

Author: Amina Nsanza Class: 5550 Data Science and Climate Change. Project: Rising Temperature Impact on Energy Poverty Code Source: Cleaning and Tidying Datasets

```
import pandas as pd
import polars as pl
import numpy as np
import matplotlib.pyplot as plt
```

Problem Statement & Data Collection and Refinement.

The ongoing rise in global temperatures has led to significant environmental impacts, from severe weather events to energy surplus and poverty. One notable consequence is the increase in energy poverty— a lack of access to modern, reliable, and affordable energy services, including electricity and clean cooking facilities. This issue disproportionately affects low-income and rural communities and exacerbates existing inequalities. This project aims to establish the correlation between rising global temperatures and energy poverty while predicting future energy poverty indexes based on temperature projections. Understanding this relationship is crucial in anticipating how energy poverty may increase in response to global temperatures, thereby informing policy decisions and targeting interventions for vulnerable populations.

The data used in this project will be from various sources: The World Bank, The Intergovernmental Panel on Climate Change (IPCC), CEIC Data, the National Oceanic and Atmospheric Administration (NOAA), and Enerdata.

Energy Poverty Index Dataset

```
path = 'Raw_Data/World_Bank_Poverty_Indices/
API_EG.ELC.ACCS.ZS_DS2_en_csv_v2_62.csv'

#Initial dataset access to electricity % of population

access_elec_df = pd.read_csv(path, skiprows=4) # Skipping metadata rows
print(access_elec_df.head())

access_elec_df.shape
```

	Country Name	Country Code	\
0	Aruba	ABW	
1	Africa Eastern and Southern	AFE	
2	Afghanistan	AFG	
3	Africa Western and Central	AFW	
4	Angola	AGO	

	Indicator Name	Indicator Code	1960	1961	1962	\
0	Access to electricity (% of population)	EG.ELC.ACCS.ZS	NaN	NaN	NaN	

1	Access to electricity (% of population)	EG.ELC.ACCS.ZS	NaN	NaN	NaN
2	Access to electricity (% of population)	EG.ELC.ACCS.ZS	NaN	NaN	NaN
3	Access to electricity (% of population)	EG.ELC.ACCS.ZS	NaN	NaN	NaN
4	Access to electricity (% of population)	EG.ELC.ACCS.ZS	NaN	NaN	NaN

	1963	1964	1965	...	2015	2016	2017	2018	\
0	NaN	NaN	NaN	...	100.000000	100.000000	100.000000	100.000000	
1	NaN	NaN	NaN	...	33.903800	38.854624	40.199898	43.017148	
2	NaN	NaN	NaN	...	71.500000	97.700000	97.700000	93.400000	
3	NaN	NaN	NaN	...	46.758739	50.906115	48.789457	51.211055	
4	NaN	NaN	NaN	...	42.000000	41.800000	42.900000	45.300000	

	2019	2020	2021	2022	2023	Unnamed: 68
0	100.000000	100.000000	100.000000	99.900000	NaN	NaN
1	44.381259	46.264875	48.100862	48.711995	NaN	NaN
2	97.700000	97.700000	97.700000	85.300000	NaN	NaN
3	51.168083	51.730899	54.224724	55.437577	NaN	NaN
4	45.600000	47.000000	48.200000	48.500000	NaN	NaN

[5 rows x 69 columns]

(266, 69)

#Cleaning the data

#Dropping null years (1960 - 1989 & 2023 and last col)

```
columns_to_drop = [col for col in access_elec_df.columns if
col.startswith(tuple(str(year) for year in range(1960, 1990)))]
```

```
access_elec_df = access_elec_df.drop(columns=columns_to_drop, axis=1)
```

```
access_elec_df = access_elec_df.drop(columns=['2023', 'Unnamed: 68'],
errors='ignore') #These cols are also empty
access_elec_df.columns.tolist()
```

```
#access_elec_df.shape
```

```
['Country Name',
'Country Code',
'Indicator Name',
'Indicator Code',
'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',  
'2018',  
'2019',  
'2020',  
'2021',  
'2022']
```

```
#Checking for Nulls in Countries and countries with nulls 50% empty years will  
be dropped.
```

```
year_columns = [col for col in access_elec_df.columns if col.isdigit()]
```

```
countries_na =  
access_elec_df[access_elec_df[year_columns].isnull().any(axis=1)]  
countries_na['Null Count'] = countries_na[year_columns].isnull().sum(axis=1)
```

```
#Count of NAs per country
```

```
countries_na_summary = countries_na[['Country Name', 'Country Code', 'Null  
Count']]
```

```
# Sort by the number of null values for better analysis
```

```
countries_na_summary = countries_na_summary.sort_values(by='Null Count',  
ascending=False)
```

```
countries_na_summary
```

```
/var/folders/19/lj7m40r97fj5_hs7nfmzyf880000gn/T/  
ipykernel_8886/3541968494.py:6: SettingWithCopyWarning:  
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/user\_guide/indexing.html#returning-a-view-versus-a-copy  
countries_na['Null Count'] = countries_na[year_columns].isnull().sum(axis=1)
```

	Country Name	Country Code	Null Count
11	American Samoa	ASM	33
110	Not classified	INX	33
261	Kosovo	XKX	23
193	Korea, Dem. People's Rep.	PRK	19
216	South Sudan	SSD	17
...
106	Indonesia	IDN	1
33	Botswana	BWA	1
42	Cameroon	CMR	1
59	Dominican Republic	DOM	1
211	El Salvador	SLV	1

```
#Countries with more than 16 years of NAs
```

```
countries_NA = countries_na_summary[countries_na_summary['Null Count'] > 16]  
print(countries_NA)
```

```
#Dropping these countries
```

```
countires_dropped = countries_NA['Country Code'] # List of country codes to drop
```

```
access_elec_df = access_elec_df[~access_elec_df['Country Code'].isin(countires_dropped)]
```

```
access_elec_df.shape
```

	Country Name	Country Code	Null Count
11	American Samoa	ASM	33
110	Not classified	INX	33
261	Kosovo	XKX	23
193	Korea, Dem. People's Rep.	PRK	19
216	South Sudan	SSD	17
131	Liberia	LBR	17

(260, 37)

```
access_elec_df.head()
```

```
#Seems a lot of cols also have NAs in the earlier years deciding whether to drop them or not
```

```
na_per_year = access_elec_df[year_columns].isnull().sum()
```

```
# Converting the result into a DataFrame for better readability
```

```
na_per_year_df = na_per_year.reset_index()
```

```
na_per_year_df.columns = ['Year', 'NA Count']
```

```
na_per_year_df
```

```
#1990 - 1992 Have a lot of NAs > 50% These
```

	Year	NA Count
0	1990	154
1	1991	143
2	1992	126
3	1993	111
4	1994	105
5	1995	98
6	1996	83
7	1997	76
8	1998	67
9	1999	58
10	2000	1
11	2001	1
12	2002	0
13	2003	0
14	2004	0
15	2005	0
16	2006	0
17	2007	0
18	2008	0
19	2009	0
20	2010	0
21	2011	0
22	2012	0
23	2013	0
24	2014	0
25	2015	0
26	2016	0
27	2017	0
28	2018	0
29	2019	0
30	2020	0
31	2021	0
32	2022	0

```
#Dropping the cols with 50%> NAs

years_to_drop = na_per_year[na_per_year > 125].index.tolist()

access_elec_df = access_elec_df.drop(columns=years_to_drop, axis=1)

remaining_years = [col for col in access_elec_df.columns if col.isdigit()]

remaining_years #Checks out
```

```
['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',
 '2018',
 '2019',
 '2020',
 '2021',
 '2022']
```

```
#Saving the cleaned df prior to applying bootstrap

path = 'Cleaned_Data/cleaned_energy_poverty_index.csv'
access_elec_df.to_csv(path, index=False)
```

```

#For other NA values using bootstrapping to fill the NAs

#Countries with NAs
#access_elec_df.columns

#getting the year columns in the dataset
year_columns = [col for col in access_elec_df.columns if col.isdigit()]

# Applying bootstrapping to fill missing vals
def bootstrap_fill(df, year_columns):
    for col in year_columns:
        # Getting non NA values n
        non_na_values = df[col].dropna()
        # Using the non NAs to do random resampling for the values with NA
        df[col] = df[col].apply(lambda x: np.random.choice(non_na_values) if
pd.isnull(x) else x)
    return df

# Creating a bootstrapped version of the dataset
access_elec_bt_df = access_elec_df.copy()
access_elec_bt_df = bootstrap_fill(access_elec_bt_df, year_columns)

# Extracting og and bootstrapped values to compare
og_vals = access_elec_df[year_columns].stack()
bt_vals = access_elec_bt_df[year_columns].stack()

access_elec_bt_df.head()

```



```
#Saving the boot_strapped
```

```
path = 'Cleaned_Data/cleaned_energy_poverty_index_bt.csv'  
access_elec_bt_df.to_csv(path, index=False)
```

```
# Getting year columns
```

```
year_columns = [col for col in access_elec_bt_df.columns if col.isdigit()]
```

```
# Calculating the mean access to electricity for all countries per year
```

```
mean_access_per_year = access_elec_bt_df[year_columns].mean()
```

```
plt.figure(figsize=(13, 6))
```

```
plt.plot(mean_access_per_year.index, mean_access_per_year.values, marker='o',  
linestyle='-')
```

```
plt.title('Bootstrapped Average Access to Electricity (% of Population) Over the  
Years')
```

