

CO2 Emissions of Food Production by Country





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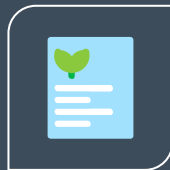
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Why we chose the data

In this analysis we will be comparing the CO2 emission rates of countries based on categorized food product production. This analysis purpose is find correlations between selected features in our data including, the name of the country producing the most emissions, the food products whose productions most or least significant impact the rates of emission and if population plays factor into rates. This analysis will consist of an overview of the data evaluated, a point-by-point analysis of the food product categories and evaluating the predictive value of the data using a machine-learning model.

We chose this dataset because we were interested in whether we could identify causality of a specific type of product with a country's overall CO2 emissions. Population can also have an effect on this, including the level of industrial development of the country. We didn't go too far down that path because that would have been a very complex program.

Investigative Query

1. Does the amount of agricultural production predict the CO2 emissions of a country?
2. What products being produced by countries have the highest and lowest CO2 emissions?
3. Can we predict the year based on CO2 emissions of a country?
4. Is there a correlation between population and the rate of production impacting CO2 emissions?

220 Countries

43 Product Categories

Measuring CO2 by kgs





Our Team



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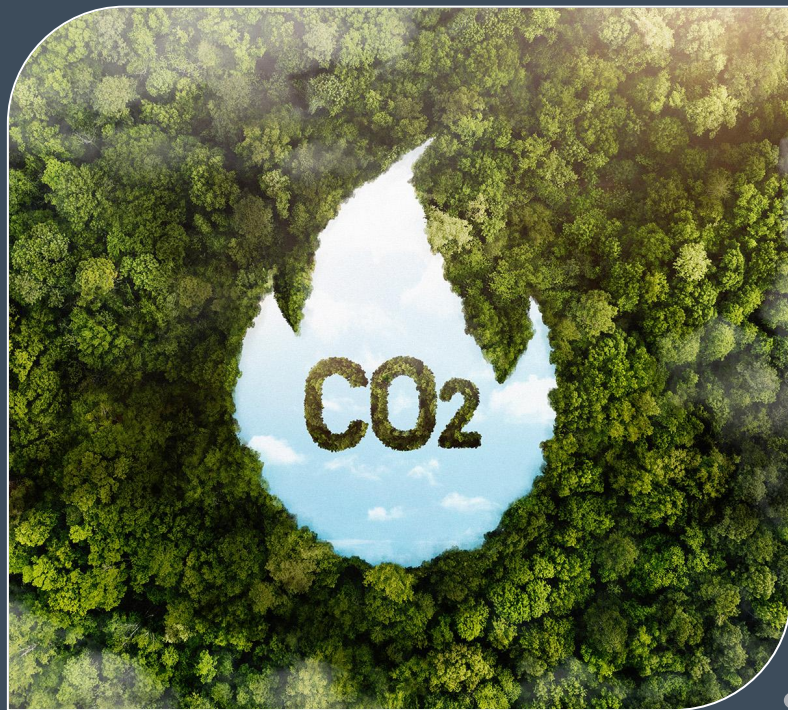
01

Introduction



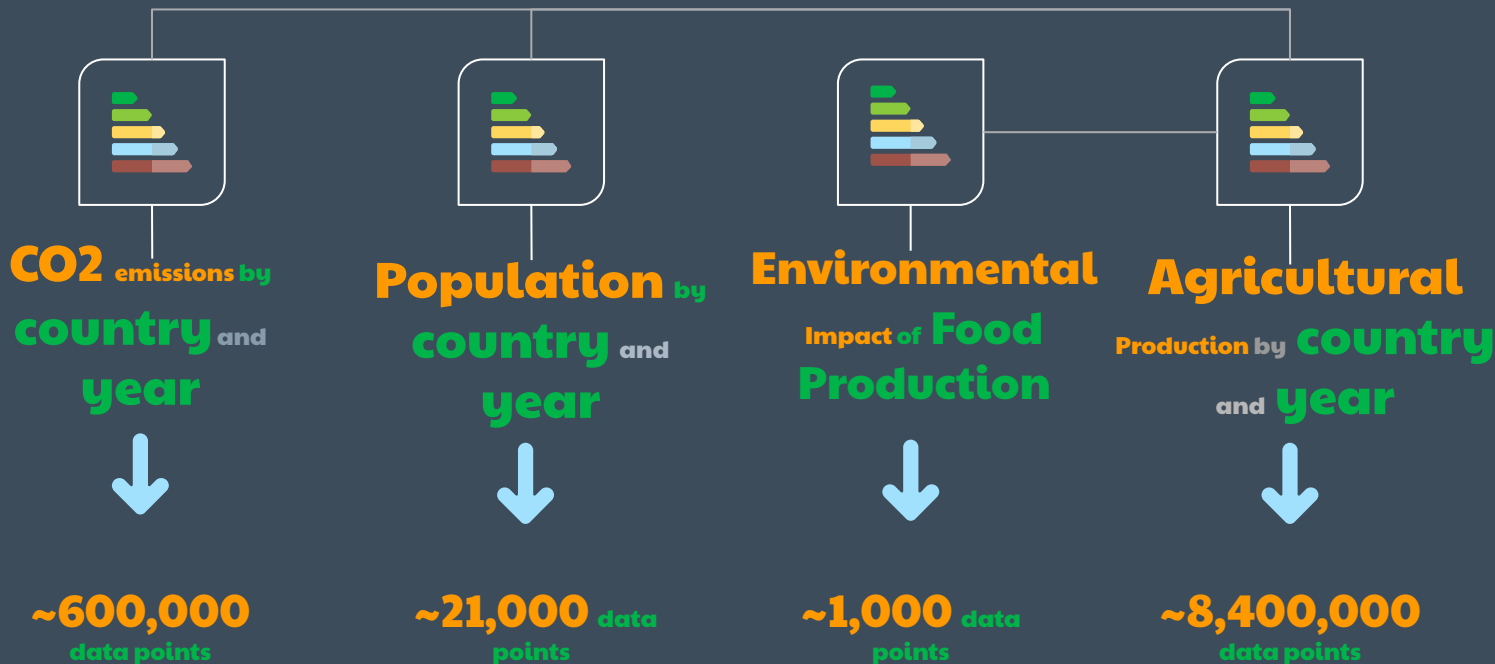


A Picture of the Analysis





Shape of the Raw Data





ETL

Extraction

Kaggle.com

-CO2 Emissions by countries by year

- Each entry (row) by country and year
- 1750 to 2020 was covered
- ~60,000 rows of data with 10 columns

