



## **DATA VISUALIZATION LAB PROJECT REPORT**

# **Tracking Sustainable Urban Mobility: A Data-Driven Approach to Reduce Carbon Emissions**

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## INTRODUCTION



Climate change is one of the defining and most urgent challenges of the 21st century. At the core, it involves an ever-increasing concentration of carbon dioxide in the atmosphere due to human industrial activity, deforestation, and fossil fuel consumption. CO<sub>2</sub> emissions are not just environmental statistics; they represent the trajectory of global economic development, energy dependency, and sustainability efforts.

This very fast growth of greenhouse gas emissions has served as a wake-up call for global action in the measurement, monitoring, and mitigation of environmental damage. From the Paris Climate Agreement to the United Nations SDG 13, Climate Action, nations have come forward to pledge reductions in emissions and hasten toward greener technologies. Understanding and predicting worldwide CO<sub>2</sub> emissions remains an ambitious analytical challenge because of the many diverse factors contributing to it: population, GDP, industry, and energy mix.

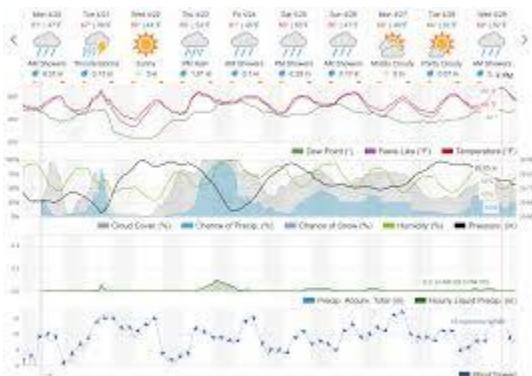
This project presents the use of Power BI integrated with R programming for the transformation of global CO<sub>2</sub> emission data into an interactive, analytical, and predictive tool. Intuitive dashboards, DAX-powered calculations, and advanced forecasting models in this project prove how data visualization may become one of the strong points in environmental intelligence and the effective design of sustainable policies.

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## PROBLEM STATEMENT

**Global CO<sub>2</sub> emissions are increasing unevenly across nations, yet decision-makers lack a unified data-driven dashboard able to analyze, compare, and project emission trends with ease.**



### Elaboration

This gap, in turn, reduces the potential of governments, researchers, and other organizations to take timely climate action. Our project bridges this gap by developing a three-page Power BI dashboard that converts raw emission datasets from multiple countries into actionable insights. Using advanced DAX measures, R-based forecasting models, and predictive analytics, such as Linear Regression and Random Forest, the dashboard empowers users to track trends in emissions, detect outliers, and provide visualizations of future trajectories. This would integrate business intelligence with data science, ensuring that environmental data is not just informative but also decision-oriented, thereby driving sustainable change through transparency and analytics..

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## **OBJECTIVES**

The main focus of this dashboard is to provide a full-fledged and interactive Power BI solution, which will enable users to analyze, compare, and forecast global CO<sub>2</sub> emissions from multiple countries. This project integrates data modeling, DAX measures, and R-based predictive analytics, with the goal of transforming raw emission data into meaningful insights for informed environmental decision-making.

In particular, the dashboard is intended to:

Visualize emission trends at the global and country levels through intuitive charts and KPIs that indicate how emissions evolve over time.

Enable cross-country comparison to identify regions contributing most to global emissions and track their progress toward sustainability targets.

Integrate forecasting models in R, using Linear Regression and Random Forest to predict future levels of emissions that could raise concern.

Provide more in-depth analyses by adding advanced DAX measures that include rolling averages, CAGR, and anomaly detection to interpret trends.

Enable data-informed environmental policy by providing a single, interactive dashboard that policymakers, researchers, and organizations can leverage to monitor and take action based on emission data.

This work bridges data visualization and sustainability analytics, transforming static data into an active decision support tool, enabling climate-conscious action.

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# DATASET DESCRIPTION

Near-real-time daily estimates of CO2 emissions from 1500 cities worldwide

Cite

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Dataset posted on 2022-03-26, 23:22 authored by [Da Huo](#), Zhu Liu, Philippe Ciais, Xiaoting Huang, Xinyu Dou, [Zhu Deng](#), Yilong Wang, Yun Li, Fouzi Benkhelifa, Taochun Sun, Duo Cui, Biqing Zhu, Geoffrey Roest, Kevin Gurney, Piyu Ke, Rui Guo, Chenxi Lu, Xiaojuan Lin, Arminel Lovell, Kyra Appleby, Philip DeCola, [Steve Davis](#)

## USAGE METRICS

3,715 views | 1,109 downloads | 1 citations

A daily city-level dataset of fossil fuel and cement CO2 emissions. It provides daily, city-level estimates of emissions from January 2019 through December 2021 for 1500 cities in 46 countries, and disaggregates five sectors: power generation, residential (buildings), industry, ground transportation, and aviation. The goal of this dataset is to improve the timeliness and temporal resolution of city-level emission inventories and includes estimates for both functional urban areas and city administrative areas that are consistent with global and regional totals. It also provides the first estimates for many cities in low-income countries. Such near-real-time CO2 dataset would be of great advantage to further monitoring the human activities and to capture the impacts of COVID-19 for long term.

