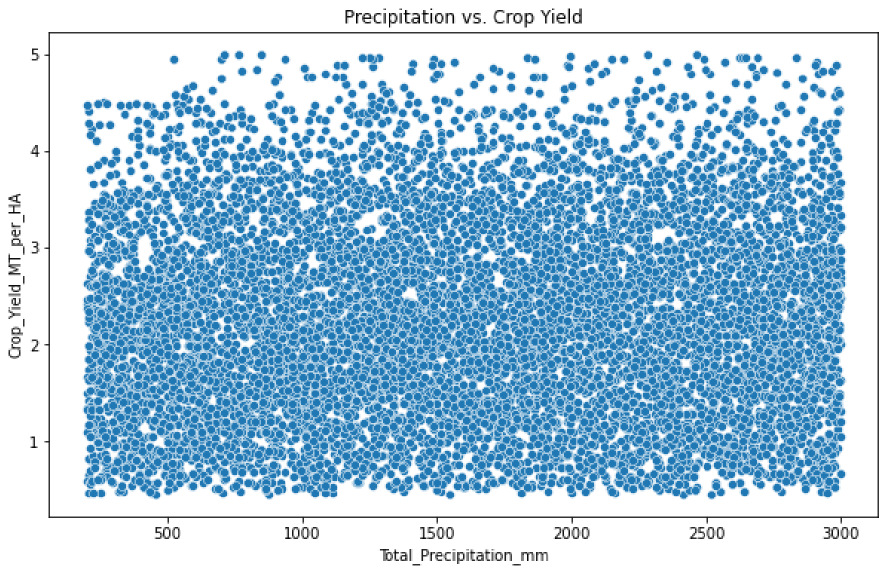
Temperature vs. Crop Yield

The scatter plot shows no clear linear relationship between **Average Temperature (°C)** and **Crop Yield (MT/HA)**, with data points scattered across the temperature range. This suggests that temperature alone is not a strong determinant of crop yield, and other factors, such as soil health and water availability, may play a more significant role.



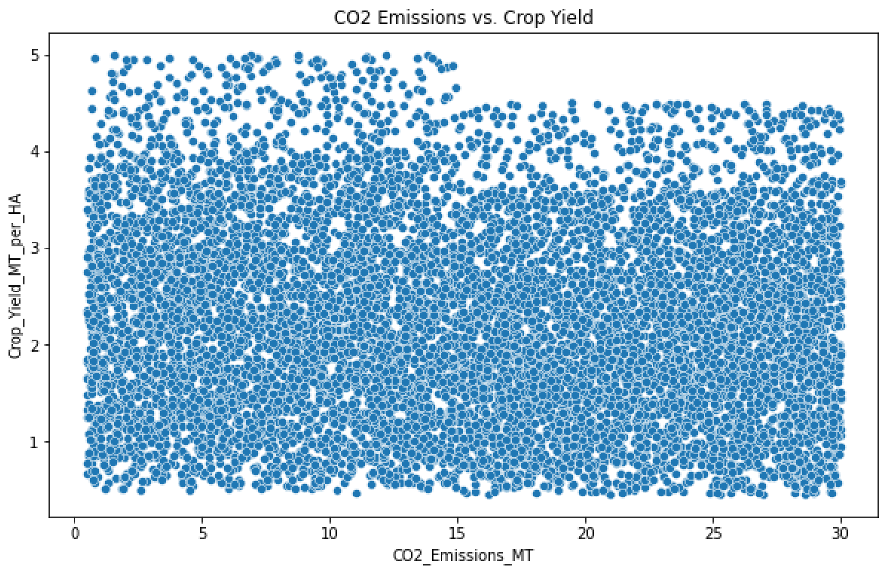
Precipitation vs. Crop Yield

The scatter plot shows no clear relationship between **Total Precipitation (mm)** and **Crop Yield (MT/HA)**, as the data points are evenly distributed across the precipitation range. This indicates that precipitation alone does not significantly influence crop yield, and other factors such as soil quality or farming practices may have a stronger impact.



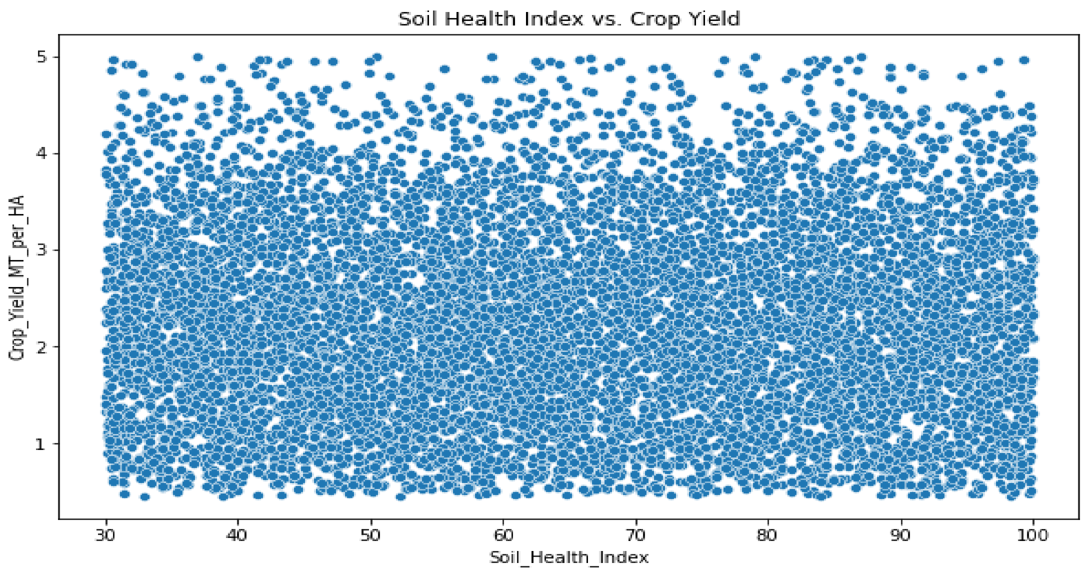
CO2 Emissions vs. Crop Yield

The scatter plot shows no significant relationship between **CO2 Emissions (MT)** and **Crop Yield (MT/HA),** as the points are uniformly scattered across the CO2 range. This suggests that CO2 emissions do not have a direct or substantial impact on crop yields in the dataset.



