code_project

August 28, 2020

Project Essentials: code

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[1]:
```
# Import of the libraries that are used
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 Part 1 - Import and exploration of the data. Initial Visualization Analysis.

2.1 1.1 - Exploring the precipitation in the state of São Paulo.

[2]:
```
### We start the descriptive analysis of the rainfall data in SP
```

[3]:
```
# Reading the file of the rain in SP
rainfallset = pd.read_csv("rainfalls_SP.csv", index_col=0)
rainfallset.head(100)
```

[3]:

Estacao	Data	Hora	Precipitacao
83781	03/10/1961	1200.0	0.0
83781	04/10/1961	1200.0	0.0
83781	05/10/1961	1200.0	0.0
83781	06/10/1961	1200.0	0.0
83781	07/10/1961	1200.0	0.0
…	…	…	…

```
83781    06/01/1962  1200.0           0.0
83781    07/01/1962  1200.0           0.0
83781    08/01/1962  1200.0          18.0
83781    09/01/1962  1200.0           0.7
83781    10/01/1962  1200.0           0.0

[100 rows x 3 columns]
```

Comment1: the data set starts at 1961

[4]:
```
rainfallset.tail()
```

[4]:
```
              Data  \
Estacao
83781
30/09/2016
83781
01/10/2016
83781
02/10/2016
83781
03/10/2016
</pre>    <div id="facebox" style="display:none  >       <div class="popup">
<table>   …

                                                  Hora  Precipitacao
Estacao
83781                                           1200.0           0.0
83781                                           1200.0           0.0
83781                                           1200.0           0.0
83781                                           1200.0           0.0
</pre>    <div id="facebox" style="display:none      NaN           NaN
```

Comment2: The data of rain fall ends in the month November 2016. The drough of SP was felt between 2014-2017. In São Paulo, it has been described as the worst drought in 100 years by the media. Check the Guardian article mentioned in the deliverable / presentation.

[5]:
```
rainfallset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 19788 entries, 83781 to </pre>    <div id="facebox" style="display:none
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Data          19788 non-null  object
 1   Hora          19787 non-null  float64
 2   Precipitacao  19787 non-null  float64
dtypes: float64(2), object(1)
```

```
memory usage: 618.4+ KB
```

[6]:
```
##convert the string concerning column Data into datetime objects
rainfallset["Data"]=pd.to_datetime(rainfallset["Data"],␣
↪infer_datetime_format=True, errors = 'coerce')
```

[7]:
```
rainfallset.info()
```

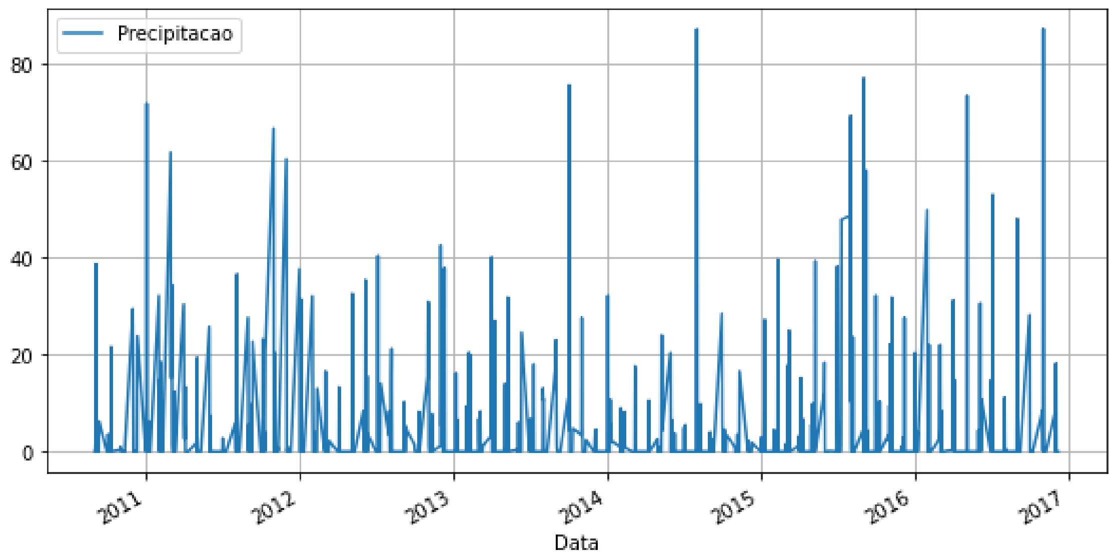
```
<class 'pandas.core.frame.DataFrame'>
Index: 19788 entries, 83781 to </pre>    <div id="facebox" style="display:none
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Data          7801 non-null   datetime64[ns]
 1   Hora          19787 non-null  float64
 2   Precipitacao  19787 non-null  float64
dtypes: datetime64[ns](1), float64(2)
memory usage: 618.4+ KB
```

[8]:
```
rainfallset.head()
```

[8]:
```
              Data    Hora  Precipitacao
Estacao
83781   1961-03-10  1200.0           0.0
83781   1961-04-10  1200.0           0.0
83781   1961-05-10  1200.0           0.0
83781   1961-06-10  1200.0           0.0
83781   1961-07-10  1200.0           0.0
```

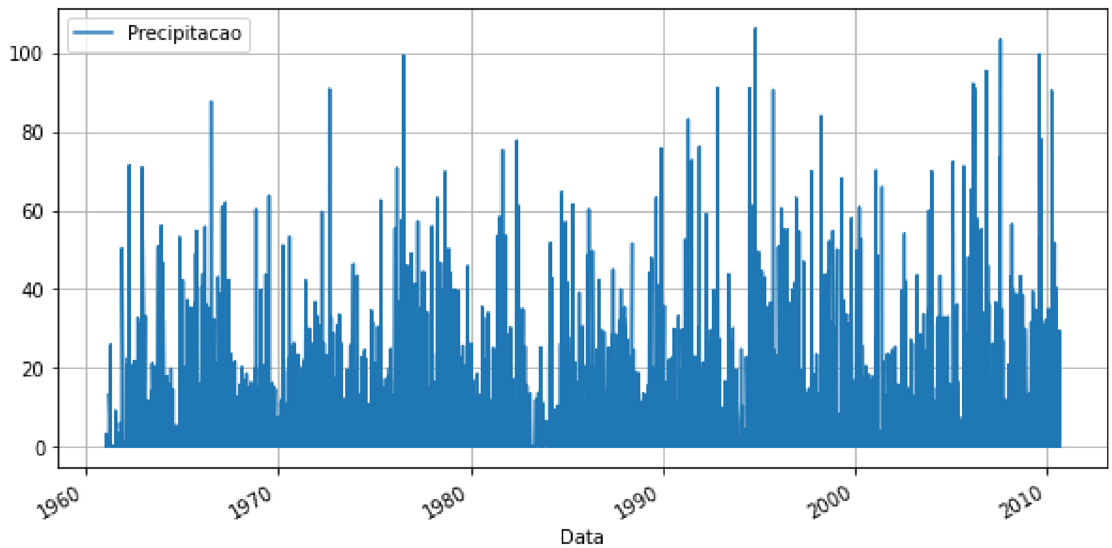
[9]:
```
#use masks to focus on specific dates and in particular the drought period␣
↪2014-2017
mask= rainfallset["Data"] >= "2010-09-02"
rainfallset[mask].plot.line(x="Data", y="Precipitacao", figsize=(10,5),␣
↪grid=True)
```

[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd87803ee20>
```



[10]:
```
#use masks to focus on specific dates and in particular the drought period␣
↪2014-2017
mask2= rainfallset["Data"] <= "2010-09-02"
rainfallset[mask2].plot.line(x="Data", y="Precipitacao", figsize=(10,5),␣
↪grid=True)
```

[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd875f2b8b0>
```



[11]:
```
rainfallset.describe(include ='all')
```

```
<ipython-input-11-2d0c528f6c65>:1: FutureWarning: Treating datetime data as
categorical rather than numeric in `.describe` is deprecated and will be removed
in a future version of pandas. Specify `datetime_is_numeric=True` to silence
this warning and adopt the future behavior now.
  rainfallset.describe(include ='all')
```

[11]:

```
                       Data     Hora  Precipitacao
count                  7801  19787.0  19787.000000
unique                 7801      NaN           NaN
top     1968-11-10 00:00:00      NaN           NaN
freq                      1      NaN           NaN
first   1961-01-11 00:00:00      NaN           NaN
last    2016-12-09 00:00:00      NaN           NaN
mean                    NaN   1200.0      4.248911
std                     NaN      0.0     10.697383
min                     NaN   1200.0      0.000000
25%                     NaN   1200.0      0.000000
50%                     NaN   1200.0      0.000000
75%                     NaN   1200.0      2.200000
max                     NaN   1200.0    151.800000
```

[12]:

```
##now separating months and years in the dataframe
rainfallset["year"] = pd.DatetimeIndex(rainfallset["Data"]).year
rainfallset["month"] = pd.DatetimeIndex(rainfallset["Data"]).month
```

[13]:

```
rainfallset.head()
```

[13]:

```
              Data    Hora  Precipitacao    year  month
Estacao
83781   1961-03-10  1200.0           0.0  1961.0    3.0
83781   1961-04-10  1200.0           0.0  1961.0    4.0
83781   1961-05-10  1200.0           0.0  1961.0    5.0
83781   1961-06-10  1200.0           0.0  1961.0    6.0
83781   1961-07-10  1200.0           0.0  1961.0    7.0
```

[14]:

```
###We see that we need to create cummulative rain months fall between years in␣
↪order to have
##better precision
####this would do by year
###annual_rainfallset=pd.pivot_table(data=rainfallset, index='year',␣
↪values='Precipitacao', aggfunc='sum')

annual_rainfallset=pd.pivot_table(data=rainfallset, index='year',␣
↪values='Precipitacao', aggfunc='sum').reset_index().
↪rename(columns={'Precipitacao': 'annual_rainfall'})
```

[15]:

```
annual_rainfallset.describe(include='all')
```

[15]:

	year	annual_rainfall
count	56.000000	56.000000
mean	1988.500000	594.369643
std	16.309506	194.823955
min	1961.000000	111.500000
25%	1974.750000	474.825000
50%	1988.500000	579.800000
75%	2002.250000	687.925000
max	2016.000000	1142.500000

[16]:
```
annual_rainfallset.head()
```

[16]:

	year	annual_rainfall
0	1961.0	144.1
1	1962.0	577.0
2	1963.0	362.7
3	1964.0	418.4
4	1965.0	649.9

[17]:
```
annual_rainfallset.info()
```

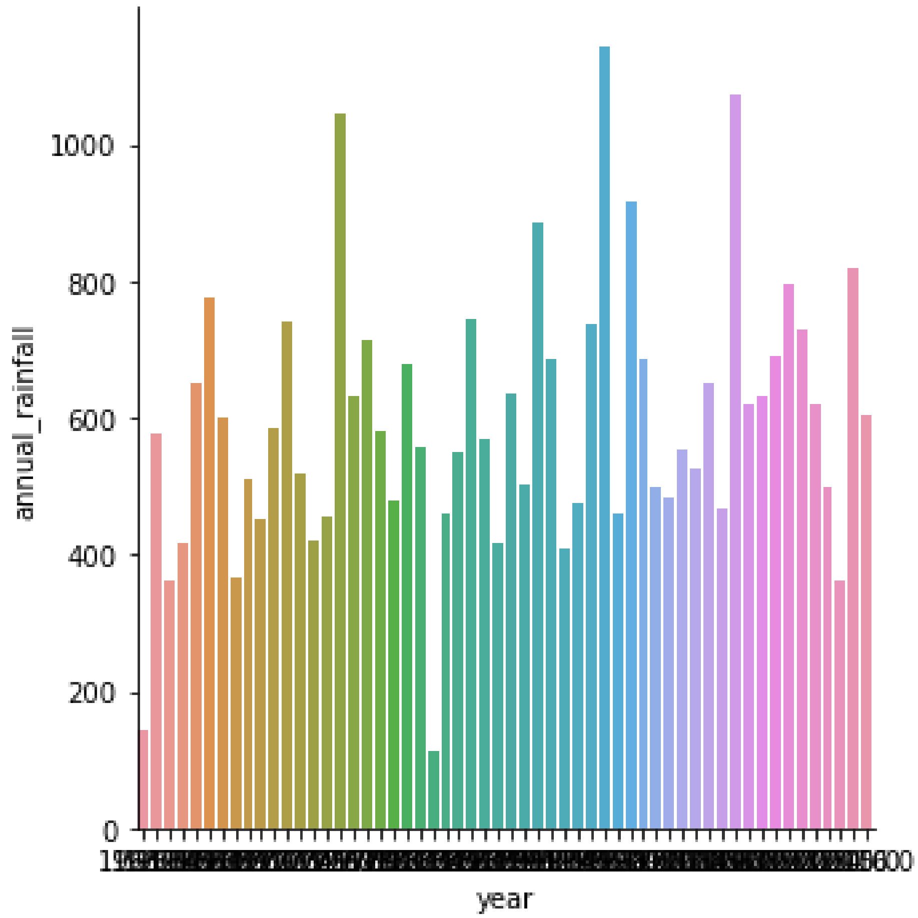
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   year             56 non-null     float64
 1   annual_rainfall  56 non-null     float64
dtypes: float64(2)
memory usage: 1.0 KB
```

[18]:
```
annual_rainfallset.columns
```

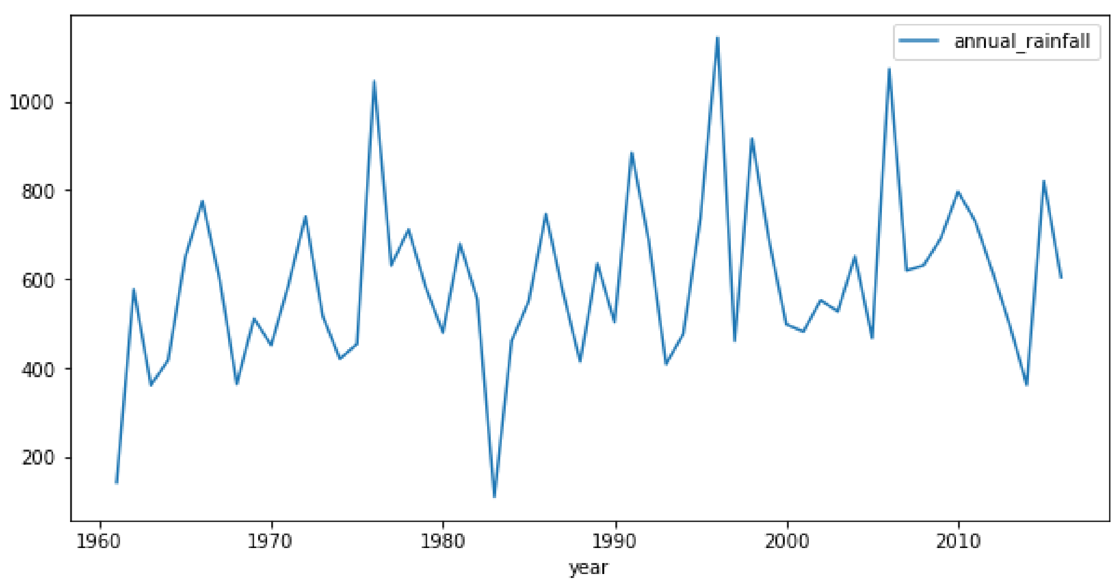
[18]: Index(['year', 'annual_rainfall'], dtype='object')

[19]:
```
# Visualisation exploratoire
##histogram with 95% confidence interval
sns.catplot(x="year", y="annual_rainfall", data=annual_rainfallset,kind="bar")
```

[19]: <seaborn.axisgrid.FacetGrid at 0x7fd873bf7100>



[20]:
```
plt=annual_rainfallset.plot.line(x="year", y="annual_rainfall", figsize=(10,5))
```

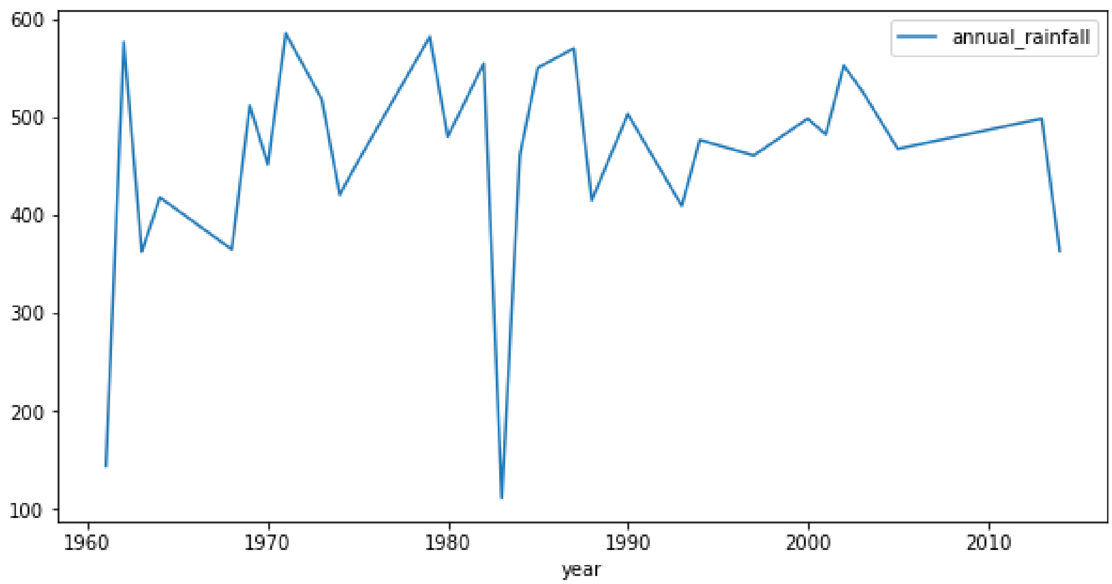


Comments: two extremely critical drough periods after the 70s': around 1980 and after 2010. We want to focus on the last period.

around 2010 the level of precipitation went down a lot. So we will try to use logistic regression that will try to predict the probability of the rainfall will go down more than the level of 2010

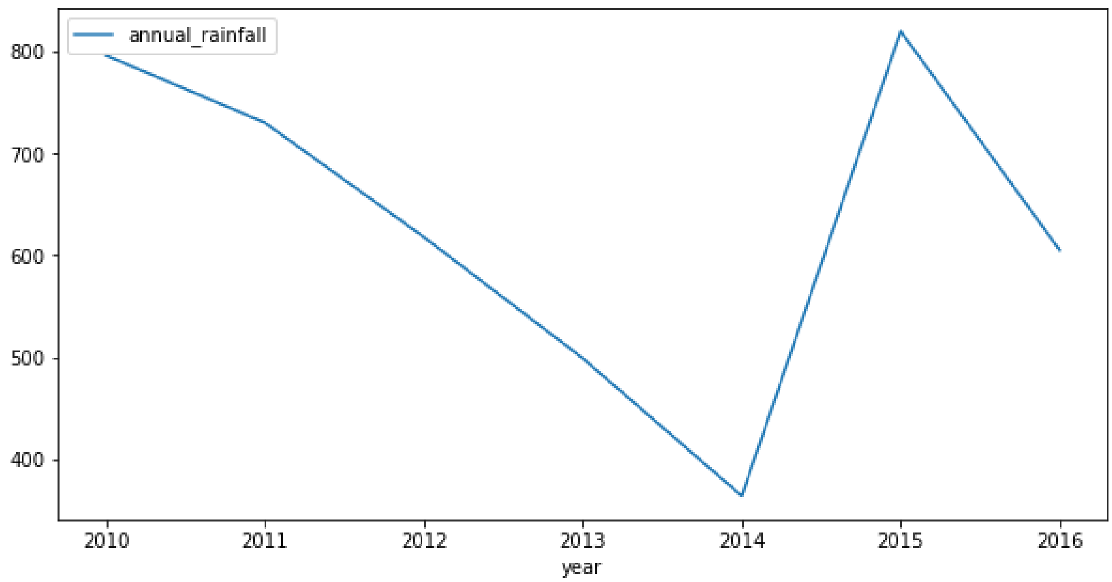
[21]:
```
#to have some idea of the critical values below 600
mask=annual_rainfallset["annual_rainfall"] <=600
annual_rainfallset[mask].plot.line(x="year", y="annual_rainfall",␣
↪figsize=(10,5))
```

[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd8739710a0>



[22]:
```
#to have some idea of the critcal values below 600
mask=annual_rainfallset["year"] >=2010
annual_rainfallset[mask].plot.line(x="year", y="annual_rainfall",␣
↪figsize=(10,5))
```

[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd873951e50>



Comment: this graph tell us how BAD was 2014!! Year to focus of the drought. The critical period comes 2011-2014. Why? 2011 the derivative is very steep negative.

