Technological Institute of the Philippines	**Quezon City - Computer Engineering**
Course Code:	CPE 311
Code Title:	Computational Thinking with Python
Summer	2024
Hands-on Activity No. 10.1	Data Analysis with Python
Name	Sumilang, Kenneth
Section	CPE32S1
Date Performed:	7/10/24
Date Submitted:	7/10/24
Instructor:	Engr. Roman M. Richard

Goal:

Perform descriptive and correlation analysis to analyze the dataset. Interpret the results of descriptive and correlation analysis.

Process

1. Gather a dataset regarding your identified problem for the ASEAN Data Science Explorer. Make sure that the dataset includes multiple variables.

```
For my datasets, I have chosen the HDI, ASEAN GDP per Capita, ASEAN
Energy Consumption, Food Production, CO2 Emissions and ASEAN Forest
Area datasets. I plan to aggregate these datasets together and
explore if there are correlations between a combination of these 6
factors.
```

Hypothesis Table

	GDP Per Capita	**CO2 Emission**	**Energy Used**	**Food Production Index**	**Forest Area**	**HDI**
GDP Per Capita	N/A	+	+	+	-	+
CO2 Emission	+	N/A	+	o	-	o
Energy Used	+	+	N/A	+	-	+
Food Production Index	+	o	+	N/A	-	+
Forest Area	-	-	-	-	N/A	o

	GDP Per Capita	CO2 Emission	Energy Used	Food Production Index	Forest Area	HDI
HDI	+	o	+	+	o	N/A

Legend:

- **+** : Positive correlation
- **-** : Negative correlation
- **o** : No correlation
- **N/A** : Not applicable

2. Load the dataset into pandas dataframe.

In [152…

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler

# Load the datasets with appropriate encoding
gdp_per_capita = pd.read_csv('GDP Per Capita.csv', encoding='ISO-8859-1')
co2_emission = pd.read_csv('co2 emission.csv', encoding='ISO-8859-1')
energy_used = pd.read_csv('energy used.csv', encoding='ISO-8859-1')
food_production_index = pd.read_csv('food production index.csv', encoding='ISO-8859-1'
forest_area = pd.read_csv('forest area.csv', encoding='ISO-8859-1')
hdi = pd.read_csv('HDI.csv', encoding='ISO-8859-1')

# Display the column names to inspect them
print("GDP Per Capita Columns:", gdp_per_capita.columns)
print("CO2 Emission Columns:", co2_emission.columns)
print("Energy Used Columns:", energy_used.columns)
print("Food Production Index Columns:", food_production_index.columns)
print("Forest Area Columns:", forest_area.columns)
print("HDI Columns:", hdi.columns)
```

```
GDP Per Capita Columns: Index(['Country ', '1960', '1961', '1962', '1963', '1964', '1
965', '1966',
       '1967', '1968', '1969', '1970', '1971', '1972', '1973', '1974', '1975',
       '1976', '1977', '1978', '1979', '1980', '1981', '1982', '1983', '1984',
       '1985', '1986', '1987', '1988', '1989', '1990', '1991', '1992', '1993',
       '1994', '1995', '1996', '1997', '1998', '1999', '2000', '2001', '2002',
       '2003', '2004', '2005', '2006', '2007', '2008', '2009', '2010', '2011',
       '2012', '2013', '2014', '2015', '2016', '2017'],
      dtype='object')
CO2 Emission Columns: Index(['Country', '1990', '1991', '1992', '1993', '1994', '199
5', '1996',
       '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
       '2006', '2007', '2008', '2009', '2010', '2011'],
      dtype='object')
Energy Used Columns: Index(['Country', '1990', '1991', '1992', '1993', '1994', '199
5', '1996',
       '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
       '2006', '2007', '2008', '2009', '2010', '2011', '2012'],
      dtype='object')
Food Production Index Columns: Index(['Country ', '1961', '1962', '1963', '1964', '19
65', '1966', '1967',
       '1968', '1969', '1970', '1971', '1972', '1973', '1974', '1975', '1976',
       '1977', '1978', '1979', '1980', '1981', '1982', '1983', '1984', '1985',
       '1986', '1987', '1988', '1989', '1990', '1991', '1992', '1993', '1994',
       '1995', '1996', '1997', '1998', '1999', '2000', '2001', '2002', '2003',
       '2004', '2005', '2006', '2007', '2008', '2009', '2010', '2011', '2012',
       '2013', '2014'],
      dtype='object')
Forest Area Columns: Index(['Country', '1990', '1991', '1992', '1993', '1994', '199
5', '1996',
       '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
       '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014',
       '2015'],
      dtype='object')
HDI Columns: Index(['Country', '2000', '2001', '2002', '2003', '2004', '2005', '200
6',
       '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
       '2016', '2017', '2018', '2019', '2020', '2021', '2022', '2023', '2024',
       'Definition', 'Data Coverage', 'Calendar Year', 'Base Year', 'Source',
       'Footnotes'],
      dtype='object')
```

3. Prepare the data by applying appropriate data preprocessing techniques.

In [153…

```python
def preprocess_dataframe(df, dataset_name):
    # Assuming the first column is the country name
    if df.columns[0] != 'Country':
        df.rename(columns={df.columns[0]: 'Country'}, inplace=True)
    year_range = [str(year) for year in range(2000, 2012)]
    columns_to_keep = ['Country'] + [year for year in year_range if year in df.columns
    df = df[columns_to_keep]

    # Handle missing values: Impute with column mean
    numeric_columns = df.select_dtypes(include=['number']).columns
    df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_c

    # Normalize the data (excluding the 'Country' column)
    scaler = StandardScaler()
```

```
    df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])

    return df
```

4. Analyze the data using descriptive analysis.

In [154…

```
#visualizing function
def plot_summary_statistics_by_country(df, value_name, title):
    plt.figure(figsize=(14, 8))
    sns.barplot(x='Country', y=value_name, data=df)
    plt.title(title)
    plt.xlabel('Country')
    plt.ylabel(value_name)
    plt.xticks(rotation=90)
    plt.show()
```

In [155…

```
gdp_per_capita = preprocess_dataframe(gdp_per_capita, "GDP Per Capita")
co2_emission = preprocess_dataframe(co2_emission, "CO2 Emission")
energy_used = preprocess_dataframe(energy_used, "Energy Used")
food_production_index = preprocess_dataframe(food_production_index, "Food Production I
forest_area = preprocess_dataframe(forest_area, "Forest Area")
hdi = preprocess_dataframe(hdi, "HDI")

# Calculate summary statistics by country
gdp_summary_by_country = gdp_per_capita.groupby('Country').describe()
gdp_summary_by_country
```

```
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:11: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_co
lumns].mean())
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:15: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:11: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_co
lumns].mean())
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:15: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:11: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_co
lumns].mean())
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:15: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:11: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_co
lumns].mean())
```