-Agricultural production by country and year

- Each entry (row) by country, product, and Element (harvest/yield/production)
- 1961 to 2021 was covered
- ~80,000 rows of data with 105 columns

-Environmental impact of food production

- Each entry (row) by higher level edible agricultural product
- 43 high-level categories with 23 columns

World Bank

-Country Population by year

- Each entry (row) by country and year
- 2000 to 2021 was covered
- ~4200 rows with 5 columns





ETL

Transform

Goals

- Set reasonable boundaries on data
- Unify the data under common measurements and categories
- Create a flat file of all relevant data for the machine learning model

Known Issues to Resolve

- Inconsistency in defining countries due to political sensitivities
- Missing population of countries for some years (most commonly in overseas possessions)
- Food production was product specific while CO2 production was at high-level categories
- New countries emerged in the time of interest and one country ceased to exist
- Data was missing for unknown reasons
- No pollution data on several products (notably farmed seafood and goat products)

Issues that Emerged

- 'Production' data was discovered to be, to some extent, based on exports including re-exports (e.g. bananas from Poland)
- Some data was probably self-report leading to questionable data (China, North Korea)





ETL

Transform

Resolutions of Issues

- Data was restricted to the years 2000 to 2020
- Variables were dropped that were not specifically needed to address the questions
- Each country was considered unique for its time period and the data as a whole even if it emerged from another country
- Categorical data was collapsed as little as possible
 - Overseas possessions and disputed territories were kept separate as much as possible
 - Agricultural products were collapsed into high-level categories for CO2 emissions
- The original source of population data was located and missing data was added
- The questionable data was treated as valid
- Missing data was treated as '0'
- Products with no CO2 data were not used in the analyses

Methods

- A 'translation table' was created that allowed joining the food products with the food categories by identifying which products fit into respective categories
- Country code IDs were added to tables to reduce issues of naming differences
- Most data were transformed in Excel
- Joining occurred in a SQL database
- Aggregating occurred in Jupyter





Creating a Database

www.quickdatabasediagrams.com

CO2_emission_by_countries

Country	varchar
Code	varchar
Calling_Code	int
Year	int
CO2_emission_(Tons)	int
Population	(2022)-< int
Area	int

World_Population_Data_2000-2021

Country_Name	int
Country_Code	int
2000_[YR2000]	int
2001_[YR2001]	int
2002_[YR2002]	int
2003_[YR2003]	int
2004_[YR2004]	int
2005_[YR2005]	int
2006_[YR2006]	int
2007_[YR2007]	int
2008_[YR2008]	int
2009_[YR2009]	int
2010_[YR2010]	int
2011_[YR2011]	int
2012_[YR2012]	int
2013_[YR2013]	int
2014_[YR2014]	int
2015_[YR2015]	int
2016_[YR2016]	int
2017_[YR2017]	int
2018_[YR2018]	int
2019_[YR2019]	int
2020_[YR2020]	int
2021_[YR2021]	int

Production_Crops_Livestock_E_All_Data

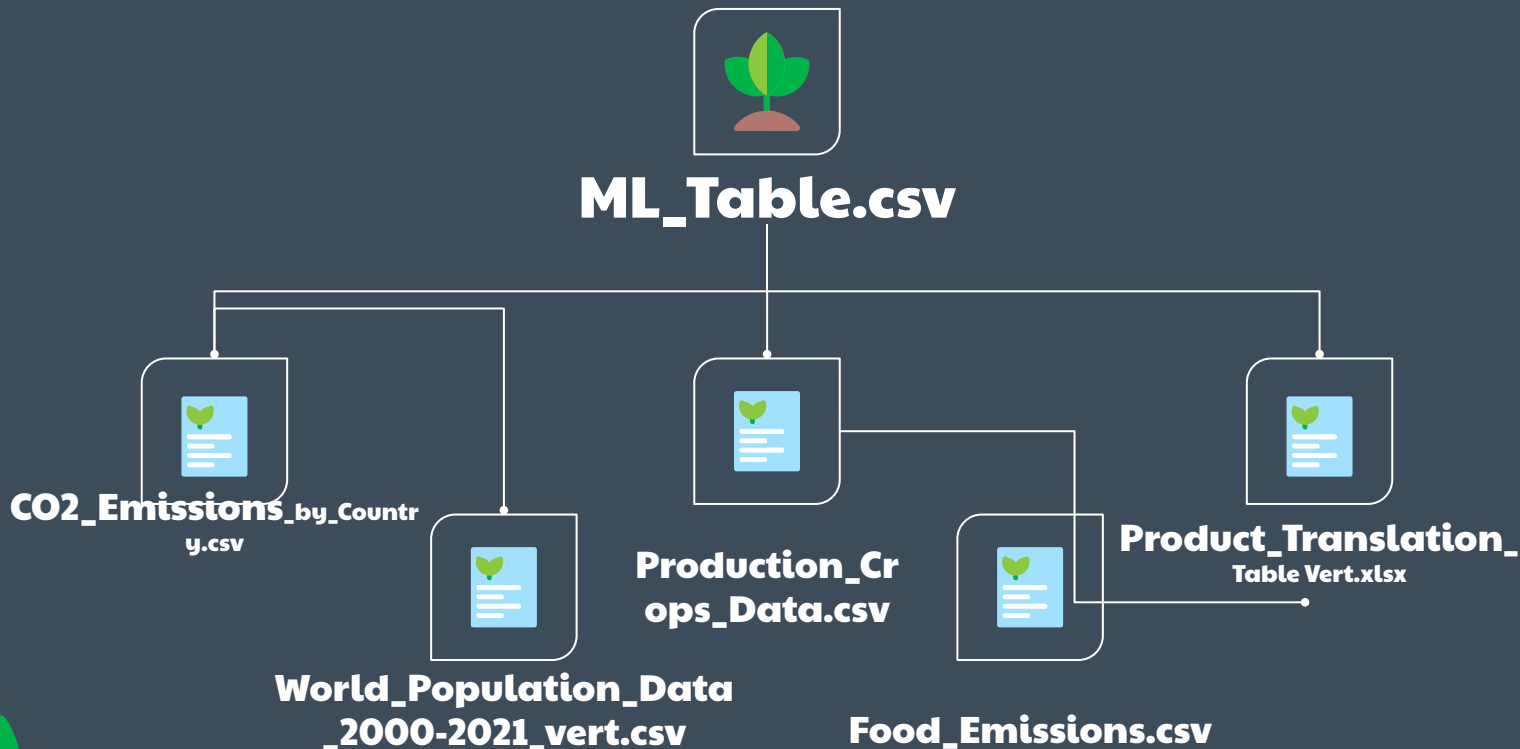
Area[country]	varchar
Item_Code_(CPC)	varchar
Item	varchar
Element_Code	int
Element	varchar
Unit	varchar
Y2000	int
Y2001	int
Y2002	int
Y2003	int
Y2004	int
Y2005	int
Y2006	int
Y2007	int
Y2008	int
Y2009	int
Y2010	int
Y2011	int
Y2012	int
Y2013	int
Y2014	int
Y2015	int
Y2016	int
Y2017	int
Y2018	int
Y2019	int
Y2020	int
Y2021	int

