SPATIAL DATA ANALYSIS

Pratical Work

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Introduction

Climate data analysis is the most fundamental step in predicting the climate change. Its main objective is to increase understanding of the atmosphere and its interaction with the oceans, cry sphere and the land surface, through various types of approaches or techniques. They are empirical studies conducted on the climate data, diagnostic analyses and mathematical data modeling.

At the end of the lecture “Spatial data analysis”, it has been given a practical work of on the lecture. This paper report the answere to the questions asked in the practical work. The paper is divided in 4 parts which are : introduction, exercise 1, exercise 2 and conclusion.

The data used for processing are : fire datasets : fires.csv and the elevation datasets: bfa_elevation. The tool used to compute is python specifically Juputer Notebook. For the purpose of the analysis, many modules has been downloaded and imported. For the report, we used Latex.

1 Exercise 1

1.1

1.1.1 Import the dataset (fires.csv)

[7]:
```
import pandas as pd
import matplotlib.pyplot as plt
import cartopy.crs as ccrs
import cartopy
import cartopy.feature as cf
import geopandas as gpd
import folium
import geopatra
import seaborn as sns
import contextily
import geoplot
import cartopy.crs as ccrs
import cartopy
import cartopy.feature as cf
import geopandas as gpd
import matplotlib.style
import matplotlib as mpl
import rasterio
mpl.style.use('default')
fire=pd.read_csv("../SpatialAnalysis2021/Data/non-spatial/fire/fire.csv")
```

1.1.2 How many fires were detected in total?

```
[8]: nf=fire.shape[0]
     print(f"Number of fire detected: {nf}")
```

```
Number of fire detected: 21460
```

1.2 During which time period were the fires detected?

```
[9]: fire.ACQ_DATE=pd.to_datetime(fire.ACQ_DATE)
     start=fire.ACQ_DATE.min()
     end=fire.ACQ_DATE.max()
     print(f"The fires has been detected between {start} and {end}")
```

```
The fires has been detected between 2019-01-01 00:00:00 and 2019-01-31 00:00:00
```

1.3

1.3.1 Identification of the ten brightest fires during this period located?

The attribute which shows the brightness in the datasets is BRIGHTNESS. For the computation, we sort the values in the datasets based on that attribute in order to have the ten brightest observation. The data has been sorted by descending values. The next table shows the ten brightest fires occurred in the period of 2019-01-01 00:00:00 and 2019-01-31 00:00:00.

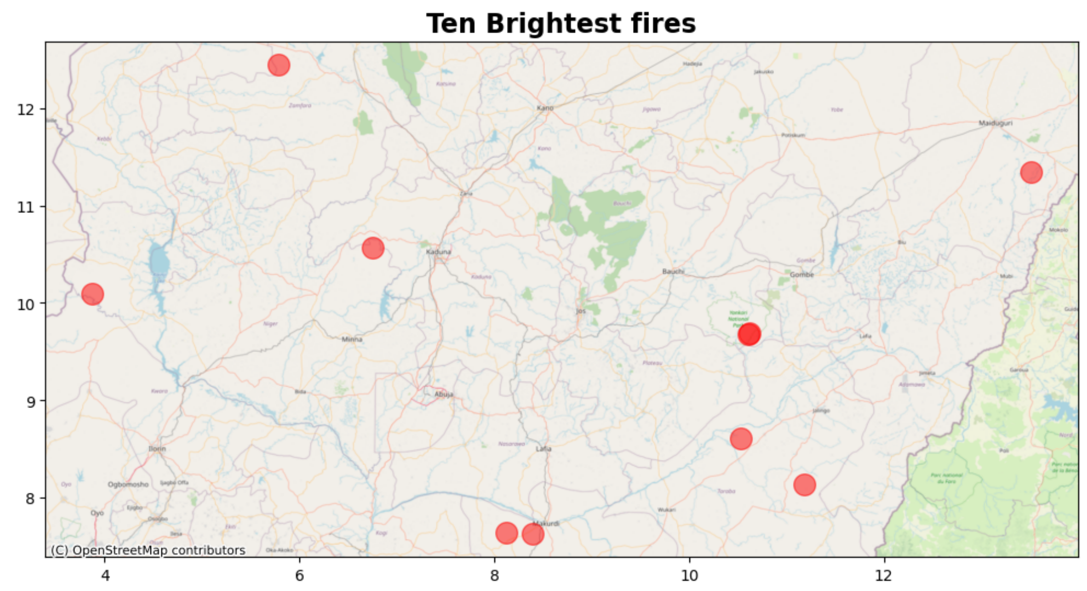
```
[10]: ten_brigh = fire.sort_values(by="BRIGHTNESS", ascending=False).head(10)
      ten_brigh=gpd.GeoDataFrame(ten_brigh, geometry=gpd.points_from_xy(ten_brigh.
       ↪LONGITUDE, ten_brigh.LATITUDE))
      ten_brigh= ten_brigh.reset_index()
      ten_brigh
```

```
[10]:    index  LATITUDE  LONGITUDE  BRIGHTNESS  SCAN  TRACK    ACQ_DATE  ACQ_TIME  \
      0  11427    9.6760    10.6130       422.9   1.0    1.0 2019-01-15      1244
      1   3495   10.5655     6.7566       421.8   1.0    1.0 2019-01-04      1303
      2  21228    8.1329    11.1870       419.7   1.0    1.0 2019-01-31      1244
      3   3319    7.6403     8.1262       418.0   1.0    1.0 2019-01-04      1302
      4  17854   12.4460     5.7779       413.4   1.1    1.0 2019-01-27      1006
      5   3346    7.6324     8.3984       405.4   1.0    1.0 2019-01-04      1302
      6   8828    8.6089    10.5270       399.9   1.7    1.3 2019-01-11      1308
      7  11430    9.6863    10.6208       397.0   1.0    1.0 2019-01-15      1244
      8  21012   11.3494    13.5145       396.7   1.2    1.1 2019-01-31      1244
      9  10353   10.0935     3.8743       395.2   1.5    1.2 2019-01-13      1257

        SATELLITE INSTRUMENT  CONFIDENCE  VERSION  BRIGHT_T31    FRP DAYNIGHT  TYPE␣
       ↪ \
      0      Aqua      MODIS         100     6.03       319.8  413.7        D     0
      1      Aqua      MODIS         100     6.03       320.2  395.6        D     0
```

```
2       Aqua       MODIS           100      6.03         322.7   381.0          D      0
3       Aqua       MODIS           100      6.03         317.6   375.0          D      0
4      Terra       MODIS           100      6.03         320.7   382.8          D      0
5       Aqua       MODIS           100      6.03         314.2   287.7          D      0
6       Aqua       MODIS           100      6.03         316.3   526.0          D      0
7       Aqua       MODIS           100      6.03         313.1   223.3          D      0
8       Aqua       MODIS           100      6.03         315.5   271.1          D      0
9       Aqua       MODIS           100      6.03         318.3   380.8          D      0

                    geometry
0   POINT (10.61300 9.67600)
1   POINT (6.75660 10.56550)
2   POINT (11.18700 8.13290)
3    POINT (8.12620 7.64030)
4   POINT (5.77790 12.44600)
5    POINT (8.39840 7.63240)
6   POINT (10.52700 8.60890)
7   POINT (10.62080 9.68630)
8  POINT (13.51450 11.34940)
9   POINT (3.87430 10.09350)
```

1.3.2 The location of ten brightest fires during this period 2019-01-01 00:00:00 and 2019-01-31 00:00:00

[11]:
```
world=gpd.read_file( gpd.datasets.get_path("naturalearth_lowres"))
nigeria=world[world.name=="Nigeria"]
fig, ax=plt.subplots(figsize=(10,10))
plt.scatter(ten_brigh.LONGITUDE, ten_brigh.LATITUDE, s=200, c="r", alpha=0.5)
contextily.add_basemap(ax, crs=nigeria.crs,
    source=contextily.providers.OpenStreetMap.Mapnik)
ax.set_title(label="Ten Brightest fires", size=17, weight="bold")
plt.margins(0)
plt.margins(0)
plt.tight_layout()
plt.show()
```



The above figure shows the ten brightest fires located in Nigeria. We can see form the graph that, the fire along the country. Two brightest fires can see in the same location around(longitude=10 and latitude =10).