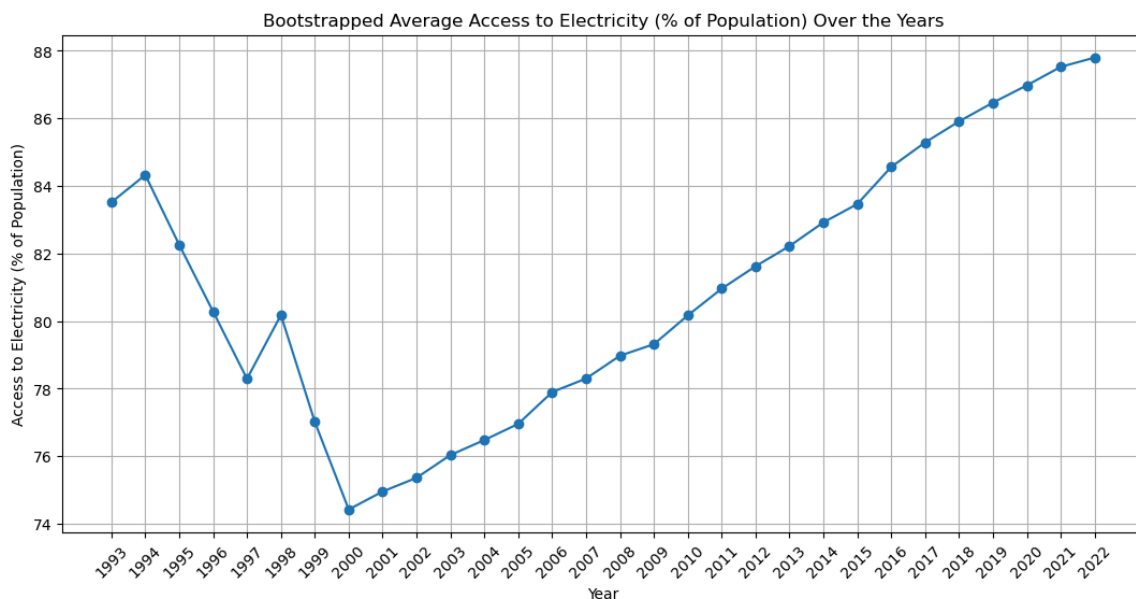
```
plt.xlabel('Year')
```

```
plt.ylabel('Access to Electricity (% of Population)')
```

```
plt.grid(True)
```

```
plt.xticks(ticks=mean_access_per_year.index,  
labels=mean_access_per_year.index, rotation=45)
```

```
plt.show()
```

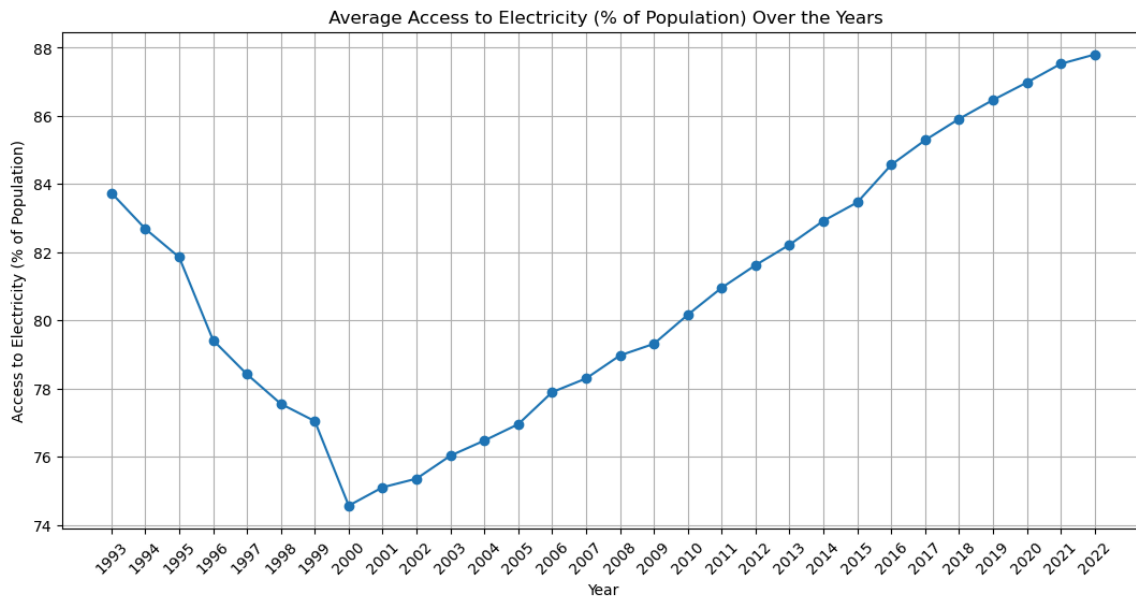


```
# Getting year columns
```

```
year_columns = [col for col in access_elec_df.columns if col.isdigit()]
```

```
# Calculating the mean access to electricity for all countries per year
mean_access_per_year = access_elec_df[year_columns].mean()

#The trend over the years
plt.figure(figsize=(13, 6))
plt.plot(mean_access_per_year.index, mean_access_per_year.values, marker='o',
linestyle='--')
plt.title(' Average Access to Electricity (% of Population) Over the Years')
plt.xlabel('Year')
plt.ylabel('Access to Electricity (% of Population)')
plt.grid(True)
plt.xticks(ticks=mean_access_per_year.index,
labels=mean_access_per_year.index, rotation=45)
plt.show()
```



Conclusion on this Dataset: This dataset showcased an increase in energy accessibility per % of population and this energy poverty index could not be used because factors like country development contribute to the number of individuals that have access to energy. Instead another Energy Poverty Index was going to be created (Using Energy Prices & Global National Income)

Cleaning the Energy Price Data (2014 - 2019)

```
path = 'Raw_Data/P_Data_Extract_From_Doing_Business/36b3e48f-46ad-4de7-899c-
c8861482c822_Data.csv'
energy_price_df = pd.read_csv(path, encoding='ISO-8859-1')
```

```
energy_price_df.head()
```

Series Name	Country Code	Country Name	Country Code	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Electricity: Price of electricity (US ...)	IC.EL-CHN	China	CHN_BEI	14.1	14.3	13.9	18.7	17.4	16.7
Electricity: Price of electricity (US ...)	IC.EL-CHN	China	CHN_BJS	9.3	9	9.3	9.2	9.3	10.9
Electricity: Price of electricity (US ...)	IC.EL-IND	India	IND_DEL	20.3	19.8	16	15.2	14.9	16.3
Electricity: Price of electricity (US ...)	IC.EL-IND	India	IND_DHA	9.3	9	9.3	9.2	9.2	9.4
Electricity: Price of electricity (US ...)	IC.EL-IDN	Indonesia	IDN_JAK	14.2	13.7	11	11.1	10.7	10.7

```
# Cleaninng the cols so its only numerical years.
year_columns = [col for col in energy_price_df.columns if col.startswith('19')
or col.startswith('20')]
renamed_columns = {col: int(col.split(' ')[0]) for col in year_columns}
energy_price_df.rename(columns=renamed_columns, inplace=True)

# dropping years 2010 to 2013 as they are mostly empty
columns_to_drop = [col for col in energy_price_df.columns if isinstance(col,
int) and 2010 <= col <= 2013]
energy_price_df = energy_price_df.drop(columns=columns_to_drop,
errors='ignore')

# dropping series same and series code cols
energy_price_df = energy_price_df.drop(columns=['Series Name', 'Series Code'],
errors='ignore')

#dropping na values

energy_price_df.columns.tolist()
```

```
['Country Name', 'Country Code', 2014, 2015, 2016, 2017, 2018, 2019]
```

```
energy_price_df.head()

#Saving the cleaned df
path = 'Cleaned_Data/cleaned_energy_price.csv'
energy_price_df.to_csv(path, index=False)
```

```
NameError: name 'energy_price_df' is not defined
[?] [0;31m-----[?]
[0m
[?] [0;31mNameError[?] [0m                                Traceback (most recent
call last)
Cell [?] [0;32mIn[3], line 1[?] [0m
[?] [0;32m--> 1[?] [0m [?] [43menergy_price_df[?] [49m[?] [38;5;241m.[?] [39mhead()
[?] [1;32m      3[?] [0m [?] [38;5;66;03m#Saving the cleaned df [?] [39;00m
[?] [1;32m                                         4[?] [0m
path      [?] [38;5;241m=[?] [39m      [?] [38;5;124m'[?] [39m[?] [38;5;124mCleaned_Data/
cleaned_energy_price.csv[?] [39m[?] [38;5;124m'[?] [39m
[?] [0;31mNameError[?] [0m: name 'energy_price_df' is not defined
```

Further Cleaning and Combining Energy Prices.

```

path = 'Cleaned_Data/cleaned_energy_price.csv'
energy_price_df = pd.read_csv(path)

#Dividing it by 100 -> USD Cents per Kwh
years = ['2014', '2015', '2016', '2017', '2018', '2019']
energy_price_df[years] = energy_price_df[years].apply(pd.to_numeric,
errors='coerce')

energy_price_df[years] = energy_price_df[years] / 100

energy_price_df.tail(7)

```

	Country Name	Country Code	2014	2015	2016	2017	2018	2019
211	Zambia	ZMB	0.045	0.048	0.038	0.047	0.047	0.046
212	Zimbabwe	ZWE	0.125	0.105	0.125	0.121	0.119	0.124
213	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
214	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
215	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
216	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
217	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```

#Energy Prices 2021
energy_price_2021_df = pd.read_excel('Raw_Data/Electricity_Prices/
Electricity_Prices2021.xlsx')

energy_price_2021_df.head()

#Drop rank col & Country code col
energy_price_2021_df = energy_price_2021_df.drop(columns=['Rank', 'Country
code'])

#Rename Coutry name -> Country Name & Changing Avg Price 1KW/h (USD) -> 2021
energy_price_2021_df = energy_price_2021_df.rename(columns={
    'Country name': 'Country Name',
    'Average price of 1KW/h (USD)': '2021'
})

```

```
#Saving the cleaned csv
path = 'Cleaned_Data/cleaned_electricity_prices2021.csv'
energy_price_2021_df.to_csv(path, index=False)
```

```
#Joining 2014 - 2019 + 2021 by Country
#energy_price_2021_df.shape 230 Countries
#energy_price_df.shape 218 Countries

#Join both datasets left to keep most of the countries
energy_prices_2014_2021 = pd.merge(energy_price_df, energy_price_2021_df,
on='Country Name', how='left')

energy_prices_2014_2021.shape
```

```
(218, 10)
```

```
#Saving
energy_prices_2014_2021.sort_values(by='Country Name')
path = 'Cleaned_Data/energy_prices_2014_2021.csv'
energy_prices_2014_2021.to_csv(path, index=False)
```

```
#Drop rows 2 - 23 there cities not countries
energy_prices_2014_2021
energy_prices_2014_2021.drop(energy_prices_2014_2021.index[0:22])

energy_prices_2014_2021.head()
```


	Country Name	Country Code	2014	2015	2016	2017	2018	2019	Conti- nental region	2021
22	Afghanistan	AFG	0.233	0.220	0.209	0.186	0.176	0.180	ASIA (EX. NEAR EAST)	0.064969
23	Albania	ALB	0.095	0.102	0.096	0.091	0.087	0.094	EAST- ERN EU- ROPE	0.115875
24	Algeria	DZA	0.027	0.027	0.030	0.026	0.022	0.021	NORTH- ERN AFRICA	0.032792
25	Angola	AGO	0.047	0.046	0.088	0.060	0.046	0.037	SUB- SAHA- RAN AFRICA	0.012713
26	Antigua and Bar- buda	ATG	0.507	0.445	0.442	0.432	0.437	0.449	CARIBBEAN	0.367061

```
energy_prices_2014_2021.shape
```

```
(196, 10)
```

```
#Add 2022 - 2023 Dataset Energy Data Set
path = 'Cleaned_Data/cleaned_energy_price_2022_2023.csv'
energy_prices_2022_2023 = pd.read_csv(path)
energy_prices_2022_2023.head()
#energy_prices_2022_2023.shape -> 147 Countries.

