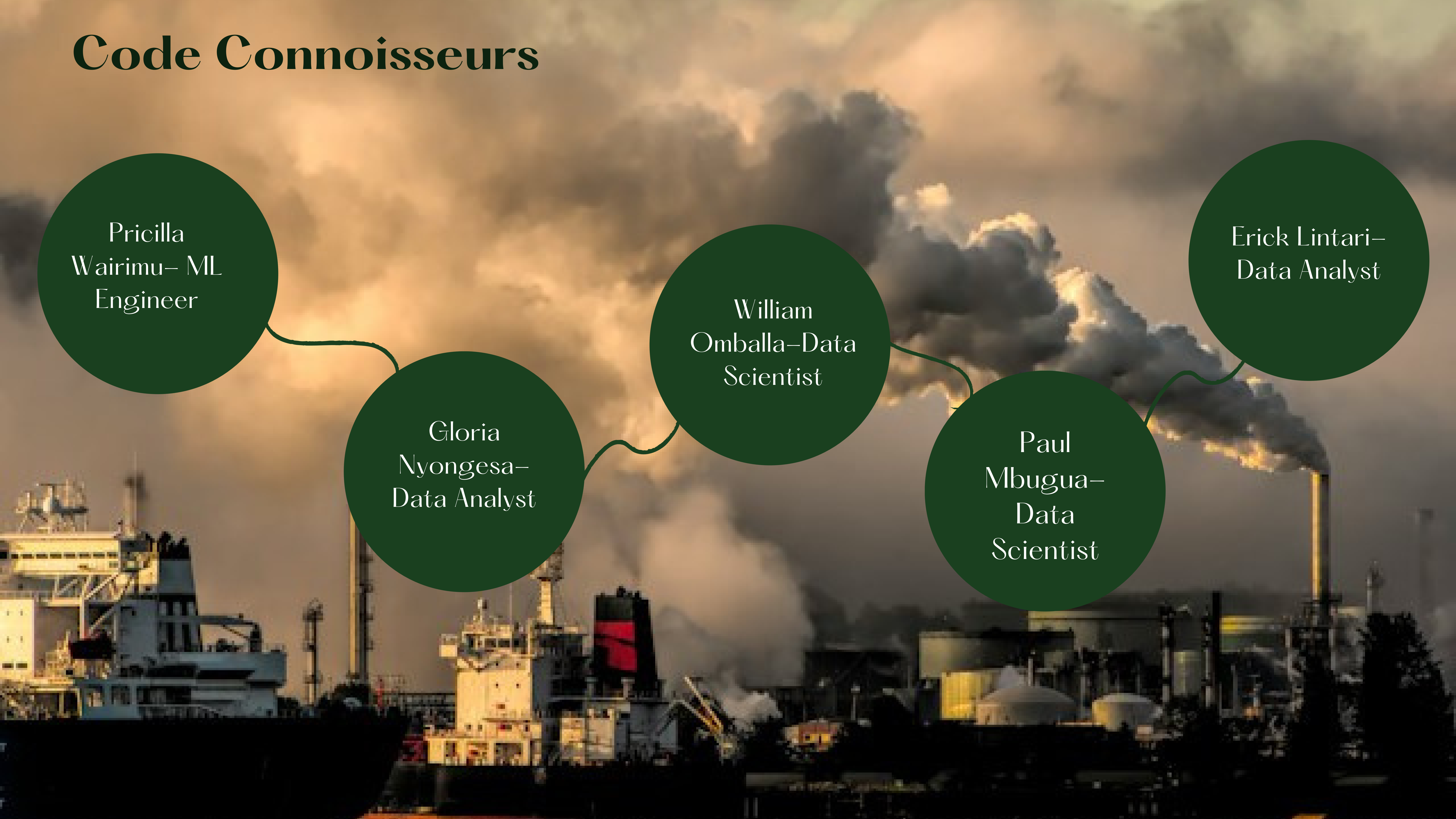
Carbon Credits Timeseries Analysis

Code Connoisseurs



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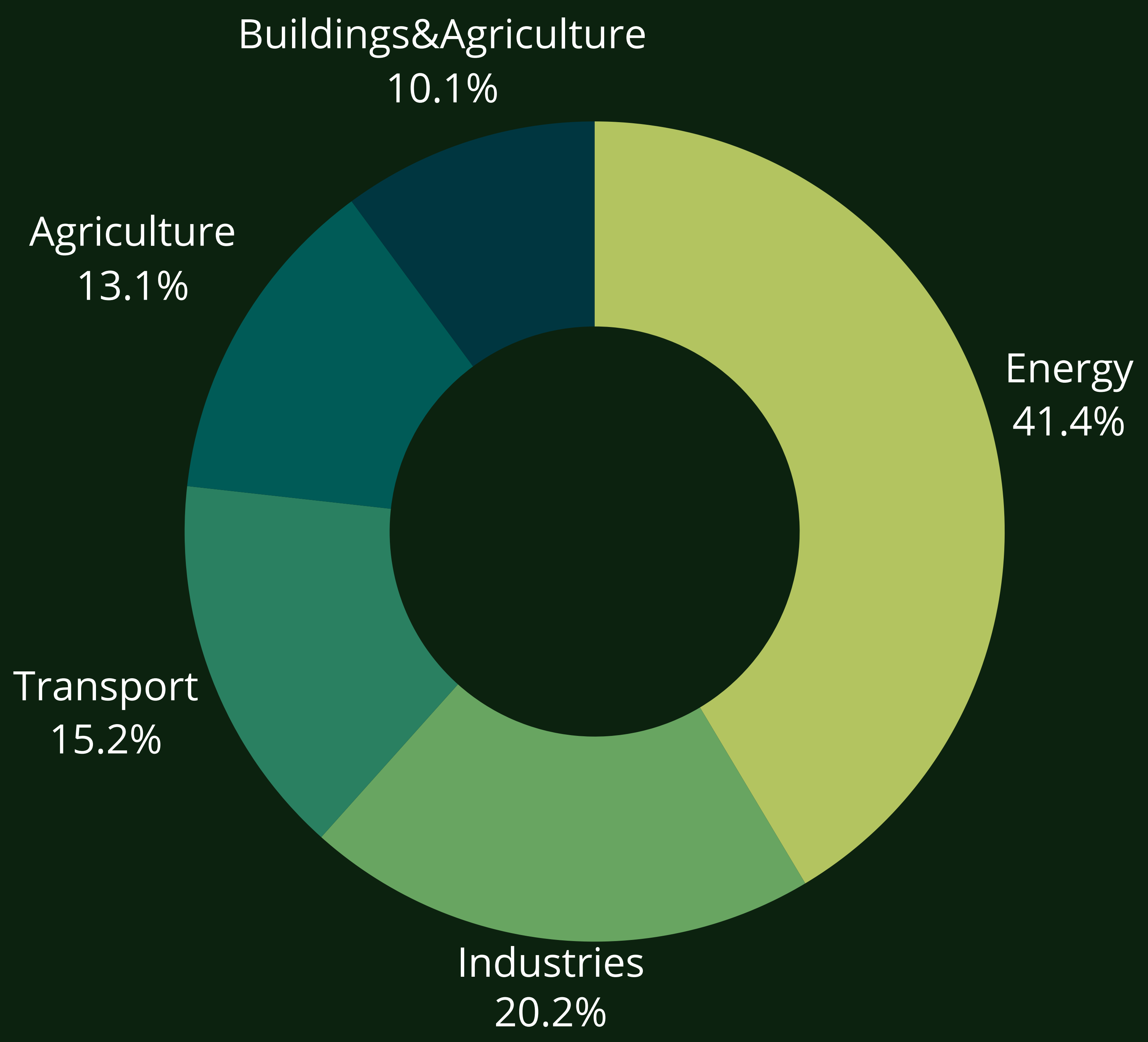
01/
Domain Understanding

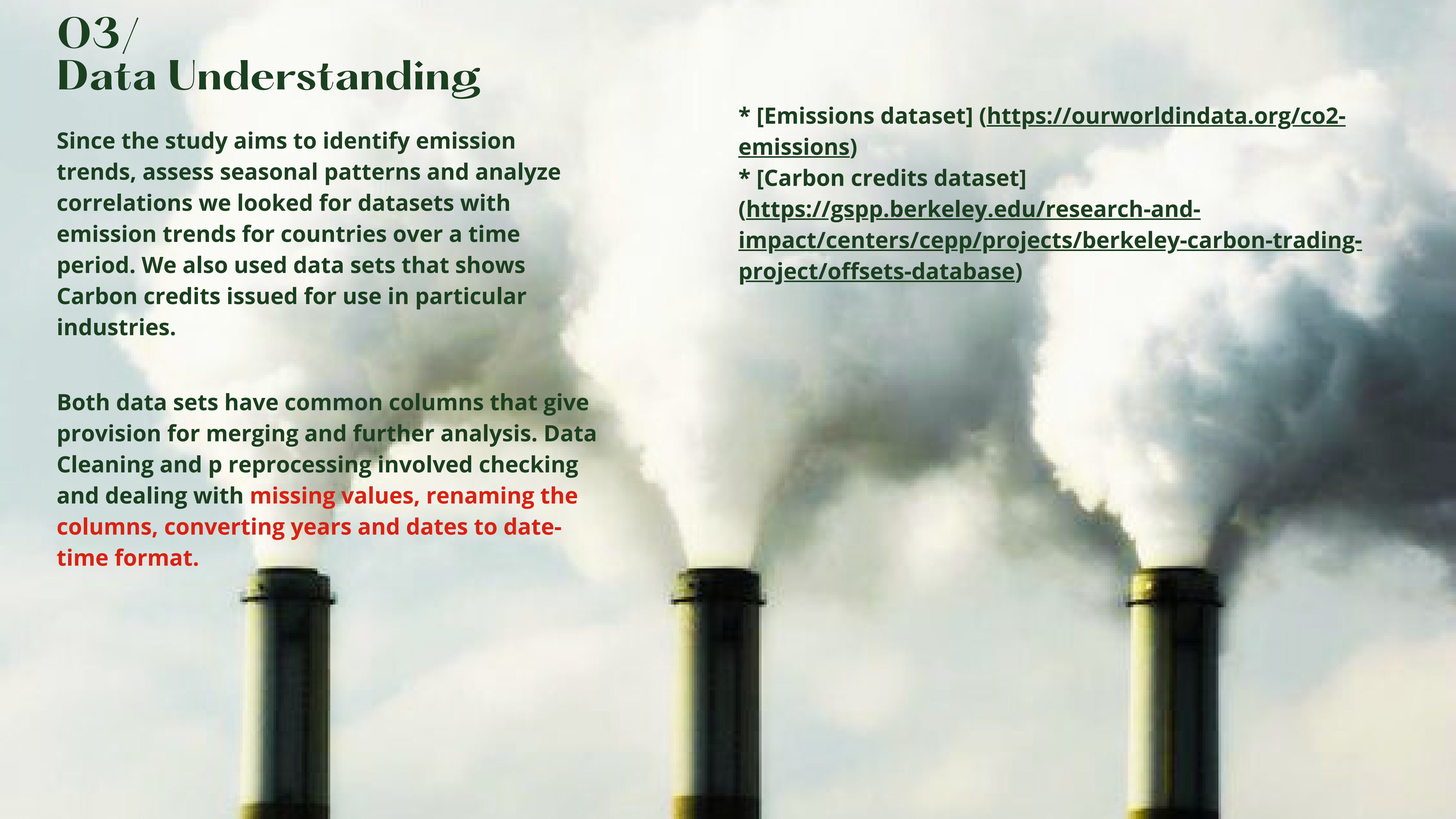
Carbon Oxide is emitted quite highly of all the green house gases.At least every sector produces an emission yearly; energy being the highest. These gases enhance the green house effect; potentially furthering global warming.