```
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:15: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:11: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_co
lumns].mean())
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:15: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:11: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, numeric_columns] = df.loc[:, numeric_columns].fillna(df.loc[:, numeric_co
lumns].mean())
C:\Users\ryzek\AppData\Local\Temp\ipykernel_34428\3218539282.py:15: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  df.iloc[:, 1:] = scaler.fit_transform(df.iloc[:, 1:])
```

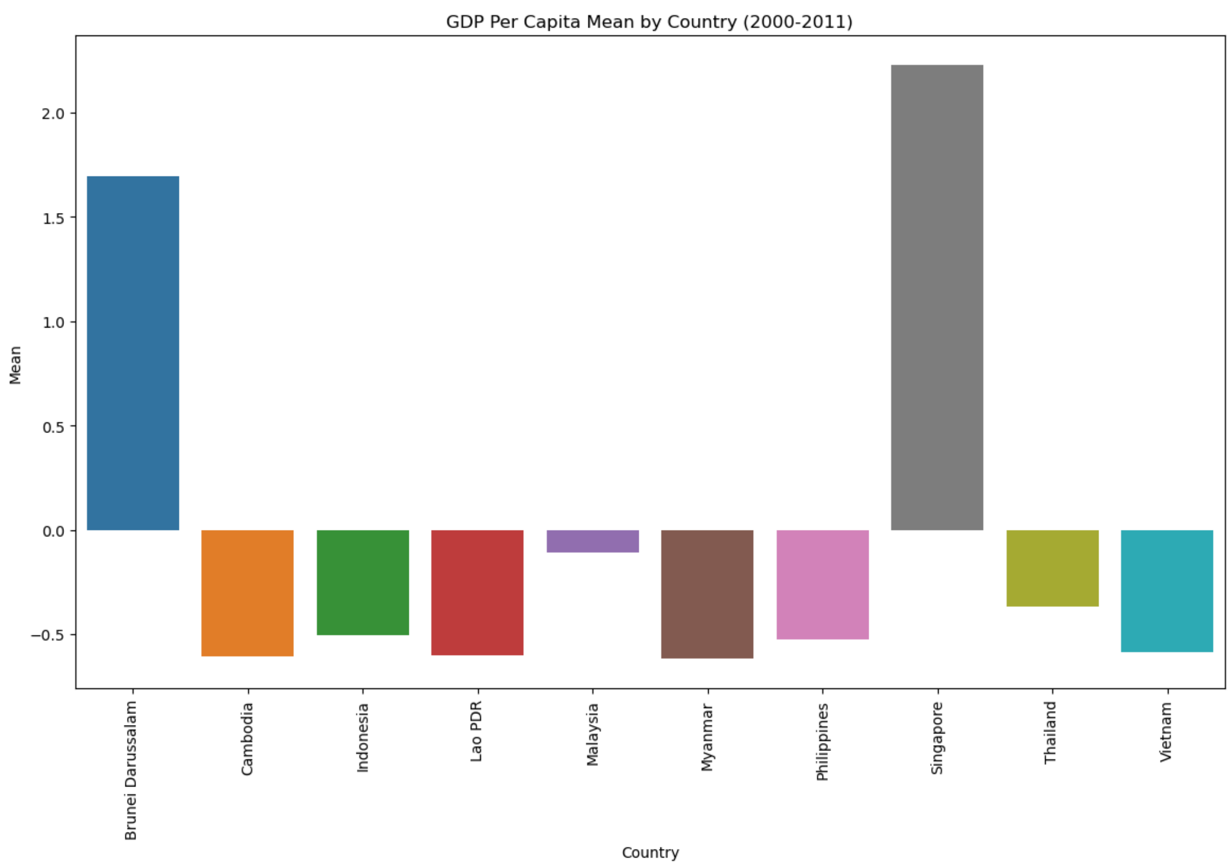
Out[155]:

	2000									
	count	mean	std	min	25%	50%	75%	max	count	
Country										
Brunei Darussalam	1.0	1.597592	NaN	1.597592	1.597592	1.597592	1.597592	1.597592	1.0	1.6(
Cambodia	1.0	-0.593021	NaN	-0.593021	-0.593021	-0.593021	-0.593021	-0.593021	1.0	-0.5!
Indonesia	1.0	-0.527468	NaN	-0.527468	-0.527468	-0.527468	-0.527468	-0.527468	1.0	-0.5:
Lao PDR	1.0	-0.590032	NaN	-0.590032	-0.590032	-0.590032	-0.590032	-0.590032	1.0	-0.5!
Malaysia	1.0	-0.129794	NaN	-0.129794	-0.129794	-0.129794	-0.129794	-0.129794	1.0	-0.1(
Myanmar	1.0	-0.606320	NaN	-0.606320	-0.606320	-0.606320	-0.606320	-0.606320	1.0	-0.6'
Philippines	1.0	-0.501696	NaN	-0.501696	-0.501696	-0.501696	-0.501696	-0.501696	1.0	-0.5(
Singapore	1.0	2.313146	NaN	2.313146	2.313146	2.313146	2.313146	2.313146	1.0	2.3(
Thailand	1.0	-0.381864	NaN	-0.381864	-0.381864	-0.381864	-0.381864	-0.381864	1.0	-0.3:
Vietnam	1.0	-0.580544	NaN	-0.580544	-0.580544	-0.580544	-0.580544	-0.580544	1.0	-0.5ł

10 rows × 96 columns

In [156…

```
gdp_mean_by_country = gdp_per_capita.groupby('Country').mean().mean(axis=1).reset_inde
plot_summary_statistics_by_country(gdp_mean_by_country, 'Mean', 'GDP Per Capita Mean b
```



GDP Analysis

There seems to be a massive disparity between Singapore and Brunei compared to the rest of the Southeast Asian countries. Note that this does not mean the other countries are poor in terms of absolute terms but they are relatively poorer than the countries mentioned. This suggests that the regional average is heavily influenced by Singapore and Brunei.

In [157…

```
co2_summary_by_country = co2_emission.groupby('Country').describe()
co2_summary_by_country
```

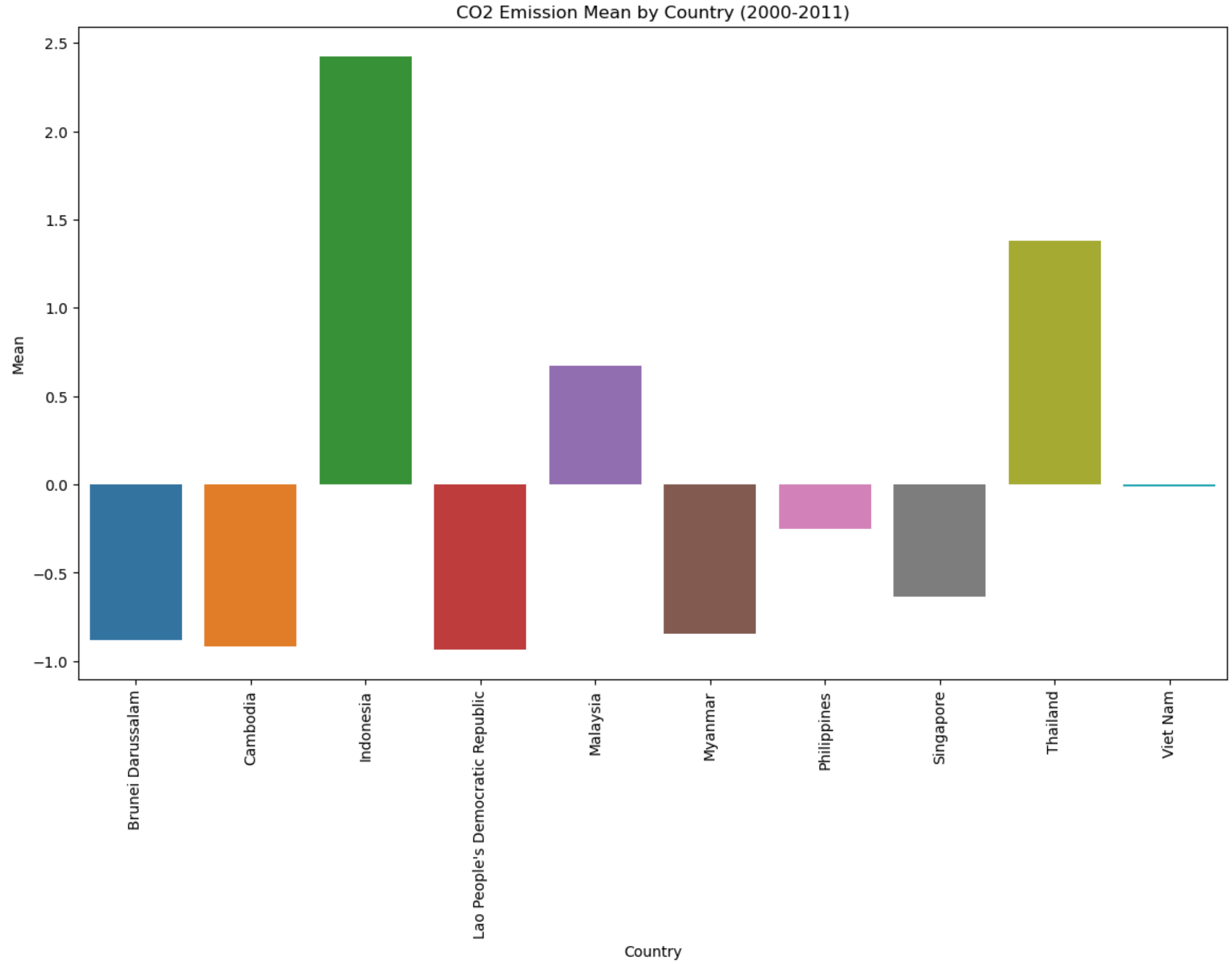
Out[157]:

	2000									
	count	mean	std	min	25%	50%	75%	max	count	
Country										
Brunei Darussalam	1.0	-0.920587	NaN	-0.920587	-0.920587	-0.920587	-0.920587	-0.920587	1.0	-0.9(
Cambodia	1.0	-0.973943	NaN	-0.973943	-0.973943	-0.973943	-0.973943	-0.973943	1.0	-0.9‹
Indonesia	1.0	2.404405	NaN	2.404405	2.404405	2.404405	2.404405	2.404405	1.0	2.4(
Lao People's Democratic Republic	1.0	-0.986926	NaN	-0.986926	-0.986926	-0.986926	-0.986926	-0.986926	1.0	-0.9!
Malaysia	1.0	0.636478	NaN	0.636478	0.636478	0.636478	0.636478	0.636478	1.0	0.6:
Myanmar	1.0	-0.869128	NaN	-0.869128	-0.869128	-0.869128	-0.869128	-0.869128	1.0	-0.8(
Philippines	1.0	-0.052213	NaN	-0.052213	-0.052213	-0.052213	-0.052213	-0.052213	1.0	-0.1‹
Singapore	1.0	-0.366232	NaN	-0.366232	-0.366232	-0.366232	-0.366232	-0.366232	1.0	-0.3!
Thailand	1.0	1.434439	NaN	1.434439	1.434439	1.434439	1.434439	1.434439	1.0	1.3ε
Viet Nam	1.0	-0.306291	NaN	-0.306291	-0.306291	-0.306291	-0.306291	-0.306291	1.0	-0.2!

10 rows × 96 columns

In [158…