Latest Dataset for:

Carbon Monitor Cities, near-real-time daily estimates of CO2 emissions from 1500 cities worldwide

## HISTORY

- **2022-03-26** - First online date, Posted date

## RELATED MATERIALS

1. URL - References <https://cities.carbonmonitor.org/>

## CATEGORIES

- [Climate change processes](#)
- [Climatology](#)
- [Environmental assessment and monitoring](#)
- [Urban and regional economics](#)
- [Urban analysis and development](#)

## KEYWORDS

CO2 emissions | city emissions  
 Near-real-time emissions  
 Greenhouse Gas | Cities  
 Climate Change | urban emissions  
 Climate Change Processes  
 Climate Science

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22	Cape Town	South Africa	1/21/2019	Aviation	0.89386093	1.548E+09
23	Cape Town	South Africa	1/22/2019	Aviation	0.88408000	1.548E+09
24	Cape Town	South Africa	1/23/2019	Aviation	0.88128007	1.548E+09
25	Cape Town	South Africa	1/24/2019	Aviation	0.89838174	1.548E+09
26	Cape Town	South Africa	1/25/2019	Aviation	0.91325722	1.548E+09
27	Cape Town	South Africa	1/26/2019	Aviation	0.83778095	1.548E+09
28	Cape Town	South Africa	1/27/2019	Aviation	0.86351911	1.549E+09
29	Cape Town	South Africa	1/28/2019	Aviation	0.76940134	1.549E+09
30	Cape Town	South Africa	1/29/2019	Aviation	0.87530009	1.549E+09
31	Cape Town	South Africa	1/30/2019	Aviation	0.89002976	1.549E+09

	A	B	C	D	E	F
1	city	country	date	sector	value (KtCO <sub>2</sub> )	timestamp
2	Lagos	Nigeria	1/1/2019	Aviation	0.26659828	1.546E+09
3	Lagos	Nigeria	1/2/2019	Aviation	0.29182745	1.546E+09
4	Lagos	Nigeria	1/3/2019	Aviation	0.29941610	1.546E+09
5	Lagos	Nigeria	1/4/2019	Aviation	0.30351734	1.547E+09
6	Lagos	Nigeria	1/5/2019	Aviation	0.31212100	1.547E+09
7	Lagos	Nigeria	1/6/2019	Aviation	0.31744840	1.547E+09
8	Lagos	Nigeria	1/7/2019	Aviation	0.29613462	1.547E+09
9	Lagos	Nigeria	1/8/2019	Aviation	0.28095234	1.547E+09
10	Lagos	Nigeria	1/9/2019	Aviation	0.28030717	1.547E+09
11	Lagos	Nigeria	1/10/2019	Aviation	0.30299283	1.547E+09
12	Lagos	Nigeria	1/11/2019	Aviation	0.27290143	1.547E+09
13	Lagos	Nigeria	1/12/2019	Aviation	0.29980941	1.547E+09
14	Lagos	Nigeria	1/13/2019	Aviation	0.30147849	1.547E+09
15	Lagos	Nigeria	1/14/2019	Aviation	0.28652719	1.547E+09
16	Lagos	Nigeria	1/15/2019	Aviation	0.27128128	1.548E+09
17	Lagos	Nigeria	1/16/2019	Aviation	0.23759759	1.548E+09
18	Lagos	Nigeria	1/17/2019	Aviation	0.28113802	1.548E+09
19	Lagos	Nigeria	1/18/2019	Aviation	0.29355814	1.548E+09
20	Lagos	Nigeria	1/19/2019	Aviation	0.29775287	1.548E+09
21	Lagos	Nigeria	1/20/2019	Aviation	0.29689783	1.548E+09
22	Lagos	Nigeria	1/21/2019	Aviation	0.28663909	1.548E+09
23	Lagos	Nigeria	1/22/2019	Aviation	0.27261289	1.548E+09
24	Lagos	Nigeria	1/23/2019	Aviation	0.27623066	1.548E+09
25	Lagos	Nigeria	1/24/2019	Aviation	0.28216680	1.548E+09
26	Lagos	Nigeria	1/25/2019	Aviation	0.29474232	1.548E+09
27	Lagos	Nigeria	1/26/2019	Aviation	0.29617754	1.548E+09
28	Lagos	Nigeria	1/27/2019	Aviation	0.30691288	1.549E+09
29	Lagos	Nigeria	1/28/2019	Aviation	0.25768473	1.549E+09
30	Lagos	Nigeria	1/29/2019	Aviation	0.27058842	1.549E+09
31	Lagos	Nigeria	1/30/2019	Aviation	0.27277764	1.549E+09
32	Lagos	Nigeria	1/31/2019	Aviation	0.28338988	1.549E+09
33	Lagos	Nigeria	2/1/2019	Aviation	0.29618326	1.549E+09

	A	B	C	D	E	F
1	city	country	date	sector	value (KtCO <sub>2</sub> )	timestamp
2	Aksu	China	1/1/2019	Aviation	0.01059782	1.546E+09
3	Aksu	China	1/2/2019	Aviation	0.01080231	1.546E+09
4	Aksu	China	1/3/2019	Aviation	0.01060016	1.546E+09
5	Aksu	China	1/4/2019	Aviation	0.01067491	1.547E+09
6	Aksu	China	1/5/2019	Aviation	0.01036011	1.547E+09
7	Aksu	China	1/6/2019	Aviation	0.01069759	1.547E+09
8	Aksu	China	1/7/2019	Aviation	0.01061270	1.547E+09
9	Aksu	China	1/8/2019	Aviation	0.01049421	1.547E+09
10	Aksu	China	1/9/2019	Aviation	0.01063461	1.547E+09
11	Aksu	China	1/10/2019	Aviation	0.01111834	1.547E+09
12	Aksu	China	1/11/2019	Aviation	0.00872450	1.547E+09
13	Aksu	China	1/12/2019	Aviation	0.01055375	1.547E+09
14	Aksu	China	1/13/2019	Aviation	0.01053555	1.547E+09
15	Aksu	China	1/14/2019	Aviation	0.01093114	1.547E+09
16	Aksu	China	1/15/2019	Aviation	0.01094986	1.548E+09
17	Aksu	China	1/16/2019	Aviation	0.00877338	1.548E+09
18	Aksu	China	1/17/2019	Aviation	0.01096279	1.548E+09
19	Aksu	China	1/18/2019	Aviation	0.01101317	1.548E+09
20	Aksu	China	1/19/2019	Aviation	0.01107642	1.548E+09
21	Aksu	China	1/20/2019	Aviation	0.01116631	1.548E+09
22	Aksu	China	1/21/2019	Aviation	0.01137256	1.548E+09
23	Aksu	China	1/22/2019	Aviation	0.01133141	1.548E+09
24	Aksu	China	1/23/2019	Aviation	0.01147675	1.548E+09
25	Aksu	China	1/24/2019	Aviation	0.01147708	1.548E+09
26	Aksu	China	1/25/2019	Aviation	0.01133024	1.548E+09
27	Aksu	China	1/26/2019	Aviation	0.01153824	1.548E+09
28	Aksu	China	1/27/2019	Aviation	0.01187683	1.549E+09
29	Aksu	China	1/28/2019	Aviation	0.01180718	1.549E+09
30	Aksu	China	1/29/2019	Aviation	0.01173754	1.549E+09
31	Aksu	China	1/30/2019	Aviation	0.01182919	1.549E+09
32	Aksu	China	1/31/2019	Aviation	0.01186364	1.549E+09
33	Aksu	China	2/1/2019	Aviation	0.01192207	1.549E+09

