AI as the Future of Climate Action

Artificial Intelligence (AI) technological breakthrough stands out as a powerful tool to accelerate progress across all SDGs. Its ability to process vast amounts of data, identify patterns, automate decision-making, significantly increase efficiency, and enhance monitoring and reporting across environmental, social, and governance (ESG) efforts will play a central role in the practice of climate action. Key roles of AI as the future of climate action include: climate forecasting, supporting early warning systems, and optimizing renewable energy development.

The advancement and sustainability of human society greatly depend on maintaining a clean and healthy environment. As developing and developed countries intensify efforts to address climate change and global warming, economic development and population growth are significant factors. As the worldwide population and production levels increase, overall wealth increases rapidly, significantly straining the environment (Glavina et al., 2025). Not only is environmental impact responsibility considered in developed and developing countries, but unfortunately, the economic agenda still dominates various sectors such as tourism, technology, and socio-economic development. Projections of the macroeconomic damage resulting from future climate change are essential in informing current public and policy debates on adaptation, mitigation, and climate justice (Notz et al., 2024). When it comes to developing countries such as Kenya and other poorer countries, climate change will significantly impact how these countries pursue economic development, with an impact on national development strategies, the field of global development, and the shape of international security.

Climate-Action Supervised and Unsupervised Learning Model

My project on addressing climate action focuses on a model to forecast carbon emissions at a national level through socio-economic metrics and population data. The model relies on supervised and unsupervised learning. Supervised learning uses linear regression to predict CO2 emissions based on GDP, population, and GDP per capita. Such data can help policymakers determine future emissions based on economic indicators. Unsupervised learning uses K-Means Clustering to group countries based on economic-emissions profile. These data provide natural groupings that can inform tailored policy approaches.

Findings reveal that higher GDP and population correlate with higher emissions. The regression model in Figure 1 shows:

Ø **South Africa** lies **very close to the line,** indicating a **strong, accurate prediction.**

Ø **Namibia & Nigeria:** Lie **above the line** → The model **overestimated** their emissions.

Ø **Kenya, Burundi, Uganda:** Lie **below the line** → the model **underestimated** their emissions.

The heatmap shows **correlation coefficients** between GDP, population, GDP per capita, and CO_2 emissions (2020 data):

- **GDP vs. Population (0.98):**
  - Strong positive correlation
  - Indicates that countries with larger populations tend to have higher GDP
- **GDP vs. CO_2 Emissions (0.35):**
  - Weak positive correlation
  - GDP alone is not a strong predictor of emissions
- **GDP per Capita vs. CO_2 Emissions (0.61):**
  - Moderate positive correlation
  - Suggests that wealthier populations contribute more to emissions
- **Population vs. CO_2 Emissions (0.26):**
  - Weak correlation
  - Population size alone does not strongly influence emissions

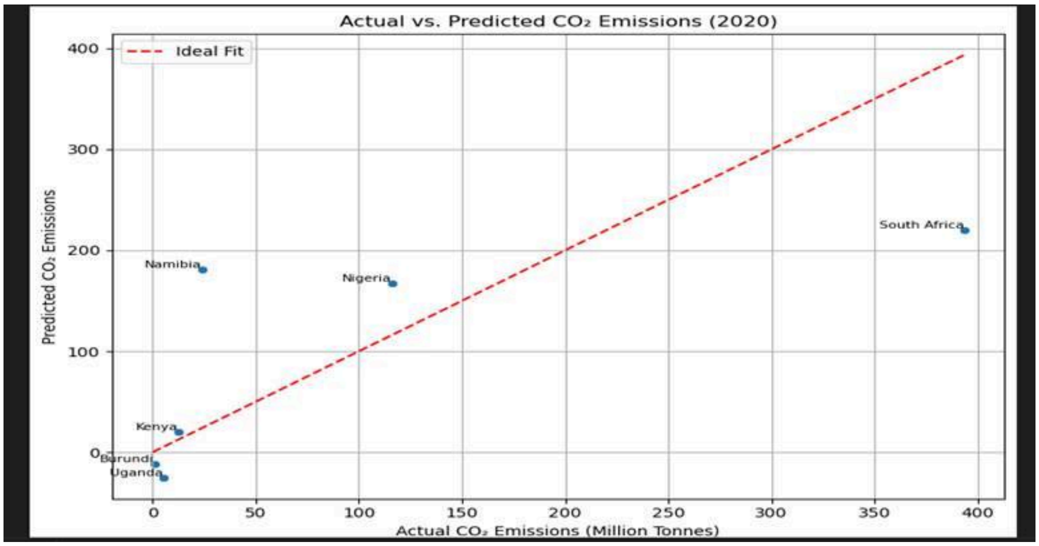

Figure 1:A regression model for CO 2 prediction based on GDP, population, and GDP per capita