```
co2_mean_by_country = co2_emission.groupby('Country').mean().mean(axis=1).reset_index(
plot_summary_statistics_by_country(co2_mean_by_country, 'Mean', 'CO2 Emission Mean by
```



CO2 Analysis

Indonesia, Malaysia and Thailand stand out the most in this chart. They pump out the most carbon dioxide in South East Asia.

In [159…

```
energy_summary_by_country = energy_used.groupby('Country').describe()
energy_summary_by_country
```

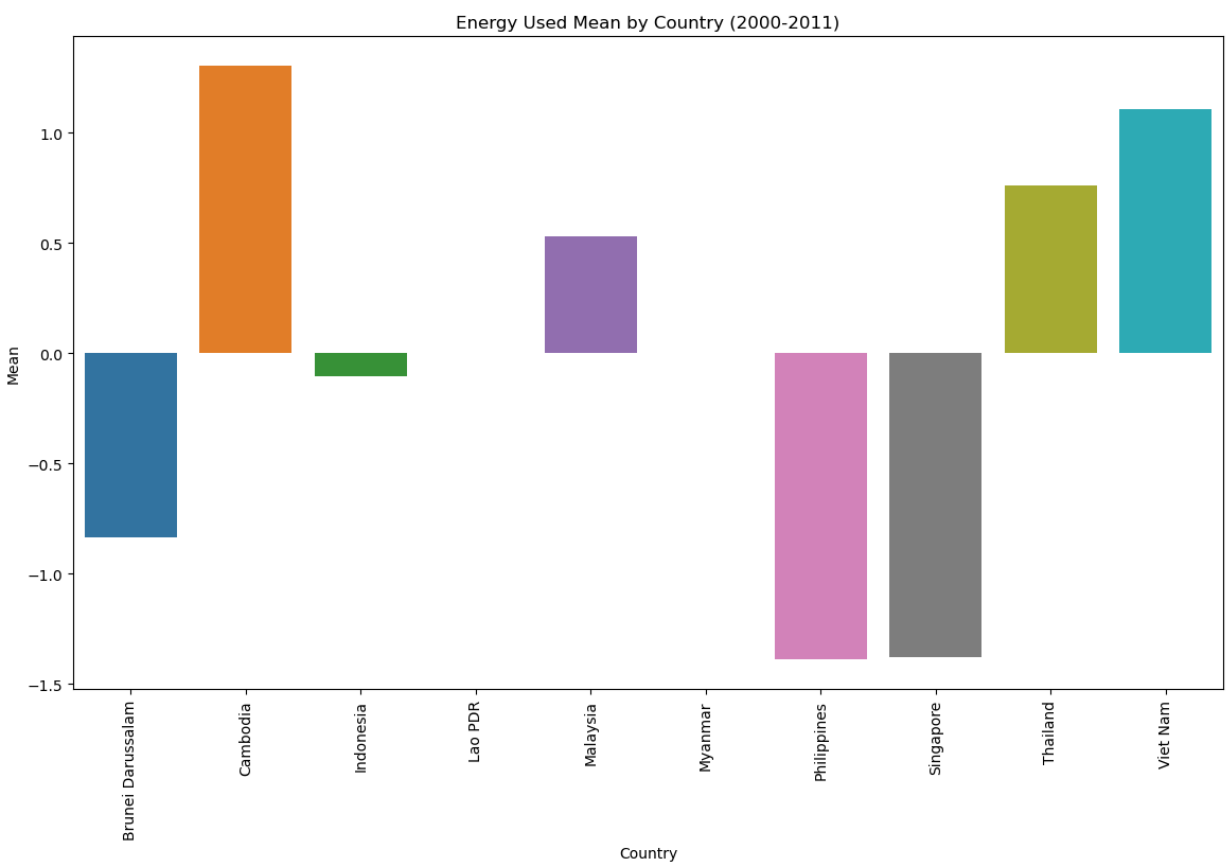
Out[159]:

	2000									
	count	mean	std	min	25%	50%	75%	max	count	
Country										
Brunei Darussalam	1.0	-1.292568	NaN	-1.292568	-1.292568	-1.292568	-1.292568	-1.292568	1.0	-1.7
Cambodia	1.0	2.783267	NaN	2.783267	2.783267	2.783267	2.783267	2.783267	1.0	2.6
Indonesia	1.0	0.103783	NaN	0.103783	0.103783	0.103783	0.103783	0.103783	1.0	0.1
Lao PDR	1.0	0.000000	NaN	0.000000	0.000000	0.000000	0.000000	0.000000	1.0	0.0
Malaysia	1.0	-0.084913	NaN	-0.084913	-0.084913	-0.084913	-0.084913	-0.084913	1.0	0.1
Myanmar	1.0	0.000000	NaN	0.000000	0.000000	0.000000	0.000000	0.000000	1.0	0.0
Philippines	1.0	-0.349088	NaN	-0.349088	-0.349088	-0.349088	-0.349088	-0.349088	1.0	-0.6
Singapore	1.0	-1.519003	NaN	-1.519003	-1.519003	-1.519003	-1.519003	-1.519003	1.0	-1.0
Thailand	1.0	-0.009435	NaN	-0.009435	-0.009435	-0.009435	-0.009435	-0.009435	1.0	0.1
Viet Nam	1.0	0.367957	NaN	0.367957	0.367957	0.367957	0.367957	0.367957	1.0	0.4

10 rows × 96 columns

In [160…

```
energy_mean_by_country = energy_used.groupby('Country').mean().mean(axis=1).reset_inde
plot_summary_statistics_by_country(energy_mean_by_country, 'Mean', 'Energy Used Mean b
```



Energy Analysis

What stands out is the Philippines and Singapore using the least amount of energy. As a person who has experienced both countries, my hypothesis is that Singapore is a manufacturing hub that has mastered energy efficiency and that being a relatively small country compared to others. The Philippines on the other hand, has a lackluster manufacturing due to electricity being so much costlier than the other Southeast Asian countries. Because of this, manufacturing isn't something that the oligarchs invest on which could probably explain why they are relatively low when it comes to energy usage.

In [161…

```
food_summary_by_country = food_production_index.groupby('Country').describe()
food_summary_by_country
```

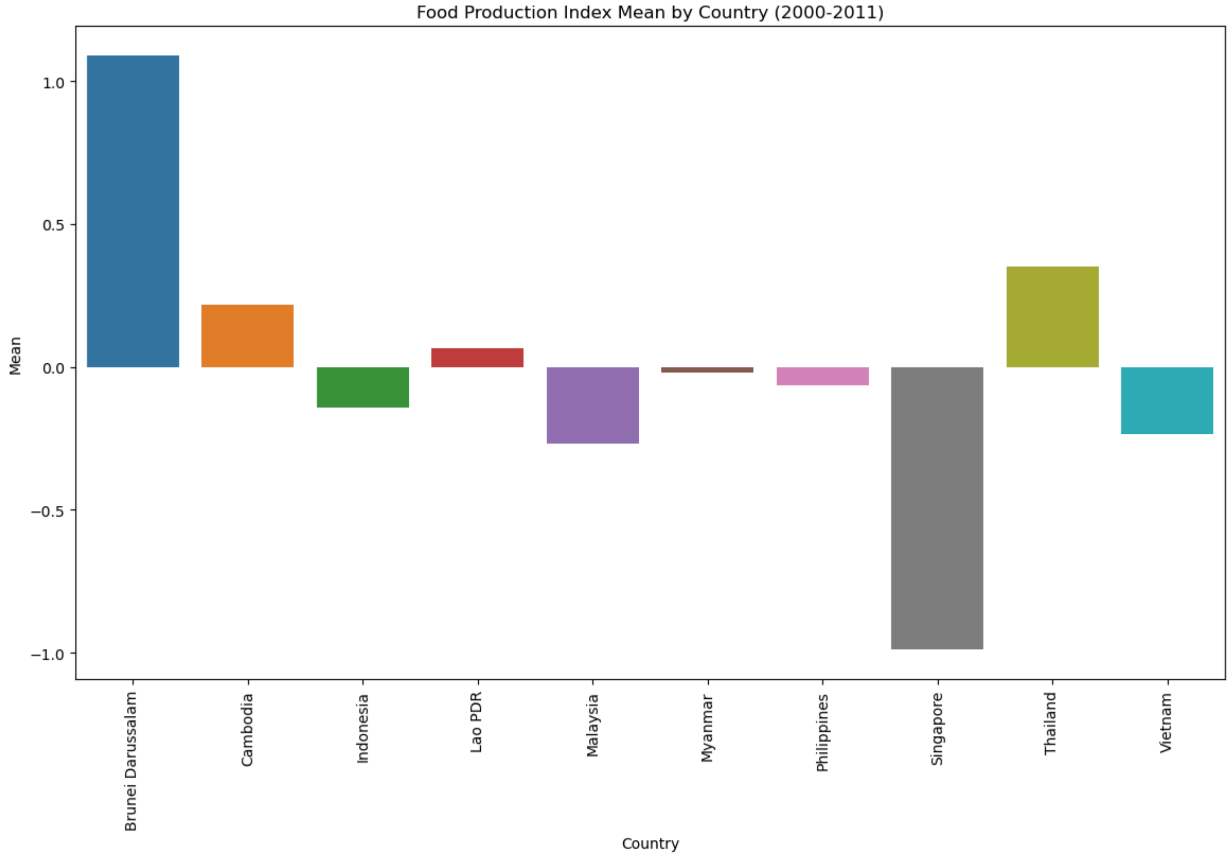
Out[161]:

	2000									
	count	mean	std	min	25%	50%	75%	max	count	
Country										
Brunei Darussalam	1.0	0.714434	NaN	0.714434	0.714434	0.714434	0.714434	0.714434	1.0	1.68
Cambodia	1.0	-0.801414	NaN	-0.801414	-0.801414	-0.801414	-0.801414	-0.801414	1.0	-1.02
Indonesia	1.0	-0.161670	NaN	-0.161670	-0.161670	-0.161670	-0.161670	-0.161670	1.0	-0.34
Lao PDR	1.0	0.374077	NaN	0.374077	0.374077	0.374077	0.374077	0.374077	1.0	0.07
Malaysia	1.0	-0.208941	NaN	-0.208941	-0.208941	-0.208941	-0.208941	-0.208941	1.0	-0.10
Myanmar	1.0	-1.012562	NaN	-1.012562	-1.012562	-1.012562	-1.012562	-1.012562	1.0	-0.59
Philippines	1.0	0.802675	NaN	0.802675	0.802675	0.802675	0.802675	0.802675	1.0	0.59
Singapore	1.0	-1.478977	NaN	-1.478977	-1.478977	-1.478977	-1.478977	-1.478977	1.0	-1.62
Thailand	1.0	2.153073	NaN	2.153073	2.153073	2.153073	2.153073	2.153073	1.0	1.59
Vietnam	1.0	-0.380695	NaN	-0.380695	-0.380695	-0.380695	-0.380695	-0.380695	1.0	-0.25

10 rows × 96 columns

In [162…