Food_emissions

Food_product	int
Land_use_change	int
Animal_Feed	int
Farm	int
Processing	int
Transport	int
Packging	int
Retail	int
Total_emissions	int
Eutrophying_emissions_per_1000kcal_(gPOâ„eq_per_1000kcal)	int
Eutrophying_emissions_per_kilogram_(gPOâ„eq_per_kilogram)	int
Eutrophying_emissions_per_100g_protein_(gPOâ„eq_per_100_grams_protein)	int
Freshwater_withdrawals_per_1000kcal_(liters_per_1000kcal)	int
Freshwater_withdrawals_per_100g_protein_(liters_per_100g_protein)	int
Freshwater_withdrawals_per_kilogram_(liters_per_kilogram)	int
Greenhouse_gas_emissions_per_1000kcal_(kgCOâ„eq_per_1000kcal)	int
Greenhouse_gas_emissions_per_100g_protein_(kgCOâ„eq_per_100g_protein)	int
Land_use_per_1000kcal_(mÂ²_per_1000kcal)	int
Land_use_per_kilogram	(mÂ²_per_kilogram)
Land_use_per_100g_protein_(mÂ²_per_100g_protein)	int
Scarcity-weighted_water_use_per_kilogram_(liters_per_kilogram)	int
Scarcity-weighted_water_use_per_100g_protein_(liters_per_100g_protein)	int
Scarcity-weighted_water_use_per_1000kcal_(liters_per_1000_kilocalories)	int



Plugging in the data





SQL Table Code



```
CREATE TABLE CO2_emission_by_countries (  
  Country_Code int NOT Null,  
  country varchar NOT NULL,  
  Year_ET int NOT NULL,  
  CO2_emissions_tonnes real NOT NULL  
  PRIMARY KEY (Country_Code, Year_ET)  
);
```



```
CREATE TABLE World_Pop_Data (  
  Country_Code int NOT NULL,  
  Country_Name varchar NOT NULL,  
  Year_Pop int NOT NULL,  
  Population real NOT NULL  
  PRIMARY KEY (Country_Code, Year_Pop)
```

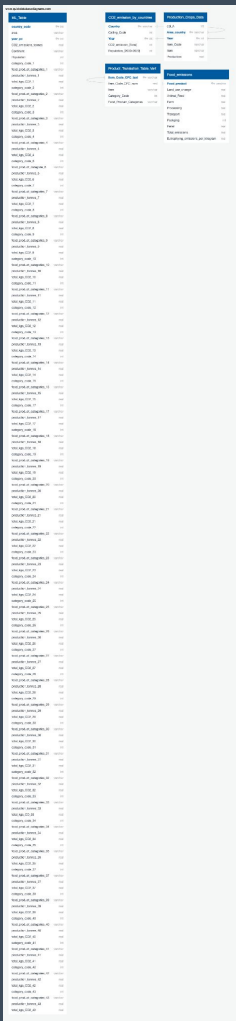


```
CREATE TABLE Production_Crops_Data (  
  Country_Code int NOT Null,  
  area varchar NOT NULL,  
  Year_PC int NOT Null,  
  item_code_PC real NOT NULL,  
  item varchar NOT NULL,  
  Unit varchar NOT NULL,  
  Production real NOT NULL  
  PRIMARY KEY ( PRIMARY KEY  
(Country_Code, Year_PC, category_code)  
);
```



```
CREATE TABLE Food_emissions (  
  Category_Code int NOT NULL,  
  Food_product varchar NOT NULL,  
  land_use_change real NOT NULL,  
  Animal_Feed real NOT NULL,  
  Farm real NOT NULL,  
  Processing real NOT NULL,  
  Transport real NOT NULL,  
  Packaging real NOT NULL,  
  Retail real NOT NULL,  
  Total_emissions real NOT NULL,  
  emissions_KGs_per_tonne real NOT NULL,  
  PRIMARY KEY (category_code)
```





```
CREATE TABLE ML Table (
    country_code int NOT NULL, --PK
    area varchar NOT NULL,
    year_pc int NOT NULL, --PK
    CO2_emissions_tonnes real NOT NULL,
    Continent varchar NOT NULL,
    Population int NOT NULL,
```

