Environmental Analysis on the African Subcontinent

Team Green With Gusto

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1. Introduction

Africa, the world's second-largest and second-most populous continent, is home to a rich diversity of ecosystems and natural resources. However, the continent faces a multitude of environmental challenges that threaten its biodiversity, natural resources, and human well-being.

Numerous studies have addressed the environmental issues plaguing Africa. A comprehensive assessment by the Intergovernmental Panel on Climate Change (IPCC) in 2007(Link) highlighted the continent's vulnerability to climate change impacts, including increased aridity, droughts, floods, and sea-level rise. The IPCC report also emphasized the need for adaptation and mitigation strategies tailored to Africa's unique context.

Subsequent studies have focused on specific environmental challenges facing Africa. For instance, a 2010 study by the United Nations Environment Programme (UNEP) (LINK) identified deforestation, land degradation, and pollution as major threats to the continent's environment. The study also underscored the interlinkages between these environmental issues and their impacts on human health, livelihoods, and economic development.

In recent years, the focus has shifted towards understanding the complex interplay between environmental factors and socioeconomic conditions in Africa. A 2017 study on Climate Change and Social Inequality(LINK) examined the relationship between poverty, inequality, and environmental degradation. The study found that poverty and inequality are often drivers of environmental degradation, as impoverished communities may resort to unsustainable practices to meet their basic needs.

Our Novel Approach :

Our project embarks on a novel journey by exploring uncharted territories in environmental research with a specific focus on the African continent. We aim to gain statistical insights into the factors and attributes influencing the African continent, employing data visualization techniques, correlation discovery, and predictive analytics. Our primary focus is on identifying correlations among diverse environmental attributes to understand the complex interplay between them. We are also utilizing these correlations to make predictions about environmental factors that contribute to the degradation and deterioration of Africa's natural environment.

We're using what other studies have found to help us explore new aspects of the environment. We believe that our unique approach will provide valuable insights into the complex environmental challenges facing Africa and contribute to the development of effective solutions.

Objectives of the Study :

Our project aims to explore a new area of research in environmental science, focusing on the African continent. We aim to gain a better understanding of the factors and conditions that affect the environment in Africa. To achieve this goal, we have set the following objectives:

1. Data Visualization

We are employing advanced data visualization techniques to present the analyzed data in visually compelling and informative ways. This approach will facilitate a better understanding and interpretation of complex environmental data.

2. Correlation Discovery

Our primary focus centers on the identification of correlations among the diverse attributes present within the African environment. By uncovering these correlations, we aim to comprehend the complex interplay between various factors and their potential consequences.

3. Predictive Analytics

Utilizing the identified correlations, our project will develop predictive models through the application of advanced analytics. These models will allow us to make informed predictions about the environmental factors contributing to the degradation and deterioration of Africa's natural environment, a forward-looking approach to addressing critical environmental concerns.

4. Interactive Website

To make sure everyone can understand our findings, we have built an interactive website. This website will serve as a dynamic platform to showcase and explore the insights derived from our research, making them accessible to a wider audience, including researchers, policymakers, and the general public.

2. <u>Methodology for Visualization and Correlation</u>

In our project, we utilize a combination of data collection techniques and data processing methods to acquire and integrate real-time data from the United Nations website (https://data.un.org/default.aspx) and other relevant sources. Our approach encompasses web scraping, data cleaning, data transformation, and the development of an API for efficient data retrieval, all of which are facilitated through Python programming. The following sections provide a detailed overview of the materials and methodologies employed in our data acquisition and processing.

Data Sources :

Our primary data source is the United Nations data repository, accessible at https://data.un.org/default.aspx. This repository serves as a comprehensive resource for a wide array of socio-economic and environmental datasets. We extract valuable data related to economic and environmental factors, such as GDP (Gross Domestic Product), as well as essential social factors including population and population density.

1. Data Acquisition

<u>Web Scraping</u> :
To gather the necessary data, we employ web scraping techniques to access the United Nations website. Web scraping involves the automated extraction of data from web pages, allowing us to access real-time information directly from the source.

2. Data Processing

<u>Data Cleaning</u> :
Raw data obtained from web scraping may contain inconsistencies, errors, or irrelevant information. Data cleaning involves the process of identifying and rectifying such issues to ensure the data's accuracy and reliability.

<u>Data Transformation</u> :
After cleaning the raw data, we convert it into a format suitable for our machine learning models. This transformation may involve structuring the data into specific variables, aggregating data points, or organizing it in a way that is conducive to our analysis.

<u>API Development</u> :
In order to streamline the process of fetching real-time data, we have created an Application Programming Interface (API). This API facilitates the rapid retrieval of data from the United Nations website, ensuring that our datasets remain up-to-date and in sync with the latest information available on the source website.

3. Data Retrieval

Data Fetching through API :

With our API in place, we can access the data as soon as it is updated on the United Nations website. This real-time data retrieval ensures that our analyses and machine learning models are based on the most current and relevant information.

Python Notebook :

The entire data processing pipeline, including web scraping, data cleaning, transformation, and API utilization, is implemented within a Python notebook. Python notebooks provide a versatile and efficient environment for data handling and analysis.

How we preprocessed the data :

We had CSV files from the mentioned website. For example, we had 'Deforestation.csv.' We kept the useful columns, removed the unnecessary ones, and merged all the relevant columns. This process resulted in a new CSV file containing only the columns pertinent to our project.

Detailed process:

1. We load data from a CSV file and prepare it for analysis.
2. We filter the data to focus on a specific category.
3. We rename a column for clarity and drop a column that is no longer needed.
4. We further filter the data to retain only the records for African countries listed in the 'africa_countries' list. This step narrows down the dataset to African countries for subsequent analysis.

Data Before Preprocessing

1	T27	CO2 emission estimates					
2	Region/Country/Area		Year	Series	Value	Footnotes	Source
3	8	Albania	1975	Emissions	4,524		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
4	8	Albania	1985	Emissions	7,145		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
5	8	Albania	2005	Emissions	3,981		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
6	8	Albania	2010	Emissions	4,074		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
7	8	Albania	2015	Emissions	3,979		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
8	8	Albania	2017	Emissions	4,493		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
9	8	Albania	2018	Emissions	4,462		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
10	8	Albania	2019	Emissions	4,183		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
11	8	Albania	1975	Emissions	1.8		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
12	8	Albania	1985	Emissions	2.3		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
13	8	Albania	2005	Emissions	1.3		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
14	8	Albania	2010	Emissions	1.4		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
15	8	Albania	2015	Emissions	1.3		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
16	8	Albania	2017	Emissions	1.5		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
17	8	Albania	2018	Emissions	1.5		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
18	8	Albania	2019	Emissions	1.4		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
19	12	Algeria	1975	Emissions	13,692		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
20	12	Algeria	1985	Emissions	42,446		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
21	12	Algeria	2005	Emissions	78,045		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
22	12	Algeria	2010	Emissions	96,452		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
23	12	Algeria	2015	Emissions	1,31,690		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
24	12	Algeria	2017	Emissions	1,31,701		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
25	12	Algeria	2018	Emissions	1,38,496		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
26	12	Algeria	2019	Emissions	1,43,586		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
27	12	Algeria	1975	Emissions	0.8		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
28	12	Algeria	1985	Emissions	1.9		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.
29	12	Algeria	2005	Emissions	2.3		International Energy Agency, IEA World Energy Balances 2021 and 2006 IPCC Guidelines for Greenhouse Gas Inventories, last accessed June 2022.

SYB65_310_202209_Carbon Dioxide

Data After Preprocessing

	A	B	C	D	E	F	G	H	I	J
1		Region/Co	Year	Emissions	Emissions	Primary en	Supply per capita (gigajoules)			
2	0	Algeria	2005	78,045	2.3	7,534	48			
3	1	Algeria	2010	96,452	2.7	6,200	46			
4	2	Algeria	2015	1,31,690	3.3	5,883	56			
5	3	Algeria	2017	1,31,701	3.2	6,285	55			
6	4	Algeria	2018	1,38,496	3.3	6,254	58			
7	5	Algeria	2019	1,43,586	3.3	5,954	58			
8	6	Angola	2005	7,510	0.3	2,889	19			
9	7	Angola	2010	15,863	0.6	4,016	20			
10	8	Angola	2015	23,293	0.8	4,030	20			
11	9	Angola	2017	18,480	0.6	4,085	18			
12	10	Angola	2018	18,409	0.5	3,794	18			
13	11	Angola	2019	20,597	0.6	3,639	17			
14	12	Benin	2005	3,198	0.3	70	14			
15	13	Benin	2010	5,148	0.5	82	16			
16	14	Benin	2015	6,002	0.5	104	17			
17	15	Benin	2017	7,455	0.6	110	19			
18	16	Benin	2018	8,044	0.6	113	19			
19	17	Benin	2019	7,941	0.6	121	19			
20	18	Botswana	2005	4,515	2.4	29	35			
21	19	Botswana	2010	3,501	1.6	30	37			
22	20	Botswana	2015	7,192	3.3	56	38			

We have applied this preprocessing to various factors, including Deforestation, Threatened species, Energy Production, population, CO2 Emission, and more.

Relevant Links:
Before preprocessing -
https://github.com/qazz625/est-project-website/tree/main/data-analysis/raw_data
After Preprocessing -
https://github.com/qazz625/est-project-website/tree/main/data-analysis/processed_data

Up till now,, we conducted various data operations, including filtering to extract data from as many African countries as feasible, data cleaning to handle the removal of excessive data and data type modifications, a comprehensive data analysis, and the merging of data based on the criteria of year and region. As a concluding step, we organized the data into pairs, resulting in files like "CO2_Energy.csv," "CO2_Endangered.csv," and "Population_Endangered.csv."

Detailed process:

1. Loads data from three separate CSV files containing information related to carbon dioxide emissions, energy production, population estimates, population density, and threatened species.
2. Modifies the data to make it suitable for analysis, including converting numerical columns to the appropriate data types and removing commas.
3. Selects and organizes specific columns of interest from each dataset.

4. Merges the modified datasets based on common columns, 'Region/Country/Area' and 'Year,' creating a combined dataset that integrates information from different sources.
5. Prints the length of the resulting merged dataset and displays the first few rows for inspection.

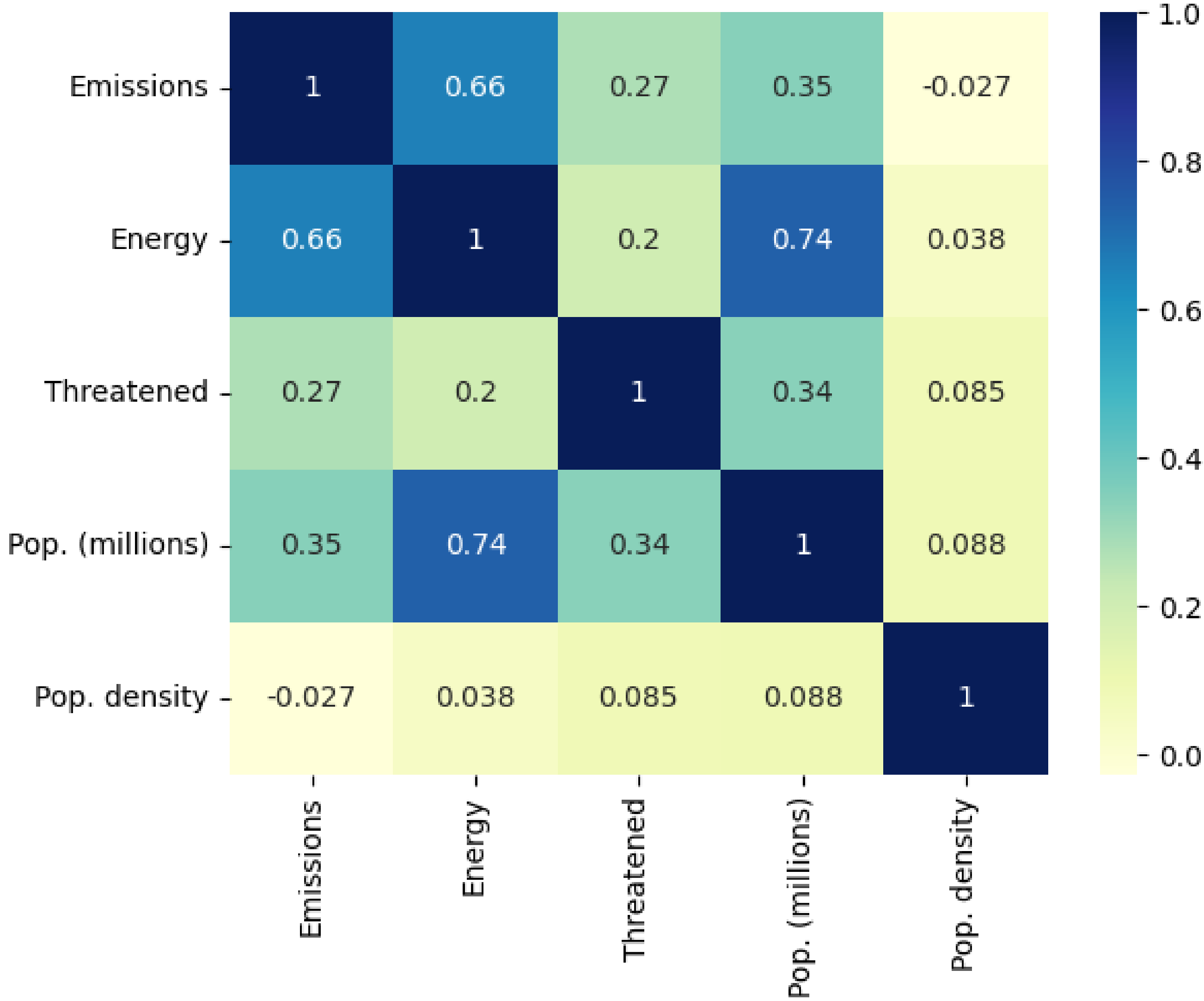
	Region/Country/Area	Year	Emissions (thousand metric tons of carbon dioxide)	Primary energy production (petajoules)	Threatened Species: Total (number)	Population mid-year estimates (millions)	Population density
0	Algeria	2010	96452	6200	105	35.86	15.1
1	Algeria	2015	131690	5883	114	39.54	16.6
2	Angola	2010	15863	4016	117	23.36	18.7
3	Angola	2015	23293	4030	130	28.13	22.6
4	Benin	2010	5148	82	62	9.45	83.8

6. Created a correlation heatmap to visualize the relationships between various environmental and socio-economic factors.

