2022-02-28-statistics-homework-FoodCC-Poland

February 27, 2022

1 Final homework

Akademia Leona Kozminskiego

Descriptive Statistics *Prof.* Katarzyna Piotrowska *Student:* Alejandro Guzmán Rivera (*23-DS*)

Instructions

A simple quantitative, explanatory research (for 5: with the theory-based justification of the hypothesis i.e. literature review with references etc.). At least one variable on the qualitative level of measurement (categorical or ordinal) and one on the quantitative (interval or ratio) level of measurement.

1. Research question and hypothesis (if applicable) – is the research descriptive or explanatory?
2. Variables' definitions (conceptualisation)
3. Operationalisation (variables' indicators, their levels and levels of measurement)
4. Subject of the study: observation unit
5. Data collection procedure
6. Data analysis 6.1. Sample description 6.2. Bivariate and/or multivariate analyses (at least two different) with the justification of the choice of the method and interpretation of the results 6.3. The purpose of use descriptive statistics (sample description, the answer to research question, other)
7. Conclusions/discussion

1.1 1. Research question

- What is the impact of crops production in Poland in Greenhouse Gasses (GHG), specifically Nitrous Oxide through the period 1961-2019?

1.2 2. Hypothesis

- There is a positive correlation between Cereals, Roots and Tubers and Potatoes production and Nitrous Oxide (N2O) emissions in Poland during the period 1971 to 2018.

1.3 3. Variables definition

[ ]:
```
variables_defi = {"y": ["N2O emissions"],
                  "x1": ["Cereals production"] ,
                  "x2": ["Roots and Tubers production"],
                  "x3": ["Potatoes production"]}
print(tabulate(variables_defi, headers="keys", tablefmt="fancy_grid",␣
 ↪stralign="center"))
```

```
      y                  x1                       x2                       x3

 N2O emissions   Cereals production   Roots and Tubers production   Potatoes
production
```

1.4 4. Subject of study

Nitrous Oxide (N2O) emissions according to crops production.

1.5 5. Data collection procedure

1.5.1 5.1 Crop production data collection procedure

5.1.1 Importing libraries

[ ]:
```
# Tables creation
from tabulate import tabulate

# Tables manipulation and numbers formatting
import pandas as pd
pd.options.display.float_format = '{:,.2f}'.format

# Statistical analysis
from matplotlib import pyplot as plt
from matplotlib import figure
from mpl_toolkits.mplot3d import Axes3D

import numpy as np
import statsmodels.api as sm
import statsmodels.formula.api as smf

# Graphics creation and aesthetics
import seaborn as sns
sns.set()
```

5.1.2 Characteristics and description of the crops dataset

According to Wąs *et al.* (2020), the level of GHG emissions depends on the type of agricultural land utilisation (type of crops) and the level of production intensity and applied techniques. About Poland case Agriculture is the largest emitter of N2O in the country, producing 78.0% of this GHG. Nearly 85.8% of N2O emissions in agriculture come from the section of agricultural soils.

The crops production dataset was obtained from originally from *data.world*. That dataset was taken in first place from the Food and Agriculture Organization of the United Nations (FAO) which contains statistics of 173 farm products around the world. The original dataset was filtered using SQL by area code, in this case "173" that corresponds to Poland.

The Nitrous Oxide (N2O) emissions dataset was obtained from The World Bank (2022) website . This dataset contains information from 1971 to 2018. To make the dataset symetric, this period was chosen also for crops dataset.

After a first analysis of the crops dataset, the three most prolific crops products produced in Poland between 1971 and 2018 are:

1. Cereals: 1,866,275,855.00
2. Roots and Tubers: 1,828,499,656.00
3. Potatoes: 1,828,499,656.00

Moren information about these production can be found in the cells below.

```
[ ]: # Import the data set from local

data_crops = pd.read_csv(r"C:
 ↪\Users\USER\Documents\Desarrollador\PYTHON\2021-Python-exercises\statistics-projects\2022-0
 ↪csv")
```

5.1.3 Characteristics of the variables in the dataset.

```
[ ]: # Description of the raw data.

data_crops_charact = ([["Variable", "Description"],
                        ['area_code', "173"],
                        ['area', "Poland"],
                        ['item_code', "Product code"],
                        ['item', "Product name"],
                        ['element_code',"Code of the element"],
                        ['element',"Type of production: Production, area␣
 ↪harvested, yield"],
                        ['unit',"Unit of measurement: tonnes, Ha, Hg/Ha"],
                        ['year',"Years (1971-2018)"]])
```

```
[ ]: print(tabulate(data_crops_charact, headers= "firstrow", tablefmt='fancy_grid'))
```

```
 Variable       Description

 area_code      173
```

area	Poland
item_code	Product code
item	Product name
element_code	Code of the element
element	Type of production: Production, area harvested, yield
unit	Unit of measurement: tonnes, Ha, Hg/Ha
year	Years (1971-2018)

[ ]:
```
# Description of the dataset according to leveles of measurement.

vars_crops_charact =    ([["Variable", "Type", "Level"],
                        ['area_code', "Integer", "Nominal"],
                        ['area', "String", "Nominal"],
                        ['item_code', "Integer", "Nominal"],
                        ['item', "String", "Nominal"],
                        ['element_code',"Integer", "Nominal"],
                        ['element',"String", "Nominal"],
                        ['unit',"String", "Nominal"],
                        ['year',"String/Float", "Ratio"]])
```