#Combine it with the other years of energy prices as final energy prices dataset
and save it

#Left Join to Perserve Countries from 2014 - 2023 Because 2014 - 2019 Had the
most prices.

energy_prices_2014_2023 = pd.merge(energy_prices_2014_2021,
energy_prices_2022_2023, on='Country Name', how='left')
```

```

# Cleaning it further

#Re-arranging the cols
columns = list(energy_prices_2014_2023.columns)
columns.insert(2, columns.pop(columns.index('Continental region')))
energy_prices_2014_2023 = energy_prices_2014_2023[columns]

#Ordering the years right

new_cols = ['Country Name', 'Country Code', 'Continental region'] + sorted(
    [col for col in energy_prices_2014_2023.columns if col.isnumeric()]
)
energy_prices_2014_2023 = energy_prices_2014_2023[new_cols]

#Dropping the empty 5 rows
energy_prices_2014_2023 = energy_prices_2014_2023[:-5]

energy_prices_2014_2023.head()

```

	Country Name	Country Code	Continental region	2014	2015	2016	2017	2018	2019	2021	2022	2023
0	Afghanistan	AFG	ASIA (EX. NEAR EAST)	0.233	0.220	0.209	0.186	0.176	0.180	0.064969	0.043	0.0421
1	Albania	ALB	EAST-EUROPE	0.095	0.102	0.096	0.091	0.087	0.094	0.115875	0.116	0.1051
2	Algeria	DZA	NORTH-EAST AFRICA	0.027	0.027	0.030	0.026	0.022	0.021	0.032792	0.039	0.0391
3	Angola	AGO	SUB-SAHARAN AFRICA	0.047	0.046	0.088	0.060	0.046	0.037	0.012713	0.016	0.0231
4	Antigua and Barbuda	ATG	CARIBBEAN	0.507	0.445	0.442	0.432	0.437	0.449	0.367061	NaN	NaN

```
energy_prices_2014_2023.shape
```

```
# Assigning Continental Region for the countries that did not have them ->
this will help to connect weather temperatures.
```

```
#How many dont have region assigned
```

```
countries_no_region = energy_prices_2014_2023['Continental
region'].isna().sum()
countries_no_region
```

```
#list of the countries
```

```
countries_no_region_list =
energy_prices_2014_2023[energy_prices_2014_2023['Continental region'].isna()]
['Country Name'].tolist()
countries_no_region_list
```

```
#Assigning them regions based the the 2021 dataset
```

```
#Region mapping
```

```
region_mapping = {
```

```

    'Bahamas, The': 'Caribbean',
    'Cabo Verde': 'Sub-Saharan Africa',
    'Congo, Dem. Rep.': 'Sub-Saharan Africa',
    'Congo, Rep.': 'Sub-Saharan Africa',
    'Egypt, Arab Rep.': 'Northern Africa',
    'Eritrea': 'Sub-Saharan Africa',
    'Gambia, The': 'Sub-Saharan Africa',
    'Hong Kong, China': 'Asia (Ex. Near East)',
    'Iran, Islamic Rep.': 'Asia (Ex. Near East)',
    'Korea, Rep.': 'Asia (Ex. Near East)',
    'Kosovo': 'Eastern Europe',
    'Kyrgyz Republic': 'Asia (Ex. Near East)',
    'Lao PDR': 'Asia (Ex. Near East)',
    'Micronesia, Fed. Sts.': 'Oceania',
    'Netherlands': 'Western Europe',
    'North Macedonia': 'Eastern Europe',
    'São Tomé and Príncipe': 'Sub-Saharan Africa',
    'Slovak Republic': 'Eastern Europe',
    'South Sudan': 'Sub-Saharan Africa',
    'St. Kitts and Nevis': 'Caribbean',
    'St. Lucia': 'Caribbean',
    'St. Vincent and the Grenadines': 'Caribbean',
    'Syrian Arab Republic': 'Near East',
    'Taiwan, China': 'Asia (Ex. Near East)',
    'Venezuela, RB': 'South America',
    'West Bank and Gaza': 'Near East',
    'Yemen, Rep.': 'Near East'

}

# assigning the regions to the corresponding countrydataset

energy_prices_2014_2023['Continental region'] =
energy_prices_2014_2023['Country Name'].map(
lambda country: region_mapping[country] if
pd.isna(energy_prices_2014_2023.loc[energy_prices_2014_2023['Country Name']
== country, 'Continental region']).all() else
energy_prices_2014_2023.loc[energy_prices_2014_2023['Country Name'] == country,
'Continental region'].values[0]

)
energy_prices_2014_2023.head()

```

	Coun- try Name	Coun- try Code	Con- ti- nen- tal re- gion	2014	2015	2016	2017	2018	2019	2021	2022	2023
0	Afghanistan	AFG	ASIA (EX. NEAR EAST)	0.233	0.220	0.209	0.186	0.176	0.180	0.064969	0.043	0.0421
1	Al- ba- nia	ALB	EAST- ERN EUROPE	0.095	0.102	0.096	0.091	0.087	0.094	0.115875	0.116	0.1051
2	Al- geria	DZA	NORTH- ERN AFRICA	0.027	0.027	0.030	0.026	0.022	0.021	0.032792	0.039	0.0391
3	An- gola	AGO	SUB- SA- HA- RAN AFRICA	0.047	0.046	0.088	0.060	0.046	0.037	0.012713	0.016	0.0231
4	Antigua and Bar- buda	ATG	CARIBBEAN	0.507	0.445	0.442	0.432	0.437	0.449	0.367061	NaN	NaN

```
#Checking if they all got assigned
countries_no_region = energy_prices_2014_2023['Continental
region'].isna().sum()
countries_no_region #Checks out
```

```
#Saving the cleaned energy_prices_2014_2023
```

```
path = 'Cleaned_Data/cleaned_energy_prices_2014_2023.csv'
energy_prices_2014_2023.to_csv(path, index=False)
```

```
#Dealing with NAs for Different Years Using Boot strapping and interpolation as
fall back for countries with insuficient data to preserve the trend.
```

```
energy_prices_2014_2023 = pd.read_csv('Cleaned_Data/
cleaned_energy_prices_2014_2023.csv')
```

```
# bootstrapping function to fill na values with bootstrapping
def bootstrap(energy_prices_2014_2023, group_col, year_cols):
```

```

"""
Fill missing values using bootstrapping.
Args: Country Cols
Returns:
- DataFrame with missing values filled.
"""
bt_data = energy_prices_2014_2023.copy()

for col in year_cols:
    for name, group in bt_data.groupby(group_col):
        # values with numbers in years
        valid_values = group[col].dropna()

        # Filling NAs with bt samples from the same country
        if not valid_values.empty:
            bt_vals = group[col].apply(
                lambda x: np.random.choice(valid_values) if pd.isna(x) else
x
            )
            bt_data.loc[group.index, col] = bt_vals

        # Interpolating any remaining missing values in the columns if some were
        added
            bt_data[col] = bt_data[col].interpolate(method='linear',
limit_direction='both') #This allows us to make sure we get all NAs but we
preserve the trend of the data.

    return bt_data

# Make sure the years are cols just incase
year_columns = [col for col in energy_prices_2014_2023.columns if
col.isnumeric()]

# Applying the bootstrap samples to the dataset for missin vals
bt_energy_prices_2014_2023 = bootstrap(energy_prices_2014_2023,
group_col="Country Name", year_cols=year_columns)

# making sure all NA are filled
NA_vals = bt_energy_prices_2014_2023.isna().sum() #Checks out.
NA_vals

```

Country Name	0
Country Code	0
Continental region	0

```

2014      0
2015      0
2016      0
2017      0
2018      0
2019      0
2021      0
2022      0
2023      0
dtype: int64

```

```

bt_energy_prices_2014_2023.head()

#Saving the bootstapped data

path = 'Cleaned_Data/bt_energy_prices_2014_2023.csv'
bt_energy_prices_2014_2023.to_csv(path, index=False)

```

Cleaning Energy Consumption Data and Creating total Energy Consumption Price per Region / Country \$/Kwh

```

bt_energy_prices_2014_2023 = pd.read_csv('Cleaned_Data/
bt_energy_prices_2014_2023.csv')

```

```

energy_consumption = pd.read_excel('Raw_Data/Electricity_Prices/electricity-
domestic-consumption-data.xlsx')

energy_consumption.head()

energy_consumption_kwh = energy_consumption.copy()

#Converting to Kwh Energy Consumption / Year from Twh Terrawatt hour -> Kilowatt
hw conversion is 1000000000
energy_consumption_kwh.iloc[:, 1:] = energy_consumption_kwh.iloc[:, 1:] *
1000000000

#Renaming cols later for combining with price
energy_consumption_kwh.rename(
    columns={col: f"energy_consumption_kwh_{col}" if isinstance(col, int) else
col for col in energy_consumption_kwh.columns},
    inplace=True
)
energy_consumption_kwh.rename(columns={"Country": "Country", "Name": "Name"},
inplace=True)

```

```
energy_consumption_kwh.head()

path = 'Cleaned_Data/energy_consumption.csv'
energy_consumption_kwh.to_csv(path, index=False)

energy_consumption_kwh.head()
```

	CountryName	energy_consumption_kwh_2014	energy_consumption_kwh_2015	energy_consumption_kwh_2016	energy_consumption_kwh_2017	energy_consumption_kwh_2018	energy_consumption_kwh_2019	energy_consumption_kwh_2020	energy_consumption_kwh_2021	energy_consumption_kwh_2022	energy_consumption_kwh_2023
0	Belgium	8.2633508e+10	8.3056608e+10	8.3581208e+10	8.3745108e+10	8.4141408e+10	8.5180008e+10	8.5380008e+10	8.608707e+10	8.7129307e+10	8.826844e+10
1	Czechia	5.5099285e+10	5.6398085e+10	5.7642145e+10	5.9151095e+10	6.065376e+10	6.2057445e+10	6.3590666e+10	6.535825e+10	6.725185e+10	6.965308e+10
2	Denmark	3.1681963e+10	3.2047673e+10	3.2448093e+10	3.2583583e+10	3.2613323e+10	3.2612113e+10	3.2612123e+10	3.4814743e+10	3.504853e+10	3.599188e+10
3	France	3.353264e+11	3.4302824e+11	3.5131504e+11	3.5750504e+11	3.6583874e+11	3.74055674e+11	3.82117494e+11	3.9214444e+11	4.0568464e+11	4.17675e+11
4	Germany	5.2482605e+11	5.2835005e+11	5.3055105e+11	5.3131805e+11	5.32180905e+11	5.3754304e+11	5.4282205e+11	5.5010204e+11	5.5933104e+11	5.681868e+11

Global Energy Consumption Visualization

