

Data Mining Project - Sustainability Around The World

Aradhya Mathur and Ozlem Gunes

Exploratory Data Analysis

```
In [1]: #Importing Libraries
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import scipy.stats as stats
import statsmodels.api as sm
```

```
In [2]: #Reading Dataset
epi2022 = pd.read_csv('epi2022.csv')
EPI = epi2022[['country', 'region', 'EPI.new',
               'PCC.new', 'CCH.new', 'CDA.new', 'CHA.new', 'FGA.new', 'NDA.new', 'BCA.new',
               'HLT.new', 'AIR.new', 'HAD.new', 'PMD.new', 'OZD.new', 'NOE.new', 'SOE.new',
               'H2O.new', 'USD.new', 'UWD.new',
               'HMT.new', 'PBD.new',
               'WMG.new', 'MSW.new', 'REC.new', 'OCP.new',
               'ECO.new', 'BDH.new', 'TBN.new', 'TBG.new', 'MPA.new', 'PAR.new', 'SHI.new',
               'ECS.new', 'TCL.new', 'GRL.new', 'WTL.new',
               'FSH.new', 'FSS.new', 'RMS.new', 'FTD.new',
               'ACD.new', 'SDA.new', 'NXA.new',
               'AGR.new', 'SPU.new', 'SNM.new',
               'WRS.new', 'WWT.new'
              ]]

#Changing column names for ease
EPI.columns = ['Country', 'Region', 'EPI',
               'PCC', 'CCH', 'CDA', 'CHA', 'FGA', 'NDA', 'BCA', 'GHN', 'LCB', 'GIB', 'GHP',
               'HLT', 'AIR', 'HAD', 'PMD', 'OZD', 'NOE', 'SOE', 'COE', 'VOE',
               'H2O', 'USD', 'UWD',
               'HMT', 'PBD',
               'WMG', 'MSW', 'REC', 'OCP',
               'ECO', 'BDH', 'TBN', 'TBG', 'MPA', 'PAR', 'SHI', 'SPI', 'BHV',
               'ECS', 'TCL', 'GRL', 'WTL',
               'FSH', 'FSS', 'RMS', 'FTD',
               'ACD', 'SDA', 'NXA',
               'AGR', 'SPU', 'SNM',
               'WRS', 'WWT']

EPI.head() #Displaying EPI dataset
```

Out[2]:

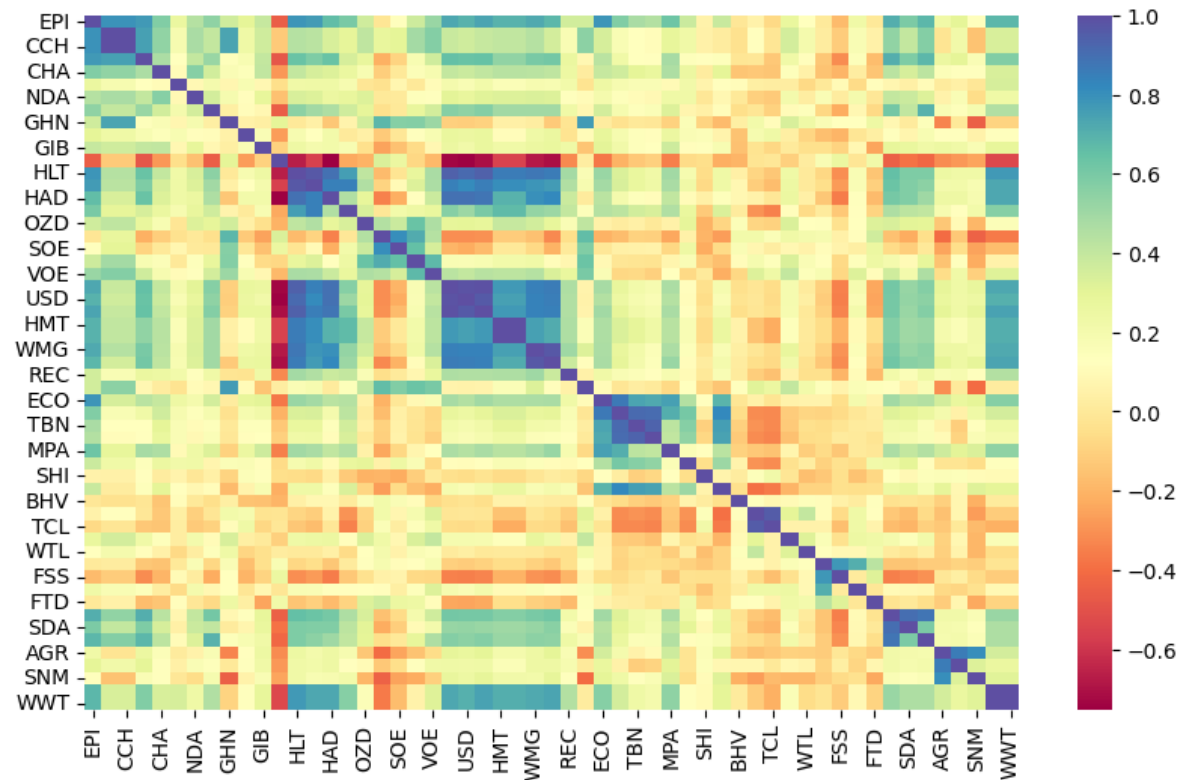
	Country	Region	EPI	PCC	CCH	CDA	CHA	FGA	NDA	BCA	...	RMS	FTD	ACD	!
0	Afghanistan	Southern Asia	43.6	65.6	65.6	83.9	50.2	54.5	63.7	42.9	...	28.2	0.6	35.5	
1	Albania	Eastern Europe	47.1	52.5	52.5	42.3	50.1	59.4	76.9	100.0	...	30.2	0.8	90.2	1
2	Algeria	Greater Middle East	29.6	20.9	20.9	18.8	36.1	76.5	46.3	63.9	...	12.4	9.3	70.8	
3	Angola	Sub-Saharan Africa	30.5	37.7	37.7	39.0	49.7	57.7	70.4	51.8	...	17.6	7.9	50.5	
4	Antigua and Barbuda	Latin America & Caribbean	52.4	60.2	60.2	37.4	50.2	60.9	79.0	69.0	...	9.0	6.4	93.2	1

5 rows × 57 columns

In [3]:

```
#Heatmap for EPI Dataset
plt.figure(figsize = (10,6))
sns.heatmap(EPI.corr(), cmap="Spectral")
```

Out[3]: <AxesSubplot:>



In [4]:

```
#EPI attributes just for USA
USA = EPI.iloc[172:173]
USA
```

```
Out[4]:
```

	Country	Region	EPI	PCC	CCH	CDA	CHA	FGA	NDA	BCA	...	RMS	FTD	ACD	SD
172	United States of America	Global West	51.1	37.2	37.2	57.8	53.3	81.7	73.6	100.0	...	13.0	10.0	100.0	100.

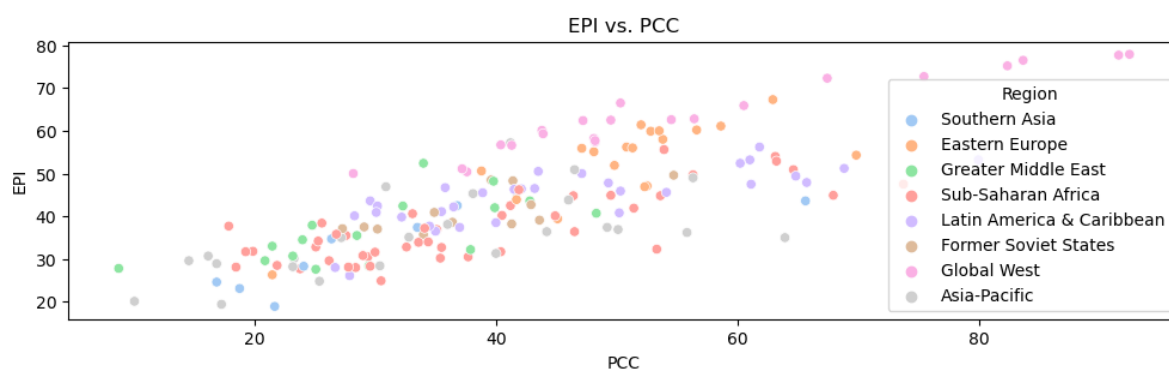
1 rows × 57 columns

```
In [5]: #Checking Original vs Expected Data
usa_pcc = USA.PCC
usa_hlt = USA.HLT
usa_eco = USA.ECO
epi_expected = 0.38*usa_pcc + 0.20*usa_hlt + 0.42*usa_eco
print('Expected EPI is:', epi_expected)
epi_original = USA.EPI
print('Original EPI is', epi_original)
```

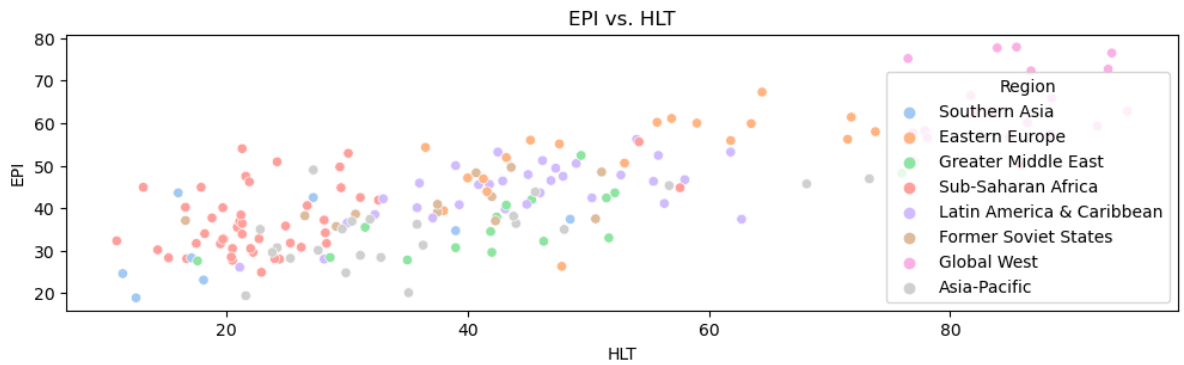
```
Expected EPI is: 172    51.084
dtype: float64
Original EPI is 172    51.1
Name: EPI, dtype: float64
```