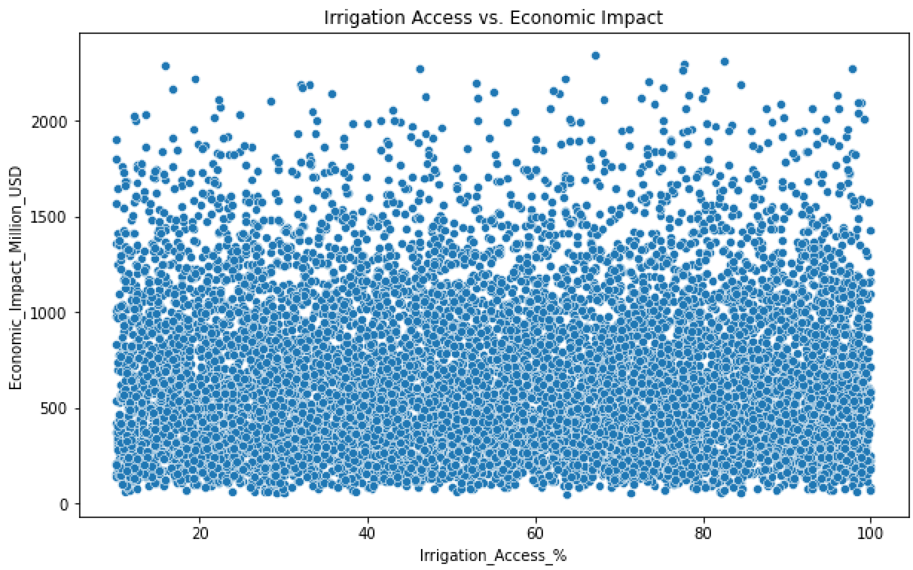
Soil Health Index vs. Crop Yield

The scatter plot shows no strong correlation between **Soil Health Index** and **Crop Yield (MT/HA)**, as the points are widely scattered across the range. This indicates that while soil health may contribute to crop yield, its direct impact is not substantial or might be influenced by other factors like irrigation or farming techniques.



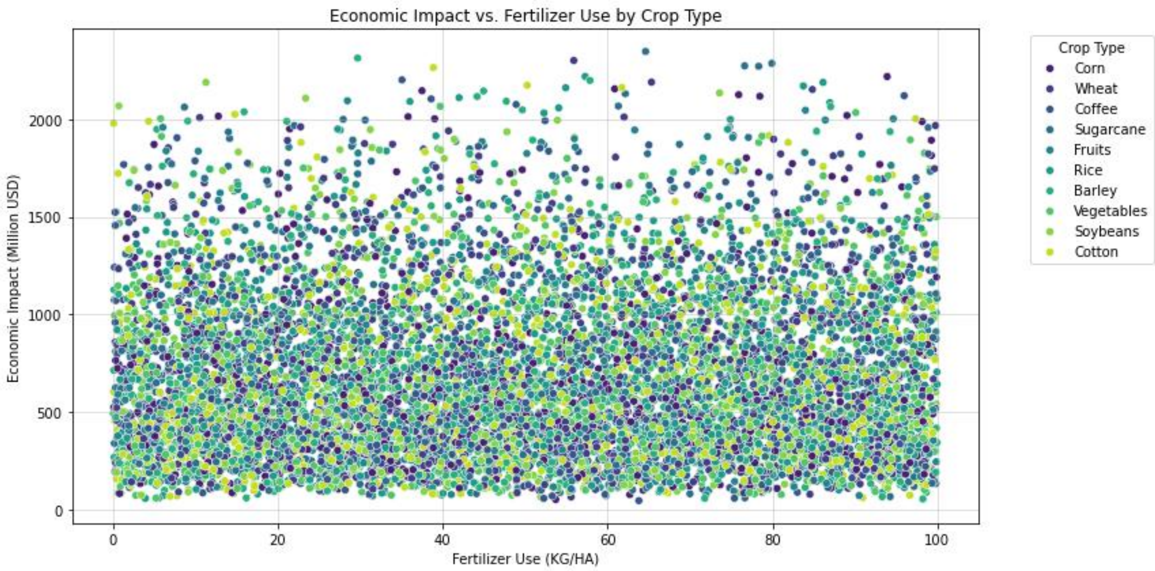
Irrigation Access vs. Economic Impact

The scatter plot shows no clear relationship between **Irrigation Access (%)** and **Economic Impact (Million USD)**, with points evenly scattered across the range. This suggests that while irrigation is crucial, its direct impact on economic outcomes may depend on other factors such as crop type, regional infrastructure, or market conditions.



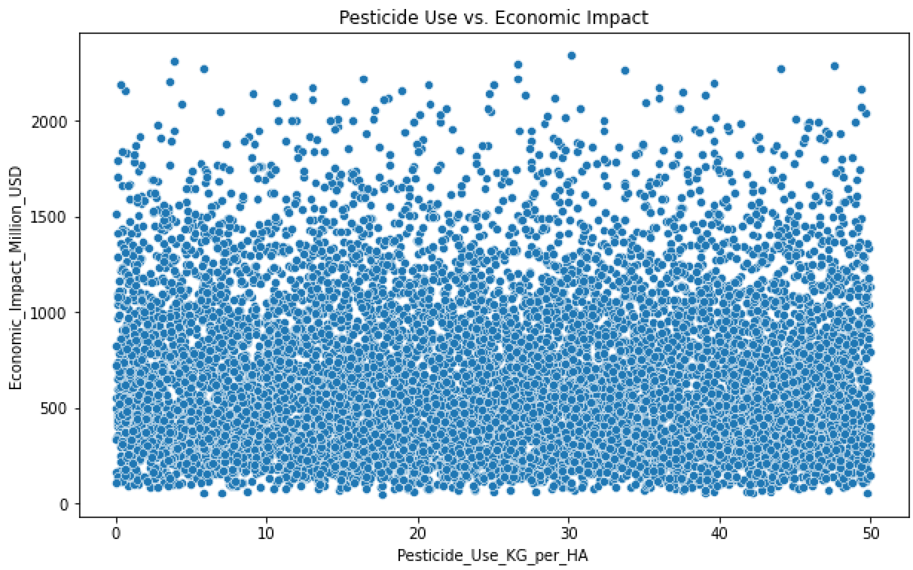
Fertilizer Use vs. Economic Impact

The scatter plot shows no clear trend between **Fertilizer Use (KG/HA)** and **Economic Impact (Million USD)**, as the points are widely dispersed. The differentiation by crop type indicates that certain crops (e.g., Sugarcane, Rice) may have higher economic impacts at varying fertilizer levels, suggesting crop-specific responses to fertilizer use.



