Investigating Global Emissions: National Footprint Accounts Dataset (1961-2013)

How can data on resource consumption be utilized to analyze the dynamics of global emissions, leading to evidence-based strategies for mitigating climate change?

Introduction

The National Footprint Accounts provide a comprehensive dataset that tracks the ecological resource use and resource capacity of nations from 1961 onwards. By analyzing this data, we hope to uncover patterns and trends that could shed light on how human activities have influenced global emissions over time.

The insights derived from this analysis could provide valuable information for policymakers, researchers, and anyone interested in reducing global emissions. By understanding the past and present, we can make informed decisions about the future and contribute to the global efforts in combating climate change.

In [2]:
```
#importing libraries to help us in probabilistic programming, clustering, performing t

import numpy as np
```

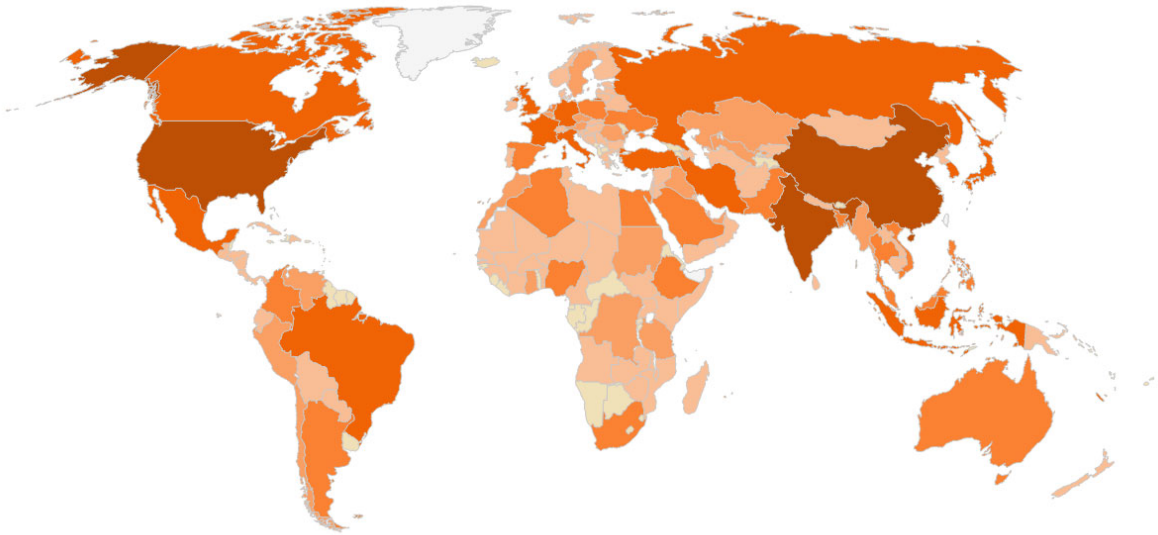
```
np.random.seed(0)
import pymc3 as pm
from sklearn.cluster import KMeans
import arviz as az
import pandas as pd
from scipy import stats
import math
import matplotlib.pyplot as plt
%matplotlib inline
```

National Footprint Accounts (NFA) Dataset

Global Footprint Network. https://www.footprintnetwork.org/resources/data/.

The National Footprint Accounts (NFA) dataset is a comprehensive resource that tracks the ecological resource use and resource capacity of nations over time[1]. This dataset is the most widely used for Ecological Footprint (EF) analysis worldwide[3].

Total Ecological Footprint across the world measuring how much demand human consumption places on the biosphere:



The NFA dataset is based on approximately **15,000 data points per country per year**[1]. It calculates the Footprints of more than **200 countries, territories, and regions from 1961 to the present**[1]. The calculations in the NFA are based on United Nations or UN-affiliated datasets, including those published by the Food and Agriculture Organization, United Nations Commodity Trade Statistics Database, and the UN Statistics Division, as well as the International Energy Agency[1].

The dataset measures the amount of biologically productive land and sea area available to provide the resources a population consumes and to absorb its wastes, given current technology and management practices[1]. It also tracks how much biologically productive area it takes to provide for all the competing demands of people[1].