Carbon credits act as permits to emit a certain amount of CO2. Businesses and individuals can buy them to "offset" their own emissions. Understanding the true impact of these projects is crucial for regulatory bodies, investors, and researchers alike.



02/
Objectives

- Track historical trends in carbon credit issuance and utilization globally.
- Identify regional disparities in carbon credit utilization and emissions reduction outcomes.
- Assess seasonal patterns of emissions to understand recurring trends.
- Detect anomalies and outliers in emissions data using advanced techniques.
- Analyze correlations between carbon credit projects and changes in emission patterns.
- Develop predictive models to estimate the impact of future carbon credit projects.



03/
Data Understanding

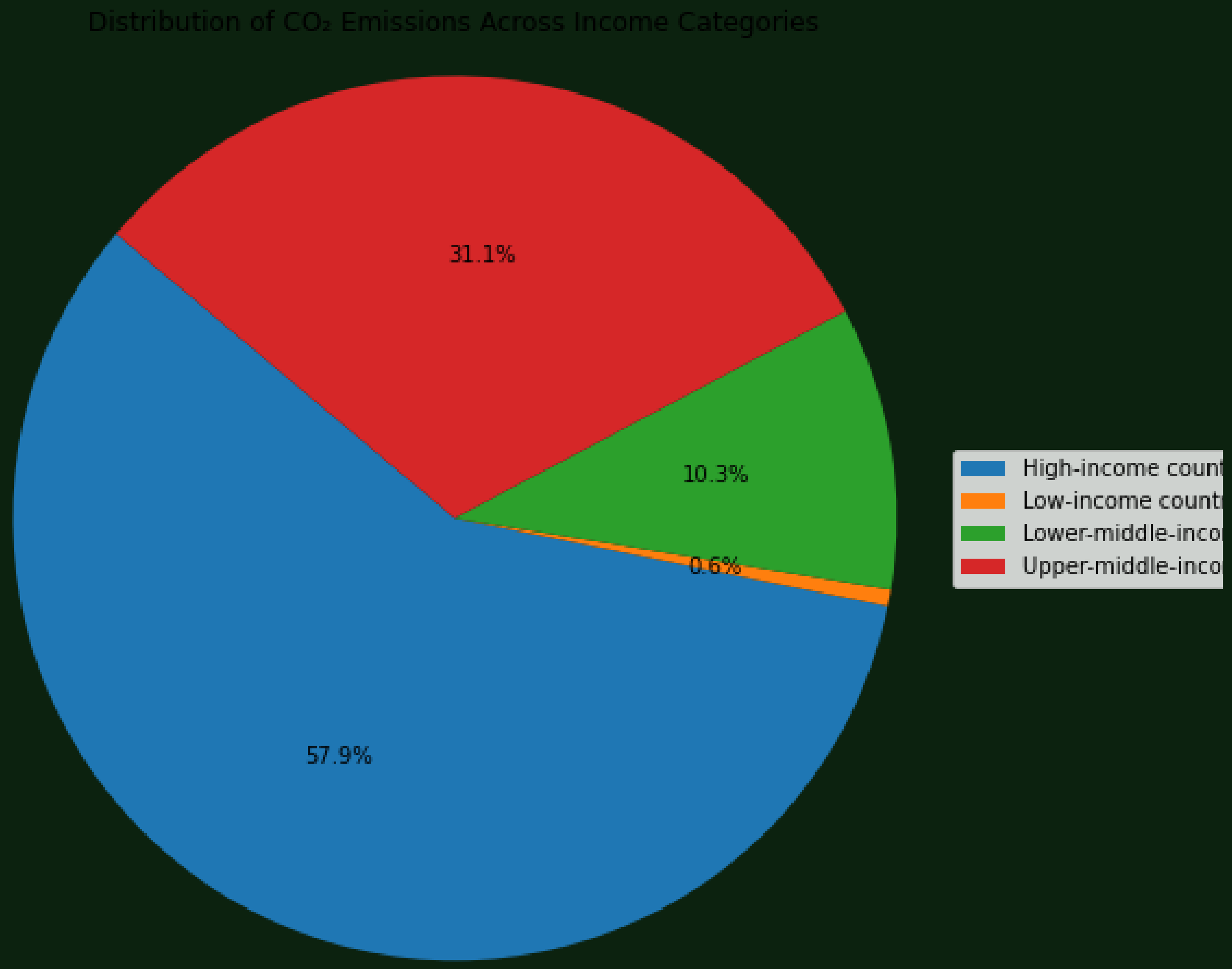
Since the study aims to identify emission trends, assess seasonal patterns and analyze correlations we looked for datasets with emission trends for countries over a time period. We also used data sets that shows Carbon credits issued for use in particular industries.

Both data sets have common columns that give provision for merging and further analysis. Data Cleaning and p reprocessing involved checking and dealing with missing values, renaming the columns, converting years and dates to date-time format.