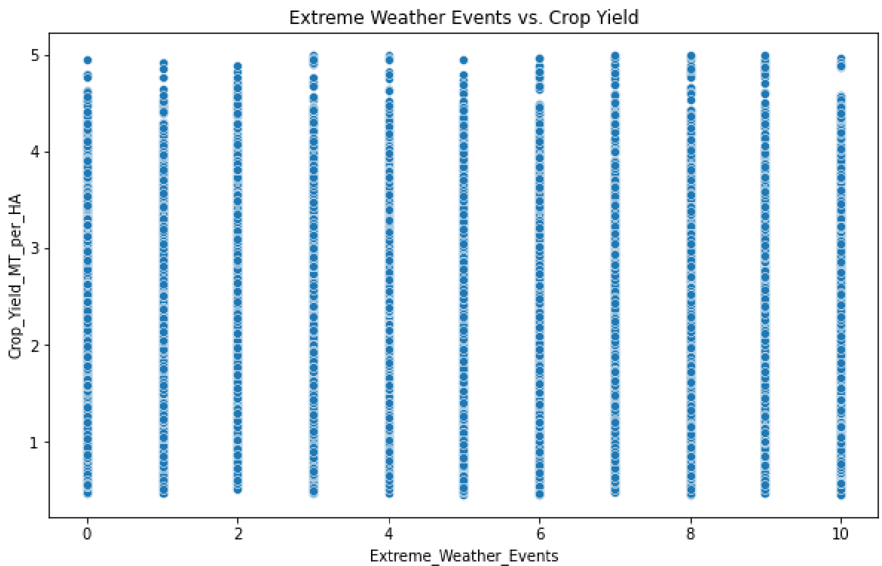
Pesticide Use vs. Economic Impact

The scatter plot shows no significant relationship between **Pesticide Use (KG/HA)** and **Economic Impact (Million USD)**, as the points are uniformly scattered. This suggests that while pesticides may be essential for crop protection, their direct impact on economic outcomes is influenced by other factors such as crop type, market conditions, or regional practices.



Extreme Weather Events vs. Crop Yield

The scatter plot indicates no clear relationship between **Extreme Weather Events** and **Crop Yield (MT/HA)**, as the points are evenly distributed across all event counts. This suggests that crop yields remain largely unaffected by the frequency of extreme weather events, possibly due to mitigation strategies or resilience in agricultural practices.

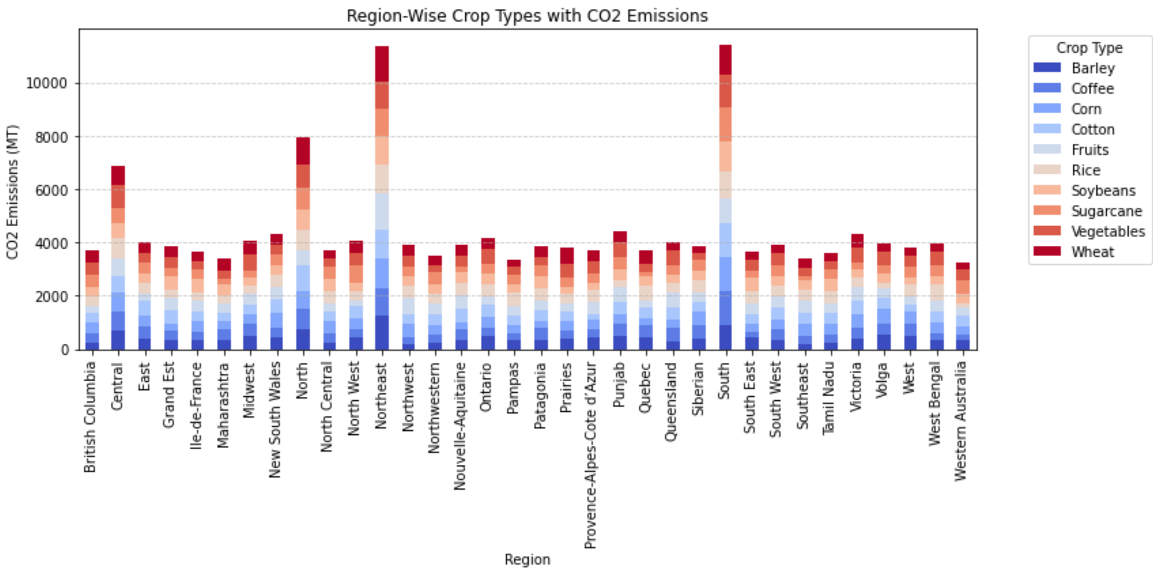


We couldn't take any information or insight from all these scatter plots!

Stacked/Grouped Bar Charts: Region-wise Crop Types with CO2 Emissions

The grouped bar chart compares **CO2 emissions** by **crop type** and **region**:

The stacked bar chart shows significant variation in **CO2 emissions** across regions, with the **Northeast**, **South** regions contributing the most. Crop types like **Sugarcane** and **Corn** appear to dominate emissions in high-contributing regions, indicating their impact.



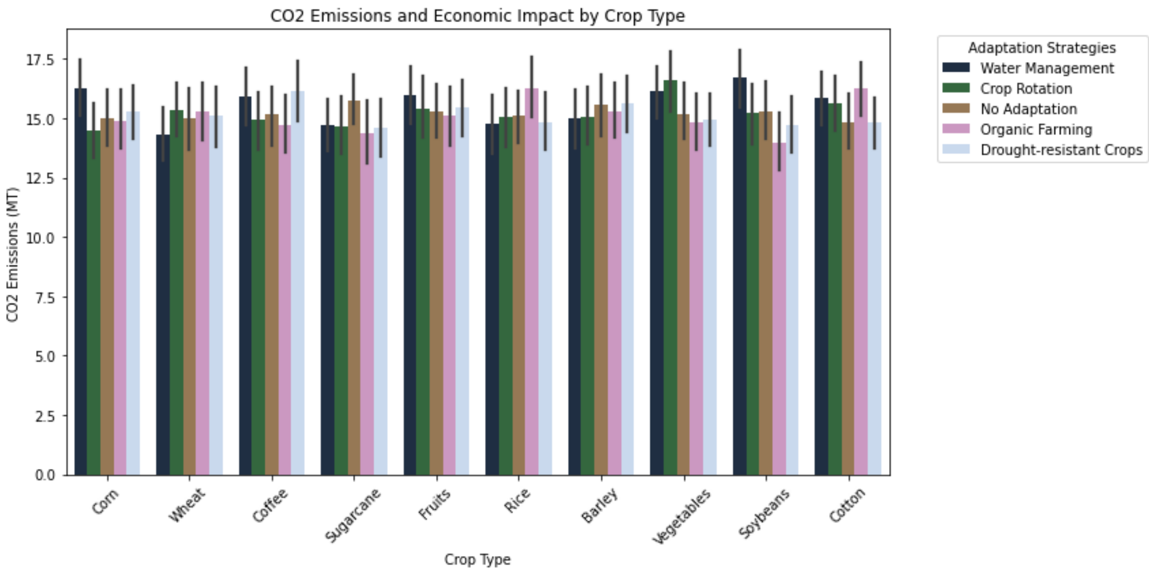
This grouped bar chart highlights the geographic and crop-specific sources of CO_2 emissions.

CO2 Emissions and Economic Impact by Crop Type

This visualization compares **CO2 emissions** across **Crop types** while factoring in the effect of different **adaptation strategies**.