7. The key observations from the heatmap analysis:

- There is a high correlation between "Emissions" and "Energy produced."
- "Energy produced" and "Population" are strongly correlated.
- "Emissions" and "Threatened Species" have a low correlation.

Heatmap showing the relationship between different parameters



CO_2 Emissions and Primary Energy Production (Region and Year Wise)

	Region/Country/Area	Year	Emissions (thousand metric tons of carbon dioxide)	Primary energy production (petajoules)
0	Algeria	2005	78045	7534
1	Algeria	2010	96452	6200
2	Algeria	2015	131690	5883
3	Algeria	2017	131701	6285
4	Algeria	2018	138496	6254

CO2 Emissions and Primary Energy Production (Different parameters)

	Emissions (thousand metric tons of carbon dioxide)	Primary energy production (petajoules)
count	176.000000	176.000000
mean	31975.414773	1266.897727
std	79466.083551	2394.076817
min	617.000000	10.000000
25%	3937.500000	96.750000
50%	7947.500000	413.500000
75%	18599.000000	814.000000
max	440028.000000	10795.000000

CO2 Emissions and Threatened species (Region and Year Wise)

	Region/Country/Area	Year	Emissions (thousand metric tons of carbon dioxide)	Threatened Species: Total (number)
0	Algeria	2005	78045	50
1	Algeria	2010	96452	105
2	Algeria	2015	131690	114
3	Algeria	2019	143586	145
4	Angola	2005	7510	76

CO_2 Emissions and Threatened species (Different parameters)

	Emissions (thousand metric tons of carbon dioxide)	Threatened Species: Total (number)
count	118.000000	118.000000
mean	30731.644068	196.186441
std	77970.542740	200.902789
min	617.000000	15.000000
25%	3878.000000	75.250000
50%	7538.000000	130.000000
75%	17122.000000	230.500000
max	440028.000000	1174.000000

Population , Population Density and Threatened species (Region and Year Wise)

	Region/Country/Area	Year	Population mid-year estimates (millions)	Population density	Threatened Species: Total (number)
0	Algeria	2010	35.86	15.1	105
1	Algeria	2015	39.54	16.6	114
2	Algeria	2020	43.45	18.2	155
3	Algeria	2022	44.90	18.9	180
4	Angola	2010	23.36	18.7	117

Population , Population Density and Threatened species (Different parameters)

	Population mid-year estimates (millions)	Population density	Threatened Species: Total (number)
count	117.000000	117.000000	117.000000
mean	31.486154	77.847009	258.290598
std	40.019896	115.856579	260.314666
min	1.090000	2.600000	18.000000
25%	6.300000	21.600000	107.000000
50%	19.880000	48.200000	161.000000
75%	37.460000	83.900000	294.000000
max	218.540000	640.100000	1464.000000

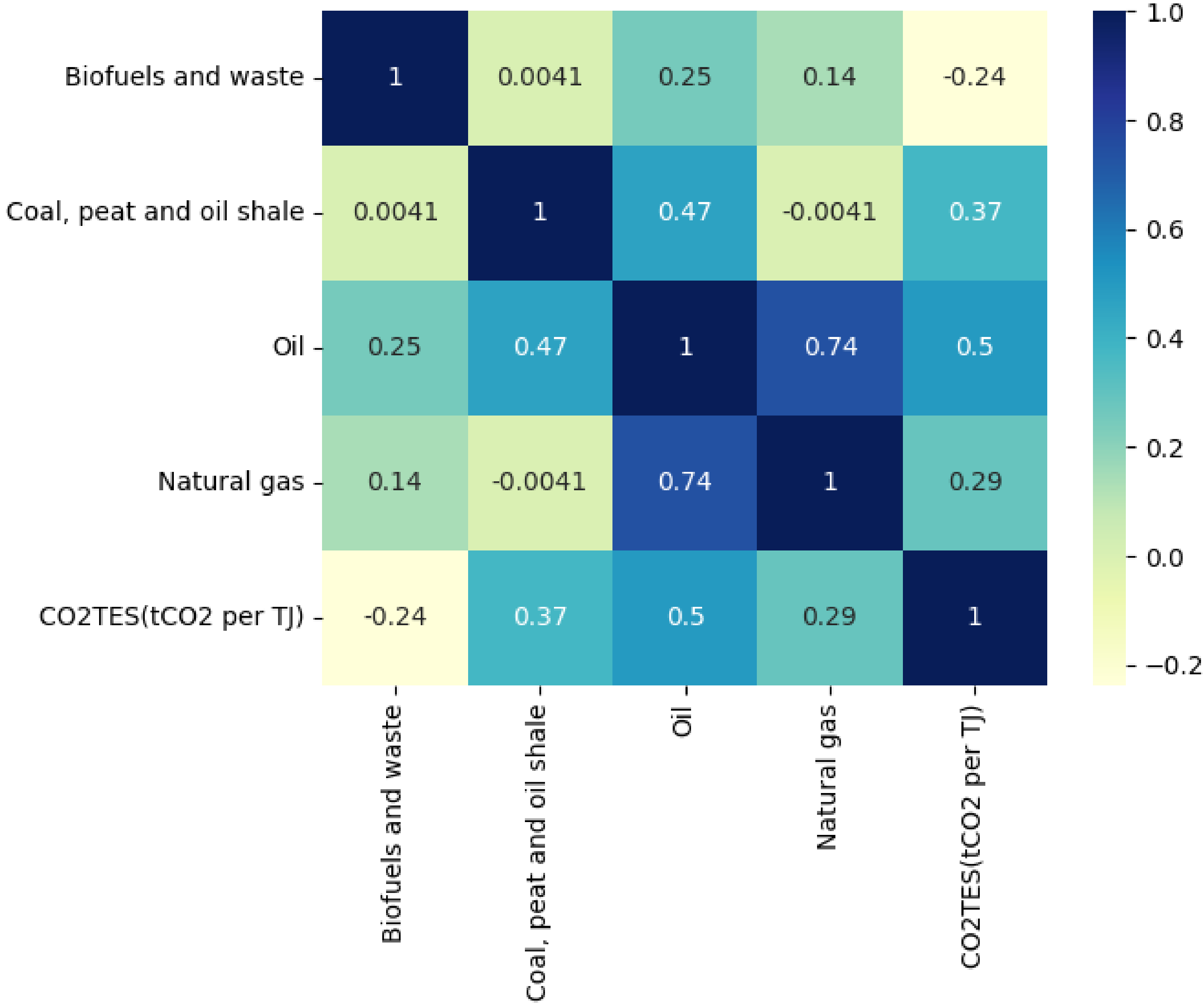
Biofuels and waste, oil, Natural gasses (Region and Year Wise)

	Biofuels and waste	Coal, peat and oil shale	Oil	Natural gas	CO2TES(tCO2 per TJ)	country	year
0	0.002251	0.384980	5.920485	2.383026	59.253	Algeria	1971
1	0.002329	0.372553	6.312181	3.058608	57.281	Algeria	1972
2	0.002381	0.414828	7.169531	3.524308	54.459	Algeria	1973
3	0.002390	0.282616	7.702091	4.081844	54.996	Algeria	1974
4	0.002433	0.326198	8.708710	4.654142	58.629	Algeria	1975

Biofuels and waste, oil, Natural gasses (Different parameters)

	Biofuels and waste	Coal, peat and oil shale	Oil	Natural gas	CO2TES(tCO2 per TJ)	year
count	1489.000000	736.000000	1489.000000	572.000000	1489.000000	2805.000000
mean	1.879437	19.303543	9.998516	9.437294	26.801398	1996.000000
std	4.602290	66.231015	17.556829	18.986965	21.968185	14.722226
min	0.000419	0.002157	0.041632	0.000303	0.329000	1971.000000
25%	0.190572	0.250003	1.188374	0.150986	9.316000	1983.000000
50%	0.689007	0.886346	2.446164	1.580009	15.614000	1996.000000
75%	1.590454	2.972576	9.636897	7.955379	47.346000	2009.000000
max	39.618539	374.369663	121.475662	107.638041	90.853000	2021.000000

Heatmap showing the relationship between different parameters



3. <u>**Methodology for Predictive Analysis**</u>

We have built two predictor models using Neural Network (Multi Layer Perceptron): the Simple Predictor and the Advanced Predictor.

1. The Simple Predictor takes two parameters, Country and Year, as input from the user and predicts CO2 emissions for that year.

2. The Advanced Predictor takes six parameters—Energy by Biofuels and Waste, Energy by Coal, Peat and Oil Shale, Energy by Oil, Energy by Natural Gas, Country, and Year—as input from the user and predicts CO2 emissions for that year.

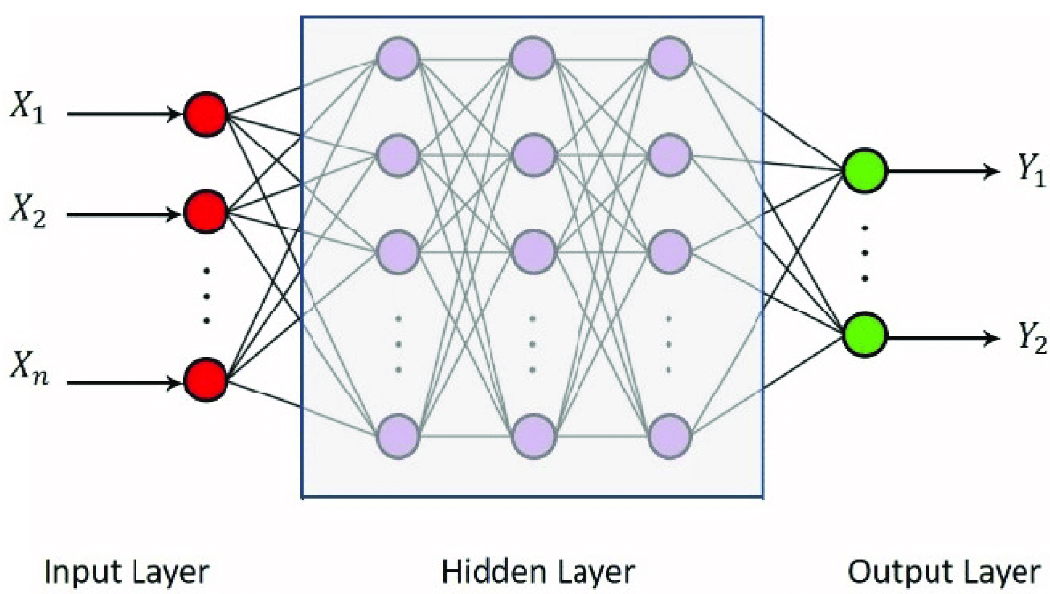
Emissions are classified into categories based on their impact on global warming potential. Here is a general division into three categories:

1. Low Threat (0-50 tons of CO2 per TJ) (color code- **#FFCCC**)

2. Moderate Threat (50-75 tons of CO2 per TJ) (color code- **#FF8080**)

3. High Threat (75-100+ tons of CO2 per TJ) (color code- **#FF0000**)

Model Architecture



Hidden Layer Sizes=(170, 170, 170): This parameter determines the architecture of the neural network. It specifies the number of neurons in each hidden layer. In our model there are three hidden layers, each containing 170 neurons. You can modify this parameter to experiment with different architectures.

max_iter=1000: This parameter sets the maximum number of iterations (epochs) for the solver to converge. In this example, the training process will stop after 1000 iterations if convergence is not achieved earlier.

random_state=42: This parameter is used to initialize the internal random number generator, ensuring reproducibility. You can change the value of random_state for different random initializations.

We experimented with different values for hidden_layer_sizes and other parameters to find the architecture that works best for our specific dataset and problem. We adjusted the architecture to get the best r2 score by increasing or decreasing the number of neurons in each layer, or making other changes based on domain knowledge and the characteristics of data. We kept in mind that the optimal architecture may vary depending on the complexity of the dataset and the nature of the problem we are trying to solve.