1.4

1.4.1 Extract all fires detected with a confidence higher than 70 percent. How much are these?

The confidence of the fire has been tracked by the attribute **CONFIDENCE**. The condition has been set to that attribute to select the fire with confidence higher than 70.

The number of fire with confidence higher than 70 is shown in the table above. The bold column title "CONFIDENCE" is the attribute which indicates the confidence of the fire. The first column indicating the index from the original datasets.
In sum the number of fire with confidence higher than 70 percent is : 7285. The distribution of those fire along the space can be see in the next graph.

[12]:
```
conf_70=fire[fire.CONFIDENCE>70]
conf_70_nb=conf_70.count()[0]
print(conf_70)
print(f"The numbe of fires with confidence higher than 70 percent is :␣
↪{conf_70_nb}")
```

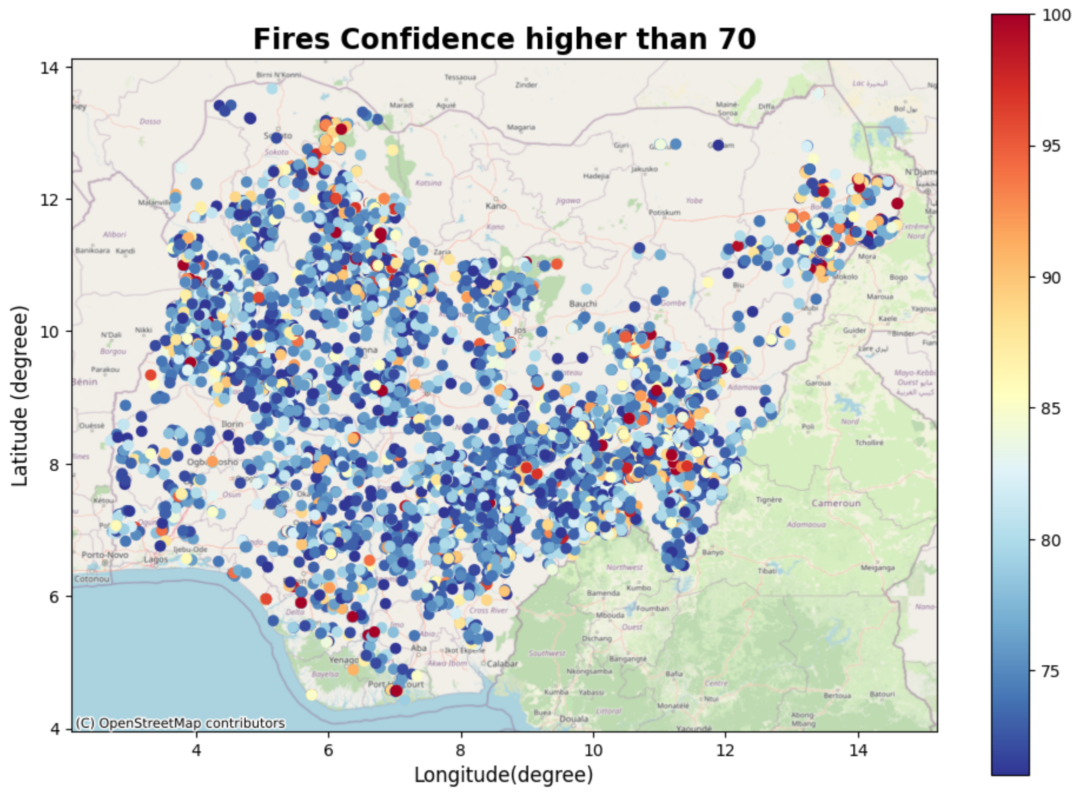
```
       LATITUDE  LONGITUDE  BRIGHTNESS  SCAN  TRACK    ACQ_DATE  ACQ_TIME  \
5        5.5644     5.7226       307.7   2.6    1.5  2019-01-01       144
7       12.2363    14.4138       331.5   1.2    1.1  2019-01-01       929
8       12.2348    14.4245       326.7   1.2    1.1  2019-01-01       929
10      12.2743    14.3043       324.3   1.2    1.1  2019-01-01       929
11      12.2660    14.2921       367.3   1.2    1.1  2019-01-01       929
...         ...        ...         ...   ...    ...         ...       ...
```

```
21450   11.4083     5.7974       307.7    1.2      1.1  2019-01-31      2210
21452   10.8918     5.7326       309.5    1.1      1.1  2019-01-31      2210
21454   10.9928     4.8431       308.2    1.0      1.0  2019-01-31      2210
21457   11.4788     6.7811       343.6    1.3      1.1  2019-01-31      2210
21458   11.4804     6.7929       323.9    1.3      1.1  2019-01-31      2210

      SATELLITE INSTRUMENT  CONFIDENCE  VERSION  BRIGHT_T31    FRP DAYNIGHT  \
5          Aqua      MODIS          72     6.03       292.5   31.6        N
7         Terra      MODIS          81     6.03       305.9   26.4        D
8         Terra      MODIS          75     6.03       306.0   18.9        D
10        Terra      MODIS          71     6.03       305.2   16.2        D
11        Terra      MODIS         100     6.03       305.5  124.4        D
...         ...        ...         ...      ...         ...    ...      ...
21450     Terra      MODIS          72     6.03       291.9   10.1        N
21452     Terra      MODIS          77     6.03       293.7   10.5        N
21454     Terra      MODIS          74     6.03       294.2    7.9        N
21457     Terra      MODIS         100     6.03       295.2   71.5        N
21458     Terra      MODIS         100     6.03       293.7   29.4        N


The number of fires with confidence higher than 70 percent is : 7285
```

1.4.2 location of fires detected with a confidence higher than 70 percent

This figure shows the distribution of the fires higher than 70 percent. The fire with the confidence higher than 70 is distributed along the country Nigeria. We can see the confidence with hundred percent are not a lot. Most of the fire have the confidence from 70 to 85 percent.

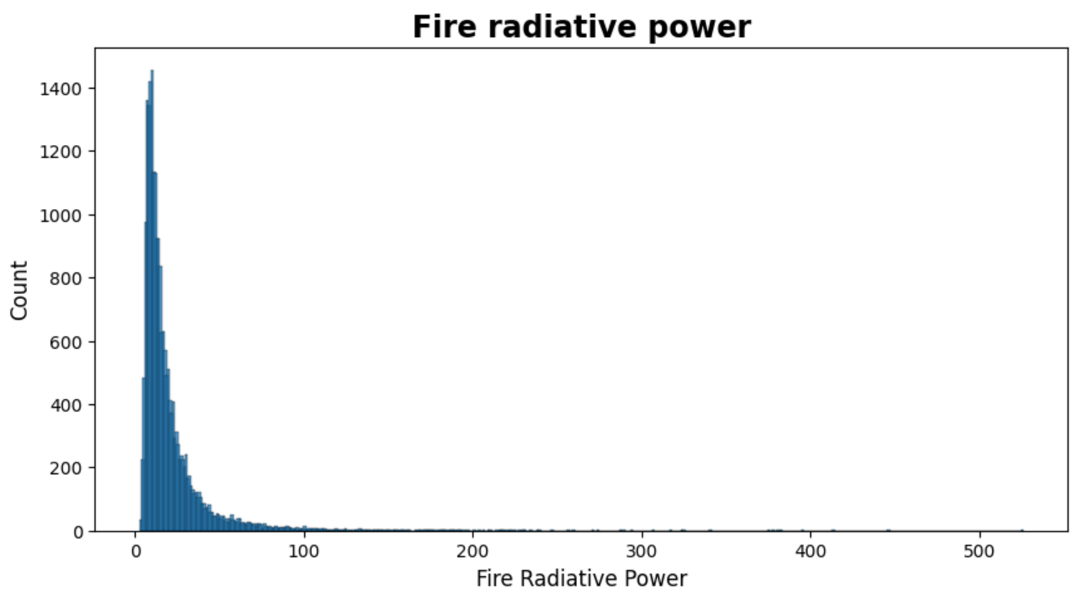
```
[13]: fig, ax=plt.subplots(figsize=(10,7))
gpd.GeoDataFrame(conf_70, geometry=gpd.points_from_xy(conf_70.
 ↪LONGITUDE,conf_70.LATITUDE)).plot(column="CONFIDENCE", legend=True,␣
 ↪cmap="RdYlBu_r",ax=ax)
ax.set_xlabel(xlabel="Longitude(degree)", size=12)
ax.set_ylabel(ylabel="Latitude (degreee)",size=12 )
contextily.add_basemap(ax, crs=nigeria.crs,
    source=contextily.providers.OpenStreetMap.Mapnik)
ax.set_title(label="Fires Confidence higher than 70", size=17, weight="bold")
plt.tight_layout()
plt.show()
```


Fires Confidence higher than 70
Latitude (degreee)
Longitude(degree)
(C) OpenStreetMap contributors
100
95
90
85
80
75

1.5 Creation of the histogram showing the distribution of the fire radiative power. Cleary indicate the description of the y-axis and x-axis.