PRIMARY K

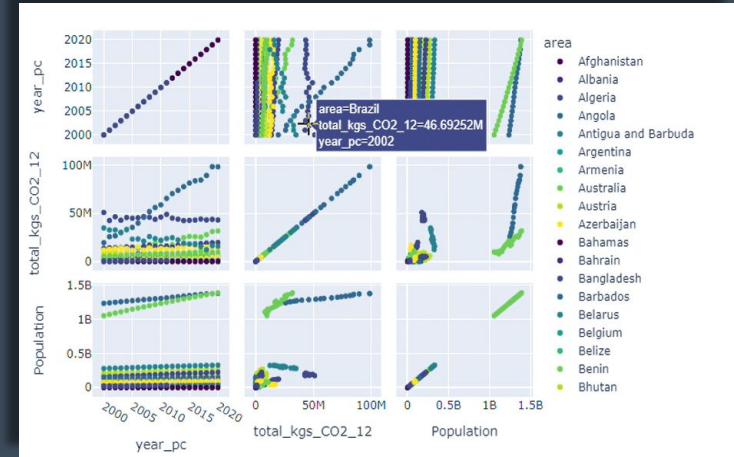
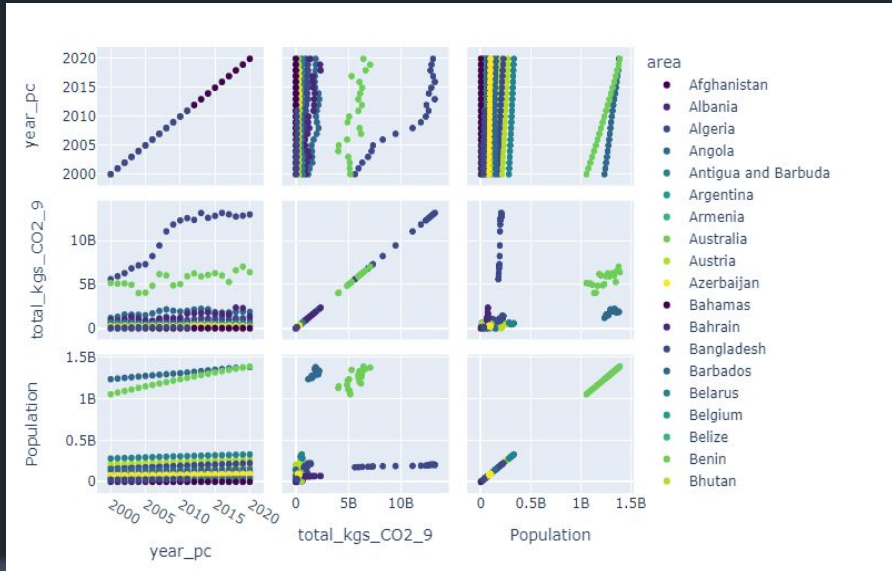
02

EDA

Exploratory Data Analysis

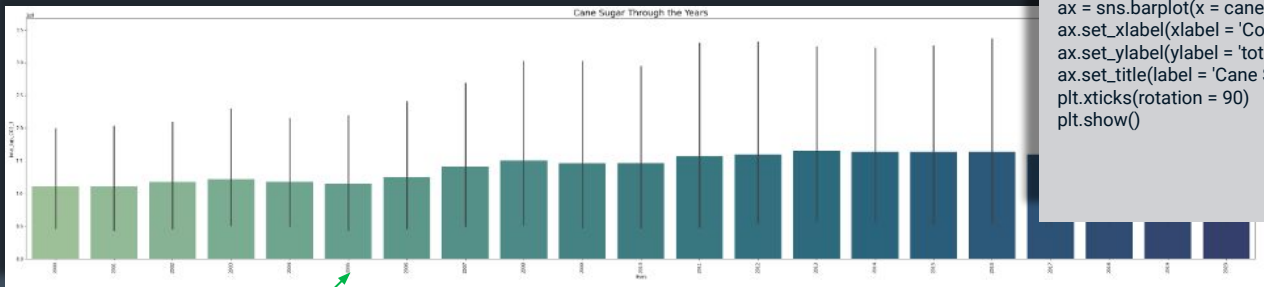


Dynamic Matrix based on Food Product



```
fig = px.scatter_matrix(cane_sugar, dimensions=["year_pc", "total_kgs_CO2_9", "Population"],
color="area", color_discrete_sequence =px.colors.sequential.Viridis)
fig.show()
```


Other Visual Tools Used in Breakdown

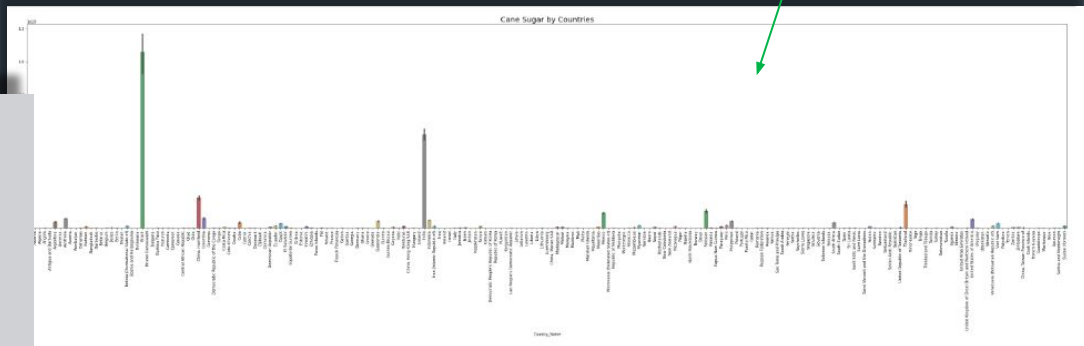


Cane_Sugar by Year

```
plt.rcParams['figure.figsize'] = (50, 10)
ax = sns.barplot(x = cane_sugar['year_pc'], y =
cane_sugar['total_kgs_CO2_9'], palette = 'crest')
ax.set_xlabel(xlabel = 'Years', fontsize = 10)
ax.set_ylabel(ylabel = 'total_kgs_CO2_9', fontsize = 10)
ax.set_title(label = 'Cane Sugar Through the Years', fontsize = 20)
plt.xticks(rotation = 90)
plt.show()
```