[ ]:
```
print(tabulate(vars_crops_charact, headers="firstrow", tablefmt="fancy_grid"))
```

Variable	Type	Level
area_code	Integer	Nominal
area	String	Nominal
item_code	Integer	Nominal
item	String	Nominal
element_code	Integer	Nominal
element	String	Nominal
unit	String	Nominal
year	String/Float	Ratio

1.5.2 5.2 Crop production dataset cleaning

5.2.1 Checking for NAN values

[ ]:
```
# Getting a sample of the NAN values
data_crops.isna().sum()
data_crops.isna().T.head().T
```

[ ]:
```
     area_code   area  item_code   item  element_code
0        False  False      False  False         False
1        False  False      False  False         False
2        False  False      False  False         False
3        False  False      False  False         False
4        False  False      False  False         False
..         …      …         …      …             …
276      False  False      False  False         False
277      False  False      False  False         False
278      False  False      False  False         False
279      False  False      False  False         False
280      False  False      False  False         False

[281 rows x 5 columns]
```

5.2.2 Replace NAN with 0 and grouping the dataset

[ ]:
```
# Replacing NAN with 0
data_crops.replace(np.nan, 0)

# Describing the data_crops dataset
dataCropsGrouped = data_crops.groupby(["item"]).sum()

#Grouping the data_crops dataset by item
dataCropsGrouped = dataCropsGrouped.drop(columns=["area_code", "item_code",␣
 ↪"element_code"])
```

[ ]:
```
# dataCropsGrouped set information
dataCropsGrouped
dataCropsGrouped.head()
dataCropsGrouped.T.head().T
```

[ ]:
```
                                       y1971       y1972       y1973  \
item
Almonds, with shell                     0.00        0.00        0.00
Anise, badian, fennel, coriander    3,400.00        0.00        0.00
Apples                            563,200.00  558,500.00  682,500.00
Apricots                                0.00        0.00        0.00
Artichokes                              0.00        0.00        0.00
…                                          …           …           …
```

```
Vegetables, leguminous nes                0.00         0.00         0.00
Vetches                              76,706.00    62,621.00    62,000.00
Walnuts, with shell                       0.00         0.00         0.00
Watermelons                               0.00         0.00         0.00
Wheat                             7,542,678.00 7,219,635.00 7,797,799.00

                                         y1974        y1975
item
Almonds, with shell                       0.00         0.00
Anise, badian, fennel, coriander          0.00         0.00
Apples                              594,300.00   840,722.00
Apricots                                  0.00         0.00
Artichokes                                0.00         0.00
…                                          …            …
Vegetables, leguminous nes                0.00         0.00
Vetches                              70,000.00    52,600.00
Walnuts, with shell                       0.00         0.00
Watermelons                               0.00         0.00
Wheat                             8,442,607.00 7,076,864.00

[102 rows x 5 columns]
```

5.2.3 Check for the most important crops from dataCropsGrouped dataset

[ ]:
```python
dataCropsGroupedSum = dataCropsGrouped.sum(axis=1)
```

[ ]:
```python
dataCropsGroupedSum.sort_values(ascending=False).head()
```

[ ]:
```
item
Cereals, Total           1,583,068,952.00
Roots and Tubers, Total  1,334,122,051.00
Potatoes                 1,334,122,051.00
Sugar Crops Primary        682,033,347.00
Sugar beet                 682,033,347.00
dtype: float64
```

[ ]:
```python
cleanDataCrops = dataCropsGroupedSum.loc[~(dataCropsGroupedSum == 0)]
```

5.2.4 Calculate mean and median

[ ]:
```python
print(f"The mean is: {dataCropsGroupedSum.mean()}")
print(f"The median is: {dataCropsGroupedSum.median()}")
```

```
The mean is: 83768657.25490196
The median is: 2892161.0
```

5.2.5 Getting all the rows above the median value (3,513,392.5)

[ ]:
```python
# Filtering data by the median value
ImportantDataCrops = cleanDataCrops[cleanDataCrops > 3513392.5]
```

```
# Ordering data by descending and getting the first values
ImportantDataCrops.sort_values(ascending=False).head()
```

[ ]:
```
item
Cereals, Total           1,583,068,952.00
Potatoes                 1,334,122,051.00
Roots and Tubers, Total  1,334,122,051.00
Sugar beet                 682,033,347.00
Sugar Crops Primary        682,033,347.00
dtype: float64
```

5.2.6 Removing all rows with 0 values from the dataCropsCleaned dataset

[ ]:
```
dataCropsCleaned = dataCropsGrouped.loc[~(dataCropsGrouped == 0).all(axis=1)]
```

5.2.7 Transpose the dataCropsCleaned dataset

[ ]:
```
# Transpose the dataframe to plot
dataCropsTransposed = dataCropsCleaned.transpose()
```