```
food_mean_by_country = food_production_index.groupby('Country').mean().mean(axis=1).re
plot_summary_statistics_by_country(food_mean_by_country, 'Mean', 'Food Production Inde
```



Food Production Analysis

I expected Thailand and Vietnam to dominate the charts but I remembered the chart was from 2000 to 2011 so they weren't a powerhouse yet. What stands out is Brunei as it produces the most food relative to other countries. I don't know much about Brunei but based on the numbers, they seem to be a country that performs well on the factors that I chose. I wonder why it isn't as powerful as other countries.

For Singapore, I completely expected it because the country is so small, there is almost no land for agriculture at all. They heavily rely on trade, financial and business service performance and in exchange, they import food.

For the Philippines, it is underperforming relative to the other Southeast Asian countries which is terrible for an "agricultural" country. Although I have thought long and hard about it, there are claims that the Philippines is not an agricultural country at all. We might have the land but we do not have large river deltas that Thailand and Vietnam have to mass produce rice for instance. Add that to the fact that the Philippines is a typhoon hub and those natural disasters can easily destroy crops in unfortunate times. Filipinos go crazy when they hear that we import rice from other countries but the numbers suggest that even back a decade or two ago, agriculture might not be our strong suit. I was told when I was young that the Philippines is a perfect country for agriculture because we don't have winter season. One can theoretically plant and harvest all year long. Apparently, this claim is closer to being incorrect.

In [163…

```
forest_summary_by_country = forest_area.groupby('Country').describe()
forest_summary_by_country
```

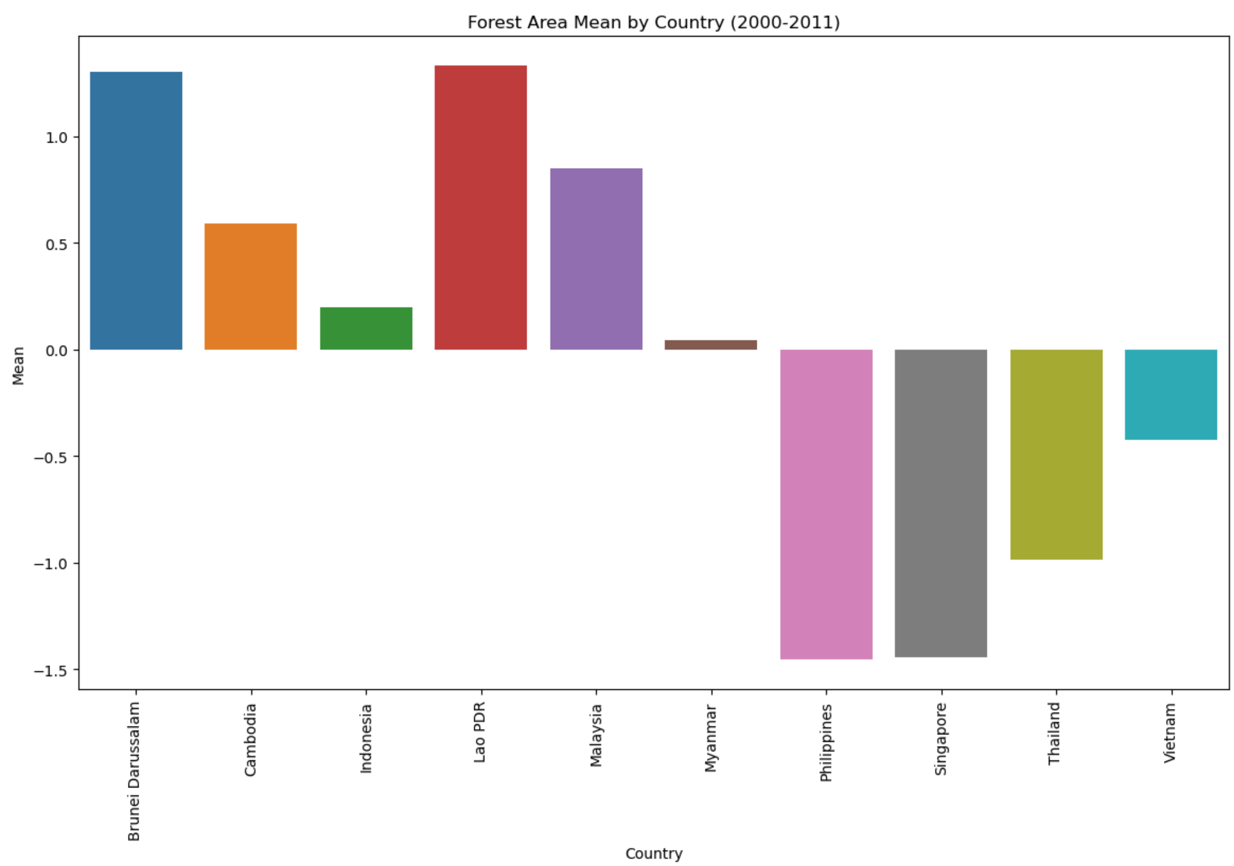
Out[163]:

	2000									
	count	mean	std	min	25%	50%	75%	max	count	
Country										
Brunei Darussalam	1.0	1.343458	NaN	1.343458	1.343458	1.343458	1.343458	1.343458	1.0	1.34
Cambodia	1.0	0.806183	NaN	0.806183	0.806183	0.806183	0.806183	0.806183	1.0	0.77
Indonesia	1.0	0.235329	NaN	0.235329	0.235329	0.235329	0.235329	0.235329	1.0	0.23
Lao PDR	1.0	1.141439	NaN	1.141439	1.141439	1.141439	1.141439	1.141439	1.0	1.17
Malaysia	1.0	0.822973	NaN	0.822973	0.822973	0.822973	0.822973	0.822973	1.0	0.81
Myanmar	1.0	0.153004	NaN	0.153004	0.153004	0.153004	0.153004	0.153004	1.0	0.13
Philippines	1.0	-1.459904	NaN	-1.459904	-1.459904	-1.459904	-1.459904	-1.459904	1.0	-1.46
Singapore	1.0	-1.414951	NaN	-1.414951	-1.414951	-1.414951	-1.414951	-1.414951	1.0	-1.41
Thailand	1.0	-0.932920	NaN	-0.932920	-0.932920	-0.932920	-0.932920	-0.932920	1.0	-0.95
Vietnam	1.0	-0.694612	NaN	-0.694612	-0.694612	-0.694612	-0.694612	-0.694612	1.0	-0.64

10 rows × 96 columns

In [164…

```
forest_mean_by_country = forest_area.groupby('Country').mean().mean(axis=1).reset_inde
plot_summary_statistics_by_country(forest_mean_by_country, 'Mean', 'Forest Area Mean b
```



Forest Area Analysis

Based on the charts, Brunei and Laos have relatively equal forest area on the positive end. Brunei has been performing well so far and Laos looks like a very underdeveloped country. I wonder how Brunei is performing so well. Another thing that I noticed is the Philippines and Singapore tied when it comes to forest area. I am slightly worried because the identity of the Philippines is that it is home to a lot of endemic species of both flora and fauna. I have always been pro-environment but as I grew up, I understood why people are cutting down trees. Preserving forests, unfortunately, do not bring in enough money and people would rather build farms, buildings and other businesses that have a better economic tradeoff than preserving them.

In [165…