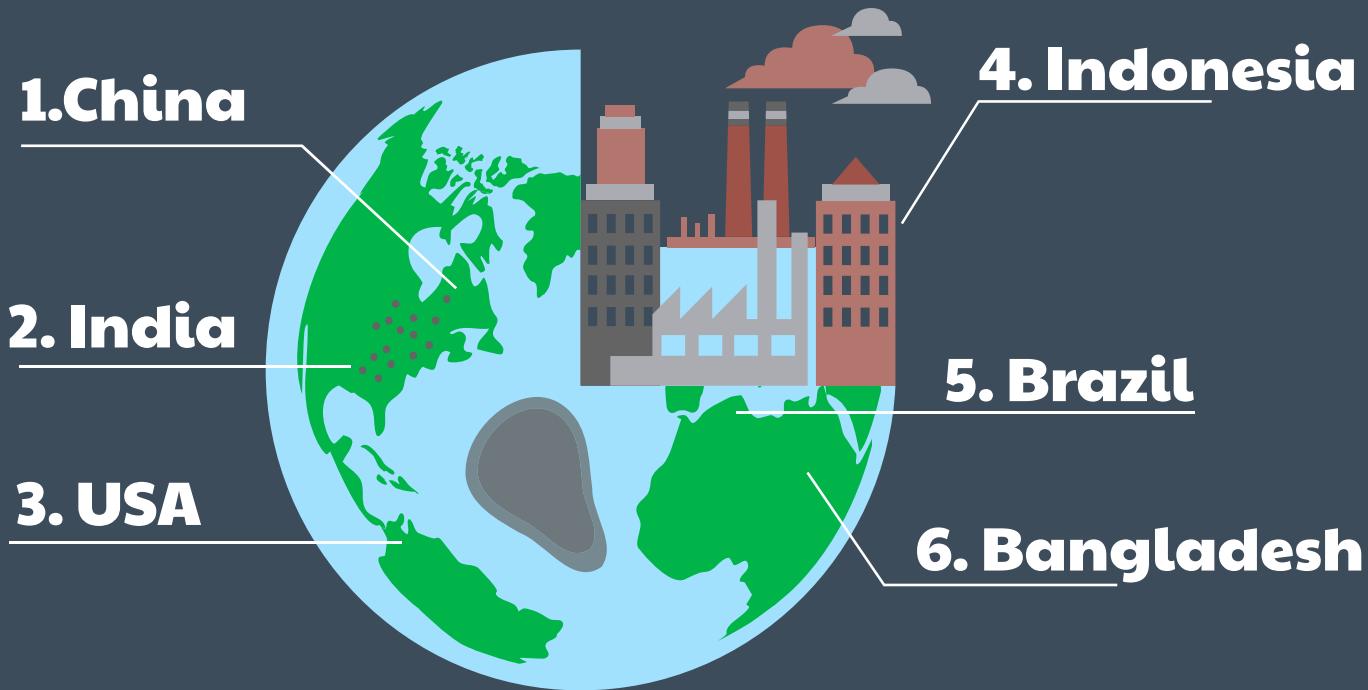
Cane_Sugar by Year

```
plt.rcParams['figure.figsize'] = (50, 10)
ax = sns.barplot(x = cane_sugar['area'], y = cane_sugar['total_kgs_CO2_9'], palette = 'deep')
ax.set_xlabel(xlabel = 'Country_Name', fontsize = 10)
ax.set_ylabel(ylabel = 'total_kgs_CO2_1', fontsize = 10)
ax.set_title(label = 'Cane Sugar by Countries', fontsize = 20)
plt.xticks(rotation = 90)
plt.show()
```