Scatter Plots for EPI vs PCC, HLT and ECO

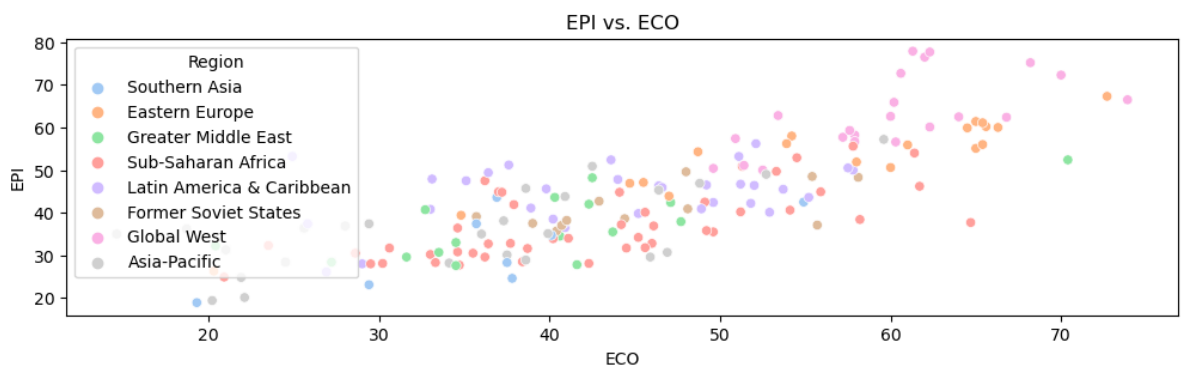
```
In [6]: #EPI vs PCC
plt.figure(figsize=(12,3))
sns.scatterplot(y=EPI.EPI, x=EPI.PCC, hue=EPI.Region, palette = 'pastel')
plt.ylabel('EPI')
plt.xlabel('PCC')
plt.title("EPI vs. PCC")
plt.show()
```



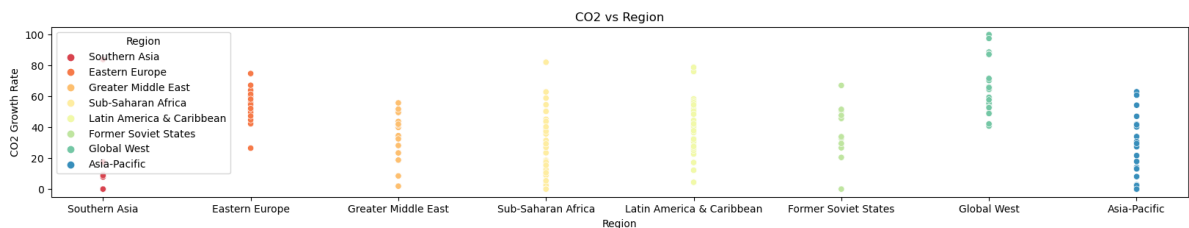
```
In [7]: #EPI vs HLT
plt.figure(figsize=(12,3))
sns.scatterplot(y=EPI.EPI, x=EPI.HLT, hue=EPI.Region, palette = 'pastel')
plt.ylabel('EPI')
plt.xlabel('HLT')
plt.title("EPI vs. HLT")
plt.show()
```



```
In [8]: # EPI vs ECO
plt.figure(figsize=(12,3))
sns.scatterplot(y=EPI.EPI, x=EPI.ECO, hue=EPI.Region, palette = 'pastel')
plt.ylabel('EPI')
plt.xlabel('ECO')
plt.title("EPI vs. ECO")
plt.show()
```



```
In [9]: #CO2 growth rate vs Region
plt.figure(figsize=(20,3))
sns.scatterplot(y=EPI.CDA, x=EPI.Region, hue=EPI.Region, palette = 'Spectral')
plt.ylabel('CO2 Growth Rate')
plt.xlabel('Region')
plt.title("CO2 vs Region")
plt.show()
```

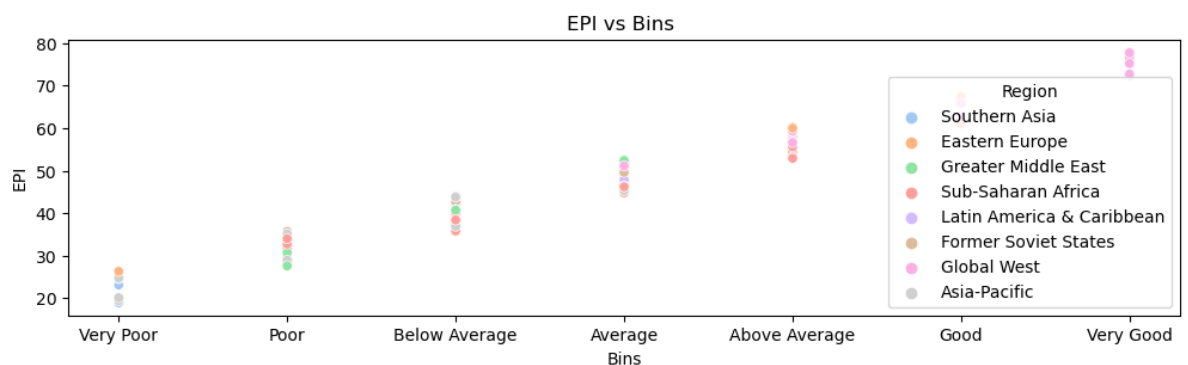


```
In [10]: #Binning
World = EPI
World['Binned'] = pd.cut(World['EPI'], bins=7, labels=["Very Poor", "Poor", "Below
World.sort_values(by=['Binned', 'EPI'])
```

Out[10]:	Country	Region	EPI	PCC	CCH	CDA	CHA	FGA	NDA	BCA	...	FTD	ACD	SDI
74	India	Southern Asia	18.9	21.7	21.7	17.6	48.0	64.2	60.7	100.0	...	3.5	54.4	51.
112	Myanmar	Asia-Pacific	19.4	17.3	17.3	0.0	30.9	69.0	22.4	31.4	...	4.3	0.0	0.
177	Viet Nam	Asia-Pacific	20.1	10.1	10.1	0.0	50.8	NaN	40.1	0.0	...	2.4	19.3	26.
12	Bangladesh	Southern Asia	23.1	18.8	18.8	9.4	37.7	NaN	56.0	46.0	...	11.3	25.8	12.
123	Pakistan	Southern Asia	24.6	16.9	16.9	8.8	24.5	76.3	31.2	41.1	...	NaN	48.0	42.
...
155	Sweden	Global West	72.7	75.4	75.4	87.2	68.5	96.0	100.0	100.0	...	8.9	100.0	100.
101	Malta	Global West	75.2	82.3	82.3	87.5	81.5	58.1	100.0	100.0	...	0.5	100.0	100.
57	Finland	Global West	76.5	83.6	83.6	88.7	72.5	92.0	95.5	100.0	...	NaN	100.0	100.
171	United Kingdom	Global West	77.7	91.5	91.5	97.5	71.8	82.4	71.0	100.0	...	9.2	100.0	100.
44	Denmark	Global West	77.9	92.4	92.4	100.0	57.5	100.0	67.0	100.0	...	9.5	100.0	100.

180 rows × 58 columns

```
In [11]: # EPI vs Bins
plt.figure(figsize=(12,3))
sns.scatterplot(y=World.EPI, x=World.Binned, hue=World.Region , palette = 'pastel')
plt.ylabel('EPI')
plt.xlabel('Bins')
plt.title("EPI vs Bins ")
plt.show()
```



```
In [12]: #Climate Change Mitigation
PCC = EPI[['Country', 'Region', 'EPI',
           'PCC', 'CCH', 'CDA', 'CHA', 'FGA', 'NDA', 'BCA', 'GHN', 'LCB', 'GIB', 'GHP']]
PCC
```

Out[12]:

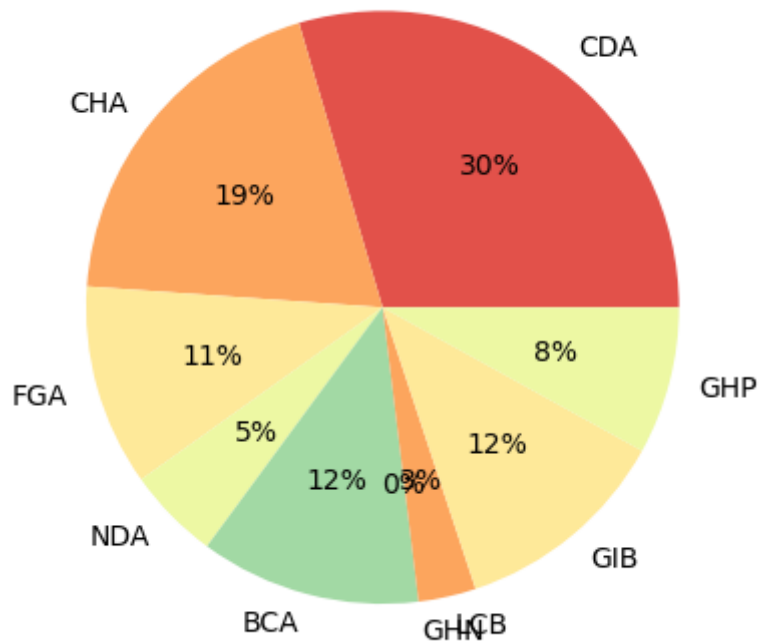
	Country	Region	EPI	PCC	CCH	CDA	CHA	FGA	NDA	BCA	GHN	LCB	GIB	
0	Afghanistan	Southern Asia	43.6	65.6	65.6	83.9	50.2	54.5	63.7	42.9	45.3	100.0	77.5	1
1	Albania	Eastern Europe	47.1	52.5	52.5	42.3	50.1	59.4	76.9	100.0	53.9	87.3	49.6	
2	Algeria	Greater Middle East	29.6	20.9	20.9	18.8	36.1	76.5	46.3	63.9	8.6	13.3	23.1	
3	Angola	Sub-Saharan Africa	30.5	37.7	37.7	39.0	49.7	57.7	70.4	51.8	26.4	37.9	45.2	
4	Antigua and Barbuda	Latin America & Caribbean	52.4	60.2	60.2	37.4	50.2	60.9	79.0	69.0	83.5	88.6	48.0	
...	
175	Vanuatu	Asia-Pacific	36.9	50.1	50.1	21.7	38.4	NaN	61.5	85.2	80.5	24.3	41.8	
176	Venezuela	Latin America & Caribbean	46.4	42.1	42.1	54.5	50.8	74.5	72.9	100.0	22.3	51.2	0.0	
177	Viet Nam	Asia-Pacific	20.1	10.1	10.1	0.0	50.8	NaN	40.1	0.0	2.5	12.5	45.9	
178	Zambia	Sub-Saharan Africa	38.4	25.6	25.6	0.0	39.7	59.4	68.9	32.0	33.7	39.1	53.8	
179	Zimbabwe	Sub-Saharan Africa	46.2	41.9	41.9	29.3	55.1	NaN	100.0	54.5	40.8	57.4	63.7	

180 rows × 14 columns

In [13]:

```
#USA
USA_PCC = PCC.iloc[172:173]
print(USA_PCC)
#Pie Chart with factors in % responsible for air quality in USA
pcc_data = [0.363*USA_PCC.CDA, 0.087*USA_PCC.CHA, 0.037*USA_PCC.FGA, 0.018*USA_PCC.CCH,
0.363*0, 0.039*USA_PCC.LCB, 0.039*USA_PCC.GIB, 0.026*USA_PCC.GHP]
pcc_labels = ['CDA', 'CHA', 'FGA', 'NDA', 'BCA',
'GHN', 'LCB', 'GIB', 'GHP']
pcc_colors = sns.color_palette('Spectral')[0:5]
plt.pie(pcc_data, labels=pcc_labels, colors = pcc_colors, autopct = '%0.0f%')
plt.show()
```

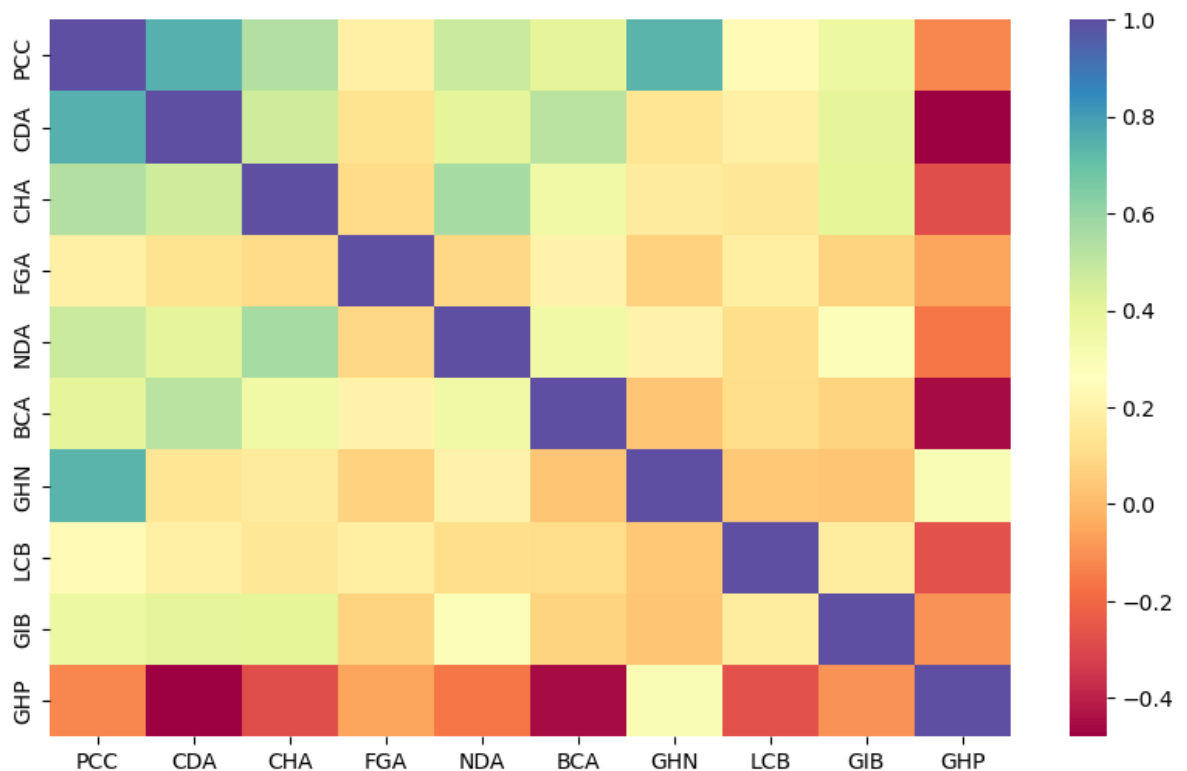
	Country	Region	EPI	PCC	CCH	CDA	CHA		
172	United States of America	Global West	51.1	37.2	37.2	57.8	53.3		
			FGA	NDA	BCA	GHN	LCB	GIB	GHP
172			81.7	73.6	100.0	0.0	50.7	61.2	5.7



```
In [15]: PCC_cor = EPI[['PCC', 'CDA', 'CHA', 'FGA', 'NDA', 'BCA', 'GHN', 'LCB', 'GIB', 'GHP']]
```

```
In [16]: #Heatmap
plt.figure(figsize = (10,6))
sns.heatmap(PCC_cor.corr(), cmap="Spectral")
```

```
Out[16]: <AxesSubplot:>
```



It is evident that CO2 Growth Rate (CDA) is the biggest factor in Climate Change. In order to mitigate climate change CO2 has to be reduced. CO2 growth rate can be defined as the average annual rate of increase or decrease in raw carbon dioxide emissions over the years


```
In [17]: #Environmental Health
HLT = EPI[['Country', 'Region', 'EPI',
          'HLT', 'AIR', 'H2O', 'HMT', 'WMG']]

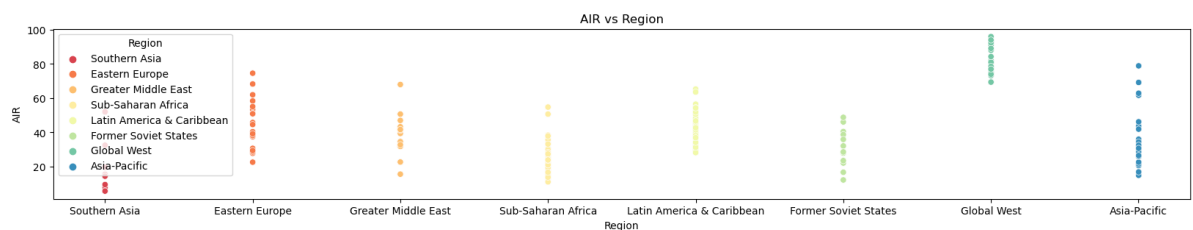
HLT
```

```
Out[17]:
```

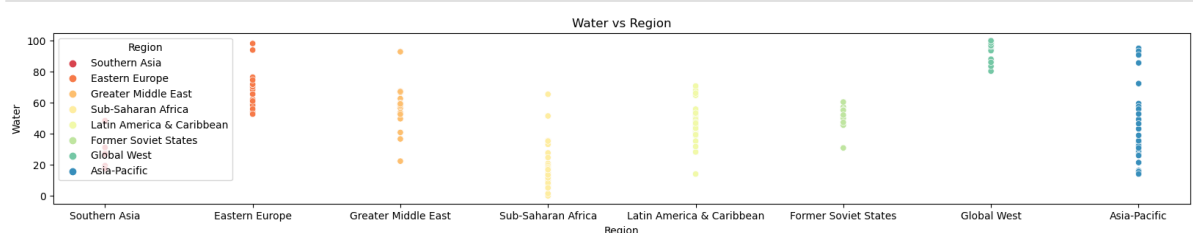
	Country	Region	EPI	HLT	AIR	H2O	HMT	WMG
0	Afghanistan	Southern Asia	43.6	16.0	15.5	28.1	0.0	4.4
1	Albania	Eastern Europe	47.1	40.0	37.5	54.1	45.5	13.4
2	Algeria	Greater Middle East	29.6	42.0	39.4	53.3	38.3	32.0
3	Angola	Sub-Saharan Africa	30.5	20.5	23.1	12.8	36.7	9.6
4	Antigua and Barbuda	Latin America & Caribbean	52.4	55.8	56.5	50.1	59.8	62.3
...
175	Vanuatu	Asia-Pacific	36.9	30.4	30.7	21.5	44.9	36.5
176	Venezuela	Latin America & Caribbean	46.4	42.9	46.7	46.8	42.5	12.1
177	Viet Nam	Asia-Pacific	20.1	35.1	26.5	52.8	47.1	25.6
178	Zambia	Sub-Saharan Africa	38.4	21.2	23.6	13.5	41.7	6.9
179	Zimbabwe	Sub-Saharan Africa	46.2	21.9	23.9	16.9	32.1	13.3