```
# numeric columns related to energy consumption for visualization

energy_consumption_columns = [col for col in energy_consumption_kwh.columns if
col.startswith("energy_consumption_kwh_")]

years = [col.split('_')[-1] for col in energy_consumption_columns]

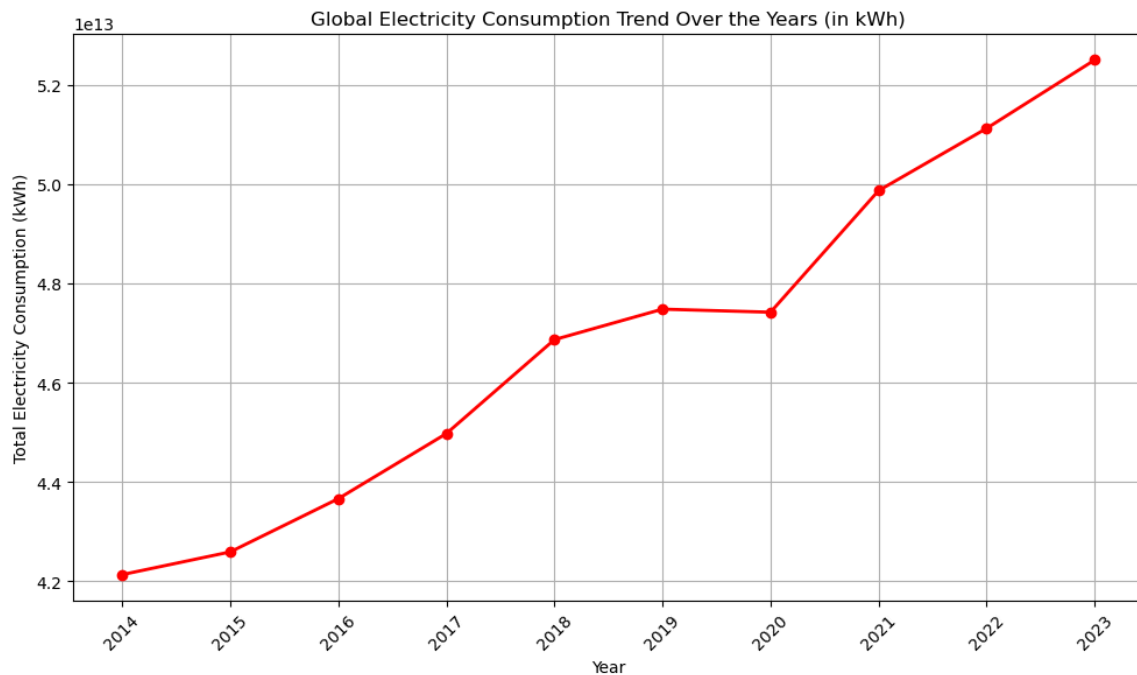
energy = energy_consumption_kwh[energy_consumption_columns].sum()

# energy consumption trend over the years

plt.figure(figsize=(10, 6))
plt.plot(years, energy, marker='o', linestyle='-', color = 'red', linewidth=2)
plt.title("Global Electricity Consumption Trend Over the Years (in kWh)")
plt.xlabel("Year")
plt.ylabel("Total Electricity Consumption (kWh)")
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
```



```
plt.show()
```



Obtaining \$ per Energy Consumption.

```
# Combining energy Consumption with energy Price by Country keeping those that
# appear in both using country name
energy_consumption_kwh.shape

# keeping only countries that appear in both
energy_consumption_price = pd.merge(energy_consumption_kwh,
bt_energy_prices_2014_2023, on="Country Name", how="inner")

# Countries analyzing.
n_countries = energy_consumption_price["Country Name"].nunique()
n_countries

energy_consumption_price.head()
```

	Coun-	en-	en-	en-	en-	en-	en-	en-	en-	en-	...	Con	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
	try	er-	er-	er-	er-	er-	er-	er-	er-	er-	ti-											
	Name	gy_-	gy_-	gy_-	gy_-	gy_-	gy_-	gy_-	gy_-	gy_-	nen-											
		con-	con-	con-	con-	con-	con-	con-	con-	con-	tal											
		sump-	sump-	sump-	sump-	sump-	sump-	sump-	sump-	sump-	re-											
tion	thou	thou	thou	thou	thou	thou	thou	thou	thou	thou	gion											
		824335086350842065408130830583068302930e+10	WEST	-195	0.192	0.169	0.167	0.158	0.162	4360520.4441												
0	gum										ERN											
											EU-											
											ROPE											
		824335086350842065408130830583068302930e+10	WEST	-147	0.145	0.225	0.214	0.203	0.242	50000570.5291												
1	mark										ERN											
											EU-											
											ROPE											
		824335086350842065408130830583068302930e+10	WEST	-142	0.143	0.145	0.130	0.130	0.161	7318218.2141												
2	Fa										ERN											
											EU-											
											ROPE											
		824335086350842065408130830583068302930e+10	WEST	-292	0.285	0.260	0.338	0.322	0.256	2270.550.5201												
3	many										ERN											
											EU-											
											ROPE											
		824335086350842065408130830583068302930e+10	WEST	-255	0.238	0.210	0.202	0.193	0.162	0090570.4611												
4	Ly										ERN											
											EU-											
											ROPE											

```
#Adding price of total consumption of electricity

# new columns for consumption price by matching years and multiplying consumption
with Kwh / $ cent
#Dividing it by 12 for monthly price. -> Not doing this will use yearly because
we switch to using gdp instead.
for year in years:
    consumption_col = f"energy_consumption_kwh_{year}"
    price_col = year # Matching year column in the energy prices dataset
    new_col_name = f"consumption_price_{year}"
    if consumption_col in energy_consumption_price.columns and price_col in
energy_consumption_price.columns:
        energy_consumption_price[new_col_name] =
        (energy_consumption_price[consumption_col] * energy_consumption_price[price_col])
```

```
energy_consumption_price.head()
```

```
yearly_consumption_price.head()
```

	Country Name	Continent	Consumption Price 2014	Consumption Price 2015	Consumption Price 2016	Consumption Price 2017	Consumption Price 2018	Consumption Price 2019	Consumption Price 2020	Consumption Price 2021	Consumption Price 2022	Consumption Price 2023
0	Belgium	WESTERN EUROPE	113531.594	146871.412	15221.398	15431.384	11741.394	17512.023	16284.093	19753.253	1851e+10	
1	Denmark	WESTERN EUROPE	6572484.646	9127.255	8216.902	8856.539	3047.892	1311.201	85161.989	9311.798	510e+10	
2	France	WESTERN EUROPE	1561636.335	3036.514	40676.986	685.795	9035.991	15717.612	3180.279	9248.794	533e+10	
3	Germany	WESTERN EUROPE	5324921.505	7981.411	12661.795	8551.680	2251.299	3101.611	1052.725	5742.411	595e+11	
4	Italy	WESTERN EUROPE	4226687.072	8846.382	9946.997	9865.856	4495.970	3006.015	3831.712	9911.311	7949e+11	

```
#Number list of countries in the dataset

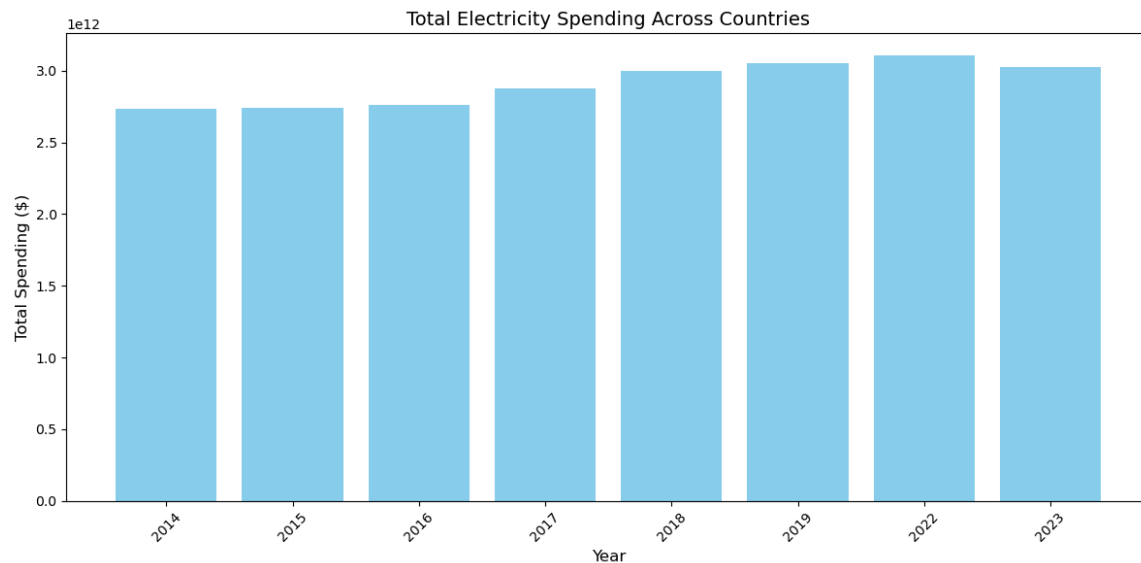
#monthly_consumption_price =
monthly_consumption_price.drop(columns=["consumption_price_2021"],
errors="ignore")
yearly_consumption_price = yearly_consumption_price.drop(columns =
["consumption_price_2021"], errors="ignore")

# Aggregate total spending per year for all countries
total_spending_per_year = yearly_consumption_price.iloc[:, 2:].sum()

# Extracting years and their corresponding total spend values
years = [col.split('_')[-1] for col in total_spending_per_year.index]
spending_values = total_spending_per_year.values