1.5.3 5.3 First plotting: dataCropsTransposed

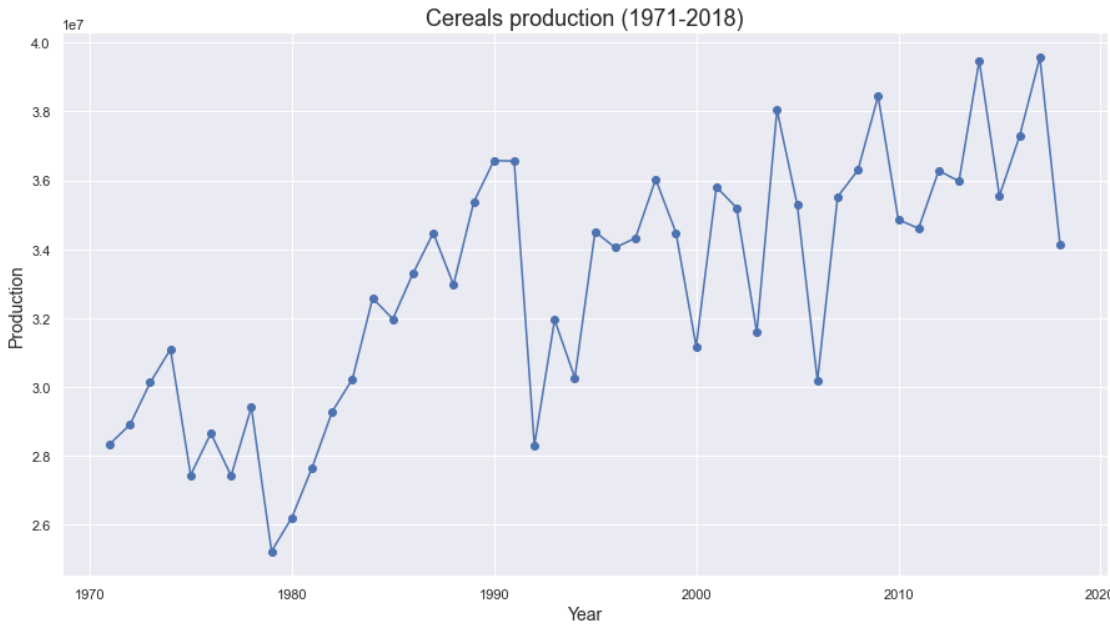
[ ]:
```
# dataCropsTransposed export to CSV to extract elements from R.
dataCropsTransposed.to_csv("dataCropsTransposed.csv", index=False, header=True)

# dataCrops was cleaned and transposed into a new dataset: cropsNitrox which␣
↪contains data about nitroux oxide and the three crops selected.
```

[ ]:
```
cropsNitrox_df = pd.read_csv(r"C:
↪\Users\USER\Documents\Desarrollador\PYTHON\2021-Python-exercises\statistics-projects\2022-0
↪csv")
```

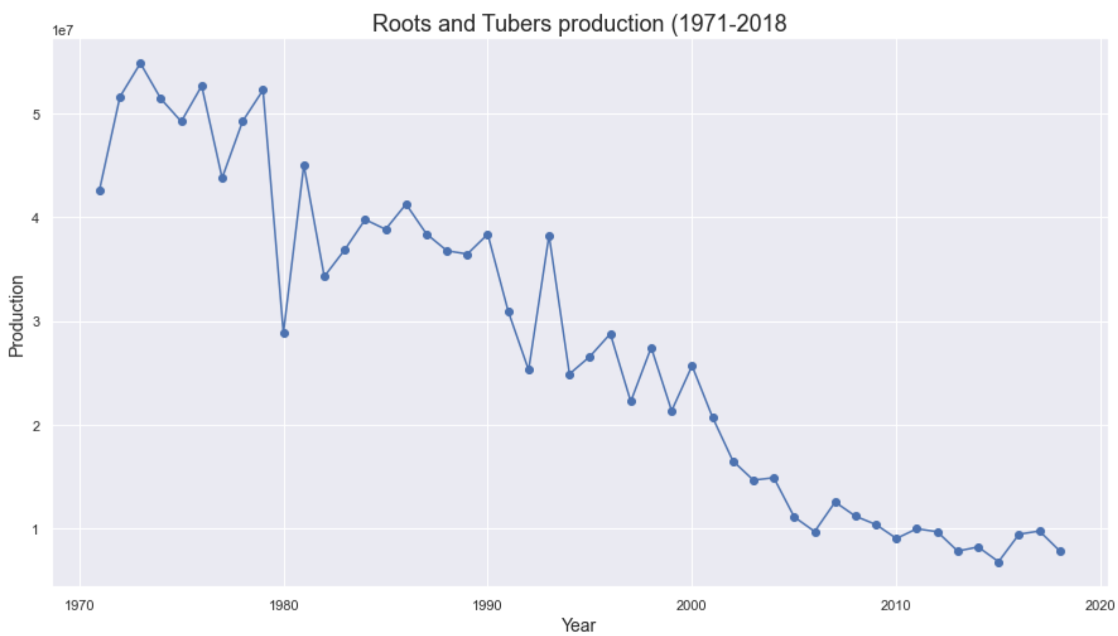
[ ]:
```
cropsNitrox_df.columns
```

[ ]:
```
Index(['Year', 'Nitrous.oxide.emissions.', 'Cereals.Total', 'Roots.and.Tubers',
       'Potatoes'],
      dtype='object')
```