How to check the minimum of 2014?

[23]:
```
##creation of an auxiliary table for that purpose
mask3 = annual_rainfallset["year"] >= 2010
filtered_data = annual_rainfallset[mask3]
print (filtered_data)
```

```
      year  annual_rainfall
49  2010.0            796.6
50  2011.0            730.4
51  2012.0            618.0
52  2013.0            498.8
53  2014.0            363.5
54  2015.0            820.1
55  2016.0            605.0
```

Critical minimum: 363.5

So now we want to create a single data frame combining C02Brazil, deflorestation of the states around Brazil and the temperatures SP

[24]:
```
critical_minimum=363.5
threshold=498.8
#the threshold is the value of 2013 when things got very bad#
```

[25]:
```python
## we want cummulative rain by month of the year in order to compare it with␣
↪other variables
##of the other files

month_rainfallset=pd.pivot_table(data=rainfallset, index=['year','month'],␣
↪values='Precipitacao', aggfunc='sum').reset_index().
↪rename(columns={'Precipitacao': 'total_rainfall'})
```

[26]:
```python
month_rainfallset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 672 entries, 0 to 671
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   year            672 non-null    float64
 1   month           672 non-null    float64
 2   total_rainfall  672 non-null    float64
dtypes: float64(3)
memory usage: 15.9 KB
```

[27]:
```python
month_rainfallset.head()
```

[27]:

	year	month	total_rainfall
0	1961.0	1.0	3.2
1	1961.0	2.0	5.7
2	1961.0	3.0	16.8
3	1961.0	4.0	26.8
4	1961.0	5.0	0.0

[28]:
```python
# in order to have coeherence between the table of the monthrainfall and the␣
↪temperatures of SP and therefore
##to merge them we need the month to be with same data type.
##first step is to convert the floats into integers
month_rainfallset['month']=month_rainfallset['month'].astype(int)
```

[29]:
```python
month_rainfallset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 672 entries, 0 to 671
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   year            672 non-null    float64
 1   month           672 non-null    int64
 2   total_rainfall  672 non-null    float64
dtypes: float64(2), int64(1)
```

```
memory usage: 15.9 KB
```

[30]:
```python
import calendar
month_rainfallset['month'] = month_rainfallset['month'].apply(lambda x:␣
↪calendar.month_abbr[x])
```

[31]:
```python
month_rainfallset.head()
```

[31]:

	year	month	total_rainfall
0	1961.0	Jan	3.2
1	1961.0	Feb	5.7
2	1961.0	Mar	16.8
3	1961.0	Apr	26.8
4	1961.0	May	0.0

[32]:
```python
month_rainfallset.tail()
```

[32]:

	year	month	total_rainfall
667	2016.0	Aug	11.7
668	2016.0	Sep	48.0
669	2016.0	Oct	28.5
670	2016.0	Nov	95.9
671	2016.0	Dec	26.2

[33]:
```python
month_rainfallset.describe(include ='all')
```

[33]:

	year	month	total_rainfall
count	672.00000	672	672.000000
unique	NaN	12	NaN
top	NaN	Apr	NaN
freq	NaN	56	NaN
mean	1988.50000	NaN	49.530804
std	16.17527	NaN	36.090199
min	1961.00000	NaN	0.000000
25%	1974.75000	NaN	23.600000
50%	1988.50000	NaN	42.450000
75%	2002.25000	NaN	67.900000
max	2016.00000	NaN	229.500000

[34]:
```python
month_rainfallset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 672 entries, 0 to 671
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   year            672 non-null    float64
 1   month           672 non-null    object
```

```
 2   total_rainfall  672 non-null    float64
dtypes: float64(2), object(1)
memory usage: 15.9+ KB
```

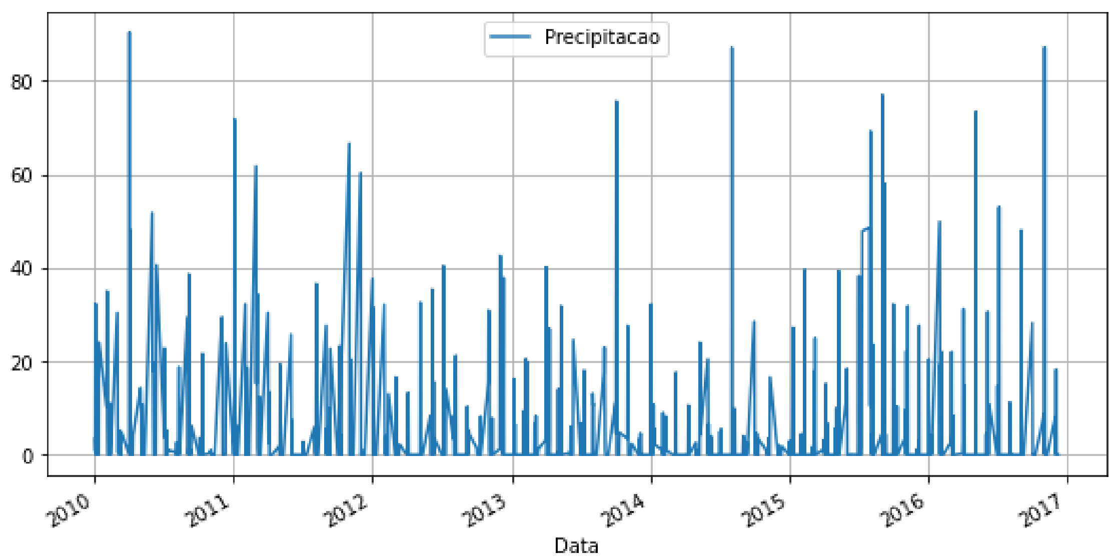
[35]:
```
## Are there missing files?
# CLEANING
month_rainfallset.isnull().any()
#No there are not missing values. We wil deal with this later.
```

[35]:
```
year              False
month             False
total_rainfall    False
dtype: bool
```

For now we would like to see when was the critical period of the drought. We use data visualization for this. Time to aggregate everything!

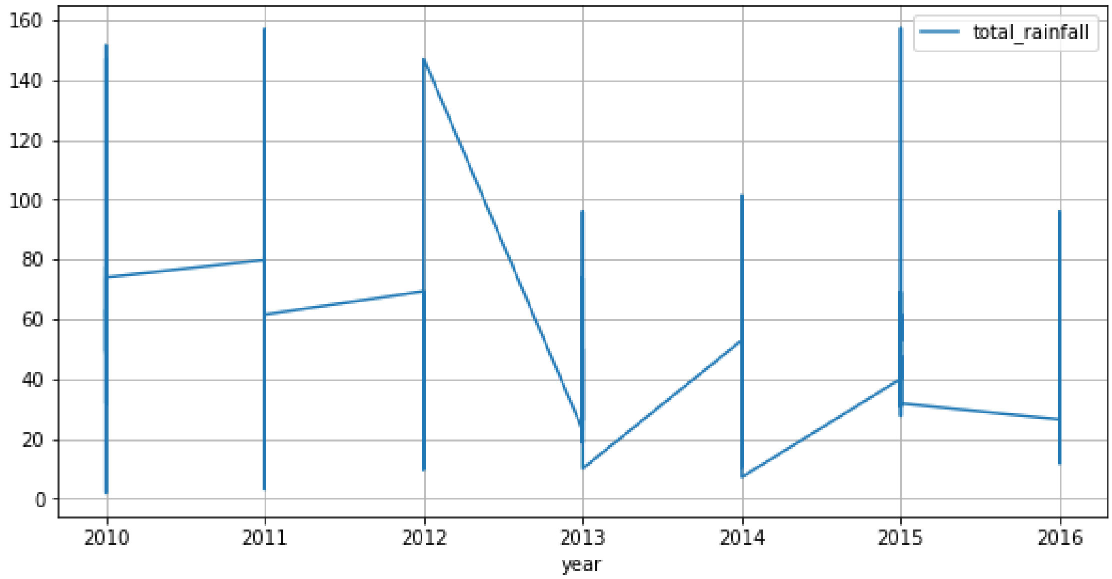
[36]:
```
#use masks to focus on specific dates and in particular the drought period␣
↪2014-207
mask= rainfallset["Data"] >= "2010-01-01"
rainfallset[mask].plot.line(x="Data", y="Precipitacao", figsize=(10,5),␣
↪grid=True)
```

[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd87391a8e0>
```



[37]:
```
##Focus on the precipitation per month
mask= month_rainfallset["year"] >= 2010
month_rainfallset[mask].plot.line(x="year", y="total_rainfall", figsize=(10,5),␣
↪grid=True)
```

[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd8738a6280>
```



[38]:
```
##We confirm the critical minimum around 2014 as empirically suffered in SP
```

Let us now think about the temperatures. We want to understand if the anomalies of temperatures were high or not in SP in the year of SP when compared with the data set of the rainfall.

2.2 1.2 - Comparing anomalies of temperatures between São Paulo, Rio and Manaus

[39]:
```
###Exploring the data of temperatures in SP
SP_temp = pd.read_csv("sp_temperatures.csv", index_col=0)
SP_temp.head(100)
```

[39]:

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	\
YEAR										
1946	999.90	999.90	999.90	999.90	999.90	999.90	999.90	999.90	999.90	
1947	999.90	23.54	21.04	19.74	19.24	999.90	15.04	16.44	18.04	
1948	23.64	22.94	20.74	20.04	18.04	16.64	17.84	15.64	18.64	
1949	22.34	21.54	23.54	19.44	17.24	17.34	16.34	17.34	18.24	
1950	22.14	22.44	22.24	20.44	19.44	17.94	16.44	19.14	19.54	
…	…	…	…	…	…	…	…	…	…	
2015	26.35	24.60	23.15	22.00	19.25	18.70	18.60	20.65	21.85	
2016	23.60	25.30	23.90	24.25	18.60	16.10	18.40	18.90	19.65	
2017	23.85	25.00	22.65	21.10	19.40	18.60	17.30	18.30	22.55	
2018	23.90	23.25	24.95	22.20	20.15	19.20	19.55	17.85	20.70	
2019	26.55	24.15	23.95	23.45	21.55	19.80	18.05	18.80	20.85	

```
           OCT      NOV      DEC    D-J-F    M-A-M    J-J-A    S-O-N   metANN
YEAR
1946    999.90   999.90    21.74   999.90   999.90   999.90   999.90   999.90
1947     17.04    18.94    20.34    22.75    20.01    15.67    18.01    19.11
1948     18.74    20.64    21.24    22.31    19.61    16.71    19.34    19.49
1949     18.74    19.74    21.54    21.71    20.07    17.01    18.91    19.42
1950     19.04    19.94    21.94    22.04    20.71    17.84    19.51    20.02
…          …       …        …        …        …       …        …        …
2015     23.00    22.95    24.50    25.17    21.47    19.32    22.60    22.14
2016     21.40    21.60    24.20    24.47    22.25    17.80    20.88    21.35
2017     22.55    21.85    23.70    24.35    21.05    18.07    22.32    21.45
2018     20.95    22.30    24.55    23.62    22.43    18.87    21.32    21.56
2019     23.45   999.90   999.90    25.08    22.98    18.88    22.62    22.39

[74 rows x 17 columns]
```

[40]:

```python
SP_temp.tail()
```

[40]:

```
        JAN    FEB    MAR    APR    MAY   JUN    JUL    AUG    SEP    OCT  \
YEAR
2015  26.35  24.60  23.15  22.00  19.25  18.7  18.60  20.65  21.85  23.00
2016  23.60  25.30  23.90  24.25  18.60  16.1  18.40  18.90  19.65  21.40
2017  23.85  25.00  22.65  21.10  19.40  18.6  17.30  18.30  22.55  22.55
2018  23.90  23.25  24.95  22.20  20.15  19.2  19.55  17.85  20.70  20.95
2019  26.55  24.15  23.95  23.45  21.55  19.8  18.05  18.80  20.85  23.45

         NOV     DEC  D-J-F  M-A-M  J-J-A  S-O-N  metANN
YEAR
2015   22.95   24.50  25.17  21.47  19.32  22.60   22.14
2016   21.60   24.20  24.47  22.25  17.80  20.88   21.35
2017   21.85   23.70  24.35  21.05  18.07  22.32   21.45
2018   22.30   24.55  23.62  22.43  18.87  21.32   21.56
2019  999.90  999.90  25.08  22.98  18.88  22.62   22.39
```

[41]:

```python
###erase last columns
SP_temp = SP_temp.drop(["D-J-F", "M-A-M", "J-J-A", "S-O-N", "metANN"], axis=1)
```

[42]:

```python
SP_temp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 74 entries, 1946 to 2019
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   JAN     74 non-null     float64
 1   FEB     74 non-null     float64
 2   MAR     74 non-null     float64
```

```
 3   APR     74 non-null     float64
 4   MAY     74 non-null     float64
 5   JUN     74 non-null     float64
 6   JUL     74 non-null     float64
 7   AUG     74 non-null     float64
 8   SEP     74 non-null     float64
 9   OCT     74 non-null     float64
 10  NOV     74 non-null     float64
 11  DEC     74 non-null     float64
dtypes: float64(12)
memory usage: 7.5 KB
```

[43]:
```
SP_temp.isnull().any()
##Comment: here it is tricky. we see. a lot error values labelled as 999.90.
####We have to deal with them later.
```

[43]:
```
JAN    False
FEB    False
MAR    False
APR    False
MAY    False
JUN    False
JUL    False
AUG    False
SEP    False
OCT    False
NOV    False
DEC    False
dtype: bool
```

[44]:
```
##We have to clean the occurrence of 999.9 as missing data.. Let's do a simple␣
↪workaround by replacing these values.
SP_temp.replace(999.90, np.nan, inplace=True)
```

[45]:
```
SP_temp.head()
```

[45]:
```
        JAN    FEB    MAR    APR    MAY    JUN    JUL    AUG    SEP    OCT  \
YEAR
1946    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN
1947    NaN  23.54  21.04  19.74  19.24    NaN  15.04  16.44  18.04  17.04
1948  23.64  22.94  20.74  20.04  18.04  16.64  17.84  15.64  18.64  18.74
1949  22.34  21.54  23.54  19.44  17.24  17.34  16.34  17.34  18.24  18.74
1950  22.14  22.44  22.24  20.44  19.44  17.94  16.44  19.14  19.54  19.04

        NOV    DEC
YEAR
1946    NaN  21.74
```

```
1947  18.94  20.34
1948  20.64  21.24
1949  19.74  21.54
1950  19.94  21.94
```

[46]:
```
SP_temp.tail()
```

[46]:
```
        JAN    FEB    MAR    APR    MAY    JUN    JUL    AUG    SEP    OCT  \
YEAR
2015  26.35  24.60  23.15  22.00  19.25  18.7  18.60  20.65  21.85  23.00
2016  23.60  25.30  23.90  24.25  18.60  16.1  18.40  18.90  19.65  21.40
2017  23.85  25.00  22.65  21.10  19.40  18.6  17.30  18.30  22.55  22.55
2018  23.90  23.25  24.95  22.20  20.15  19.2  19.55  17.85  20.70  20.95
2019  26.55  24.15  23.95  23.45  21.55  19.8  18.05  18.80  20.85  23.45

        NOV    DEC
YEAR
2015  22.95  24.50
2016  21.60  24.20
2017  21.85  23.70
2018  22.30  24.55
2019    NaN    NaN
```

[47]:
```
SP_temp.columns
```

[47]:
```
Index(['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG', 'SEP', 'OCT',
       'NOV', 'DEC'],
      dtype='object')
```

[48]:
```
#it retrieves the % values null that are missing --- approximately 5, 6%%. it␣
↪is still a lot.
##Let us replace it by median temperature
SP_temp.isnull().sum() / len(SP_temp)
```

[48]:
```
JAN    0.067568
FEB    0.067568
MAR    0.067568
APR    0.067568
MAY    0.054054
JUN    0.067568
JUL    0.067568
AUG    0.054054
SEP    0.040541
OCT    0.040541
NOV    0.040541
DEC    0.040541
dtype: float64
```

[49]:
```python
# it replaces the values that are missing by a benchmark value, in this case by␣
↪the
#medianne
SP_temp = SP_temp.fillna(SP_temp.median())
# the next command confirms that no value now is missing in the table
SP_temp.isnull().any()
```

[49]:
```
JAN    False
FEB    False
MAR    False
APR    False
MAY    False
JUN    False
JUL    False
AUG    False
SEP    False
OCT    False
NOV    False
DEC    False
dtype: bool
```

[50]:
```python
SP_temp.columns
```

[50]:
```
Index(['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG', 'SEP', 'OCT',
       'NOV', 'DEC'],
      dtype='object')
```

[51]:
```python
###to make this table compatible with the data of the rainfall
###this is a series now
SP_temp_Series= SP_temp.stack(level=-1)

print(SP_temp_Series)
```

```
YEAR
1946  JAN    23.670
      FEB    24.090
      MAR    23.320
      APR    21.370
      MAY    18.835
              …
2019  AUG    18.800
      SEP    20.850
      OCT    23.450
      NOV    21.640
      DEC    22.740
Length: 888, dtype: float64
```

[52]:
```
SP_temp= SP_temp_Series.to_frame()
SP_temp.head(10)
```

[52]:
```
                0
YEAR
1946 JAN  23.670
     FEB  24.090
     MAR  23.320
     APR  21.370
     MAY  18.835
     JUN  17.690
     JUL  17.530
     AUG  18.550
     SEP  19.540
     OCT  20.800
```