	A	B	C	D	E	F
1	city	country	date	sector	value (KtCO <sub>2</sub> )	timestamp
2	Aracaju	Brazil	1/1/2019	Aviation	0.00165947	1.546E+09
3	Aracaju	Brazil	1/2/2019	Aviation	0.00215021	1.546E+09
4	Aracaju	Brazil	1/3/2019	Aviation	0.00218786	1.546E+09
5	Aracaju	Brazil	1/4/2019	Aviation	0.00217019	1.547E+09
6	Aracaju	Brazil	1/5/2019	Aviation	0.00210712	1.547E+09
7	Aracaju	Brazil	1/6/2019	Aviation	0.00204273	1.547E+09
8	Aracaju	Brazil	1/7/2019	Aviation	0.00215303	1.547E+09
9	Aracaju	Brazil	1/8/2019	Aviation	0.00211200	1.547E+09
10	Aracaju	Brazil	1/9/2019	Aviation	0.00211542	1.547E+09
11	Aracaju	Brazil	1/10/2019	Aviation	0.00224371	1.547E+09
12	Aracaju	Brazil	1/11/2019	Aviation	0.00189848	1.547E+09
13	Aracaju	Brazil	1/12/2019	Aviation	0.00213065	1.547E+09
14	Aracaju	Brazil	1/13/2019	Aviation	0.00201117	1.547E+09
15	Aracaju	Brazil	1/14/2019	Aviation	0.00213234	1.547E+09
16	Aracaju	Brazil	1/15/2019	Aviation	0.00213986	1.548E+09
17	Aracaju	Brazil	1/16/2019	Aviation	0.00185007	1.548E+09
18	Aracaju	Brazil	1/17/2019	Aviation	0.00212740	1.548E+09
19	Aracaju	Brazil	1/18/2019	Aviation	0.00216256	1.548E+09
20	Aracaju	Brazil	1/19/2019	Aviation	0.00206904	1.548E+09
21	Aracaju	Brazil	1/20/2019	Aviation	0.00198309	1.548E+09
22	Aracaju	Brazil	1/21/2019	Aviation	0.00208877	1.548E+09
23	Aracaju	Brazil	1/22/2019	Aviation	0.00211605	1.548E+09
24	Aracaju	Brazil	1/23/2019	Aviation	0.00206368	1.548E+09
25	Aracaju	Brazil	1/24/2019	Aviation	0.00210088	1.548E+09
26	Aracaju	Brazil	1/25/2019	Aviation	0.00208565	1.548E+09
27	Aracaju	Brazil	1/26/2019	Aviation	0.00198907	1.548E+09
28	Aracaju	Brazil	1/27/2019	Aviation	0.00196451	1.549E+09
29	Aracaju	Brazil	1/28/2019	Aviation	0.00179075	1.549E+09
30	Aracaju	Brazil	1/29/2019	Aviation	0.00206852	1.549E+09

This dashboard focuses on the development of a complete, interactive Power BI solution that will

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be used for the analysis, comparison, and forecasting of global CO<sub>2</sub> emissions across various countries. This project will put into practice data modeling, DAX measures, and R-based predictive analytics with the intent of transforming raw emission data into meaningful insights to make informed environmental decisions.

Specifically, the dashboard has been targeted to:

- Visualize the evolution of emissions in intuitive charts and KPIs at global and country levels to showcase how emissions are evolving over time.
- Allow for cross-country comparison, identifying the regions that contribute most to global emissions and tracking their progress toward achieving sustainability targets.
- Integrate the forecast models in R, by implementing Linear Regression and Random Forest to predict future levels of emissions that could raise concerns.
- Provide more in-depth analyses by adding advanced DAX measures that include rolling averages, CAGR, and anomaly detection for trend interpretation.
- Enable data-informed environmental policy by providing a single, interactive dashboard which policymakers, researchers, and organizations can use to monitor and take action in light of the emission data.
- This work bridges data visualization and sustainability analytics by turning static data into an active decision support tool and enabling climate-conscious action.

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# **DATA PREPROCESSING**

## **Data Preprocessing Steps**

Extensive data preprocessing was done prior to developing the Power BI dashboard to make the data accurate, consistent, and ready for visualization and predictive modeling. The following steps summarize the entire process:

- Data Collection and Consolidation**

Datasets from ten countries, namely India, the United States, the United Kingdom, Germany, Italy, Japan, Russia, Brazil, South Africa, and Nigeria, were collected from reliable open data sources such as the World Bank and Our World in Data.

All the datasets were imported and integrated into one standard structure for uniform processing.

- Data Cleaning**

After identifying duplicate records and missing values, these were removed or imputed using the average or median, depending on the distribution of the data.

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Non-numeric columns or inconsistent values, such as commas, spaces, and string-formatted numbers, were standardized.

Country names and column headers were aligned to a consistent naming convention; for example, EmissionCo2, Country, Year.

- **Date Formatting**

Original datasets contained inconsistent date formats-some contained only the year, others had a year-month format.