The radiative power of fire is observed through the attribute FRP of the datasets. This attribute stands for Force Radiative Power.

[14]:
```python
fig, ax=plt.subplots(figsize=(10,5))
sns.histplot(fire['FRP'],shrink=2,ax=ax)
ax.set_xlabel(xlabel="Fire Radiative Power", size=12)
ax.set_ylabel(ylabel="Count",size=12 )
ax.set_title(label="Fire radiative power", size=17, weight="bold")
plt.show()
```



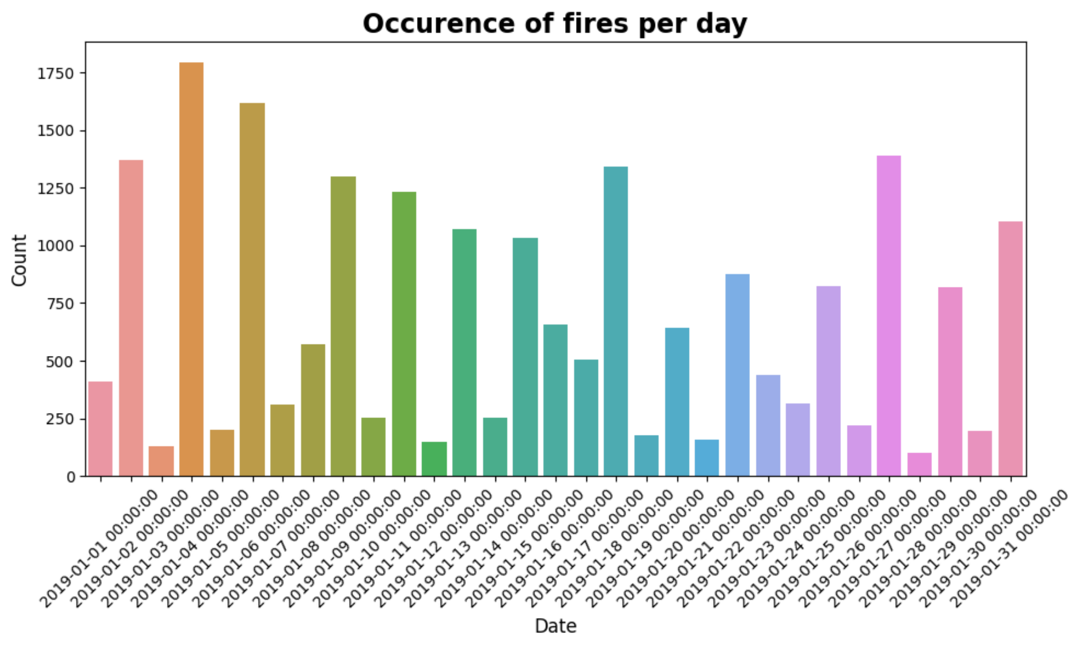
The number of occurrence of the Fire Radiative Power is shown in the histogram above. The radiative power is in the range of 0 to 200. We can see, most of the fire has the radiative power in the range of 0 to 25. We deduct that there have not been more fire with highe radiative power.

1.6

1.6.1 Creation of the plot showing the numbers of fires for each day.

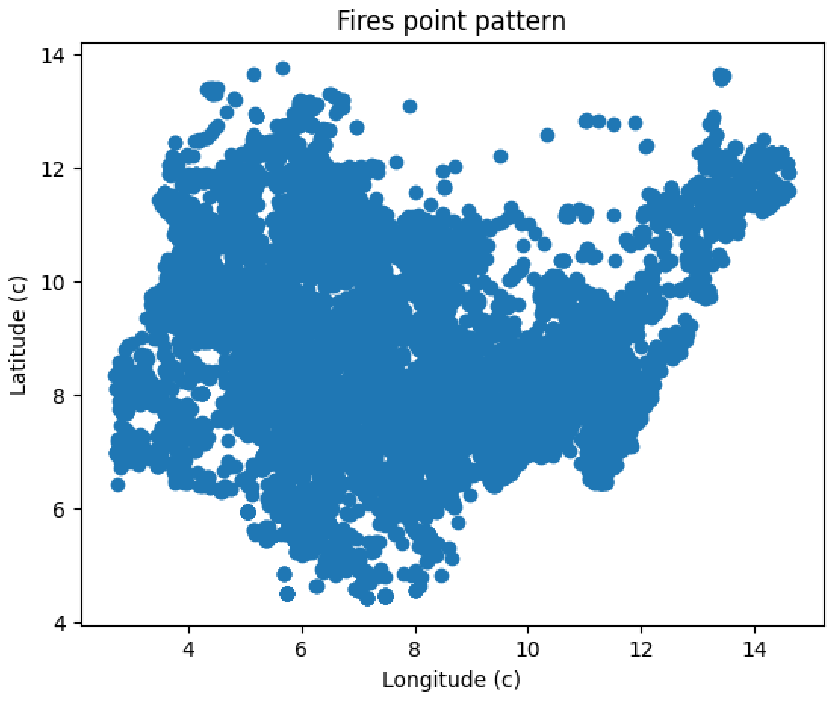
The above figure shows the occurrence of fires per day. We can from the figure, there have been more fire in 2019-01-04 specifically 1750 fires. The lowest value is show at the date 2019-01-28 specifically around 100 occurrences.

[15]:
```
fire_day=fire.groupby(by=fire.ACQ_DATE).count()
plt.figure(figsize=(10,6))
ax = sns.barplot(x=fire_day.index,y=fire_day.SCAN)
ax.set_xlabel(xlabel="Date", size=12)
ax.set_ylabel(ylabel="Count",size=12 )
ax.set_title(label="Occurence of fires per day", size=17, weight="bold")

ax.set_xticklabels(ax.get_xticklabels(), rotation=45)

plt.tight_layout()
plt.savefig("Number of fire per day",bbox_inches="tight", format="svg")
plt.show()
```



