# Climate Foresight:
# The Defining Crisis of Our Time

PREDICTING $CO_2$ EMISSIONS, TEMPERATURE RISE, AND SEA LEVEL TRENDS USING MACHINE LEARNING

PRESENTED BY: GROUP 8

# Business Understanding

CLIMATE CHANGE IS A DEFINING CRISIS, DRIVING EXTREME WEATHER AND ECONOMIC LOSSES.

- Machine learning provides data-driven insights to forecast key climate indicators:
- $CO_2$ emissions per capita
- Average temperature rise
- Global sea level trends
- Stakeholders: Governments, NGOs, investors, and policymakers need predictive tools for proactive climate action.

# Problem statement

**Gaps in climate forecasting:**

Many regions lack predictive models for emissions, temperature, and sea level rise.

**Consequences:**

Misaligned policies

Delayed adaptation efforts

Inefficient climate investments

# Business Problem

NEED FOR ACCURATE FORECASTS TO:

TRACK EMISSIONS REDUCTIONS (E.G., PARIS AGREEMENT)

PLAN RESILIENT INFRASTRUCTURE

OPTIMIZE CLIMATE FINANCE

# Objectives

| Predict | Identify | Evaluate |
|---|---|---|
| Predict $CO_2$ emissions, temperature, and sea level trends using ML. | Identify key drivers (e.g., renewable energy, deforestation). | Evaluate models using $R^2$, RMSE, and feature importance. |

# Data Sources

Climate Data (Our World in Data, World Bank)

$CO_2$ & GHG emissions by sector

Key indicators: Renewable energy adoption, population growth, temperature anomalies

Climate Risk Index Dataset

182 countries

Climate vulnerability rankings

Economic losses from extreme weather

# Proposed Solution

Hybrid ML pipeline:

Supervised learning (Random Forest, XGBoost) for $CO_2$ and temperature.

Time-series forecasting for long-term trends.

Actionable insights for policymakers and investors.

# Data Preparation

## Steps Taken:

Handled missing values (median imputation for temperature, mean for forest cover).

Checked for outliers (extreme $CO_2$ emitters, temperature anomalies).

Normalized data for model training.

## Visualizations:

Correlation heatmaps showed relationships between emissions, renewables, temperature.

Time-series trends revealed rising $CO_2$ and temperature over decades.

# Exploratory Data Analysis (EDA)

Key Findings:

1. $CO_2$ Emissions & Population Growth - Strong correlation (0.89–0.99)

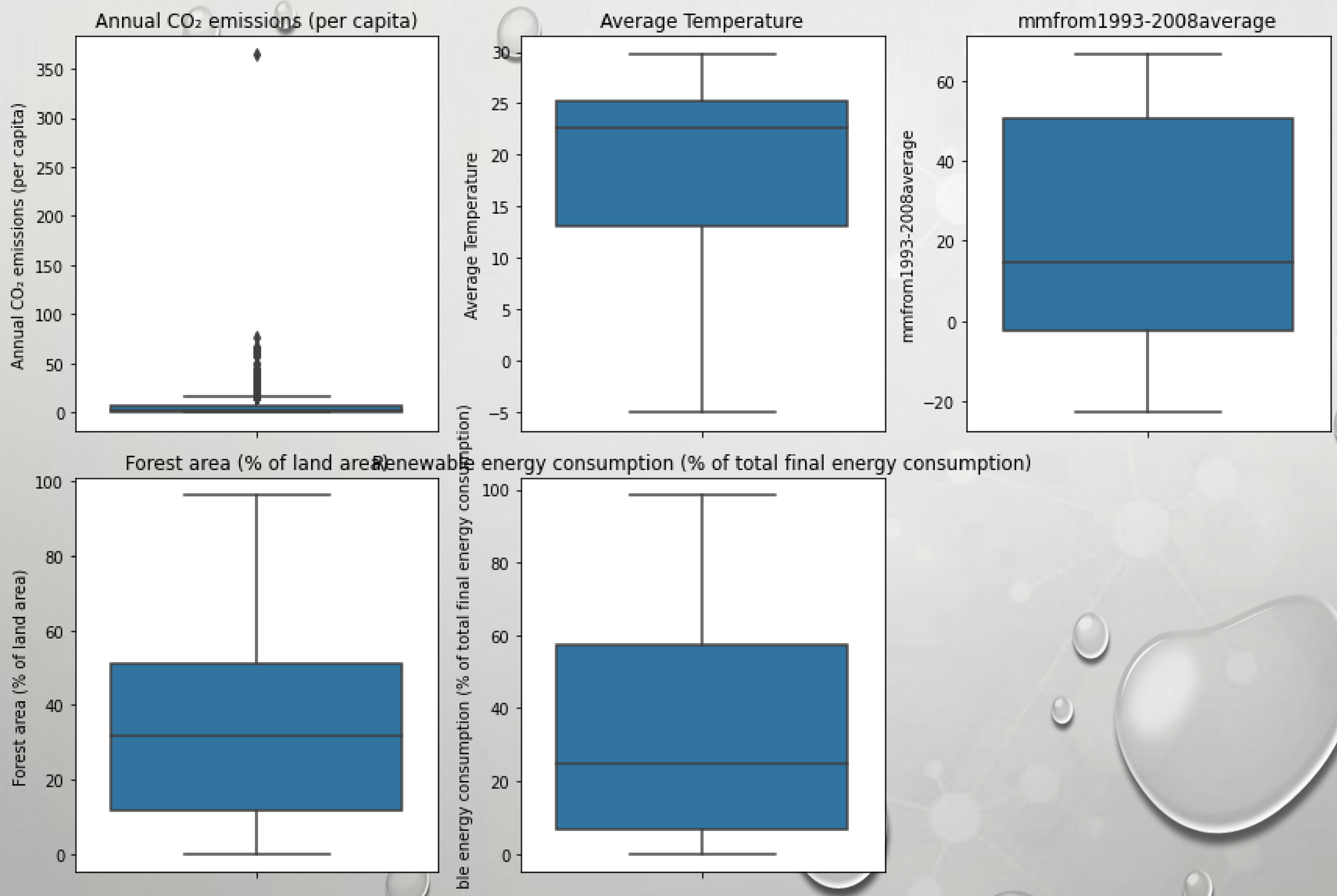
2. Renewable Energy Reduces Emissions - Negative correlation (-0.50)

