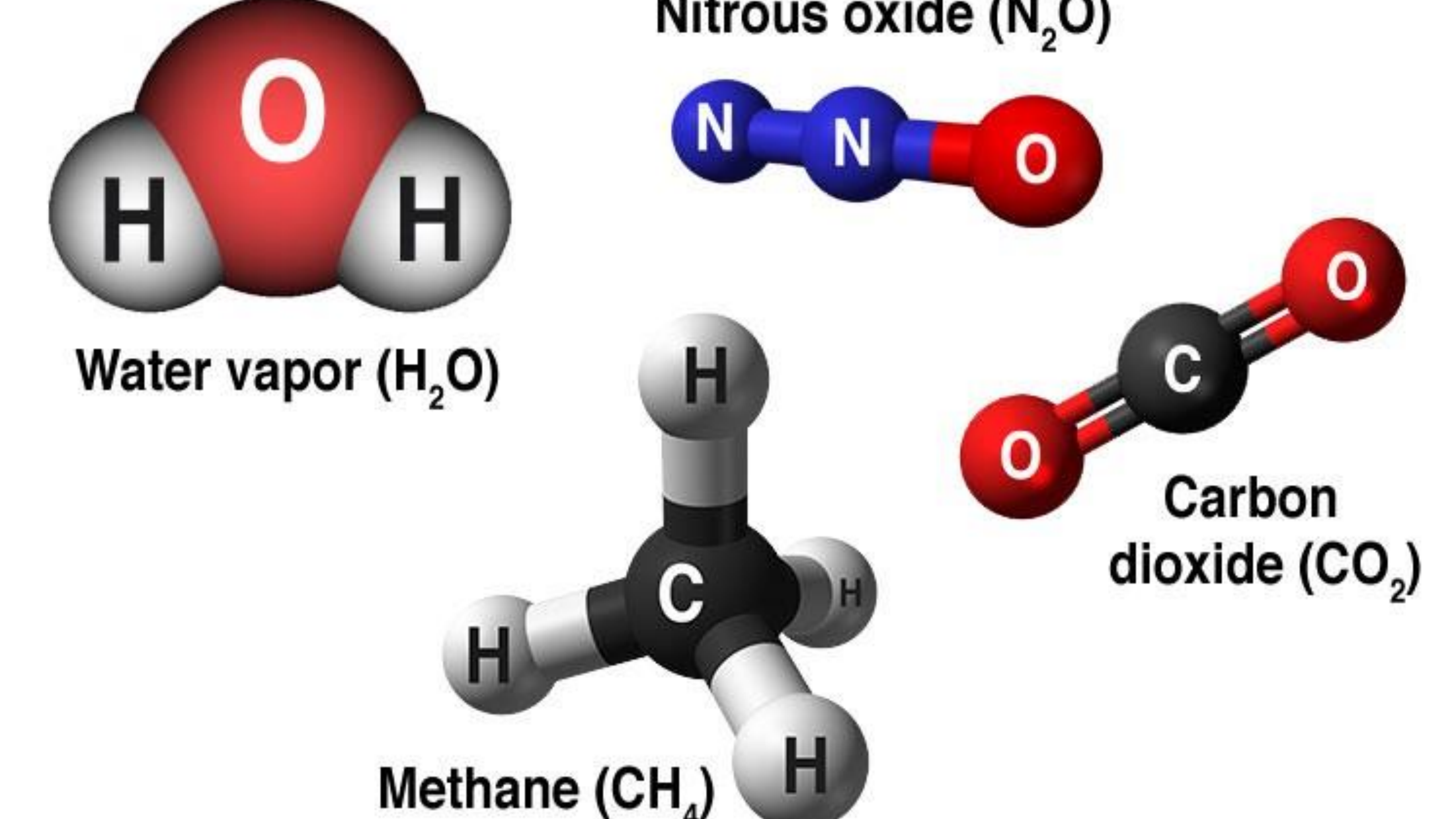
Climate Change and Food Scarcity in Developing Regions: An analysis in Python

One of the most important environmental issues discussed today is global warming. This is due to the impacts our warming climate has on crop yields, weather patterns, sea levels, wildfire incidents, and ecological systems. Global temperatures have risen at a faster rate than at any time since records began to be kept in the 1850s, and temperatures are expected to increase by another 1.8 to 5.8°C by the end of this century. Global warming is caused by the emission of greenhouse gases like carbon dioxide, methane, water vapor, chlorofluorocarbons and nitrous oxide.


Nitrous oxide (N_2O)
Water vapor (H_2O)
Carbon dioxide (CO_2)
Methane (CH_4)

These gases have an insulating effect on the climate which causes the atmosphere to trap heat and warm the earth. Many of these gases are released from factory farming, car exhaust, airplane exhaust, and fossil fuel extraction.

If we don't tackle the issue of climate change quickly, ecosystems will continue to be disrupted, sea levels will continue to rise, and crop yields (food production) will decrease. Regarding food production, crop weeds, insects and pest infestations are projected to rise as a result of the warming climate.