1.6.2 Convert the dataset into a spatial geopandas dataframe.

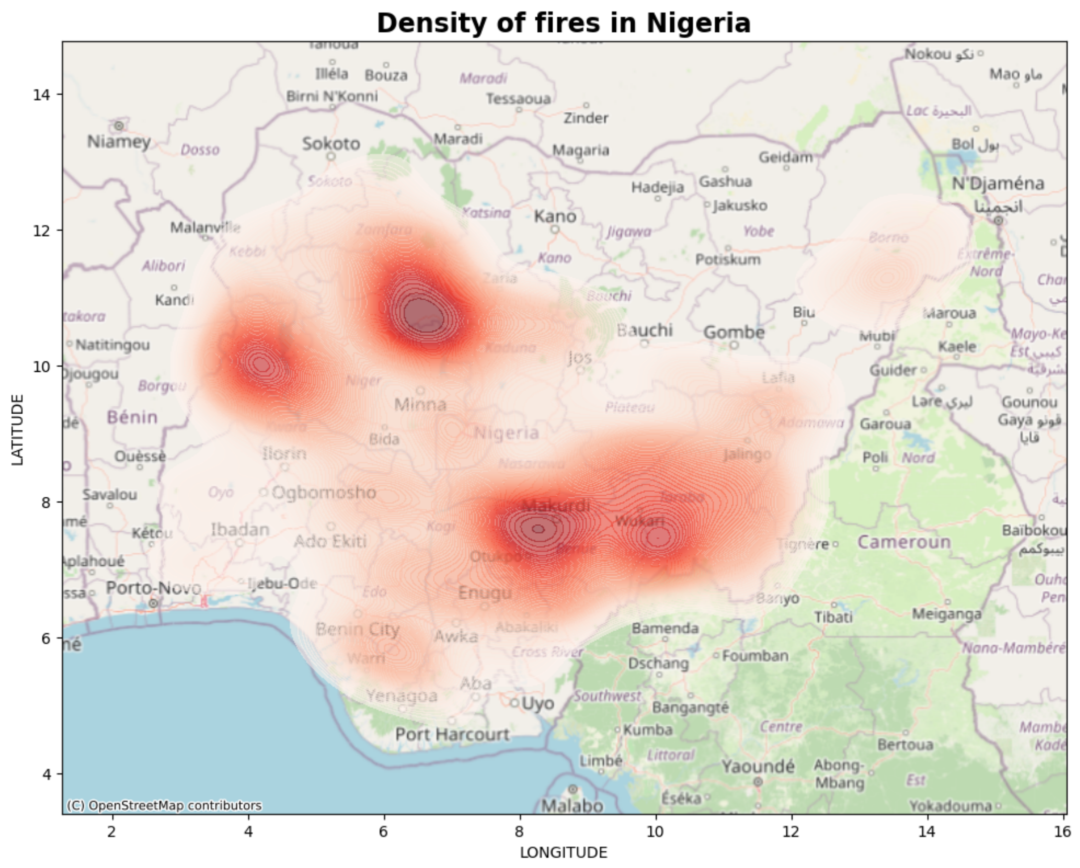
```
[16]: fire_geo=gpd.GeoDataFrame(fire, geometry=gpd.points_from_xy(fire.LONGITUDE,␣
        ↪fire.LATITUDE))
      fig, ax=plt.subplots(figsize=(15,5))
      fire_geo.plot(ax=ax)
      ax.set(title="Fires point pattern", xlabel='Longitude (c)', ylabel='Latitude␣
        ↪(c)')
      plt.show()
```



1.7 Creation of the heat map showing the density of fires in Nigeria.

The density of fire is shown in the above figure. There four big block of fire in south east and north west of the country.

[17]:
```
fig, ax=plt.subplots(figsize=(10,10))
sns.kdeplot(x=fire_geo.LONGITUDE, y=fire_geo.LATITUDE,
                n_levels=70, shade=True,
                alpha=0.55, cmap='Reds', zorder=100, ax=ax)
contextily.add_basemap(ax, crs=nigeria.crs,
    source=contextily.providers.OpenStreetMap.Mapnik)

ax.set_title(label="Density of fires in Nigeria", size=17, weight="bold")

plt.margins(0)
ax.margins(0)
plt.tight_layout()
plt.show()
```



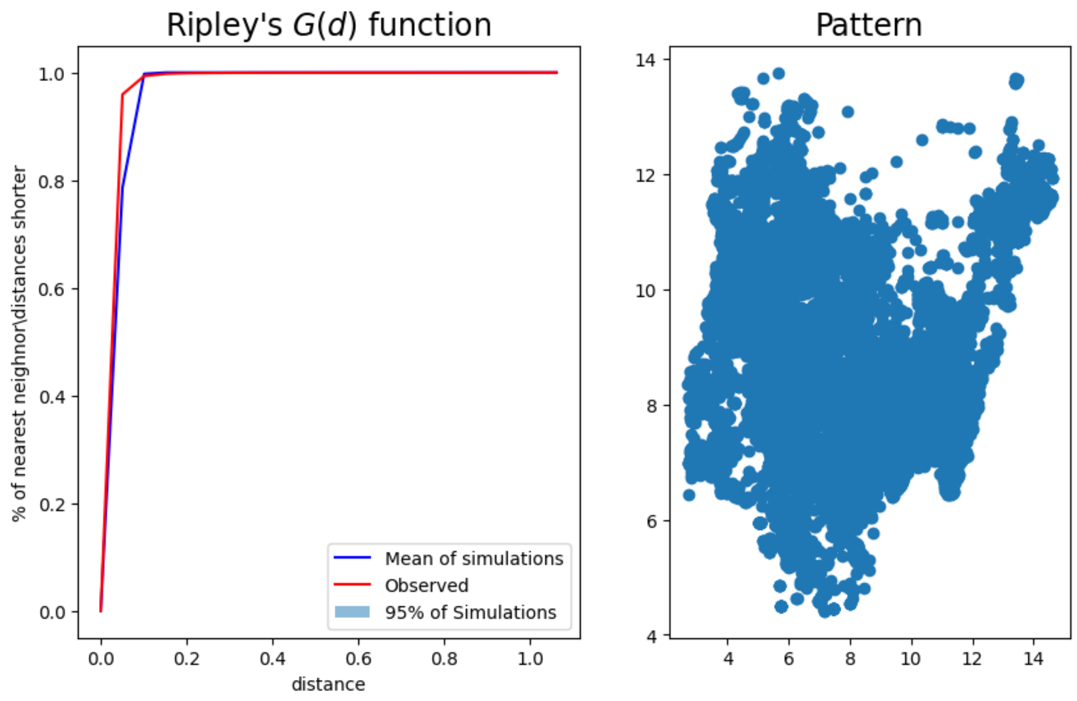
1.8 Investigate if the fire detected in Nigeria are distributed rather regular/clustered(if so to identify the main cluster and explain)

As defined by Diggle (2006) Spatial Point Processes are stochastic mechanisms which generate a series of events across a region. The locations of the events generated by a point process are a point pattern. Spatial Point Processes are generally static, whereby the statistical parameters of the underlying process do not vary over space (invariant under translation), and isotropic, whereby that they exhibit the same value when measured from different directions (invariant under rotation). Clustered Patterns are more grouped than random patterns. Visually, we can observe more points at short distances. There are two sources of clustering.

In order to test either the point pattern are clustered or regular, we have used the G function to do the test. The G function is defined as follows: for a given distance d, G(d) is the proportion of nearest neighbor distances that are less than d. A Simulation envelope is a computer intensive technique for inferring whether an observed pattern significantly deviates from what would be expected under a specific process. Here, we always use CSR as the benchmark. In order to contruct a simulation envelope for a given function, we did a CSR simulation of 100 times.

[18]:
```
from pointpats import PointPattern
from shapely.geometry import Point, LineString, Polygon
import pointpats.quadrat_statistics as qs
from pointpats._deprecated_distance_statistics import  K,L,G,F, Genv, Fenv,␣
 ↪Jenv, Kenv, Lenv
from pointpats import PoissonPointProcess
```

[19]:
```
#Create the point pattern from the data
pp=PointPattern(fire_geo[["LONGITUDE", "LATITUDE"]])
#G function test
g_test=G(pp, intervals=60)
realizations = PoissonPointProcess(pp.window, pp.n, 100, asPP=True) #␣
 ↪simulate CSR 100 times
genv = Genv(pp, intervals=20, realizations=realizations)  #The same for other
#The plotting
f, ax=plt.subplots(1,2, figsize=(10,6), gridspec_kw=dict(width_ratios=(10,8)))
ax[0].fill_between(genv.d, genv.low, genv.high, alpha=.5, label="95% of␣
 ↪Simulations")
ax[0].plot(genv.d, genv.mean, color="blue", label="Mean of simulations")
ax[0].plot(*genv.observed.T, label="Observed", color="red")
ax[0].set(xlabel="distance", ylabel="% of nearest neighnor\distances shorter")
ax[0].legend()
ax[0].set_title(r"Ripley's $G(d) $ function", size=17)
ax[1].scatter(pp.df.x, pp.df.y)
ax[1].set_title("Pattern", size=17)
plt.savefig("G compa 1", format="svg")
```