```
hdi_summary_by_country = hdi.groupby('Country').describe()
hdi_summary_by_country
```

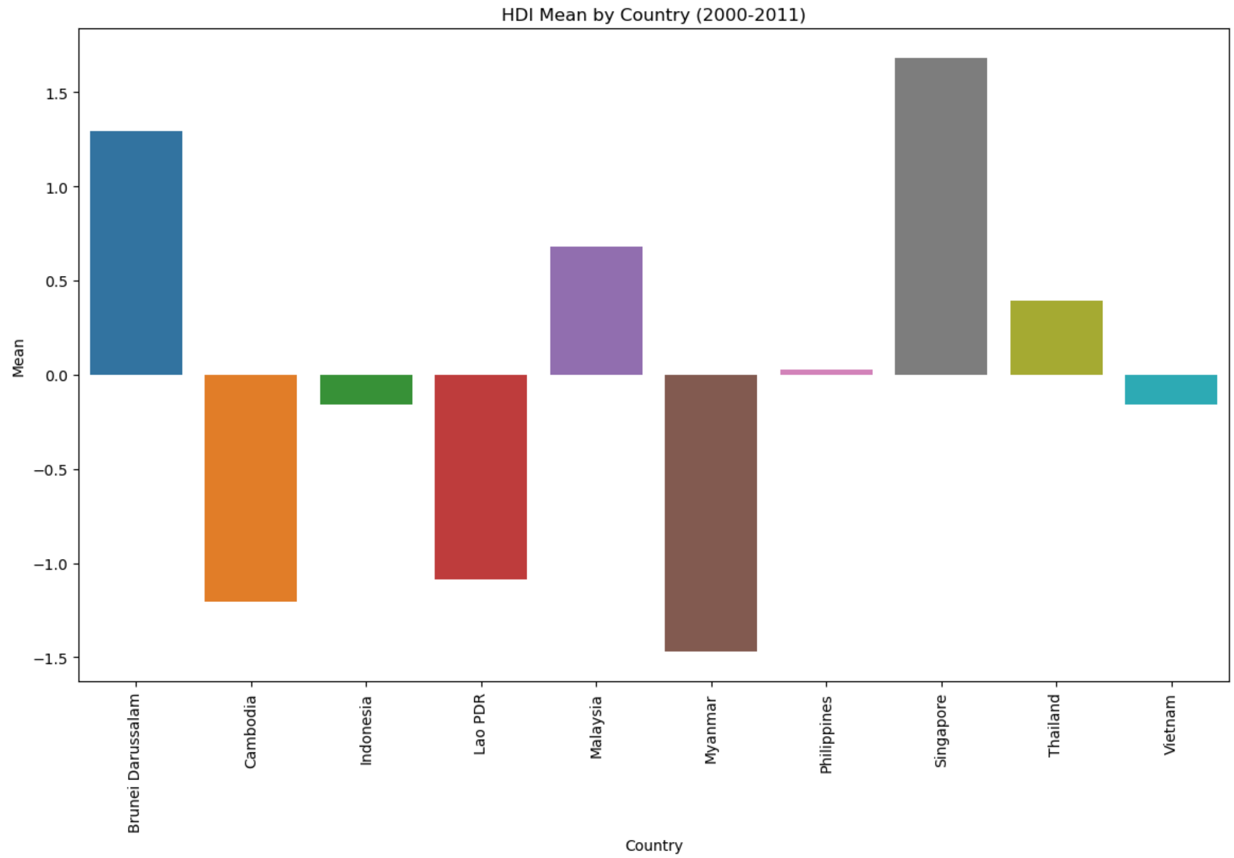
Out[165]:

	2000									
	count	mean	std	min	25%	50%	75%	max	count	
Country										
Brunei Darussalam	1.0	1.385896	NaN	1.385896	1.385896	1.385896	1.385896	1.385896	1.0	1.37
Cambodia	1.0	-1.341741	NaN	-1.341741	-1.341741	-1.341741	-1.341741	-1.341741	1.0	-1.31
Indonesia	1.0	-0.131041	NaN	-0.131041	-0.131041	-0.131041	-0.131041	-0.131041	1.0	-0.12
Lao PDR	1.0	-1.021262	NaN	-1.021262	-1.021262	-1.021262	-1.021262	-1.021262	1.0	-1.05
Malaysia	1.0	0.766302	NaN	0.766302	0.766302	0.766302	0.766302	0.766302	1.0	0.74
Myanmar	1.0	-1.448568	NaN	-1.448568	-1.448568	-1.448568	-1.448568	-1.448568	1.0	-1.46
Philippines	1.0	0.139587	NaN	0.139587	0.139587	0.139587	0.139587	0.139587	1.0	0.12
Singapore	1.0	1.549697	NaN	1.549697	1.549697	1.549697	1.549697	1.549697	1.0	1.55
Thailand	1.0	0.282022	NaN	0.282022	0.282022	0.282022	0.282022	0.282022	1.0	0.31
Vietnam	1.0	-0.180893	NaN	-0.180893	-0.180893	-0.180893	-0.180893	-0.180893	1.0	-0.16

10 rows × 96 columns

In [166…

```
hdi_mean_by_country = hdi.groupby('Country').mean().mean(axis=1).reset_index(name='Mea
plot_summary_statistics_by_country(hdi_mean_by_country, 'Mean', 'HDI Mean by Country (
```



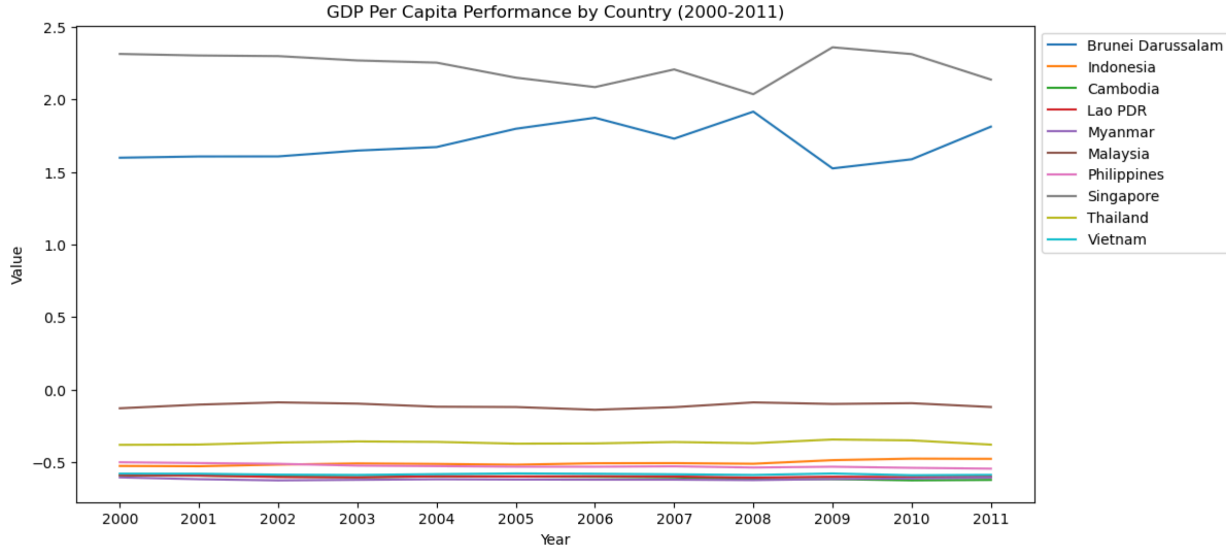
HDI Analysis

Not surprised that Brunei and Singapore lead the way when it comes to HDI. GDP and HDI seem to have a strong correlation.

In [167…

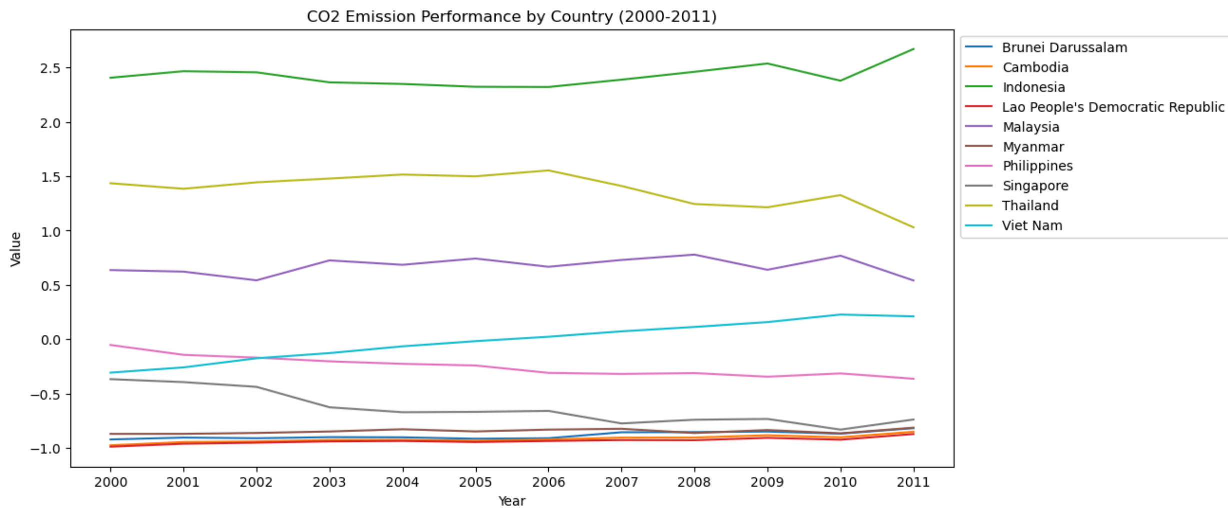
```
def plot_performance_by_country(df, title):
    plt.figure(figsize=(12, 6))
    for country in df['Country']:
        country_data = df[df['Country'] == country].iloc[:, 1:].T
        plt.plot(country_data.index, country_data.values, label=country)
    plt.title(title)
    plt.xlabel('Year')
    plt.ylabel('Value')
    plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
    plt.show()