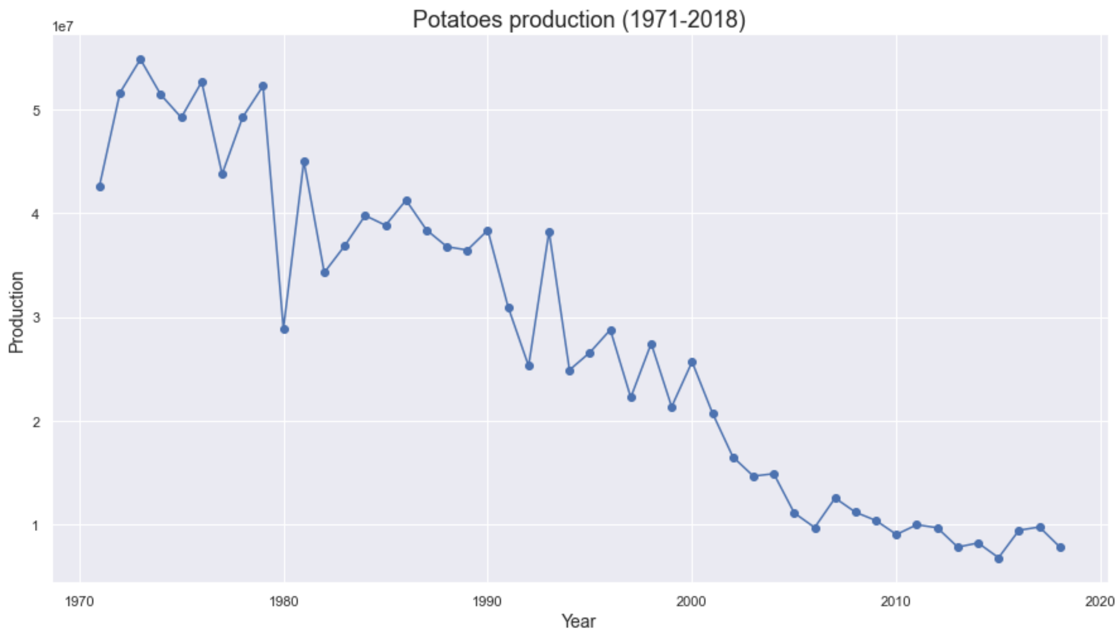
[ ]:
```
# Plot cereals

plt.figure(figsize=(15,8))
plt.xlabel("Year", fontsize= 14)
plt.ylabel("Production", fontsize= 14)
plt.title("Cereals production (1971-2018)", fontsize= 18)

plt.plot(cropsNitrox_df["Year"], cropsNitrox_df["Cereals.Total"], "b-o")
plt.show();
```



[ ]:
```python
# Plot "Roots and Tubers"
plt.figure(figsize=(15,8))
plt.xlabel("Year", fontsize= 14)
plt.ylabel("Production", fontsize= 14)
plt.title("Roots and Tubers production (1971-2018", fontsize= 18)

plt.plot(cropsNitrox_df["Year"], cropsNitrox_df["Roots.and.Tubers"], "b-o")
plt.show();
```

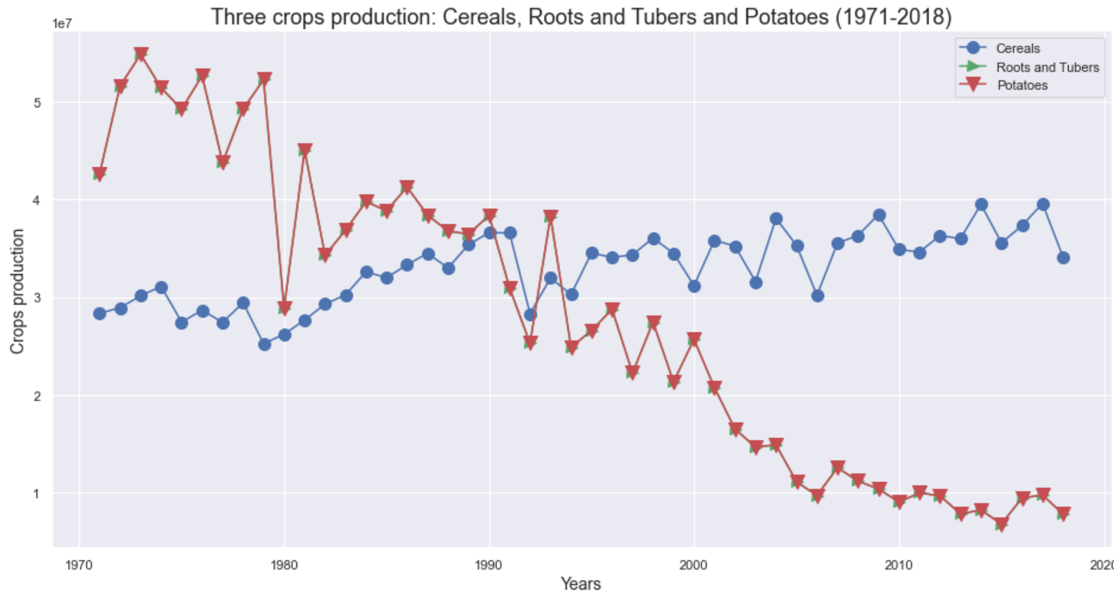


[ ]:
```python
# Plot "Potatoes"

plt.figure(figsize=(15,8))
plt.xlabel("Year", fontsize = 14)
plt.ylabel("Production", fontsize = 14)
plt.title("Potatoes production (1971-2018)", fontsize=18)

plt.plot(cropsNitrox_df["Year"], cropsNitrox_df["Potatoes"], "b-o")
plt.show();
```