[53]:
```
SP_temp=SP_temp.reset_index()
SP_temp.head()
```

[53]:

	YEAR	level_1	0
0	1946	JAN	23.670
1	1946	FEB	24.090
2	1946	MAR	23.320
3	1946	APR	21.370
4	1946	MAY	18.835

[54]:
```
SP_temp = SP_temp.rename(columns = {'YEAR': 'year', 'level_1': 'month', 0:␣
 ↪'avtemp_SP'}, inplace = False)
```

[55]:
```
SP_temp.head(10)
```

[55]:

	year	month	avtemp_SP
0	1946	JAN	23.670
1	1946	FEB	24.090
2	1946	MAR	23.320
3	1946	APR	21.370
4	1946	MAY	18.835
5	1946	JUN	17.690
6	1946	JUL	17.530
7	1946	AUG	18.550
8	1946	SEP	19.540
9	1946	OCT	20.800

[56]:
```
#temperature benchmark for SP
tempSP_benchmark=SP_temp.loc[:,"avtemp_SP"].median()
print(tempSP_benchmark)
```

20.89

[57]:
```
SP_temp["temp_anom_SP"]=0
SP_temp.head()
```

[57]:

	year	month	avtemp_SP	temp_anom_SP
0	1946	JAN	23.670	0
1	1946	FEB	24.090	0
2	1946	MAR	23.320	0
3	1946	APR	21.370	0
4	1946	MAY	18.835	0

[58]:
```
####table with temperature anomalies
for i in range(len(SP_temp)):
    SP_temp.loc[i, "temp_anom_SP"]=abs(SP_temp.loc[i, "avtemp_SP"]-␣
 ↪tempSP_benchmark)
SP_temp.head()
```

[58]:

	year	month	avtemp_SP	temp_anom_SP
0	1946	JAN	23.670	2.780
1	1946	FEB	24.090	3.200
2	1946	MAR	23.320	2.430
3	1946	APR	21.370	0.480
4	1946	MAY	18.835	2.055

We will calculate the anomalies of temperatures (internal) regarding the statistical localization estimate given by the median of the last 40years. Also we need to prepare this table to merge with other tables: CO2, rainfall…

[59]:
```
##creation of an auxiliary table for that purpose
mask = (SP_temp["year"] >= 1961) &(SP_temp["year"]<2017)
SP_temp_reduced=SP_temp[mask]
SP_temp_reduced.head(16)
```

[59]:

	year	month	avtemp_SP	temp_anom_SP
180	1961	JAN	23.670	2.780
181	1961	FEB	24.090	3.200
182	1961	MAR	23.320	2.430
183	1961	APR	21.370	0.480
184	1961	MAY	18.835	2.055
185	1961	JUN	17.690	3.200
186	1961	JUL	17.530	3.360
187	1961	AUG	18.550	2.340
188	1961	SEP	19.540	1.350
189	1961	OCT	20.800	0.090
190	1961	NOV	21.640	0.750
191	1961	DEC	22.740	1.850
192	1962	JAN	23.670	2.780

```
193  1962   FEB    24.090        3.200
194  1962   MAR    23.320        2.430
195  1962   APR    21.370        0.480
```

NOW WE ARE GOING TO IMPORT THE DATA FILES OF TEMPERATURES OF RIO AND MANAUS (THE CITIES ELECTED) IN ORDER TO DO SOME COMPARATIVE ANALYSIS OF THE TEMPERATURE ANOMALIES. THE TEMPERATURE ANOMLAY IS DEFINED AS THE DIFFERENCE BETWEEN THE TEMPERATURE AND A BENCHMARK CASE. HERE WE CHOOSE AS BENCHMARKS THE MEDIAN TEMPERATURE OF THE BIG (NOT REDUCED TO 1961-2016 DATA SETS)

[60]:
```
###Preparing and cleaning the file on the temperatures of Rio
```

[61]:
```
Rio_temp = pd.read_csv("rio_temperatures.csv", index_col=0)
Rio_temp.head(100)
```

[61]:
```
         JAN     FEB     MAR     APR     MAY     JUN     JUL     AUG     SEP  \
YEAR
1973   27.73   27.97   25.70   26.49   22.42   22.76   22.14   21.03   21.46
1974   26.68   27.16   26.56   23.94   22.76   20.70   21.20   21.81   22.91
1975   25.27   26.92   26.43   22.82   21.37   20.50   19.68   22.98   22.40
1976   27.48   26.20   25.55   24.99   22.01   21.18   20.14   21.15   21.27
1977   27.13   28.51   26.88   24.22   22.35   22.13   23.07   22.29   22.44
1978   27.44   26.55   26.42   23.39   21.85   20.03   21.94   21.28   22.49
1979   23.86   25.69   24.80   23.36   23.05   20.30   20.29   22.42   22.05
1980   25.39   27.24   27.83   24.63   23.41   21.20   21.81   22.22   21.05
1981   27.42   28.06   26.26   23.85   22.87   20.94   19.90   21.50   23.19
1982   24.55   27.51   25.00   22.73   21.58   22.44   21.30   22.34   22.41
1983   26.81   27.63   25.99   24.08   23.82   21.18   21.55   20.91   20.53
1984   28.56   28.85   26.54   24.46   24.77   22.91   22.20   21.00   21.91
1985   25.53  999.90  999.90  999.90  999.90  999.90  999.90  999.90  999.90
1986  999.90   27.93   26.95   25.97  999.90   22.70   21.09   22.66   21.46
1987   27.68   27.25   25.86   25.85   22.73   20.48   22.43   20.80   21.02
1988   28.82   26.03   26.49   24.65   22.70   19.74   19.24   21.36   21.89
1989   26.98   26.59   26.45   25.43   21.92   20.90   19.47   21.67   21.70
1990   28.63   27.47   27.50   27.05   22.19   21.50   20.25   19.95   21.17
1991   25.44   26.43   25.52   24.72   21.69   21.42   19.64   20.91   20.80
1992   27.37  999.90   26.75   24.63   23.55   23.31   20.77   20.94   21.74
1993   27.48   27.25   26.81   25.68   22.85   20.98  999.90  999.90  999.90
1994  999.90  999.90   26.56   24.97   23.95   21.16   21.59   20.85   22.72
1995   28.64   27.59   26.75   24.97   23.17   21.84   23.06   23.90   23.05
1996   28.48   28.17   26.76   25.09   22.01   21.16   19.65   20.59   21.44
1997   26.52   28.03   25.35   24.57   22.43   21.53   22.00   21.76   23.28
1998   28.57   28.32   27.72   26.03   22.89   20.59   21.30   23.21   23.48
1999   27.83   27.96   27.00   24.69   22.21   21.25   21.56   20.94   22.77
2000   27.08   26.89   25.85   24.95   22.78   21.94   20.23   21.46   22.28
2001   28.25   28.55   27.83   27.17   23.24   22.67   21.32   22.23   22.20
```

2002	27.04	26.29	27.72	26.34	23.38	23.08	21.27	23.49	21.78
2003	26.94	999.90	999.90	999.90	999.90	999.90	999.90	999.90	999.90
2004	999.90	999.90	25.61	25.42	22.46	21.50	20.70	21.23	23.76
2005	26.75	26.12	26.64	26.09	23.85	22.41	20.91	23.41	22.18
2006	27.62	27.60	27.01	24.88	21.94	21.39	21.47	22.63	22.23
2007	999.90	999.90	999.90	999.90	999.90	999.90	999.90	999.90	999.90
2008	26.25	26.54	26.37	25.28	22.69	21.59	21.08	22.66	21.88
2009	26.32	27.96	26.55	24.21	23.16	20.71	21.21	21.88	24.01
2010	28.58	29.10	26.49	24.59	22.87	20.35	21.93	21.25	22.74
2011	28.14	28.69	25.50	25.48	21.86	20.52	20.61	22.32	21.79
2012	25.87	27.90	26.57	25.29	22.25	22.67	21.67	22.07	23.02
2013	26.13	28.18	26.18	24.20	22.94	22.59	20.86	21.71	23.42
2014	28.99	28.95	27.59	25.99	23.29	22.84	21.44	22.64	23.89
2015	29.93	28.43	26.78	25.93	23.18	21.98	22.93	23.53	23.28
2016	27.08	28.98	27.43	27.93	22.93	20.53	21.53	23.23	23.03
2017	28.92	28.27	26.97	25.52	22.57	21.97	20.02	22.42	24.22
2018	28.06	27.21	27.81	26.26	23.81	22.91	22.96	21.91	23.71
2019	30.25	28.05	27.50	26.55	24.85	23.10	21.75	22.30	23.05

	OCT	NOV	DEC	D-J-F	M-A-M	J-J-A	S-O-N	metANN
YEAR								
1973	22.46	23.06	25.85	27.45	24.87	21.98	22.33	24.16
1974	22.80	24.51	24.54	26.56	24.42	21.24	23.41	23.91
1975	22.65	24.11	26.53	25.58	23.54	21.05	23.05	23.31
1976	22.06	24.40	25.56	26.74	24.18	20.82	22.58	23.58
1977	23.92	24.48	24.84	27.07	24.48	22.50	23.61	24.42
1978	23.51	25.00	25.66	26.28	23.89	21.08	23.67	23.73
1979	24.25	24.07	26.02	25.07	23.74	21.00	23.46	23.32
1980	23.10	24.20	27.01	26.22	25.29	21.74	22.78	24.01
1981	22.49	25.25	25.73	27.50	24.33	20.78	23.64	24.06
1982	23.50	26.15	24.98	25.93	23.10	22.03	24.02	23.77
1983	23.03	25.25	25.94	26.47	24.63	21.21	22.94	23.81
1984	24.44	25.11	25.24	27.78	25.26	22.04	23.82	24.72
1985	999.90	999.90	999.90	25.65	999.90	999.90	999.90	999.90
1986	23.04	25.76	26.17	999.90	25.45	22.15	23.42	24.60
1987	22.96	24.59	26.07	27.03	24.81	21.24	22.86	23.99
1988	22.19	23.57	25.75	26.97	24.61	20.11	22.55	23.56
1989	22.07	24.85	25.86	26.44	24.60	20.68	22.87	23.65
1990	24.21	26.19	26.08	27.32	25.58	20.57	23.86	24.33
1991	23.59	24.49	27.26	25.98	23.98	20.66	22.96	23.39
1992	23.67	23.83	25.38	27.58	24.98	21.67	23.08	24.33
1993	999.90	999.90	999.90	26.70	25.11	999.90	999.90	999.90
1994	24.56	25.63	27.32	999.90	25.16	21.20	24.30	24.48
1995	23.21	25.13	25.93	27.85	24.96	22.93	23.80	24.89
1996	23.50	23.96	26.51	27.53	24.62	20.47	22.97	23.90
1997	24.25	26.27	27.77	27.02	24.12	21.76	24.60	24.38
1998	23.23	23.54	26.86	28.22	25.55	21.70	23.42	24.72

```
1999   21.62   23.04   25.70   27.55   24.63   21.25   22.48   23.98
2000   25.24   25.28   26.75   26.56   24.53   21.21   24.27   24.14
2001   23.06   24.47   25.82   27.85   26.08   22.07   23.24   24.81
2002   25.67   25.67   26.45   26.38   25.81   22.61   24.37   24.80
2003  999.90  999.90  999.90   26.96  999.90  999.90  999.90  999.90
2004   23.19   25.07   25.65  999.90   24.50   21.14   24.01   24.14
2005   25.45   24.60   25.26   26.17   25.53   22.24   24.08   24.51
2006   23.55   24.57   26.62   26.83   24.61   21.83   23.45   24.18
2007   24.91   25.07   26.97  999.90  999.90  999.90   24.36  999.90
2008   24.37   24.27   25.39   26.59   24.78   21.78   23.51   24.16
2009   24.07   27.91   26.20   26.56   24.64   21.27   25.33   24.45
2010   22.86   24.45   26.92   27.96   24.65   21.18   23.35   24.28
2011   23.71   23.24   25.47   27.92   24.28   21.15   22.91   24.07
2012   25.22   24.14   28.53   26.41   24.70   22.14   24.13   24.35
2013   23.60   24.75   26.05   27.61   24.44   21.72   23.92   24.42
2014   24.84   25.84   28.38   28.00   25.62   22.31   24.86   25.20
2015   25.33   26.43  999.90   28.91   25.30   22.81   25.01   25.51
2016   24.48   24.78   27.22   27.63   26.10   21.76   24.10   24.90
2017   25.97   25.47   27.01   28.14   25.02   21.47   25.22   24.96
2018   24.56   25.61   27.55   27.43   25.96   22.59   24.63   25.15
2019   25.25  999.90  999.90   28.62   26.30   22.38   24.74   25.51
```

[62]:

```python
Rio_temp.tail()
```

[62]:

```
        JAN    FEB    MAR    APR    MAY    JUN    JUL    AUG    SEP    OCT  \
YEAR
2015  29.93  28.43  26.78  25.93  23.18  21.98  22.93  23.53  23.28  25.33
2016  27.08  28.98  27.43  27.93  22.93  20.53  21.53  23.23  23.03  24.48
2017  28.92  28.27  26.97  25.52  22.57  21.97  20.02  22.42  24.22  25.97
2018  28.06  27.21  27.81  26.26  23.81  22.91  22.96  21.91  23.71  24.56
2019  30.25  28.05  27.50  26.55  24.85  23.10  21.75  22.30  23.05  25.25

         NOV     DEC  D-J-F  M-A-M  J-J-A  S-O-N  metANN
YEAR
2015   26.43  999.90  28.91  25.30  22.81  25.01   25.51
2016   24.78   27.22  27.63  26.10  21.76  24.10   24.90
2017   25.47   27.01  28.14  25.02  21.47  25.22   24.96
2018   25.61   27.55  27.43  25.96  22.59  24.63   25.15
2019  999.90  999.90  28.62  26.30  22.38  24.74   25.51
```

Attention: the data set starts at 1973. We will have to intersect this information with starting at 1973 or later for a second data set of temperatures of SP in order to compare anomalies of temperatures

[63]:

```python
###erase last columns
Rio_temp = Rio_temp.drop(["D-J-F", "M-A-M", "J-J-A", "S-O-N", "metANN"], axis=1)
```

[64]:
```
Rio_temp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 47 entries, 1973 to 2019
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   JAN     47 non-null     float64
 1   FEB     47 non-null     float64
 2   MAR     47 non-null     float64
 3   APR     47 non-null     float64
 4   MAY     47 non-null     float64
 5   JUN     47 non-null     float64
 6   JUL     47 non-null     float64
 7   AUG     47 non-null     float64
 8   SEP     47 non-null     float64
 9   OCT     47 non-null     float64
 10  NOV     47 non-null     float64
 11  DEC     47 non-null     float64
dtypes: float64(12)
memory usage: 4.8 KB
```

[65]:
```
Rio_temp.isnull().any()
##Comment: as in the SP_temp files we have numbers 999.00 that we have to handle
```

[65]:
```
JAN    False
FEB    False
MAR    False
APR    False
MAY    False
JUN    False
JUL    False
AUG    False
SEP    False
OCT    False
NOV    False
DEC    False
dtype: bool
```

[66]:
```
##Cleaning these values.
Rio_temp.replace(999.90, np.nan, inplace=True)
```

[67]:
```
Rio_temp = Rio_temp.fillna(Rio_temp.median())
# the next command confirms that no value now is missing in the table
Rio_temp.isnull().any()
```

[67]:
```
JAN    False
FEB    False
MAR    False
APR    False
MAY    False
JUN    False
JUL    False
AUG    False
SEP    False
OCT    False
NOV    False
DEC    False
dtype: bool
```

[68]:
```
###to make this table compatible with the data of the rainfall
###this is a series now
Rio_temp_Series= Rio_temp.stack(level=-1)

print(Rio_temp_Series)
```

```
YEAR
1973  JAN    27.73
      FEB    27.97
      MAR    25.70
      APR    26.49
      MAY    22.42
             …
2019  AUG    22.30
      SEP    23.05
      OCT    25.25
      NOV    24.75
      DEC    26.06
Length: 564, dtype: float64
```

[69]:
```
Rio_temp= Rio_temp_Series.to_frame()
Rio_temp.head(10)
```

[69]:
```
              0
YEAR
1973 JAN  27.73
     FEB  27.97
     MAR  25.70
     APR  26.49
     MAY  22.42
     JUN  22.76
     JUL  22.14
     AUG  21.03
```

```
SEP   21.46
OCT   22.46
```

[70]:
```
Rio_temp=Rio_temp.reset_index()
Rio_temp.head()
```

[70]:
```
   YEAR level_1      0
0  1973     JAN  27.73
1  1973     FEB  27.97
2  1973     MAR  25.70
3  1973     APR  26.49
4  1973     MAY  22.42
```

[71]:
```
Rio_temp.tail()
```

[71]:
```
     YEAR level_1      0
559  2019     AUG  22.30
560  2019     SEP  23.05
561  2019     OCT  25.25
562  2019     NOV  24.75
563  2019     DEC  26.06
```

[72]:
```
Rio_temp = Rio_temp.rename(columns = {'YEAR': 'year', 'level_1': 'month', 0:␣
 ↪'avtemp_Rio'}, inplace = False)
```

[73]:
```
Rio_temp.head()
```

[73]:
```
   year month  avtemp_Rio
0  1973   JAN       27.73
1  1973   FEB       27.97
2  1973   MAR       25.70
3  1973   APR       26.49
4  1973   MAY       22.42
```

[74]:
```
##benchmark temperature for Rio
tempRio_benchmark=Rio_temp.loc[:, "avtemp_Rio"].median()
print(tempRio_benchmark)
```

```
24.205
```

[75]:
```
Rio_temp.describe(include='all')
```

[75]:
```
              year month  avtemp_Rio
count   564.000000   564  564.000000
unique         NaN    12         NaN
top            NaN   SEP         NaN
freq           NaN    47         NaN
```

```
mean    1996.000000   NaN   24.275612
std       13.576701   NaN    2.401399
min     1973.000000   NaN   19.240000
25%     1984.000000   NaN   22.245000
50%     1996.000000   NaN   24.205000
75%     2008.000000   NaN   26.262500
max     2019.000000   NaN   30.250000
```

[76]:
```
###table with temperature anomalies
Rio_temp["temp_anom_Rio"]=0
for i in range(len(Rio_temp)):
    Rio_temp.loc[i, "temp_anom_Rio"]= abs(Rio_temp.loc[i,␣
 ↪"avtemp_Rio"]-tempRio_benchmark)
Rio_temp.head()
```

[76]:

	year	month	avtemp_Rio	temp_anom_Rio
0	1973	JAN	27.73	3.525
1	1973	FEB	27.97	3.765
2	1973	MAR	25.70	1.495
3	1973	APR	26.49	2.285
4	1973	MAY	22.42	1.785

[77]:
```
####Import and cleaning/preparation of the file concerning the temperatures of␣
 ↪Manaus
```