4. Methodology for Website Creation

In this section we describe the tools and methods used to create the frontend and the backend of the website. The source code of the website (both frontend and backend) can be found at https://github.com/qazz625/est-project-website

Website Backend

The back-end of the website has been created using Python and various python libraries. We used Flask, a lightweight and flexible Python web framework, as the foundation of our backend. To ensure dynamic and interactive user interfaces, we integrated various APIs to facilitate communication between the backend and frontend components. A significant feature of our backend involves real-time scraping of data from the UN website, achieved through the use of BeautifulSoup. This scraping process ensures that our users have access to the latest and most accurate information available on the UN website. Our backend services also incorporate machine learning models to provide users with accurate predictions of total carbon dioxide (CO2) emissions. We carefully developed and trained these models to analyze various input parameters and deliver insightful predictions.

Our methodology involved loading these machine learning models seamlessly into the Flask application, ensuring a smooth integration that aligns with the overall architecture. Upon receiving user inputs through the website interface, our backend processes the data using the loaded machine learning models. The predictions generated by these models are then relayed back to the user, offering the estimated CO2 emissions based on their input parameters. Also created a service that fetches and displays the latest environment specific news. We implemented this by integrating an external API that aggregates real-time environmental news from reputable sources. Upon user selection of specific countries, our backend processes this input and fetches relevant environmental news articles associated with those countries. The retrieved news is then dynamically presented on the website.

Libraries Used

1. Flask: Web framework for building web applications in Python.
2. BeautifulSoup (bs4): Library for pulling data out of HTML and XML files.
3. Requests: HTTP library for making requests to web servers.
4. JSON: Library for working with JSON data in Python.
5. Threading: Module for creating and managing threads for parallel execution.
6. Serpapi: Python client for accessing search engine results via the SerpApi service.
7. CSV: Module for reading and writing CSV (Comma Separated Values) files.
8. Werkzeug.utils: Part of the Werkzeug library, provides utility functions for various web-related tasks in Flask applications.

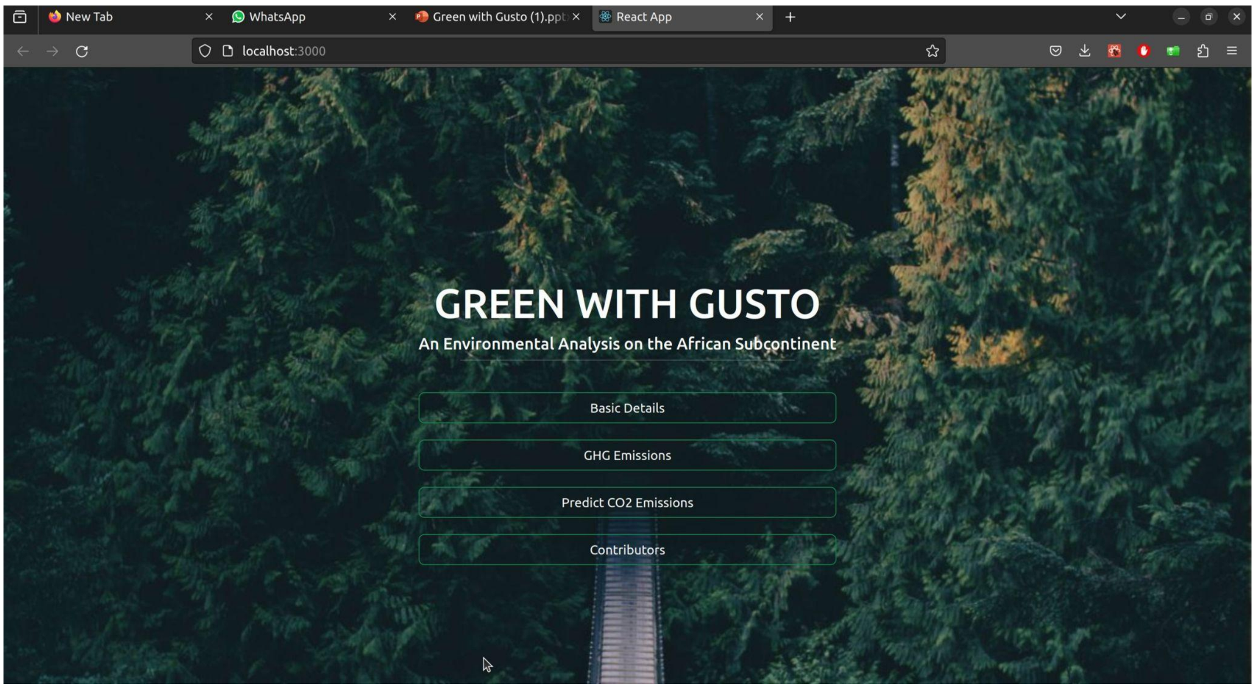
Website Frontend

The front-end of the website has been created using React and Javascript libraries. There are 5 pages for the website and each page except the homepage has a navigation bar to access other pages.

1. The Home Page

This is the landing page of the website and is used to navigate to other pages.

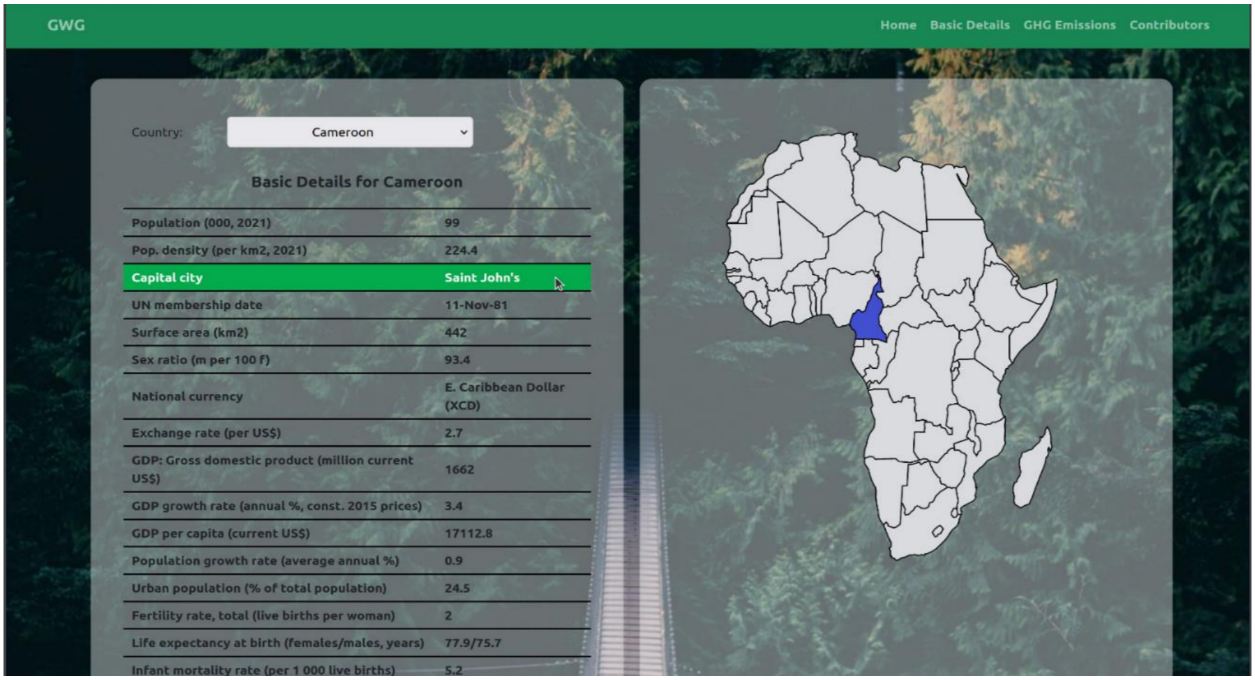
Home Page



2. Country Statistics Page

In this page the user can select a country and view basic details like population, capital city, currency, etc. The country can be selected either by selection from the dropdown or clicking directly on a country on the map. Hovering over a country on a map will display the country name in a tooltip.

African Countries Statistics Page

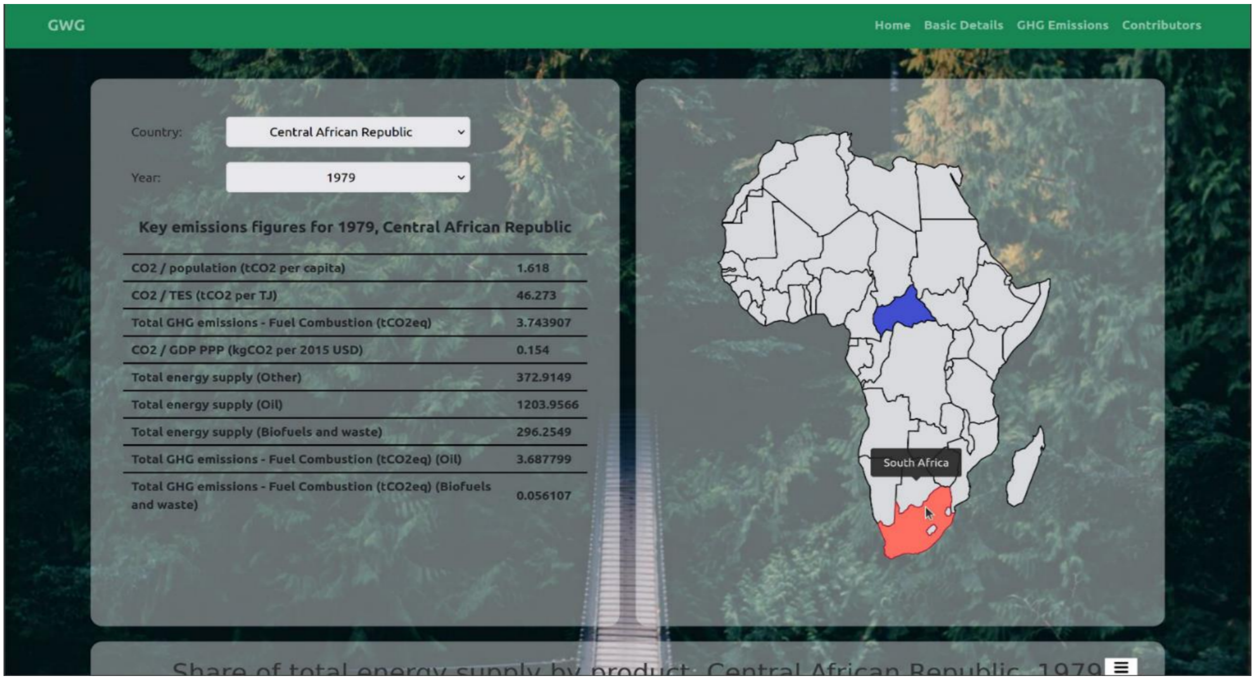


3. GHG and Energy Emission Page

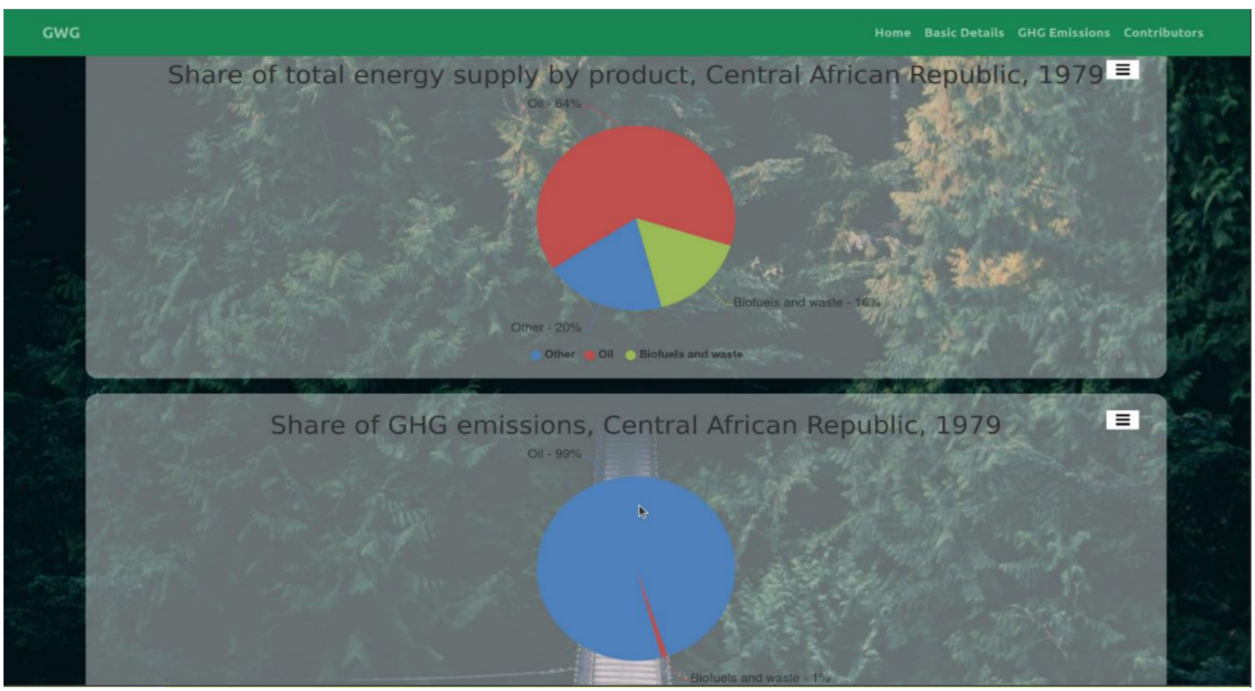
In this page the user can view the GHG emission and energy consumption statistics like per capita CO2 emission, total energy supply due to oil, natural gas, etc. Similar to the previous page, users can select the country either from the dropdown or from the map.