180 rows × 8 columns

```
In [18]: #Air Quality vs Region (Each dot represents a country in that region)
plt.figure(figsize=(20,3))
sns.scatterplot(y=HLT.AIR, x=HLT.Region, hue=EPI.Region, palette = 'Spectral')
plt.ylabel('AIR')
plt.xlabel('Region')
plt.title("AIR vs Region")
plt.show()
```



```
In [19]: #Water Quality vs Region (Each dot represents a country in that region)
plt.figure(figsize=(20,3))
sns.scatterplot(y=HLT.H2O, x=HLT.Region, hue=EPI.Region, palette = 'Spectral')
plt.ylabel('Water')
plt.xlabel('Region')
plt.title("Water vs Region")
plt.show()
```



```
In [20]: #Air Quality and its components
AIR = epi2022[['country', 'AIR.new', 'HAD.new', 'PMD.new', 'OZD.new', 'NOE.new', 'SOE.new', 'COE.new', 'VOE.new']]
AIR.columns = ['Country', 'AIR', 'HAD', 'PMD', 'OZD', 'NOE', 'SOE', 'COE', 'VOE']
AIR
```

```
Out[20]:
```

	Country	AIR	HAD	PMD	OZD	NOE	SOE	COE	VOE
0	Afghanistan	15.5	7.4	16.0	18.4	37.8	61.2	42.7	37.5
1	Albania	37.5	34.5	36.7	63.7	29.5	43.3	61.5	46.9
2	Algeria	39.4	78.4	12.1	35.6	8.2	27.6	39.9	30.7
3	Angola	23.1	17.9	24.0	36.8	32.4	60.2	30.3	8.3
4	Antigua and Barbuda	56.5	69.3	37.1	100.0	77.2	62.2	91.6	91.4
...
175	Vanuatu	30.7	6.1	34.5	62.7	100.0	82.8	100.0	71.2
176	Venezuela	46.7	74.4	25.1	59.2	30.5	60.6	58.2	10.5
177	Viet Nam	26.5	24.9	28.4	41.3	14.9	33.2	8.4	17.6
178	Zambia	23.6	12.6	28.6	36.4	37.6	43.9	46.6	12.8
179	Zimbabwe	23.9	10.4	30.1	43.5	34.8	55.0	45.5	17.7

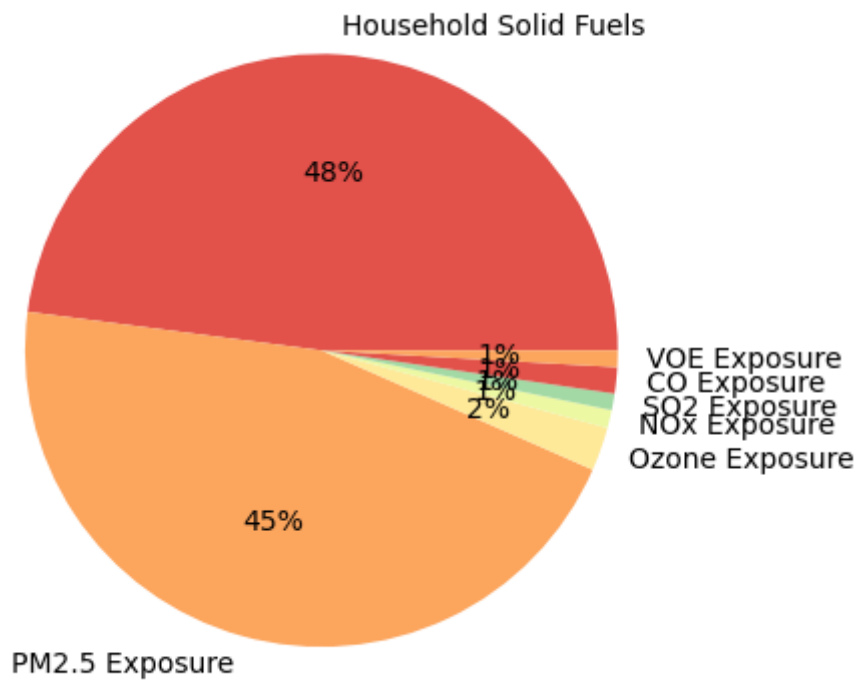
180 rows × 9 columns

```
In [21]: #Quality of Air in USA
USA_AIR = AIR.iloc[172:173]
USA_AIR
```

```
Out[21]:
```

	Country	AIR	HAD	PMD	OZD	NOE	SOE	COE	VOE
172	United States of America	77.0	97.2	74.6	36.7	15.2	34.7	54.9	34.8

```
In [22]: #Pie Chart with factors in % responsible for air quality in USA
air_data = [0.38*USA_AIR.HAD, 0.47*USA_AIR.PMD, USA_AIR.OZD*0.05, USA_AIR.NOE*0.05, USA_AIR.SOE*0.05, USA_AIR.COE*0.05, USA_AIR.VOE*0.05]
air_labels = ['Household Solid Fuels', 'PM2.5 Exposure', 'Ozone Exposure', 'NOx Exposure', 'Sulfur Dioxide Exposure', 'Carbon Monoxide Exposure', 'Lead Exposure']
air_colors = sns.color_palette('Spectral')[0:5]
plt.pie(air_data, labels=air_labels, colors = air_colors, autopct = '%0.0f%%')
plt.show()
```



```
In [23]: #Clustering
Global_West = HLT.loc[HLT['Region'] == 'Global West']
Binned_Global_West = Global_West
Binned_Global_West
```

Out[23]:

	Country	Region	EPI	HLT	AIR	H2O	HMT	WMG
7	Australia	Global West	60.1	86.4	91.1	87.1	76.4	69.0
8	Austria	Global West	66.5	81.7	75.0	94.7	90.7	77.4
15	Belgium	Global West	58.2	77.9	74.6	93.6	66.6	68.0
30	Canada	Global West	50.0	85.9	88.0	88.1	95.6	59.5
44	Denmark	Global West	77.9	85.5	80.5	97.5	100.0	68.3
57	Finland	Global West	76.5	93.4	93.5	100.0	100.0	69.6
58	France	Global West	62.5	83.9	82.0	96.3	83.1	63.8
62	Germany	Global West	62.4	82.0	75.2	99.1	89.8	69.0
73	Iceland	Global West	62.8	94.7	96.0	100.0	95.1	73.9
78	Ireland	Global West	57.4	88.3	89.1	97.4	81.8	67.9
80	Italy	Global West	57.7	76.9	69.4	98.3	80.6	60.6
95	Luxembourg	Global West	72.3	86.7	81.0	98.7	95.1	79.1
101	Malta	Global West	75.2	76.5	73.2	99.8	49.9	63.5
115	Netherlands	Global West	62.6	83.3	76.8	100.0	94.1	66.2
116	New Zealand	Global West	56.7	84.9	93.2	80.4	74.6	60.9
121	Norway	Global West	59.3	92.2	92.4	100.0	93.0	70.7
130	Portugal	Global West	50.4	76.6	78.1	83.5	64.6	62.5
151	Spain	Global West	56.6	78.1	74.0	96.9	70.5	61.4
155	Sweden	Global West	72.7	93.1	94.0	98.6	96.9	70.8
156	Switzerland	Global West	65.9	88.4	84.3	100.0	94.0	76.4
171	United Kingdom	Global West	77.7	83.9	78.6	100.0	93.6	62.6
172	United States of America	Global West	51.1	76.8	77.0	86.1	75.1	54.3

```
In [24]: #Binning
Binned_Global_West['Binned'] = pd.cut(Binned_Global_West['HLT'], bins=3, labels=["I
```

```
In [25]: Binned_Global_West.sort_values(by=['Binned'], ascending=False)
```

Out[25]:

	Country	Region	EPI	HLT	AIR	H2O	HMT	WMG	Binned
155	Sweden	Global West	72.7	93.1	94.0	98.6	96.9	70.8	High
57	Finland	Global West	76.5	93.4	93.5	100.0	100.0	69.6	High
121	Norway	Global West	59.3	92.2	92.4	100.0	93.0	70.7	High
73	Iceland	Global West	62.8	94.7	96.0	100.0	95.1	73.9	High
7	Australia	Global West	60.1	86.4	91.1	87.1	76.4	69.0	Mid
115	Netherlands	Global West	62.6	83.3	76.8	100.0	94.1	66.2	Mid
171	United Kingdom	Global West	77.7	83.9	78.6	100.0	93.6	62.6	Mid
156	Switzerland	Global West	65.9	88.4	84.3	100.0	94.0	76.4	Mid
116	New Zealand	Global West	56.7	84.9	93.2	80.4	74.6	60.9	Mid
95	Luxembourg	Global West	72.3	86.7	81.0	98.7	95.1	79.1	Mid
78	Ireland	Global West	57.4	88.3	89.1	97.4	81.8	67.9	Mid
58	France	Global West	62.5	83.9	82.0	96.3	83.1	63.8	Mid
44	Denmark	Global West	77.9	85.5	80.5	97.5	100.0	68.3	Mid
30	Canada	Global West	50.0	85.9	88.0	88.1	95.6	59.5	Mid
80	Italy	Global West	57.7	76.9	69.4	98.3	80.6	60.6	Low
8	Austria	Global West	66.5	81.7	75.0	94.7	90.7	77.4	Low
101	Malta	Global West	75.2	76.5	73.2	99.8	49.9	63.5	Low
62	Germany	Global West	62.4	82.0	75.2	99.1	89.8	69.0	Low
130	Portugal	Global West	50.4	76.6	78.1	83.5	64.6	62.5	Low
151	Spain	Global West	56.6	78.1	74.0	96.9	70.5	61.4	Low
15	Belgium	Global West	58.2	77.9	74.6	93.6	66.6	68.0	Low
172	United States of America	Global West	51.1	76.8	77.0	86.1	75.1	54.3	Low

In [26]:

```
#HLT Table correlation
HLT.corr().sort_values('HLT', ascending=False)
```

Out[26]:

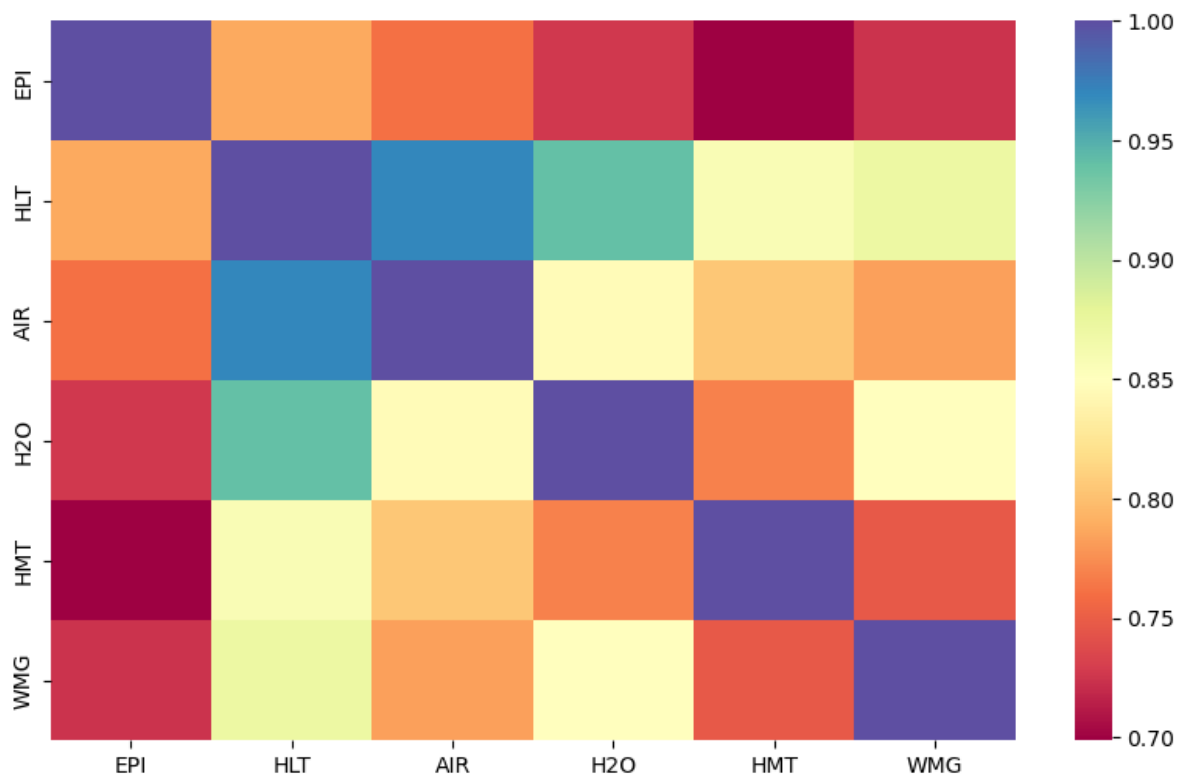
	EPI	HLT	AIR	H2O	HMT	WMG
HLT	0.787318	1.000000	0.970419	0.940909	0.856427	0.870691
AIR	0.760892	0.970419	1.000000	0.844808	0.803768	0.782319
H2O	0.726705	0.940909	0.844808	1.000000	0.768442	0.848365
WMG	0.724086	0.870691	0.782319	0.848365	0.746793	1.000000
HMT	0.698676	0.856427	0.803768	0.768442	1.000000	0.746793
EPI	1.000000	0.787318	0.760892	0.726705	0.698676	0.724086

In [27]:

```
#Heatmap for Environmental Health
plt.figure(figsize = (10,6))
sns.heatmap(HLT.corr(), cmap="Spectral")
```

Out[27]:

<AxesSubplot:>



```
In [28]: #Ecosystem Vitality
ECO = EPI[['Country', 'Region', 'EPI', 'ECO',
          'BDH', 'ECS', 'FSH', 'ACD', 'AGR', 'WRS']]
ECO
```

Out[28]:

	Country	Region	EPI	ECO	BDH	ECS	FSH	ACD	AGR	WRS
0	Afghanistan	Southern Asia	43.6	36.9	30.7	61.8	NaN	35.5	44.2	0.0
1	Albania	Eastern Europe	47.1	45.5	63.9	24.2	17.3	90.2	28.9	1.9
2	Algeria	Greater Middle East	29.6	31.6	22.7	23.7	18.5	70.8	63.3	33.1
3	Angola	Sub-Saharan Africa	30.5	28.6	30.1	29.4	24.3	50.5	24.9	0.0
4	Antigua and Barbuda	Latin America & Caribbean	52.4	43.6	54.2	39.5	19.7	93.2	5.1	15.7
...
175	Vanuatu	Asia-Pacific	36.9	28.0	20.0	38.6	21.0	63.9	33.0	4.5
176	Venezuela	Latin America & Caribbean	46.4	52.0	71.5	33.6	27.7	74.0	43.6	6.4
177	Viet Nam	Asia-Pacific	20.1	22.1	27.9	8.5	24.2	19.3	39.6	0.3
178	Zambia	Sub-Saharan Africa	38.4	58.2	91.0	19.9	NaN	32.2	53.2	4.5
179	Zimbabwe	Sub-Saharan Africa	46.2	61.7	83.7	17.7	NaN	87.8	42.8	37.2

180 rows × 10 columns

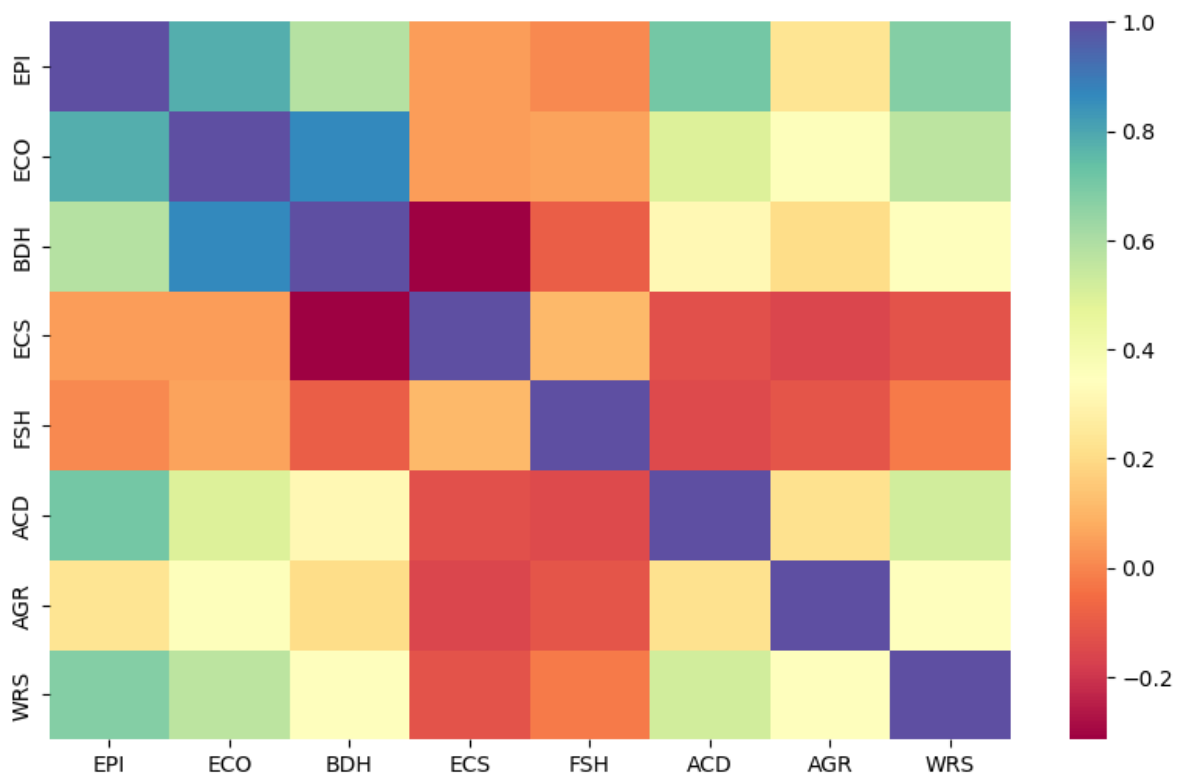
```
In [29]: ECO.corr().sort_values('ECO', ascending=False)
```

```
Out[29]:
```

	EPI	ECO	BDH	ECS	FSH	ACD	AGR	WRS
ECO	0.781626	1.000000	0.864343	0.047428	0.056680	0.495587	0.353924	0.563578
BDH	0.578987	0.864343	1.000000	-0.315252	-0.091273	0.316346	0.205035	0.350663
EPI	1.000000	0.781626	0.578987	0.049305	0.005269	0.708948	0.230961	0.678510
WRS	0.678510	0.563578	0.350663	-0.120850	-0.023635	0.517148	0.351885	1.000000
ACD	0.708948	0.495587	0.316346	-0.135172	-0.148010	1.000000	0.223374	0.517148
AGR	0.230961	0.353924	0.205035	-0.159578	-0.119157	0.223374	1.000000	0.351885
FSH	0.005269	0.056680	-0.091273	0.106555	1.000000	-0.148010	-0.119157	-0.023635
ECS	0.049305	0.047428	-0.315252	1.000000	0.106555	-0.135172	-0.159578	-0.120850

```
In [30]: #Heatmap for Ecosystem Vitality
plt.figure(figsize = (10,6))
sns.heatmap(ECO.corr(), cmap="Spectral")
```

```
Out[30]: <AxesSubplot:>
```



```
In [31]: x = ECO.BDH
y = ECO.ECO
stats.spearmanr(x,y)
```

```
Out[31]: SpearmanrResult(correlation=0.8829896851952493, pvalue=2.306222299508134e-60)
```

```
In [32]: #Binning
Binned_ECO = ECO
ECO_Global_West = Binned_ECO.loc[Binned_ECO['Region'] == 'Global West']
ECO_Global_West['Binned'] = pd.cut(ECO_Global_West['ECO'], bins=3, labels=["Low",
ECO_Global_West.sort_values('Binned', ascending=False)
```