[ ]:
```python
# Base of the plot
plt.figure(figsize=(16,8))
plt.xlabel("Years", fontsize= 14)
plt.ylabel("Crops production", fontsize= 14)
plt.title("Three crops production: Cereals, Roots and Tubers and Potatoes␣
↪(1971-2018)", fontsize=18)

# Plot itself
plt.plot(cropsNitrox_df["Year"],cropsNitrox_df["Cereals.Total"], "b-o",␣
↪markersize=10, label="Cereals")
plt.plot(cropsNitrox_df["Year"], cropsNitrox_df["Roots.and.Tubers"], "g->",␣
↪markersize = 9, label = "Roots and Tubers")
```

```
plt.plot(cropsNitrox_df["Year"], cropsNitrox_df["Potatoes"], 'r-v', markersize␣
↪= 12, label = "Potatoes")
plt.legend()
plt.show();
```



1.5.4 5.4 GHG emission data collection procedure

The Nitrous Oxide (N2O) dataset were gathered from the *databank.worldbank.org.* Those datasets were filtered using the the tools provided by the website itself (using SQL) to include only Poland from the period from 1971 to 2018.

5.2.1 Loading the dataset

[ ]:
```
# Loading Nitrous Oxide (N2O) dataset
data_nitrox = pd.read_csv(r"C:
↪\Users\USER\Documents\Desarrollador\PYTHON\2021-Python-exercises\statistics-projects\2022-0
↪csv", index_col=None)
```

5.2.2 Describing the N20 dataset

[ ]:
```
data_nitrox.columns
```

[ ]:
```
Index(['Year', 'Nitrous oxide emissions (thousand metric tons of CO2
equivalent)'], dtype='object')
```

[ ]:
```
vars_ghg_charact = ([["Variable", "Description", "Type", "Level"],
                     ["Series Name", "Nitrous Oxide", "String", "Nominal"],
                     ["Series Code", "Code of the series", "String", "Nominal"],
                     ["Country Name", "Poland", "String", "Nominal"],
```

```
                    ["Country Code", "POL", "String", "Nominal"],
                    ["Year", "From 1971 to 2018", "Integer", "Interval"]])

print(tabulate(vars_ghg_charact, headers="firstrow", tablefmt="fancy_grid"))
```

Variable	Description	Type	Level
Series Name	Nitrous Oxide	String	Nominal
Series Code	Code of the series	String	Nominal
Country Name	Poland	String	Nominal
Country Code	POL	String	Nominal
Year	From 1971 to 2018	Integer	Interval

[ ]:
```
print(data_nitrox["Nitrous oxide emissions (thousand metric tons of CO2␣
↪equivalent)"].describe())
```

```
count       48.00
mean    30,026.39
std      8,996.23
min     20,500.00
25%     23,230.00
50%     24,595.00
75%     38,085.51
max     46,495.35
Name: Nitrous oxide emissions (thousand metric tons of CO2 equivalent), dtype:
float64
```

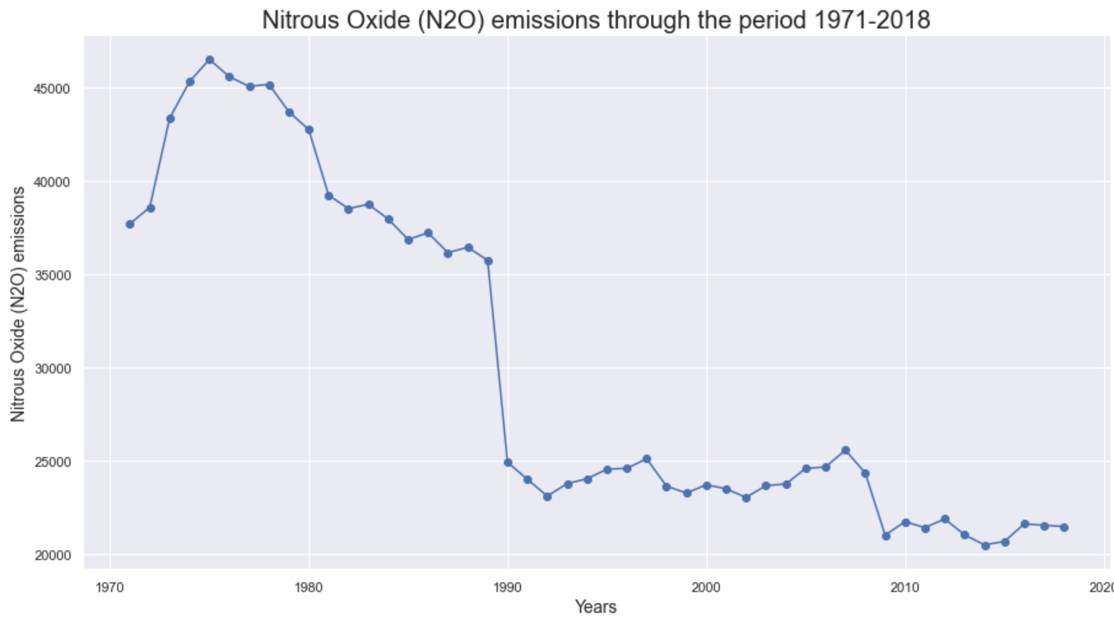
5.2.3 Preparing data_nitrox dataset for plotting