3. Temperature Trends - Rising since 1990, accelerating post-2005

4. Forest Cover Decline - Deforestation contributes to $CO_2$ emissions

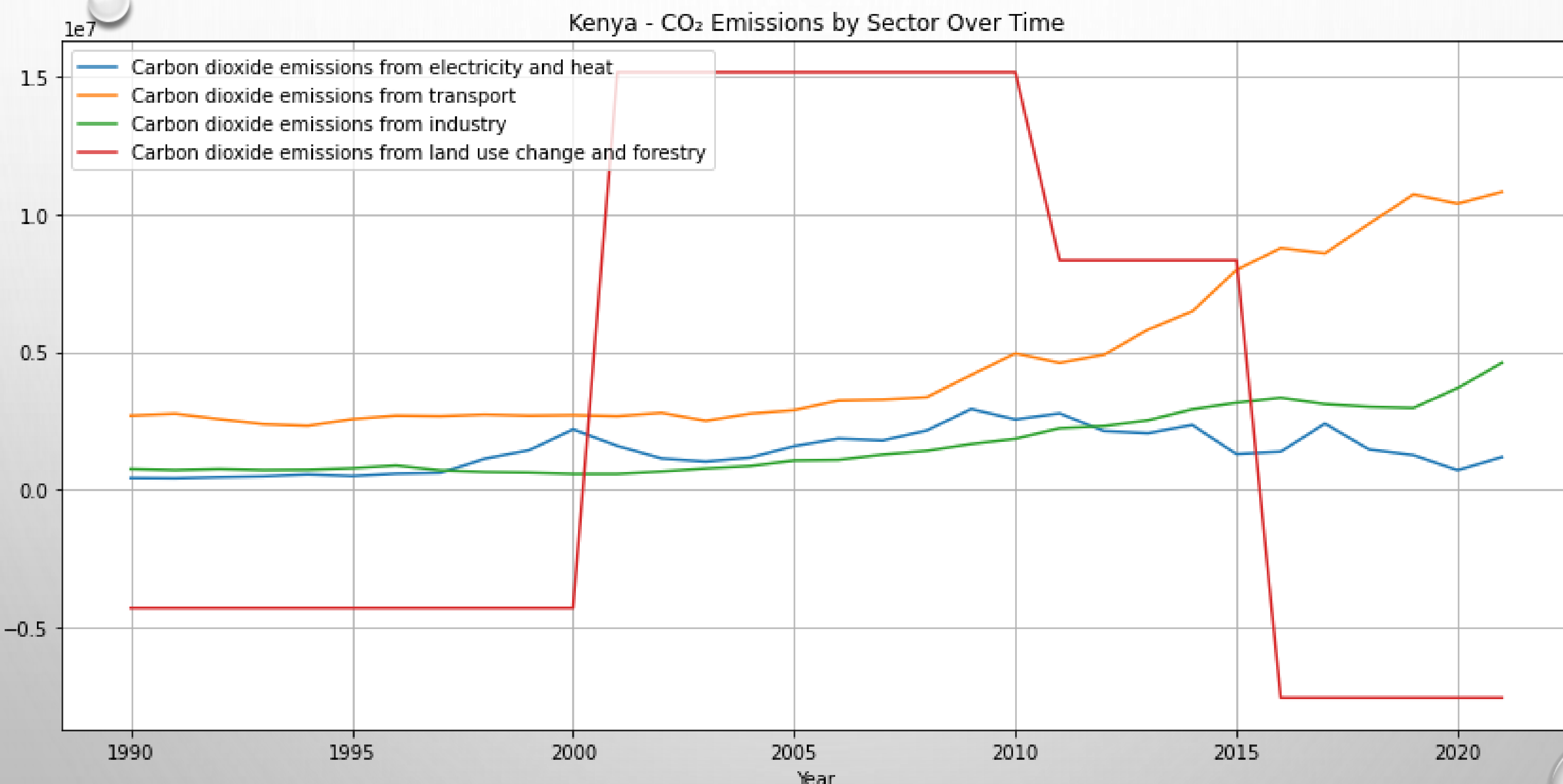
5. East Africa Case Study - Rapid population growth + deforestation = rising climate risks