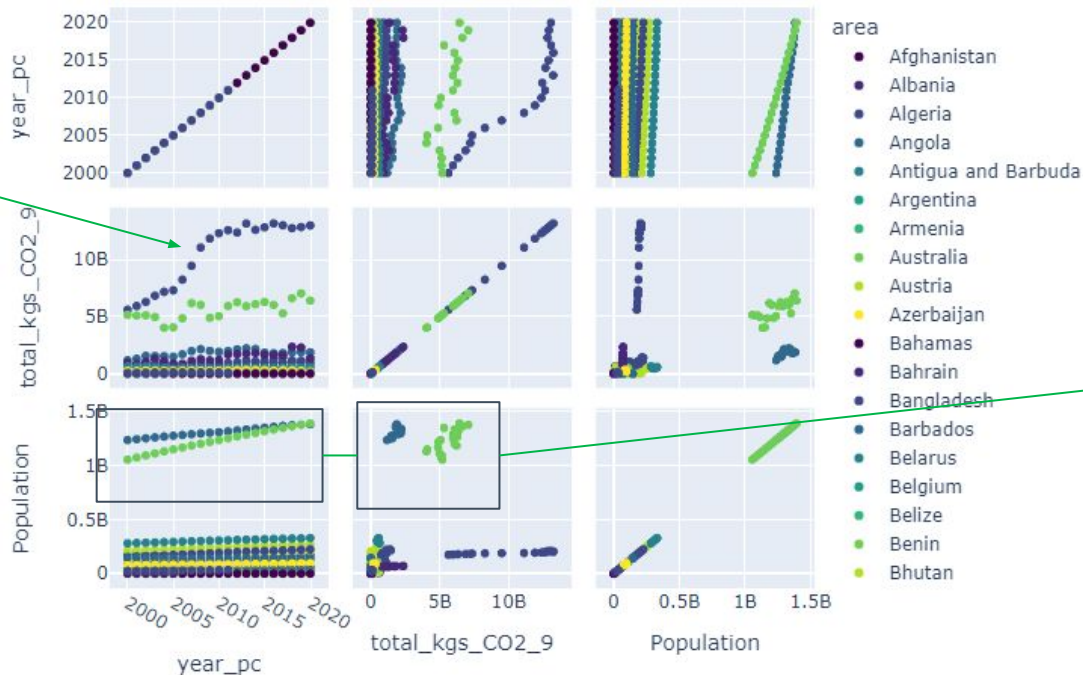
World Population





Matrix

Brazil - 13.1B
kgs CO2
produced from
the production of
cane sugar

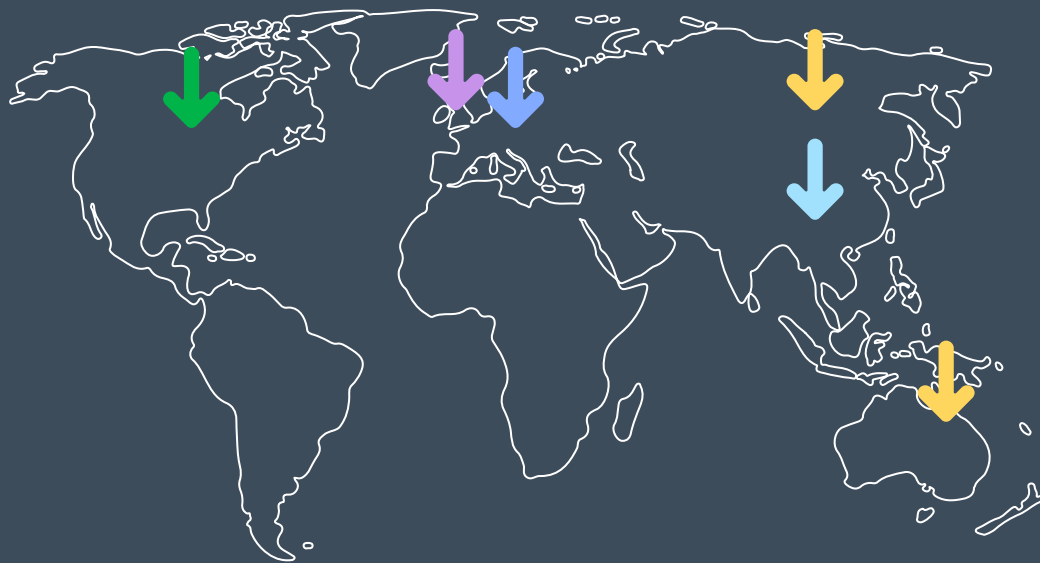


Population
Country
populations stay
clustered
according to
normal
population trends
but have no
direct correlation
to amount of
production
emissions

China - Blue
India - Green



Countries with highest CO2 Production



USA



Russia



Germany



China



UK/Northern
Ireland





Matrix

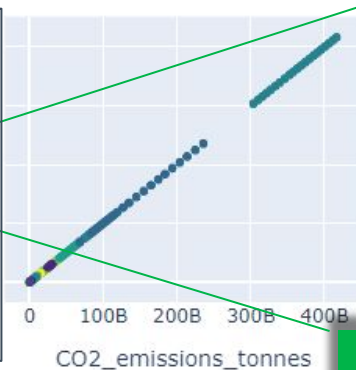
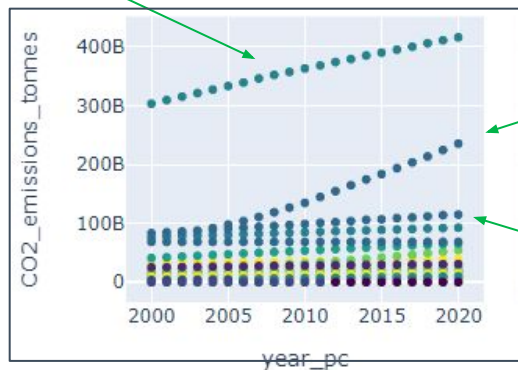
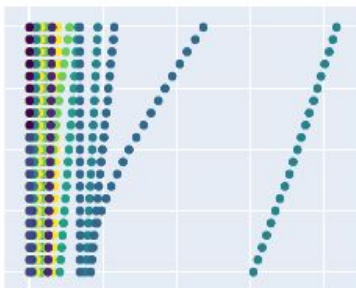
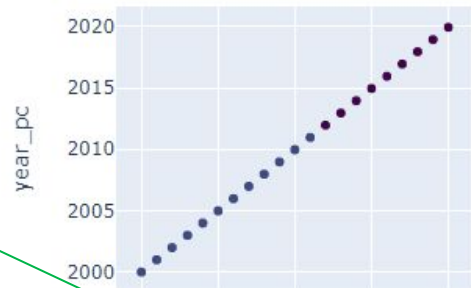
USA

China

2020:(Tonnes)

1. USA 417B
2. China 236B
3. Russia 115B
4. Germany 92.64B
5. UK/IR 68.5B

Russia



- United Kingdom of Great Britain and Northern Ireland
- United States of America
- Uruguay
- Uzbekistan
- Vanuatu
- Venezuela (Bolivarian Republic of)
- Viet Nam
- Palestine
- Yemen
- Zambia
- Zimbabwe
- China, Taiwan Province of
- Cook Islands
- French Guyana
- Guadeloupe
- Martinique
- Niue
- Reunion
- Serbia and Montenegro
- Sudan (former)