# Plot the total spend per year
plt.figure(figsize=(12, 6))
plt.bar(years, spending_values, color='skyblue')
```

```
plt.title("Total Electricity Spending Across Countries", fontsize=14)
plt.xlabel("Year", fontsize=12)
plt.ylabel("Total Spending ($)", fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



```
#Adding GDP of the 39 countries.
```

```
n_countries = yearly_consumption_price["Country Name"].unique().tolist()
```

```
yearly_consumption_price.shape
n_countries
```

```
['Belgium',
 'Denmark',
 'France',
 'Germany',
 'Italy',
 'Netherlands',
 'Poland',
 'Portugal',
 'Romania',
 'Spain',
 'Sweden',
 'United Kingdom',
 'Norway',
```

```
'Azerbaijan',
'Kazakhstan',
'Uzbekistan',
'Canada',
'United States',
'Argentina',
'Brazil',
'Chile',
'Colombia',
'Mexico',
'China',
'India',
'Indonesia',
'Japan',
'Malaysia',
'Singapore',
'Thailand',
'Vietnam',
'Australia',
'New Zealand',
'Algeria',
'Nigeria',
'South Africa',
'Kuwait',
'Saudi Arabia',
'United Arab Emirates']
```

```
#path = 'Cleaned_Data/monthly_consumption_price.csv'

path = 'Cleaned_Data/yearly_consumption_price.csv'

yearly_consumption_price.to_csv(path, index=False)
```

Income Data Cleaning This Analysis will not be included in final results.

```
""">#Assigning the right dollar amount depending on low or high income
income_data = pd.read_csv('Cleaned_Data/clean_household_income.csv')

income_data.tail()

#Drop 2021 & renaming cols to include income for differentiation

income_data = income_data.drop(columns=["2021"], errors="ignore")
income_data.rename(columns=lambda col: f"income_{col}" if col.isdigit() else
col, inplace=True)

#Joining with Energy Prices Data by the countries
```

```
energy_income = pd.merge(income_data, monthly_consumption_price, on="Country
Name", how="inner")
```

```
#Create % of Income Goes to Electricity
energy_income.head() """ #Code Removed -> Using GDP
```

```
'#Assigning the right dollar amount depending on low
or high income \nincome_data = pd.read_csv(\'Cleaned_Data/
clean_household_income.csv\')\n\nincome_data.tail()\n\n#Drop 2021 &
renaming cols to include income for
differentiation\n\nincome_data = income_data.drop(columns=["2021"],
errors="ignore")\nincome_data.rename(columns=lambda col: f"income_{col}" if
col.isdigit() else col, inplace=True)\n\n#Joining with Energy Prices Data by
the countries \nenergy_income = pd.merge(income_data, monthly_consumption_price,
on="Country Name", how="inner")\n\n#Create % of Income Goes to
Electricity\nenergy_income.head() '
```

```
""">#Visual of country income per grouped income
#Converting the income into approximations income for analysis
# Low = 1,000, Lower Middle = 3,000, Upper Middle = 8,000, High = 13,000
income_value_mapping = {
    "1,046-4,125": 3000,
    "1,026-4,035": 3000,
    "1,006-3,955": 3000,
    "996-3,895": 3000,
    "1,026-3,995": 3000,
    "1,036 - 4,045": 3000,
    "1,046 - 4,095": 3000,
    "1,086 - 4,255": 3000,
    "1,136 - 4,465": 3000,
    "4,046-12,735": 8000,
    "4,036-12,475": 8000,
    "3,956-12,235": 8000,
    "3,896-12,055": 8000,
    "3,996-12,375": 8000,
    "4,046 - 12,535": 8000,
    "4,096 - 12,695": 8000,
    "4,256 - 13,205": 8000,
    "4,466 - 13,845": 8000,
    "> 12,735": 13000,
    "> 12,475": 13000,
    "> 12,235": 13000,
    "> 12,055": 13000,
    "> 12,375": 13000,
    "> 13,205": 13000,
    "> 13,845": 13000,
    "1,000-4,125": 3000,
```

```

    "1,026 - 4,095": 3000,
    "4,256-13,205": 8000
}

numeric_energy_income = energy_income.replace(income_value_mapping)
numeric_energy_income.head()"""

```

```

'#Visual of country income per grouped income \n#Converting the income into
approximations income for analysis \n# Low = 1,000, Lower Middle = 3,000, Upper
Middle = 8,000, High = 13,000\nincome_value_mapping = {\n    "1,046-4,125": 3000,
\n    "1,026-4,035": 3000,\n    "1,006-3,955": 3000,\n    "996-3,895": 3000,\n
"1,026-3,995": 3000,\n    "1,036 - 4,045": 3000,\n    "1,046 - 4,095": 3000,\n
"1,086 - 4,255": 3000,\n    "1,136 - 4,465": 3000,\n    "4,046-12,735": 8000,\n
"4,036-12,475": 8000,\n    "3,956-12,235": 8000,\n    "3,896-12,055": 8000,\n
"3,996-12,375": 8000,\n    "4,046 - 12,535": 8000,\n    "4,096 - 12,695": 8000,\n
"4,256 - 13,205": 8000,\n    "4,466 - 13,845": 8000,\n    "> 12,735": 13000,\n
"> 12,475": 13000,\n    "> 12,235": 13000,\n    "> 12,055": 13000,\n    "> 12,375":
13000,\n    "> 13,205": 13000,\n    "> 13,845": 13000,\n    "1,000-4,125": 3000,\n
"1,026 - 4,095": 3000,\n    "4,256-13,205": 8000\n}\n\nnumeric_energy_income
= energy_income.replace(income_value_mapping)\nnumeric_energy_income.head()'

```

```

""">#Creating an avg income using the income columns alone
#income_columns = [col for col in numeric_energy_income.columns if
col.startswith("income_")]
#average_income_trend = numeric_energy_income[income_columns].mean()

#average_income_trend #Why are the constant?

#2nd attempt at avgs. Cols (2- 9)

income_columns2 = numeric_energy_income.columns[1:9]
average_income_trend2 = numeric_energy_income[income_columns2].mean()

# Display the updated results
#average_income_trend
average_income_trend2 #Same constant value.
"" #Gave me inconsistencies and showed no difference in monthly income in
different years.

```

```

'#Creating an avg income using the income columns alone
\n#income_columns = [col for col in numeric_energy_income.columns
if col.startswith("income_")]\n#average_income_trend =
numeric_energy_income[income_columns].mean()\n\n#average_income_trend #Why are
the constant? \n\n#2nd attempt at avgs. Cols (2- 9)\n\nincome_columns2
= numeric_energy_income.columns[1:9] \naverage_income_trend2 =

```



```
numeric_energy_income[income_columns2].mean()\n\n# Display the updated results\n#average_income_trend\n#average_income_trend2 #Same constant value. \n'
```

Switching to Consider GDP Prices Instead of Monthly Income

```
yearly_consumption_price = pd.read_csv('Cleaned_Data/
yearly_consumption_price.csv')
yearly_gdp = pd.read_csv('Raw_Data/Income_Price/WITS_Country_Timeseries.csv')

yearly_gdp.head()

#Combining GDP with the yearly consumption of energy

energy_consumption_gdp = pd.merge(yearly_gdp, yearly_consumption_price,
on='Country Name', how='inner')

print(energy_consumption_gdp.shape)
energy_consumption_gdp.head()
```

```
(39, 20)
```

[illegible]

	Coun-	-Con-1	-Con-2	-Con-3	-Con-4	-Con-5	-Con-6	-Con-7	-Con-8	-Con-9	-Con-10	-Con-11	-Con-12	-Con-13	-Con-14	-Con-15	-Con-16	-Con-17	-Con-18	-Con-19	-Con-20	-Con-21	-Con-22	-Con-23
	try	ti-																						
	Name	nen-																						
		tal																						
		re-																						
		gion																						
0	ANC	ER	165	97	90	63	70	69	70	61	70	64	70	67	116	67	116	67	20	61	135	51	137	65
	ge-	ERN																						
	ria	AFRICA																						
1	ArS	OL	262	90	71	57	56	210	65	210	65	210	65	210	65	210	65	210	65	210	65	210	65	210
	gentina	AMER-																						
		ICA																						
2	Aus	OC	167	59	56	52	65	62	61	72	62	73	62	69	15	27	107	54	125	54	125	54	125	54
	tralia	NIA																						
3	Azer-	CE	239	70	57	73	67	106	64	67	112	67	124	65	103	25	107	100	84	154	56	89	69	109
	ba	FORMER																						
	jan	USSR)																						
4	Bel	WE	534	60	34	76	65	102	55	102	55	102	55	102	55	102	55	102	55	102	55	102	55	102
	gium	ERN																						
		EU-																						
		ROPE																						

	Coun-	Con-	2014	2015	2016	2017	2018	2019	2022	con-	con-	con-	con-	con-	con-	con-	con-
	try	inen-								sump	sump	sump	sump	sump	sump	sump	sump
	Nam	etal	re-							tion	_prie	_prie	_prie	_prie	_prie	_prie	_prie
		gion									2004	2005	2006	2007	2008	2009	2022_2023
0	ge-	ERN															
	ria	AFRICA															
1	gentin	AMER-															
	ICA																
2	Aus-	OCEA															
	tralia	NIA															
3	Azer-	CIS															
	ba	(FORMER															
	jan	USSR)															
4	gium	ERN															
	EU-																
	ROPE																

#Dropping the 2023

```
energy_consumtion_gdp =
energy_consumtion_gdp.drop(columns=['consumption_price_2023'])

energy_consumtion_gdp.head()
```

	Coun- try	Con- tinen- tal region	2014	2015	2016	2017	2018	2019	2022	con- sump- tion	con- sump- tion	con- sump- tion	con- sump- tion	con- sump- tion	con- sump- tion	con- sump- tion
0	ge- ria	AFRICA	110659710603110609110749111047611049113055411376592503090900820720232922665089e+09													
1	gentin	AMER- ICA	Ar-SO5763209474206751203613048210477110277110860130885100830236741090551325668981206e+09													
2	Aus- tralia	OCEA NIA	46759050130061202642028220022207542055482633006730987607412887416907209e+10													
3	Azer- bai- jan	FORMER USSR)	CL523973076078671008666341208174208721061341056359348092190212302089000789091e+09													
4	Bel- gium	WESE ERN EU- ROPE	539062334060610276103292058610786010413150468742122085103841030470093905e+10													

```
#Renaming the 2014 - 2022 to add GDP to it
```

```
gdp_columns = [col for col in ["2014", "2015", "2016", "2017", "2018", "2019",  
"2022"] if col in energy_consumption_gdp.columns]  
energy_consumption_gdp.rename(columns={col: f"gdp_{col}" for col in gdp_columns},  
inplace=True)
```

```
path = 'Cleaned_Data/energy_consumption_gdp.csv'  
energy_consumption_gdp.to_csv(path, index=False)
```

Creating a energy poverty index per % of how much the enrgy price is compared to the GDP.

```
energy_consumption_gdp = pd.read_csv('Cleaned_Data/energy_consumption_gdp.csv')  
energy_consumption_gdp.head()
```