The statistics are also displayed in the form of graphs. There are three graphs. The first graph shows the shares of total energy supply for the selected country in the selected year in a pie chart. The second graph shows the shares of the GHG emissions in a pie chart. The third graph shows the amounts of total GHG emissions of the country over the years. (from 1971 to 2021).

GHG and Energy Emission - Textual Information



GHG and Energy Emission - Graphical Information



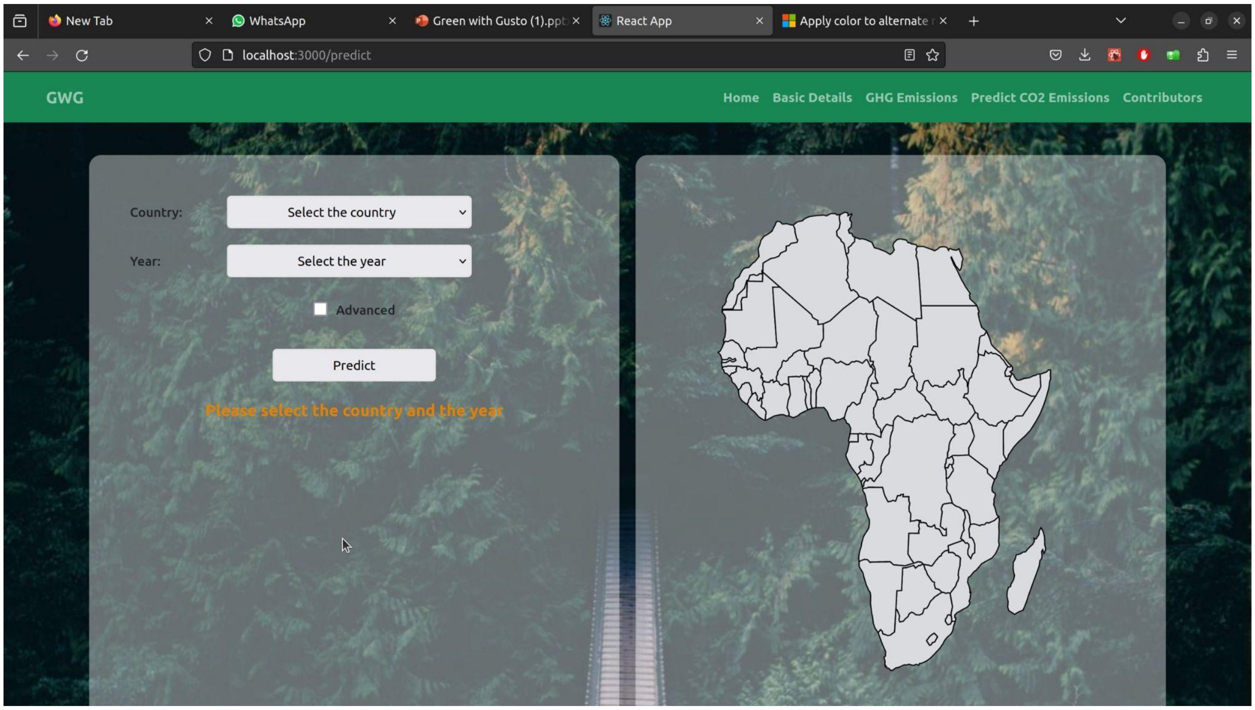
GHG and Energy Emission - Graphical Information

4. GHG Emission Predictor Page

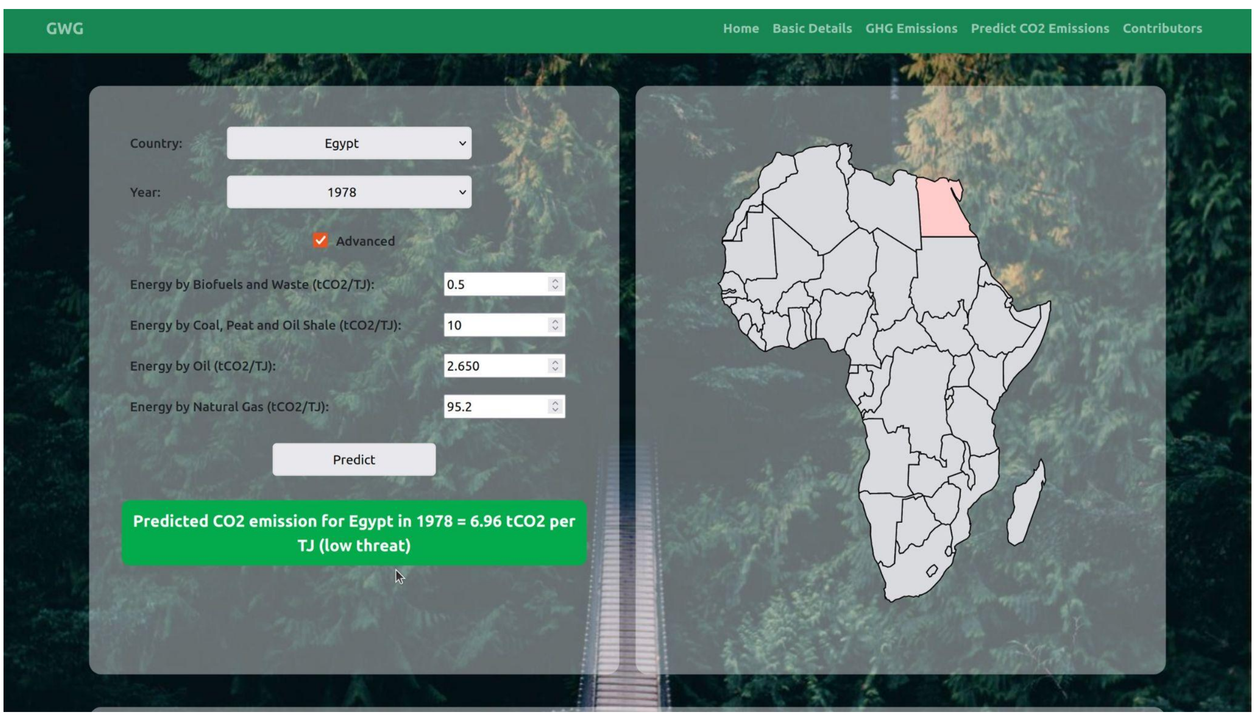
This page displays the predicted CO2 emission of a country for a particular year. The request is sent to the backend where the model is running and the response from the backend to the frontend contains the predicted result. By selecting the “Advanced” checkbox the user can give inputs to run the advanced predictor. The threat level is displayed on the map as a shade of red color depending on the severity. A lighter shade means lower threat.

When the user selects a country, this page also displays some environment related news on the website. Clicking on the link for any of these articles will redirect the user to the corresponding page where the article was originally published.

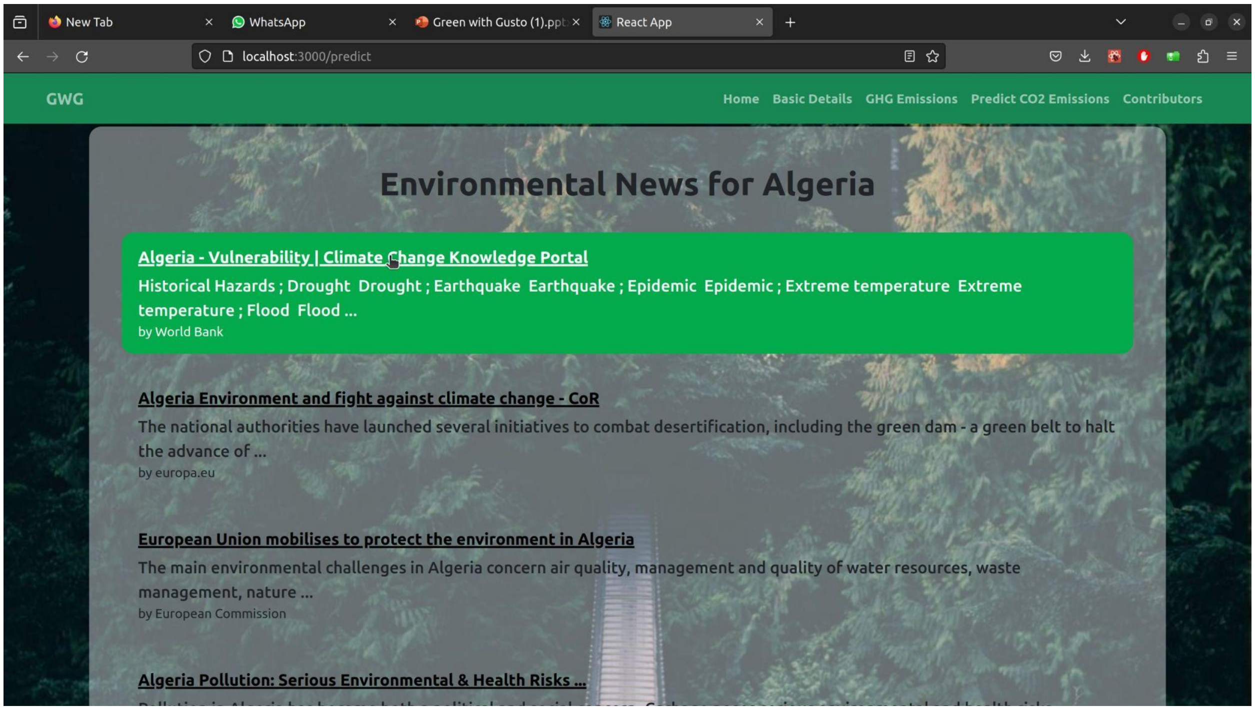
Total CO2 Emission Simple Predictor



Total CO2 Emission Advance Predictor



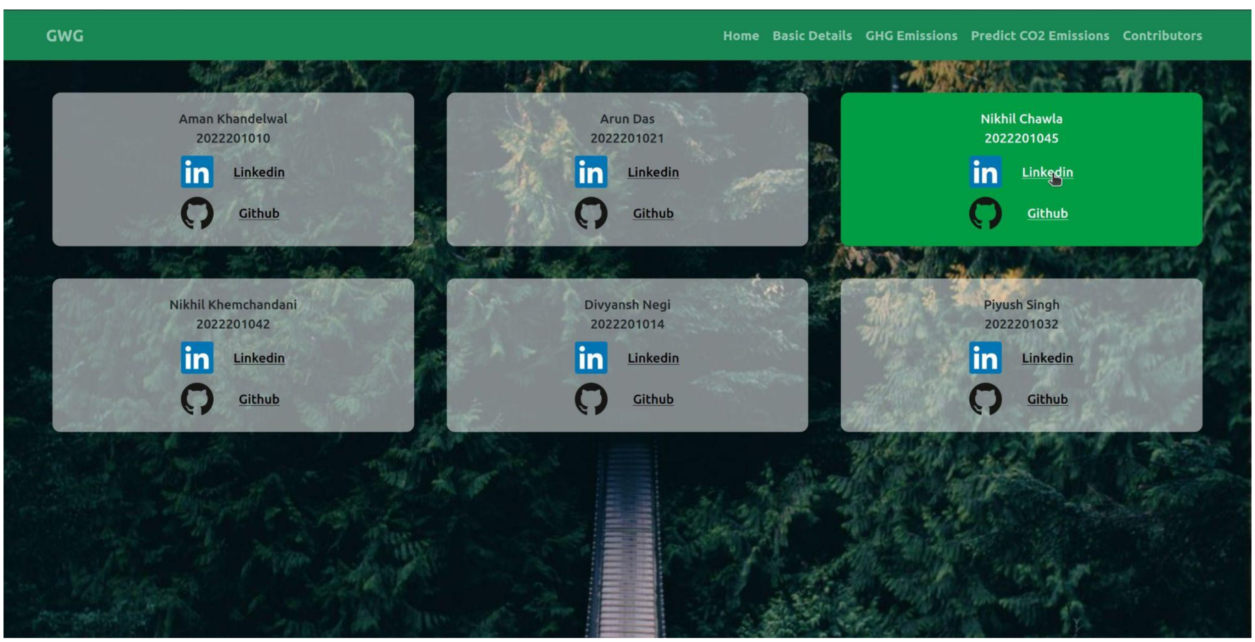
Country Environmental News



5. The Contributors Page

This is the final page containing the names and roll numbers of the members of our group and links to everyone's Github and Linkedin profiles.