Climate change may have detrimental consequences for developing countries where decreased food production may result in increased malnutrition, population displacement, and disease propagation due to overcrowding

Additionally, the World Health Organization (WHO) claims that for infectious diseases climate change is a threat multiplier:

It takes existing threats — whether from a cholera outbreak, the spread of Zika to new geographical areas, or the severe malnutrition that accompanies drought — and enhances them. The risks are familiar but their impact is amplified in frequency and severity. A changing climate can expand the distribution of infectious diseases, especially those transmitted by mosquitoes and other vectors, and invite the emergence of others. The emergence of Nipah virus and Hanta virus as human pathogens has been traced to extreme weather events that forced animal hosts to leave their ecological niches and invade human settlements.

Yale Climate Connection also states:

- *In addition, rising temperatures can alter exposures to some pathogens and toxins. Consider:* Salmonella, Campylobacter, Vibrio parahaemolyticus *in raw oysters, and mycotoxigenic fungi, which can all potentially thrive in warmer environments. More carbon dioxide in the atmosphere also can decrease dietary iron, zinc, protein, and other macro- and micronutrients in certain crops.*

Given the future implications of climate change on food production and disease propagation, public education on the impacts of climate change is crucial. In this post we will perform simple exploratory analysis of public climate change data provided by datahub and global crop yield data provided by ourworldindata.org. In another post, we will take a closer look at some infectious disease data.

We start by importing the python library Pandas:

- import pandas as pd

The first dataset we will look at it is the annual global temparature data. We can read the data into a dataframe and print the first five rows:

```
df_global_temp = pd.read_csv("annual_temp.csv")
print(df_global_temp.head())
```

	Source	Year	Mean
0	GCAG	2016	0.9363
1	GISTEMP	2016	0.9900
2	GCAG	2015	0.8998
3	GISTEMP	2015	0.8700
4	GCAG	2014	0.7408

Next we can filter our data so that we only get records corresponding to the NASA GISTEMP source:

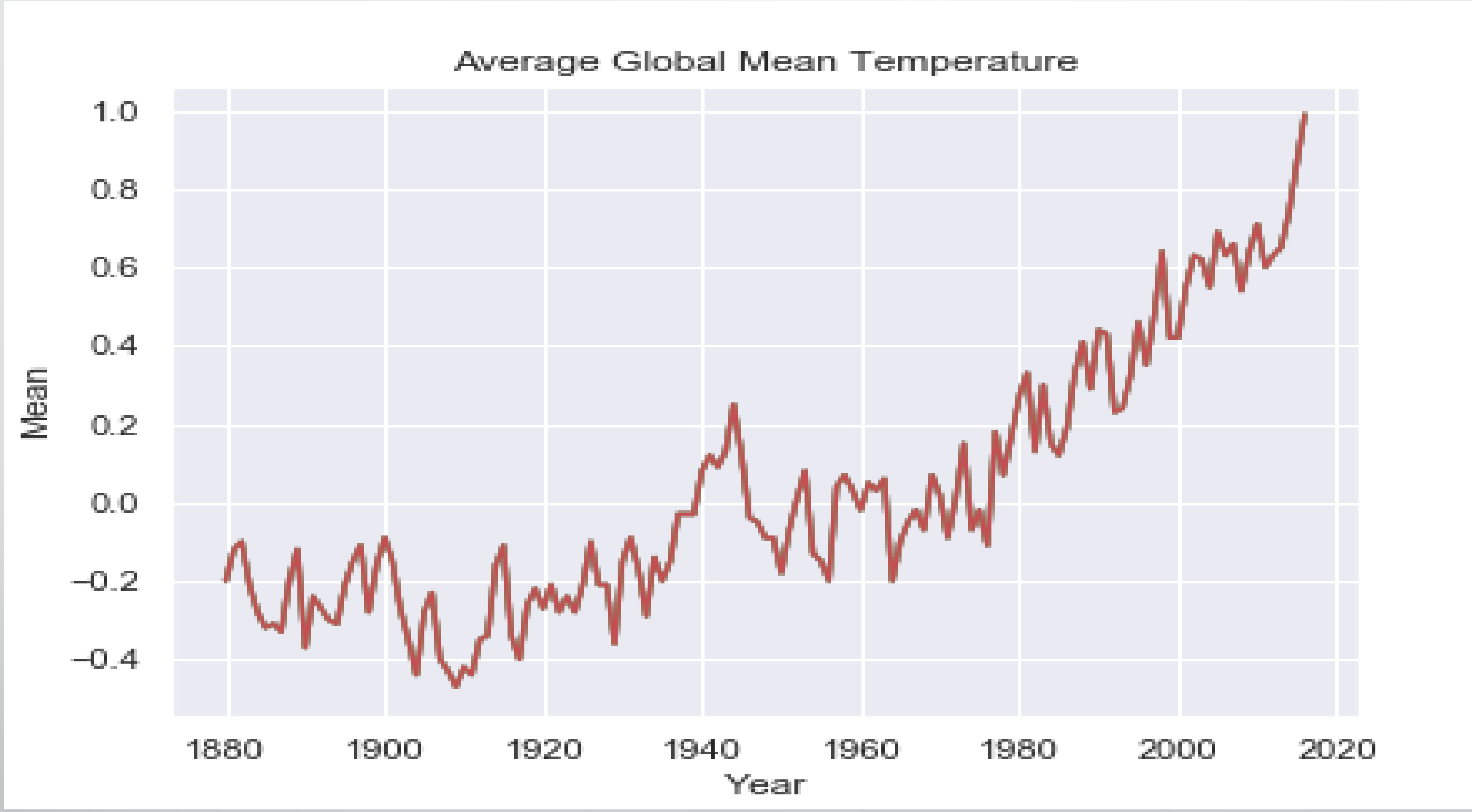
```
df_global_temp = df_global_temp[df_global_temp['Source'] ==
'GISTEMP'].reset_index()[["Source", "Year", "Mean"]]
print(df_global_temp.head())
```