# Box plot



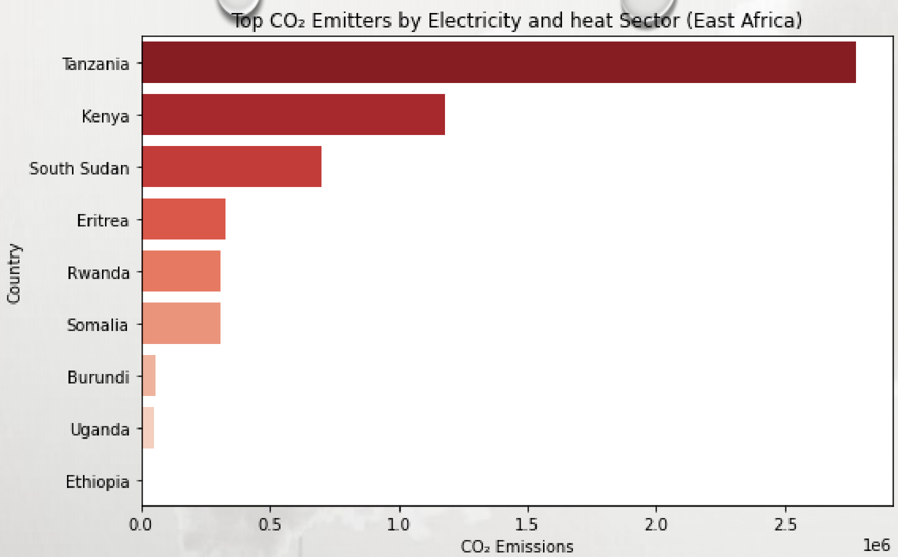
Annual CO₂ emissions (per capita)
Average Temperature
mmfrom1993-2008average
Forest area (% of land area)
Renewable energy consumption (% of total final energy consumption)