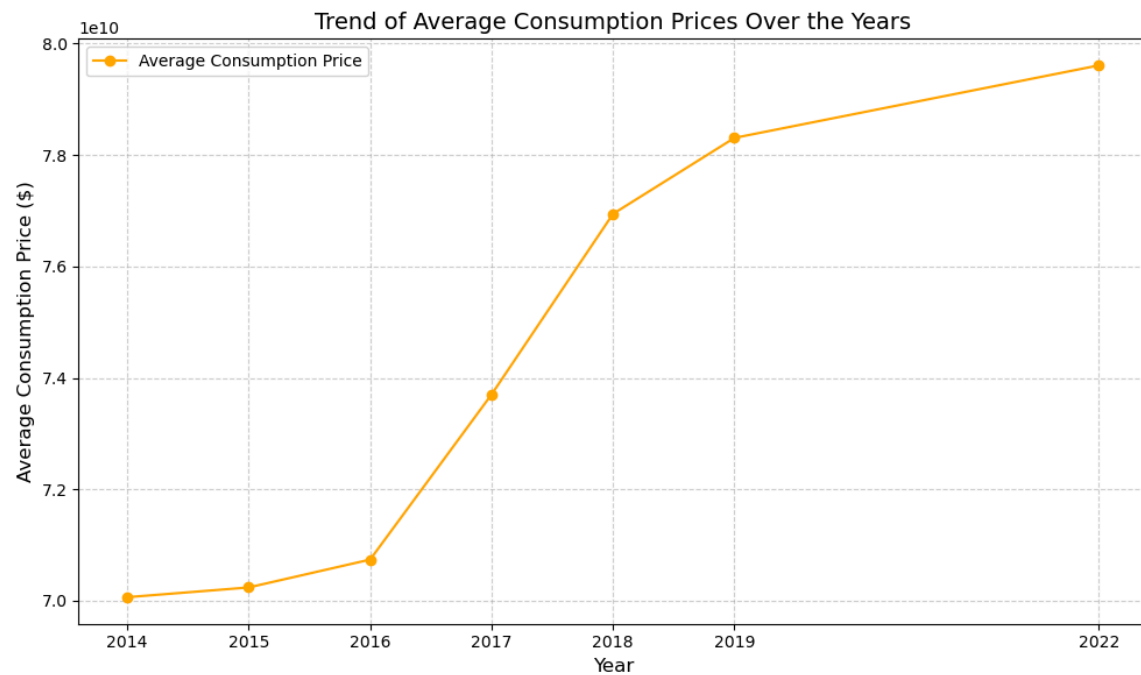
	Coun- try	Conti- nent- tal region	Gdp_2014	Gdp_2015	Gdp_2016	Gdp_2017	Gdp_2018	Gdp_2019	Gdp_2022	con- sump- tion_ price_2014	con- sump- tion_ price_2015	con- sump- tion_ price_2016	con- sump- tion_ price_2017	con- sump- tion_ price_2018	con- sump- tion_ price_2019	con- sump- tion_ price_2022
0	ge- ria	AFRICA	Al-NORTHERN	11065972000	117000117049	111047610949	113055417376	115050300000	118207023290	2665089e+09						
1	gentin	AMERICA	Ar-SOUTH	211209474	22067512036	23048210477	24027110277	25086013088	26083023674	10905103566	8981206e+09					
2	Aus- tralia	OCEANIA	Aus-OCEANIA	467500501	5006100264	52028220022	54205540863	5631006730	587074120874	16707209e+10						
3	Azer- baijan	FORMER USSR	Azer-CIS	239730760	2786700866	3141208174	3572106134	4056309348	450212302089	10789091e+09						
4	Belgium	EU-ROPE	Bel-WESTERN	359062334	4060610270	4503292058	49786011041	5430468742	5920810384	10470093905e+10						

```
#Rechecking the trend of consumption price

years = [2014, 2015, 2016, 2017, 2018, 2019, 2022]
consumption_columns = [f"consumption_price_{year}" for year in years]

avg_consumption_prices= energy_consumtion_gdp[consumption_columns].mean()

plt.figure(figsize=(10, 6))
plt.plot(years, avg_consumption_prices, marker='o', label="Average Consumption Price", color = 'orange')
plt.title("Trend of Average Consumption Prices Over the Years", fontsize=14)
plt.xlabel("Year", fontsize=12)
plt.ylabel("Average Consumption Price ($)", fontsize=12)
plt.xticks(years)
plt.grid(True, linestyle='--', alpha=0.6)
plt.legend()
plt.tight_layout()
plt.show()
```



```
# Trend per Regions.

regions = energy_consumption_gdp['Continental region'].unique()
region_trends = {}

for region in regions:
    region_data = energy_consumption_gdp[energy_consumption_gdp['Continental
region'] == region]
    region_trends[region] = region_data[consumption_columns].mean().values

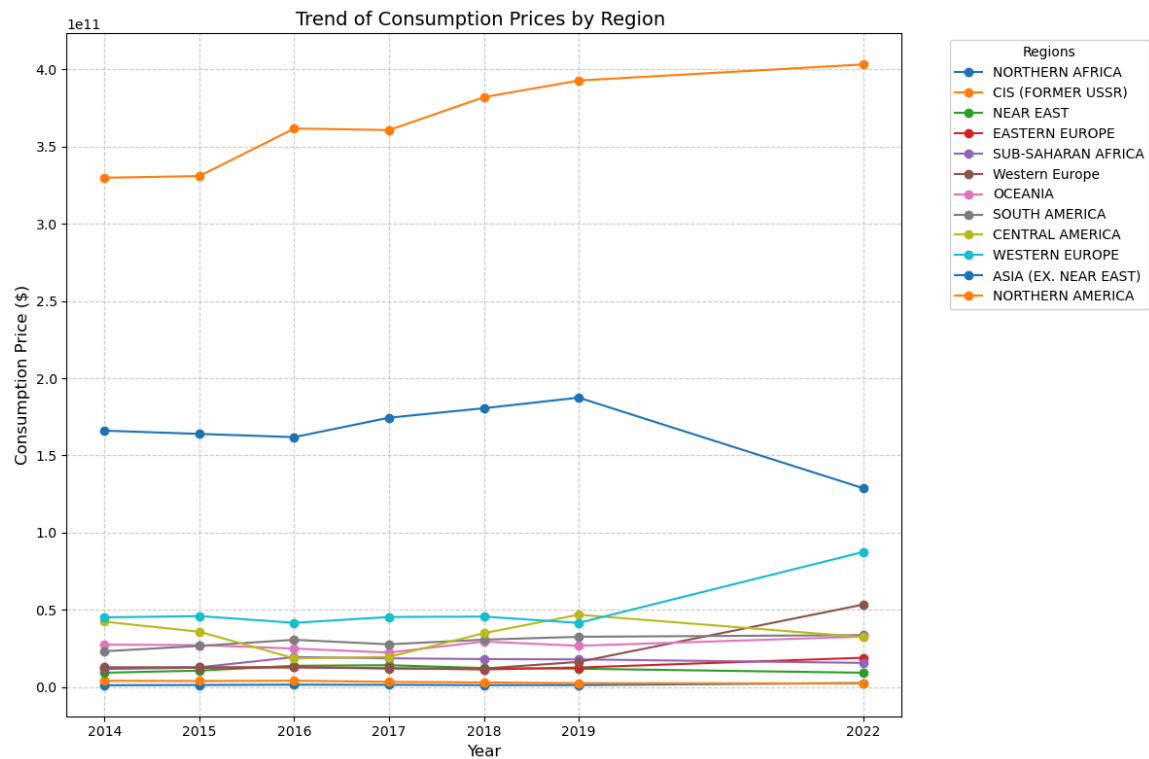
# Sorting the regions by total avg consumption price across years
sorted_regions = sorted(region_trends.keys(), key=lambda x:
sum(region_trends[x]))

sorted_region_trends = {region: region_trends[region] for region in
sorted_regions}

plt.figure(figsize=(12, 8))
for region, prices in sorted_region_trends.items():
    plt.plot(years, prices, marker='o', label=region)

plt.title("Trend of Consumption Prices by Region ", fontsize=14)
plt.xlabel("Year", fontsize=12)
plt.ylabel("Consumption Price ($) ", fontsize=12)
plt.xticks(years)
plt.grid(True, linestyle='--', alpha=0.6)
```

```
plt.legend(title="Regions", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



```
# Creating the index which is a % of GDP that goes towards energy

# new columns for the poverty index for each year
for year in years:
    gdp_column = f"gdp_{year}"
    consumption_column = f"consumption_price_{year}"
    poverty_index_column = f"poverty_index_{year}"

    # the poverty index as the percentage of GDP spent on energy
    energy_consumption_gdp[poverty_index_column] =
    (energy_consumption_gdp[consumption_column] / energy_consumption_gdp[gdp_column])
    * 100
```



```

year in years]].mean()
avg_consumption = gdp_energy_price_poverty_index[[f"consumption_price_{year}"
for year in years]].mean()

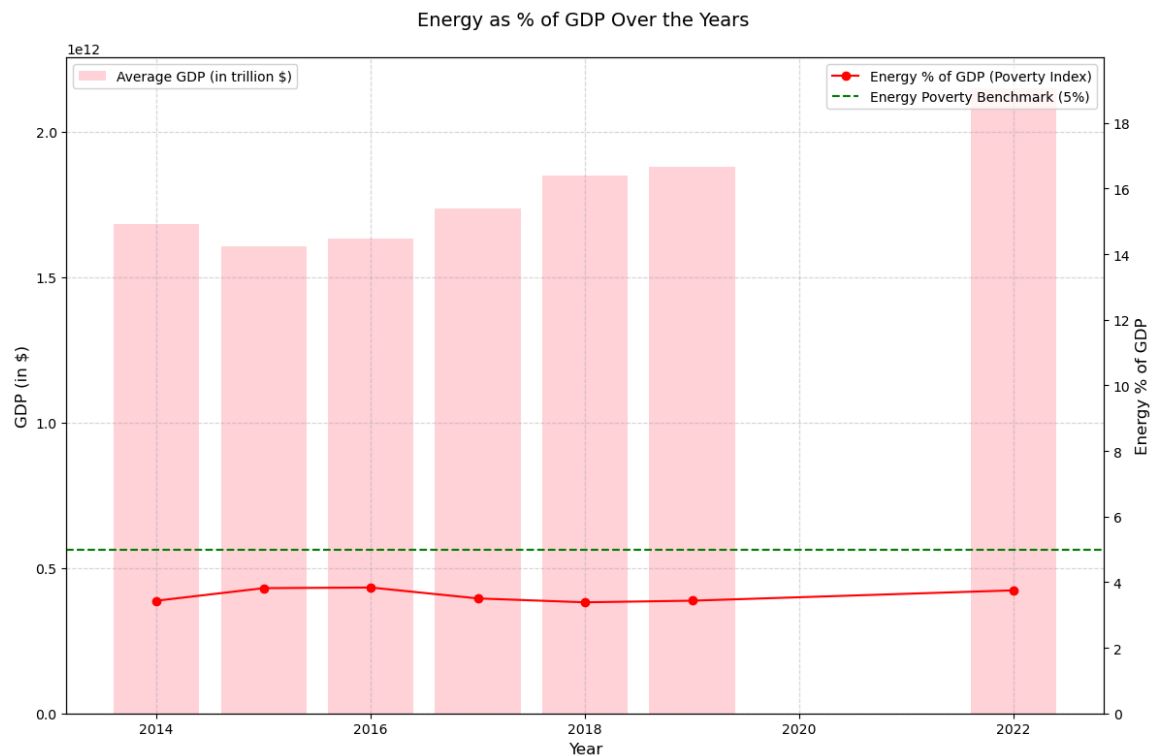
# benchmark line at 5% visualization
fig, ax1 = plt.subplots(figsize=(12, 8))