[ ]:
```
# Transforming the data to numeric
pd.to_numeric(data_nitrox["Nitrous oxide emissions (thousand metric tons of CO2␣
↪equivalent)"]);
```

5.2.4 Plotting data_nitrox

[ ]:
```
# Base of the plot
plt.figure(figsize=(15,8))
plt.xlabel("Years", fontsize=14)
plt.ylabel("Nitrous Oxide (N2O) emissions", fontsize=14)
plt.title("Nitrous Oxide (N2O) emissions through the period 1971-2018",␣
↪fontsize=20)


# Plot
```

```
plt.plot(data_nitrox["Year"], data_nitrox["Nitrous oxide emissions (thousand␣
↪metric tons of CO2 equivalent)"], "b-o")
plt.show();
```



1.6 6. Data analysis

6.1 Descriptive analysis

6.2 Bivariate analysis

6.2.1 Scatter plot and Regression: N2O vs Cereals

[ ]:
```
y = data_nitrox["Nitrous oxide emissions (thousand metric tons of CO2␣
↪equivalent)"].tolist()
x1 = cropsNitrox_df["Cereals.Total"].tolist()
```

It is observed that none of the variables studied: Cereals (x1), Roots and Tubers (x2) and Potatoes (x3) present extreme data. This is also not the case for Nitrous Oxide (N2O) emissions. However, the scatter in the data for Potatoes and Roots and Tubers appears to be considerable in comparison.

[ ]:
```
X_cereals = sm.add_constant(x1)
results_cereals = sm.OLS(y,X_cereals).fit()
results_cereals.summary()
```

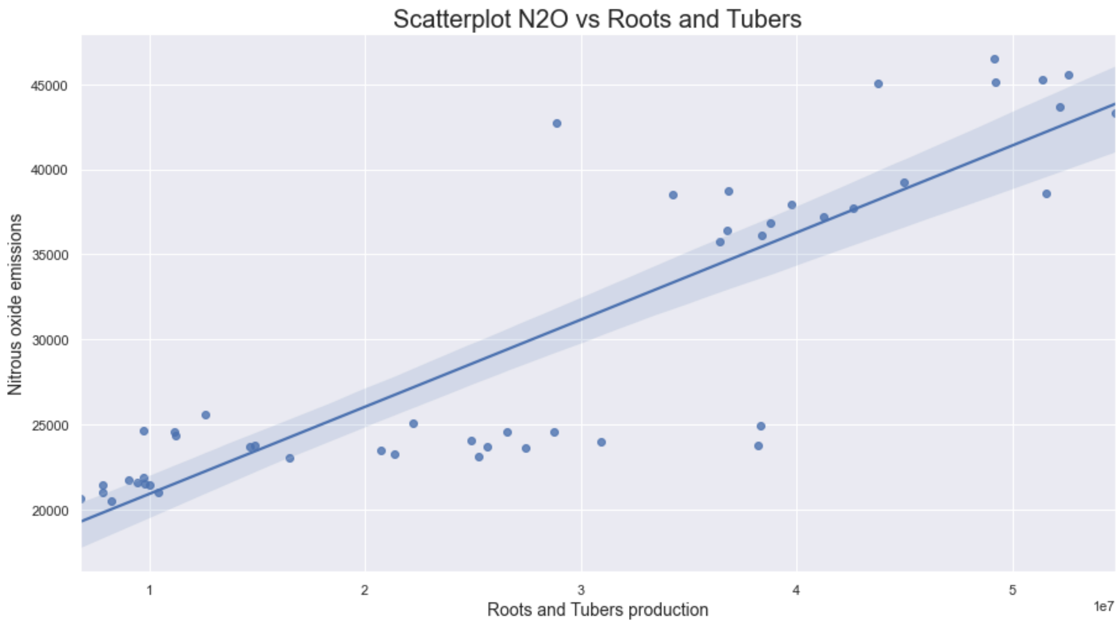
[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:                      y   R-squared:                       0.552
Model:                            OLS   Adj. R-squared:                  0.542
Method:                 Least Squares   F-statistic:                     56.57
Date:                Fri, 25 Feb 2022   Prob (F-statistic):           1.51e-09
Time:                        13:25:19   Log-Likelihood:                -485.38
No. Observations:                  48   AIC:                             974.8
Df Residuals:                      46   BIC:                             978.5
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       9.057e+04   8097.572     11.185      0.000    7.43e+04    1.07e+05
x1            -0.0018      0.000     -7.521      0.000      -0.002      -0.001
==============================================================================
Omnibus:                        0.590   Durbin-Watson:                   0.885
Prob(Omnibus):                  0.744   Jarque-Bera (JB):                0.580
Skew:                          -0.245   Prob(JB):                        0.748
Kurtosis:                       2.776   Cond. No.                     3.06e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.06e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

6.2.2 Scatter plot and Regression: Nitrous Oxide vs Roots and Tubers

[ ]:
```
x2 = cropsNitrox_df["Roots.and.Tubers"].tolist()
```

[ ]:
```
# Base of the plot
plt.figure(figsize=(15,8))
plt.xlabel("Roots and Tubers production", fontsize=14)
plt.ylabel("Nitrous oxide emissions", fontsize=14)
plt.title("Scatterplot N2O vs Roots and Tubers", fontsize=20)

# Plot itself
sns.regplot(x= x2, y= y)
plt.show();
```