* [Emissions dataset] (https://ourworldindata.org/co2-emissions)
* [Carbon credits dataset] (https://gspp.berkeley.edu/research-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/offsets-database)

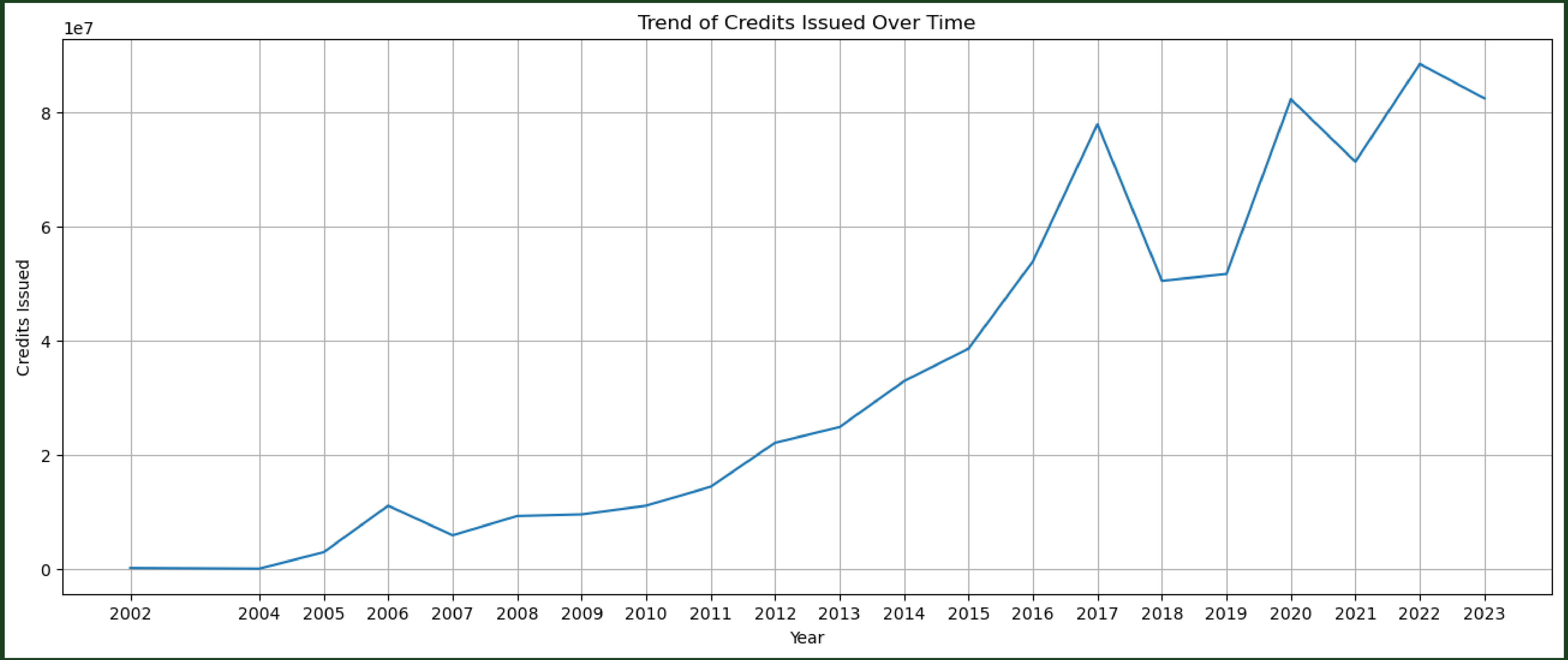
04/
Exploratory Data Analysis

Top CO_2 Emitting Countries Classified by Income Levels



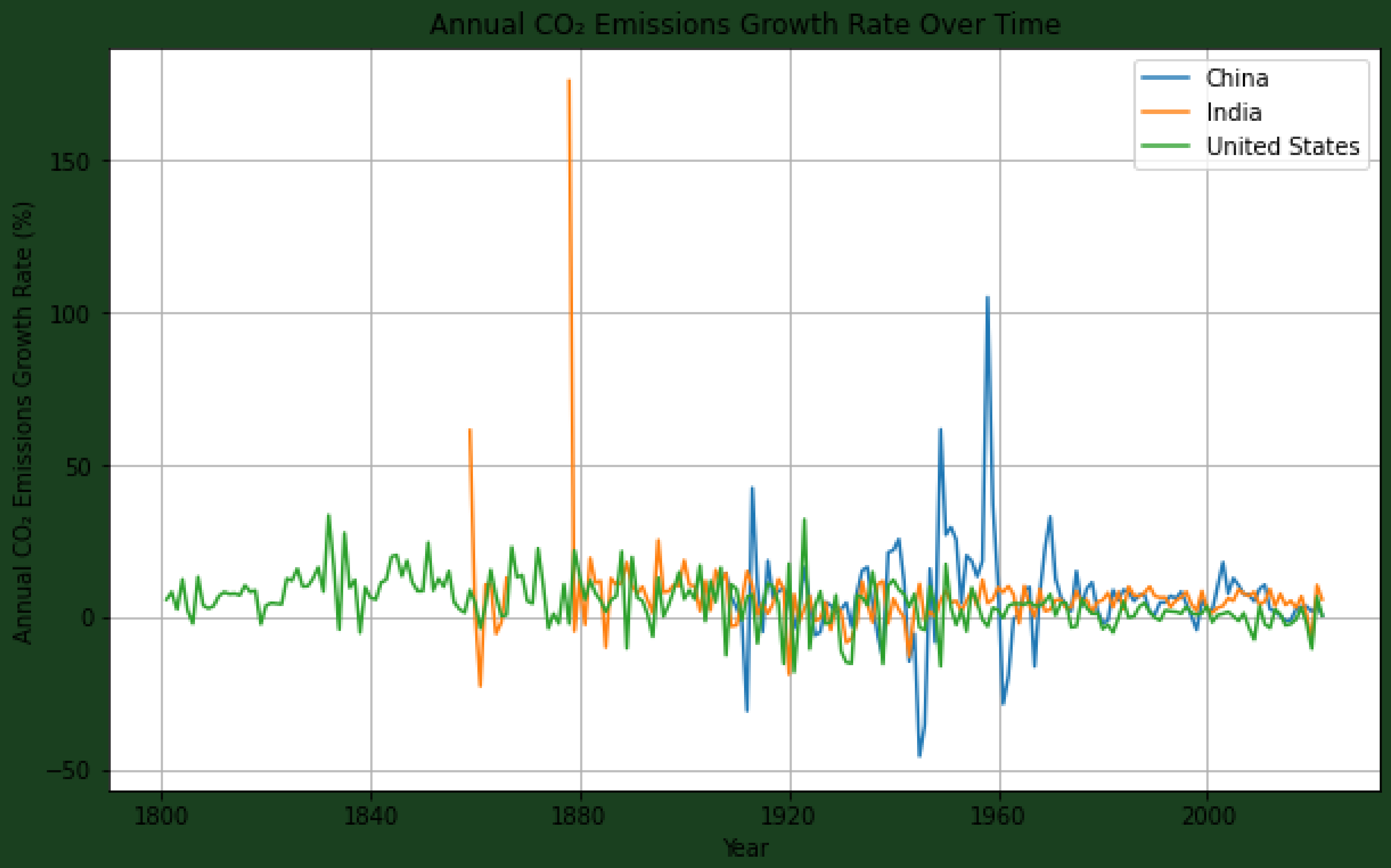
Among the Upper-middle-income countries are China, Brazil, Russia, and South Africa, which rank among the world's largest emitters of greenhouse gases (GHG), collectively emitting over 15 billion metric tonnes of CO2. A