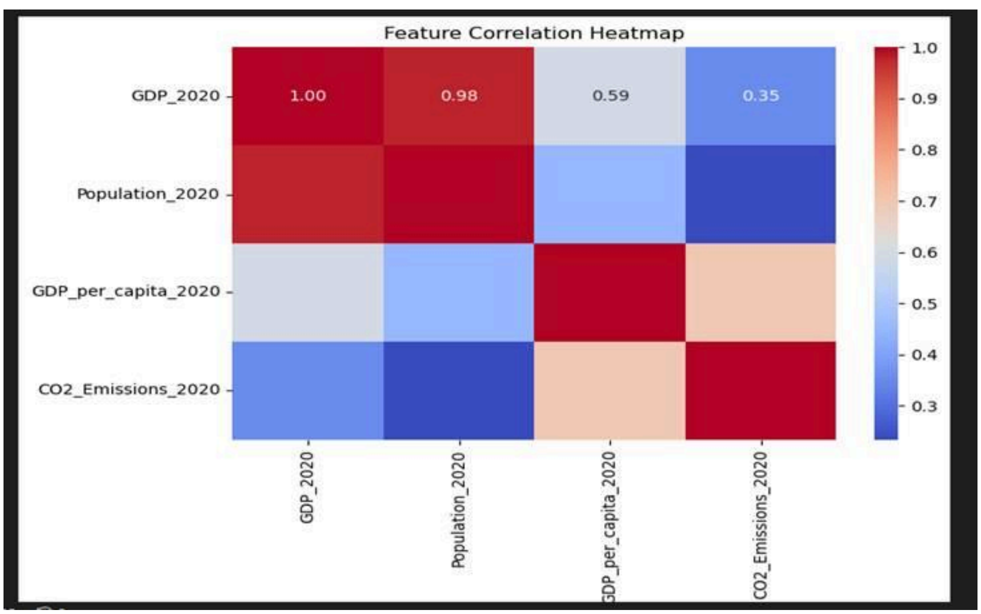

Figure 2: A heat map of the relationship between GDP, population, and carbon emissions

Overall, the regression model demonstrates moderate predictive power. The model can be improved by adding data on energy consumption, more countries, industrial activity, carbon intensity, log transformation, and interaction terms.

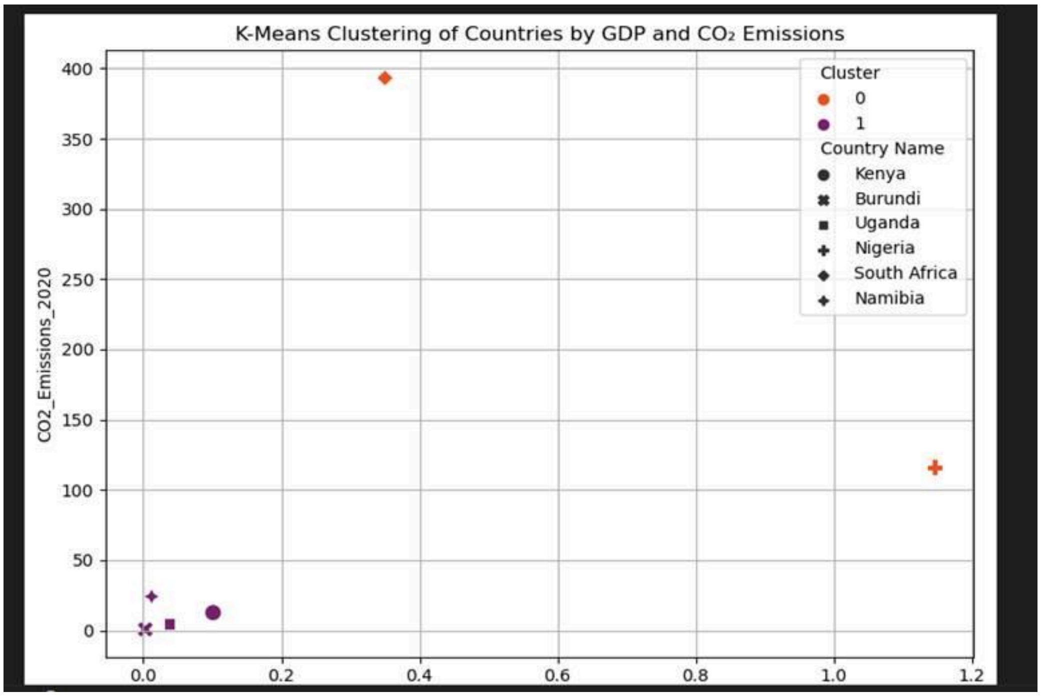

Figure 3:K-Means clustering results

K-Means Clustering Results

The scatter plot shows the K-Means clustering results applied to GDP and CO_2 emissions. Countries are grouped into 2 clusters:

- Cluster 0 (orange): Includes South Africa and Nigeria, which are characterized by high GDP and emissions.
- Cluster 1 (purple): Includes Kenya, Uganda, Burundi, and Namibia – all have lower GDP and lower emissions.

This clustering supports the patterns observed in the correlation matrix and suggests that emissions profiles naturally fall into distinct economic bands.

SDG 13 Context

Supervised Learning:

- Used here via linear Regression to predict CO_2 emissions based on GDP, population, and GDP per capita.
- Helps policymakers estimate future emissions if economic indicators change.

Unsupervised Learning:

- Applied using K-Means Clustering to group countries by economic-emissions profile.
- Reveals natural groupings that can inform tailored policy approaches.

Conclusion (Implications for Climate Action)

The model above can help track progress, model the impact of development, and prioritize interventions. Low-emission, low-GDP nations may need support for scaling without replicating high-emission paths. High-GDP, high-emission countries can focus on cleaner technologies to reduce carbon intensity.

References

Glavina, A., Mišić, K., Baleta, J., Wang, J., & Mikulčić, H. (2025). Economic development and climate change: Achieving a sustainable balance. *Cleaner engineering and technology*, 100939 https://www.sciencedirect.com/science/article/pii/S266679082500062X

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