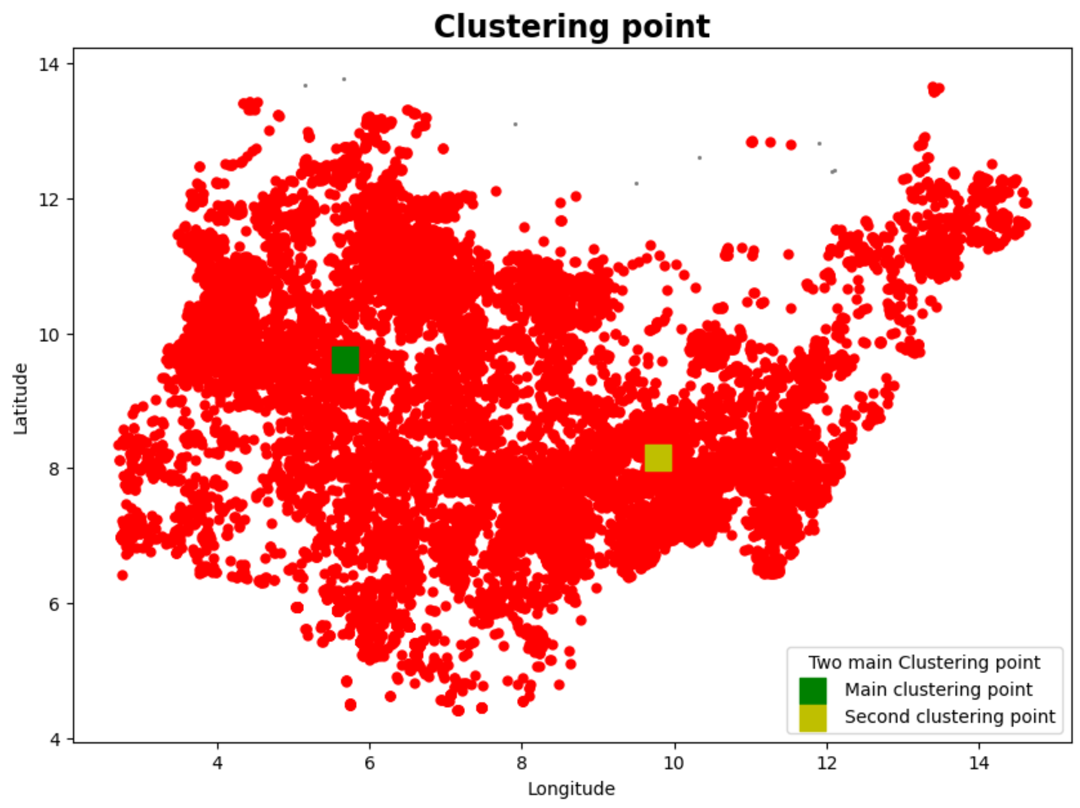


It can be seen from the figure the G function curbe at the left figure increases rapidly at short distance. This mean that the average distance between point in the space is low. By then, the points are distributed clustered. By the then, the observed curbe (G function) is upon the mean of simulations.

- Identificaiton of the clustered points

[20]:
```
from sklearn.cluster import dbscan
import seaborn as sns
from sklearn.cluster import KMeans
cs, lbls = dbscan(pp.df[['x', 'y']])
lbls = pd.Series(lbls, index=pp.df.index)
#Create 2 mains clustered point from the point patttern
kmeans = KMeans(n_clusters=2).fit(pp.df)
k_value=kmeans.cluster_centers_
#PLot the point pattern with the 2 main clustered point
f, ax = plt.subplots(figsize=(10, 7))
noise = pp.df.loc[lbls==-1, ['x', 'y']]
plt.scatter(noise['x'], noise['y'], c='grey', s=5, linewidth=0)
plt.scatter(pp.df.loc[pp.df.index.difference(noise.index), 'x'], \
            pp.df.loc[pp.df.index.difference(noise.index), 'y'], \
           c='red', linewidth=0)
plt.scatter(*k_value[0], s=200, c="g", marker='s', label="Main clustering␣
 ↪point")
plt.scatter(*k_value[1], s=200, c="y", marker='s', label="Second clustering␣
 ↪point")
ax.legend(title="Two main Clustering point")
```

```python
ax.set_ylabel(ylabel="Latitude")
ax.set_xlabel(xlabel="Longitude")
ax.set_title(label="Clustering point", size=17, weight="bold")
plt.show()
```



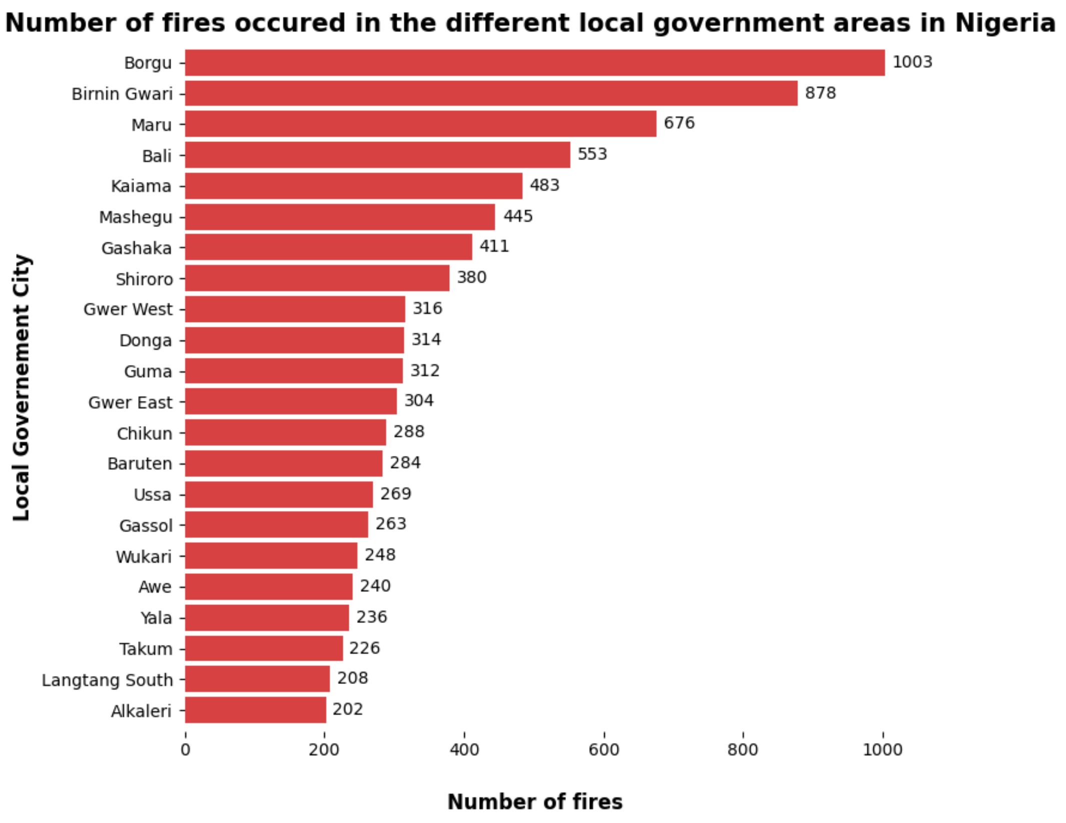
The two howed in the figure represent the main clustering point. The fires are clustered around two major points.

1.9 Count the fires occurring in the different local government areas in Nigeria. How much are they?

The number of fire in each different local government ares in Nigeria is computed using the file new_lga_nigeria_2003.shp. The module of sjoin of the package geopandas has been used to join the two dataset by the method

[21]:
```python
#Load nigeria shape file
nigeria_local = gpd.read_file('../last/SpatialAnalysis2021/Data/vector/fires/
 ↪new_lga_nigeria_2003.shp')
# Do the spatial join of the fires datasets and the nigeria shape file
fire_local=gpd.sjoin(nigeria_local,fire_geo.set_crs(nigeria_local.crs))
#Create a variable containing the values of local governement area in Nigeria␣
 ↪shape file(count)
y = fire_local['LGA'].value_counts(ascending=True)
```

```
#Select the local governement area which has more than 200 fires to simplify␣
↪the plotting
y=y[y>200]
#Plotting
ax = y.plot(kind='barh', figsize=(8, 7), color='#d84141', zorder=2, width=0.
↪85)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)
# Set x-axis label
ax.set_xlabel("Number of fires", labelpad=20, weight='bold', size=12)
ax.set_title("Number of fires occured in the different local government areas␣
↪in Nigeria ", weight='bold', size=15)
# Set y-axis label
ax.set_ylabel("Local Governement City", weight='bold', size=12)
for i, v in enumerate(y):
    ax.text(v + 10, i, str(v), color='black', fontsize=10, ha='left',␣
↪va='center')
plt.margins(0)
ax.margins(0)
plt.tight_layout()
```



The number of fire in different local region in Nigeria is showed in the figure above. The local region which has the most fire is Borou couting 1003 followed by Brimin Gwari counting 878.