All date columns have been unified into the Date format YYYY-MM-DD using as.Date() in R and via Power Query transformations in Power BI.

In Power BI, a Calendar Table (Date Table) was created using DAX to enable time intelligence features such as Year-over-Year (YoY), Month-on-Month (MoM) analysis, and alignment for forecasts.

- **Data Transformation in Power Query**

All datasets were loaded into the Power Query Editor in Power BI for transformation.

Append Queries were used to combine all the country datasets into one master dataset.

New calculated columns were added that allowed for comparisons and aggregation, such as Total Emission and Region.

Outliers were detected visually and handled using transformation rules to make accurate trend analysis.

## DATA MODEL

### Model Architecture

In the model, there is one central fact table – Fact\_Emissions – which includes the quantitative metrics such as total CO<sub>2</sub> emissions, emission per capita, energy consumption, and the year.

Supporting dimensions would include Dim\_Country-country names, region, continent; Dim\_Date-calendar attributes, year, month, quarter; and Dim\_Sector-industry classification, where

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applicable.

## **Relationships and Keys**

Relationships were established using the CountryID and DateKey as primary-foreign key pairs between the dimension and fact tables.

The one-to-many relationships make sure that proper data aggregation and filtering occur whenever the users apply slicers for country, region, or time period selections.

## Calculated Columns and Measures

Key DAX measures were created for insights such as:

Total CO2 Emission =  $\text{SUM}(\text{Fact\_Emissions}[\text{EmissionCO2}])$

YOY Change =  $(\text{Current Year} - \text{Previous Year}) / \text{Previous Year}$

## **Forecasted Emission derived from R integration results.**

Calculated columns such as Continent and Emission Category have been added to allow for comparative and visual analysis.

## **Optimisation**

Thereafter, the model was optimized by removing redundant columns, enabling query folding in Power Query, and setting the right data types.

Hierarchies, such as Year → Quarter → Month, were created to support drill-down visualizations.

## **DAX QUERIES**

```
Total Emissions = SUM(FactEmission[Emission])
```

This DAX measure calculates the total CO<sub>2</sub> emitted by summing up all emission values from the datasets.

It helps visualize the overall carbon output for any selected country, year, or region in the dashboard.

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```
Emission per Capita = DIVIDE([Total Emissions], SUM(FactEmission[Population]))
```

This measure calculates the average CO<sub>2</sub> emission per person by dividing the total emissions by the total population.

It provides a fair comparison between countries of different sizes, showing how much CO<sub>2</sub> each person contributes on average.

```
DAX
```

```
YOY Growth =
DIVIDE(
    [Total Emissions] - CALCULATE([Total Emissions], PREVIOUSYEAR(DimYear[Year])),
    CALCULATE([Total Emissions], PREVIOUSYEAR(DimYear[Year]))
)
```

This DAX measure calculates the year-over-year (YOY) percentage change in CO<sub>2</sub> emissions. It compares the total emissions of the current year with the previous year to identify whether emissions have increased or decreased.

This helps track annual growth trends and understand how fast emissions are rising or reducing over time.

```
Rank =
RANKX(
    FILTER(FactEmission, FactEmission[Year] = EARLIER(FactEmission[Year])),
    [Emission]
)
```

This DAX measure assigns a rank to each country based on its CO<sub>2</sub> emissions for a specific year. It helps identify which countries are the highest or lowest emitters within the same year, making annual comparisons clear and dynamic.

```

Top Country =
FIRSTNONBLANK(
    TOPN(1, VALUES(FactEmission[Country]), [Total Emissions]),
    "Unknown"
)

```

This measure dynamically returns the name of the country with the highest total CO<sub>2</sub> emissions within the current filter context (such as a specific year or region). It is mainly used in card visuals or KPIs to instantly highlight the top-emitting country in the dashboard.