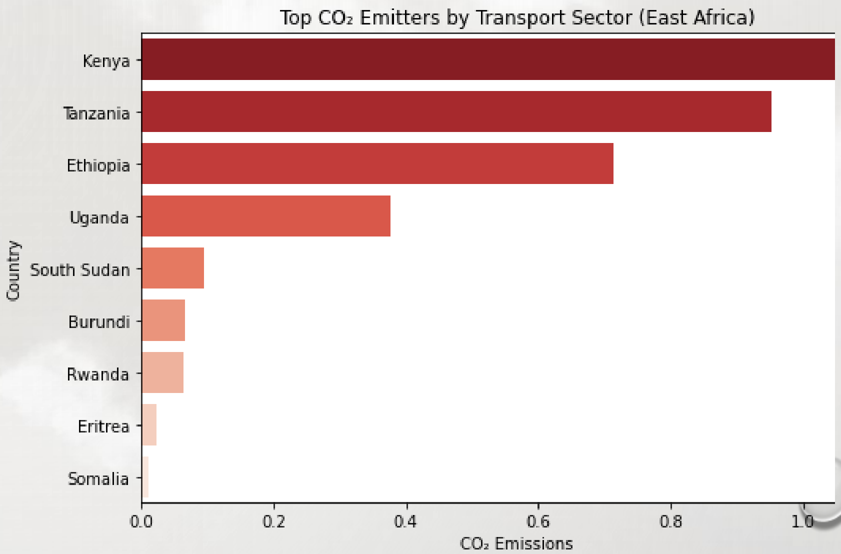
# Emissions

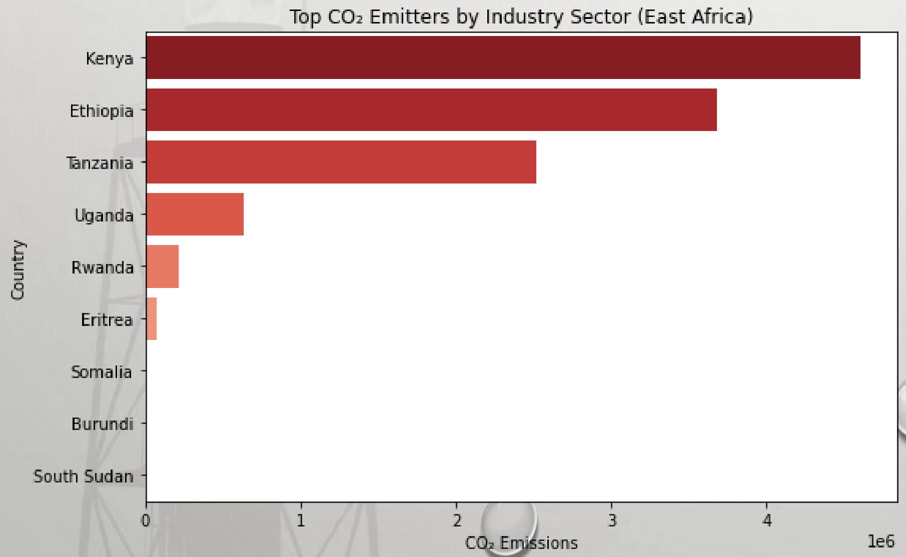


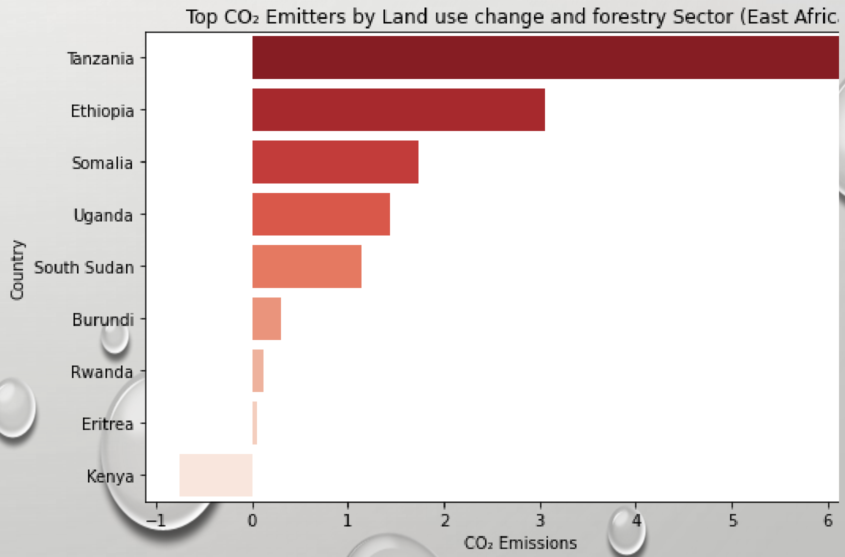
Kenya - CO₂ Emissions by Sector Over Time
1e7
Carbon dioxide emissions from electricity and heat
Carbon dioxide emissions from transport
Carbon dioxide emissions from industry
Carbon dioxide emissions from land use change and forestry
1.5
1.0
0.5
0.0
−0.5
1990
1995
2000
2005
2010
2015
2020
Year