[78]:
```
Manaus_temp = pd.read_csv("manaus_temperatures.csv", index_col=0)
Manaus_temp.head(100)
```

[78]:

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	\
YEAR										
1910	27.29	26.99	26.49	26.19	27.19	27.49	27.69	27.99	28.99	
1911	26.99	27.39	27.39	27.29	27.19	26.99	27.39	28.29	28.99	
1912	28.99	28.79	28.29	27.99	27.29	28.09	27.39	28.79	28.29	
1913	27.19	28.09	27.29	27.59	26.99	27.59	27.69	27.69	28.69	
1914	28.79	27.69	27.69	27.59	27.59	27.49	28.59	28.39	29.59	
…	…	…	…	…	…	…	…	…	…	
2005	29.18	28.34	28.05	28.25	28.74	29.08	28.83	30.04	30.13	
2006	28.54	27.86	28.22	27.96	27.68	28.54	28.87	29.67	30.15	
2007	27.58	29.33	27.76	28.08	28.45	28.60	28.84	28.70	29.22	
2008	27.56	27.68	27.21	28.15	27.63	27.99	29.11	29.72	29.18	
2009	27.48	27.44	27.89	28.43	28.05	28.17	999.90	999.90	999.90	

	OCT	NOV	DEC	D-J-F	M-A-M	J-J-A	S-O-N	metANN
YEAR								
1910	28.29	28.29	27.79	27.33	26.62	27.72	28.52	27.55
1911	29.09	28.79	28.29	27.39	27.29	27.56	28.96	27.80
1912	29.29	29.19	27.49	28.69	27.86	28.09	28.92	28.39

```
1913   28.69   28.79   28.49  27.59  27.29   27.66   28.72   27.82
1914   29.09   28.89   28.79  28.32  27.62   28.16   29.19   28.32
…      …     …     …     …     …     …     …     …
2005   30.47   29.41   28.03  28.77  28.35   29.32   30.00   29.11
2006   30.75   28.55   28.86  28.14  27.95   29.03   29.82   28.74
2007   29.99   29.71   27.99  28.59  28.10   28.71   29.64   28.76
2008   28.86   28.65   28.31  27.74  27.66   28.94   28.90   28.31
2009  999.90  999.90  999.90  27.74  28.12  999.90  999.90  999.90

[100 rows x 17 columns]
```

[79]:
```
Manaus_temp.tail()
```

[79]:
```
        JAN     FEB    MAR    APR    MAY    JUN    JUL    AUG    SEP    OCT  \
YEAR
2015  28.10   28.59  28.25  28.45  28.50  29.00  29.30  30.80  32.30  31.65
2016  30.10  999.90  28.45  28.80  29.15  28.85  29.25  30.05  29.55  30.45
2017  27.85   27.75  27.95  28.20  29.30  29.10  28.80  30.85  29.80  29.30
2018  28.05   28.35  28.65  28.05  28.20  28.50  29.15  29.65  30.40  31.20
2019  27.95   28.10  28.95  28.40  28.20  28.75  29.10  29.60  30.40  29.00

        NOV     DEC  D-J-F  M-A-M  J-J-A  S-O-N  metANN
YEAR
2015   30.6   30.15  28.66  28.40  29.70  31.52   29.57
2016   29.9   28.10  30.00  28.80  29.38  29.97   29.54
2017   29.5   28.20  27.90  28.48  29.58  29.53   28.88
2018   29.9   27.50  28.20  28.30  29.10  30.50   29.02
2019  999.9  999.90  27.85  28.52  29.15  29.54   28.76
```

Manaus temperatures were collected between 1910 and 2019. As usual we have numbers 999.90 listed often which means no data available. Need to clean this as done to the other files

[80]:
```
###erase last columns
Manaus_temp = Manaus_temp.drop(["D-J-F", "M-A-M", "J-J-A", "S-O-N", "metANN"],
 ↪axis=1)
```

[81]:
```
Manaus_temp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110 entries, 1910 to 2019
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   JAN     110 non-null    float64
 1   FEB     110 non-null    float64
 2   MAR     110 non-null    float64
 3   APR     110 non-null    float64
 4   MAY     110 non-null    float64
```

```
 5   JUN     110 non-null    float64
 6   JUL     110 non-null    float64
 7   AUG     110 non-null    float64
 8   SEP     110 non-null    float64
 9   OCT     110 non-null    float64
 10  NOV     110 non-null    float64
 11  DEC     110 non-null    float64
dtypes: float64(12)
memory usage: 11.2 KB
```

[82]:
```
Manaus_temp.isnull().any()
##Comment: as in the SP_temp files we have numbers 999.00 that we have to handle
```

[82]:
```
JAN    False
FEB    False
MAR    False
APR    False
MAY    False
JUN    False
JUL    False
AUG    False
SEP    False
OCT    False
NOV    False
DEC    False
dtype: bool
```

[83]:
```
##Cleaning these values.
Manaus_temp.replace(999.90, np.nan, inplace=True)
```

[84]:
```
Manaus_temp = Manaus_temp.fillna(Manaus_temp.median())
# the next command confirms that no value now is missing in the table
Manaus_temp.isnull().any()
```

[84]:
```
JAN    False
FEB    False
MAR    False
APR    False
MAY    False
JUN    False
JUL    False
AUG    False
SEP    False
OCT    False
NOV    False
DEC    False
dtype: bool
```

[85]:
```python
###to make this table compatible with the data of rainfall
###this is a series now
Manaus_temp_Series= Manaus_temp.stack(level=-1)

print(Manaus_temp_Series)
```

```
YEAR
1910  JAN    27.29
      FEB    26.99
      MAR    26.49
      APR    26.19
      MAY    27.19
             …
2019  AUG    29.60
      SEP    30.40
      OCT    29.00
      NOV    28.39
      DEC    27.72
Length: 1320, dtype: float64
```

[86]:
```python
Manaus_temp= Manaus_temp_Series.to_frame()
Manaus_temp.head(10)
```

[86]:
```
               0
YEAR
1910 JAN   27.29
     FEB   26.99
     MAR   26.49
     APR   26.19
     MAY   27.19
     JUN   27.49
     JUL   27.69
     AUG   27.99
     SEP   28.99
     OCT   28.29
```

[87]:
```python
Manaus_temp.columns
```

[87]:
```
RangeIndex(start=0, stop=1, step=1)
```

[88]:
```python
Manaus_temp=Manaus_temp.reset_index()
Manaus_temp.head()
```

[88]:
```
   YEAR level_1      0
0  1910     JAN  27.29
1  1910     FEB  26.99
2  1910     MAR  26.49
```

```
3  1910     APR  26.19
4  1910     MAY  27.19
```

[89]:
```
Manaus_temp = Manaus_temp.rename(columns = {'YEAR': 'year','level_1': 'month',␣
↪0: 'avtemp_Manaus'}, inplace = False)
```

[90]:
```
Manaus_temp.head()
```

[90]:
```
   year month  avtemp_Manaus
0  1910   JAN          27.29
1  1910   FEB          26.99
2  1910   MAR          26.49
3  1910   APR          26.19
4  1910   MAY          27.19
```

[91]:
```
#temperature benchmark for Manaus
tempManaus_benchmark=Manaus_temp.loc[:, "avtemp_Manaus"].median()
print(tempManaus_benchmark)
```

```
27.72
```

[92]:
```
##confirmation
Manaus_temp.describe(include='all')
```

[92]:
```
               year month  avtemp_Manaus
count   1320.000000  1320    1320.000000
unique          NaN    12            NaN
top             NaN   MAY            NaN
freq            NaN   110            NaN
mean    1964.500000   NaN      27.831886
std       31.764987   NaN       0.949510
min     1910.000000   NaN      24.890000
25%     1937.000000   NaN      27.190000
50%     1964.500000   NaN      27.720000
75%     1992.000000   NaN      28.422500
max     2019.000000   NaN      32.300000
```

[93]:
```
##table with temperature anomalies
Manaus_temp["temp_anom_Manaus"]=0
for i in range(len(Manaus_temp)):
    Manaus_temp.loc[i, "temp_anom_Manaus"]= abs(Manaus_temp.loc[i,␣
↪"avtemp_Manaus"]- tempManaus_benchmark)
Manaus_temp.head()
```

[93]:
```
   year month  avtemp_Manaus  temp_anom_Manaus
0  1910   JAN          27.29              0.43
1  1910   FEB          26.99              0.73
```

```
2  1910   MAR          26.49              1.23
3  1910   APR          26.19              1.53
4  1910   MAY          27.19              0.53
```

###Determining the benchmark temperatures. We use the median which is supported by the scientific community. Check references

[94]:
```
#Building one only table to have the temperatures of SP, RJ and MN
```

[95]:
```
SP_temp.head()
```

[95]:
```
   year month  avtemp_SP  temp_anom_SP
0  1946   JAN     23.670         2.780
1  1946   FEB     24.090         3.200
2  1946   MAR     23.320         2.430
3  1946   APR     21.370         0.480
4  1946   MAY     18.835         2.055
```

[96]:
```
SP_temp.tail()
```

[96]:
```
     year month  avtemp_SP  temp_anom_SP
883  2019   AUG      18.80          2.09
884  2019   SEP      20.85          0.04
885  2019   OCT      23.45          2.56
886  2019   NOV      21.64          0.75
887  2019   DEC      22.74          1.85
```

[97]:
```
Rio_temp.head()
```

[97]:
```
   year month  avtemp_Rio  temp_anom_Rio
0  1973   JAN       27.73          3.525
1  1973   FEB       27.97          3.765
2  1973   MAR       25.70          1.495
3  1973   APR       26.49          2.285
4  1973   MAY       22.42          1.785
```

[98]:
```
Rio_temp.tail()
```

[98]:
```
     year month  avtemp_Rio  temp_anom_Rio
559  2019   AUG       22.30          1.905
560  2019   SEP       23.05          1.155
561  2019   OCT       25.25          1.045
562  2019   NOV       24.75          0.545
563  2019   DEC       26.06          1.855
```

[99]:
```
Manaus_temp.head()
```

[99]:

	year	month	avtemp_Manaus	temp_anom_Manaus
0	1910	JAN	27.29	0.43
1	1910	FEB	26.99	0.73
2	1910	MAR	26.49	1.23
3	1910	APR	26.19	1.53
4	1910	MAY	27.19	0.53

[100]:
```
Manaus_temp.tail()
```

[100]:

	year	month	avtemp_Manaus	temp_anom_Manaus
1315	2019	AUG	29.60	1.88
1316	2019	SEP	30.40	2.68
1317	2019	OCT	29.00	1.28
1318	2019	NOV	28.39	0.67
1319	2019	DEC	27.72	0.00

Comments: SP reading of temperatures goes from January 1946 to December 2019 RJ reading of temperatures goes from January 1973 to December 2019 MN reading of temperatures goes from January 1910 to December 2019

[101]:
```
##creation of an auxiliary tables for  purpose of comparing anomalies␣
↪temperatures
mask = (SP_temp["year"] >= 1973) &(SP_temp["year"]<2020)
SP_subset =SP_temp[mask]
SP_subset.head(16)
```

[101]:

	year	month	avtemp_SP	temp_anom_SP
324	1973	JAN	24.51	3.62
325	1973	FEB	25.18	4.29
326	1973	MAR	22.22	1.33
327	1973	APR	23.85	2.96
328	1973	MAY	18.73	2.16
329	1973	JUN	18.97	1.92
330	1973	JUL	18.42	2.47
331	1973	AUG	17.28	3.61
332	1973	SEP	18.28	2.61
333	1973	OCT	19.44	1.45
334	1973	NOV	19.82	1.07
335	1973	DEC	22.63	1.74
336	1974	JAN	23.22	2.33
337	1974	FEB	24.54	3.65
338	1974	MAR	23.06	2.17
339	1974	APR	20.21	0.68

[102]:
```
SP_subset.tail()
```

[102]:

	year	month	avtemp_SP	temp_anom_SP
883	2019	AUG	18.80	2.09
884	2019	SEP	20.85	0.04
885	2019	OCT	23.45	2.56
886	2019	NOV	21.64	0.75
887	2019	DEC	22.74	1.85

[103]:

```
##creation of  auxiliary tables for  purpose of comparing anomalies temperatures
mask = (Rio_temp["year"] >= 1973) &(Rio_temp["year"]<2020)
Rio_subset =Rio_temp[mask]
Rio_subset.head(16)
```

[103]:

	year	month	avtemp_Rio	temp_anom_Rio
0	1973	JAN	27.73	3.525
1	1973	FEB	27.97	3.765
2	1973	MAR	25.70	1.495
3	1973	APR	26.49	2.285
4	1973	MAY	22.42	1.785
5	1973	JUN	22.76	1.445
6	1973	JUL	22.14	2.065
7	1973	AUG	21.03	3.175
8	1973	SEP	21.46	2.745
9	1973	OCT	22.46	1.745
10	1973	NOV	23.06	1.145
11	1973	DEC	25.85	1.645
12	1974	JAN	26.68	2.475
13	1974	FEB	27.16	2.955
14	1974	MAR	26.56	2.355
15	1974	APR	23.94	0.265

[104]:

```
Rio_subset.tail()
```

[104]:

	year	month	avtemp_Rio	temp_anom_Rio
559	2019	AUG	22.30	1.905
560	2019	SEP	23.05	1.155
561	2019	OCT	25.25	1.045
562	2019	NOV	24.75	0.545
563	2019	DEC	26.06	1.855

[105]:

```
##creation of  auxiliary tables for  purpose of comparing anomalies temperatures
mask = (Manaus_temp["year"] >= 1973) &(Manaus_temp["year"]<2020)
Manaus_subset =Manaus_temp[mask]
Manaus_subset.head(16)
```

[105]:

	year	month	avtemp_Manaus	temp_anom_Manaus
756	1973	JAN	27.99	0.27
757	1973	FEB	27.64	0.08

```
758  1973   MAR          27.92                0.20
759  1973   APR          27.81                0.09
760  1973   MAY          26.99                0.73
761  1973   JUN          27.83                0.11
762  1973   JUL          27.68                0.04
763  1973   AUG          28.16                0.44
764  1973   SEP          28.11                0.39
765  1973   OCT          28.51                0.79
766  1973   NOV          28.42                0.70
767  1973   DEC          27.30                0.42
768  1974   JAN          27.16                0.56
769  1974   FEB          26.77                0.95
770  1974   MAR          26.84                0.88
771  1974   APR          27.36                0.36
```

[106]:
```
Manaus_subset.tail()
```

[106]:
```
      year month  avtemp_Manaus  temp_anom_Manaus
1315  2019   AUG          29.60              1.88
1316  2019   SEP          30.40              2.68
1317  2019   OCT          29.00              1.28
1318  2019   NOV          28.39              0.67
1319  2019   DEC          27.72              0.00
```

[107]:
```
result=SP_subset.merge(Rio_subset)
result.head()
```

[107]:
```
   year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio
0  1973   JAN      24.51          3.62       27.73          3.525
1  1973   FEB      25.18          4.29       27.97          3.765
2  1973   MAR      22.22          1.33       25.70          1.495
3  1973   APR      23.85          2.96       26.49          2.285
4  1973   MAY      18.73          2.16       22.42          1.785
```

[108]:
```
result2=result.merge(Manaus_subset)
result2.head()
```

[108]:
```
   year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio  \
0  1973   JAN      24.51          3.62       27.73          3.525
1  1973   FEB      25.18          4.29       27.97          3.765
2  1973   MAR      22.22          1.33       25.70          1.495
3  1973   APR      23.85          2.96       26.49          2.285
4  1973   MAY      18.73          2.16       22.42          1.785

   avtemp_Manaus  temp_anom_Manaus
0          27.99              0.27
1          27.64              0.08
```

```
2           27.92              0.20
3           27.81              0.09
4           26.99              0.73
```

[109]:
```
table_temp=result2
table_temp.head()
```

[109]:
```
   year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio  \
0  1973   JAN      24.51          3.62       27.73          3.525
1  1973   FEB      25.18          4.29       27.97          3.765
2  1973   MAR      22.22          1.33       25.70          1.495
3  1973   APR      23.85          2.96       26.49          2.285
4  1973   MAY      18.73          2.16       22.42          1.785

   avtemp_Manaus  temp_anom_Manaus
0          27.99              0.27
1          27.64              0.08
2          27.92              0.20
3          27.81              0.09
4          26.99              0.73
```

3 Part 2 : Construction of the final data set for analysis.

[110]:
```
month_rainfallset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 672 entries, 0 to 671
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   year            672 non-null    float64
 1   month           672 non-null    object
 2   total_rainfall  672 non-null    float64
dtypes: float64(2), object(1)
memory usage: 15.9+ KB
```

[111]:
```
month_rainfallset.head()
```

[111]:
```
     year month  total_rainfall
0  1961.0   Jan             3.2
1  1961.0   Feb             5.7
2  1961.0   Mar            16.8
3  1961.0   Apr            26.8
4  1961.0   May             0.0
```

[112]:
```
month_rainfallset.tail()
```

[112]:
```
       year month  total_rainfall
667  2016.0   Aug            11.7
668  2016.0   Sep            48.0
669  2016.0   Oct            28.5
670  2016.0   Nov            95.9
671  2016.0   Dec            26.2
```

[113]:
```
month_rainfallset.reset_index(drop=True)
```

[113]:
```
       year month  total_rainfall
0    1961.0   Jan             3.2
1    1961.0   Feb             5.7
2    1961.0   Mar            16.8
3    1961.0   Apr            26.8
4    1961.0   May             0.0
..      …    …               …
667  2016.0   Aug            11.7
668  2016.0   Sep            48.0
669  2016.0   Oct            28.5
670  2016.0   Nov            95.9
671  2016.0   Dec            26.2

[672 rows x 3 columns]
```

[114]:
```
SP_temp_reduced.head()
```

[114]:
```
     year month  avtemp_SP  temp_anom_SP
180  1961   JAN     23.670         2.780
181  1961   FEB     24.090         3.200
182  1961   MAR     23.320         2.430
183  1961   APR     21.370         0.480
184  1961   MAY     18.835         2.055
```

[115]:
```
SP_temp_reduced.tail()
```

[115]:
```
     year month  avtemp_SP  temp_anom_SP
847  2016   AUG      18.90          1.99
848  2016   SEP      19.65          1.24
849  2016   OCT      21.40          0.51
850  2016   NOV      21.60          0.71
851  2016   DEC      24.20          3.31
```

[116]:
```
SP_temp_reduced.reset_index(drop=True)
```

[116]:
```
     year month  avtemp_SP  temp_anom_SP
0    1961   JAN     23.670         2.780
1    1961   FEB     24.090         3.200
```

```
2    1961   MAR     23.320        2.430
3    1961   APR     21.370        0.480
4    1961   MAY     18.835        2.055
..    …    …        …          …
667  2016   AUG     18.900        1.990
668  2016   SEP     19.650        1.240
669  2016   OCT     21.400        0.510
670  2016   NOV     21.600        0.710
671  2016   DEC     24.200        3.310

[672 rows x 4 columns]
```