03

Machine Learning



Comparing Models

Extra Trees Regressor

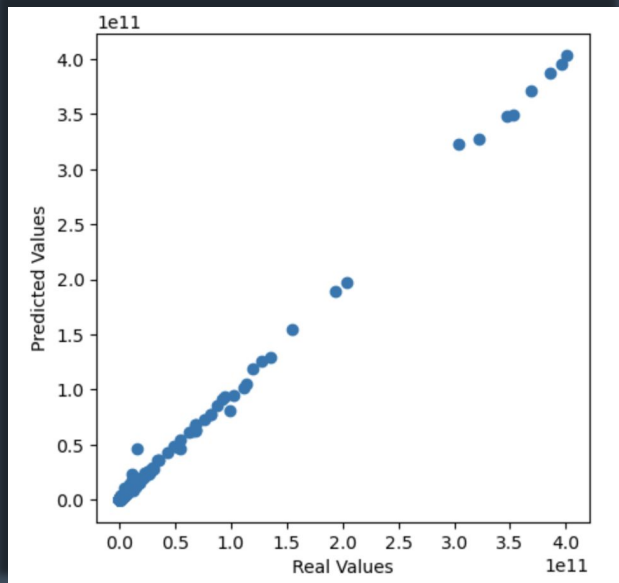
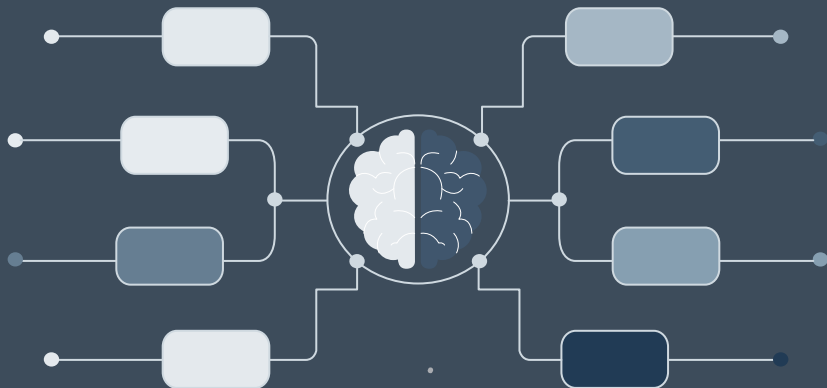
Mean Absolute Error: 335260395.91
Mean Squared Error: 2.560554705606461e+18
R-squared scores: 1.0

XG Boost Regressor

Mean Absolute Error: 973339725.21
Mean Squared Error: 1.5453724753182904e+19
R-squared scores: 0.99

Random Forest Regressor

Mean Absolute Error: 441338770.84
Mean Squared Error: 9.226496706567215e+18
R-squared scores: 0.99



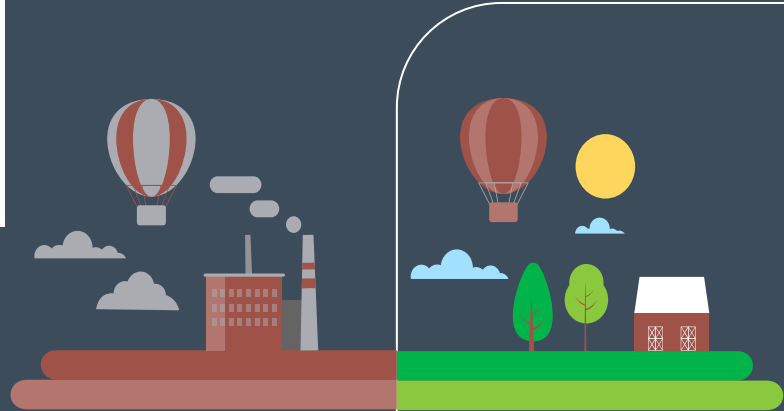
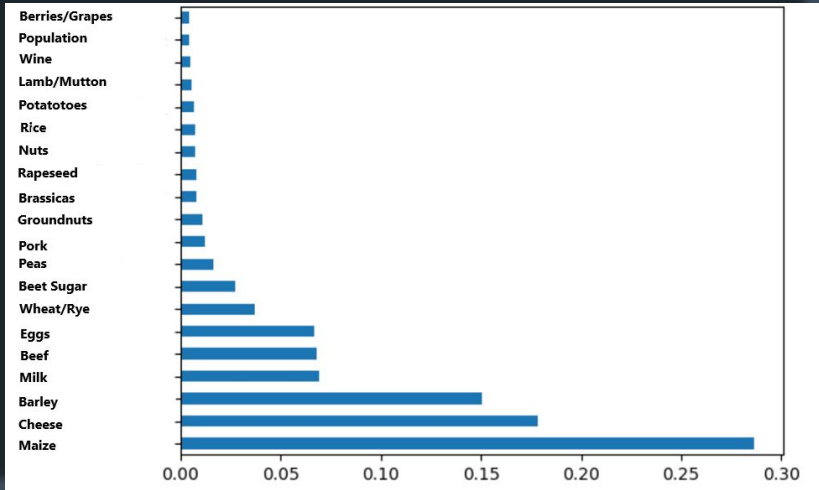
Tuning the Model

New Metrics

Mean Absolute Error: 287839779.42

Mean Squared Error: 1.527854974380916e+18

R-squared scores: 1.0



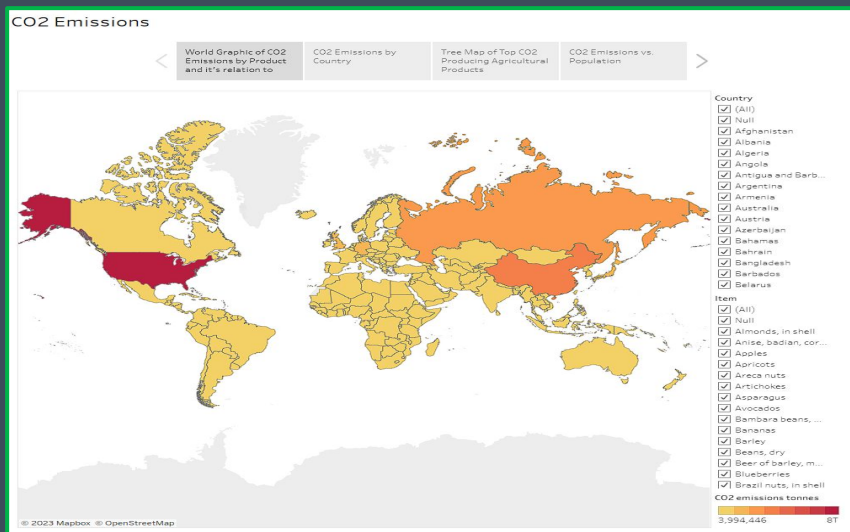
04

Findings





Tableau Dashboard





Food Products with highest CO2 Production

Maize(Corn)