# Emissions

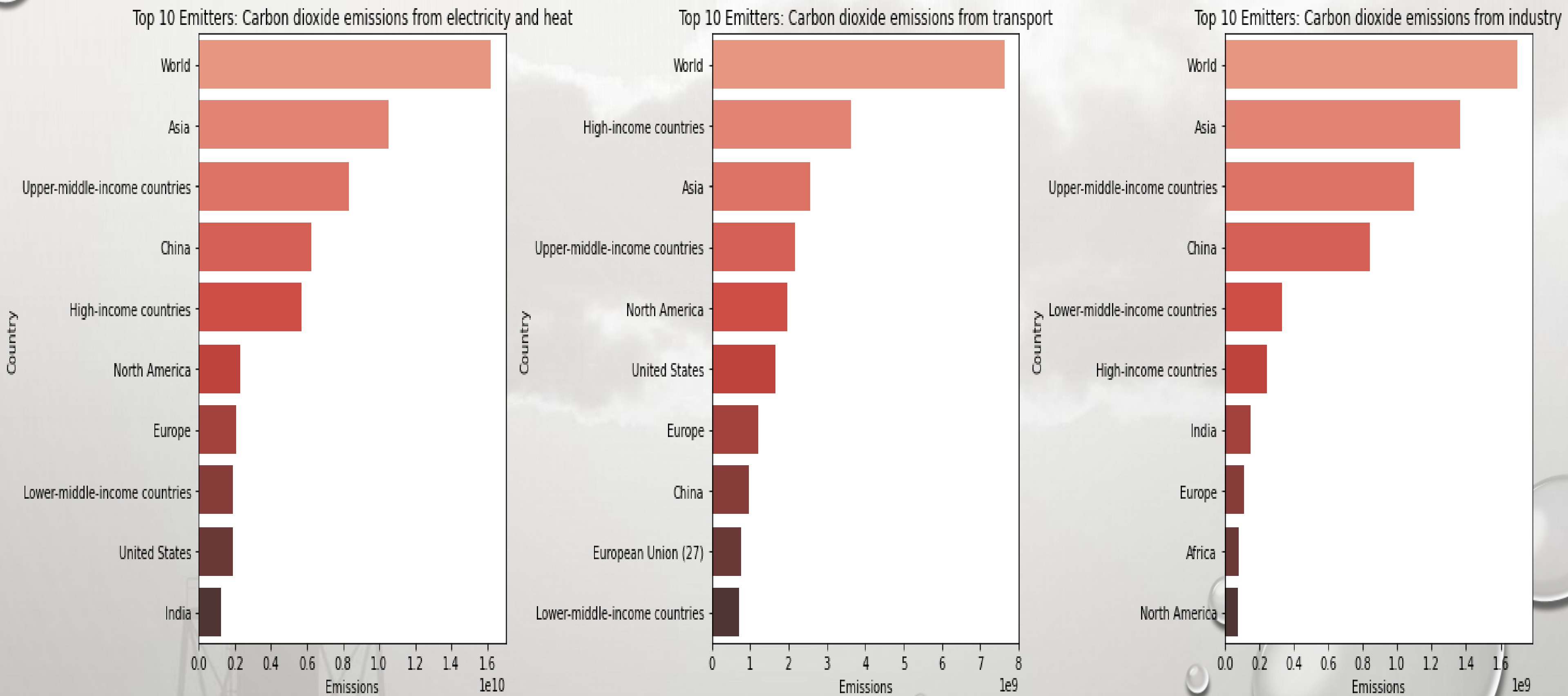

Top CO₂ Emitters by Electricity and heat Sector (East Africa)
Tanzania
Kenya
South Sudan
Eritrea
Rwanda
Somalia
Burundi
Uganda
Ethiopia
Country
0.0
0.5
1.0
1.5
2.0
2.5
1e6
CO₂ Emissions


Top CO₂ Emitters by Transport Sector (East Africa)
Kenya
Tanzania
Ethiopia
Uganda
South Sudan
Burundi
Rwanda
Eritrea
Somalia
Country
0.0
0.2
0.4
0.6
0.8
1.0
CO₂ Emissions

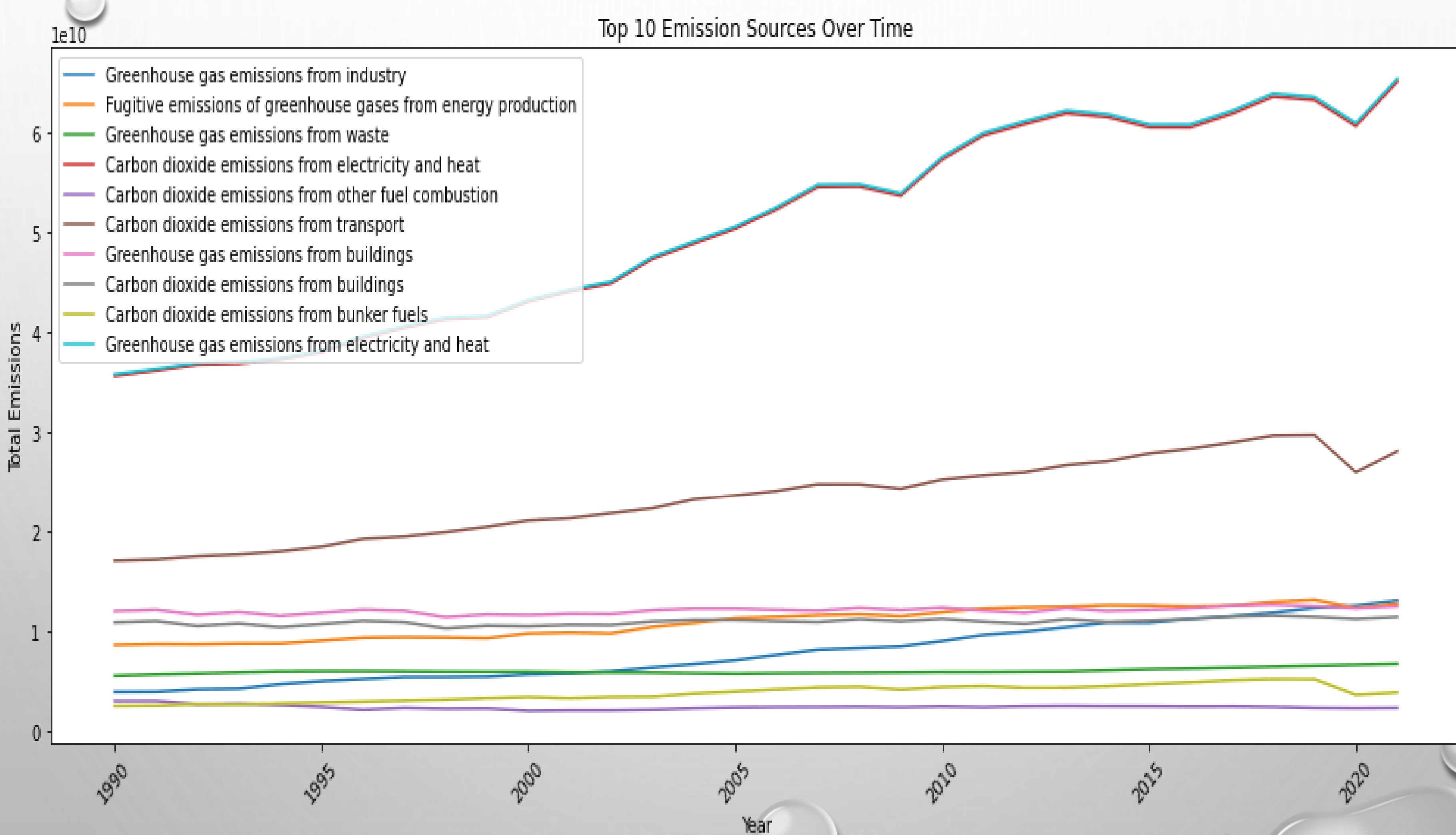

Top CO₂ Emitters by Industry Sector (East Africa)
Kenya
Ethiopia
Tanzania
Uganda
Rwanda
Eritrea
Somalia
Burundi
South Sudan
Country
0
1
2
3
4
1e6
CO₂ Emissions