[ ]:
```
X_RootsTubers = sm.add_constant(x2)
results_RootsTubers = sm.OLS(y, X_RootsTubers).fit()
results_RootsTubers.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.552
Model:                            OLS   Adj. R-squared:                  0.542
Method:                 Least Squares   F-statistic:                     56.57
Date:                Fri, 25 Feb 2022   Prob (F-statistic):           1.51e-09
Time:                        17:51:03   Log-Likelihood:                -485.38
No. Observations:                  48   AIC:                             974.8
Df Residuals:                      46   BIC:                             978.5
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       9.057e+04   8097.572     11.185      0.000     7.43e+04    1.07e+05
x1            -0.0018      0.000     -7.521      0.000       -0.002      -0.001
==============================================================================
Omnibus:                        0.590   Durbin-Watson:                   0.885
Prob(Omnibus):                  0.744   Jarque-Bera (JB):                0.580
Skew:                          -0.245   Prob(JB):                        0.748
```

```
Kurtosis:                       2.776   Cond. No.                    3.06e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.06e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

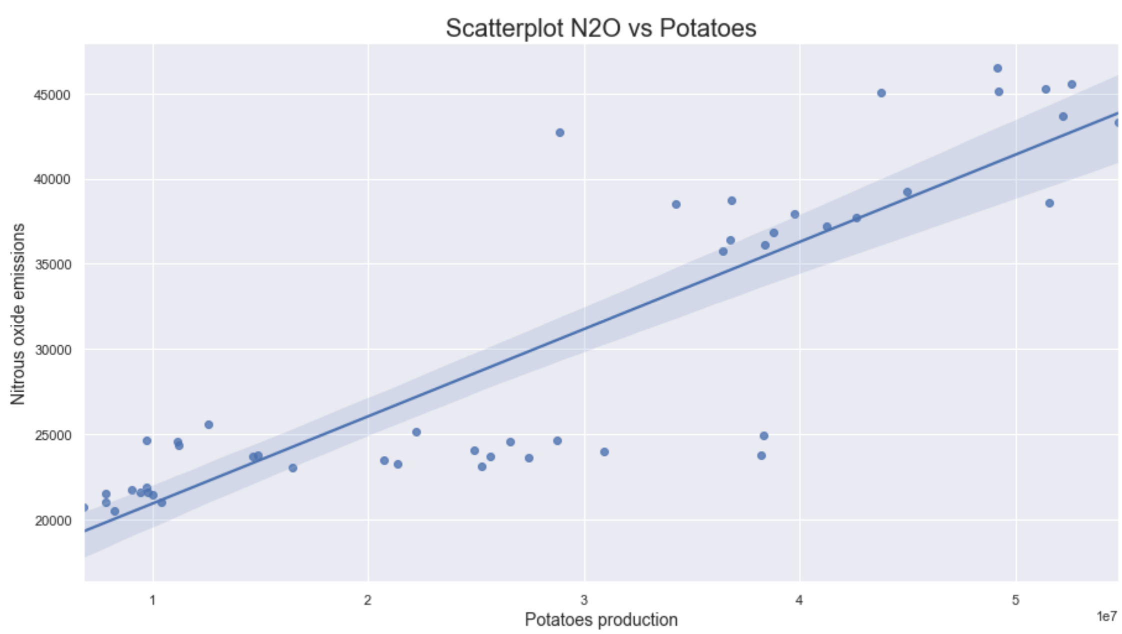
Explanation

- The graph shows two separate groups. The mayority of the observations seems to be spread of the line of regression.
- The data seems to have a negative correlation.
- Due P < 0.05, the variable is significative.
- Due the low value of R2, the model seems to be weak the explain the variability of the data.

6.2.3 Scatter plot and Regression: Nitrox vs Potatoes

```
[ ]: x3 = cropsNitrox_df["Potatoes"].tolist()
```

```
[ ]: # Base of the plot
plt.figure(figsize=(15,8))
plt.xlabel("Potatoes production", fontsize=14)
plt.ylabel("Nitrous oxide emissions", fontsize=14)
plt.title("Scatterplot N2O vs Potatoes", fontsize=20)

# Scatterplot itself
sns.regplot(x= x3, y= y)
plt.show();
```



```
[ ]: X_Potatoes = sm.add_constant(x3)
     results_Potatoes = sm.OLS(y, X_Potatoes).fit()
     results_Potatoes.summary()
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.766
Model:                            OLS   Adj. R-squared:                  0.761
Method:                 Least Squares   F-statistic:                     150.6
Date:                Fri, 25 Feb 2022   Prob (F-statistic):           4.13e-16
Time:                        13:25:26   Log-Likelihood:                -469.77
No. Observations:                  48   AIC:                             943.5
Df Residuals:                      46   BIC:                             947.3
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        1.58e+04   1322.186     11.946      0.000    1.31e+04    1.85e+04
x1             0.0005   4.17e-05     12.271      0.000       0.000       0.001
==============================================================================
Omnibus:                        4.151   Durbin-Watson:                   0.774
Prob(Omnibus):                  0.126   Jarque-Bera (JB):                3.277
Skew:                          -0.379   Prob(JB):                        0.194
Kurtosis:                       4.031   Cond. No.                     6.60e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 6.6e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Explanation * The graph shows two separate groups of data in which, the mayority of the observations seems to be spread from the line of regression. * This data seems to have a positive correlation. * Due P < 0.05, the variable is significative. * Due the low value of R2, the model seems to be weak the explain the variability of the data.