# Y-axis for GDP
ax1.bar(years, avg_gdp, alpha=0.7, label="Average GDP (in trillion $)",
color='pink')
ax1.set_ylabel("GDP (in $)", fontsize=12)
ax1.set_xlabel("Year", fontsize=12)
ax1.legend(loc="upper left")
ax1.grid(alpha=0.5, linestyle='--')

# Y-axis for poverty index
ax2 = ax1.twinx()
ax2.plot(years, avg_poverty_index, marker='o', color='red', label="Energy % of
GDP (Poverty Index)")
ax2.axhline(y=5, color='green', linestyle='--', linewidth=1.5, label="Energy
Poverty Benchmark (5%)") # benchmark line of 5%
ax2.set_ylabel("Energy % of GDP", fontsize=12, color='black')
ax2.tick_params(axis='y', labelcolor='black')
ax2.set_ylim(1, 20)
ax2.set_yticks(range(0, 20, 2)) #increment of 2%
ax2.legend(loc="upper right")

fig.suptitle("Energy as % of GDP Over the Years", fontsize=14)
fig.tight_layout()
plt.show()

```



Energy Poverty Index: This represents the percentage of GDP that goes toward energy consumption for every country.

5%Threshold: There is 10% rule that suggests households should spend no more than 10% of their income on energy, exceeding this threshold could hinder their ability to afford other necessities, placing them in energy poverty (Lu, 2023). Applying this principle to GDP, a 5% threshold was established as the benchmark for energy poverty. This is based on household income typically representing 50-70% of GDP, with 10% of that being 5-7%. The lower end (5%) was chosen to account for developing countries. In this dataset, countries / regions spending more than 5% of their GDP on energy are classified as energy poverty regions.

```
#Visual of Energy Poverty per Region to see the ones that did surpass the
threshold.
# the regional averages for GDP and poverty index per year
regions = gdp_energy_price_poverty_index['Continental region'].unique()

regional_gdp = {}
regional_poverty_index = {}

for region in regions:
    region_data =
    gdp_energy_price_poverty_index[gdp_energy_price_poverty_index['Continental
region'] == region]
```

```

    regional_gdp[region] = region_data[[f"gdp_{year}" for year in years]].mean()
    regional_poverty_index[region] = region_data[[f"poverty_index_{year}" for
year in years]].mean()

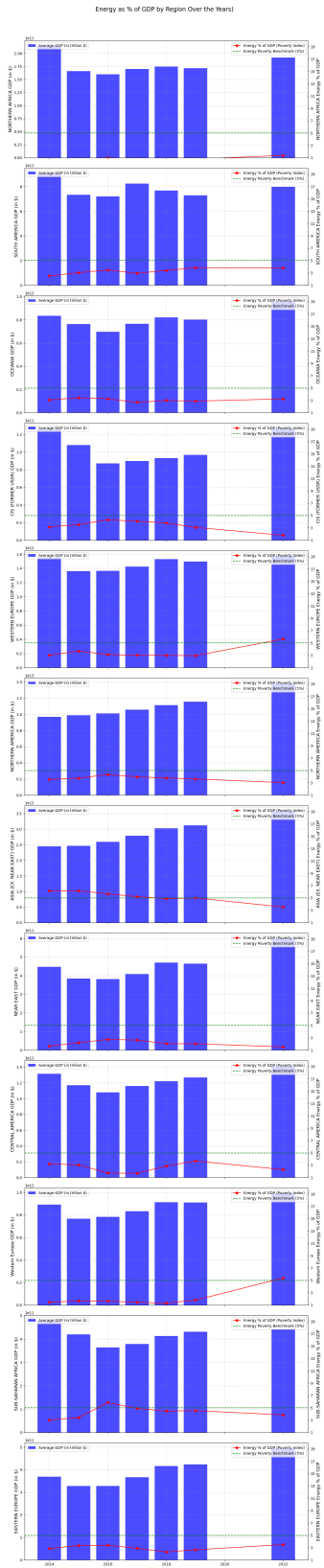
# regional data
fig, ax = plt.subplots(len(regions), 1, figsize=(12, len(regions) * 5),
sharex=True)

for i, region in enumerate(regions):
    # subplots for each region
    ax1 = ax[i]
    ax1.bar(years, regional_gdp[region], alpha=0.7, color='blue', label="Average
GDP (in trillion $)")
    ax1.set_ylabel(f"{region} GDP (in $)", fontsize=12)
    ax1.legend(loc="upper left")
    ax1.grid(alpha=0.5, linestyle='--')

    # re-stating the for poverty index as before
    ax2 = ax1.twinx()
    ax2.plot(years, regional_poverty_index[region], marker='o', color='red',
label="Energy % of GDP (Poverty Index)")
    ax2.axhline(y=5, color='green', linestyle='--', linewidth=1.5, label="Energy
Poverty Benchmark (5%)")
    ax2.set_ylabel(f"{region} Energy % of GDP", fontsize=12, color='black')
    ax2.tick_params(axis='y', labelcolor='black')
    ax2.set_ylim(2, 20)
    ax2.set_yticks(range(1, 21, 2))
    ax2.legend(loc="upper right")

fig.suptitle("Energy as % of GDP by Region Over the Years)", fontsize=16)
fig.tight_layout(rect=[0, 0, 1, 0.97])
plt.show()

```



Cleaning Weather Data and Seeing if there Correlation Between the energy poverty and weather anomalies.

```
#Past Weather data and finding correlation among energy prices.

past_weather_data = [
    ('Raw_Data/Weather_Data/Africa.csv', 'Africa'),
    ('Raw_Data/Weather_Data/Asia.csv', 'Asia'),
    ('Raw_Data/Weather_Data/Atlantic_MDR.csv', 'Atlantic MDR'),
    ('Raw_Data/Weather_Data/Caribbean.csv', 'Caribbean'),
    ('Raw_Data/Weather_Data/East_Pacific.csv', 'East Pacific'),
    ('Raw_Data/Weather_Data/Europe.csv', 'Europe'),
    ('Raw_Data/Weather_Data/North_America.csv', 'North America'),
    ('Raw_Data/Weather_Data/Northern_Hemisphere.csv', 'Northern Hemisphere'),
    ('Raw_Data/Weather_Data/Oceania.csv', 'Oceania'),
    ('Raw_Data/Weather_Data/South_America.csv', 'South America')
]

# Cleaning all the files the data and change the cols
def clean_data(file_path, region, start_row=4):
    try:

        df = pd.read_csv(file_path, skiprows=start_row, header=None)
        # renaming the cols based on year and anomaly
        df.columns = ["Year", "Anomaly"]
        # adding the continental Region column so we can join with energy prices
        later.
        df["Continental Region"] = region
        return df
    except Exception as e:
        print(f"Error processing file {file_path}: {e}")
        return None
```

```
# processing all files using the function
cleaned_files = []
for file_path, region in past_weather_data:
    cleaned_df = clean_data(file_path, region)
    if cleaned_df is not None:
        cleaned_files.append(cleaned_df)

# combining all files in a df
combined_weather_data = pd.concat(cleaned_files, ignore_index=True)

# restructuring the and dropping anomaly col so that every year is a col like
the energy price dataset.
cleaned_weather_data_past = combined_weather_data.pivot(
```

```

index="Continental Region", columns="Year", values="Anomaly"
).reset_index()
cleaned_weather_data_past

```

Year	Con- ti- nen- tal Re- gion	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Year
0	Africa	0.55	0.56	0.67	0.72	0.65	0.66	0.72	0.63	0.57	0.59	Anom- aly
1	Asia	0.55	0.56	0.67	0.72	0.65	0.66	0.72	0.63	0.57	0.59	Anom- aly
2	At- lantic MDR	0.52	0.50	0.83	0.83	0.61	0.40	0.79	0.74	0.68	0.81	Anom- aly
3	Caribbean	0.62	0.65	0.92	0.91	0.77	0.55	0.93	0.83	0.74	0.70	Anom- aly
4	East Pa- cific	0.61	1.19	1.42	0.84	0.85	0.82	0.76	0.59	0.56	0.40	Anom- aly
5	Eu- rope	1.10	1.75	1.55	1.40	1.54	1.68	1.96	1.94	1.29	1.98	Anom- aly
6	North Amer- ica	0.50	1.03	1.89	1.68	1.19	0.86	1.15	1.41	1.18	1.42	Anom- aly
7	North- ern Hemi- sphere	0.82	0.97	1.22	1.32	1.19	1.09	1.28	1.34	1.17	1.20	Anom- aly
8	Ocea- nia	1.10	0.91	1.32	0.78	1.12	1.06	1.03	0.83	1.00	0.53	Anom- aly
9	South Amer- ica	0.78	1.22	1.44	1.18	1.11	1.16	1.29	1.13	1.01	1.19	Anom- aly

```

#Further clean dropping first and last col of year anomaly data and save

```

```

cleaned_weather_data_past = cleaned_weather_data_past.iloc[:, -13:-1]
#Dropping the 2020, 2021 and 2023
col = ["2020", "2021", "2023"]
cleaned_weather_data_past = cleaned_weather_data_past.drop(columns=col,
errors='ignore')

path = 'Cleaned_Data/cleaned_weather_data_past.csv'
cleaned_weather_data_past.to_csv(path, index=False)

```

```
cleaned_weather_data_past.head()
```

```
#Dropping the 2020, 2021 and 2023
```

	Year	Continental Region	2014	2015	2016	2017	2018	2019	2022
0		Africa	0.55	0.56	0.67	0.72	0.65	0.66	0.57
1		Asia	0.55	0.56	0.67	0.72	0.65	0.66	0.57
2		Atlantic MDR	0.52	0.50	0.83	0.83	0.61	0.40	0.68
3		Caribbean	0.62	0.65	0.92	0.91	0.77	0.55	0.74
4		East Pacific	0.61	1.19	1.42	0.84	0.85	0.82	0.56

Combining the past weather anomalies and energy poverty index & renaming according to the regions in past weather regions.