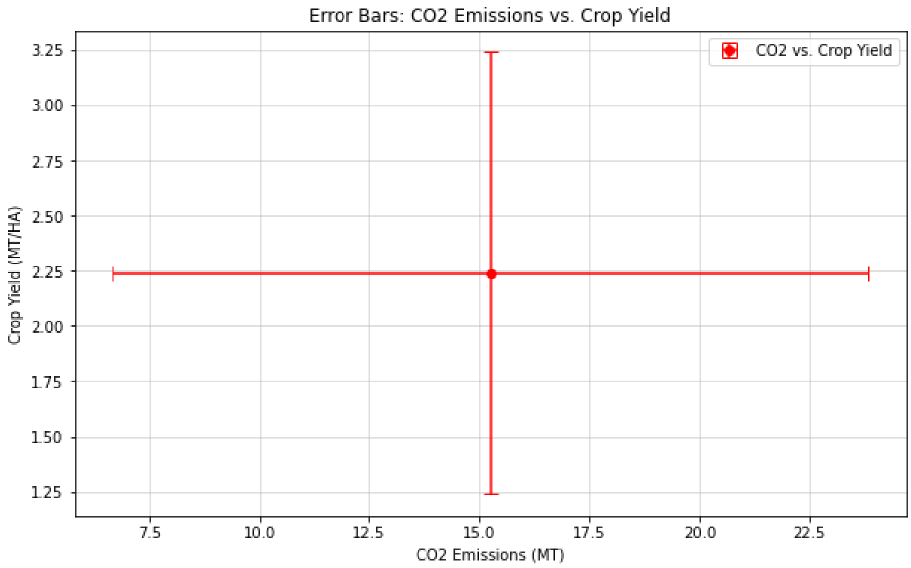
Insights:

1. **High CO2 Emissions Consistency**:
    - CO2 emissions remain relatively high and similar across most crop types regardless of the adaptation strategy used.
    - Crops like **Barley** and **Vegetables** exhibit slightly higher variability in emissions.
2. **Adaptation Strategy Impact**:
    - The adoption of specific strategies (e.g., Water Management or Organic Farming) does not significantly reduce emissions for many crops.
    - However, certain crops, such as **Cotton**, show slight differences across strategies, indicating a potential for emissions reduction depending on the technique used.
3. **Crop Type Influence**:
    - The crop type itself plays a major role in determining the overall CO2 emissions, as evidenced by relatively uniform emissions across strategies for certain crops.
4. **Actionable Insight**:
    - This analysis suggests the need to focus on crop-specific solutions for reducing CO2 emissions. Strategies like **organic farming** or **drought-resistant crops** could be explored further for crops where they appear to reduce emissions slightly



Error Bars: CO2 Emissions vs. Crop Yield

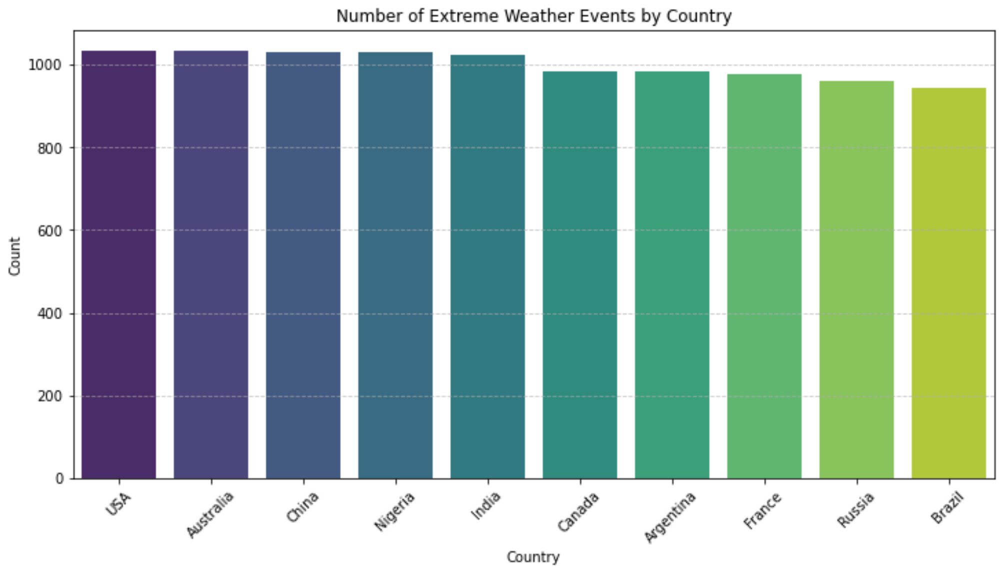
The error bar plot shows the average **CO2 Emissions (15 MT)** and **Crop Yield (2.25 MT/HA)** with their respective variability. The large error ranges suggest significant variability in both metrics, indicating that their relationship may be influenced by diverse external factors or inconsistencies in the data.



Count Plot: Extreme Weather Events by Country

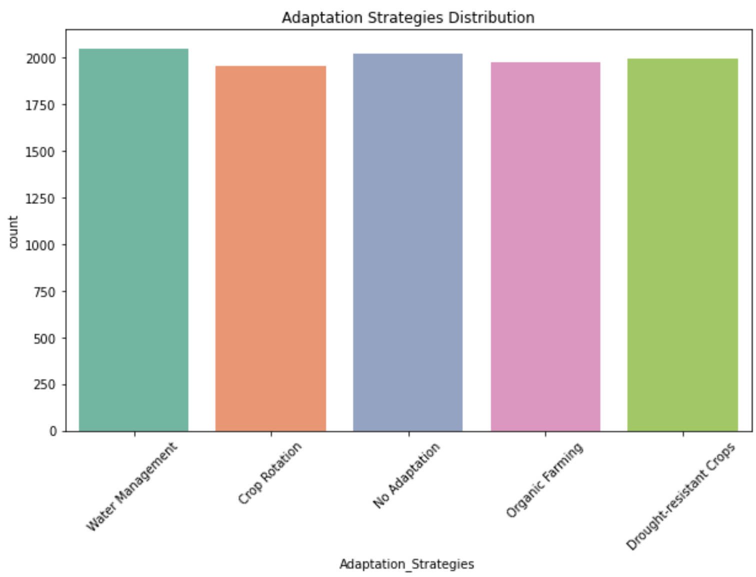
The count plot shows the **number of extreme weather events** by country:

- Countries with frequent extreme weather events may face challenges in sustaining agricultural productivity due to climate variability. This visualization underscores the need for adaptive strategies to manage weather-related risks.