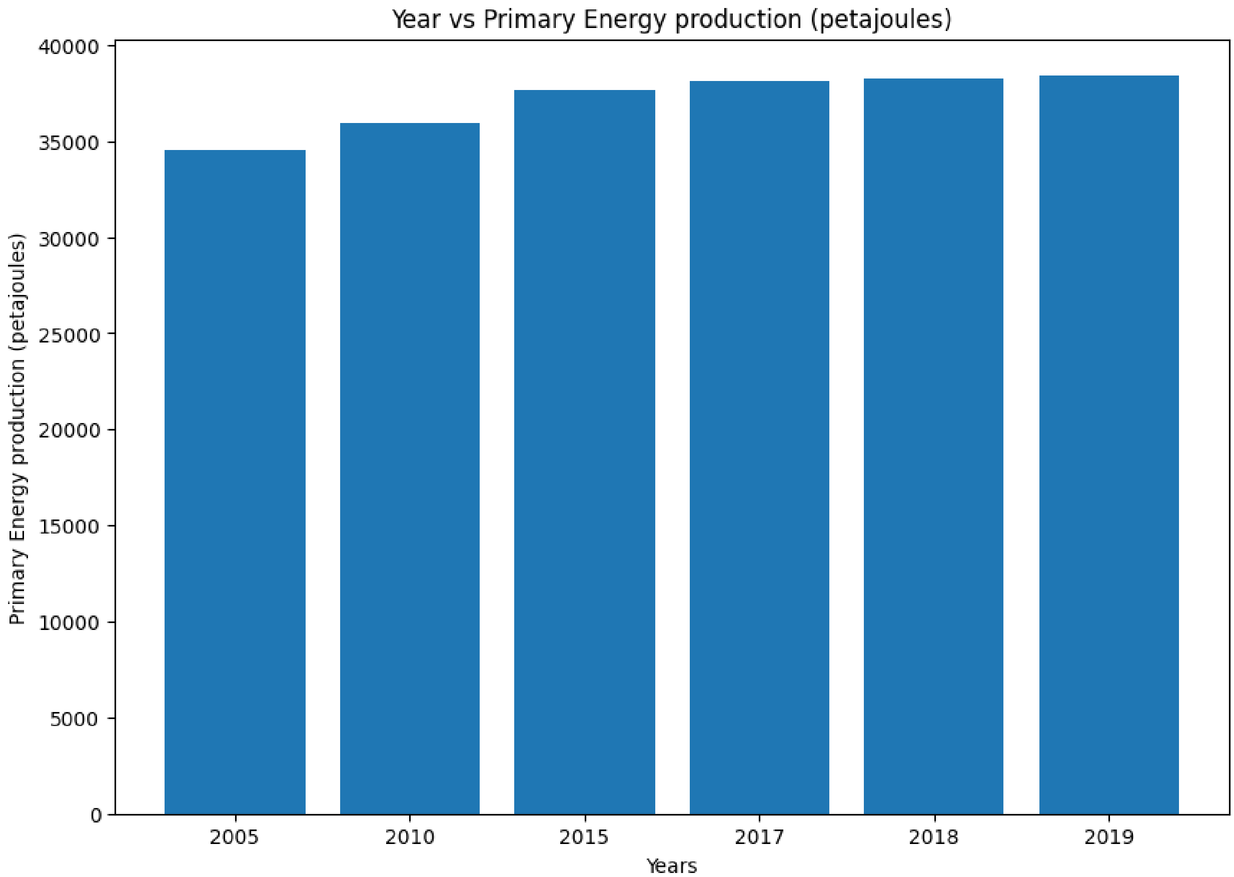
Contributors Page



Libraries Used

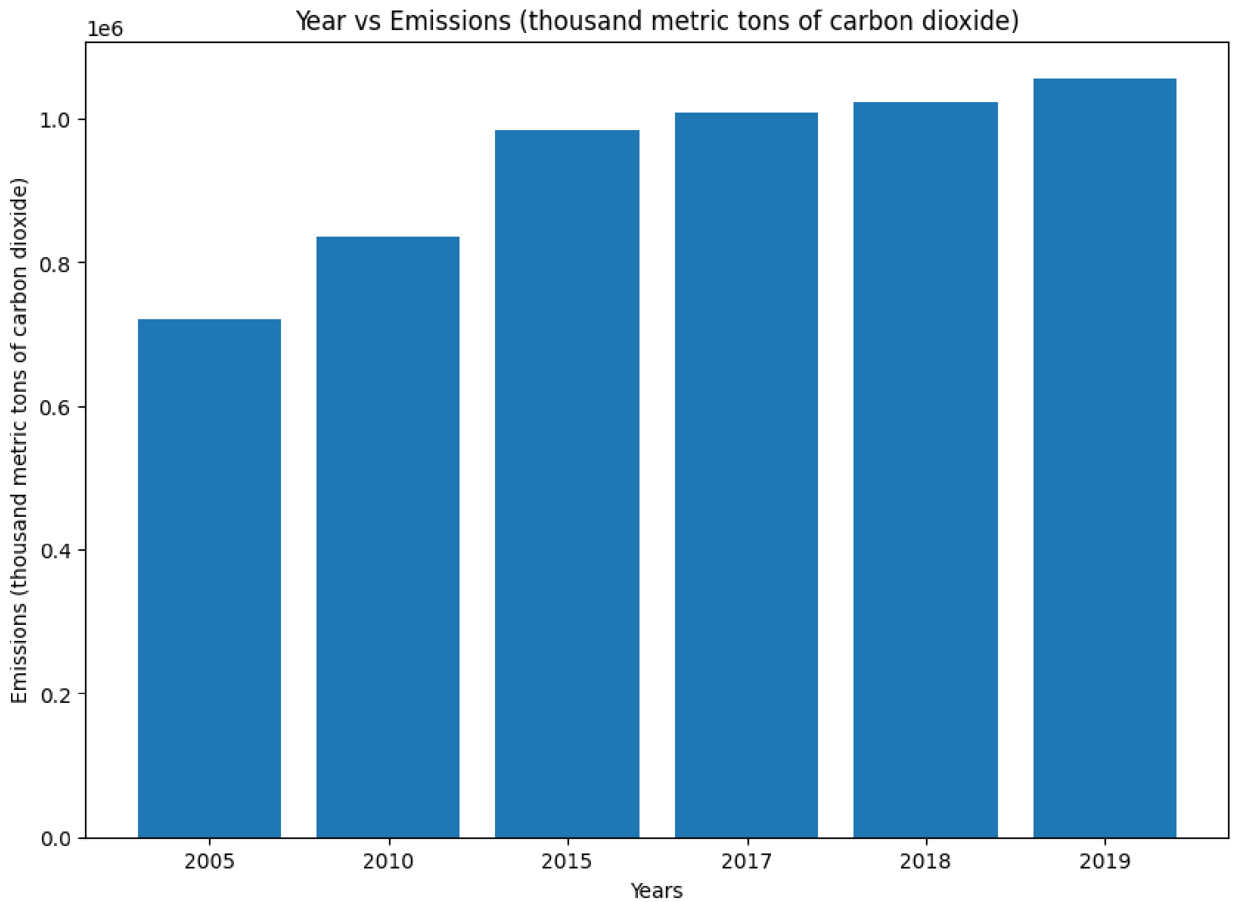
1. React: Framework used to create the frontend of the website.
2. React Simple Maps: Used to create the interactive maps shown in the website.
3. Bootstrap: Used for styling and beautification of the frontend.
4. CanvasJS: Used for creating the pie charts and line graphs in react.
5. https://cartographyvectors.com/geo/africa: The GeoJSON file format used to display the map has been obtained from this website.

5. **Results and Inferences**



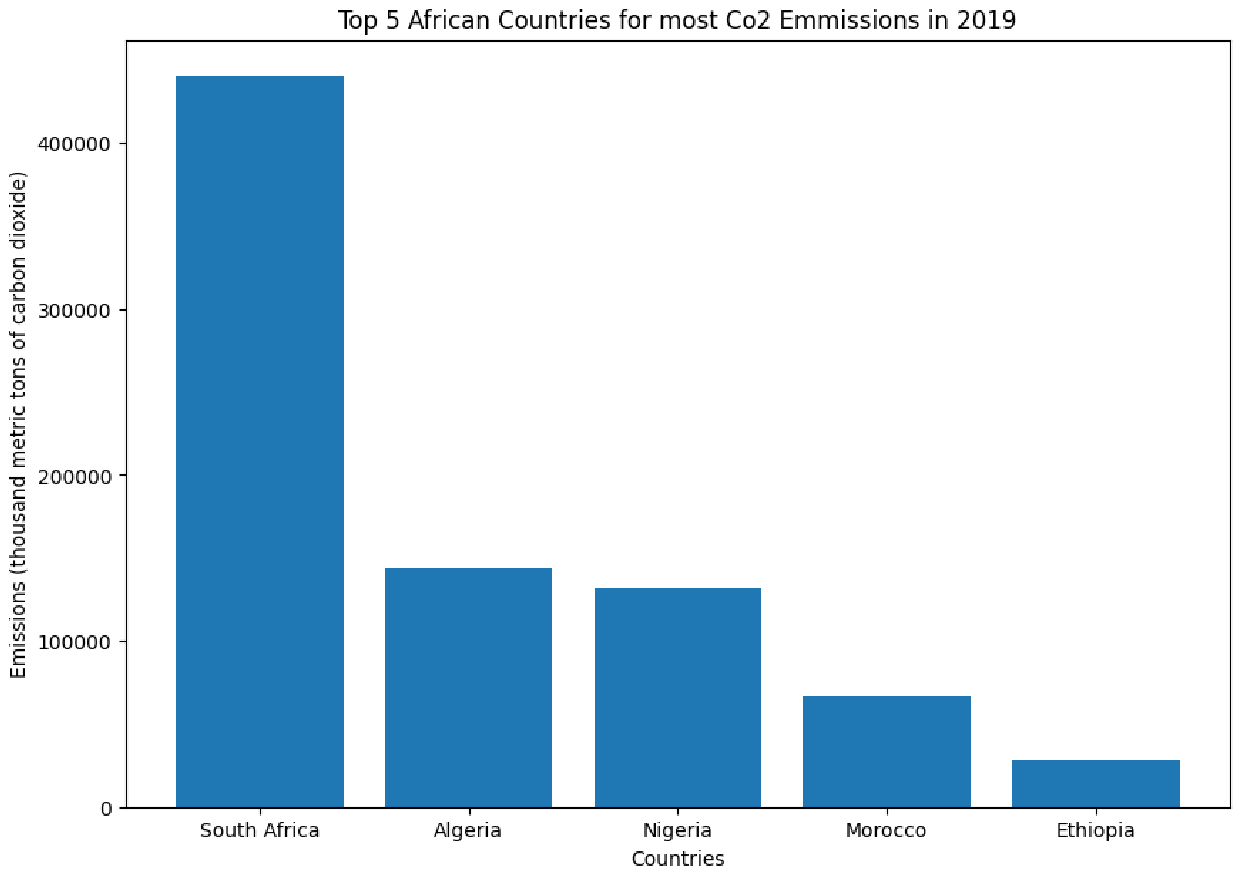
INFERENCE :

Graph shows how the Energy Produced in Africa has been increasing gradually with time.



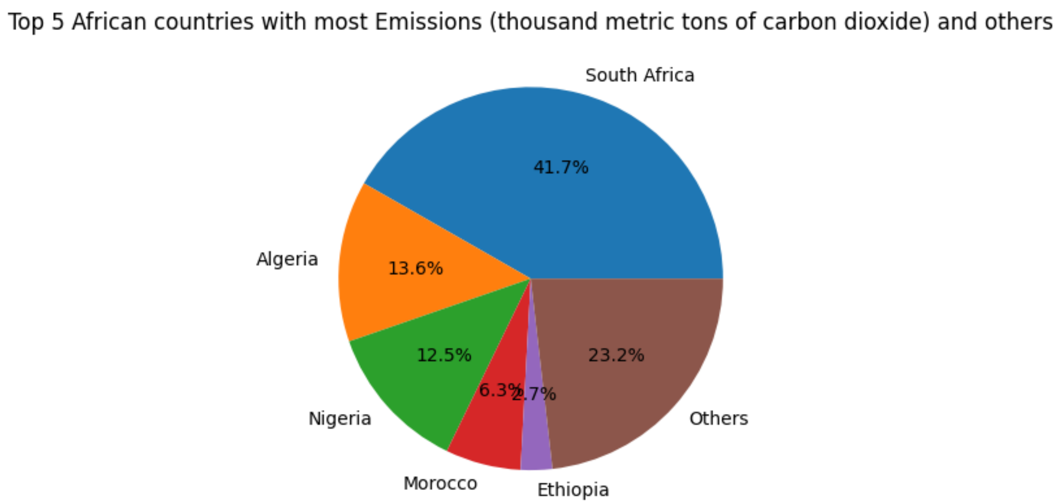
INFERENCE :

1. Graph shows how the CO2 Emissions in Africa has been increasing gradually with time
2. Also Note Energy Production Growth rate is not as fast as CO2 Emissions Growth rate, by looking at both the graphs
3. These findings are in line with the findings mentioned in [9] and [10] which say that the increase in these emissions is due to the increasing economic growth of African countries. One solution proposed in the papers is to switch to renewable energy resources.