```

1 DataTable =
2 ADDCOLUMNS (
3     CALENDAR (
4         MINX ( 'dataset', 'dataset'[Date] ),
5         MAXX ( 'dataset', 'dataset' [Date] )
6     ),
7     "Year", YEAR ( [Date] ),
8     "Month Number", MONTH ( [Date] ),
9     "Month Name", FORMAT ( [Date], "MMM" ),
10    "Quarter", "Q" & FORMAT ( [Date], "Q" ),
11    "Year-Month", FORMAT ( [Date], "YYYY-MM" ),
12    "Day", DAY ( [Date] ),
13    "Weekday", FORMAT ( [Date], "DDD" ),
14    "Week Number", WEEKNUM ( [Date] )
15 )
16

```

---

This DAX query creates a custom Date Table, which is essential for time intelligence functions in Power BI.

It automatically generates a continuous list of dates between the earliest and latest date in the dataset and adds extra columns like Year, Month, Quarter, and Week for flexible filtering and grouping.

By using this Date Table, visuals such as trend charts and time-series analyses (like CO<sub>2</sub> emission

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over years) work correctly and efficiently.

## DASHBOARDS



## Dashboard Overview (Global Emission Analysis)

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This page provides a comprehensive overview of global CO<sub>2</sub> emissions across all countries. The Total Emission and Average Emission KPIs highlight the overall carbon output, while the CAGR (Compound Annual Growth Rate) shows a slight negative value, suggesting a small decline in the emission growth rate globally.

The world map visualization helps identify major emission contributors like the USA, China, India, and Japan.

The Z-Score scatter plot and 3-Month Moving Average trend display emission stability and fluctuation patterns over time, giving a complete snapshot of the global emission scenario.



## India — CO<sub>2</sub> Emission Dashboard

This visual focuses on India's total and average CO<sub>2</sub> emissions over recent years. The dashboard reveals India's total emission of approximately 872K metric tons, making it one of the top contributors globally. The line chart shows a noticeable upward trend, supported by a 3-month moving average, indicating consistent growth due to industrial and population expansion.

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The donut chart illustrates regional distribution within India, while the map visual marks India as a major emission hotspot in South Asia.

The Z-Score chart confirms stable emission growth aligned with national development trends.



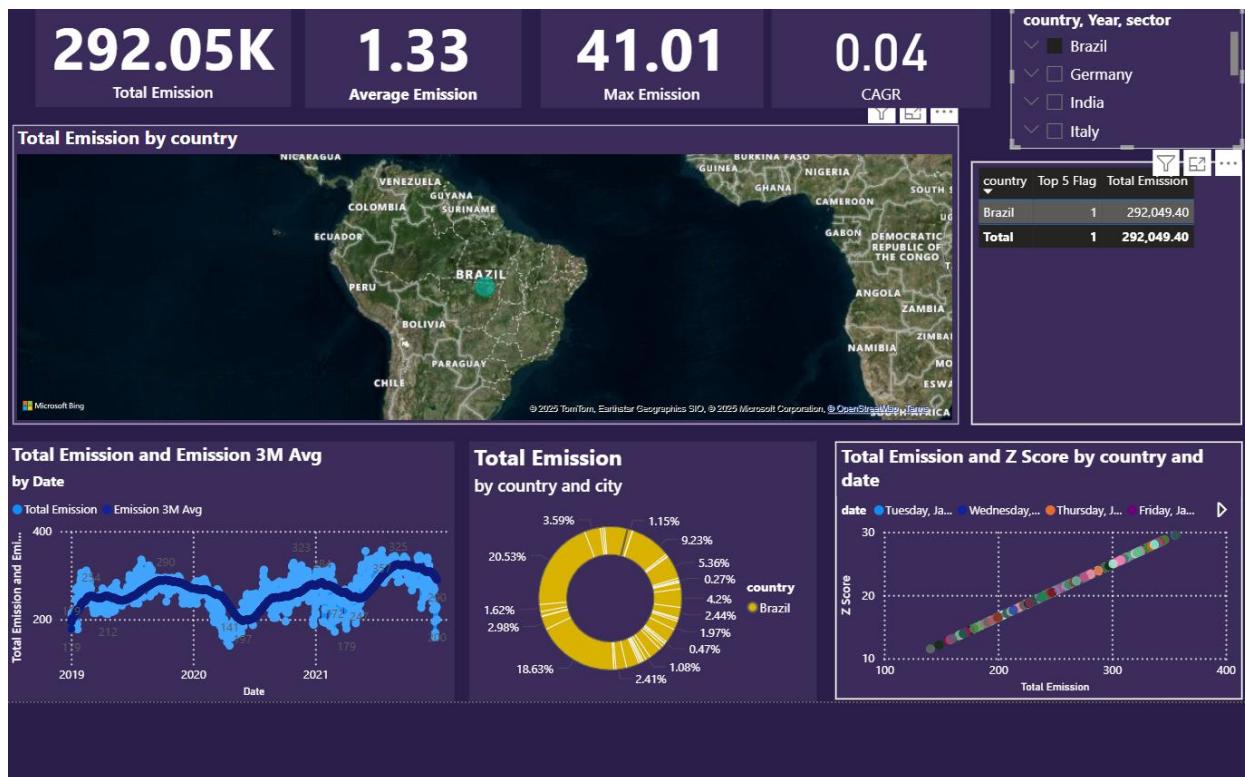
## Germany — CO<sub>2</sub> Emission Dashboard

Germany's dashboard highlights a total emission of around 557K metric tons with a slightly negative CAGR (-0.07), reflecting effective emission control measures.

The time-series visual shows moderate fluctuations, indicating progress in sustainability initiatives and green energy transitions.

The donut chart provides a breakdown of emissions by city, while the map visual pinpoints Germany's geographic emission concentration across Western Europe.

This analysis demonstrates Germany's efforts toward decarbonization and cleaner energy adoption.



## Brazil — CO<sub>2</sub> Emission Dashboard

Brazil's dashboard shows a total emission of 292K metric tons with a positive CAGR (0.04), suggesting gradual growth.

The trend chart illustrates stable emission behavior with periodic variations, largely influenced by energy production and deforestation patterns.