significant number of high-income countries are located in Europe and North America. These nations have made substantial reductions in their carbon emissions over the years. In contrast, the majority of African countries fall into the low-income category and are generally small emitters

Trend of Carbon Credits Over the years



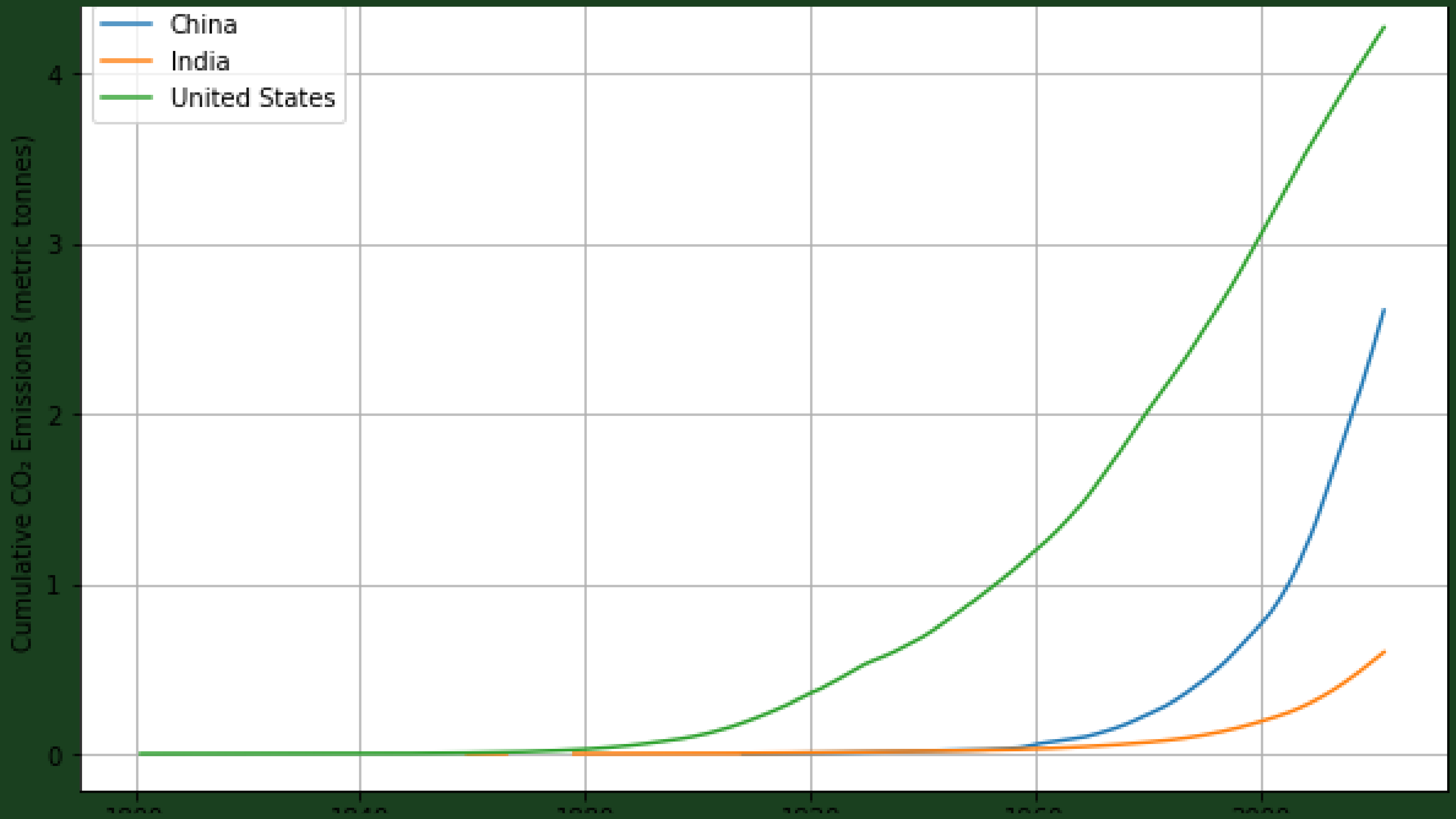
- There is an upward trend for the number of credits issued.However, there was a slight drop between 2017 and 2018 due to President Trump's exit from the Paris Agreement, and the aftermath of the COVID-19 pandemic in 2020.