In [9]:
```
df = pd.read_csv("NFA 2017 Edition.csv")
pd.set_option('display.max_colwidth', None)
```

```
C:\Users\Abhinav Uni\AppData\Local\Temp\ipykernel_2652\1618232535.py:1: DtypeWarning:
Columns (11) have mixed types. Specify dtype option on import or set low_memory=Fals
e.
  df = pd.read_csv("NFA 2017 Edition.csv")
```

In [10]:
```
df
```

Out[10]:

	country	year	country_code	record	crop_land	grazing_land	forest_land
0	Armenia	1992	1	AreaPerCap	0.140020	0.199159	0.097000
1	Armenia	1992	1	AreaTotHA	483000.000000	687000.000000	334600.000000
2	Armenia	1992	1	BiocapPerCap	0.276531	0.134892	0.083839
3	Armenia	1992	1	BiocapTotGHA	953895.034844	465308.532841	289203.573356
4	Armenia	1992	1	EFConsPerCap	0.477412	0.175880	0.000001
...	...	...	...	...	...	...	...
99451	Saint Vincent and Grenadines	2013	191	EFExportsTotGHA	NaN	NaN	NaN
99452	Saint Vincent and Grenadines	2013	191	EFImportsPerCap	NaN	NaN	NaN
99453	Saint Vincent and Grenadines	2013	191	EFImportsTotGHA	NaN	NaN	NaN
99454	Saint Vincent and Grenadines	2013	191	EFProdPerCap	NaN	NaN	NaN
99455	Saint Vincent and Grenadines	2013	191	EFProdTotGHA	NaN	NaN	NaN

99456 rows × 12 columns

Data Cleaning: Handling Null/Missing Values

During our initial data exploration, we discovered that some countries did not have recorded values for land or carbon emissions. This could be due to a lack of data collection in these regions, or it could indicate that these countries did not emit any carbon, which seems highly unlikely given the global nature of carbon emissions.

In [11]:
```
missing_values = df.isnull().sum()
missing_values
```

Out[11]:
```
country              0
year                 0
country_code         0
record               0
crop_land        18216
grazing_land     18216
forest_land      18216
fishing_ground   18216
built_up_land    18216
carbon           18216
total                0
QScore               0
dtype: int64
```

To ensure the accuracy and reliability of our analysis, we made the decision to exclude these records from our dataset. This step is crucial in optimizing our analysis as it helps to prevent potential skewing of our results due to incomplete or inaccurate data.

By doing so, we are focusing our analysis on more reliable and complete data, thereby enhancing the validity of our insights and conclusions. This rigorous approach to data cleaning underscores our commitment to delivering a robust and meaningful analysis of global emissions trends.

In [12]:
```
# drop the rows that has NaN values

df = df.dropna()
df
```

Out[12]:

	country	year	country_code	record	crop_land	grazing_land	forest_land	t
0	Armenia	1992	1	AreaPerCap	0.140020	0.199159	0.097000	
1	Armenia	1992	1	AreaTotHA	483000.000000	687000.000000	334600.000000	
2	Armenia	1992	1	BiocapPerCap	0.276531	0.134892	0.083839	
3	Armenia	1992	1	BiocapTotGHA	953895.034844	465308.532841	289203.573356	
4	Armenia	1992	1	EFConsPerCap	0.477412	0.175880	0.000001	
...	...	...	...	...	...	...	...	
99355	Vanuatu	2013	155	EFExportsTotGHA	26579.249964	661.594604	6037.791864	
99356	Vanuatu	2013	155	EFImportsPerCap	0.103218	0.040232	0.039395	
99357	Vanuatu	2013	155	EFImportsTotGHA	26131.183585	10185.274161	9973.483797	
99358	Vanuatu	2013	155	EFProdPerCap	0.958186	0.075730	0.245805	
99359	Vanuatu	2013	155	EFProdTotGHA	242579.122476	19172.136759	62229.145562	

81240 rows × 12 columns

country: The name of the country to which the data row pertains.

year: The calendar year for which the data is recorded.

country_code: A unique numerical identifier assigned to each country.

record: The type of data record, which could indicate whether the data is per capita, total area, or another metric.

crop_land: The area of land used for crop production within the country, typically measured in hectares or global hectares.