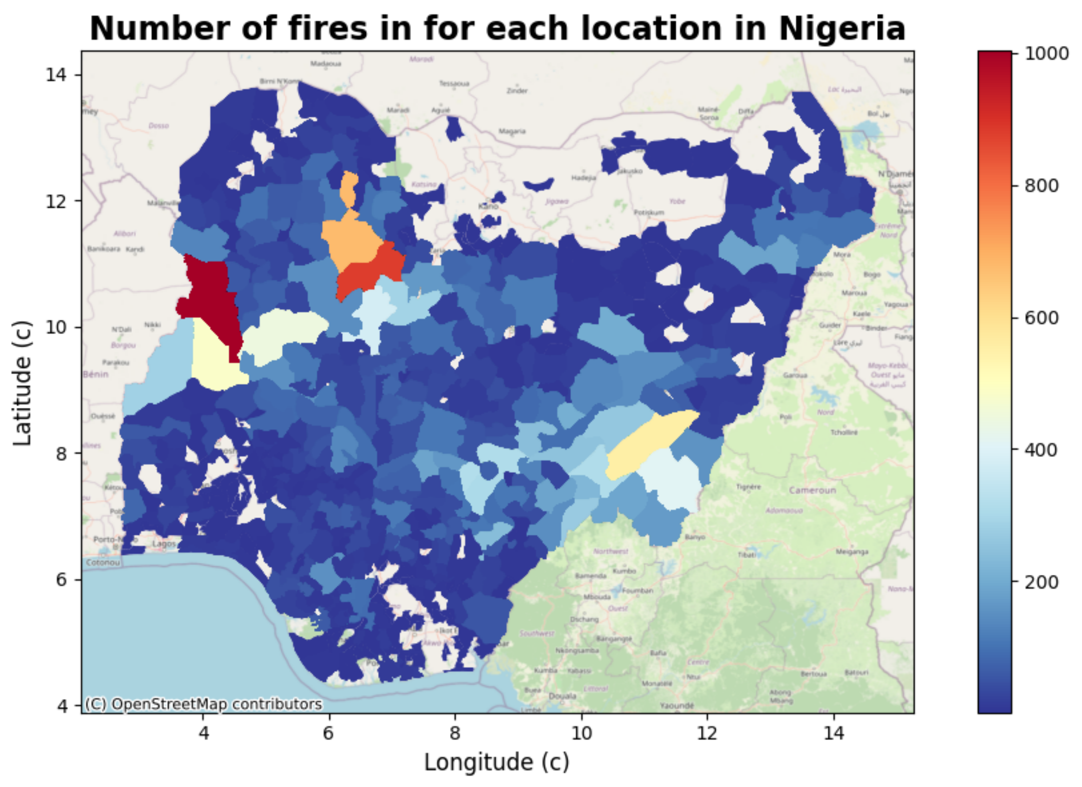
1.10 Create a map displaying the number of fires for each local government area.

[22]:
```python
nigeria_local.shape[0]
fire_local=gpd.sjoin(nigeria_local,fire_geo.set_crs(nigeria_local.crs))
y = fire_local['LGA'].value_counts(ascending=True)
fire_local_geom_lga= fire_local[["LGA", "geometry"]]

nb_fire_lga= y.to_frame("nfire").reset_index()
nb_fire_lga=nb_fire_lga.rename(columns={"index":"LGA"})
fire_loc_nb=fire_local_geom_lga.merge(nb_fire_lga, on="LGA")
```

We first pick the the fire occured only in nigeria. We then select the column LGA abd "geometry" from the geodatframe to facilitate the operation. We transform the variable containing the number of fire of each region(calculated above) to a data frame and rename the name of the column containing the cities to "LGA".

At this step, both the data of fire in Nigeria and the data number of fire of each region contains the column "LGA". We then merge them using based on that column.

[23]:
```python
fig, ax=plt.subplots(figsize=(10,6))
fire_loc_nb.plot(column="nfire", legend=True, cmap="RdYlBu_r",ax=ax)
ax.set_title(label="Number of fires in for each location in Nigeria",␣
 ↪size=17, weight="bold")
ax.set_xlabel(xlabel="Longitude (c)", size=12)
ax.set_ylabel(ylabel="Latitude (c)", size=12)
contextily.add_basemap(ax, crs=nigeria.crs,
    source=contextily.providers.OpenStreetMap.Mapnik)

plt.tight_layout()
plt.show()
```


Number of fires in for each location in Nigeria
Latitude (c)
Longitude (c)
(C) OpenStreetMap contributors
14
12
10
8
6
4
4
6
8
10
12
14
1000
800
600
400
200

The figure shows the number of fires in each location of Nigeria. We can see the Norht West part of Nigeria has the highest value.

1.11 Investigation of Spatial Correlation

The spatial correlation can be to investigate whether or not spatial objects with similar values are clustered, randomly distributed or dispersed. Statistics relies on observations being independent from one another. If autocorrelation exists in a time or space, then this violates the fact that observations are independent from one another. On the other hand, it also implies that there could be something interesting regarding die data distribution, which may be interesting to investigate.

For this study, we will be used the local correlation. The local correlation enables us to detect Hot Spots, Cold Spots, and Spatial Outliers. These types of local spatial autocorrelation describe similarities or dissimilarities between a specific polygon with its neighboring polygons. The upper left quadrant for example indicates that polygons with low values are surrounded by polygons with high values. The lower right quadrant shows polygons with high values surrounded by neighbors with low values. This indicates an association of dissimilar values.

[24]:
```
dfsjoin = gpd.sjoin(nigeria_local,fire_geo.set_crs(nigeria_local.crs))
dfsjoin
y = dfsjoin['LGA'].value_counts(ascending=True)
lga_index = nigeria_local.set_index('LGA')
lga_count  = dfsjoin.groupby(by='LGA')[["LGA"]].count()
lga_count.rename(columns={'LGA':'nfires'},inplace=True)
```

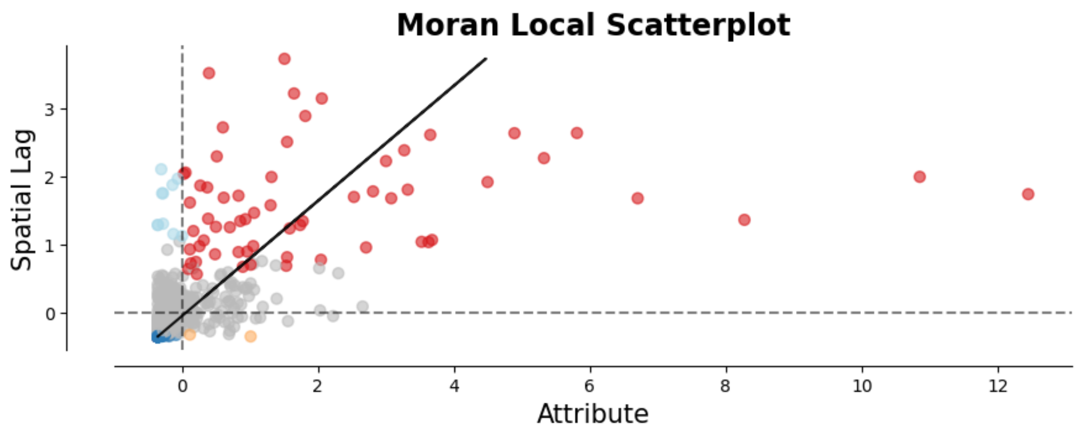
```
lga_merge = lga_index.merge(lga_count,how='left', left_index=True,␣
↪right_index=True)
lga_merge = lga_merge.fillna(0.0)
```

[25]:
```
import libpysal as lps
from spreg import OLS
from scipy.linalg import inv
from splot.libpysal import plot_spatial_weights
import mapclassify as mc
from esda.moran import Moran, Moran_Local
from splot.esda import moran_scatterplot
```

[26]:
```
wq=lps.weights.Queen.from_dataframe(lga_merge, geom_col="geometry")
wq.transform = 'r'
my_v=fire_loc_nb["nfire"]
```