# Plot each factor by country
plot_performance_by_country(gdp_per_capita, 'GDP Per Capita Performance by Country (20
```



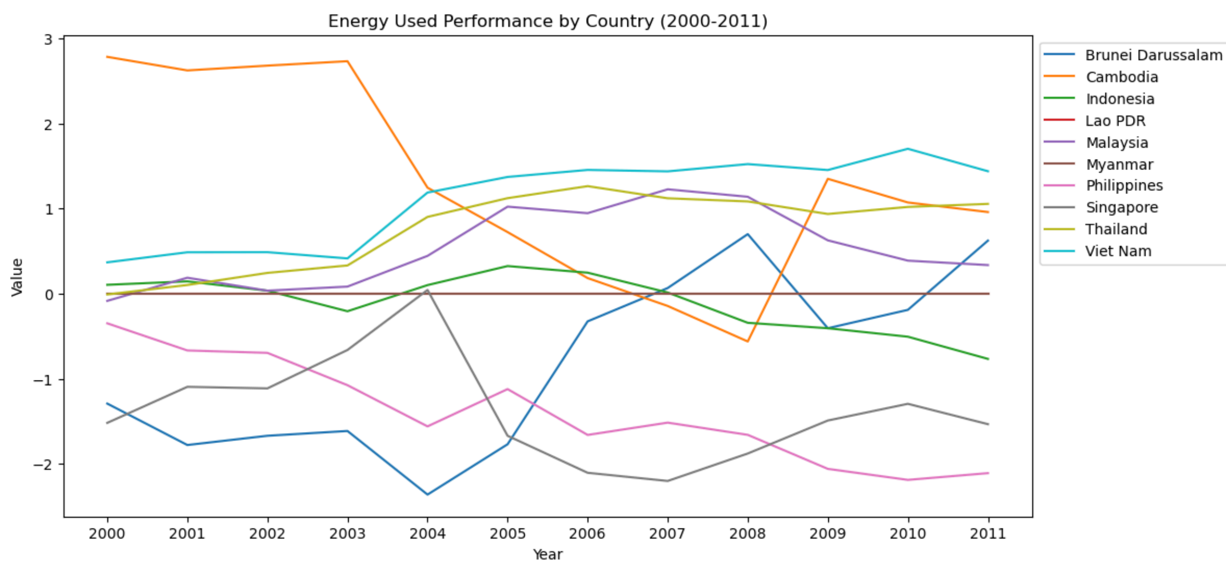
In [168…

```
plot_performance_by_country(co2_emission, 'CO2 Emission Performance by Country (2000-2
```



In [169…

```
plot_performance_by_country(energy_used, 'Energy Used Performance by Country (2000-201
```

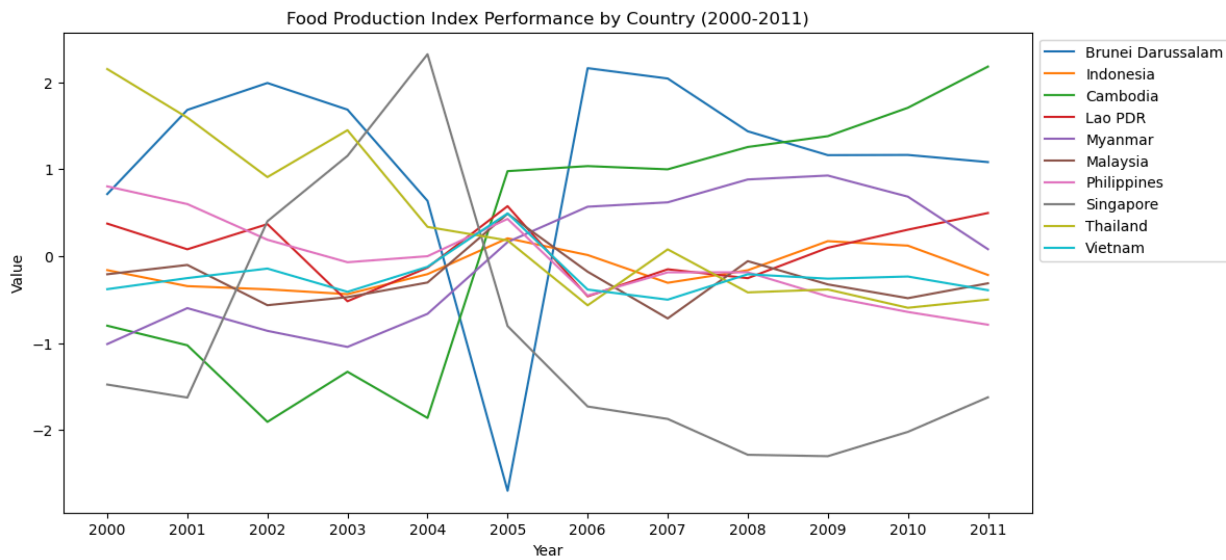


Energy Analysis

I don't why why Brunei has a straight line from 2000 to 2001. Seems odd. Cambodia had a steep fall off to their usual energy consumption from 2004 to 2008, I think something happened along the way. Indonesia seems to be trending from middle to low which is a good thing. Singapore had a huge spike in energy from 2002 to 2004, I think something happened around that time too. Philippines has been consistently trending downwards in this time span or other countries could be spending more energy while Philippines maintains its usual consumption which makes it seem like its trending downwards.

In [170…

```
plot_performance_by_country(food_production_index, 'Food Production Index Performance
```

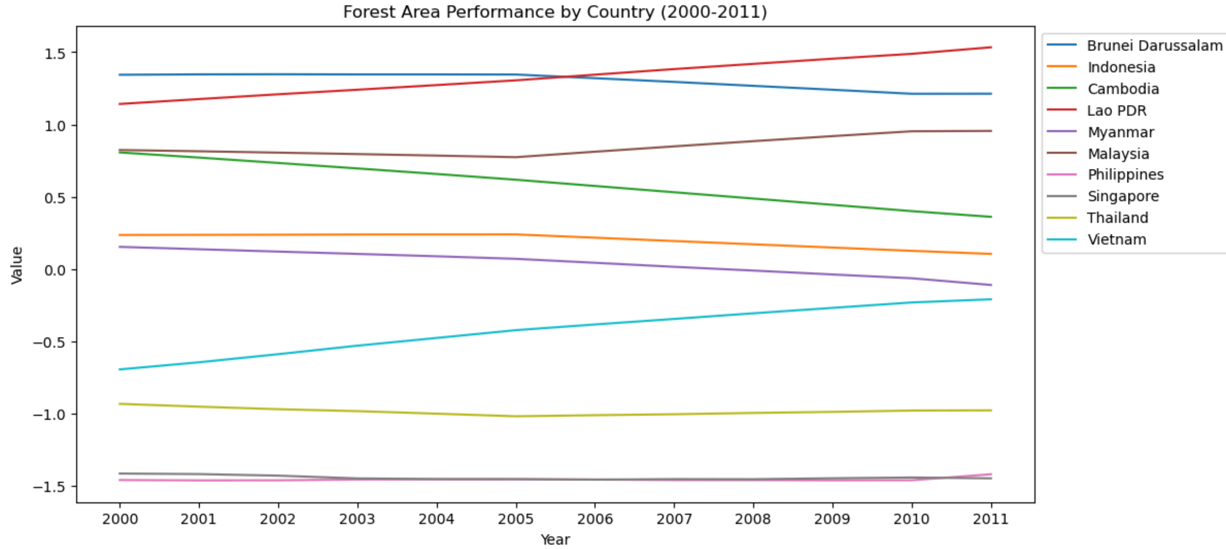


Food Production Analysis

There are huge fluctuations on this chart specificaly Brunei, Singapore, Cambodia. All in all Brunei was a food production power house and something happened in 2005 that made them the worst food producing country that year and went back up first place the year after. Something definetely happened that year. I was surprised that Singapore was once upon a time, a top food produced and then came down to its usual numbers. Something happened in 2004 for Singapore for sure. Lastly, there was a huge improvement for Cambodia in terms of food production between 2004 and 2005.

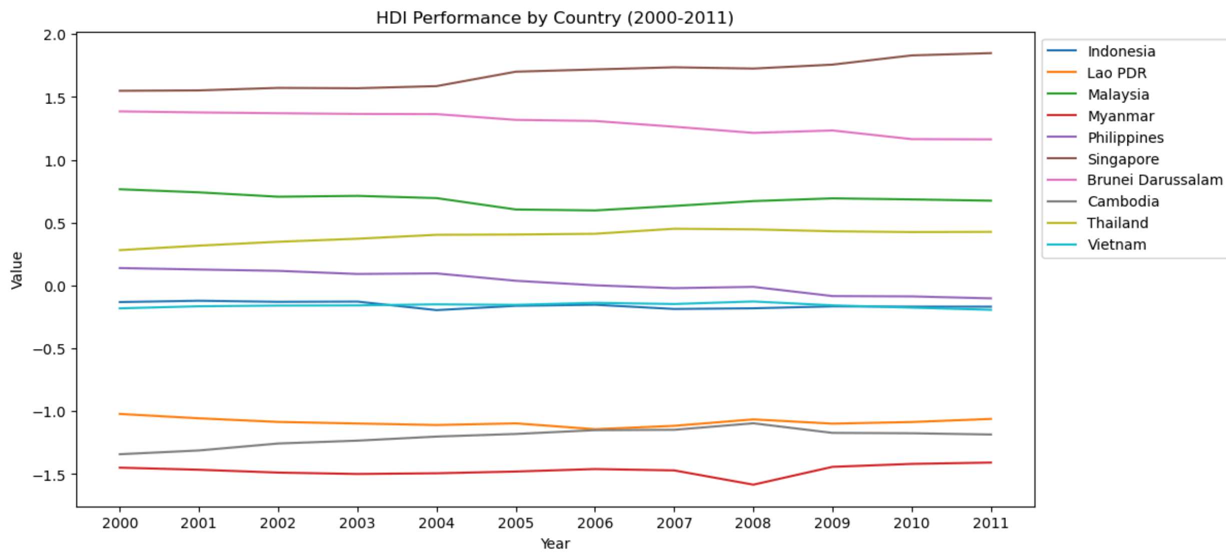
In [171…