18,467,107,546
Tonnes

Rice

14,367,247,693
Tonnes

Sugar Cane

34,684,911,578
Tonnes

Wheat

14,130,705,994
Tonnes

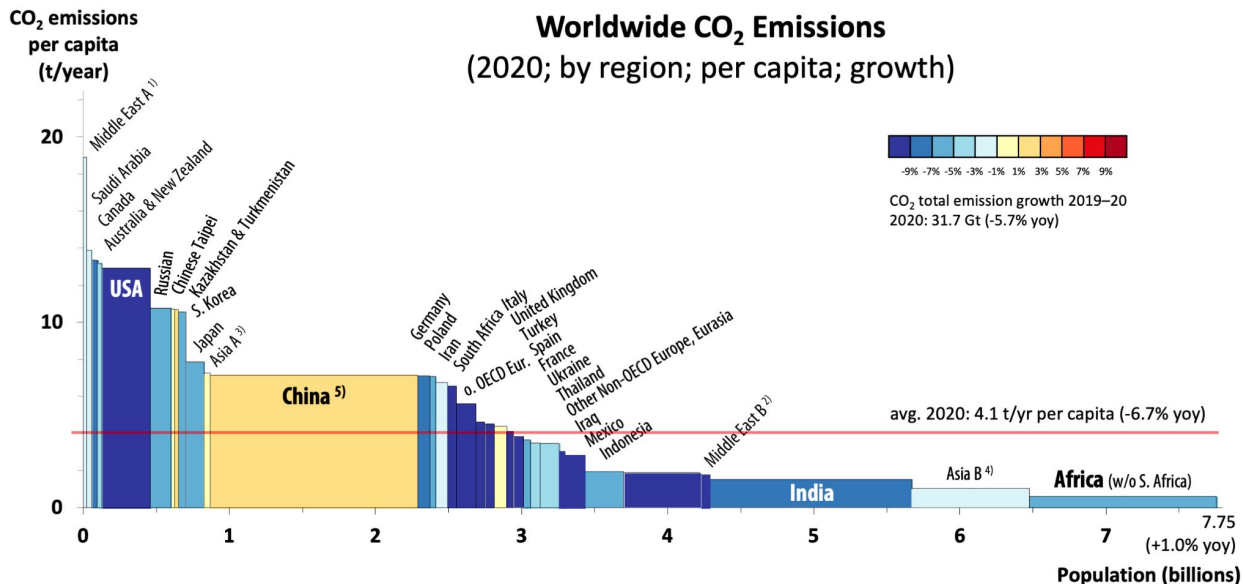


27,630,468,397,999.0

The **BIG** number



Note for Future Analysis



Notes:

CO₂ emissions from fuel combustion only; no other greenhouse gases or natural sources; aviation and marine bunkers not shown as territory but included in average and totals.

¹⁾ Middle East A: Bahrain, Oman, Kuwait, Qatar, United Arab Emirates

²⁾ Middle East B: Israel, Jordan, Lebanon, Syrian Arab Republic, Yemen

³⁾ Asia A: Brunei Darussalam, Malaysia, Mongolia, Singapore

⁴⁾ Asia B: Asia without Asia A, China, India, Thailand, Chinese Taipei, Indonesia, S. Korea, Japan

⁵⁾ China: People's Rep. of China, Hong Kong

Attribution:

Based on IEA (2022), "Greenhouse gas emissions from energy", www.iea.org/statistics. All rights reserved; as modified by Thomas Schulz, AQAL Capital GmbH.

This map is without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

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Version: 12-Nov-2022 by Thomas Schulz, AQAL Capital GmbH

blog commentary: <https://aqalcapital.com/2020-worldwide-co2-emissions>





Noteworthy further research directions should someone widen the scope of the project:

Study other greenhouse gases in the light of their effects on global warming.

Fun fact: methane—CH₄—is 20X more powerful than CO₂ in furthering global warming.

This has many implications for the rise in Earth's mean temperature, especially in the short term—accelerating us toward a “tipping point.”

So why are we so interested in CO₂?

Because, even so, methane is only 25% of global warming. CO₂ is 74%—almost 3X as much.





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Thank You !

Questions?

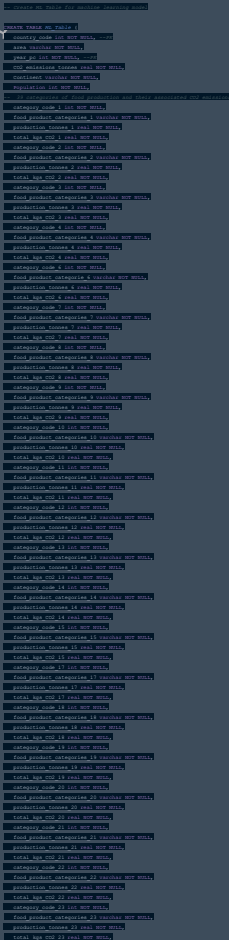




Resources

- Database 1 CO2 Emissions by Country | Kaggle
- Database 2 Environmental Impact of Food | Kaggle
- Database 3 Population | WorldBank
- Database 4 Emissions from Food | Environmental Impact of Food| Kaggle



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