	Source	Year	Mean
0	GISTEMP	2016	0.99
1	GISTEMP	2015	0.87
2	GISTEMP	2014	0.74
3	GISTEMP	2013	0.65
4	GISTEMP	2012	0.63

	Source	Year	Mean
0	GISTEMP	2016	0.99
1	GISTEMP	2015	0.87
2	GISTEMP	2014	0.74
3	GISTEMP	2013	0.65
4	GISTEMP	2012	0.63

Next we can plot the mean annual temperature vs. time. We proceed by importing the python visualization package ‘seaborn’ and making a line plot of the time series:

- import seaborn as sns
  sns.set()
  sns.lineplot(df_global_temp['Year'], df_global_temp['Mean'])
  plt.ylabel("Mean")
  plt.title("Average Global Mean Temperature")


Average Global Mean Temperature
Mean
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
1880
1900
1920
1940
1960
1980
2000
2020
Year

Next we can look at the annual global production of rice and wheat provided by ourworldindata.org. Let’s read the ‘rice-yield.csv’ data into a dataframe and look at the first five rows:

- df_rice = pd.read_csv("rice-yields.csv")
  df_rice.head()

	Entity	Code	Year	(tonnes per hectare)
0	Afghanistan	AFG	1961	1.5190
1	Afghanistan	AFG	1962	1.5190
2	Afghanistan	AFG	1963	1.5190
3	Afghanistan	AFG	1964	1.7273
4	Afghanistan	AFG	1965	1.7273

We can also look at the unique set of regions:

- from collections import Counter
  print(set(df_rice['Entity'].values))
  print("NUMBER OF REGIONS: ", len(set(df_rice['Entity'].values)))

- Countries in the Rice Yield Data set in coming page:-

```
{'Kazakhstan', 'Syria', 'Paraguay', 'Peru', 'Russia', 'Zambia', 'Dominican Republic', 'Northern America', 'Vietnam', 'Niger', 'Northern Africa', 'Nigeria',
'Malaysia', 'Spain', 'Trinidad and Tobago', 'Chile', 'Cuba', 'Southern Asia', 'Latvia', 'Turkey', 'Mauritius', 'Western Africa', 'Thailand', 'Brazil', 'Eastern
Africa', 'Oceania', 'Portugal', 'South Korea', 'Mexico', 'Nicaragua', 'Solomon Islands', 'Panama', 'USSR', 'Suriname', 'Bangladesh', 'Belize', 'Ghana',
'Guinea', 'Hungary', 'Kyrgyzstan', 'Madagascar', 'China', 'Nepal', 'Argentina', 'Sierra Leone', 'Benin', 'Guatemala', 'Belarus', 'Uganda', 'Comoros', 'Western
Europe', 'Central African Republic', 'United States', 'Angola', 'Papua New Guinea', 'Southern Europe', 'Guyana', 'Lithuania', 'Saint Vincent and the
Grenadines', 'Gambia', 'Burkina Faso', 'Bolivia', 'Bulgaria', 'El Salvador', 'Congo', 'Central Asia', 'Bhutan', 'Tanzania', 'Mauritania', 'Uzbekistan',
'Moldova', 'Estonia', 'Costa Rica', 'Caribbean', 'Indonesia', 'French Guiana', 'Hong Kong', 'Eastern Asia', 'Haiti', 'Ukraine', 'Iran', 'Democratic Republic of
Congo', 'Saudi Arabia', 'Southern Africa', 'Iraq', 'Greece', 'South Africa', 'Pakistan', 'Togo', 'Europe', 'Turkmenistan', 'Honduras', 'Georgia', 'Sudan',
'Guinea-Bissau', 'Timor', 'Albania', 'Eastern Europe', 'Philippines', 'Morocco', 'Puerto Rico', 'France', 'Sri Lanka', 'Somalia', 'North Korea', 'Cambodia',
'Gabon', 'Liberia', 'Mozambique', 'Myanmar', 'India', 'Zimbabwe', 'Rwanda', 'Kenya', 'South America', 'Tajikistan', 'Japan', 'Senegal', 'Uruguay', 'Swaziland',
"Cote d'Ivoire", 'Afghanistan', 'Laos', 'Ecuador', 'Mali', 'Chad', 'Macedonia', 'Algeria', 'Colombia', 'Fiji', 'World', 'Central America', 'Azerbaijan',
'Venezuela', 'Yugoslavia', 'Italy', 'Ethiopia', 'Romania', 'Burundi', 'Brunei', 'Malawi', 'Jamaica', 'Australia', 'Taiwan', 'Cameroon', 'Armenia', 'Egypt',
'Micronesia'}
```