```
plot_performance_by_country(forest_area, 'Forest Area Performance by Country (2000-201
```



In [172…

```
plot_performance_by_country(hdi, 'HDI Performance by Country (2000-2011)')
```



1. Perform correlation analysis.

In [173…

```
# Combine datasets into a single DataFrame
combined_df = pd.DataFrame()

# Add Country and Year columns for merging
for df, name in zip([gdp_per_capita, co2_emission, energy_used, food_production_index,
                    ['GDP', 'CO2', 'Energy', 'Food', 'Forest', 'HDI']):
    temp_df = df.melt(id_vars=['Country'], var_name='Year', value_name=name)
    if combined_df.empty:
        combined_df = temp_df
    else:
        combined_df = pd.merge(combined_df, temp_df, on=['Country', 'Year'], how='oute

# Convert Year to integer
combined_df['Year'] = combined_df['Year'].astype(int)

# Display the first few rows of the combined dataframe
combined_df.head(20)
```

Out[173]:

	Country	Year	GDP	CO2	Energy	Food	Forest	HDI
0	Brunei Darussalam	2000	1.597592	-0.920587	-1.292568	0.714434	1.343458	1.385896
1	Indonesia	2000	-0.527468	2.404405	0.103783	-0.161670	0.235329	-0.131041
2	Cambodia	2000	-0.593021	-0.973943	2.783267	-0.801414	0.806183	-1.341741
3	Lao PDR	2000	-0.590032	NaN	0.000000	0.374077	1.141439	-1.021262
4	Myanmar	2000	-0.606320	-0.869128	0.000000	-1.012562	0.153004	-1.448568
5	Malaysia	2000	-0.129794	0.636478	-0.084913	-0.208941	0.822973	0.766302
6	Philippines	2000	-0.501696	-0.052213	-0.349088	0.802675	-1.459904	0.139587
7	Singapore	2000	2.313146	-0.366232	-1.519003	-1.478977	-1.414951	1.549697
8	Thailand	2000	-0.381864	1.434439	-0.009435	2.153073	-0.932920	0.282022
9	Vietnam	2000	-0.580544	NaN	NaN	-0.380695	-0.694612	-0.180893
10	Brunei Darussalam	2001	1.606232	-0.903299	-1.779502	1.683269	1.346217	1.377460
11	Indonesia	2001	-0.529349	2.464382	0.144284	-0.345788	0.235974	-0.120573
12	Cambodia	2001	-0.594100	-0.944085	2.623831	-1.026925	0.770617	-1.311693
13	Lao PDR	2001	-0.593363	NaN	0.000000	0.078292	1.175285	-1.055931
14	Myanmar	2001	-0.618942	-0.868705	0.000000	-0.598931	0.136582	-1.465150
15	Malaysia	2001	-0.104362	0.621987	0.187035	-0.101779	0.814306	0.741709
16	Philippines	2001	-0.507425	-0.142791	-0.667981	0.598931	-1.462430	0.127881
17	Singapore	2001	2.302427	-0.393318	-1.095489	-1.628465	-1.418741	1.552839
18	Thailand	2001	-0.379895	1.383861	0.101533	1.594539	-0.952362	0.317875
19	Vietnam	2001	-0.581222	NaN	NaN	-0.253143	-0.645448	-0.164418

In [174…

```
# Calculate the correlation matrix
correlation_matrix = combined_df.drop(columns=['Country', 'Year']).corr()