Adaptation Strategies Distribution

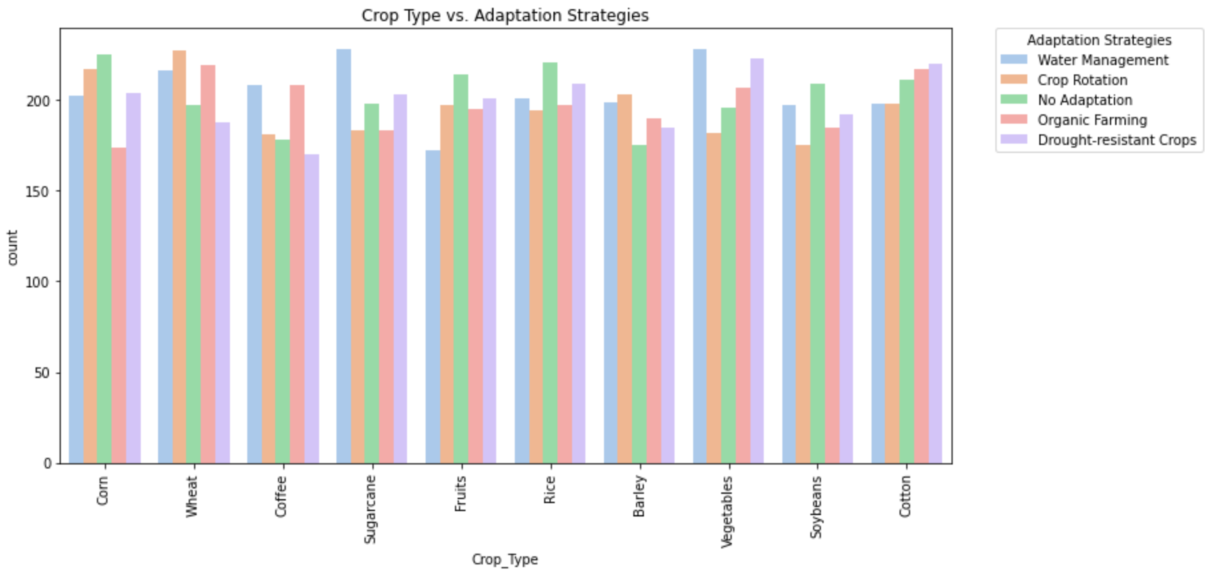
The count plot shows that the distribution of **adaptation strategies** is relatively balanced, with no significant dominance of one strategy over others. This indicates a diverse approach to agricultural adaptation, suggesting flexibility and varied needs across different regions or conditions.



Crop Type vs. Adaptation Strategy

A stacked count plot showing the frequency of **adaptation strategies** employed for each **crop type.**

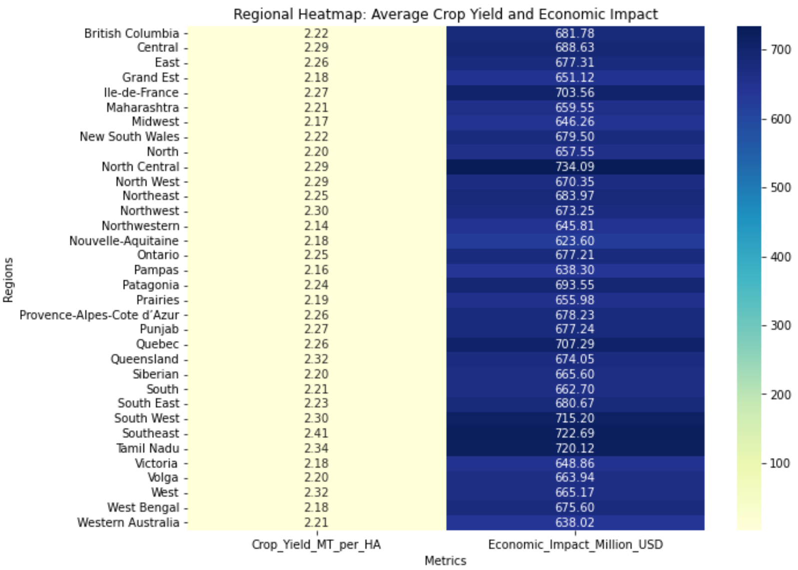
- **Insights**: Highlights which strategies are most used for specific crops, such as crop rotation or water management.



Regional Heatmaps: Average Crop Yield and Economic Impact

The regional heatmap highlights the **average crop yield** and **economic impact** across different regions:

- Regions with higher crop yields also tend to experience higher economic impacts, reflecting the importance of agriculture to these regions' economies.

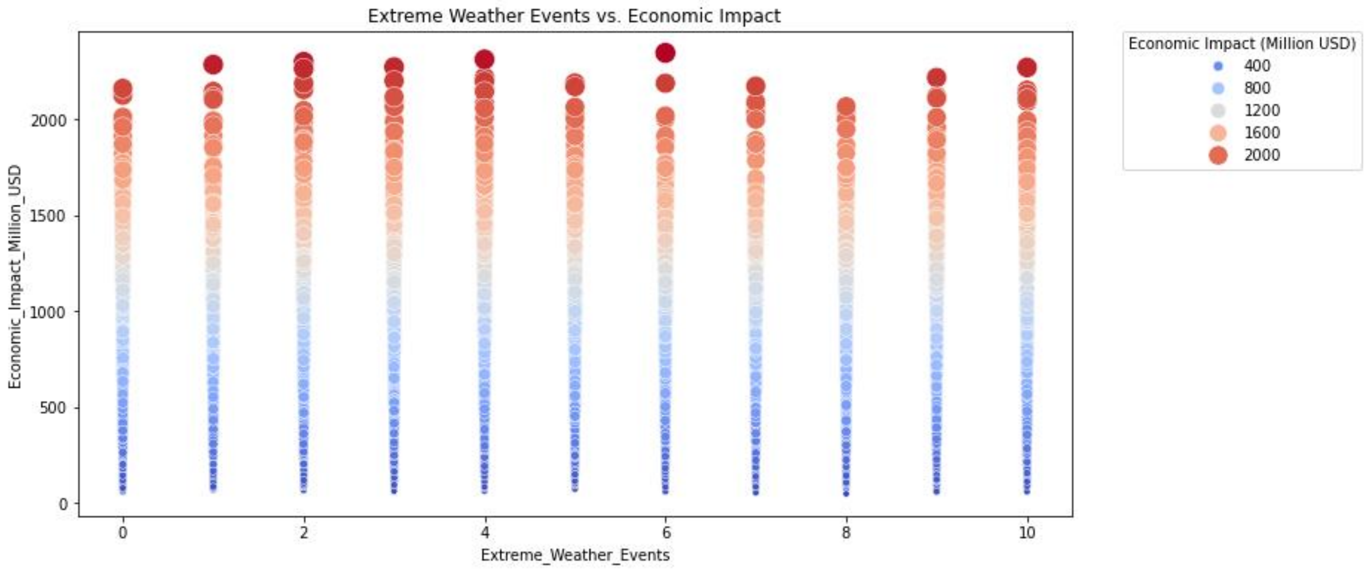


This heatmap provides a clear view of regional disparities in agricultural productivity and economic contribution.