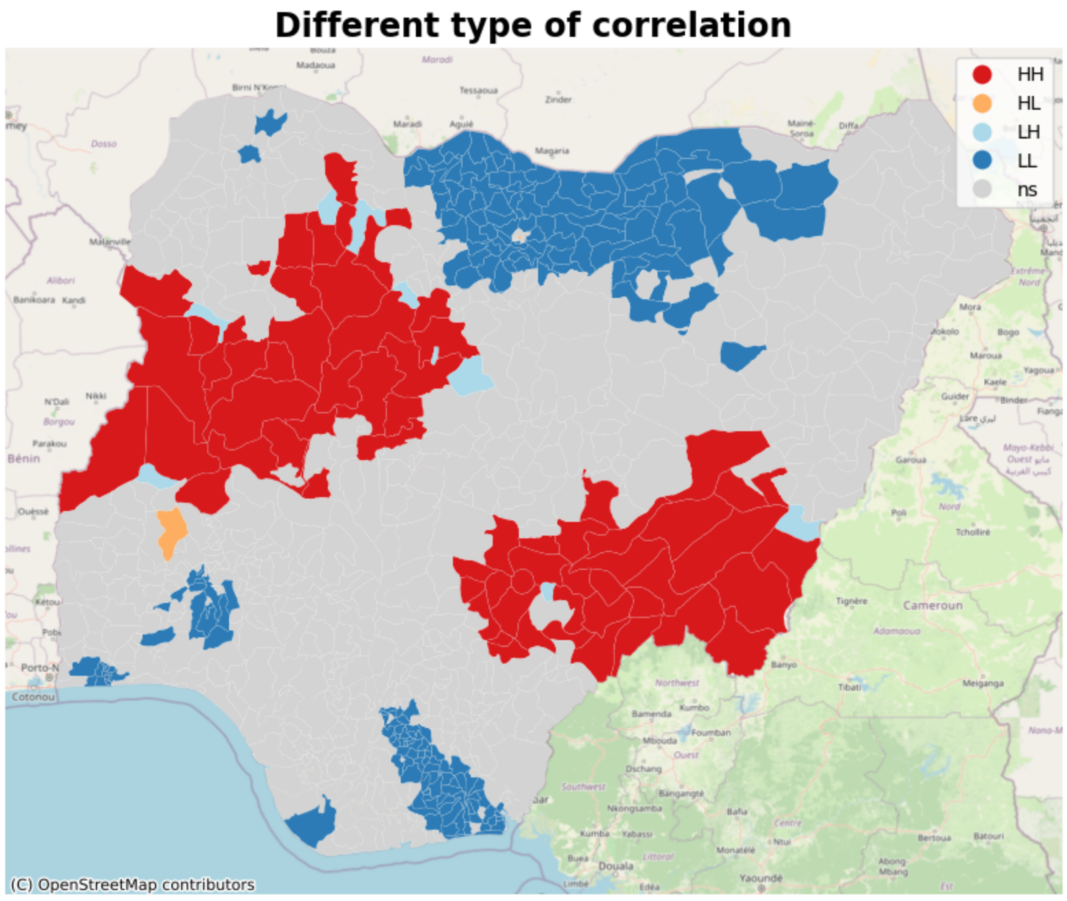
Correlation

[27]:
```
fig, ax=plt.subplots(figsize=(10,8))
moran_loc = Moran_Local(lga_merge.nfires, wq)
moran_scatterplot(moran_loc, p=0.05, ax=ax)
ax.set_ylabel('Spatial Lag', size=15)
ax.set_xlabel('Attribute', size=15)
ax.set_title("Moran Local Scatterplot", size=17, weight="bold")
plt.show()
```



These types of local spatial autocorrelation describe similarities or dissimilarities between a specific polygon with its neighboring polygons. The upper left quadrant for example indicates that polygons with low values are surrounded by polygons with high values (LH). The lower right quadrant shows polygons with high values surrounded by neighbors with low values (HL). This indicates an association of dissimilar values. The next figure will give more detail.

[28]:
```
from splot.esda import lisa_cluster
## We can see which polygon care similar in term of the value of the variable␣
↪chosen.
## High High, Low Low,...
fig, ax=plt.subplots(figsize=(12,8))
lisa_cluster(moran_loc, lga_merge, p=0.05, ax=ax)
contextily.add_basemap(ax, crs=nigeria.crs,
    source=contextily.providers.OpenStreetMap.Mapnik)

ax.set_title("Different type of correlation", size=17, weight="bold")
plt.show()
```



The blue color in the figure shows the area with low values surrounded by area with high number of fires(LH). These regions are located in the noth and south par of the country. The red color is the area high surrouned with neighbor with high value of number of fire. The LL stands for the area with low value of number of fire surrouned by area with low value of number of fire.
We can see the center part of the country which are not significant.

2 Exercise 2

2.1 Choice of spatial interpolation technique to create continuous elevation raster

Spatial interpolation is a technique exploring values of samples at known geographical locations (points, areas units) to estimate values at further, unknown geographical locations (points, area units). There are many interpolation tools available, but these tools can usually be grouped into two categories:

- deterministic: using mathematical functions, based on either the extent of similarity (IDW) or the degree of smoothing (RBF)
- geostatistical: use both mathematical and statistical methods to predict values at all locations within region of interest and to provide probabilistic estimates of the quality of the interpolation based on the spatial autocorrelation among data points

For this exercise, we will be used a geostistical method to interpolate. The method is spline interpolation.

In mathematics, a spline is a special function defined piecewise by polynomials. In interpolating problems, spline interpolation is often preferred to polynomial interpolation because it yields similar results, even when using low degree polynomials, while avoiding Runge's phenomenon for higher degrees.[7]

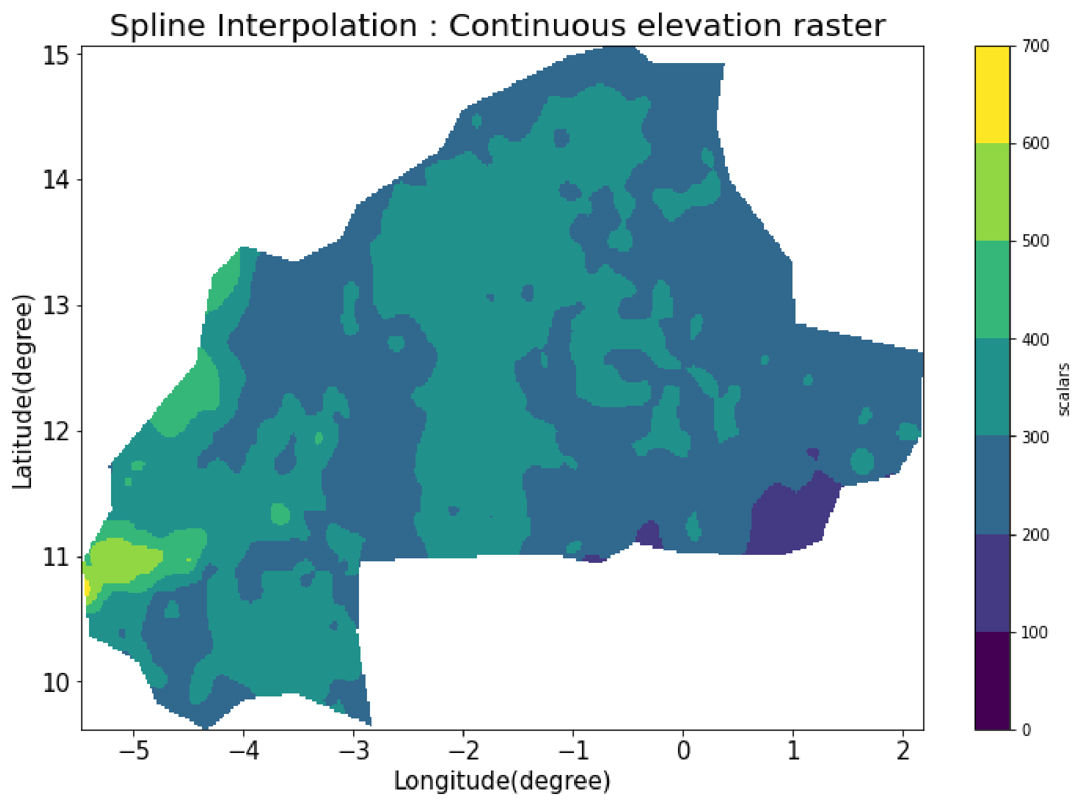
This method is best suited for generating smoothly changing surfaces susch as the elevation (the case of this study).