Out[32]:

	Country	Region	EPI	ECO	BDH	ECS	FSH	ACD	AGR	WRS	Binned
95	Luxembourg	Global West	72.3	70.0	84.8	18.1	0.0	100.0	55.9	98.0	High
8	Austria	Global West	66.5	73.9	86.0	28.0	10.4	100.0	70.6	94.0	High
62	Germany	Global West	62.4	66.8	88.5	17.9	26.9	100.0	60.9	97.0	High
101	Malta	Global West	75.2	68.2	72.9	100.0	47.8	100.0	28.3	0.0	High
171	United Kingdom	Global West	77.7	62.3	81.5	23.6	17.0	100.0	45.0	99.0	Mid
156	Switzerland	Global West	65.9	60.2	62.5	30.7	NaN	100.0	41.1	97.0	Mid
155	Sweden	Global West	72.7	60.6	68.8	29.3	15.3	100.0	74.0	100.0	Mid
151	Spain	Global West	56.6	60.3	85.8	13.4	16.4	100.0	31.8	91.1	Mid
116	New Zealand	Global West	56.7	57.9	76.6	26.9	7.4	76.0	64.9	79.9	Mid
115	Netherlands	Global West	62.6	60.0	80.1	24.4	13.0	100.0	29.3	100.0	Mid
7	Australia	Global West	60.1	62.3	82.1	20.1	14.6	88.6	67.9	92.9	Mid
58	France	Global West	62.5	64.0	86.5	21.5	19.5	100.0	49.5	88.0	Mid
57	Finland	Global West	76.5	62.0	71.1	20.1	42.4	100.0	62.7	100.0	Mid
44	Denmark	Global West	77.9	61.3	76.9	16.4	10.9	100.0	75.7	100.0	Mid
15	Belgium	Global West	58.2	57.9	82.4	16.3	16.4	100.0	33.1	68.2	Mid
80	Italy	Global West	57.7	57.2	76.5	26.1	16.8	100.0	38.8	58.8	Low
78	Ireland	Global West	57.4	50.9	59.6	17.4	18.2	95.4	48.7	87.0	Low
73	Iceland	Global West	62.8	53.4	57.0	77.4	19.2	95.8	18.5	15.3	Low
121	Norway	Global West	59.3	57.6	71.2	30.8	39.7	100.0	25.5	64.3	Low
130	Portugal	Global West	50.4	49.6	70.5	8.6	14.7	100.0	23.5	59.2	Low
30	Canada	Global West	50.0	52.5	62.9	29.8	12.8	100.0	42.1	67.4	Low
172	United States of America	Global West	51.1	51.4	60.6	20.1	17.2	100.0	61.4	58.9	Low

Frequent Pattern Mining using Apriori Algorithm

Luxembourg, Austria, Germany and Malta have the best Ecosystem Vitality score among countries lying in Global West

```
In [33]: FP_AIR_df = epi2022[['country', 'region', 'AIR.new', 'HAD.new', 'PMD.new', 'OZD.new', 'NOE.new', 'SOE.new', 'COE.new', 'VOE.new']]
FP_AIR_df.columns = ['Country', 'Region', 'AIR', 'HAD', 'PMD', 'OZD', 'NOE', 'SOE', 'COE', 'VOE']
```

```
In [34]: FP_AIR_df['AIR_BIN'] = pd.cut(FP_AIR_df['AIR'], bins=3, labels=["Poor AIR", "Average AIR", "Great AIR"])
FP_AIR_df['HAD_BIN'] = pd.cut(FP_AIR_df['HAD'], bins=3, labels=["Poor HAD", "Average HAD", "Great HAD"])
FP_AIR_df['PMD_BIN'] = pd.cut(FP_AIR_df['PMD'], bins=3, labels=["Poor PMD", "Average PMD", "Great PMD"])
FP_AIR_df['OZD_BIN'] = pd.cut(FP_AIR_df['OZD'], bins=3, labels=["Poor OZD", "Average OZD", "Great OZD"])
FP_AIR_df['NOE_BIN'] = pd.cut(FP_AIR_df['NOE'], bins=3, labels=["Poor NOE", "Average NOE", "Great NOE"])
FP_AIR_df['SOE_BIN'] = pd.cut(FP_AIR_df['SOE'], bins=3, labels=["Poor SOE", "Average SOE", "Great SOE"])
FP_AIR_df['COE_BIN'] = pd.cut(FP_AIR_df['COE'], bins=3, labels=["Poor COE", "Average COE", "Great COE"])
FP_AIR_df['VOE_BIN'] = pd.cut(FP_AIR_df['VOE'], bins=3, labels=["Poor VOE", "Average VOE", "Great VOE"])
FP_AIR_df
```

Out[34]:

	Country	Region	AIR	HAD	PMD	OZD	NOE	SOE	COE	VOE	AIR_BIN	HAD_BIN
0	Afghanistan	Southern Asia	15.5	7.4	16.0	18.4	37.8	61.2	42.7	37.5	Poor AIR	Poor HAD
1	Albania	Eastern Europe	37.5	34.5	36.7	63.7	29.5	43.3	61.5	46.9	Average AIR	Average HAD
2	Algeria	Greater Middle East	39.4	78.4	12.1	35.6	8.2	27.6	39.9	30.7	Average AIR	Great HAD
3	Angola	Sub-Saharan Africa	23.1	17.9	24.0	36.8	32.4	60.2	30.3	8.3	Poor AIR	Poor HAD
4	Antigua and Barbuda	Latin America & Caribbean	56.5	69.3	37.1	100.0	77.2	62.2	91.6	91.4	Average AIR	Great HAD
...
175	Vanuatu	Asia-Pacific	30.7	6.1	34.5	62.7	100.0	82.8	100.0	71.2	Poor AIR	Poor HAD
176	Venezuela	Latin America & Caribbean	46.7	74.4	25.1	59.2	30.5	60.6	58.2	10.5	Average AIR	Great HAD
177	Viet Nam	Asia-Pacific	26.5	24.9	28.4	41.3	14.9	33.2	8.4	17.6	Poor AIR	Poor HAD
178	Zambia	Sub-Saharan Africa	23.6	12.6	28.6	36.4	37.6	43.9	46.6	12.8	Poor AIR	Poor HAD
179	Zimbabwe	Sub-Saharan Africa	23.9	10.4	30.1	43.5	34.8	55.0	45.5	17.7	Poor AIR	Poor HAD

180 rows × 18 columns

```
In [35]: FP_AIR_df.drop(['AIR', 'HAD', 'PMD', 'OZD', 'NOE', 'SOE', 'COE', 'VOE'], axis=1)
```

Out[35]:

	Country	Region	AIR_BIN	HAD_BIN	PMD_BIN	OZD_BIN	NOE_BIN	SOE_BIN	COE_BIN
0	Afghanistan	Southern Asia	Poor AIR	Poor HAD	Poor PMD	Poor OZD	Average NOE	Average SOE	Average COE
1	Albania	Eastern Europe	Average AIR	Average HAD	Average PMD	Average OZD	Poor NOE	Average SOE	Average COE
2	Algeria	Greater Middle East	Average AIR	Great HAD	Poor PMD	Average OZD	Poor NOE	Poor SOE	Average COE
3	Angola	Sub-Saharan Africa	Poor AIR	Poor HAD	Poor PMD	Average OZD	Poor NOE	Average SOE	Poor COE
4	Antigua and Barbuda	Latin America & Caribbean	Average AIR	Great HAD	Average PMD	Great OZD	Great NOE	Average SOE	Great COE
...
175	Vanuatu	Asia-Pacific	Poor AIR	Poor HAD	Average PMD	Average OZD	Great NOE	Great SOE	Great COE
176	Venezuela	Latin America & Caribbean	Average AIR	Great HAD	Poor PMD	Average OZD	Poor NOE	Average SOE	Average COE
177	Viet Nam	Asia-Pacific	Poor AIR	Poor HAD	Poor PMD	Average OZD	Poor NOE	Poor SOE	Poor COE
178	Zambia	Sub-Saharan Africa	Poor AIR	Poor HAD	Poor PMD	Average OZD	Average NOE	Average SOE	Average COE
179	Zimbabwe	Sub-Saharan Africa	Poor AIR	Poor HAD	Poor PMD	Average OZD	Average NOE	Average SOE	Average COE

180 rows × 10 columns

APRIORI ALGORITHM (AIR DATASET)

```
In [36]: def load_df():
    return FP_AIR_df.values.tolist()

def gen_cand1(itemset):
    CANDIDATE1 = []
    for i in itemset:
        for j in i:
            if not [j] in CANDIDATE1:
                CANDIDATE1.append([j])
    return list(map(frozenset, CANDIDATE1))

itemset = load_df()
CANDIDATE1 = gen_cand1(itemset)

def database_scan(Db, Ck, min_sup):
    sup_count = {}
    sup_data = {}
```

```

r_list = []
Db_length = len(Db)
for t in Db:
    for i in Ck:
        if i.issubset(t):
            if not i in sup_count: sup_count[i]=1
            else: sup_count[i] += 1

total_items = int(Db_length)
for key in sup_count:
    support = sup_count[key]/total_items
    if support >= min_sup:
        r_list.insert(0,key)
    sup_data[key] = support
return r_list, sup_data

def generate_apriori(L_k, k):
    Ck = []
    for l in range(len(L_k)):
        for i in range(l+1, len(L_k)):
            l1 = list(L_k[l]):k-2]
            l2 = list(L_k[i]):k-2]
            l1.sort()
            l2.sort()
            if l1==l2:
                Ck.append(L_k[l] | L_k[i])
    return Ck

def apriori(itemset, min_sup = 0.12):
    CANDIDATE1 = gen_cand1(itemset)
    D = list(map(set, itemset))
    L1, sup_data = database_scan(D, CANDIDATE1, min_sup)
    L = [L1]
    k = 2
    while (len(L[k-2]) > 0):
        Ck = generate_apriori(L[k-2], k)
        L_k, sup = database_scan(D, Ck, min_sup)
        sup_data.update(sup)
        L.append(L_k)
        k += 1
    return L, sup_data
L,sdata = apriori(itemset)
new_list = []
for index in range(len(L)):
    print("\nL{} ".format(index))
    print("Number of patterns={} \n".format(len(L[index])))
    apriori_freq_pattern = [list(i) for i in L[index]]
    print(apriori_freq_pattern)