The donut chart displays proportional emissions across major Brazilian regions, while the map visual identifies emission hotspots around industrial cities like São Paulo.

Brazil's data reveals a balanced yet upward trajectory in emissions, underscoring the impact of agricultural and energy sector activities.

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## Italy — CO<sub>2</sub> Emission Dashboard

Italy records a total emission of 155K metric tons with a slight decline (CAGR -0.05).

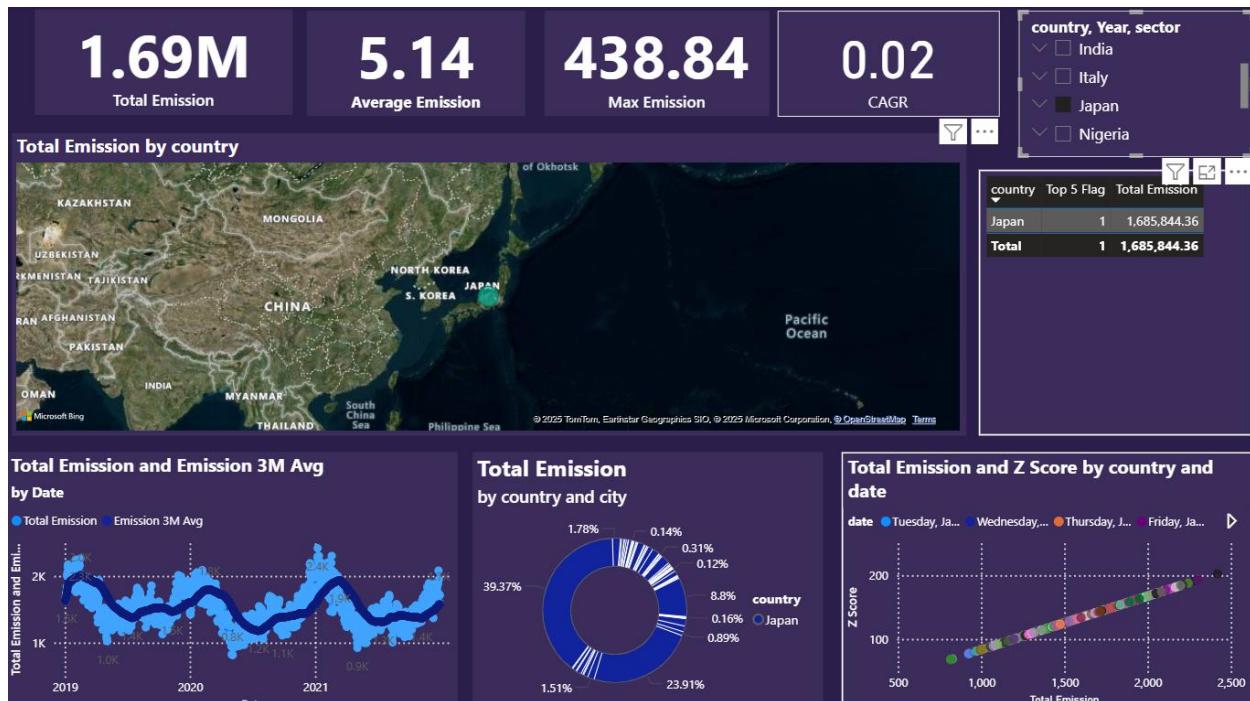
The visuals show stable emission levels over time, with moderate fluctuations due to transportation and industrial factors.

The 3-month moving average chart confirms seasonal variation, while the donut chart reveals emissions concentrated in major industrial cities.

This reflects Italy's continued efforts toward emission stabilization through renewable adoption.

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## Japan — CO<sub>2</sub> Emission Dashboard

Japan's dashboard highlights 1.68M metric tons of total emissions and a positive CAGR of 0.02, showing gradual growth.

The map visual locates Japan's industrial emission zones, while the trend chart displays recurring emission patterns across years.

The donut chart confirms emissions are primarily from dense metropolitan and industrial regions, indicating energy and transport dominance in Japan's emission profile.

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## Nigeria — CO<sub>2</sub> Emission Dashboard

Nigeria has relatively low total emissions (14K metric tons) but shows a slight positive CAGR (0.04).

The line chart depicts steady emission growth tied to rapid urbanization and industrial development. The donut chart and map view illustrate Nigeria's emissions being centralized around key cities. Although total emissions remain low, the trend suggests a gradual increase in carbon activity with future industrialization.

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## Russia — CO<sub>2</sub> Emission Dashboard

Russia shows a total CO<sub>2</sub> emission of 1.50M metric tons and a CAGR of 0.04, indicating consistent growth.

The map visual highlights emissions distributed across the vast region, while the 3M average chart shows periodic peaks due to industrial activity and energy demand.

The donut chart shows Russia's emissions dominated by the energy and transport sectors, making it one of the world's top emitters.

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## South Africa — CO<sub>2</sub> Emission Dashboard

South Africa records 95.9K metric tons in total emissions with a CAGR of 0.01, suggesting near-stable levels.

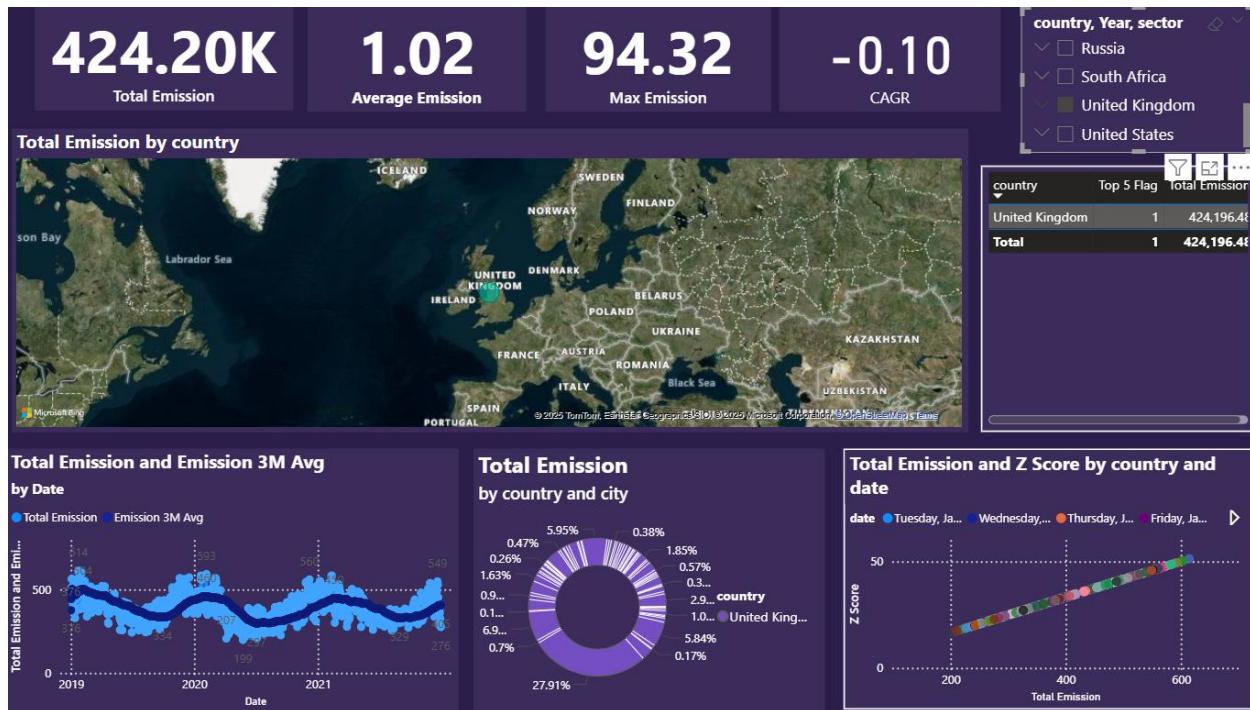
The trend graph shows cyclical fluctuations tied to mining and energy production.

The donut chart visualizes emissions mainly from industrial cities, while the map view identifies southern regions as high emitters.

This data indicates South Africa's reliance on coal-based energy as the primary contributor.

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## United Kingdom — CO<sub>2</sub> Emission Dashboard

The UK's dashboard shows 424K metric tons of total emissions with a negative CAGR (-0.10), indicating successful emission reduction.

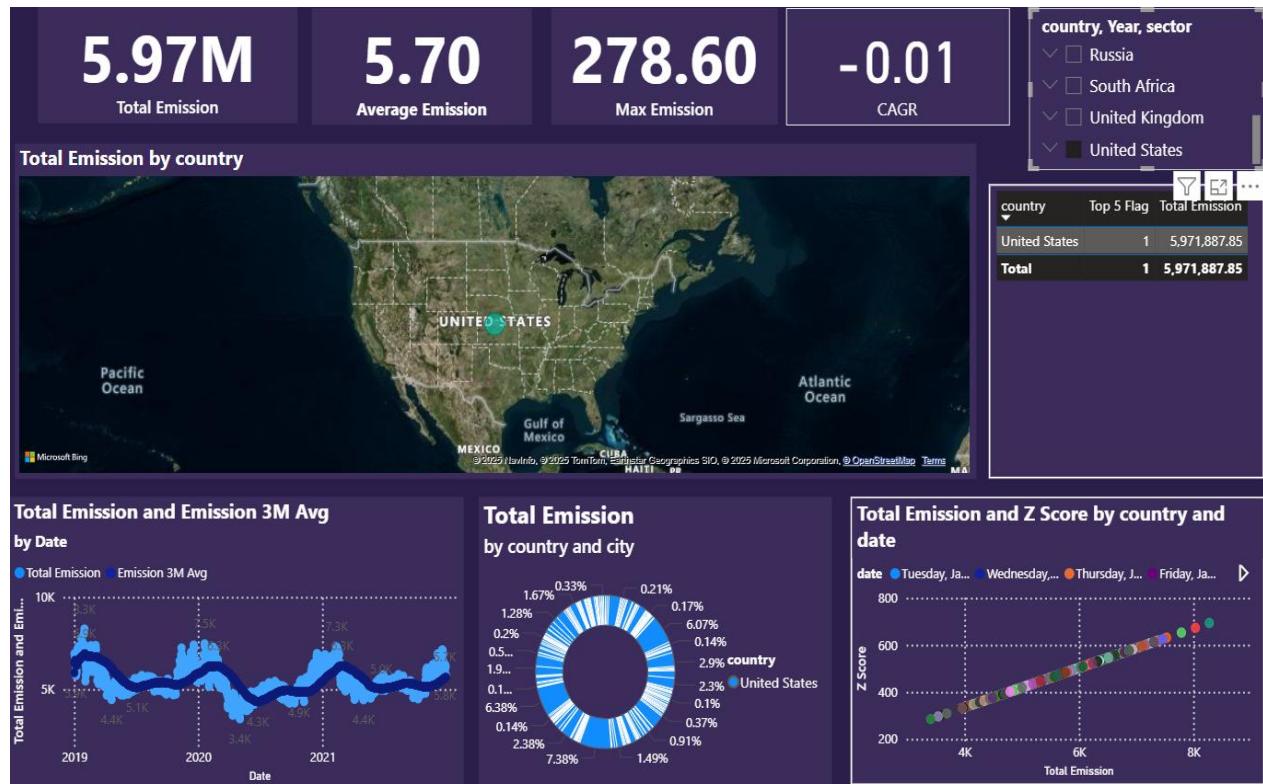
The trend chart shows gradual decline due to policy-driven renewable energy adoption.

The map and donut visuals reveal evenly distributed emissions across industrial regions.

Overall, the UK demonstrates strong climate progress through energy diversification and carbon regulation.