Bubble Chart:

Extreme Weather Events vs. Economic Impact

The bubble plot shows no clear relationship between the number of **Extreme Weather Events** and **Economic Impact (Million USD)**, as bubbles are distributed evenly across event counts. Larger economic impacts are observed across all event frequencies, suggesting that other factors, like crop resilience or market conditions, may mitigate the impact of extreme weather events.



5. Conclusion

1. **Crop Yield and Economic Impact**:
    - Higher crop yields are positively associated with greater economic impact, as seen in the bar chart categorizing yields. However, scatter plots show variability, indicating that other factors, such as crop type and region, significantly influence economic outcomes.
2. **Adaptation Strategies**:
    - Adaptation strategies like crop rotation, organic farming, and water management are evenly distributed across regions and crop types. This diversity highlights the flexibility of farmers in adopting strategies tailored to specific needs rather than universally applying one method.
3. **Environmental Factors**:
    - Variables like **CO2 emissions**, **temperature**, and **precipitation** do not show a clear or strong correlation with crop yield or economic impact. This suggests that these factors may not directly affect outcomes or are mitigated by adaptation measures and agricultural practices.
4. **Regional Variability**:
    - Some regions, such as the **Northeast** and **South**, exhibit significantly higher CO2 emissions and economic impacts compared to others. This highlights regional disparities in agricultural productivity and environmental impact.

Overall Takeaways:

The dataset reveals that while environmental factors and extreme weather events play a role, economic impact and crop yield are heavily influenced by **adaptation strategies**, **regional practices**, and **crop-specific factors**. These findings emphasize the importance of tailored agricultural policies and investments to enhance productivity and resilience across regions.

6. Appendix: Code Used to Generate the Figures

Below is the code used to generate all the figures in this report:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import numpy as np


data = pd.read_csv('climate_change_impact_on_agriculture.csv')


data = data.dropna(subset=['Year'])

data['Year'] = pd.to_numeric(data['Year'], errors='coerce')


data_numeric = data.select_dtypes(include=[np.number])


trend_data = data.groupby('Year').mean(numeric_only=True)


crop_type_counts = data['Crop_Type'].value_counts()

adaptation_strategy_counts = data['Adaptation_Strategies'].value_counts()

region_counts = data['Region'].value_counts()


# 1. Heatmap

correlation_matrix = data_numeric.corr()

plt.figure(figsize=(12, 8))
```

```
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm", cbar=True)

plt.title("Correlation Heatmap")

plt.show()


time_series_data = data.groupby('Year', as_index=False).mean(numeric_only=True)


#Economic Impact Over Time

plt.figure(figsize=(12, 6))

plt.plot(time_series_data['Year'], time_series_data['Economic_Impact_Million_USD'], label='Economic Impact (Million USD)', color='blue', marker='o')

plt.title("Economic Impact Over Time", fontsize=16)

plt.xlabel("Year", fontsize=12)

plt.ylabel("Economic Impact (Million USD)", fontsize=12)

plt.grid(alpha=0.5)

plt.legend()

plt.tight_layout()

plt.show()


#Average Temperature Over Time

plt.figure(figsize=(12, 6))

plt.plot(time_series_data['Year'], time_series_data['Average_Temperature_C'], label='Average Temperature (°C)', color='red', marker='s')

plt.title("Average Temperature Over Time", fontsize=16)

plt.xlabel("Year", fontsize=12)

plt.ylabel("Temperature (°C)", fontsize=12)

plt.grid(alpha=0.5)

plt.legend()

plt.tight_layout()

plt.show()
```

```
plt.figure(figsize=(12, 6))

plt.plot(trend_data.index, trend_data['Total_Precipitation_mm'], label='Total Precipitation (mm)', color='blue')

plt.title("Trend of Total Precipitation Over Time")

plt.xlabel("Year")

plt.ylabel("Total Precipitation (mm)")

plt.legend()

plt.grid(True)

plt.show()


plt.figure(figsize=(12, 6))

plt.plot(trend_data.index, trend_data['Soil_Health_Index'], label='Soil Health Index', color='green')

plt.title("Trend of Soil Health Index Over Time")

plt.xlabel("Year")

plt.ylabel("Soil Health Index")

plt.legend()

plt.grid(True)

plt.show()


#Line Plot: Year vs. Crop Yield

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

sns.lineplot(data=data, x="Year", y="Crop_Yield_MT_per_HA", ci=None)

plt.title("Crop Yield Over Time")

plt.xlabel("Year")

plt.ylabel("Crop Yield (MT/HA)")

plt.grid(alpha=0.5)

plt.show()


data['Crop_Yield_Category'] = pd.cut(data['Crop_Yield_MT_per_HA'], bins=5, labels=['Very Low', 'Low',
'Medium', 'High', 'Very High'])

# Calculate the average Economic Impact by Crop Yield Category
```

```
avg_economic_impact = data.groupby('Crop_Yield_Category')['Economic_Impact_Million_USD'].mean()


#bar chart

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

avg_economic_impact.plot(kind='bar', color='skyblue', edgecolor='black')

plt.title("Average Economic Impact by Crop Yield Category", fontsize=14)

plt.xlabel("Crop Yield Category", fontsize=12)

plt.ylabel("Average Economic Impact (Million USD)", fontsize=12)

plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.tight_layout()

plt.xticks(rotation=0)

plt.show()



#Economic Impact and Irrigation Access

crop_economic_impact =
data.groupby('Crop_Type')['Economic_Impact_Million_USD'].mean().sort_values(ascending=False)

country_irrigation_access =
data.groupby('Country')['Irrigation_Access_%'].mean().sort_values(ascending=False)


plt.figure(figsize=(12, 6))

crop_economic_impact.plot(kind='bar', color='skyblue', edgecolor='black')

plt.title("Average Economic Impact by Crop Type")

plt.xlabel("Crop Type")

plt.ylabel("Economic Impact (Million USD)")

plt.xticks(rotation=45)

plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()


plt.figure(figsize=(12, 6))
```

```
country_irrigation_access.plot(kind='bar', color='orange', edgecolor='black')
plt.title("Average Irrigation Access by Country")
plt.xlabel("Country")
plt.ylabel("Irrigation Access (%)")
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

#Soil Health by Region
region_soil_health_data = data.groupby("Region")["Soil_Health_Index"].mean().sort_values()
plt.figure(figsize=(10, 6))
region_soil_health_data.plot(kind="bar", color="chocolate", edgecolor="black")
plt.title("Soil Health Index by Region")
plt.xlabel("Region")
plt.ylabel("Average Soil Health Index")
plt.xticks(rotation=90)
plt.grid(axis="y", alpha=0.5)
plt.tight_layout()
plt.show()