[117]:
```
SP_temp_reduced.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 672 entries, 180 to 851
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   year          672 non-null    int64
 1   month         672 non-null    object
 2   avtemp_SP     672 non-null    float64
 3   temp_anom_SP  672 non-null    float64
dtypes: float64(2), int64(1), object(1)
memory usage: 26.2+ KB
```

[118]:
```
###merged table with temperatures SP and rainfall monthly
###it is missing CO2 emissions

merged_table = pd.concat([month_rainfallset.
 ↪reset_index(drop=True),SP_temp_reduced.reset_index(drop=True)], axis=1)
merged_table.head()
```

[118]:

	year	month	total_rainfall	year	month	avtemp_SP	temp_anom_SP
0	1961.0	Jan	3.2	1961	JAN	23.670	2.780
1	1961.0	Feb	5.7	1961	FEB	24.090	3.200
2	1961.0	Mar	16.8	1961	MAR	23.320	2.430
3	1961.0	Apr	26.8	1961	APR	21.370	0.480
4	1961.0	May	0.0	1961	MAY	18.835	2.055

[119]:
```
merged_table.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 672 entries, 0 to 671
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
```

```
 0   year            672 non-null    float64
 1   month           672 non-null    object
 2   total_rainfall  672 non-null    float64
 3   year            672 non-null    int64
 4   month           672 non-null    object
 5   avtemp_SP       672 non-null    float64
 6   temp_anom_SP    672 non-null    float64
dtypes: float64(4), int64(1), object(2)
memory usage: 36.9+ KB
```

[120]:
```
##C02 emissions
C02dataset = pd.read_csv("emission data.csv", index_col=0)
C02dataset.head(100)
```

[120]:
```
                    1751  1752  1753  1754  1755  1756  1757  1758  1759  1760  \
Country
Afghanistan            0     0     0     0     0     0     0     0     0     0
Africa                 0     0     0     0     0     0     0     0     0     0
Albania                0     0     0     0     0     0     0     0     0     0
Algeria                0     0     0     0     0     0     0     0     0     0
Americas (other)       0     0     0     0     0     0     0     0     0     0
…                    …     …     …     …     …     …     …     …     …     …
Honduras               0     0     0     0     0     0     0     0     0     0
Hong Kong              0     0     0     0     0     0     0     0     0     0
Hungary                0     0     0     0     0     0     0     0     0     0
Iceland                0     0     0     0     0     0     0     0     0     0
India                  0     0     0     0     0     0     0     0     0     0

                    …          2008          2009          2010          2011  \
Country             …
Afghanistan         …  8.515264e+07  9.191295e+07  1.003652e+08  1.125912e+08
Africa              …  3.183077e+10  3.301904e+10  3.421283e+10  3.541120e+10
Albania             …  2.287948e+08  2.331696e+08  2.377643e+08  2.430001e+08
Algeria             …  2.894820e+09  3.015005e+09  3.132819e+09  3.252626e+09
Americas (other)    …  7.746025e+10  7.961787e+10  8.187178e+10  8.416656e+10
…                 …           …           …           …           …
Honduras            …  1.471331e+08  1.548141e+08  1.626148e+08  1.713883e+08
Hong Kong           …  1.119846e+09  1.161828e+09  1.202302e+09  1.245877e+09
Hungary             …  4.437652e+09  4.489433e+09  4.541554e+09  4.591912e+09
Iceland             …  1.097158e+08  1.134469e+08  1.170678e+08  1.205542e+08
India               …  3.001075e+10  3.173087e+10  3.343090e+10  3.524807e+10

                          2012          2013          2014          2015  \
Country
Afghanistan       1.233332e+08  1.333337e+08  1.431228e+08  1.532303e+08
Africa            3.664504e+10  3.789569e+10  3.918617e+10  4.047518e+10
Albania           2.479062e+08  2.529662e+08  2.586784e+08  2.646261e+08
```

```
Algeria            3.380736e+09  3.513171e+09  3.656348e+09  3.806940e+09
Americas (other)   8.654197e+10  8.894874e+10  9.139192e+10  9.382747e+10
…                           …             …             …             …
Honduras           1.801754e+08  1.890464e+08  1.983226e+08  2.083778e+08
Hong Kong          1.289063e+09  1.333827e+09  1.379790e+09  1.422492e+09
Hungary            4.638720e+09  4.682488e+09  4.726403e+09  4.773069e+09
Iceland            1.240429e+08  1.275247e+08  1.309865e+08  1.345230e+08
India              3.723183e+10  3.922971e+10  4.143724e+10  4.371365e+10

                           2016          2017
Country
Afghanistan        1.654882e+08  1.785029e+08
Africa             4.178583e+10  4.311757e+10
Albania            2.708990e+08  2.772782e+08
Algeria            3.957319e+09  4.107870e+09
Americas (other)   9.624253e+10  9.864116e+10
…                           …             …
Honduras           2.189540e+08  2.296231e+08
Hong Kong          1.465728e+09  1.508760e+09
Hungary            4.820647e+09  4.870991e+09
Iceland            1.380129e+08  1.414930e+08
India              4.609110e+10  4.855786e+10

[100 rows x 267 columns]
```

[121]:
```
CO2dataset.columns
```

[121]:
```
Index(['1751', '1752', '1753', '1754', '1755', '1756', '1757', '1758', '1759',
       '1760',
       …
       '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016',
       '2017'],
      dtype='object', length=267)
```

[122]:
```
df_tr = CO2dataset.transpose()
df_tr.head()
```

[122]:
```
Country  Afghanistan  Africa  Albania  Algeria  Americas (other)  Andorra  \
1751             0.0     0.0      0.0      0.0               0.0      0.0
1752             0.0     0.0      0.0      0.0               0.0      0.0
1753             0.0     0.0      0.0      0.0               0.0      0.0
1754             0.0     0.0      0.0      0.0               0.0      0.0
1755             0.0     0.0      0.0      0.0               0.0      0.0

Country  Angola  Anguilla  Antarctic Fisheries  Antigua and Barbuda  …  \
1751        0.0       0.0                  0.0                  0.0  …
1752        0.0       0.0                  0.0                  0.0  …
```

```
1753        0.0       0.0                   0.0                   0.0  …
1754        0.0       0.0                   0.0                   0.0  …
1755        0.0       0.0                   0.0                   0.0  …

Country  Uruguay  Uzbekistan  Vanuatu  Venezuela  Vietnam  \
1751         0.0         0.0      0.0        0.0      0.0
1752         0.0         0.0      0.0        0.0      0.0
1753         0.0         0.0      0.0        0.0      0.0
1754         0.0         0.0      0.0        0.0      0.0
1755         0.0         0.0      0.0        0.0      0.0

Country  Wallis and Futuna Islands       World  Yemen  Zambia  Zimbabwe
1751                           0.0   9350528.0    0.0     0.0       0.0
1752                           0.0  18704720.0    0.0     0.0       0.0
1753                           0.0  28058912.0    0.0     0.0       0.0
1754                           0.0  37416768.0    0.0     0.0       0.0
1755                           0.0  46778288.0    0.0     0.0       0.0

[5 rows x 231 columns]
```

[123]:
```
df_tr.columns
```

[123]:
```
Index(['Afghanistan', 'Africa', 'Albania', 'Algeria', 'Americas (other)',
       'Andorra', 'Angola', 'Anguilla', 'Antarctic Fisheries',
       'Antigua and Barbuda',
       …
       'Uruguay', 'Uzbekistan', 'Vanuatu', 'Venezuela', 'Vietnam',
       'Wallis and Futuna Islands', 'World', 'Yemen', 'Zambia', 'Zimbabwe'],
      dtype='object', name='Country', length=231)
```

[124]:
```
##to find Brazil
filter_col = [col for col in df_tr if col.startswith('B')]
filter_col
```

[124]:
```
['Bahamas',
 'Bahrain',
 'Bangladesh',
 'Barbados',
 'Belarus',
 'Belgium',
 'Belize',
 'Benin',
 'Bermuda',
 'Bhutan',
 'Bolivia',
 'Bonaire Sint Eustatius and Saba',
 'Bosnia and Herzegovina',
```

```
 'Botswana',
 'Brazil',
 'British Virgin Islands',
 'Brunei',
 'Bulgaria',
 'Burkina Faso',
 'Burundi']
```

[125]:
```python
df_tr['Brazil'].head()
```

[125]:
```
1751    0.0
1752    0.0
1753    0.0
1754    0.0
1755    0.0
Name: Brazil, dtype: float64
```

[126]:
```python
CO2_Brazildata=df_tr['Brazil']
CO2_Brazildata.head()
```

[126]:
```
1751    0.0
1752    0.0
1753    0.0
1754    0.0
1755    0.0
Name: Brazil, dtype: float64
```

[127]:
```python
CO2_Brazildata.isnull().any()
##no empty spaces
```

[127]:
```
False
```

[128]:
```python
CO2_Brazildata= CO2_Brazildata.to_frame()
CO2_Brazildata.head(10)
```

[128]:

	Brazil
1751	0.0
1752	0.0
1753	0.0
1754	0.0
1755	0.0
1756	0.0
1757	0.0
1758	0.0
1759	0.0
1760	0.0

[129]:
```python
CO2_Brazildata=CO2_Brazildata.reset_index()
CO2_Brazildata.head()
```

[129]:

	index	Brazil
0	1751	0.0
1	1752	0.0
2	1753	0.0
3	1754	0.0
4	1755	0.0

[130]:
```python
CO2_Brazildata.columns
```

[130]: `Index(['index', 'Brazil'], dtype='object')`

[131]:
```python
#renaming the columns
CO2_Brazildata = CO2_Brazildata.rename(columns = {'level_0': '','index':␣
↪'Year', 'Brazil': 'CO2'}, inplace = False)
CO2_Brazildata.head()
```

[131]:

	Year	CO2
0	1751	0.0
1	1752	0.0
2	1753	0.0
3	1754	0.0
4	1755	0.0

[132]:
```python
CO2_Brazildata.tail()
```

[132]:

	Year	CO2
262	2013	1.220949e+10
263	2014	1.272902e+10
264	2015	1.324110e+10
265	2016	1.371484e+10
266	2017	1.419091e+10

[133]:
```python
#problem here with the tyoe of object for the year
CO2_Brazildata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 267 entries, 0 to 266
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Year    267 non-null    object 
 1   CO2     267 non-null    float64
dtypes: float64(1), object(1)
memory usage: 4.3+ KB
```

[134]:
```
CO2_Brazildata['Year']=CO2_Brazildata['Year'].astype(float)
CO2_Brazildata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 267 entries, 0 to 266
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Year    267 non-null    float64
 1   CO2     267 non-null    float64
dtypes: float64(2)
memory usage: 4.3 KB
```

[135]:
```
##creation of an auxiliary table to merge with the merged_table
mask = (CO2_Brazildata["Year"] >= 1961) &(CO2_Brazildata["Year"]<2017)
CO2_Brazildata_reduced=CO2_Brazildata[mask]
CO2_Brazildata_reduced.head(16)
```

[135]:

	Year	CO2
210	1961.0	6.374138e+08
211	1962.0	6.910452e+08
212	1963.0	7.465961e+08
213	1964.0	8.032628e+08
214	1965.0	8.595924e+08
215	1966.0	9.238041e+08
216	1967.0	9.898835e+08
217	1968.0	1.067155e+09
218	1969.0	1.151288e+09
219	1970.0	1.244818e+09
220	1971.0	1.347176e+09
221	1972.0	1.461190e+09
222	1973.0	1.593210e+09
223	1974.0	1.736137e+09
224	1975.0	1.886651e+09
225	1976.0	2.041049e+09

[136]:
```
###We see that we need to create cummulative rain months fall between years in␣
↪order to have
##better precision
####this would do by year
###annual_rainfallset=pd.pivot_table(data=rainfallset, index='year',␣
↪values='Precipitacao', aggfunc='sum')

annual_rainfallset=pd.pivot_table(data=rainfallset, index='year',␣
↪values='Precipitacao', aggfunc='sum').reset_index().
↪rename(columns={'Precipitacao': 'annual_rainfall'})
```

[137]:
```
annual_rainfallset.head()
```

[137]:

	year	annual_rainfall
0	1961.0	144.1
1	1962.0	577.0
2	1963.0	362.7
3	1964.0	418.4
4	1965.0	649.9

[138]:
```
CO2_Brazildata_reduced=CO2_Brazildata_reduced.reset_index(drop=True)
CO2_Brazildata_reduced.head()
```

[138]:

	Year	CO2
0	1961.0	637413757.0
1	1962.0	691045205.0
2	1963.0	746596143.0
3	1964.0	803262819.0
4	1965.0	859592436.0

[139]:
```
CO2_Brazildata_reduced.tail()
```

[139]:

	Year	CO2
51	2012.0	1.171590e+10
52	2013.0	1.220949e+10
53	2014.0	1.272902e+10
54	2015.0	1.324110e+10
55	2016.0	1.371484e+10

[140]:
```
CO2_Brazildata_reduced.columns
```

[140]:
```
Index(['Year', 'CO2'], dtype='object')
```

[141]:
```
annual_rainfallset.head()
```

[141]:

	year	annual_rainfall
0	1961.0	144.1
1	1962.0	577.0
2	1963.0	362.7
3	1964.0	418.4
4	1965.0	649.9

[142]:
```
annual_rainfallset.tail()
```

[142]:

	year	annual_rainfall
51	2012.0	618.0
52	2013.0	498.8
53	2014.0	363.5

```
54   2015.0            820.1
55   2016.0            605.0
```

[143]:
```python
merged_table2 = pd.concat([annual_rainfallset.
 ↪reset_index(drop=True),CO2_Brazildata_reduced.reset_index(drop=True)],␣
 ↪axis=1)
merged_table2.head()
```

[143]:

	year	annual_rainfall	Year	CO2
0	1961.0	144.1	1961.0	637413757.0
1	1962.0	577.0	1962.0	691045205.0
2	1963.0	362.7	1963.0	746596143.0
3	1964.0	418.4	1964.0	803262819.0
4	1965.0	649.9	1965.0	859592436.0

[144]:
```python
data_annual_CO2_rain = merged_table2.drop("Year", axis=1)
data_annual_CO2_rain.head()
```

[144]:

	year	annual_rainfall	CO2
0	1961.0	144.1	637413757.0
1	1962.0	577.0	691045205.0
2	1963.0	362.7	746596143.0
3	1964.0	418.4	803262819.0
4	1965.0	649.9	859592436.0

[145]:
```python
###joining the annual temperature anonalies
##we are using the dataframe SP_temp_reduced
SP_temp_reduced.head()
```

[145]:

	year	month	avtemp_SP	temp_anom_SP
180	1961	JAN	23.670	2.780
181	1961	FEB	24.090	3.200
182	1961	MAR	23.320	2.430
183	1961	APR	21.370	0.480
184	1961	MAY	18.835	2.055

[146]:
```python
SP_temp_reduced.columns
```

[146]:
```
Index(['year', 'month', 'avtemp_SP', 'temp_anom_SP'], dtype='object')
```

[147]:
```python
SP_temp_reduced = SP_temp_reduced.rename(columns = {'year': 'Year', 'month':␣
 ↪'month', 'avtemp_SP':'avtemp_SP', 'tenp_anom_SP': 'temp_anom_SP'}, inplace =␣
 ↪False)
SP_temp_reduced.head()
```

[147]:

	Year	month	avtemp_SP	temp_anom_SP
180	1961	JAN	23.670	2.780

```
181  1961   FEB     24.090          3.200
182  1961   MAR     23.320          2.430
183  1961   APR     21.370          0.480
184  1961   MAY     18.835          2.055
```

[148]:
```
SP_temp_reduced.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 672 entries, 180 to 851
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Year           672 non-null    int64
 1   month          672 non-null    object
 2   avtemp_SP      672 non-null    float64
 3   temp_anom_SP   672 non-null    float64
dtypes: float64(2), int64(1), object(1)
memory usage: 26.2+ KB
```

[149]:
```
###joining the annual temperature anonalies
##we are using the dataframe SP_temp_reduced
SP_temp_reduced_annual=pd.pivot_table(data=SP_temp_reduced, index='Year',␣
 ↪values='temp_anom_SP', aggfunc='mean').reset_index().
 ↪rename(columns={'temp_anom_SP': 'avgtemp_anom_SP'})
```

[150]:
```
SP_temp_reduced_annual.head()
```

[150]:

	Year	avgtemp_anom_SP
0	1961	1.990417
1	1962	1.832083
2	1963	2.199167
3	1964	2.308333
4	1965	1.483333

[151]:
```
##checking compatability of type data
data_annual_CO2_rain.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   year             56 non-null     float64
 1   annual_rainfall  56 non-null     float64
 2   CO2              56 non-null     float64
dtypes: float64(3)
memory usage: 1.4 KB
```

[152]:
```
SP_temp_reduced_annual.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Year             56 non-null     int64
 1   avgtemp_anom_SP  56 non-null     float64
dtypes: float64(1), int64(1)
memory usage: 1.0 KB
```

[153]:
```
#we have to convert the data of data in the column year as before
data_annual_C02_rain['year']=data_annual_C02_rain['year'].astype(float)
C02_Brazildata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 267 entries, 0 to 266
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Year    267 non-null    float64
 1   CO2     267 non-null    float64
dtypes: float64(2)
memory usage: 4.3 KB
```

[154]:
```
##merging the tables
annual_table_SP = pd.concat([data_annual_C02_rain.
↪reset_index(drop=True),SP_temp_reduced_annual.reset_index(drop=True)],␣
↪axis=1)
annual_table_SP.head()
```

[154]:

	year	annual_rainfall	CO2	Year	avgtemp_anom_SP
0	1961.0	144.1	637413757.0	1961	1.990417
1	1962.0	577.0	691045205.0	1962	1.832083
2	1963.0	362.7	746596143.0	1963	2.199167
3	1964.0	418.4	803262819.0	1964	2.308333
4	1965.0	649.9	859592436.0	1965	1.483333

Conclusion: 3 tables to understand and visualize. Resume the relations

[155]:
```
###erase a column
annual_table_SP= annual_table_SP.drop(["Year"], axis=1)
annual_table_SP.head()
```

[155]:

	year	annual_rainfall	CO2	avgtemp_anom_SP
0	1961.0	144.1	637413757.0	1.990417
1	1962.0	577.0	691045205.0	1.832083

```
2  1963.0            362.7  746596143.0         2.199167
3  1964.0            418.4  803262819.0         2.308333
4  1965.0            649.9  859592436.0         1.483333
```

4 Part 3 : Preparation of data and visualization.

[156]:
```
## Initial data visualization
###We resumed the info of the data sets in two data frames
temptable=table_temp
temptable.head()
```