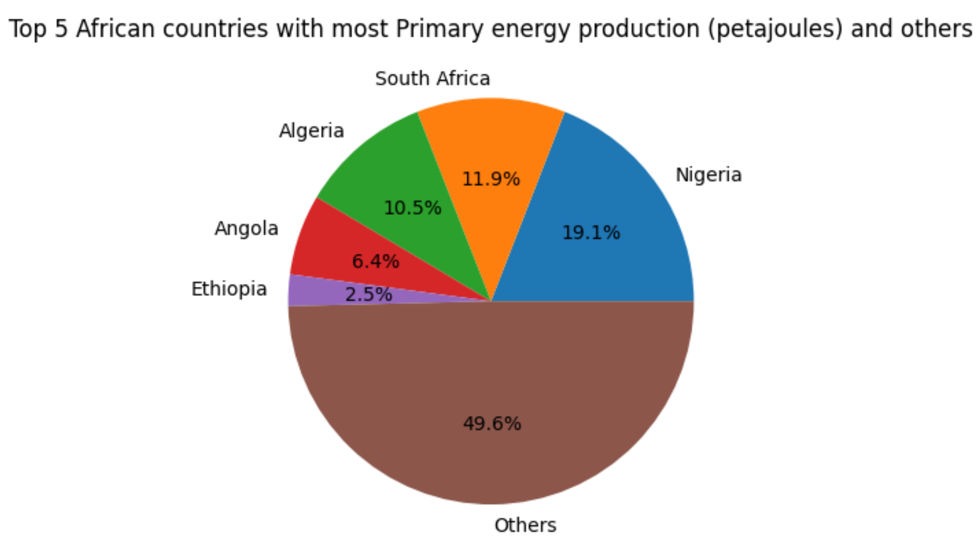
INFERENCE :

Below graph shows Top 5 CO2 Emissions in Africa, Out of which South Africa is at top. (REFERENCE)



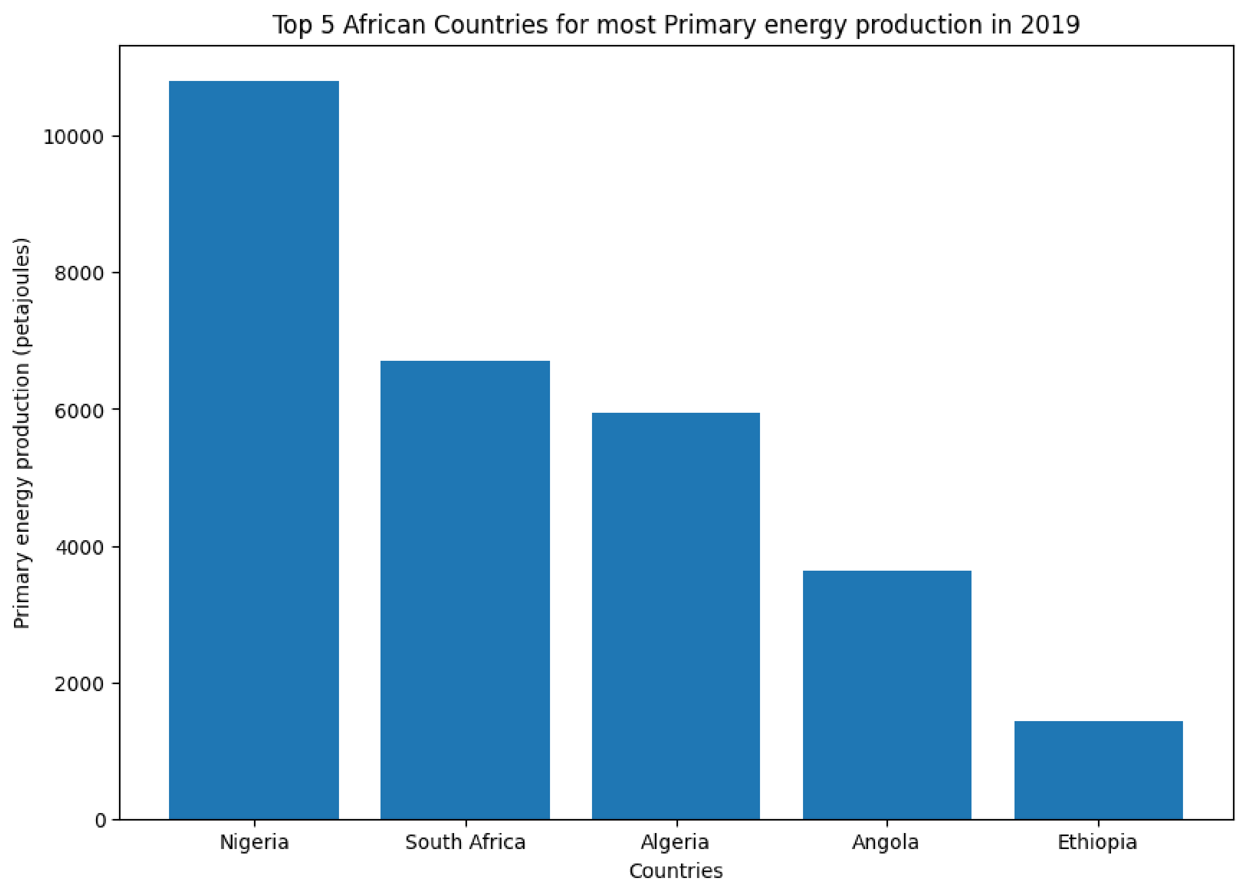
INFERENCE :

1. The pie chart above illustrates that South Africa's CO_2 emissions account for a significant 41.7%, a notably higher proportion compared to other countries.
2. The top 5 countries collectively contribute nearly 80% of the total CO_2 emissions, while the remaining nations account for the remaining 20%.



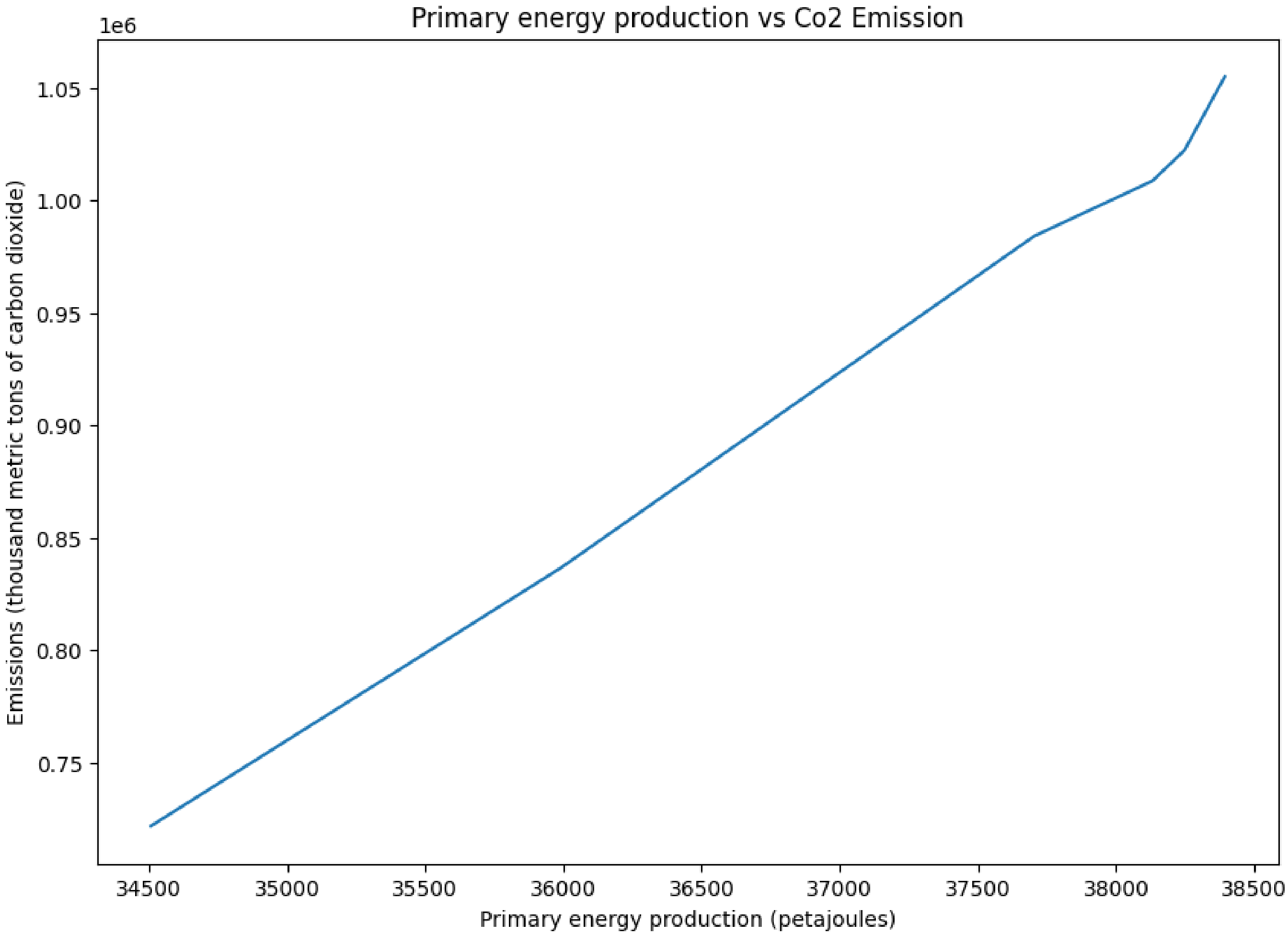
INFERENCE :

The pie chart shows the percentage of energy production by the top 5 and other countries, out of which Nigeria is at the top.



<u>INFERENCE :</u>

1. The graph displays the leading five energy-producing countries in Africa, with Nigeria occupying the top position.
2. It's worth noting that while South Africa leads in CO_2 emissions, its energy production is approximately 60% of what Nigeria generates, even though Nigeria's CO_2 emissions are less than 30% of South Africa's emissions.

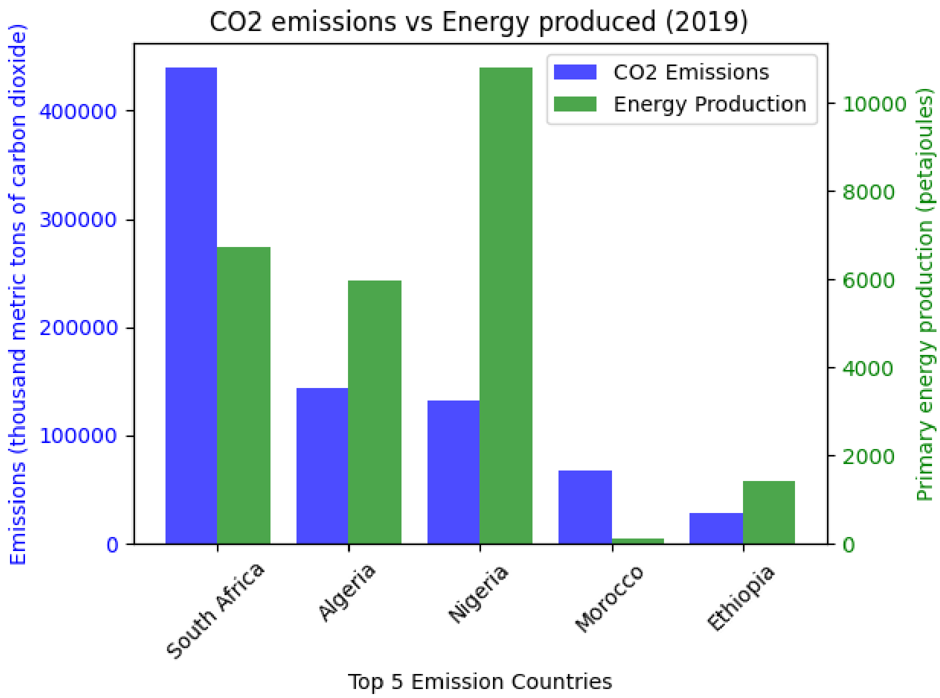


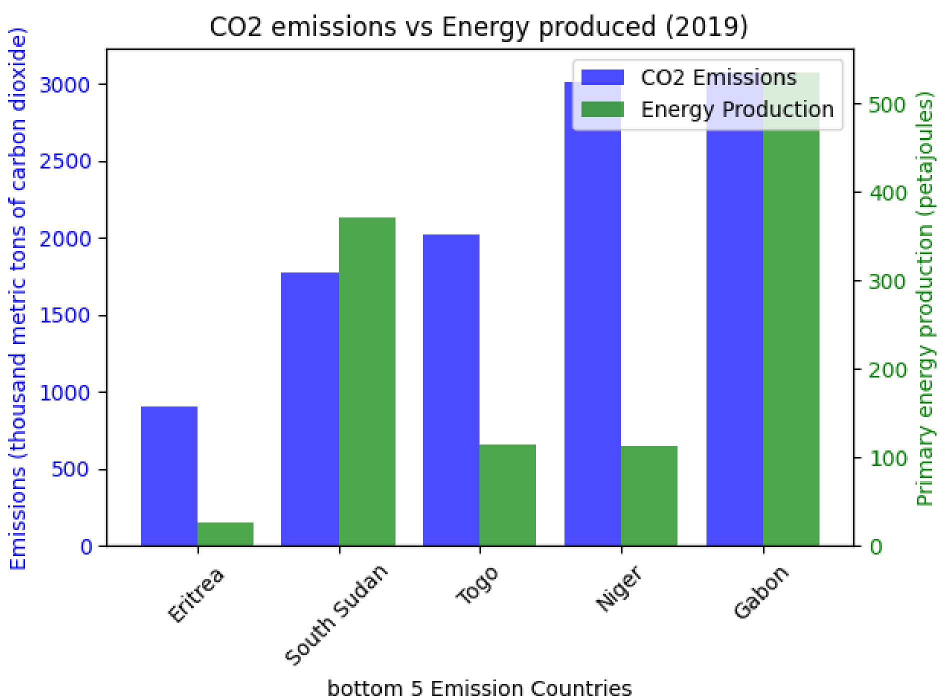
INFERENCE :

The above line graph shows how CO_2 Emissions increase when Energy production increases (overall i.e. irrespective of year and energy).