#Extreme Weather by Region
extreme_weather_region_data = data.groupby("Region")["Extreme_Weather_Events"].sum().sort_values()
plt.figure(figsize=(10, 6))
extreme_weather_region_data.plot(kind="bar", color="salmon", edgecolor="black")
plt.title("Total Extreme Weather Events by Region")
plt.xlabel("Region")
plt.ylabel("Number of Events")
plt.xticks(rotation=90)
plt.grid(axis="y", alpha=0.5)
```

```
plt.tight_layout()

plt.show()


#Year vs. Extreme Weather Events

yearly_weather_data = data.groupby("Year", as_index=False).mean(numeric_only=True)

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

sns.barplot(data=yearly_weather_data, x="Year", y="Extreme_Weather_Events", color="blue")

plt.xticks(rotation=45)

plt.title("Year vs. Extreme Weather Events")

plt.xlabel("Year")

plt.ylabel("Extreme Weather Events")

plt.grid(axis="y", alpha=0.5)

plt.show()


#Country vs. Crop Yield

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

country_yield_data = data.groupby("Country", as_index=False).mean(numeric_only=True)

sns.barplot(data=country_yield_data, x="Country", y="Crop_Yield_MT_per_HA", ci=None, color="skyblue")

plt.xticks(rotation=90)

plt.title("Country vs. Crop Yield")

plt.xlabel("Country")

plt.ylabel("Crop Yield (MT/HA)")

plt.grid(axis="y", alpha=0.5)

plt.tight_layout()

plt.show()


#Region vs. Economic Impact

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

region_impact_data = data.groupby("Region", as_index=False).mean(numeric_only=True)
```

```
sns.barplot(data=region_impact_data, x="Region", y="Economic_Impact_Million_USD", ci=None, color="lightgreen")

plt.xticks(rotation=90)

plt.title("Region vs. Economic Impact")

plt.xlabel("Region")

plt.ylabel("Economic Impact (Million USD)")

plt.grid(axis="y", alpha=0.5)

plt.tight_layout()

plt.show()


#Adaptation Strategies vs. Economic Impact

adaptation_data = data.groupby("Adaptation_Strategies", as_index=False).mean(numeric_only=True)

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

sns.barplot(data=adaptation_data, x="Adaptation_Strategies", y="Economic_Impact_Million_USD", ci=None, color="orange")

plt.xticks(rotation=45)

plt.title("Adaptation Strategies vs. Economic Impact")

plt.xlabel("Adaptation Strategies")

plt.ylabel("Economic Impact (Million USD)")

plt.grid(axis="y", alpha=0.5)

plt.tight_layout()

plt.show()


#Histograms: Precipitation

plt.figure(figsize=(12, 6))

plt.hist(data['Total_Precipitation_mm'], bins=20, color='steelblue', edgecolor='black', alpha=0.8)

plt.title("Distribution of Total Precipitation (mm)", fontsize=16, weight='bold')

plt.xlabel("Total Precipitation (mm)", fontsize=12)

plt.ylabel("Frequency", fontsize=12)

plt.xticks(ticks=range(0, 3100, 500), fontsize=10)
```

```
plt.yticks(fontsize=10)

plt.grid(axis='y', linestyle='--', alpha=0.3)

plt.tight_layout()

plt.show()


#distribution of the Soil Health Index

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

plt.hist(data['Soil_Health_Index'], bins=15, color='green', edgecolor='black', alpha=0.7)

plt.title("Distribution of Soil Health Index", fontsize=14)

plt.xlabel("Soil Health Index", fontsize=12)

plt.ylabel("Frequency", fontsize=12)

plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.tight_layout()

plt.show()


#Pie Charts

# Proportion of Crop Types

plt.figure(figsize=(12, 12))

explode_crop = [0.1 if i == max(crop_type_counts.values) else 0 for i in crop_type_counts.values]

plt.pie(crop_type_counts.values, labels=crop_type_counts.index, autopct='%1.1f%%', startangle=140,
explode=explode_crop)

plt.title("Proportion of Crop Types", fontsize=16, weight='bold')

plt.tight_layout()

plt.show()


# Proportion of Adaptation Strategies

plt.figure(figsize=(12, 12))

explode_adaptation = [0.1 if i == max(adaptation_strategy_counts.values) else 0 for i in
adaptation_strategy_counts.values]

plt.pie(adaptation_strategy_counts.values, labels=adaptation_strategy_counts.index, autopct='%1.1f%%',
startangle=140, explode=explode_adaptation)
```

```
plt.title("Proportion of Adaptation Strategies", fontsize=16, weight='bold')

plt.tight_layout()

plt.show()


# Proportion of Regions

plt.figure(figsize=(12, 12))

explode_region = [0.1 if i == max(region_counts.values) else 0 for i in region_counts.values]

plt.pie(region_counts.values, labels=region_counts.index, autopct='%1.1f%%', startangle=140,
explode=explode_region)

plt.title("Proportion of Regions", fontsize=16, weight='bold')

plt.tight_layout()

plt.show()


#boxplots

sns.boxplot(x='Crop_Type',y='Average_Temperature_C',data=data,palette='muted')

plt.xticks(rotation=45)

plt.title('Average Temperature distribution for each crop type')

plt.show()


sns.boxplot(x='Crop_Type',y='Soil_Health_Index',data=data, palette='muted')

plt.title('Soil Health Index for each crop type')

plt.xticks(rotation=45)

plt.show()


sns.boxplot(x='Country',y='CO2_Emissions_MT',data=data,palette='muted')

plt.xticks(rotation=45)

plt.title("CO2 Emissions for each Country")

plt.show()


# 7. Violin Plot
```

```
plt.figure(figsize=(12, 6))

sns.violinplot(x='Crop_Type', y='Irrigation_Access_%', data=data, palette='muted')

plt.title("Irrigation Access by Crop Type")

plt.xlabel("Crop Type")

plt.ylabel("Irrigation Access (%)")

plt.xticks(rotation=45)

plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()


# 8. Scatter Plots

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

plt.scatter(data['CO2_Emissions_MT'], data['Crop_Yield_MT_per_HA'], alpha=0.7, edgecolor='none')

plt.title("CO2 Emissions vs. Crop Yield")

plt.xlabel("CO2 Emissions (MT)")

plt.ylabel("Crop Yield (MT/HA)")

plt.grid(alpha=0.5)

plt.show()


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

plt.scatter(data['Soil_Health_Index'], data['Economic_Impact_Million_USD'], alpha=0.7, color='green',
edgecolor='none')

plt.title("Soil Health vs. Economic Impact")

plt.xlabel("Soil Health Index")

plt.ylabel("Economic Impact (Million USD)")

plt.grid(alpha=0.5)

plt.show()