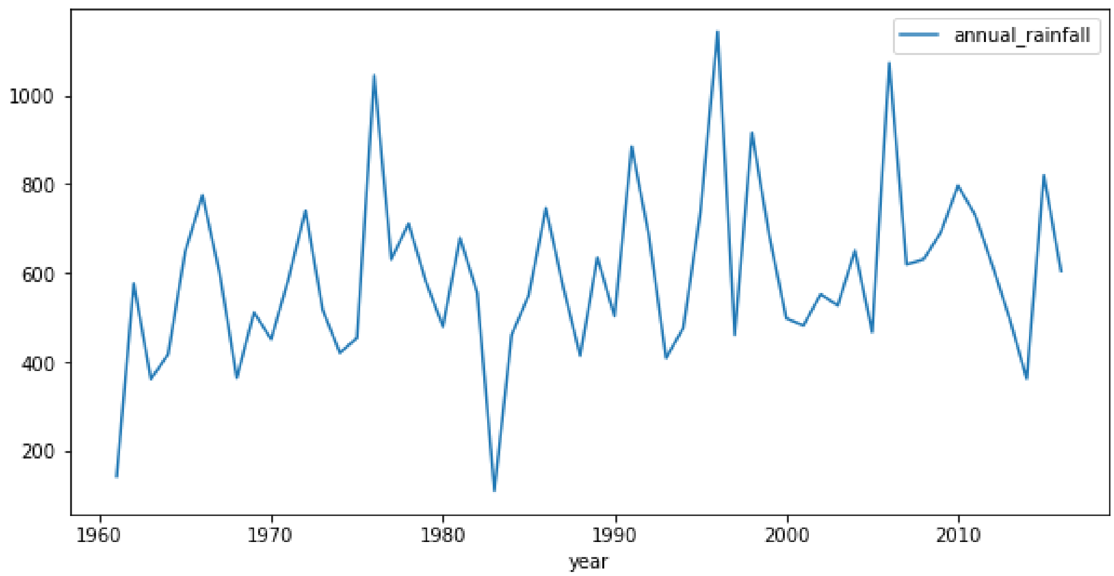
[156]:
```
   year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio  \
0  1973   JAN      24.51          3.62       27.73          3.525
1  1973   FEB      25.18          4.29       27.97          3.765
2  1973   MAR      22.22          1.33       25.70          1.495
3  1973   APR      23.85          2.96       26.49          2.285
4  1973   MAY      18.73          2.16       22.42          1.785

   avtemp_Manaus  temp_anom_Manaus
0          27.99              0.27
1          27.64              0.08
2          27.92              0.20
3          27.81              0.09
4          26.99              0.73
```

[157]:
```
SP_data=annual_table_SP
SP_data.head()
```

[157]:
```
     year  annual_rainfall          CO2  avgtemp_anom_SP
0  1961.0            144.1  637413757.0         1.990417
1  1962.0            577.0  691045205.0         1.832083
2  1963.0            362.7  746596143.0         2.199167
3  1964.0            418.4  803262819.0         2.308333
4  1965.0            649.9  859592436.0         1.483333
```

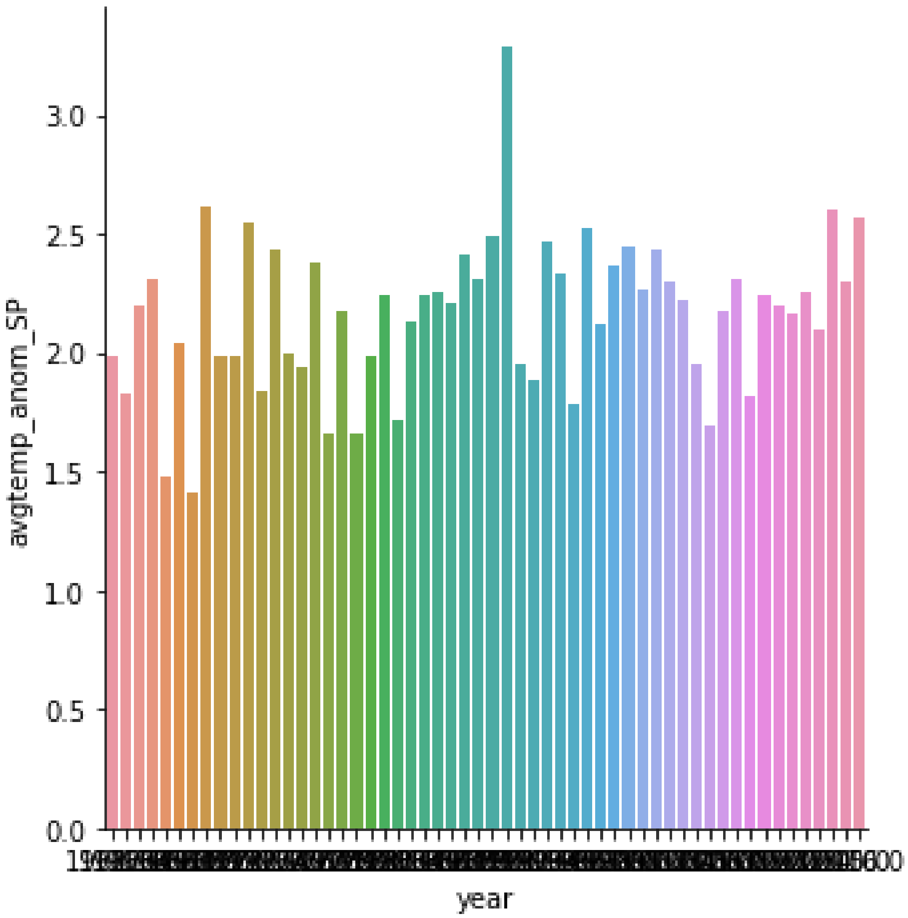
[158]:
```
SP_data.plot.line(x="year", y="annual_rainfall", figsize=(10,5))
```

[158]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5db45e4f10>
```



[159]:
```
# Visualisations exploratoire
sns.catplot(x="year", y="avgtemp_anom_SP", data = SP_data, kind="bar")
```

[159]:
```
<seaborn.axisgrid.FacetGrid at 0x7f5dafb83f10>
```

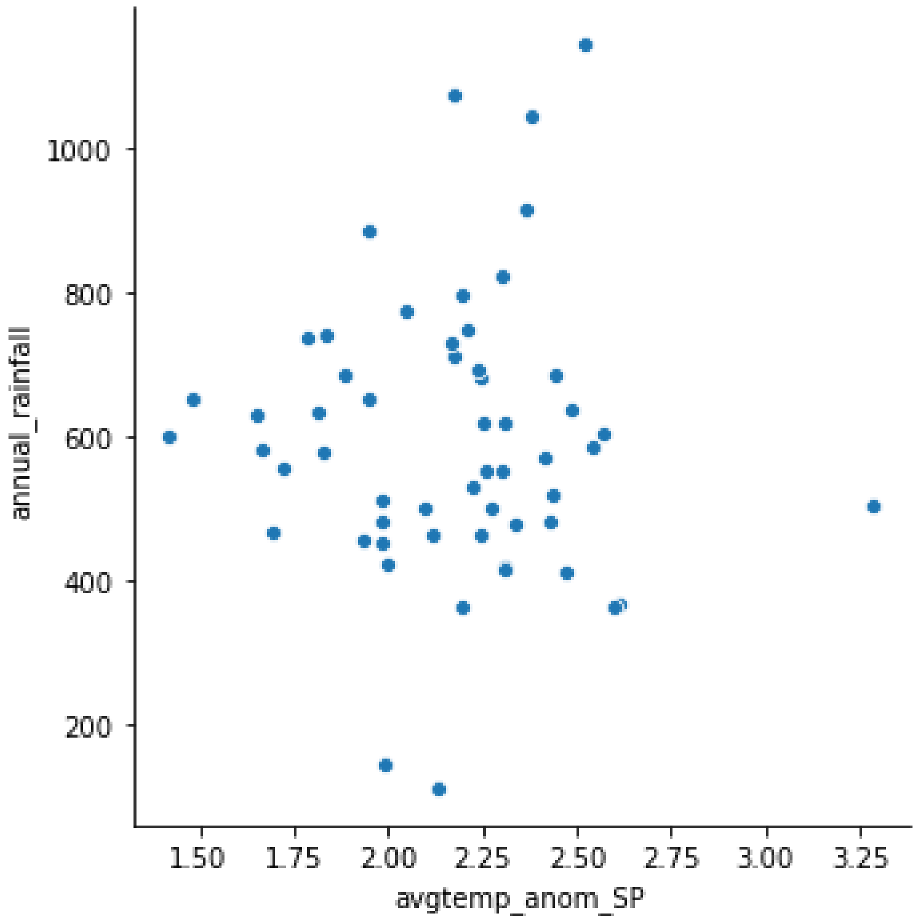


[160]:
```
### I decided to do the visualizations in tableau
##We export the two new data frames
temptable.to_csv("temptable.csv")
```

[161]:
```
#export the annual table respecting to SP
annual_table_SP.to_csv("annual_table_SP.csv")
```

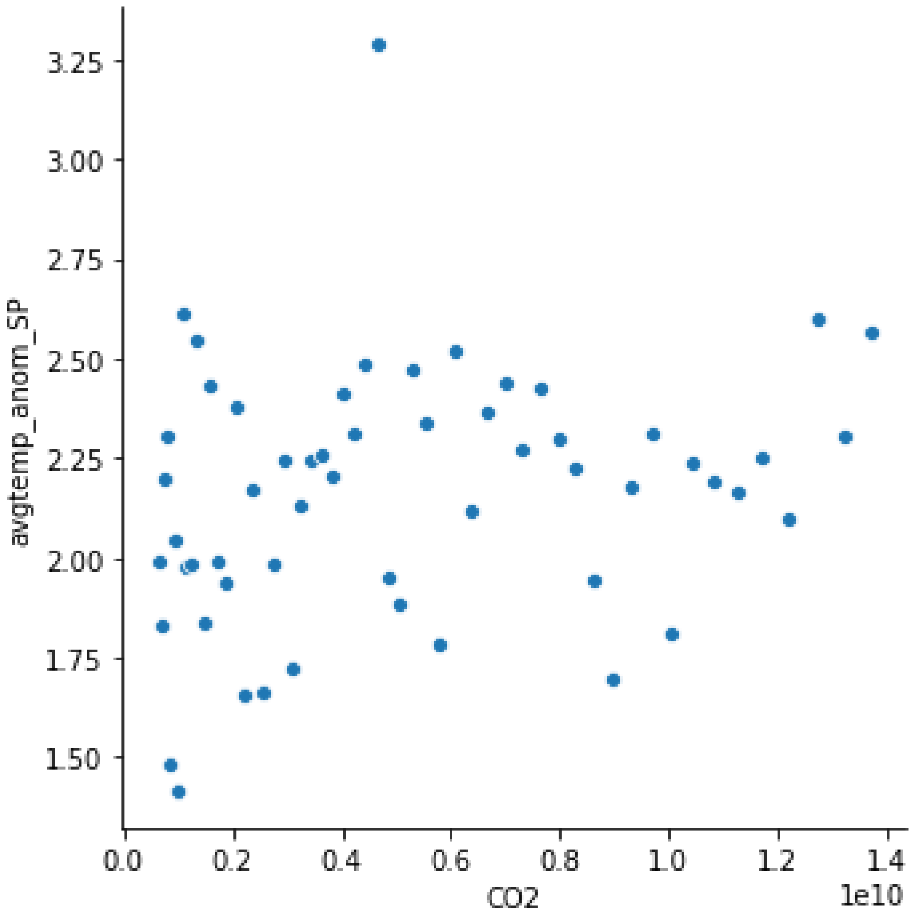
Conclusions: the anomalies temperatures of SP were significantly bigger in the period of the drought in comparison with Rio and Manaus. Check comparative powerpoint file.

[162]:
```
##avgtemp_anom_SP and annualrainfall
sns.relplot(x="avgtemp_anom_SP", y="annual_rainfall", data=SP_data);
```

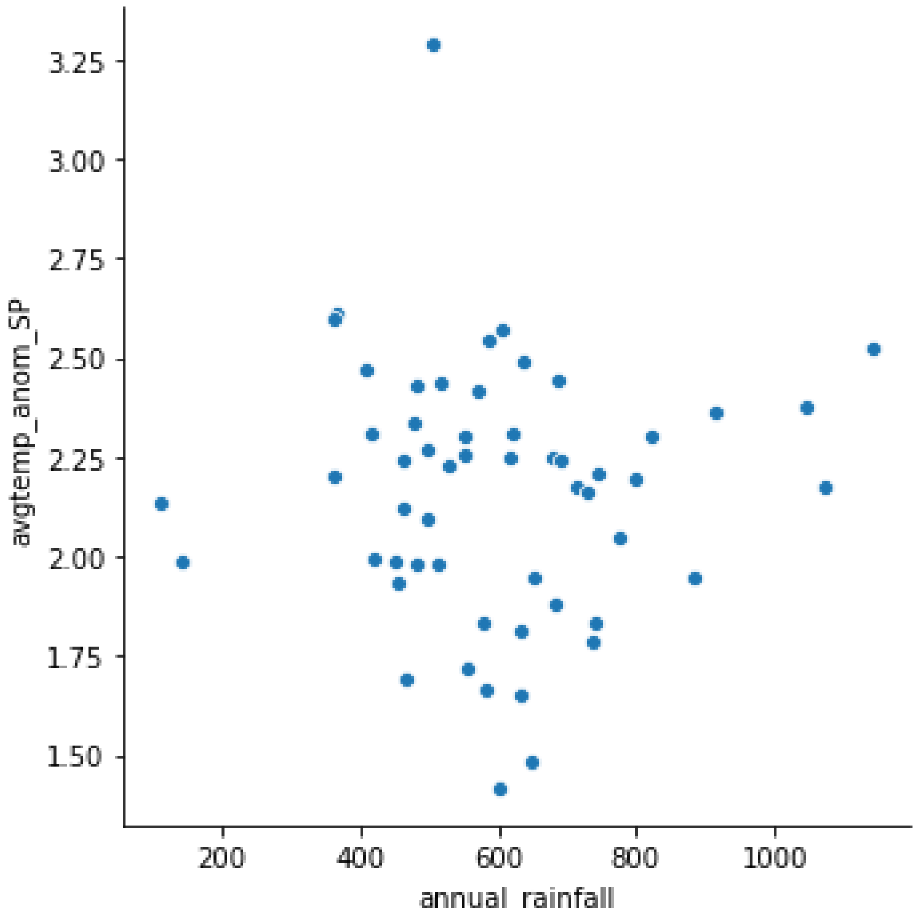


No big graphical evidences of correlation! To be explained in the presentation and in the deliveravle

[163]:
```
sns.relplot(x="CO2", y="avgtemp_anom_SP", data=SP_data);
```

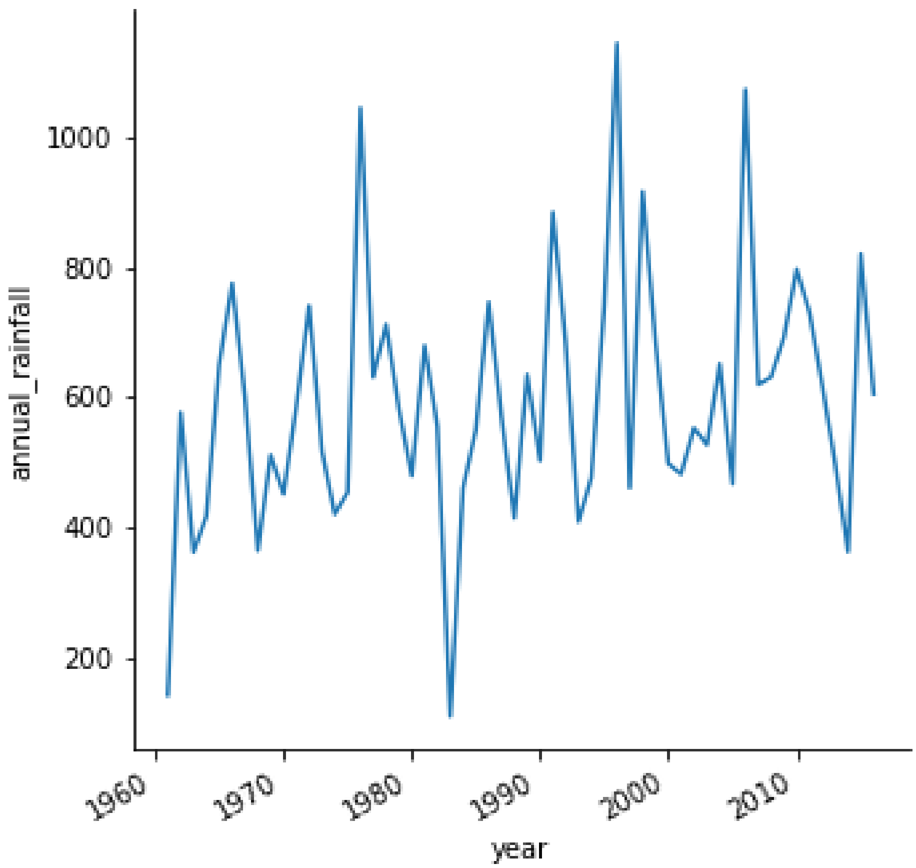


[164]:
```
##avgtemp_anom_SP and annualrainfall
sns.relplot(x="annual_rainfall", y="avgtemp_anom_SP", data=SP_data);
```

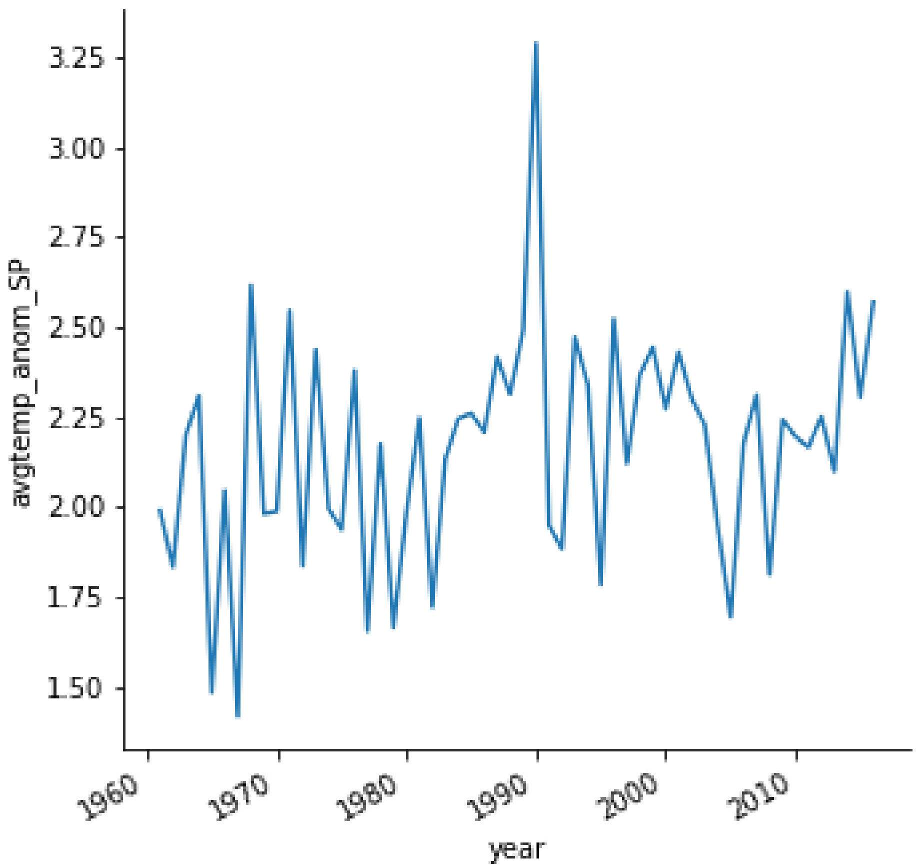


[165]:

```
 g= sns.relplot(x="year", y="annual_rainfall", kind="line", data=SP_data)
g.fig.autofmt_xdate()
```

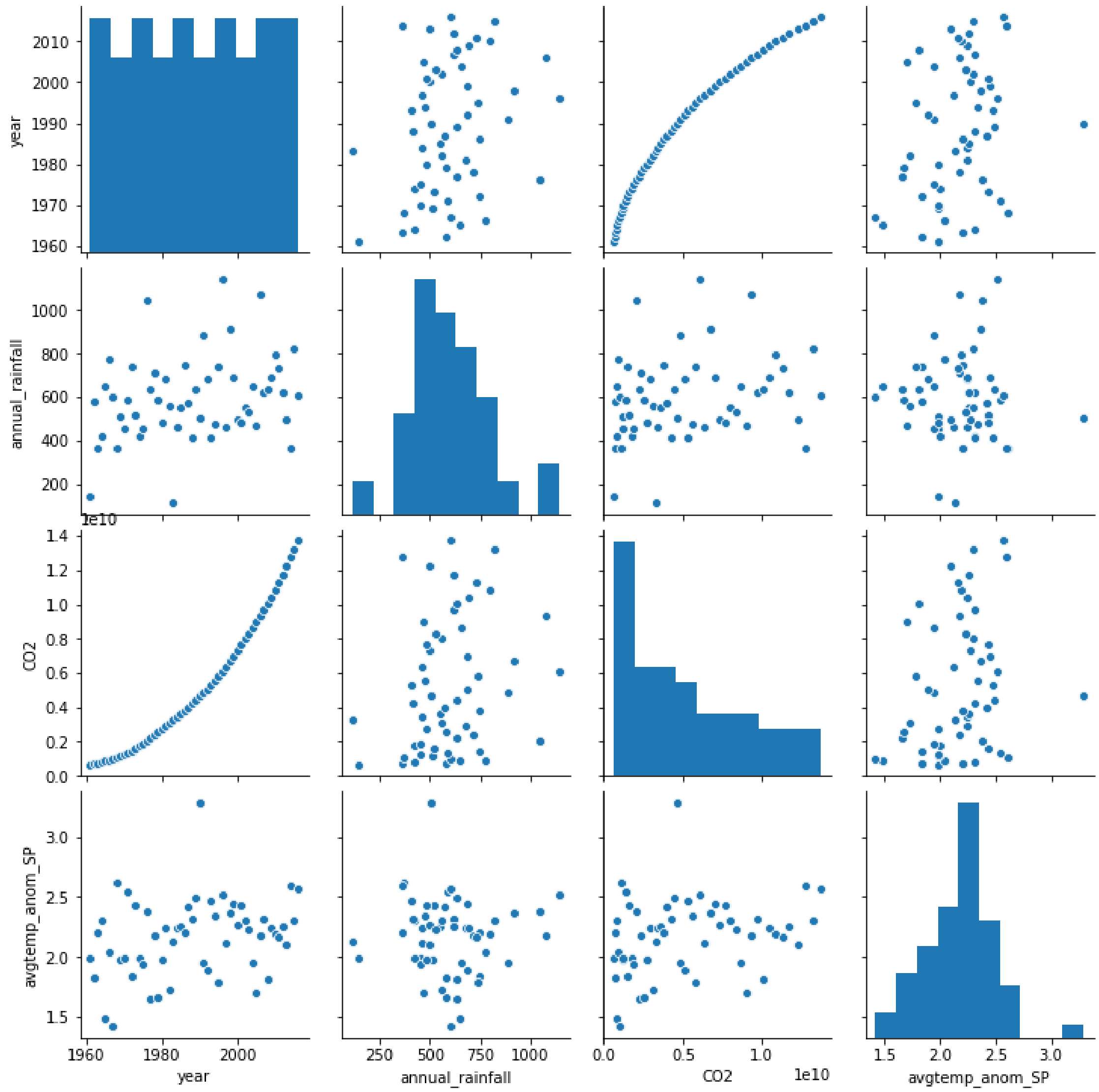


[166]:
```
g= sns.relplot(x="year", y="avgtemp_anom_SP", kind="line", data=SP_data)
g.fig.autofmt_xdate()
```



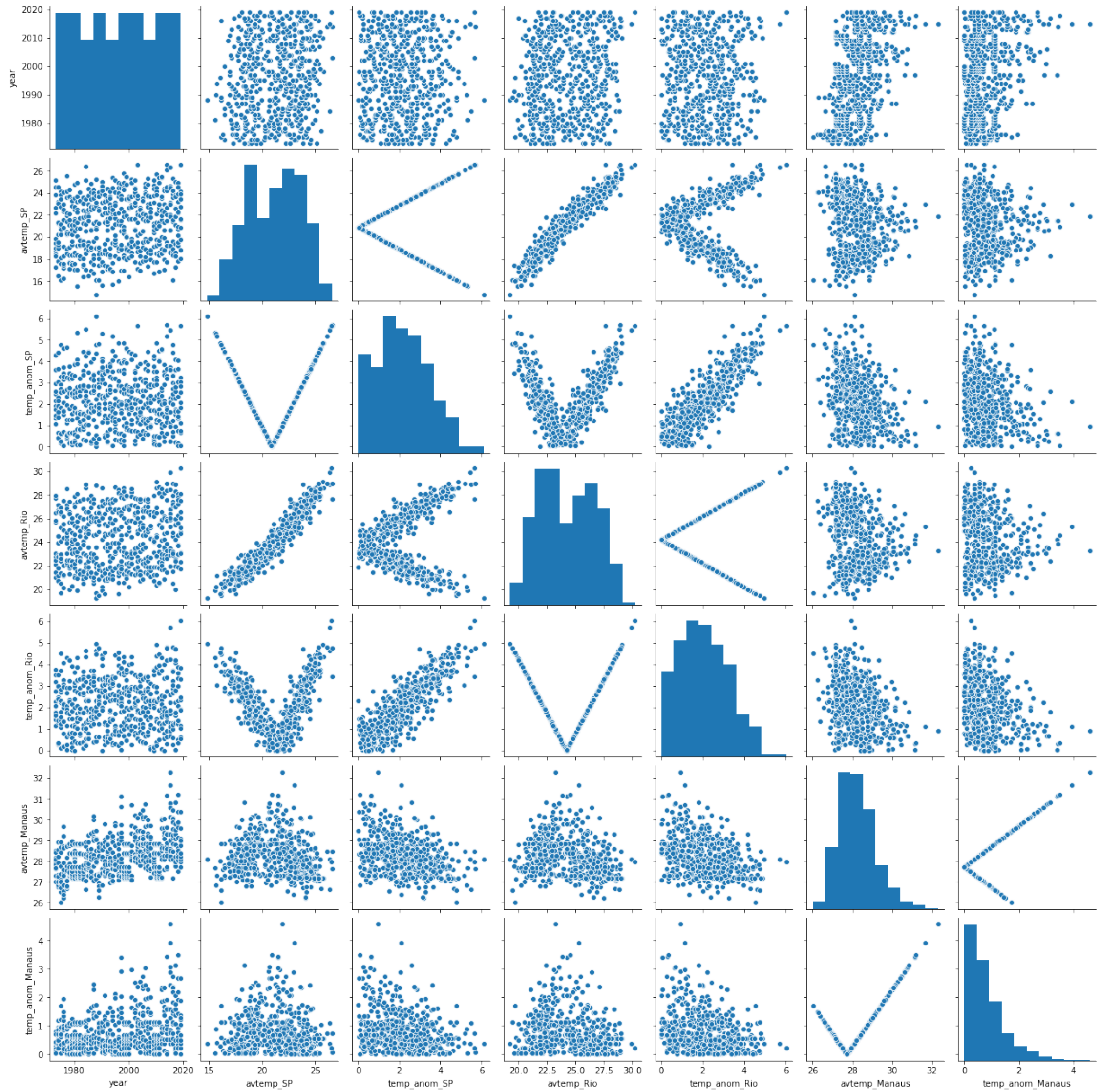
[167]:
```
##plots of all possible permutations of parameters
sns.pairplot(SP_data)
```

[167]: <seaborn.axisgrid.PairGrid at 0x7f5daf7b4ca0>



[168]:
```
##focus specially on the clouds of points between the average temperature
 ↪anomalies
##which suggests some relation between these variables.
sns.pairplot(temptable)
```

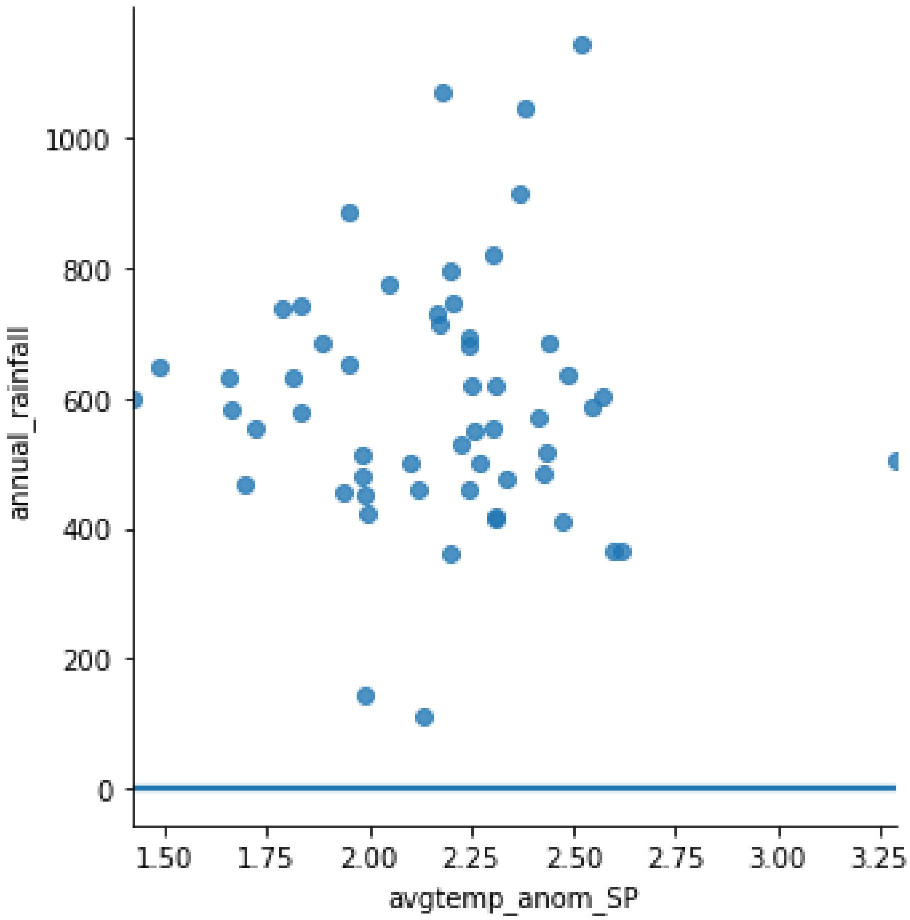
[168]: <seaborn.axisgrid.PairGrid at 0x7f5db22eadc0>



[169]:
```
#Not meaninful
sns.lmplot(x="avgtemp_anom_SP", y="annual_rainfall", data=SP_data,␣
 ↪logistic=True)
## a simple logistic regression curve
```

```
/opt/conda/lib/python3.8/site-
packages/statsmodels/genmod/families/family.py:894: RuntimeWarning: divide by
zero encountered in true_divide
  n_endog_mu = self._clean((1. - endog) / (1. - mu))
```

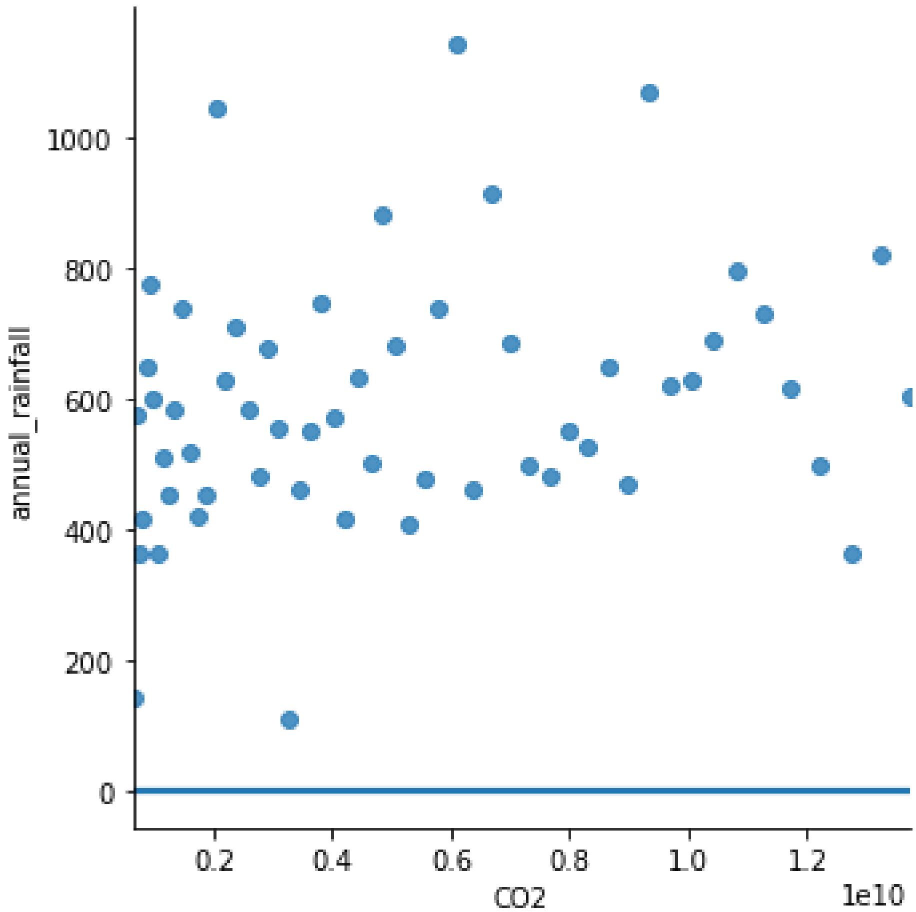
[169]:
```
<seaborn.axisgrid.FacetGrid at 0x7f5dada47c10>
```



[170]:
```
sns.lmplot(x="CO2", y="annual_rainfall", data=SP_data, logistic=True)
## a simple logistic regression curve
##Not meaningful
```

```
/opt/conda/lib/python3.8/site-
packages/statsmodels/genmod/families/family.py:894: RuntimeWarning: divide by
zero encountered in true_divide
  n_endog_mu = self._clean((1. - endog) / (1. - mu))
```

[170]: <seaborn.axisgrid.FacetGrid at 0x7f5dad961460>



[ ]:

[171]:
```
## Determination of the independent variables and the target variable.
```

[172]:
```
SP_data.head()
```

[172]:

	year	annual_rainfall	CO2	avgtemp_anom_SP
0	1961.0	144.1	637413757.0	1.990417
1	1962.0	577.0	691045205.0	1.832083
2	1963.0	362.7	746596143.0	2.199167
3	1964.0	418.4	803262819.0	2.308333
4	1965.0	649.9	859592436.0	1.483333

[173]:
```
SP_data.columns
```

[173]:
```
Index(['year', 'annual_rainfall', 'CO2', 'avgtemp_anom_SP'], dtype='object')
```

[174]:
```
##Separation of the variable target and the variables explicatives
# target varaible
y = SP_data["annual_rainfall"]

# The variables explicatives
# Drop => suppression de la colonne 'Purchased'
X = SP_data.drop(["year","annual_rainfall"], axis=1)
```

[175]:
```
X.head(2)
```

[175]:

	CO2	avgtemp_anom_SP
0	637413757.0	1.990417
1	691045205.0	1.832083

[176]:
```
y.head(2)
```

[176]:
```
0    144.1
1    577.0
Name: annual_rainfall, dtype: float64
```

[177]:
```
# Normalisation des données StandardScaler
from sklearn.preprocessing import StandardScaler

sc_x = StandardScaler()
X = sc_x.fit_transform(X)
```

[178]:
```
print(X)
```

```
[[-1.20397062e+00 -5.47942020e-01]
 [-1.18992740e+00 -1.04475524e+00]
 [-1.17538157e+00  1.07066984e-01]
 [-1.16054359e+00  4.49606622e-01]
 [-1.14579386e+00 -2.13905172e+00]
 [-1.12898026e+00 -3.76672201e-01]
 [-1.11167758e+00 -2.34562142e+00]
 [-1.09144433e+00  1.41185538e+00]
 [-1.06941445e+00 -5.78012294e-01]
 [-1.04492380e+00 -5.57093842e-01]
 [-1.01812171e+00  1.19221164e+00]
 [-9.88267430e-01 -1.03560341e+00]
 [-9.53698529e-01  8.49672002e-01]
 [-9.16273481e-01 -5.33560585e-01]
 [-8.76861973e-01 -7.16597033e-01]
 [-8.36433344e-01  6.71865166e-01]
 [-7.93993663e-01 -1.60301640e+00]
 [-7.47926582e-01  3.12375979e-02]
 [-6.98920644e-01 -1.56902392e+00]
```

```
 [-6.50280435e-01 -5.72782681e-01]
 [-6.05643972e-01  2.56110948e-01]
 [-5.60923342e-01 -1.39383189e+00]
 [-5.17606835e-01 -9.95027222e-02]
 [-4.73719861e-01  2.48266529e-01]
 [-4.26604000e-01  2.95333044e-01]
 [-3.74960962e-01  1.33215048e-01]
 [-3.21075855e-01  7.86916648e-01]
 [-2.66726173e-01  4.60065848e-01]
 [-2.11184911e-01  1.01701961e+00]
 [-1.57003295e-01  3.52200414e+00]
 [-1.00122994e-01 -6.77374937e-01]
 [-4.29399899e-02 -8.86559449e-01]
 [ 1.68483136e-02  9.62108677e-01]
 [ 7.95529360e-02  5.41124846e-01]
 [ 1.46476604e-01 -1.19772141e+00]
 [ 2.20106536e-01  1.11899706e+00]
 [ 2.97766412e-01 -1.41339625e-01]
 [ 3.78495254e-01  6.27413457e-01]
 [ 4.61312773e-01  8.73205259e-01]
 [ 5.46210298e-01  3.34555140e-01]
 [ 6.33401956e-01  8.31368357e-01]
 [ 7.19139692e-01  4.26073365e-01]
 [ 8.02278238e-01  1.93355595e-01]
 [ 8.89649979e-01 -6.85219356e-01]
 [ 9.79224200e-01 -1.47750570e+00]
 [ 1.06876173e+00  3.64672107e-02]
 [ 1.16221974e+00  4.60065848e-01]
 [ 1.26181181e+00 -1.10881799e+00]
 [ 1.35610040e+00  2.40422110e-01]
 [ 1.46378229e+00  9.39929515e-02]
 [ 1.57642742e+00 -1.40078914e-04]
 [ 1.69689343e+00  2.69184980e-01]
 [ 1.82613927e+00 -2.09324591e-01]
 [ 1.96217554e+00  1.35694444e+00]
 [ 2.09626250e+00  4.33917784e-01]
 [ 2.22031013e+00  1.26542622e+00]]
```

[179]:
```
# Division du dataset en train et un test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.3,␣
↪random_state=0)
```

[180]:
```
print("Number of lines of X_train = {}".format(len(X_train)))
print("Number of lines of  X_test = {}".format(len(X_test)))
print("Number of lines of  y_train = {}".format(len(y_train)))
print(" Number of lines of  = {}".format(len(y_test)))
```