Annual CO_2 Emissions Growth Rate Over Time



This interactive chart displays the year-on-year growth in annual CO_2 emissions for selected countries. A positive figure indicates that emissions in a given year were higher than the previous year. A negative figure indicates that emissions were lower than the previous year

Cumulative CO_2 Emissions Over Time



Throughout the 1800s, CO2 emissions for the US remained relatively low, but began to rise steadily around the turn of the 20th century, peaking in the 1900s and continuing to grow thereafter. The US was the world's largest emitter of CO2 until 2006, when China surpassed it to become the world's largest polluter. China's emissions started to increase around the 1970s and experienced a sharp rise in the 2000s. On the other hand, India, the third-largest emitter of CO2 in the world, had relatively low emissions until the 1970s, after which it began to steadily increase.

4.1/
Correlation Analysis & Statistical Tests

Pearson‘s correlation & Spearman Correlation

Pearson correlation coefficient:
-0.000226632(-0.0002)
Spear man correlation coefficient:
-0.00197392(-0.002)
This checks the correlation between ‘Annual CO_2 emissions and Total Offset credits issued.
Both coefficients indicate a weak negative relationship between the variables

Augmented Dickey–Fuller Test

The ADF test results suggest that the time series data is non stationary. A high p-value, indicates strong evidence towards the presence of a unit root.
ADF statistic <critical values at the 1%, 5%, and 10% significance levels hence acceptance of the null hypothesis of non-stationarity. The time series data is non stationary. Differencing will be used to achieve stationarity.

05/ Modelling

Auto correlation and partial Auto Correlation

High auto correlation informed the choice of the base line model since it showed that at certain lag intervals the model is able to predict future values with ease. Since past variables easily influence future predictions.

After removing non-stationarity through differencing and picking features our model of choice was ARIMA.

Order Selection

Our ARIMA hyper parameters were :

- p-1
- d-0
- q-1

Hence an ARIMA (1,0,1)