There are a total of 148 regions. Knowing that developing regions are more vulnerable to the risks that climate change pose, it would be useful to narrow our scope. Time Magazine stated Nigeria, Haiti, Yemen, Philippines and Fiji will face the most severe consequences of climate change.

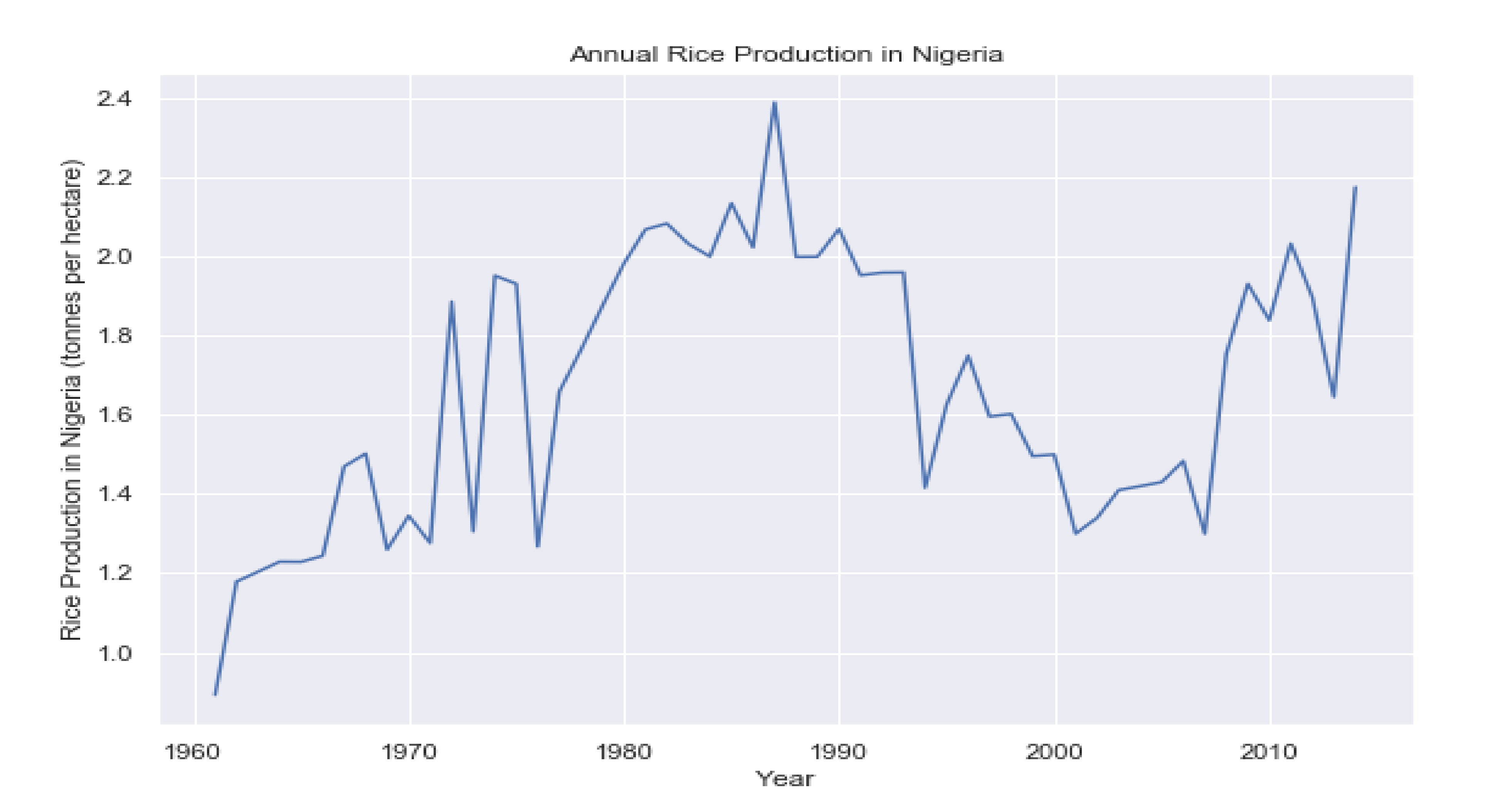
With that in mind we can start by looking at rice production in Nigeria:

- df_rice = pd.read_csv("rice-yields.csv")
  df_rice = df_rice[df_rice['Entity']=='Nigeria'].reset_index()[["Entity", "Code", "Year", ' (tonnes per hectare)']]
  print(df_rice.head())

	Entity	Code	Year	(tonnes per hectare)
0	Nigeria	NGA	1961	0.8926
1	Nigeria	NGA	1962	1.1789
2	Nigeria	NGA	1963	1.2037
3	Nigeria	NGA	1964	1.2291
4	Nigeria	NGA	1965	1.2287

Next we can plot the crop yield for rice in Nigeria from 1960–2014:

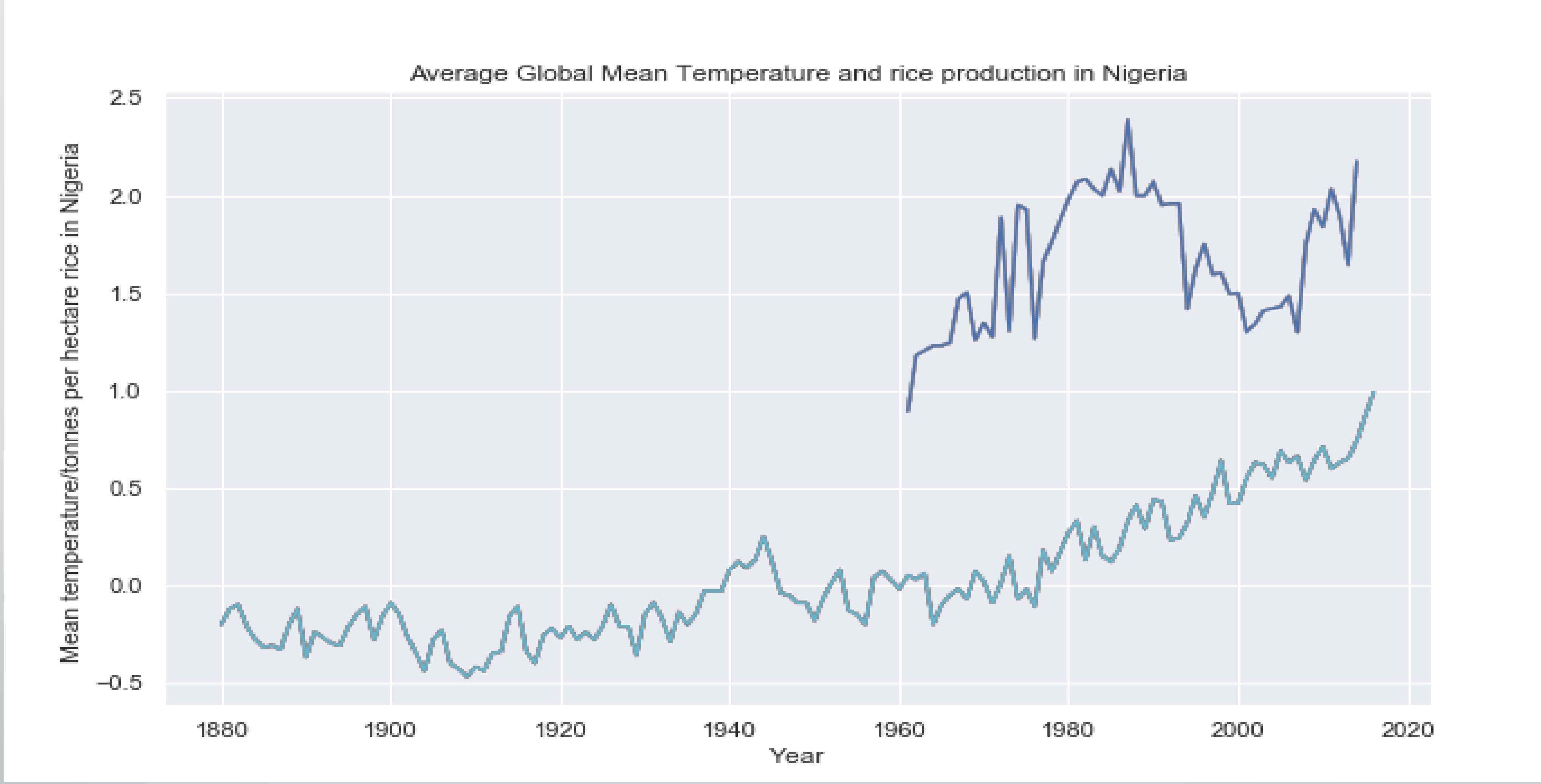
- sns.lineplot(df_rice['Year'], df_rice[' (tonnes per hectare)'])
plt.ylabel("Rice Production in Nigeria (tonnes per hectare)")
plt.title("Annual Rice production in Nigeria")


Annual Rice Production in Nigeria
Rice Production in Nigeria (tonnes per hectare)
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
1960
1970
1980
1990
2000
2010
Year

Next we can overlay the global annual mean temperature and the crop yields for rice in Nigeria:

- sns.set()
  sns.lineplot(df_global_temp['Year'], df_global_temp['Mean'])
  plt.ylabel("Mean")
  plt.title("Average Global Mean Temperature and rice production in Nigeria")

  sns.lineplot(df_rice['Year'], df_rice[' (tonnes per hectare)'])
  plt.ylabel("Mean temperature/tonnes per hectare rice in Nigeria ")



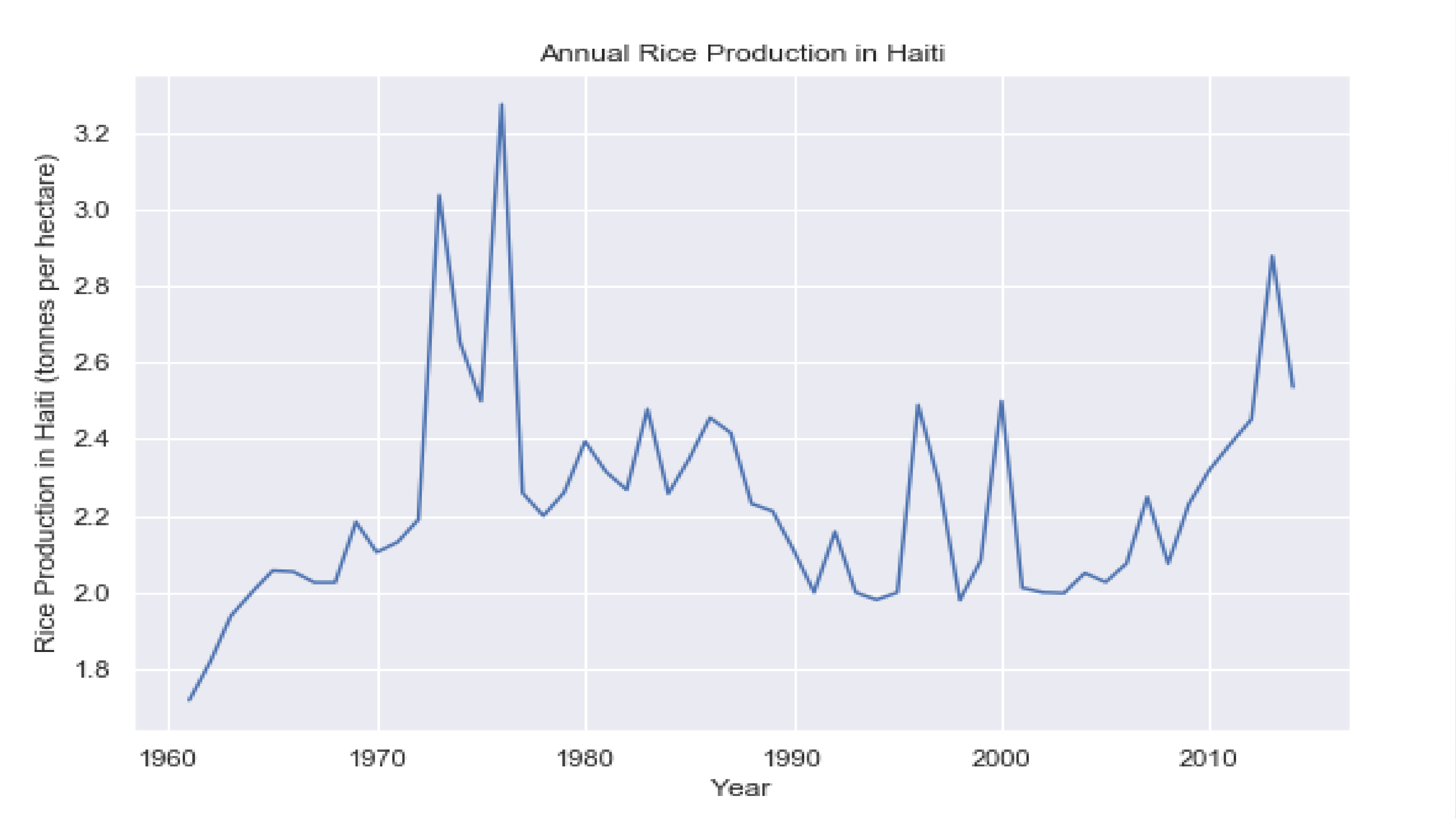
Average Global Mean Temperature and rice production in Nigeria
Mean temperature/tonnes per hectare rice in Nigeria
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
1880
1900
1920
1940
1960
1980
2000
2020
Year

Interestingly enough, there seems to be a significant drop in rice production in Nigeria between 1987 and 2006.