```
Number of lines of X_train = 39
Number of lines of  X_test = 17
Number of lines of  y_train = 39
 Number of lines of  = 17
```

Comment: small data set, specially the stresstest dataset.

[181]:
```python
##Modelling with statsmodel
```

[182]:
```python
import statsmodels.api as sm

X_train2 = sm.add_constant(X_train)
model = sm.OLS(y_train, X_train2)
results = model.fit()
# Avec  statsmodel, on a une sortie qui ressemble beaucoup à celle de R
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        annual_rainfall   R-squared:                       0.028
Model:                            OLS   Adj. R-squared:                 -0.026
Method:                 Least Squares   F-statistic:                    0.5129
Date:                Thu, 27 Aug 2020   Prob (F-statistic):              0.603
Time:                        23:11:06   Log-Likelihood:                -256.92
No. Observations:                  39   AIC:                             519.8
Df Residuals:                      36   BIC:                             524.8
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        580.6273     29.293     19.821      0.000     521.218     640.037
x1            26.3527     28.228      0.934      0.357     -30.896      83.602
x2             4.0844     28.846      0.142      0.888     -54.418      62.587
==============================================================================
Omnibus:                       11.657   Durbin-Watson:                   1.336
Prob(Omnibus):                  0.003   Jarque-Bera (JB):               12.943
Skew:                           0.949   Prob(JB):                      0.00155
Kurtosis:                       5.088   Cond. No.                         1.30
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

ATEENTION: Adj. R-squared: value not coherent… The test is not relevant here. The data is very sparse. Also the hypothesis of data being normally distributed just works good for big sets data thanks to the Central Limit theorem which is not evidently the case

[183]:
```
## Conclusions about anomalies temperatures and annual rainfall SP.
```

[184]:
```
##Using Spearman correlation
#gapminder.gdpPercap.corr(gapminder.lifeExp, method="spearman")
```

Spearman correlation coefficient is a good coefficient of correlation to estimate some statistical correlation between variables when we do not know the shape of the distributions (no enough data to postulate Normality of the underlying distributions). It just supposes some kind of monotonic dependence between the variables which is not the case here maybe due to the seasonality of the rainfalls. BAD INDICATOR FOR US IN THIS CONTEXT!

[187]:
```
SP_data.annual_rainfall.corr(SP_data.avgtemp_anom_SP, method="spearman")
```

[187]:
```
-0.09046634427746485
```

Negative low correlation!! Strange conclusion.

[189]:
```
SP_data_selected2=SP_data.drop(["year", "avgtemp_anom_SP"], axis=1)
```

[190]:
```
SP_data_selected2.annual_rainfall.corr(SP_data_selected2.CO2, method="spearman")
```

[190]:
```
0.2651401230348599
```

We find very low correlations between annual rainfall and CO2 emissions which would go against empirical evidence.

5 Partie 4 : Modelization.

5.1 4.1 - Initial considerations about the anomalies of temperatures.

[191]:
```
temptable.head()
```

[191]:
```
   year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio  \
0  1973   JAN      24.51          3.62       27.73          3.525
1  1973   FEB      25.18          4.29       27.97          3.765
2  1973   MAR      22.22          1.33       25.70          1.495
3  1973   APR      23.85          2.96       26.49          2.285
4  1973   MAY      18.73          2.16       22.42          1.785

   avtemp_Manaus  temp_anom_Manaus
0          27.99              0.27
1          27.64              0.08
2          27.92              0.20
3          27.81              0.09
4          26.99              0.73
```

[192]:
```
temptable.temp_anom_Rio.corr(temptable.temp_anom_SP, method="spearman")
```

[192]: 0.8482802069432448

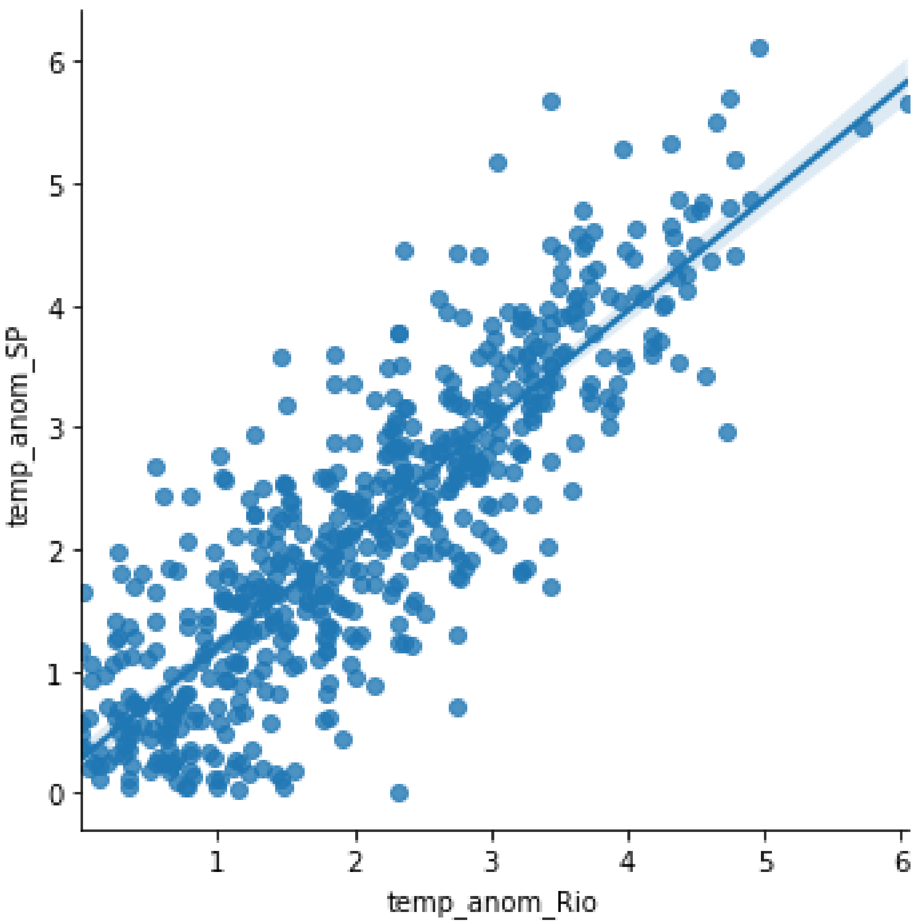
##There is high correlation between the temperatures anomalies of SP and the temperature anomalies in Rio.

[193]:
```
##By graphical inspection in tableau we see a local maximum for
##the anomaly temperature  for Rioin 2017.
#
```

[194]:
```
threshold_Rio =2.379
#by inpsection on the tableau file avg_temp_SP
```

[195]:
```
sns.lmplot(x="temp_anom_Rio", y="temp_anom_SP", data=temptable)
## strong correlation
```

[195]: <seaborn.axisgrid.FacetGrid at 0x7f5da64fac40>



5.2 4.2 -Multilinear regression.

[196]:
```
# Separation of the explicative variables and the target variable
X = temptable.drop(["year","month", "avtemp_Rio", "temp_anom_Rio"  ], axis=1)
y = temptable["temp_anom_Rio"]
```

[197]:
```
X.head()
```

[197]:

	avtemp_SP	temp_anom_SP	avtemp_Manaus	temp_anom_Manaus
0	24.51	3.62	27.99	0.27
1	25.18	4.29	27.64	0.08
2	22.22	1.33	27.92	0.20
3	23.85	2.96	27.81	0.09
4	18.73	2.16	26.99	0.73

[198]:
```
y.head()
```

[198]:
```
0    3.525
1    3.765
2    1.495
3    2.285
4    1.785
Name: temp_anom_Rio, dtype: float64
```

[199]:
```
# Feature scaling----> Standardization
from sklearn.preprocessing import StandardScaler

sc_x = StandardScaler()
X = sc_x.fit_transform(X)
```

[200]:
```
## Separation of the data set- training/test
# Train_test_split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,␣
 ↪random_state=0)
```

[201]:
```
print("Number of lines of X_train = {}".format(len(X_train)))
print("Number of lines of X_test = {}".format(len(X_test)))
print("Number of lines of y_train = {}".format(len(y_train)))
print("Number of lines of y_test = {}".format(len(y_test)))
```

```
Number of lines of X_train = 394
Number of lines of X_test = 170
Number of lines of y_train = 394
Number of lines of y_test = 170
```

[202]:
```python
# Création du modèle
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

[202]: LinearRegression()

[203]:
```python
##regression coefficients
regressor.coef_
```

[203]: array([-0.02153784, 1.0250486 , 0.02971434, -0.05948205])

[204]:
```python
# Vérifcation de l'overfitting
print(" Score de Train : {}\n Score de Test : {}".format(regressor.
 ↪score(X_train, y_train), regressor.score(X_test, y_test)))
```

```
 Score de Train : 0.7363617287232707
 Score de Test : 0.7050952691196659
```

We have overfitting. Score takes respect to R^2. Due to the difference between the size of the training set and the test set. There is still a significant difference.

[205]:
```python
# Coefficients of regression
feature_importance = pd.DataFrame({"features": ['avtemp_SP',
                                                'temp_anom_SP',
                                                'avtemp_Manaus',
                                                'temp_anom_Manaus',

                                                ],
                                   "values":regressor.coef_})

feature_importance.sort_values(["values"], ascending=False)
```

[205]:

	features	values
1	temp_anom_SP	1.025049
2	avtemp_Manaus	0.029714
0	avtemp_SP	-0.021538
3	temp_anom_Manaus	-0.059482

5.3 4.3 -Logistic regression

[206]:
```python
####Logistic regression using scikit
```

[209]:
```python
threshold_Rio= 0.62
###FINAL DECISION FOR THE THRESHOLD FOR ANOMALY TEMPERATURES RIO
#The 2-degree increase in global average surface temperature
#that has occurred since the pre-industrial era (1880-1900) might seem small,
```

```
#but it means a significant increase in accumulated heat.#
# check climate.gov

#GLOBAL anomaly of 2010, a threshold alarming warmest year
```

[210]:
```
temptable.head()
```

[210]:
```
   year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio  \
0  1973   JAN      24.51          3.62       27.73          3.525
1  1973   FEB      25.18          4.29       27.97          3.765
2  1973   MAR      22.22          1.33       25.70          1.495
3  1973   APR      23.85          2.96       26.49          2.285
4  1973   MAY      18.73          2.16       22.42          1.785

   avtemp_Manaus  temp_anom_Manaus
0          27.99              0.27
1          27.64              0.08
2          27.92              0.20
3          27.81              0.09
4          26.99              0.73
```

Preparation of the binary variable:

[211]:
```
temptable["bad_numbers"]=0
for i in range(len(temptable)):
    if temptable.loc[i, "temp_anom_Rio"] < threshold_Rio:
        temptable.loc[i, "bad_numbers"]=0
    else:
        temptable.loc[i, "bad_numbers"]=1
temptable.head(100)
```

[211]:
```
    year month  avtemp_SP  temp_anom_SP  avtemp_Rio  temp_anom_Rio  \
0   1973   JAN      24.51          3.62       27.73          3.525
1   1973   FEB      25.18          4.29       27.97          3.765
2   1973   MAR      22.22          1.33       25.70          1.495
3   1973   APR      23.85          2.96       26.49          2.285
4   1973   MAY      18.73          2.16       22.42          1.785
..   …    …         …             …          …              …
95  1980   DEC      22.74          1.85       27.01          2.805
96  1981   JAN      23.67          2.78       27.42          3.215
97  1981   FEB      24.97          4.08       28.06          3.855
98  1981   MAR      23.23          2.34       26.26          2.055
99  1981   APR      21.37          0.48       23.85          0.355

    avtemp_Manaus  temp_anom_Manaus  bad_numbers
0          27.990             0.270            1
1          27.640             0.080            1
```

```
2           27.920              0.200            1
3           27.810              0.090            1
4           26.990              0.730            1
..             …                  …           …
95          27.720              0.000            1
96          27.160              0.560            1
97          27.160              0.560            1
98          27.215              0.505            1
99          27.305              0.415            0

[100 rows x 9 columns]
```

[212]:
```
###New variables target and explicative variables
```

[213]:
```
# Separation of the explicative variables and the target variable
# X = dataset.iloc[:, :-1]
# y = dataset.iloc[:, -1]
X = temptable.drop(["year","month", "avtemp_Rio", "temp_anom_Rio",␣
 ↪"bad_numbers"  ], axis=1)
y = temptable["bad_numbers"]
```

[214]:
```
# Feature scaling----> Standardization
from sklearn.preprocessing import StandardScaler

sc_x = StandardScaler()
X = sc_x.fit_transform(X)
```

[215]:
```
## Separation of the data set- training/test
# Train_test_split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,␣
 ↪random_state=0)
```

[216]:
```
print("Number of lines of  X_train = {}".format(len(X_train)))
print("Number of lines of X_test = {}".format(len(X_test)))
print("Number of lines of y_train = {}".format(len(y_train)))
print("Number of lines of y_test = {}".format(len(y_test)))
```

```
Number of lines of  X_train = 394
Number of lines of X_test = 170
Number of lines of y_train = 394
Number of lines of y_test = 170
```

[217]:
```
# THE LOGISTIC MODEL
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression()
```

```
classifier.fit(X_train, y_train)
```

[217]:
```
LogisticRegression()
```

[218]:
```
# Evaluation du modèle
print("Train score : {}".format(classifier.score(X_train, y_train)))
print("Test score : {}".format(classifier.score(X_test, y_test)))
```

```
Train score : 0.8629441624365483
Test score : 0.8705882352941177
```

[219]:
```
##The R^2 model is high and we can see no overfitting/underfitting. The error␣
↪difference
#can be considered neglegible
```

[220]:
```
coefs = classifier.coef_
coefs
```

[220]:
```
array([[-1.21972331,  2.25736008,  0.01612904, -0.27531315]])
```

[221]:
```
# Coefficients of the logistic regression
feature_importance = pd.DataFrame({"features": ['avtemp_SP',
                                                'temp_anom_SP',
                                                'avtemp_Manaus',
                                                'temp_anom_Manaus',

                                                ],
                                   "values": classifier.coef_.squeeze()})

feature_importance.sort_values(["values"], ascending=False)
```

[221]:

	features	values
1	temp_anom_SP	2.257360
2	avtemp_Manaus	0.016129
3	temp_anom_Manaus	-0.275313
0	avtemp_SP	-1.219723

[222]:
```
####PREDICTION
```

[223]:
```
# Calculus of probabilities for each mass of the test sample
y_pred_prob = classifier.predict_proba(X_test)
y_pred_prob[:5]
```

[223]:
```
array([[0.16085699, 0.83914301],
       [0.00855615, 0.99144385],
       [0.64050984, 0.35949016],
       [0.00988722, 0.99011278],
```

```
        [0.00735367, 0.99264633]])
```

[224]:
```
# Identifier for each mass temperature of the test sample
y_test_pred = classifier.predict(X_test)
print(y_test_pred)
```

```
[1 1 0 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

[225]:
```
#Notorious it is more probable that the anomaly
#temperatures in Rio surpasses the threshold fixed
threshold_Rio
```

[225]:
```
0.62
```

[226]:
```
y_train_pred=classifier.predict(X_train)
y_train_pred[:15]
```

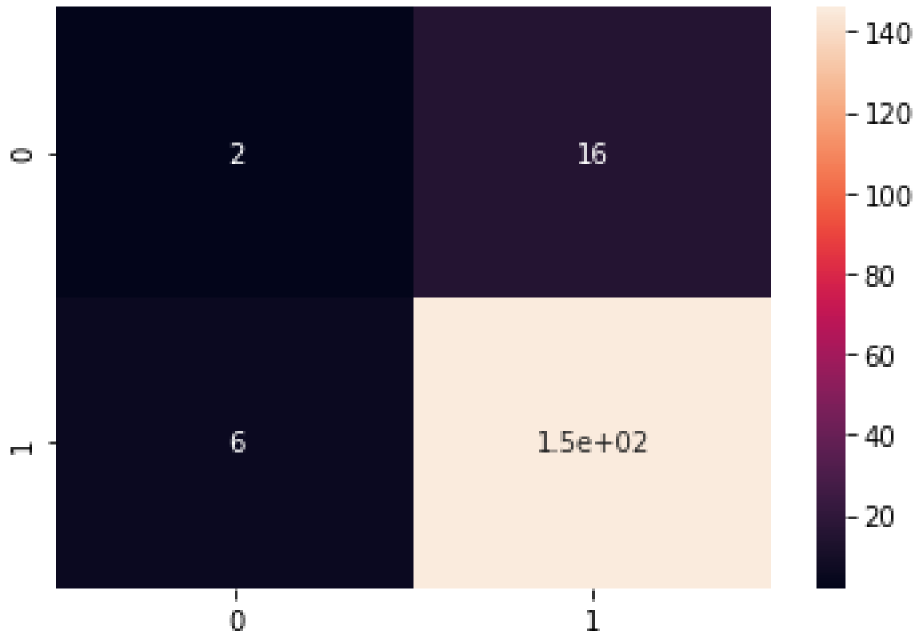
[226]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

[227]:
```
# Matrice de confusion
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_test_pred)
cm
```

[227]:
```
array([[  2,  16],
       [  6, 146]])
```

[228]:
```
# Visualisation via Seaborn
sns.heatmap(cm, annot=True)
```

[228]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5da5f7a5e0>
```



Comment: huge proportion of true negatives in comparison with false negatives. GOOD OUTCOME.

[229]:
```
TN=146
FN=16
TP=2
FP=6
```

[230]:
```
Accuracy =  (TN+TP) / (TP+FN+TN+FP)
Accuracy
```

[230]:
```
0.8705882352941177
```

[231]:
```
print("The accuracy of the model is", Accuracy)
```

```
The accuracy of the model is 0.8705882352941177
```

[232]:
```
Precision=TP/(TP+FN)
```

[233]:
```
print("The precision of the model is", 1- Precision)
```

```
The precision of the model is 0.8888888888888888
```

[234]:
```
##Matrix confusion used in Bayesian statistics
```

[ ]:
```

```