Train–Test Split

Did a 80, 20 train test split on the data

Model Evaluation Metrics

Low RMSE value indicates that the model is a good fit

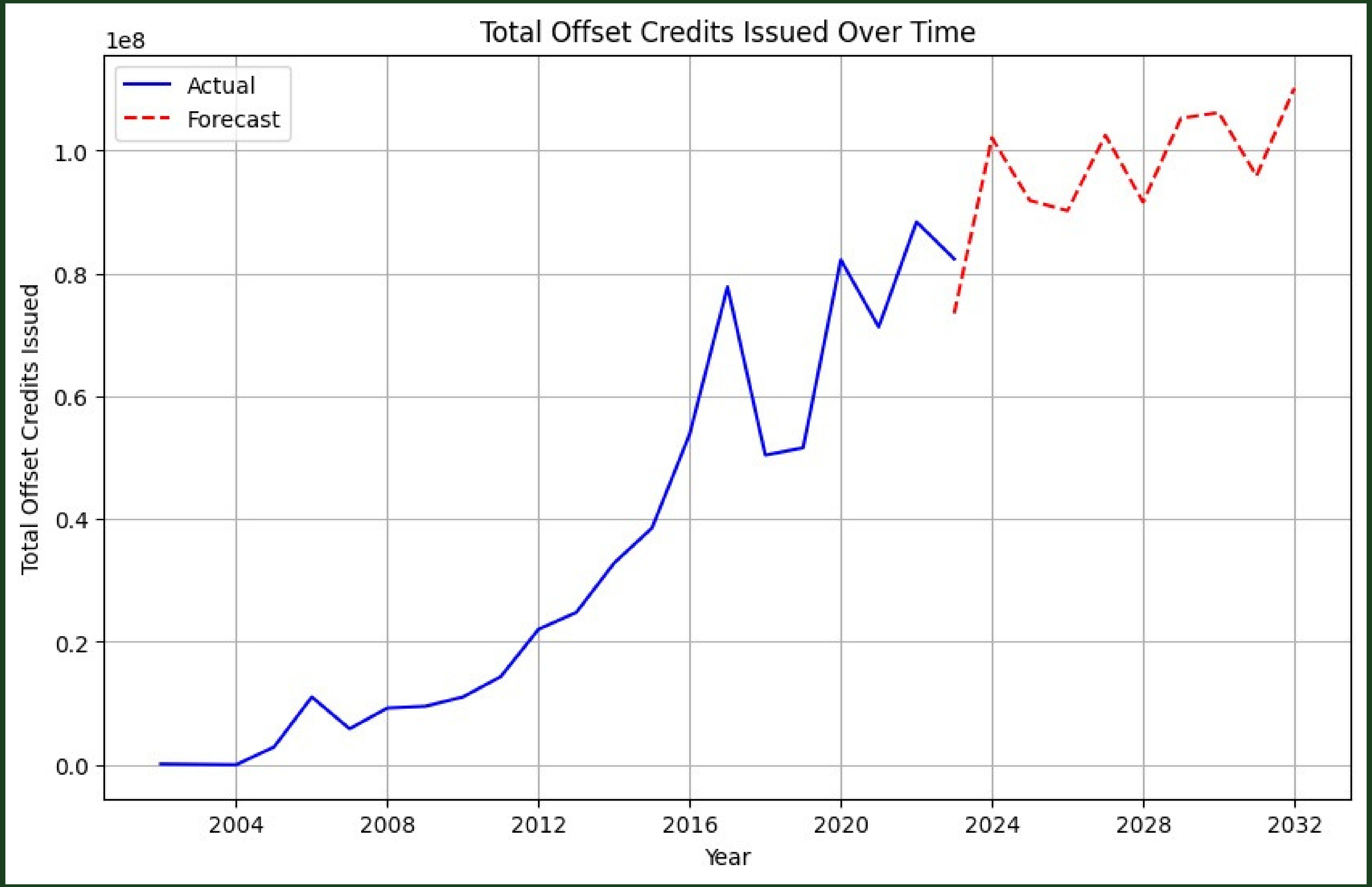
5.1/
Tuning & Further Modelling

Tuning involves experimenting with different hyper-parameter values in order to find a combination that gives the best performance
Created a loop to iterate over p,d,q order combinations and found the best hyper parameters to be: ARIMA(6,0,1)

Simple Exponential Smoothing

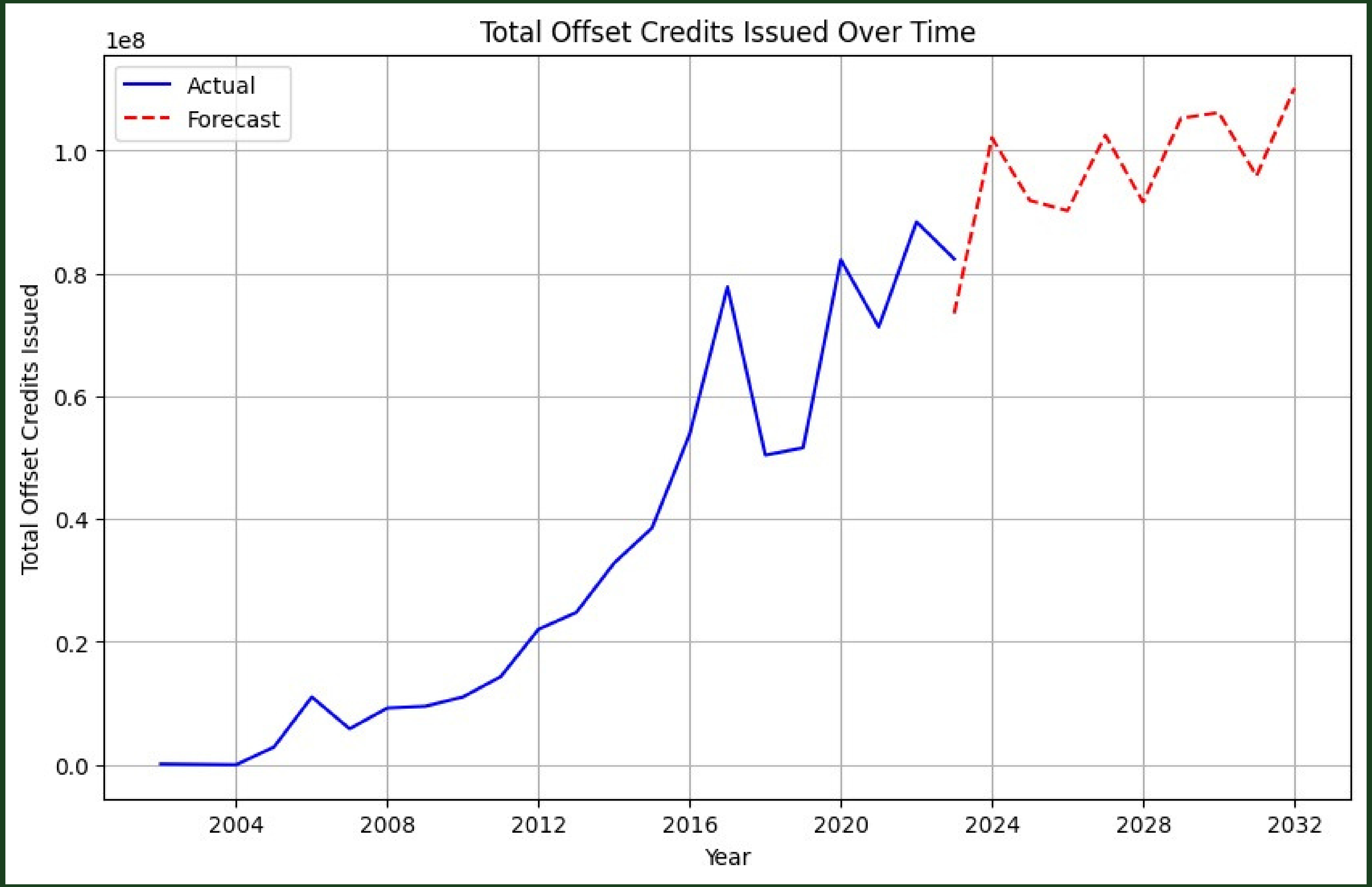
Exponential Smoothing (ETS) is a time series forecasting method that updates equations recursively to estimate the level, trend, and seasonality components. Achieved an accuracy of 0.0247