A new file was created in RStudio. This file contains the two datasets merged. After, it was created a descriptive analysis of the data.

[ ]:
```
CropsNitrox = pd.read_csv(r"C:
↪\Users\USER\Documents\Desarrollador\PYTHON\2021-Python-exercises\statistics-projects\2022-0
↪csv")
```

[ ]:
```
CropsNitrox.loc[ : , CropsNitrox.columns != "Year"].describe()
```

[ ]:

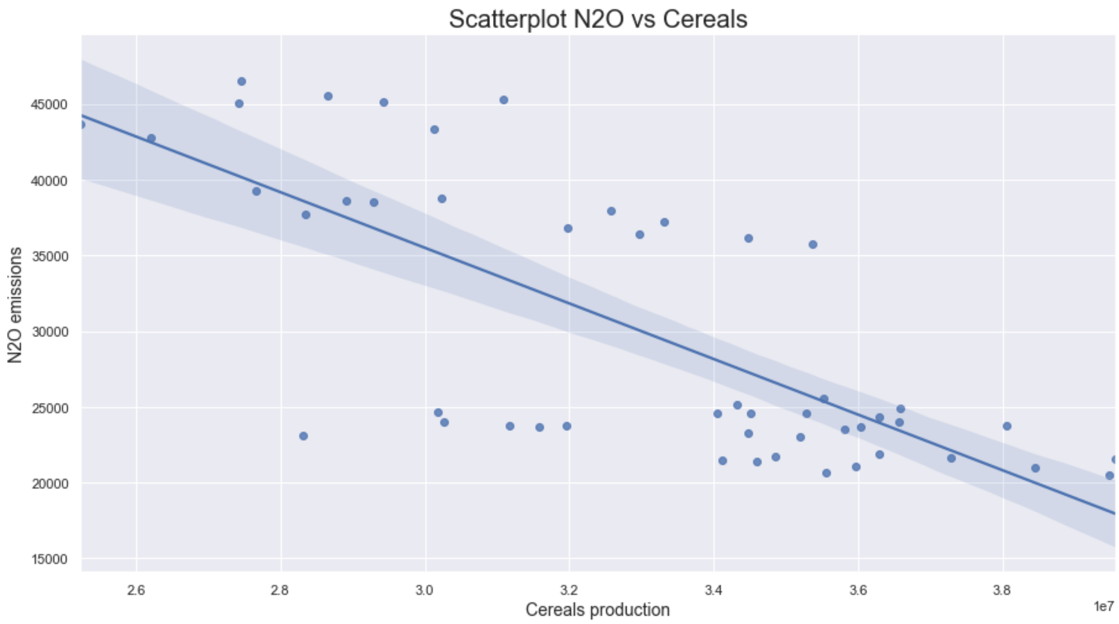
	Nitrous.oxide.emissions.	Cereals.Total	Roots.and.Tubers	Potatoes
count	48.00	48.00	48.00	48.00
mean	30,026.39	32,980,603.17	27,794,209.40	27,794,209.40
std	8,996.23	3,639,354.81	15,377,540.62	15,377,540.62
min	20,500.00	25,234,198.00	6,824,231.00	6,824,231.00
25%	23,230.00	30,170,408.00	11,184,625.75	11,184,625.75
50%	24,595.00	34,084,246.00	27,010,621.50	27,010,621.50
75%	38,085.51	35,616,846.50	39,051,279.75	39,051,279.75
max	46,495.35	39,568,956.00	54,800,486.00	54,800,486.00

- It seems that the data, at least with the current variables (Cereals, Roots and Tubers and Potatoes), are not sufficient to explain nitrous oxide emissions. It will be necessary to add more variables to find a model that better explains the problem.
- However, it seems that at least with the variable "Cereals", they show a positive correlation, however, as mentioned above, given the values of R2 and adjusted R2, the models are weak in explaining the variability.

Explanation * The graph shows two separate groups of data in which, the mayority of the observations seems to be spread from the line of regression. * This data seems to have a positive correlation. * P < 0.05, so the variable is significative. * Due the low value of R2, the model seems to be weak the explain the variability of the data.

7. Conclusion/Discussion

[ ]:
```
# Base of the plot
plt.figure(figsize=(15,8))
plt.xlabel("Cereals production", fontsize= 14)
plt.ylabel("N2O emissions", fontsize=14)
plt.title("Scatterplot N2O vs Cereals", fontsize=20)

# Scatterplot itself
sns.regplot(x= x1, y= y)
plt.show();
```



2 References

- The World Bank. (2022). Nitrous oxide emissions (thousand metric tons of CO2 equivalent) | Data. https://data.worldbank.org/indicator/EN.ATM.NOXE.KT.CE
- Wąs, Adam; Kobus, Paweł; Krupin, Vitaliy; Witajewski-Baltvilks, Jan; Cygler, M. (2020). Asessng Climate Policy Impacts in Poland's Agriculture -Options Overview- (Issue June). https://climatecake.ios.edu.pl/aktualnosci/news-cake/new-cake-analysis-assessing-climate-policy-impacts-in-polands-agriculture-options-overview/?lang=en