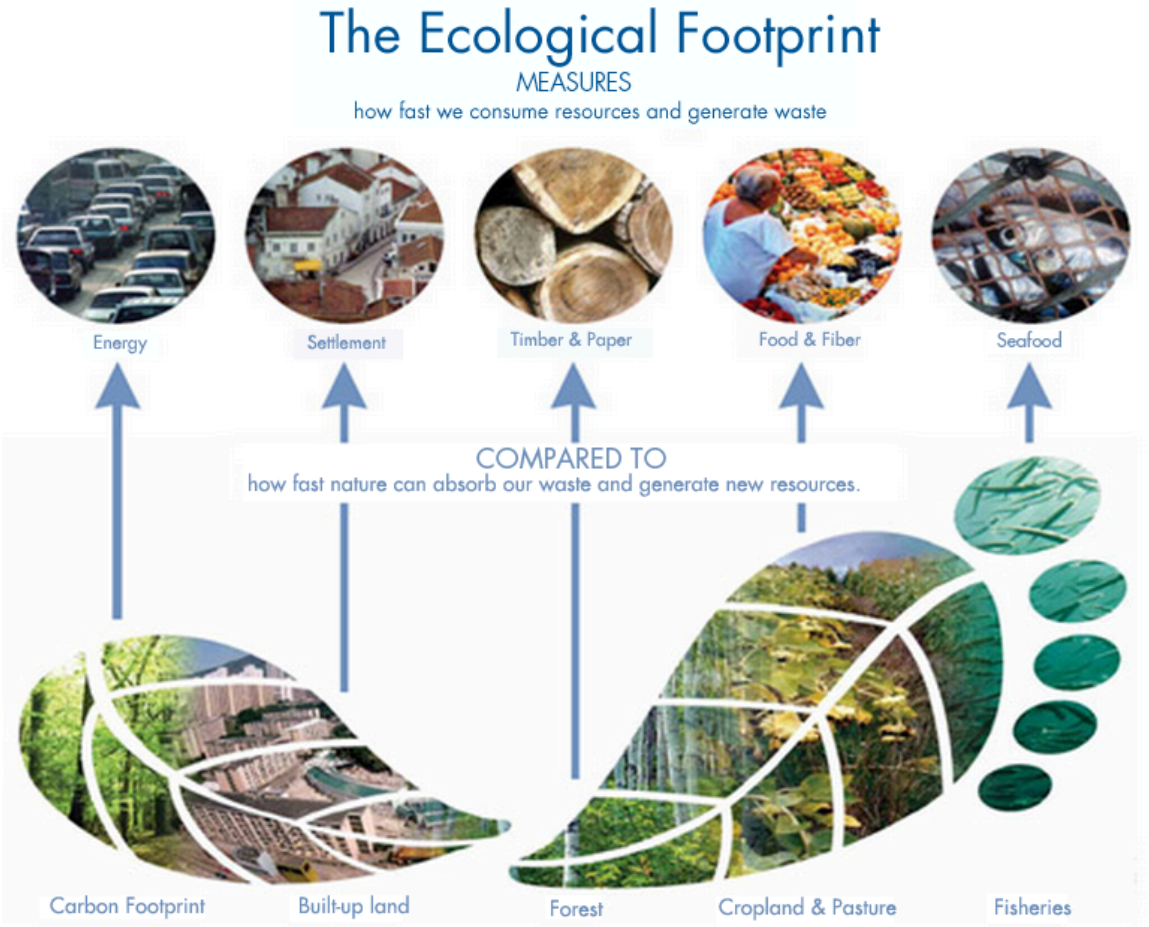
grazing_land: The area of land designated for grazing livestock within the country.

forest_land: The area covered by forests within the country, reflecting the extent of forested land used for various purposes.

fishing_ground: The water area used for fishing, indicating the country's dependency on aquatic resources.

built_up_land: The area occupied by human infrastructure like buildings, roads, and other constructions.

carbon: A representation of the carbon footprint, indicating the amount of forest land required to sequester the carbon dioxide emissions of the country.



In [5]:
```
df.head(20)
```

	country	year	country_code	record	crop_land	grazing_land	forest_land	fishi
0	Armenia	1992	1	AreaPerCap	1.400203e-01	0.199159	0.097000	
1	Armenia	1992	1	AreaTotHA	4.830000e+05	687000.000000	334600.000000	127(
2	Armenia	1992	1	BiocapPerCap	2.765314e-01	0.134892	0.083839	
3	Armenia	1992	1	BiocapTotGHA	9.538950e+05	465308.532841	289203.573356	472
4	Armenia	1992	1	EFConsPerCap	4.774125e-01	0.175880	0.000001	
5	Armenia	1992	1	EFConsTotGHA	1.646834e+06	606697.374570	4.328034	141
6	Armenia	1992	1	EFExportsPerCap	1.535785e-03	0.002071	0.000000	
7	Armenia	1992	1	EFExportsTotGHA	5.297689e+03	7143.838664	0.000000	15
8	Armenia	1992	1	EFImportsPerCap	2.024169e-01	0.056342	0.000001	
9	Armenia	1992	1	EFImportsTotGHA	6.982370e+05	194350.774605	4.328034	113
10	Armenia	1992	1	EFProdPerCap	2.765314e-01	0.121609	0.000000	
11	Armenia	1992	1	EFProdTotGHA	9.538950e+05	419490.438629	0.000000	43
12	Armenia	1993	1	AreaPerCap	1.463051e-01	0.204174	0.099238	
13	Armenia	1993	1	AreaTotHA	4.930000e+05	688000.000000	334400.000000	127(
14	Armenia	1993						