5.2/
Fore casting

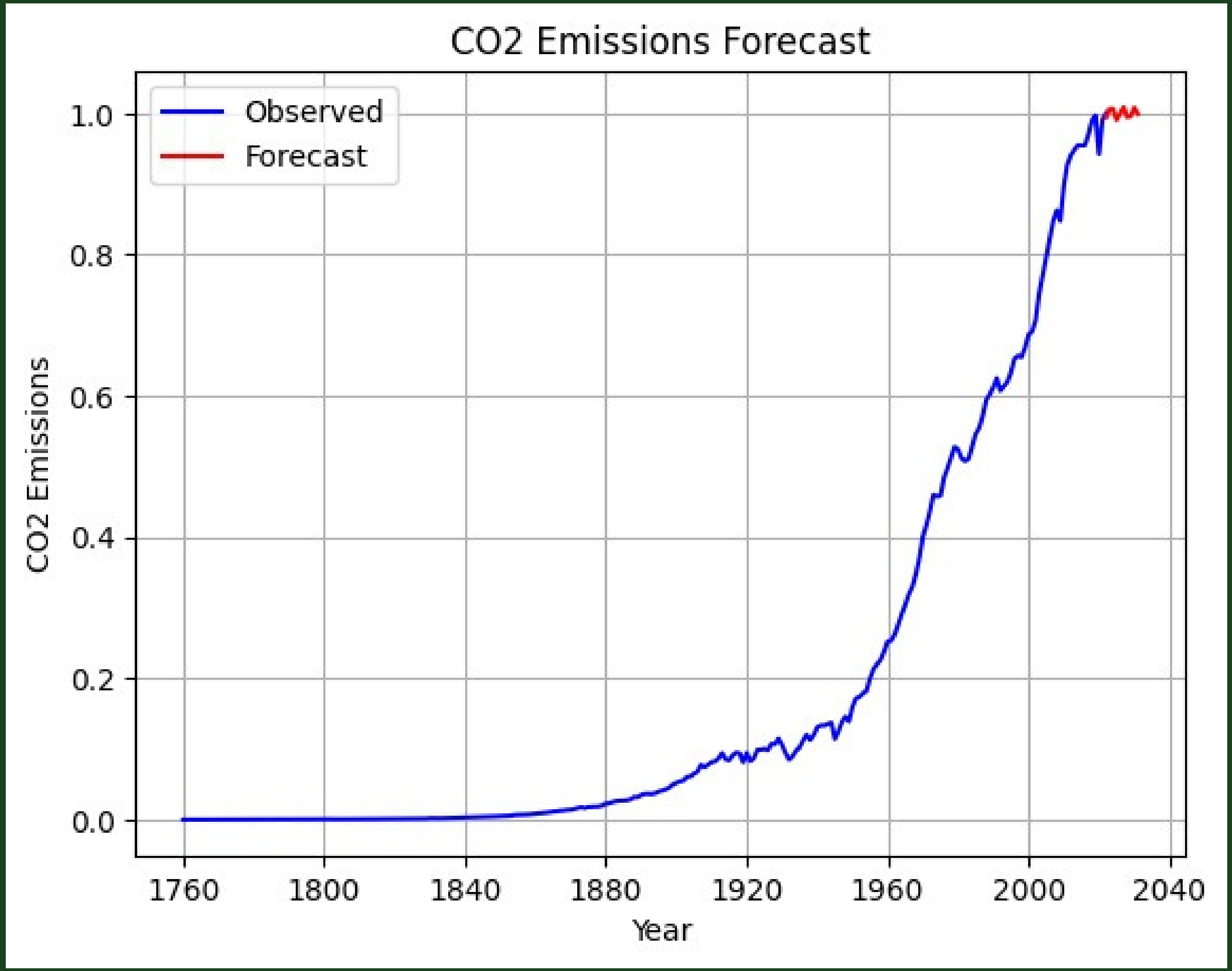


The graph displays the future prediction of carbon credits. As seen if companies continuously engage in carbon credit initiatives there will be a reduction in emissions over time.

5.2/
Fore casting



Time series Forecasting leverages historical data patterns to make informed predictions about future trends or values.



The graph is a forecast of CO2 emissions in the future. As seen there the emissions are predicted to be almost the same as historical emissions showing a need for policies to curb them

06/ Conclusions

Effective implementation of carbon credit systems, alongside supportive government policies, can incentivize companies to reduce carbon emissions. Drawing from successful models like the U.S. cap-and-trade system, carbon pricing and emissions trading programs offer a market-driven approach to mitigate greenhouse gas emissions. Collaborative efforts among stakeholders can expedite the transition to a low-carbon economy, fostering a sustainable future for current and future generations.

6.1/ Recommendations & Next Steps

Recommendations

- Implement Carbon Credits Projects: Invest in initiatives like renewable energy projects and afforestation to offset carbon emissions.
- Utilize Market-Based Incentives: Adopt carbon pricing and emissions trading programs to incentivize emission reductions.
- Promote Adoption of Cleaner Technologies: Encourage businesses to transition to cleaner technologies and sustainable practices.
- Reduce Carbon Footprints through Cap-and-Trade Mechanism: Implement effective cap-and-trade systems to regulate emissions and provide flexibility for compliance.

Next Steps

- Monitor and Evaluate Impact: This involves tracking emission trends, analyzing project performance, and assessing the effectiveness of implemented measures.
- Refine Strategies Based on Results: Based on the evaluation findings, refine strategies and approaches to optimize the effectiveness of carbon credit initiatives.

Thanks!