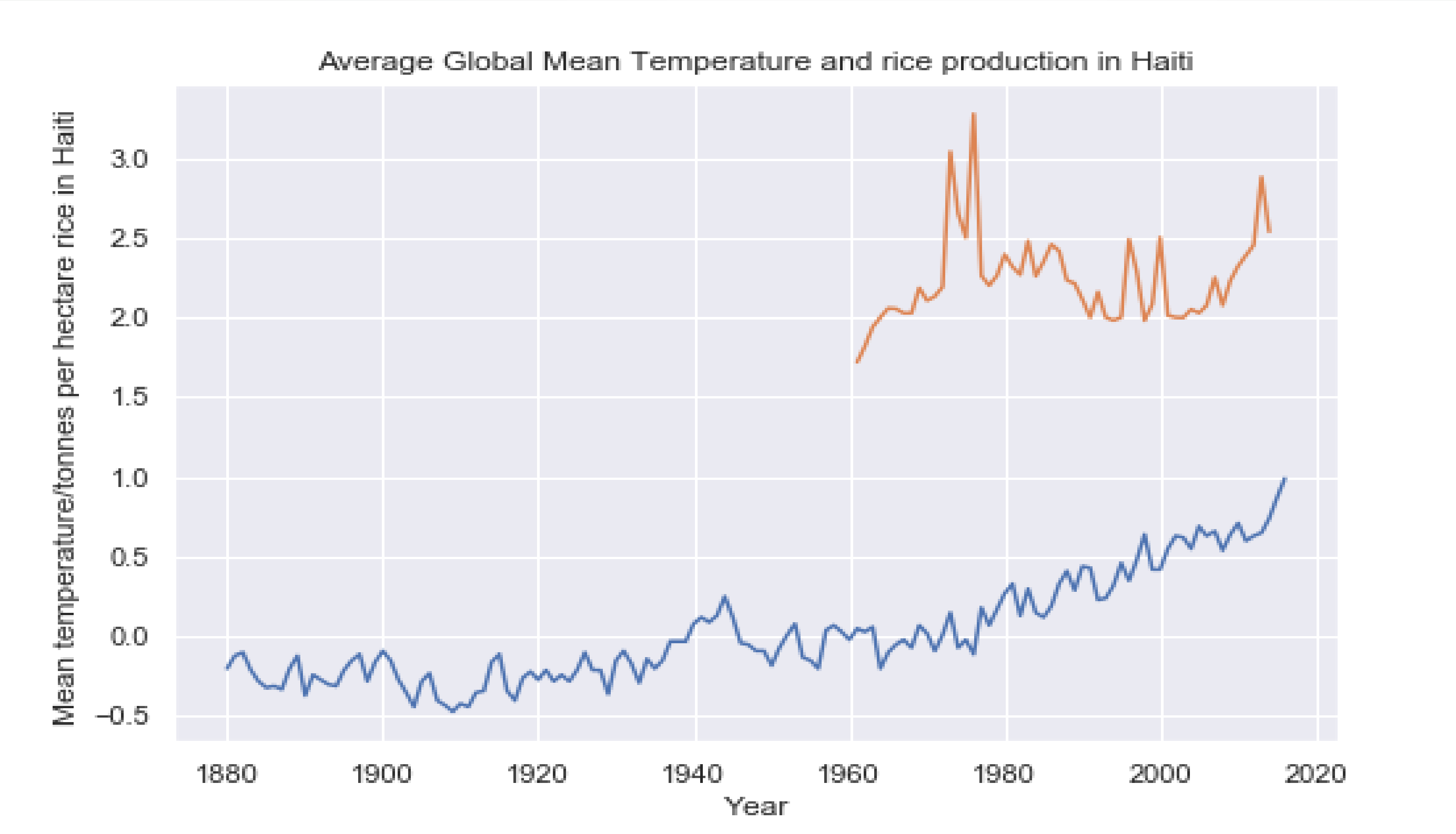
We can also look at rice production in Haiti:

- ```
  df_rice = pd.read_csv("rice-yields.csv")
  df_rice = df_rice[df_rice['Entity']=='Haiti'].reset_index()[["Entity", "Code", "Year", ' (tonnes per hectare)']]
  print(df_rice.head())
  ```
  ```

	Entity	Code	Year	(tonnes per hectare)
0	Haiti	HTI	1961	1.7188
1	Haiti	HTI	1962	1.8182
2	Haiti	HTI	1963	1.9394
3	Haiti	HTI	1964	2.0000
4	Haiti	HTI	1965	2.0571


Annual Rice Production in Haiti
Rice Production in Haiti (tonnes per hectare)
3.2
3.0
2.8
2.6
2.4
2.2
2.0
1.8
1960
1970
1980
1990
2000
2010
Year

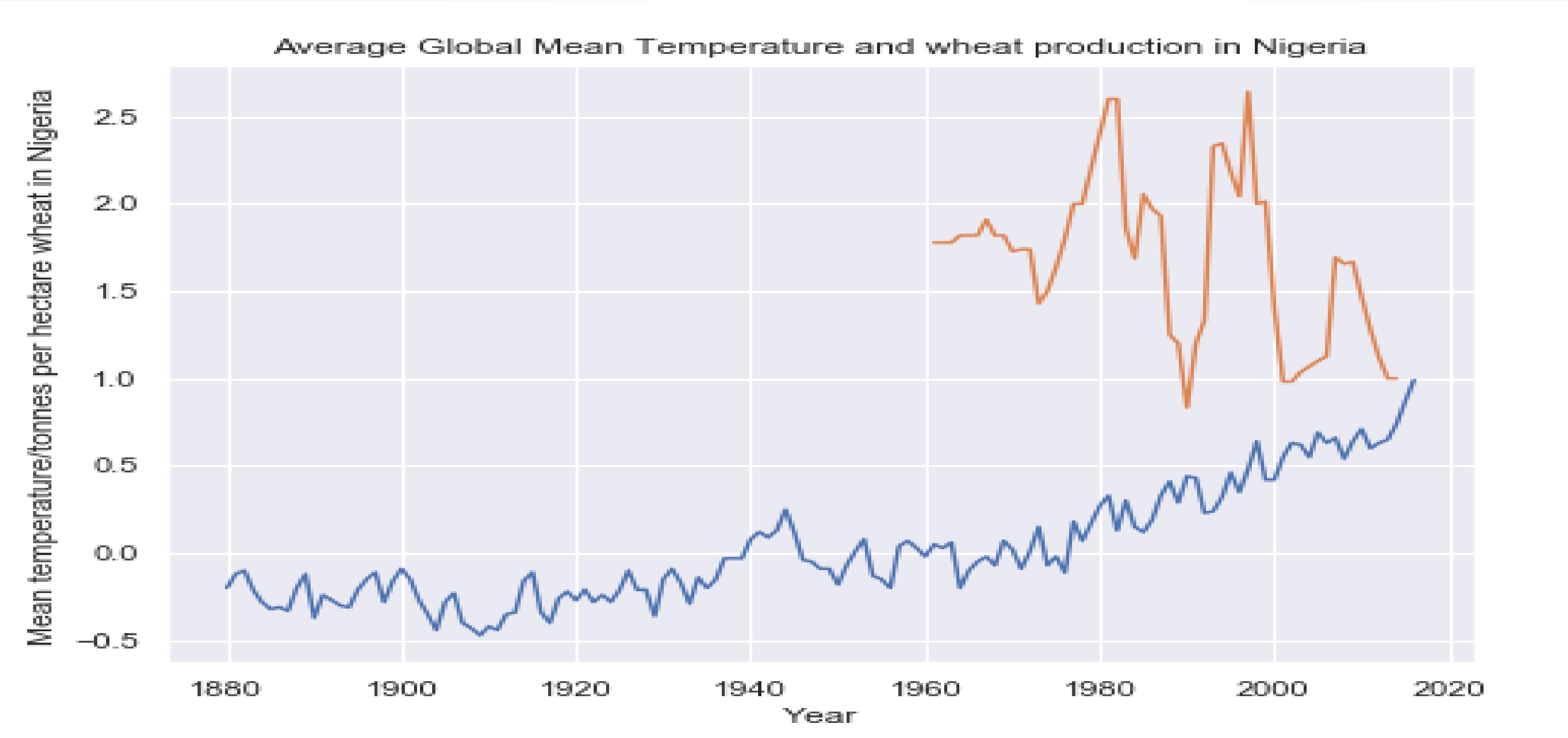
And we can look at it overlaid with the climate data:


Average Global Mean Temperature and rice production in Haiti
Mean temperature/tonnes per hectare rice in Haiti
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
1880
1900
1920
1940
1960
1980
2000
2020
Year

There also seems to be a slight drop in rice production in Haiti.

- We can also look at the same plots for wheat production in Nigeria:

```
df_wheat = pd.read_csv("wheat-yields.csv")
df_wheat =
df_wheat[df_wheat['Entity']=='Nigeria'].reset_index()[["Entity", "Code",
"Year", ' (tonnes per hectare)']]
print(df_rice.head())
sns.set()
sns.lineplot(df_global_temp['Year'], df_global_temp['Mean'])
plt.ylabel("Mean")
plt.title("Average Global Mean Temperature and wheat production in
Nigeria")sns.lineplot(df_wheat['Year'], df_wheat[' (tonnes per hectare)'])
plt.ylabel("Mean temperature/tonnes per hectare wheat in Nigeria ")
```


Average Global Mean Temperature and wheat production in Nigeria
Mean temperature/tonnes per hectare wheat in Nigeria
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
1880
1900
1920
1940
1960
1980
2000
2020
Year

Again, there seems to be a downward trend in wheat production in Nigeria with increase in yearly global temperature.

A much more exhaustive analysis would be required to draw any conclusions from the data at this point, but so far our analysis seems to be in concert with what has been reported in the literature. We will conclude our analysis here but feel free to look at crop yields in other regions as well as some of the other climate change data available on datahub.

As stated before, in addition to impacting crop yields, scientists believe climate change is having an impact on the spread of infectious diseases. In the next post we will analyze publicly available infectious disease data along with the the climate change data and see if we detect any trends. The datasets and code in this post are available on GitHub. Thank you for reading!