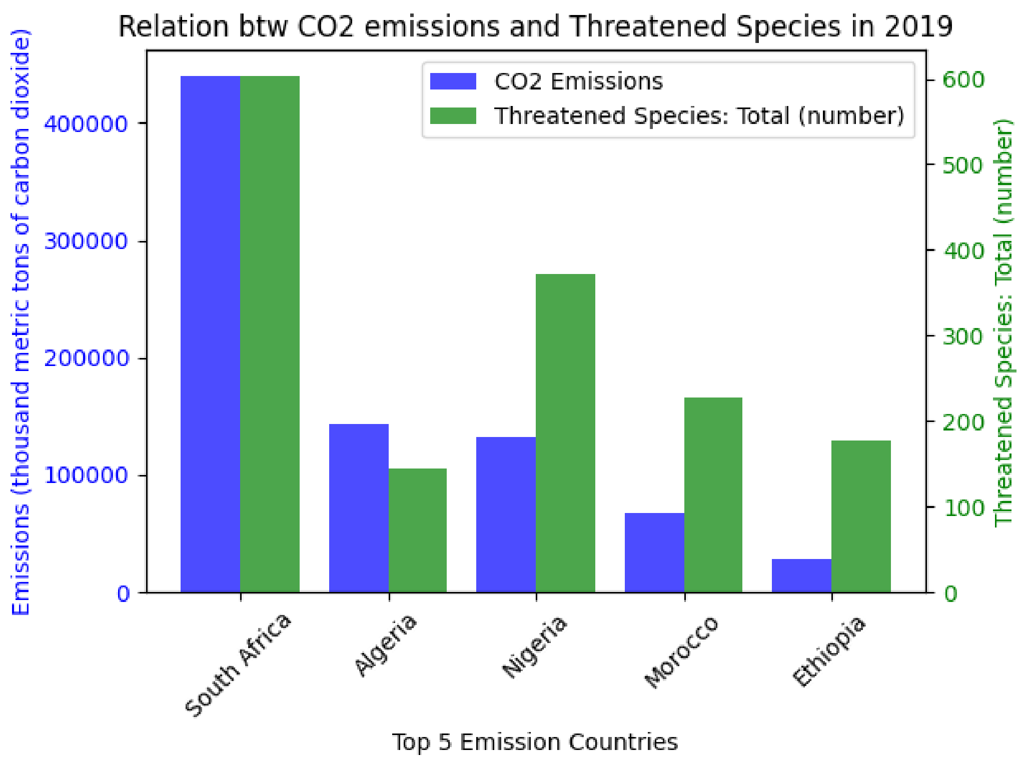
Other Results in terms of Bar Graphs

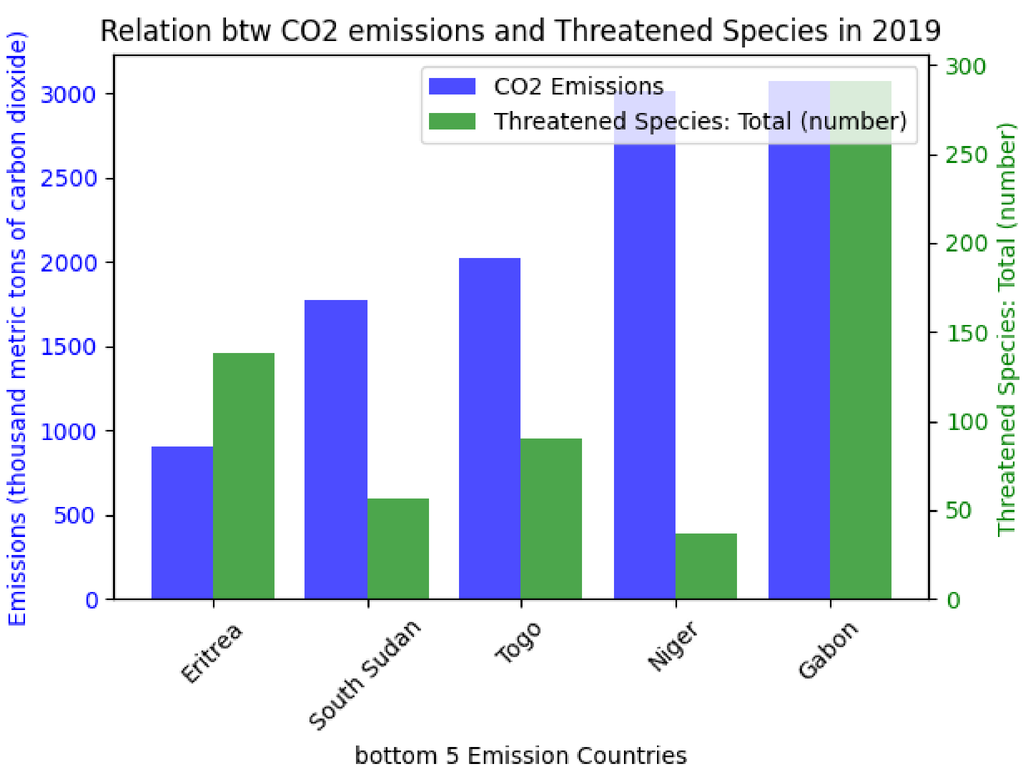
Relation between CO_2 Emission v/s Energy Produced (2019)





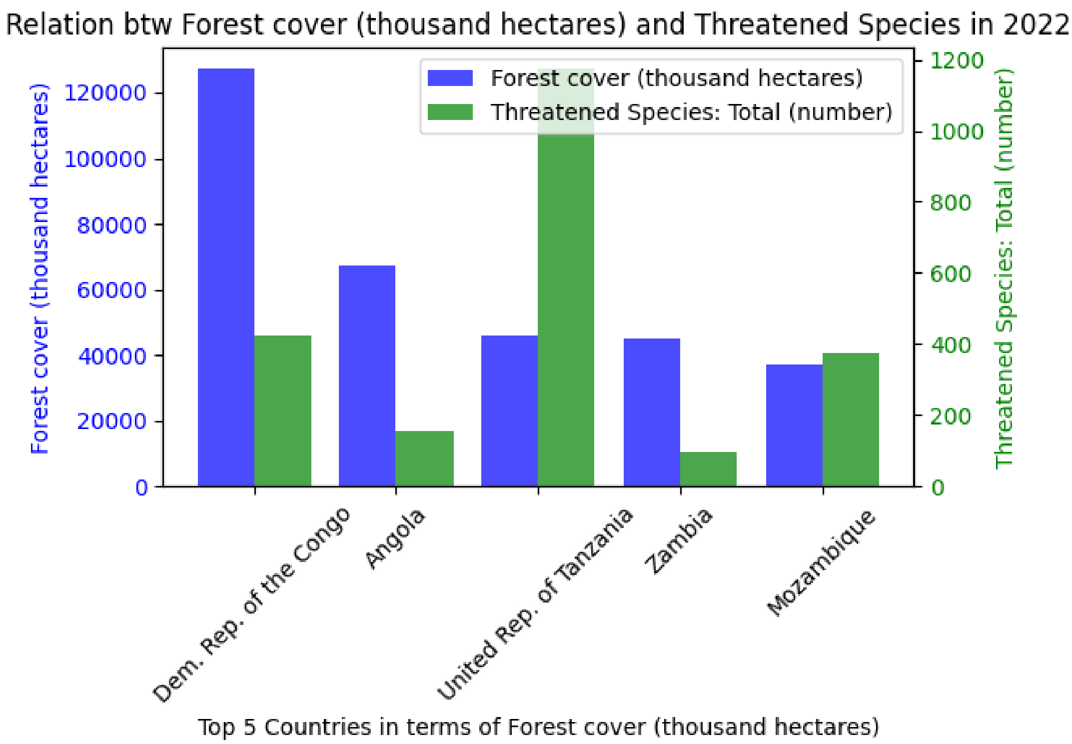
Relation between CO_2 Emission v/s Threatened Species (2019)

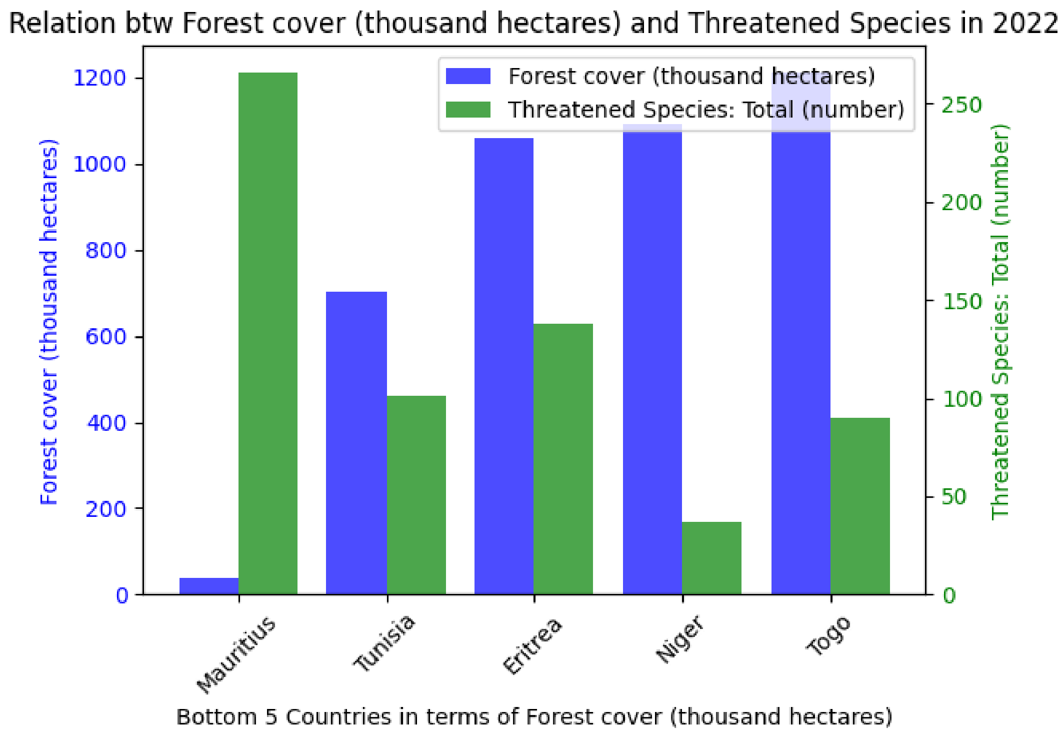




From the above graphs we can see that a rise in CO_2 levels can affect threatened species (plants as well as animals). These findings were also observed in [11] and [12] which conclude that the increase in CO_2 levels can cause physiological responses in plants and woody species are particularly sensitive to it.

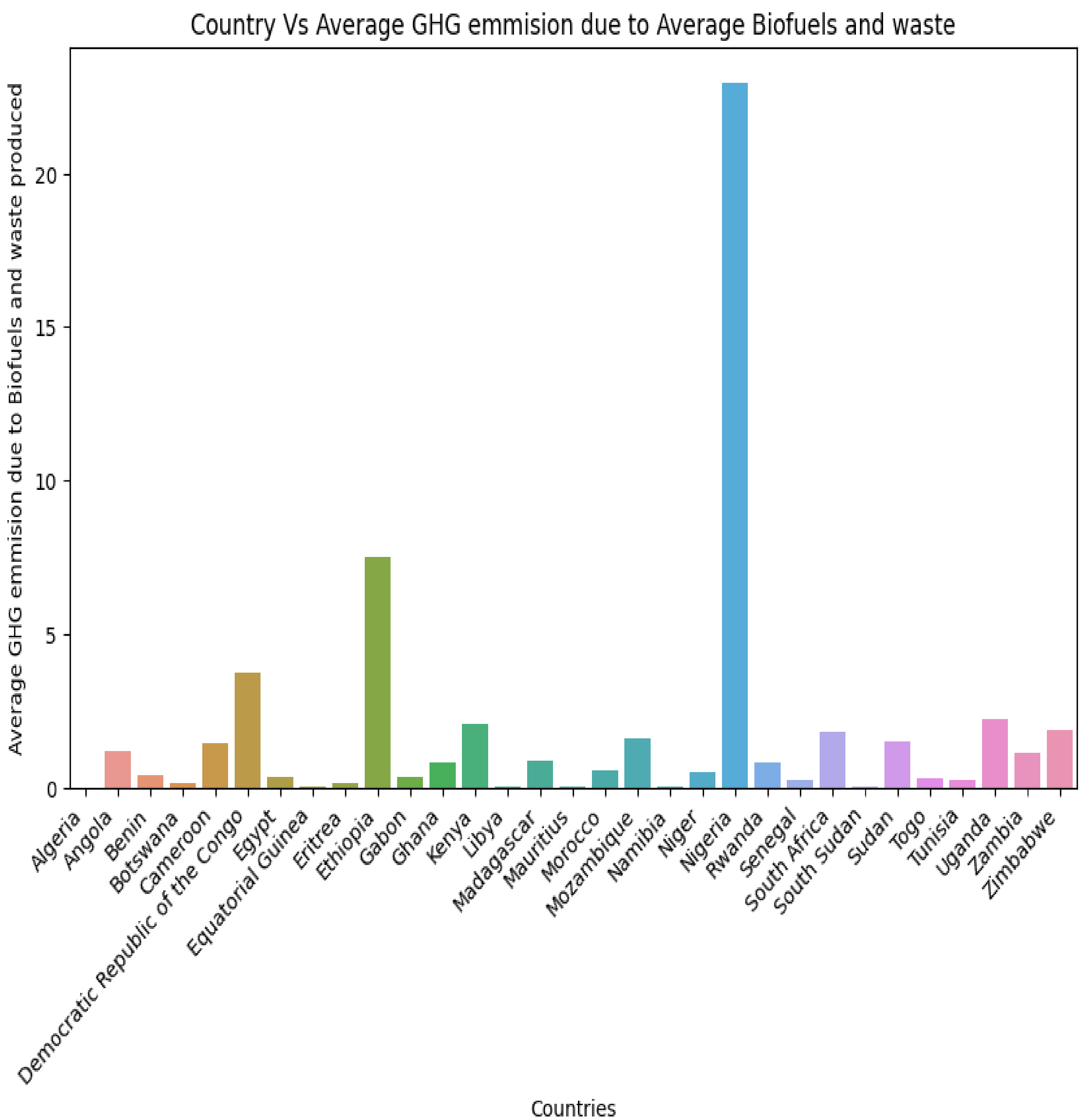
Relation between Forest Cover and Threatened Species (2022)