Top CO₂ Emitters by Land use change and forestry Sector (East Afric
Tanzania
Ethiopia
Somalia
Uganda
South Sudan
Burundi
Rwanda
Eritrea
Kenya
Country
−1
0
1
2
3
4
5
6
CO₂ Emissions

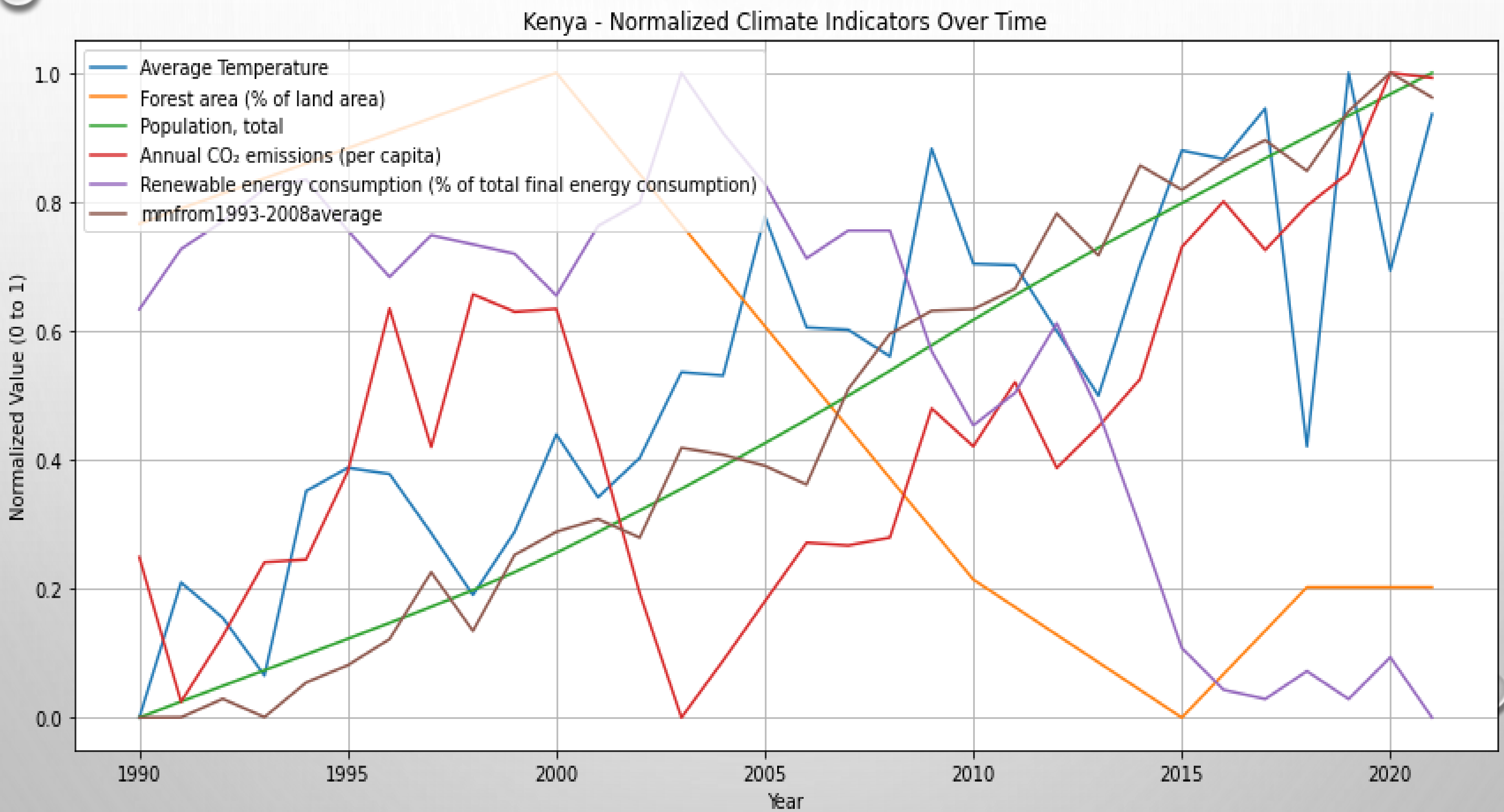
# Emissions by sector



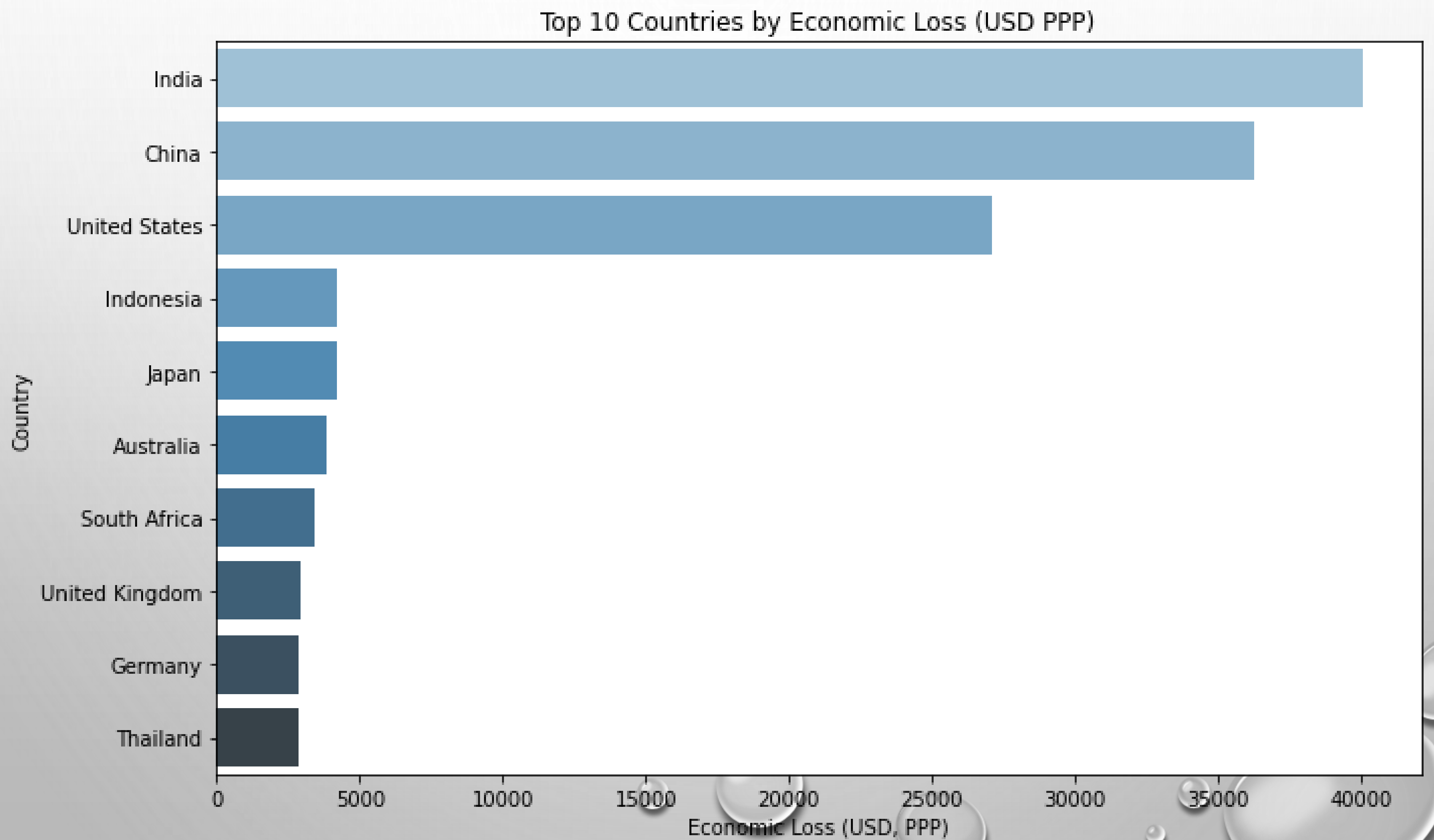
# Top 10 Emission Sources Over Time



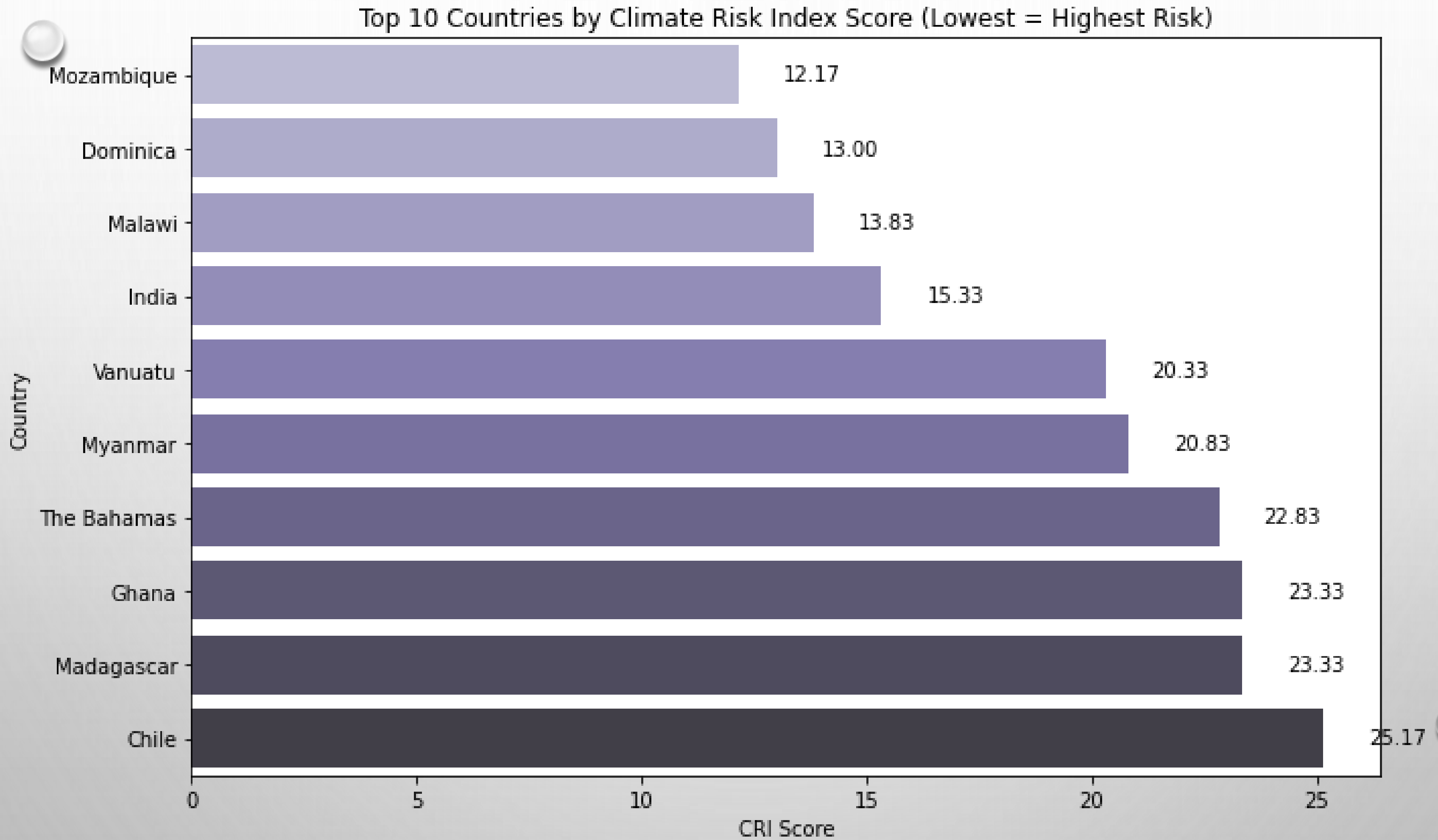
# Indicators


Kenya - Normalized Climate Indicators Over Time
Average Temperature
Forest area (% of land area)
Population, total
Annual CO₂ emissions (per capita)
Renewable energy consumption (% of total final energy consumption)
mmfrom1993-2008average
Normalized Value (0 to 1)
0.0
0.2
0.4
0.6
0.8
1.0
1990
1995
2000
2005
2010
2015
2020
Year

# Top 10 Countries by Economic Loss (USD PPP)



# Top 10 Countries by Climate Risk Index Score



# Modeling & Results

| **$CO_2$ Emissions Prediction (Per Capita):** |
|---|
| Best Model: XGBoost (Non-Tuned) ($R^2$: 0.977, RMSE: 1.06) |