```

#adding weather to weather cols
cleaned_weather_data_past.rename(columns=lambda col: f"weather_{col}" if
col.isdigit() else col, inplace=True)

cleaned_weather_data_past.head()
# Renaming regional cols of poverty index so they match that of per past weather
region. This will also be done for the future weather prdictions. #10 regions.
cleaned_weather_data_past.shape

gdp_energy_price_poverty_index.shape #39 countries should stay the same after
merge. -> 2 countries were dropped.

```

```
(39, 23)
```

```

# region mapping to align better with weather regions
refined_region_mapping = {
    'NORTHERN AFRICA': 'Africa',

```



```

'SOUTH AMERICA': 'South America',
'OCEANIA': 'Oceania',
'CIS (FORMER USSR)': 'Asia',
'WESTERN EUROPE': 'Europe',
'NORTHERN AMERICA': 'North America',
'ASIA (EX. NEAR EAST)': 'Asia',
'NEAR EAST': 'Asia',
'CENTRAL AMERICA': 'Central America',
'SUB-SAHARAN AFRICA': 'Africa',
'EASTERN EUROPE': 'Europe'
}

gdp_energy_price_poverty_index['Mapped Region']
= gdp_energy_price_poverty_index['Continental
region'].map(refined_region_mapping)

# merging both datasets.
energy_index_past_weather = pd.merge(
    cleaned_weather_data_past,
    gdp_energy_price_poverty_index,
    left_on='Continental Region',
    right_on='Mapped Region',
    how='inner'
)

print(energy_index_past_weather.head())
print(energy_index_past_weather.shape)

```

	Continental	Region	weather_2014	weather_2015	weather_2016	weather_2017	\
0		Africa	0.55	0.56	0.67	0.72	
1		Africa	0.55	0.56	0.67	0.72	
2		Africa	0.55	0.56	0.67	0.72	
3		Asia	0.55	0.56	0.67	0.72	
4		Asia	0.55	0.56	0.67	0.72	

	weather_2018	weather_2019	weather_2022	Country Name	Continental region	\
0	0.65	0.66	0.57	Algeria	NORTHERN AFRICA	
1	0.65	0.66	0.57	Nigeria	SUB-SAHARAN AFRICA	
2	0.65	0.66	0.57	South Africa	SUB-SAHARAN AFRICA	
3	0.65	0.66	0.57	Azerbaijan	CIS (FORMER USSR)	
4	0.65	0.66	0.57	China	ASIA (EX. NEAR EAST)	

	...	consumption_price_2019	consumption_price_2022	poverty_index_2014	\
0	...	1.329216e+09	2.665089e+09	0.587191	
1	...	3.261033e+09	8.078539e+08	0.677614	
2	...	3.270208e+10	3.059550e+10	5.390580	
3	...	1.039147e+09	1.089051e+09	2.011522	

```

4    ...          9.611643e+11          6.124248e+11          6.872319

      poverty_index_2015 poverty_index_2016 poverty_index_2017 \
0          0.829379          0.995413          0.876373
1          1.314681          1.271323          1.169959
2          5.525253         10.441043          8.642432
3          2.945881          3.219049          2.983395
4          6.631112          6.775796          7.208289

      poverty_index_2018 poverty_index_2019 poverty_index_2022 Mapped Region
0          0.741677          0.773880          1.388697          Africa
1          0.864181          0.687232          0.169224          Africa
2          8.083663          8.416853          7.538250          Africa
3          2.384563          2.157060          1.383430           Asia
4          6.985615          6.730842          3.409330           Asia

[5 rows x 32 columns]
(37, 32)

```

```

#Dropping the Index Regions
energy_index_past_weather.drop(columns=['Continental region'], inplace=True)
#Mapped Region
energy_index_past_weather.drop(columns=['Mapped Region'], inplace=True)

#Moving Country up
columns_order = ['Continental Region', 'Country Name'] + [col for col in
energy_index_past_weather.columns if col not in ['Continental Region', 'Country
Name']]

#Saving the combined df
energy_index_past_weather = energy_index_past_weather[columns_order]

path = 'Cleaned_Data/energy_index_past_weather.csv'
energy_index_past_weather.to_csv(path, index=False)

energy_index_past_weather.head()

```



```

tidy_data['Year'] = tidy_data['Metric'].str.extract(r'(\d{4})').astype(int)
tidy_data['Metric'] = tidy_data['Metric'].str.extract(r'([a-zA-Z_]+)')

# Pivoting it to have one column per metric
tidy_energy_index_past_weather = tidy_data.pivot_table(
    index=['Continental Region', 'Country Name', 'Year'],
    columns='Metric',
    values='Value',
    aggfunc='first'
).reset_index()

# Renaming cols
tidy_energy_index_past_weather.columns = ['Continental Region', 'Country Name',
'Year', 'Consumption Price', 'GDP', 'Poverty Index', 'Weather Anomaly']

#tidy_energy_index_past_weather.head() checked out

#Save it
path = 'Cleaned_Data/tidy_energy_index_past_weather.csv'
tidy_energy_index_past_weather.to_csv(path, index=False)
tidy_energy_index_past_weather.shape

#Drop all cols except poverty_index and region and Year to have index and
weather data only to move forward.

tidy_index_past_weather = tidy_energy_index_past_weather[['Continental Region',
'Year', 'Poverty Index', 'Weather Anomaly']]

#Save it this is the one to continue with in Analysis and model training and
predicting.

path = 'Cleaned_Data/tidy_index_past_weather.csv'
tidy_index_past_weather.to_csv(path, index=False)

tidy_index_past_weather.shape#checkout

tidy_index_past_weather.head()#checkout

```

```
(259, 4)
```

Cleaning future weather anomalies to make sure its the same region as the past data

```

weather_temp = pd.read_csv('Raw_Data/Weather_Data/Weather_Extremes.csv',
skiprows=1 )
weather_temp.head()

# Drop the last column this was empty
weather_temp.drop(weather_temp.columns[-1], axis=1, inplace=True)

#Dropping irrelevant cols to fit the past weather dataset (scenarion, mask, region
label, season, everything but Year and Median (this is going to be th temo
anamoly in C), Region, Year )
weather_temp.head()

col_keep = [' Region', ' Year', ' median'] #They all had spaces why it gave me
an error ->come back and rename.

# Filter the DataFrame to keep only the specified columns
weather_temp = weather_temp[col_keep]

#weather_temp.shape (999 rows of regions before drop) -> Now its =

weather_temp.head()

#weather_temp.columns

```

	Region	Year	median
0	Africa: Sahara	2035	0.9
1	Africa: Sahara	2065	1.2
2	Africa: Sahara	2100	1.1
3	Africa: Sahara	2035	0.9
4	Africa: Sahara	2065	1.3

```
weather_temp.columns
```

```
Index([' Region', ' Year', ' median'], dtype='object')
```

```

#Change the region names into the same ones as the old past weather and convert
year rows into cols for the different regions. And drop the sea temperatures
because the past weather data had land

```

```

# Mapping for regions to exhaust them all
region_mapping = {
    'Africa: Sahara': 'Africa',

```

```

'West Africa': 'Africa',
'East Africa': 'Africa',
'Southern Africa': 'Africa',
'West Asia': 'Asia',
'Central Asia': 'Asia',
'Eastern Asia': 'Asia',
'South Asia': 'Asia',
'Southeast Asia (land)': 'Asia',
'Tibetan Plateau': 'Asia',
'North Asia': 'Asia',
'North Indian Ocean': 'Atlantic MDR',
'Caribbean (land and sea)': 'Caribbean',
'Equatorial Pacific': 'East Pacific',
'Southern Pacific': 'East Pacific',
'Northern Tropical Pacific': 'East Pacific',
'Central Europe': 'Europe',
'Northern Europe': 'Europe',
'Southern Europe/Mediterranean': 'Europe',
'Central North America': 'North America',
'Eastern North America': 'North America',
'West North America': 'North America',
'Alaska/NW Canada': 'North America',
'Arctic (land)': 'Northern Hemisphere',
'Arctic (sea)': 'Northern Hemisphere',
'Australia/North Australia': 'Oceania',
'South Australia/New Zealand': 'Oceania',
'Central America': 'South America',
'South America: Amazon': 'South America',
'Northeast Brazil': 'South America',
'West Coast South America': 'South America',
'Southeastern South America': 'South America'
}

# dropping sea temp rows
weather_temp = weather_temp[~weather_temp[' Region'].str.contains('sea',
case=False, na=False)]

# switch teh region names & only keeping the re-named ones
weather_temp[' Region'] = weather_temp[' Region'].replace(region_mapping)
weather_temp = weather_temp[weather_temp[' Region'].isin(region_mapping.values())]

# renaming to make sure is the same as past data
weather_temp.rename(columns={' Region': 'Continental Region'}, inplace=True)
weather_temp.rename(columns={' median': 'Weather Anomaly'}, inplace=True)

cleaned_regions = weather_temp['Continental Region'].unique()

```

```
weather_temp.head(), cleaned_regions
```

```
( Continental Region   Year  Weather Anomaly
0           Africa  2035           0.9
1           Africa  2065           1.2
2           Africa  2100           1.1
3           Africa  2035           0.9
4           Africa  2065           1.3,
array(['Africa', 'Northern Hemisphere', 'Asia', 'Oceania',
       'South America', 'Europe', 'North America', 'East Pacific',
       'Atlantic MDR'], dtype=object))
```

```
#weather_temp. shape

path = 'Cleaned_Data/tidy_future_weather.csv'
weather_temp.to_csv(path, index=False)
```

Initial Analysis: At first glance, the dataset reveals that while energy prices have decreased, energy consumption continues to rise, indicating a potential ongoing risk of energy poverty. However, the data shows that energy poverty doesn't steadily increase but instead fluctuates across different regions and years. The second source code will explore whether there is a connection between energy poverty and temperature trends and then predict future energy poverty indexes.

```
(810, 3)
```