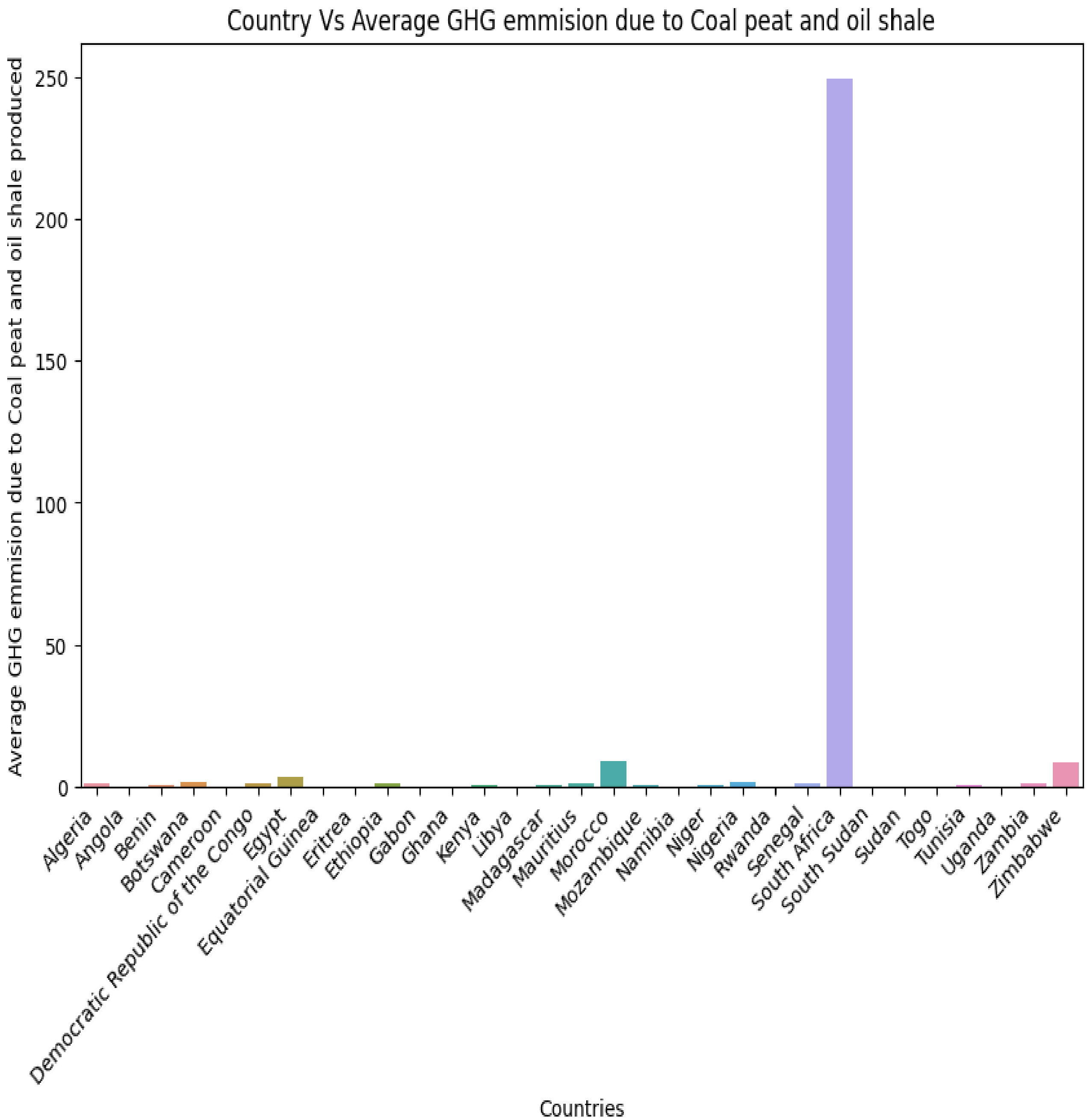


The above graphs highlight a correlation between the increase in deforestation and its impact on threatened species, which comprises both plants and animals. This observed relationship aligns with the findings presented in references [13], [14], and [15] and collectively reveal the intricate link between deforestation and biodiversity vulnerability. The findings also underscore the significant threat posed to plant and animal species, highlighting the critical importance of addressing deforestation promptly for global biodiversity conservation.

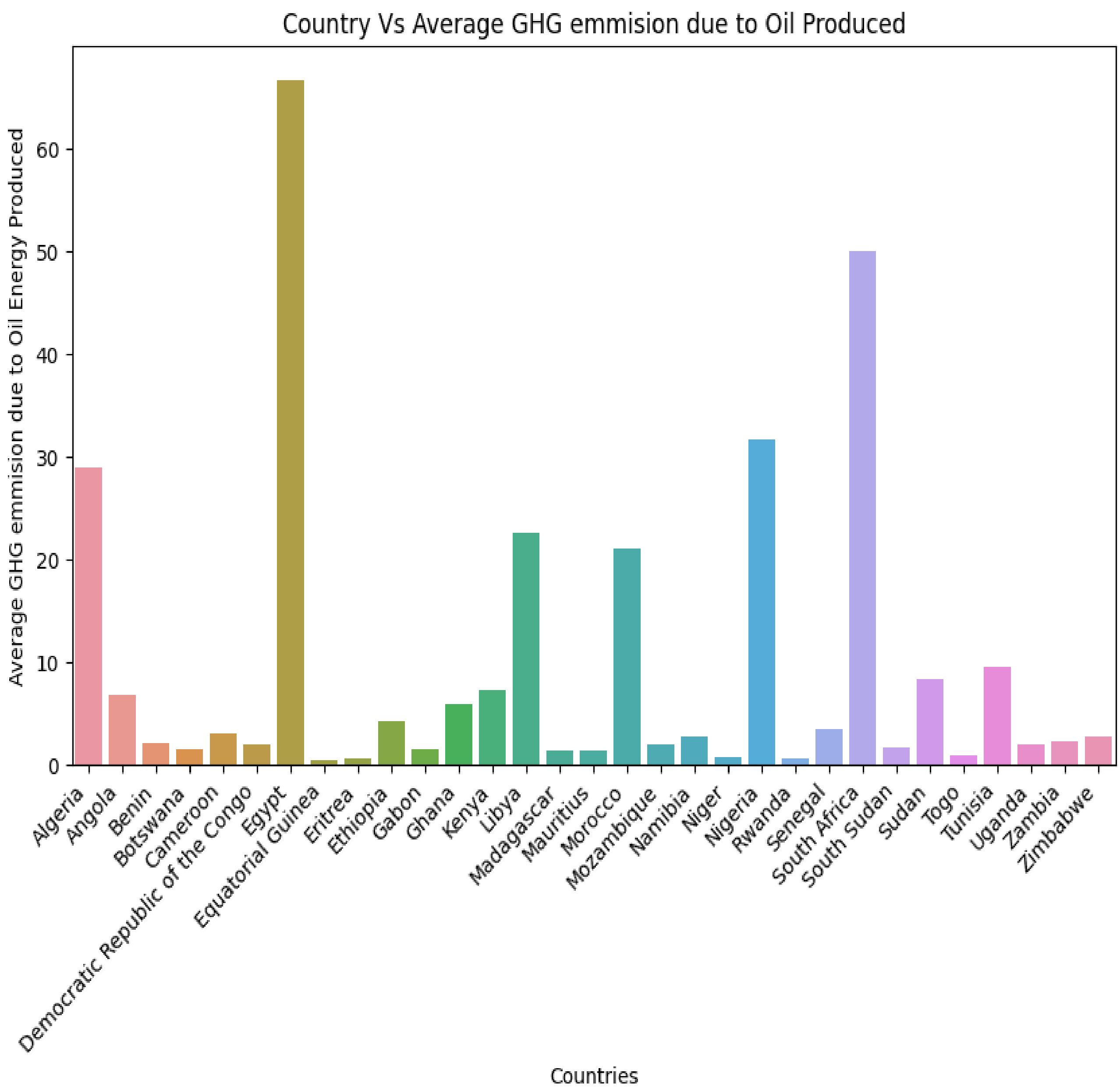
Country wise GHG Emission due to Biofuel and Waste



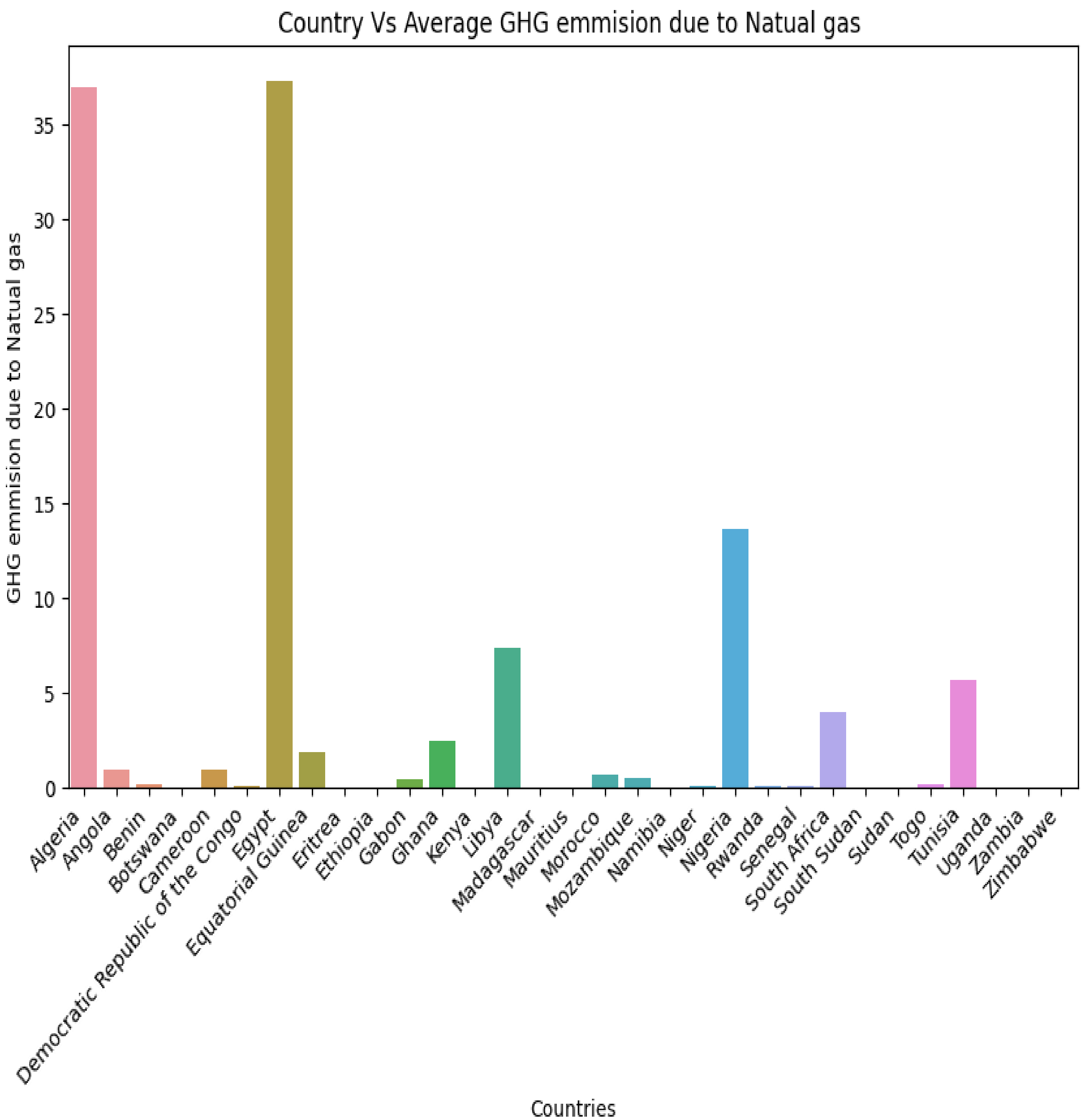
Country wise GHG Emission due to Coal peat and Oil shale



Country wise GHG Emission due to oil Produced



Country wise GHG Emission due to Natural Gas



6. Acknowledgements and References

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