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## United States — CO<sub>2</sub> Emission Dashboard

The USA stands as the largest emitter with 5.97M metric tons of CO<sub>2</sub>, though showing a slight decline (CAGR -0.01).

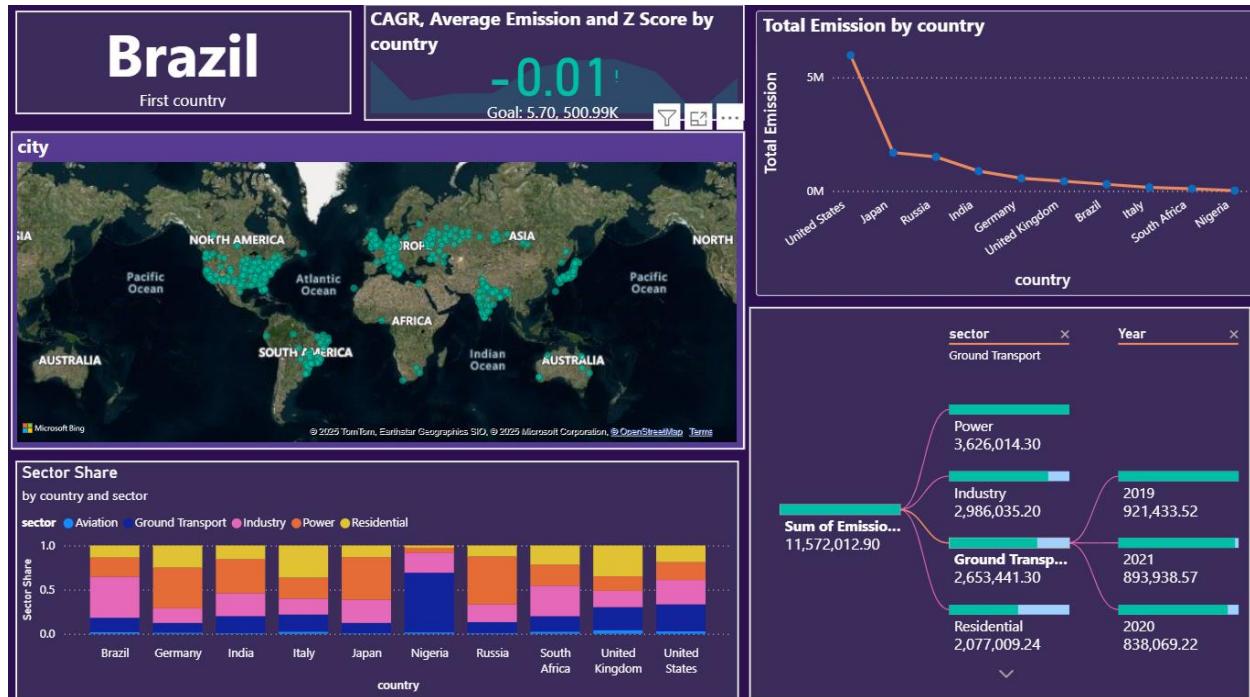
The time-series graph shows cyclical emission trends influenced by industrial output and transportation.

The donut and map visuals confirm emissions concentrated in major economic hubs.

Despite reductions, the U.S. remains a global emission leader, emphasizing the importance of cleaner energy transition.

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## Comparative Analysis Dashboard

This dashboard provides a cross-country comparison of CO<sub>2</sub> emissions, showing how different nations and sectors contribute to global totals.

The world map highlights emission intensity across regions, where high-emission countries like the USA, Japan, Russia, and India stand out clearly.

The line chart ranks countries from highest to lowest emitters, helping identify key contributors and their relative impact.

The sector share chart divides emissions into categories such as Power, Industry, Transport, Residential, and Aviation, showing that power and transport are the largest emission sources worldwide.

Overall, this page gives a clear global picture of emission distribution by country and sector, helping understand each nation's carbon footprint in the global context.

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## R Integration — Forecasting Dashboard (Model 1)

This page integrates R-based predictive modeling into Power BI.

The Random Forest Forecast ( $R^2 = 0.889$ , RMSE = 6.57) and Linear Regression Forecast ( $R^2 = 0.993$ , RMSE = 0.019) show accurate future emission predictions.

The rolling 12-month average displays emission trends over time, while the YoY % by Year chart compares annual changes.

## R Integration — Forecasting Dashboard (Model 2)

This second forecasting panel presents refined Random Forest ( $R^2 = 0.898$ ) and Linear Regression ( $R^2 = 0.986$ ) models.

The trend graphs display predicted vs actual emissions, confirming model reliability.

The rolling average line chart highlights gradual emission increase, and the YoY bar chart shows small recovery after a temporary decline.

This validates that integrating R with Power BI provides robust, data-driven forecasting for environmental analysis.

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## **INSIGHTS AND STORYTELLING**

Global CO<sub>2</sub> emissions provide a number of insights into the world's environmental and industrial landscape. The results identify current emission patterns, as well as the longterm trajectory of global carbon output, which reveals striking contrasts between developed and developing nations.

### **Global Emission Trends**

The dashboard analysis highlights that the most industrialized nations, namely China, the United States, and India, are the prime contributors to global CO<sub>2</sub> emissions. Together, China and the U.S. account for over 40% of the planet's total global emissions, making them the most influential players in the global carbon footprint. India, when judged against the top two, has shown a strong upward trend, directly linked to rapid industrialization, population growth, and energy demand.