#Temperature vs. Crop Yield

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

sns.scatterplot(data=data, x="Average_Temperature_C", y="Crop_Yield_MT_per_HA")

plt.title("Temperature vs. Crop Yield")
```

```
plt.xlabel("Average Temperature (°C)")
plt.ylabel("Crop Yield (MT/HA)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#Precipitation vs. Crop Yield
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x="Total_Precipitation_mm", y="Crop_Yield_MT_per_HA")
plt.title("Precipitation vs. Crop Yield")
plt.xlabel("Total Precipitation (mm)")
plt.ylabel("Crop Yield (MT/HA)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#CO2 Emissions vs. Crop Yield
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x="CO2_Emissions_MT", y="Crop_Yield_MT_per_HA")
plt.title("CO2 Emissions vs. Crop Yield")
plt.xlabel("CO2 Emissions (MT)")
plt.ylabel("Crop Yield (MT/HA)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#Soil Health Index vs. Crop Yield
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x="Soil_Health_Index", y="Crop_Yield_MT_per_HA")
```

```
plt.title("Soil Health Index vs. Crop Yield")
plt.xlabel("Soil Health Index")
plt.ylabel("Crop Yield (MT/HA)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#Irrigation Access vs. Economic Impact
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x="Irrigation_Access_%", y="Economic_Impact_Million_USD")
plt.title("Irrigation Access vs. Economic Impact")
plt.xlabel("Irrigation Access (%)")
plt.ylabel("Economic Impact (Million USD)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#Economic Impact vs. Fertilizer Use by Crop Type
plt.figure(figsize=(12, 6))
sns.scatterplot(
    data=data,
    x="Fertilizer_Use_KG_per_HA",
    y="Economic_Impact_Million_USD",
    hue="Crop_Type",
    palette="viridis"
)
plt.title("Economic Impact vs. Fertilizer Use by Crop Type")
plt.xlabel("Fertilizer Use (KG/HA)")
plt.ylabel("Economic Impact (Million USD)")
```

```
plt.legend(title="Crop Type", bbox_to_anchor=(1.05, 1), loc="upper left")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()
#Pesticide Use vs. Economic Impact
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x="Pesticide_Use_KG_per_HA", y="Economic_Impact_Million_USD")
plt.title("Pesticide Use vs. Economic Impact")
plt.xlabel("Pesticide Use (KG/HA)")
plt.ylabel("Economic Impact (Million USD)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#Extreme Weather Events vs. Crop Yield
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x="Extreme_Weather_Events", y="Crop_Yield_MT_per_HA")
plt.title("Extreme Weather Events vs. Crop Yield")
plt.xlabel("Extreme Weather Events")
plt.ylabel("Crop Yield (MT/HA)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()

#Stacked Bar Chart: Region-Wise Crop Types with CO2 Emissions
region_crop_data = data.groupby(['Region', 'Crop_Type'])['CO2_Emissions_MT'].sum().unstack()
region_crop_data.plot(kind='bar', stacked=True, figsize=(12, 6), cmap='coolwarm')
plt.title("Region-Wise Crop Types with CO2 Emissions")
plt.xlabel("Region")
```

```python
plt.ylabel("CO2 Emissions (MT)")
plt.legend(title="Crop Type", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=90)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

#CO2 Emissions and Economic Impact by Crop Type
plt.figure(figsize=(12, 6))
sns.barplot(
    data=data,
    x="Crop_Type",
    y="CO2_Emissions_MT",
    hue="Adaptation_Strategies",
    palette="cubehelix"
)
plt.title("CO2 Emissions and Economic Impact by Crop Type")
plt.xlabel("Crop Type")
plt.ylabel("CO2 Emissions (MT)")
plt.legend(title="Adaptation Strategies", bbox_to_anchor=(1.05, 1), loc="upper left")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

#Error Bars: CO2 Emissions vs. Crop Yield
co2_mean = data['CO2_Emissions_MT'].mean()
co2_std = data['CO2_Emissions_MT'].std()
crop_yield_mean = data['Crop_Yield_MT_per_HA'].mean()
crop_yield_std = data['Crop_Yield_MT_per_HA'].std()
```

```
plt.figure(figsize=(10, 6))
plt.errorbar(co2_mean, crop_yield_mean, xerr=co2_std, yerr=crop_yield_std, fmt='o', color='red', ecolor='red', capsize=5, label='CO2 vs. Crop Yield')
plt.title("Error Bars: CO2 Emissions vs. Crop Yield")
plt.xlabel("CO2 Emissions (MT)")
plt.ylabel("Crop Yield (MT/HA)")
plt.legend()
plt.grid(alpha=0.5)
plt.show()

#Extreme Weather Events by Country
plt.figure(figsize=(12, 6))
sns.countplot(x='Country', data=data, order=data['Country'].value_counts().index, palette='viridis')
plt.title("Number of Extreme Weather Events by Country")
plt.xlabel("Country")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

#Adaptation Strategies Distribution
plt.figure(figsize=(10, 6))
sns.countplot(data=data, x="Adaptation_Strategies", palette="Set2")
plt.xticks(rotation=45)
plt.title("Adaptation Strategies Distribution")
plt.xlabel("Adaptation Strategies")
plt.ylabel("Count")
plt.grid(axis="y", alpha=0.5)
plt.tight_layout()
```

```
plt.show()

#Crop Type vs. Adaptation Strategies
plt.figure(figsize=(12, 6))
sns.countplot(data=data, x="Crop_Type", hue="Adaptation_Strategies", palette="pastel")
plt.xticks(rotation=90)
plt.legend(
    title="Adaptation Strategies",
    loc="upper left",
    bbox_to_anchor=(1.05, 1),  # Move legend completely outside the plot
    borderaxespad=0
)
plt.title("Crop Type vs. Adaptation Strategies")
plt.xlabel("Crop Type")
plt.ylabel("Count")
plt.grid(axis="y", alpha=0.5)
plt.tight_layout()
plt.show()

#Regional Heatmap
regional_data = data.groupby('Region')[['Crop_Yield_MT_per_HA', 'Economic_Impact_Million_USD']].mean()
plt.figure(figsize=(10, 8))
sns.heatmap(regional_data, annot=True, fmt=".2f", cmap="YlGnBu", cbar=True)
plt.title("Regional Heatmap: Average Crop Yield and Economic Impact")
plt.xlabel("Metrics")
plt.ylabel("Regions")
plt.show()

#Extreme Weather Events vs. Economic Impact
```

```python
plt.figure(figsize=(12, 6))
sns.scatterplot(
    data=data,
    x="Extreme_Weather_Events",
    y="Economic_Impact_Million_USD",
    size="Economic_Impact_Million_USD",
    sizes=(20, 200),
    hue="Economic_Impact_Million_USD",
    palette="coolwarm"
)
plt.legend(
    title="Economic Impact (Million USD)",
    loc="upper left",
    bbox_to_anchor=(1.05, 1),  # Move legend outside the plot
    borderaxespad=0
)
plt.title("Extreme Weather Events vs. Economic Impact")
plt.xlabel("Extreme Weather Events")
plt.ylabel("Economic Impact (Million USD)")
plt.grid(alpha=0.5)
plt.tight_layout()
plt.show()
```