# Display the correlation matrix
correlation_matrix
```

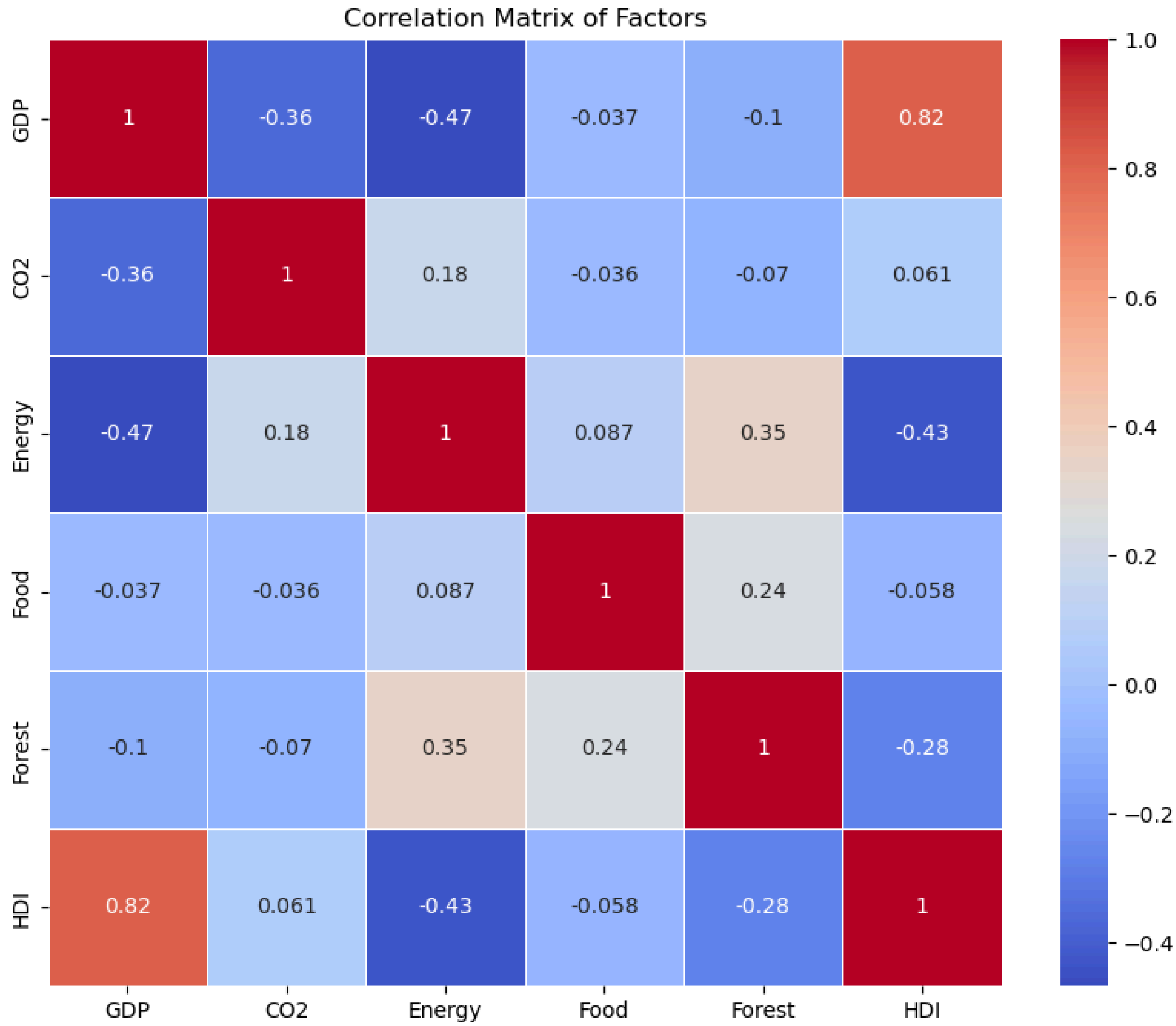
Out[174]:

	GDP	CO2	Energy	Food	Forest	HDI
GDP	1.000000	-0.364180	-0.466580	-0.036992	-0.100421	0.816344
CO2	-0.364180	1.000000	0.177145	-0.036222	-0.069866	0.061129
Energy	-0.466580	0.177145	1.000000	0.086935	0.346337	-0.434315
Food	-0.036992	-0.036222	0.086935	1.000000	0.242100	-0.057520
Forest	-0.100421	-0.069866	0.346337	0.242100	1.000000	-0.277524
HDI	0.816344	0.061129	-0.434315	-0.057520	-0.277524	1.000000

In [175…

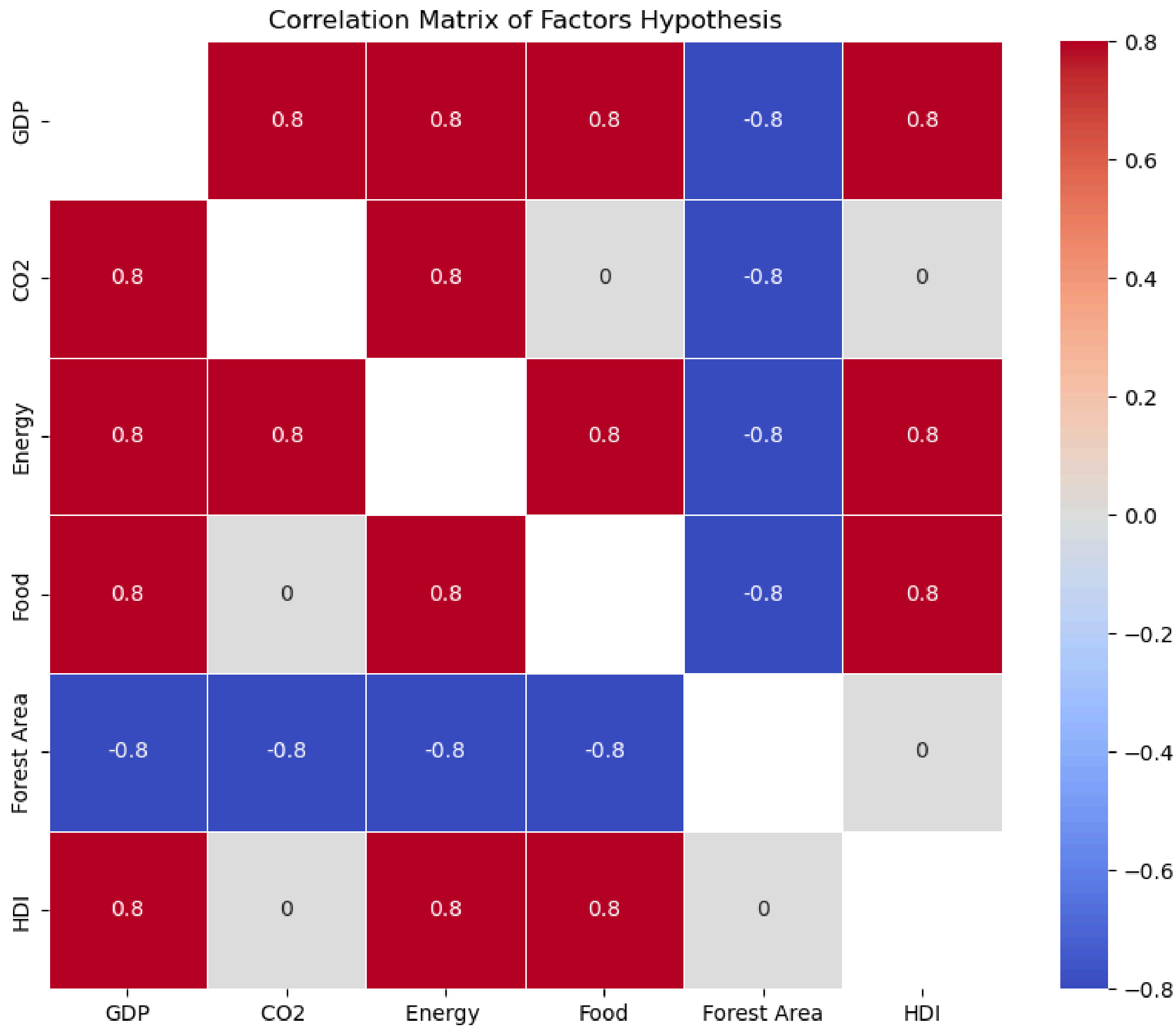
```
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# Plot the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix of Factors')
plt.show()
```



In [176…

```
# Plot the correlation matrix
def create_custom_hypothesis_df():
    hypothesis_values = {
        'GDP': [np.nan, 0.8, 0.8, 0.8, -0.8, 0.8],
        'CO2 ': [0.8, np.nan, 0.8, 0.0, -0.8, 0.0],
        'Energy ': [0.8, 0.8, np.nan, 0.8, -0.8, 0.8],
        'Food': [0.8, 0.0, 0.8, np.nan, -0.8, 0.8],
        'Forest Area': [-0.8, -0.8, -0.8, -0.8, np.nan, 0.0],
        'HDI': [0.8, 0.0, 0.8, 0.8, 0.0, np.nan]
    }
    hypothesis_df = pd.DataFrame(hypothesis_values, index=['GDP', 'CO2', 'Energy', 'Fo
    return hypothesis_df
custom_hypothesis_df = create_custom_hypothesis_df()
plt.figure(figsize=(10, 8))
sns.heatmap(custom_hypothesis_df, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix of Factors Hypothesis')
plt.show()
```



Correlation Matrix Interpretation

GDP vs. HDI: There is a strong positive correlation (0.82). This suggests that higher GDP per capita is associated with higher Human Development Index (HDI) values. Generally, wealthier countries tend to have better human development outcomes.

GDP vs. Energy: There is a moderate negative correlation (-0.48). This might suggest that as GDP per capita increases, energy usage decreases, possibly indicating improved energy efficiency in wealthier countries.

GDP vs. CO2: There is a moderate negative correlation (-0.36). Higher GDP per capita is associated with lower CO2 emissions, which could suggest that wealthier countries may have better pollution control measures or a transition to cleaner energy sources.

Energy vs. HDI: There is a moderate negative correlation (-0.53). This indicates that higher energy consumption is associated with lower HDI, which might suggest inefficiencies or higher energy usage in less developed countries.

Energy vs. Forest: There is a moderate positive correlation (0.36). This could indicate that countries with more forest areas also tend to have higher energy consumption, possibly due to industrial or agricultural activities.

Forest vs. HDI: There is a weak negative correlation (-0.28). This suggests a slight tendency for countries with higher forest cover to have lower HDI, which might indicate less developed countries with larger forest areas.

CO2 vs. HDI: There is a weak positive correlation (0.061). This suggests a slight tendency for higher CO2 emissions to be associated with higher HDI, possibly indicating industrial activities that contribute to both development and emissions.

Food vs. Other Variables: The food production index shows very weak correlations with other variables, suggesting that food production may not be strongly associated with the other factors in the dataset.

Summary and Learnings

The activity provided a comprehensive analysis of the selected datasets, revealing important trends and correlations within ASEAN countries. The insights gained from the descriptive and correlation analysis can inform policy decisions aimed at reducing economic inequality and promoting balanced growth in the region. The actual practice of Data Analysis is essential in gauging relative performance but there are certain limitations to this activity such as while we can measure how a country performs relatively to other countries, sometimes a country 'underperforming' could be interpreted as an not a 'bad' thing. For example, Singapore is the lowest when it comes to food production but due to it's identity as a very small country and the entire country is excellent on things not related to agriculture. Why would they invest in an industry that will set them up to fail? I think that is something the Philippines should take into consideration. What if we completely give up or at the very least lessen our expectations and investment on agriculture at all because it has been a losing battle?

Another limitation of this analysis is its focus on relative performance rather than absolute measures. The datasets provided were composed of raw numbers without clear labels or units, which made it difficult to interpret certain data points, such as those in the 'energy used.csv' file. For example, it was unclear whether the energy usage figures represented kilowatt-hours per hour, per year, or some other unit. This lack of clarity can lead to misinterpretations. Additionally, the analysis did not account for factors like land mass and population size, which are critical for accurate comparisons. Without considering these variables, a country might be wrongly labeled as inefficient when, in fact, it performs comparably to more efficient countries on a per capita or per area basis.