| Key Drivers: Population growth, renewable energy adoption, forest cover |
| **Average Temperature Prediction:** |
| Best Model: Tuned XGBoost ($R^2$: 0.983, RMSE: 0.98°C) |
| Key Drivers: $CO_2$ emissions, sea level anomalies, time trend |

# Model Performance Summary

- Comparison of Models:
- XGBoost (Non-Tuned): $R^2 = 0.977$ ($CO_2$), RMSE = 1.06
- Tuned XGBoost: $R^2 = 0.983$ (Temp), RMSE = 0.98
- Random Forest: $R^2 = 0.981$ (Temp), RMSE = 1.04
- Linear Regression: Poor performance ($R^2 < 0.3$)

# Key Insights & Recommendations

1. Emissions Reduction Strategies:

- Shift to renewables (solar, wind) to lower $CO_2$ from electricity/heat.

- Urban planning to reduce transport emissions (e.g., electric vehicles).

2. Temperature Mitigation:

- Reforestation to offset $CO_2$ impact.

- Early warning systems for heatwaves.

3. Policy & Investment Implications:

- Target high-emission sectors (energy, industry).

- Climate-resilient infrastructure in vulnerable regions (e.g., East Africa).

# Key Takeaways

XGBoost and Random Forest outperformed in predicting $CO_2$ and temperature.

Proactive measures can now be guided by data-driven insights.

Machine learning enables precise climate forecasting.

# Next Steps

**1.Granular Forecasting**

Introduce regional or subnational models for localized climate adaptation.

**2.Add Economic and Policy Indicators**

Include climate finance, policy commitments, and infrastructure metrics to deepen insights.

**3.Uncertainty Quantification**

Incorporate confidence intervals or probabilistic modeling to express uncertainty in long-term forecasts

**4.Deploy models for real-time climate monitoring.**

Expand forecasting to regional sea level rise.

# Q&A

THANK YOU!

# LINKS

## TABLEAU

HTTPS://PUBLIC.TABLEAU.COM/APP/PROFILE/GRACE.MWENDE/VIZ/CLIMATECHANGEPROJECT/CO2EMISSIONSDASHBOARD?PUBLISH=YES

## GITHUB

**https://github.com/Angoye/Capstone-Project---Group-8**

## STREAMLIT