```

L0

Number of patterns=29

[['Asia-Pacific', [0.0], ['Great AIR'], ['Global West'], ['Great SOE'], ['Great VOE'], ['Great COE'], ['Great NOE'], ['Great OZD'], [100.0], ['Latin America & Caribbean'], ['Poor COE'], ['Sub-Saharan Africa'], ['Poor VOE'], ['Poor SOE'], ['Great HAD'], ['Poor NOE'], ['Average OZD'], ['Average PMD'], ['Average HAD'], ['Average AIR'], ['Average VOE'], ['Average COE'], ['Average SOE'], ['Average NOE'], ['Poor OZD'], ['Poor PMD'], ['Poor HAD'], ['Poor AIR']]]

L1

Number of patterns=114

[['Average PMD', 'Poor AIR'], ['Average PMD', 'Poor HAD'], ['Sub-Saharan Africa', 'Average COE'], ['Great SOE', 'Poor AIR'], ['Great SOE', 'Poor HAD'], ['Average NOE', 'Sub-Saharan Africa'], ['Average NOE', 'Average OZD'], ['Poor VOE', 'Average NOE'], ['Great SOE', 'Poor PMD'], [0.0, 'Poor AIR'], [0.0, 'Poor NOE'], [0.0, 'Poor VOE'], [0.0, 'Poor COE'], ['Poor SOE', 'Poor AIR'], ['Poor VOE', 'Poor OZD'], ['Poor COE', 'Poor OZD'], ['Poor SOE', 'Poor COE'], ['Great SOE', 'Great COE'], ['Average VOE', 'Great HAD'], ['Great HAD', 'Global West'], ['Poor NOE', 'Great AIR'], ['Great HAD', 'Great AIR'], ['Great AIR', 'Global West'], ['Average HAD', 'Poor PMD'], ['Poor OZD', 'Poor NOE'], ['Average PMD', 'Poor VOE'], ['Average PMD', 'Great SOE'], ['Great SOE', 'Average OZD'], ['Great SOE', 'Poor VOE'], ['Great HAD', 'Average SOE'], ['Average AIR', 'Latin America & Caribbean'], ['Great HAD', 100.0], [100.0, 'Great COE'], ['Great NOE', 'Great COE'], ['Great VOE', 100.0], ['Great VOE', 'Great COE'], ['Average OZD', 'Poor AIR'], ['Poor HAD', 'Average OZD'], ['Poor NOE', 'Poor AIR'], ['Poor HAD', 'Poor NOE'], ['Poor VOE', 'Poor AIR'], ['Poor VOE', 'Poor HAD'], ['Poor VOE', 'Average SOE'], ['Sub-Saharan Africa', 'Poor AIR'], ['Poor HAD', 'Sub-Saharan Africa'], ['Sub-Saharan Africa', 'Poor PMD'], ['Sub-Saharan Africa', 'Average OZD'], ['Poor VOE', 'Sub-Saharan Africa'], ['Poor COE', 'Poor AIR'], ['Poor COE', 'Poor HAD'], ['Poor COE', 'Poor PMD'], ['Poor COE', 'Average OZD'], ['Poor COE', 'Poor NOE'], ['Poor VOE', 'Poor COE'], ['Average AIR', 'Poor PMD'], ['Poor PMD', 'Average OZD'], ['Poor NOE', 'Poor PMD'], ['Great HAD', 'Average COE'], ['Average AIR', 'Great HAD'], ['Great HAD', 'Average OZD'], ['Great HAD', 'Poor NOE'], ['Poor SOE', 'Poor PMD'], ['Poor SOE', 'Average OZD'], ['Poor SOE', 'Poor NOE'], ['Poor VOE', 'Poor PMD'], ['Poor VOE', 'Average COE'], ['Average AIR', 'Poor VOE'], ['Poor VOE', 'Average OZD'], ['Poor VOE', 'Poor NOE'], ['Poor VOE', 'Poor SOE'], ['Average AIR', 'Average SOE'], ['Average AIR', 'Average COE'], ['Average AIR', 'Average VOE'], ['Average COE', 'Average HAD'], ['Average VOE', 'Average HAD'], ['Average AIR', 'Average HAD'], ['Average PMD', 'Average SOE'], ['Average PMD', 'Average COE'], ['Average PMD', 'Average AIR'], ['Average PMD', 'Average HAD'], ['Average SOE', 'Average OZD'], ['Average COE', 'Average OZD'], ['Average VOE', 'Average OZD'], ['Average AIR', 'Average OZD'], ['Average HAD', 'Average OZD'], ['Average PMD', 'Average OZD'], ['Poor NOE', 'Average SOE'], ['Poor NOE', 'Average COE'], ['Average VOE', 'Poor NOE'], ['Average AIR', 'Poor NOE'], ['Poor NOE', 'Average HAD'], ['Average PMD', 'Poor NOE'], ['Poor NOE', 'Average OZD'], ['Poor HAD', 'Poor AIR'], ['Poor PMD', 'Poor AIR'], ['Poor HAD', 'Poor PMD'], ['Poor OZD', 'Poor AIR'], ['Poor OZD', 'Poor HAD'], ['Poor OZD', 'Poor PMD'], ['Average NOE', 'Poor AIR'], ['Average NOE', 'Poor HAD'], ['Average NOE', 'Poor PMD'], ['Average SOE', 'Poor AIR'], ['Poor HAD', 'Average SOE'], ['Average SOE', 'Poor PMD'], ['Average NOE', 'Average SOE'], ['Average COE', 'Poor AIR'], ['Poor HAD', 'Average COE'], ['Average COE', 'Poor PMD'], ['Average NOE', 'Average COE'], ['Average SOE', 'Average COE'], ['Average VOE', 'Poor PMD'], ['Average VOE', 'Average SOE'], ['Average VOE', 'Average COE']]]

L2

Number of patterns=121

[['Average PMD', 'Poor VOE', 'Poor HAD'], ['Average PMD', 'Poor VOE', 'Poor AIR'], ['Average PMD', 'Poor HAD', 'Poor AIR'], ['Poor VOE', 'Poor HAD', 'Average COE'], ['Poor VOE', 'Average COE', 'Poor AIR'], ['Poor HAD', 'Average COE', 'Average OZD'], ['Poor VOE', 'Average NOE', 'Average COE'], ['Great SOE', 'Poor HAD', 'Poor AIR'], ['Poor VOE', 'Average NOE', 'Sub-Saharan Africa'], ['Poor VOE', 'Average NOE', 'Poor HAD'], ['Poor VOE', 'Average NOE', 'Poor AIR'], ['Average NOE', 'Sub-Saharan Africa']]]