Meanwhile, countries like Germany, Italy, and the United Kingdom show a stable downward trend in their emissions because of the adoption of renewable energy sources, increases in efficiency, and better environmental legislation. These variations show how national policy, energy structure, and stage of economic development influence global emission behavior.

### **Insights by Region & Sector**

The Comparative Analysis Dashboard also shows region-based variation in emissions. North America and Asia dominate the global emission map with high levels of industrial and transport-related activities. In Europe, the emission trends go downhill, proving that green energy does indeed work. Africa and South America contribute smaller shares but show gradual increases due to urbanization and infrastructure expansion. Sectoral breakdowns show that Power and Transport are the most emitting sectors globally, followed by Industry, while Residential and

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Aviation contribute comparatively lesser. This underlines the need for clean energy generation and sustainable transport systems worldwide.

### **Forecasting and Predictive Insights**

The integration of R-based models within Power BI adds a predictive dimension to the analysis. Both Linear Regression and Random Forest models were used for the prediction of future CO<sub>2</sub> emissions. While both models performed well, the Random Forest model showed higher accuracy in capturing the complexity and non-linearity present in real-world emissions. The performance of the model was checked with the help of the coefficient of determination, R<sup>2</sup>, and root mean square error, RMSE, values shown clearly on the dashboard for transparency. The forecasting results imply that global emissions will further increase steadily and, assuming the current mitigation strategies continue, may stabilize after 2035.

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## **CONCLUSION**

The project effectively demonstrates the combined power of data visualization and predictive analytics in coming to a higher understanding of global patterns of CO<sub>2</sub> emissions and their environmental implications in the long term.

Such work culminated in a system that not only presented historical emission trends but forecasted future trajectories with strong analytical accuracy and visual clarity-a result of combining the powerful interactive features of Power BI with the statistical modeling capabilities of R. Through this end-to-end analytical approach, the project was successfully able to:-

1. Emission hotspots and high-growth regions were identified, featuring where the co-emission activities are globally the most intensive.
2. Provided country-level insights into both total and per capita emissions, allowing for fair comparison across countries with different sizes and levels of development.
3. Implemented predictive modeling by using the Linear Regression and Random Forest algorithms that provide transparent and reliable emission forecasts.
4. Improved capability for decision-making by converting raw datasets into meaningful, actionable insights using intuitive and interactive dashboards. These results showcase the power of integrating visualization, analytics, and machine learning in the solution of global challenges such as climate change. It makes a case for data-driven toolsets to inform sustainable development policy formulation for accountability and concretizes international cooperation on a path toward a cleaner, more sustainable future.

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