aran Africa', 'Poor HAD'], ['Average NOE', 'Sub-Saharan Africa', 'Poor AIR'], ['Po
 or VOE', 'Average NOE', 'Poor PMD'], ['Poor VOE', 'Poor OZD', 'Poor HAD'], ['Poor
 VOE', 'Poor COE', 'Poor SOE'], ['Poor SOE', 'Poor COE', 'Poor NOE'], ['Poor VOE',
 'Poor OZD', 'Poor PMD'], ['Poor VOE', 'Poor OZD', 'Poor COE'], ['Poor VOE', 'Poor
 OZD', 'Poor AIR'], ['Poor SOE', 'Poor NOE', 'Poor AIR'], ['Poor SOE', 'Poor PMD',
 'Poor AIR'], ['Average COE', 'Average OZD', 'Poor AIR'], ['Great HAD', 'Average SO
 E', 'Average OZD'], ['Average VOE', 'Great HAD', 'Poor NOE'], ['Average VOE', 'Gre
 at HAD', 'Average OZD'], ['Poor NOE', 'Great HAD', 'Average SOE'], ['Great HAD',
 'Average SOE', 'Average COE'], ['Great HAD', 'Great AIR', 'Global West'], ['Averag
 e VOE', 'Poor NOE', 'Poor PMD'], ['Poor NOE', 'Average COE', 'Poor AIR'], ['Poor O
 ZD', 'Poor NOE', 'Poor AIR'], ['Average PMD', 'Poor VOE', 'Poor NOE'], ['Average P
 MD', 'Poor VOE', 'Average OZD'], ['Poor PMD', 'Average OZD', 'Poor AIR'], ['Poor V
 OE', 'Poor COE', 'Poor NOE'], ['Poor VOE', 'Poor COE', 'Poor PMD'], ['Poor COE',
 'Poor NOE', 'Average OZD'], ['Poor COE', 'Poor NOE', 'Poor PMD'], ['Poor COE', 'Po
 or NOE', 'Poor AIR'], ['Poor COE', 'Poor PMD', 'Poor AIR'], ['Poor COE', 'Poor HA
 D', 'Poor AIR'], ['Poor VOE', 'Sub-Saharan Africa', 'Average OZD'], ['Poor VOE',
 'Sub-Saharan Africa', 'Poor PMD'], ['Poor HAD', 'Sub-Saharan Africa', 'Poor PMD'],
 ['Poor HAD', 'Sub-Saharan Africa', 'Poor AIR'], ['Sub-Saharan Africa', 'Average OZ
 D', 'Poor AIR'], ['Sub-Saharan Africa', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Ave
 rage SOE', 'Poor PMD'], ['Poor VOE', 'Poor HAD', 'Poor NOE'], ['Poor VOE', 'Poor H
 AD', 'Average OZD'], ['Poor VOE', 'Poor HAD', 'Poor PMD'], ['Poor VOE', 'Poor HA
 D', 'Poor COE'], ['Poor VOE', 'Poor HAD', 'Sub-Saharan Africa'], ['Poor VOE', 'Poo
 r HAD', 'Average SOE'], ['Poor VOE', 'Poor NOE', 'Poor AIR'], ['Poor VOE', 'Averag
 e OZD', 'Poor AIR'], ['Poor VOE', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Poor CO
 E', 'Poor AIR'], ['Poor VOE', 'Sub-Saharan Africa', 'Poor AIR'], ['Poor VOE', 'Ave
 rage SOE', 'Poor AIR'], ['Poor VOE', 'Poor HAD', 'Poor AIR'], ['Poor HAD', 'Poor N
 OE', 'Poor AIR'], ['Poor NOE', 'Average OZD', 'Poor AIR'], ['Poor NOE', 'Poor PM
 D', 'Poor AIR'], ['Poor HAD', 'Average OZD', 'Poor AIR'], ['Poor HAD', 'Sub-Sahara
 n Africa', 'Average OZD'], ['Poor PMD', 'Average COE', 'Average OZD'], ['Poor VO
 E', 'Poor SOE', 'Poor NOE'], ['Poor VOE', 'Poor NOE', 'Average OZD'], ['Poor VOE',
 'Average COE', 'Average OZD'], ['Poor VOE', 'Poor NOE', 'Poor PMD'], ['Poor VOE',
 'Average OZD', 'Poor PMD'], ['Poor SOE', 'Poor NOE', 'Average OZD'], ['Poor SOE',
 'Poor NOE', 'Poor PMD'], ['Great HAD', 'Poor NOE', 'Average OZD'], ['Great HAD',
 'Poor NOE', 'Average COE'], ['Great HAD', 'Average COE', 'Average OZD'], ['Average
 OZD', 'Poor NOE', 'Poor PMD'], ['Poor NOE', 'Average COE', 'Poor PMD'], ['Poor NO
 E', 'Average HAD', 'Average OZD'], ['Average VOE', 'Poor NOE', 'Average COE'], ['A
 verage VOE', 'Poor NOE', 'Average SOE'], ['Poor NOE', 'Average COE', 'Average OZ
 D'], ['Average HAD', 'Poor NOE', 'Average COE'], ['Poor NOE', 'Average OZD', 'Aver
 age SOE'], ['Poor NOE', 'Average COE', 'Average SOE'], ['Average PMD', 'Poor NOE',
 'Average OZD'], ['Average AIR', 'Poor NOE', 'Average OZD'], ['Average VOE', 'Avera
 ge COE', 'Average OZD'], ['Average VOE', 'Average SOE', 'Average OZD'], ['Average
 VOE', 'Poor NOE', 'Average OZD'], ['Average SOE', 'Average COE', 'Average OZD'],
 ['Average PMD', 'Poor NOE', 'Average AIR'], ['Average PMD', 'Average AIR', 'Averag
 e OZD'], ['Average PMD', 'Average HAD', 'Average AIR'], ['Average PMD', 'Poor NO
 E', 'Average COE'], ['Average PMD', 'Average COE', 'Average OZD'], ['Average PMD',
 'Average SOE', 'Poor NOE'], ['Average PMD', 'Average SOE', 'Average OZD'], ['Avera
 ge AIR', 'Poor NOE', 'Average HAD'], ['Average AIR', 'Poor NOE', 'Average COE'],
 ['Average AIR', 'Average COE', 'Average OZD'], ['Average AIR', 'Average SOE', 'Poo
 r NOE'], ['Average VOE', 'Average SOE', 'Average COE'], ['Average VOE', 'Average C
 OE', 'Poor PMD'], ['Average COE', 'Poor PMD', 'Poor AIR'], ['Average SOE', 'Averag
 e COE', 'Poor PMD'], ['Average SOE', 'Poor PMD', 'Poor AIR'], ['Average COE', 'Ave
 rage NOE', 'Poor HAD'], ['Average NOE', 'Poor HAD', 'Poor PMD'], ['Average NOE',
 'Average COE', 'Poor AIR'], ['Average NOE', 'Poor PMD', 'Poor AIR'], ['Average NO
 E', 'Poor HAD', 'Poor AIR'], ['Poor OZD', 'Poor HAD', 'Poor PMD'], ['Poor OZD', 'P
 oor PMD', 'Poor AIR'], ['Poor OZD', 'Poor HAD', 'Poor AIR'], ['Poor HAD', 'Average
 SOE', 'Poor PMD'], ['Poor HAD', 'Average COE', 'Poor AIR'], ['Poor HAD', 'Average
 SOE', 'Poor AIR'], ['Poor HAD', 'Poor PMD', 'Poor AIR']]

L3

Number of patterns=31

[['Poor VOE', 'Average COE', 'Poor HAD', 'Poor AIR'], ['Average NOE', 'Poor HAD',
 'Sub-Saharan Africa', 'Poor AIR'], ['Poor VOE', 'Average NOE', 'Poor PMD', 'Poor A
 IR'], ['Poor VOE', 'Average NOE', 'Poor HAD', 'Poor AIR'], ['Poor VOE', 'Average N

OE', 'Sub-Saharan Africa', 'Poor AIR'], ['Poor VOE', 'Average NOE', 'Poor HAD', 'Sub-Saharan Africa'], ['Poor VOE', 'Poor HAD', 'Poor OZD', 'Poor AIR'], ['Poor SOE', 'Poor NOE', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Poor COE', 'Poor SOE', 'Poor NOE'], ['Great HAD', 'Average COE', 'Poor NOE', 'Average SOE'], ['Poor VOE', 'Poor HAD', 'Average SOE', 'Poor AIR'], ['Poor VOE', 'Poor HAD', 'Sub-Saharan Africa', 'Poor AIR'], ['Poor VOE', 'Poor COE', 'Poor HAD', 'Poor AIR'], ['Poor VOE', 'Poor HAD', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Poor HAD', 'Sub-Saharan Africa', 'Poor PMD'], ['Poor VOE', 'Poor HAD', 'Average OZD', 'Poor AIR'], ['Poor VOE', 'Poor HAD', 'Poor NOE', 'Poor AIR'], ['Poor HAD', 'Sub-Saharan Africa', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Sub-Saharan Africa', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Poor COE', 'Poor PMD', 'Poor AIR'], ['Poor VOE', 'Poor COE', 'Poor NOE', 'Poor AIR'], ['Poor VOE', 'Poor COE', 'Poor NOE', 'Poor PMD'], ['Great HAD', 'Average COE', 'Poor NOE', 'Average OZD'], ['Average VOE', 'Average COE', 'Average SOE', 'Average OZD'], ['Average COE', 'Poor NOE', 'Average OZD', 'Average SOE'], ['Average VOE', 'Poor NOE', 'Average OZD', 'Average SOE'], ['Average VOE', 'Average COE', 'Poor NOE', 'Average OZD'], ['Average VOE', 'Average COE', 'Poor NOE', 'Average SOE'], ['Poor HAD', 'Average SOE', 'Poor PMD', 'Poor AIR'], ['Poor HAD', 'Poor OZD', 'Poor PMD', 'Poor AIR'], ['Average NOE', 'Poor HAD', 'Poor PMD', 'Poor AIR']]

L4

Number of patterns=3

[['Average NOE', 'Sub-Saharan Africa', 'Poor AIR', 'Poor VOE', 'Poor HAD'], ['Sub-Saharan Africa', 'Poor AIR', 'Poor VOE', 'Poor HAD', 'Poor PMD'], ['Average VOE', 'Average COE', 'Average SOE', 'Average OZD', 'Poor NOE']]

L5

Number of patterns=0

[]

['Poor VOE', 'Poor HAD', 'Poor AIR', 'Average NOE', 'Sub-Saharan Africa']

['Poor VOE', 'Poor HAD', 'Poor AIR', 'Sub-Saharan Africa', 'Poor PMD']

It can be inferred that there is a good chance that if a country has Poor VOE, Poor HAD, Poor AIR, Average NOE it lies in Sub-Saharan Africa

Similarly, it can also be inferred that there is a good chance that if a country has Poor VOE, Poor HAD, Poor AIR, Poor PMD it lies in Sub-Saharan Africa

Observations

1) EPI Score has three major components a) Climate Change Mitigation Score b)

Environmental Health Score c) Ecosystem Vitality Score

2) Environment Health scores of Global west countries are very high whereas scores of Sub Saharan African countries are very poor.

3) Ecosystem Vitality scores of Global west and Eastern Europe countries are quite high.

4) All the countries which have Very Good EPI score lie in Global West.

5) It is evident that CO2 Growth Rate (CDA) is the biggest factor in Climate Change. In order to mitigate climate change CO2 has to be reduced. CO2 growth rate can be defined as the average annual rate of increase or decrease in raw carbon dioxide emissions over the years

6) Iceland, Norway, Sweden, Finland have the best EPI scores among countries lying in Global West regions.

7) Air Quality scores of Southern Asian countries are very bad while that of Global West are very impressive

8) Water Quality scores of Sub Saharan Africa region is worst while Global West and Eastern

Europe have good scores.

9) Luxembourg, Austria, Germany and Malta have the best Ecosystem Vitality score among countries lying in Global West

10) It can be inferred that there is a good chance that if a country has Poor VOE, Poor HAD, Poor AIR, Average NOE it lies in Sub-Saharan Africa

11) Similarly, it can also be inferred that there is a good chance that if a country has Poor VOE, Poor HAD, Poor AIR, Poor PMD it lies in Sub-Saharan Africa