[29]:
```
import geopandas as gpd
import pandas as pd
import numpy as np
import pandas as pd
import cartopy.crs as ccrs
import verde as vd
import cartopy
import matplotlib.pyplot as plt
import rioxarray
import rasterio
import matplotlib.pyplot as plt
from rasterio.plot import show
from shapely.geometry import mapping
import json
import earthpy as et
import earthpy.plot as ep
import earthpy.spatial as es
import cartopy as cp
import seaborn as sns
import xarray
```

[30]:
```
eleve=gpd.read_file("../../SDA_Project_Files/Burkina/bfa_elevation.shp")
world = gpd.read_file(
    gpd.datasets.get_path('naturalearth_lowres')
)
region=world[world.name=="Burkina Faso"]

eleve=eleve.to_crs("epsg:4326")
```

[31]:
```
coordinates = (eleve.geometry.x.values, eleve.geometry.y.values)
spline = vd.Spline().fit(coordinates, eleve.SRTM30mBur)
grid_spline = spline.grid(spacing=0.02, dims=["latitude", "longitude"])
grid_spline=grid_spline.rio.write_crs(region.crs)
spline_cliped=grid_spline.rio.clip(region.geometry.apply(mapping), region.crs)
```

[32]:
```
fig, ax=plt.subplots(figsize=(12,8))
spline_cliped.scalars.plot(ax=ax)
ax.set_title("Spline Interpolation : The Shuttle Radar Topography Mission␣
 ↪(SRTM30mBur)", size=15)
plt.show()
```



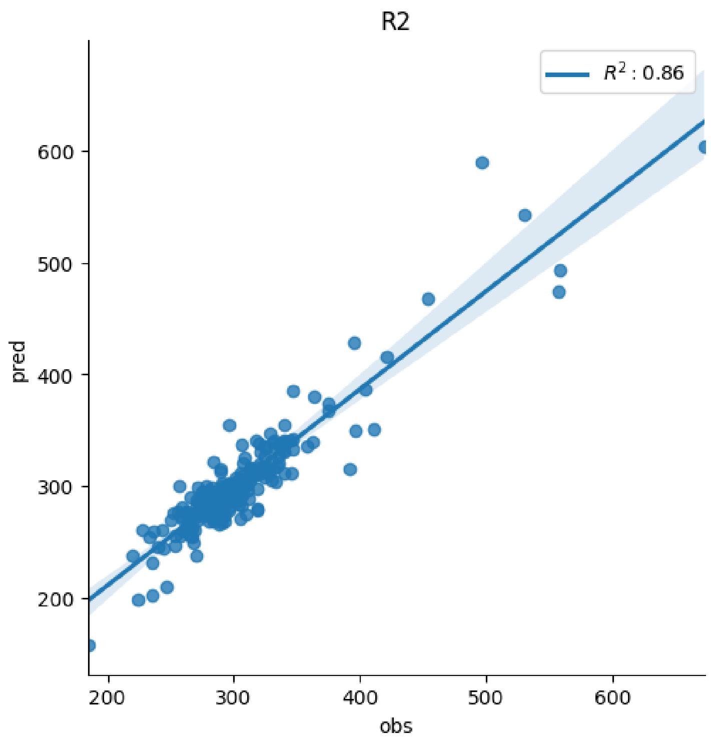
- The reason of the choice of spline interpolation

The spline method is geostatiscal method of interpolation. It works like the trend surface. It is similare to a rubber dis passing through the points, which is bent while the overall curvature of the surface is minimized. This method works with the data we have.

Then, the accuracy of the output of the spline mehtod is also very important. Let's compute the R^2 function.

[33]:
```
train, test = vd.train_test_split(
    coordinates, eleve.SRTM30mBur, test_size=0.2, random_state=0,
)

spline = vd.Spline().fit(*train)

test_values = np.array(list(test[1]))
prediction = spline.predict(test[0])

df = pd.DataFrame({'obs':test_values[0], 'pred':prediction})
correlation_matrix = np.corrcoef(test_values[0], prediction)
correlation_xy = correlation_matrix[0,1]
r_squared = correlation_xy**2
```

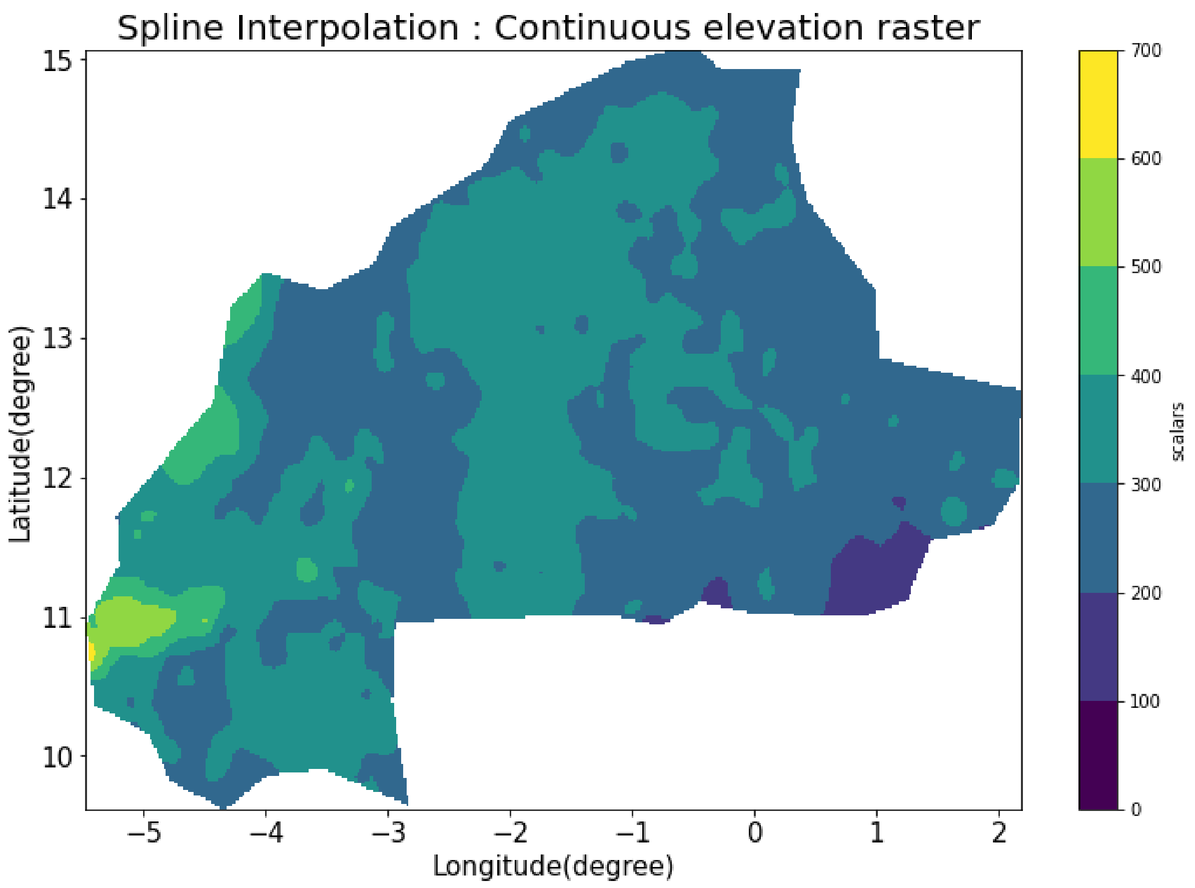
[34]:
```
p = sns.lmplot(x='obs',y='pred',data=df,
        line_kws={'label':"Linear Reg"}, legend=True)

ax = p.axes[0, 0]
ax.legend()
leg = ax.get_legend()
L_labels = leg.get_texts()
label_line_2 = r'$R^2:{0:.2f}$'.format(r_squared)
L_labels[0].set_text(label_line_2)
ax.set_title("R2")
plt.savefig("raster/r2", format="svg")
plt.show()
```

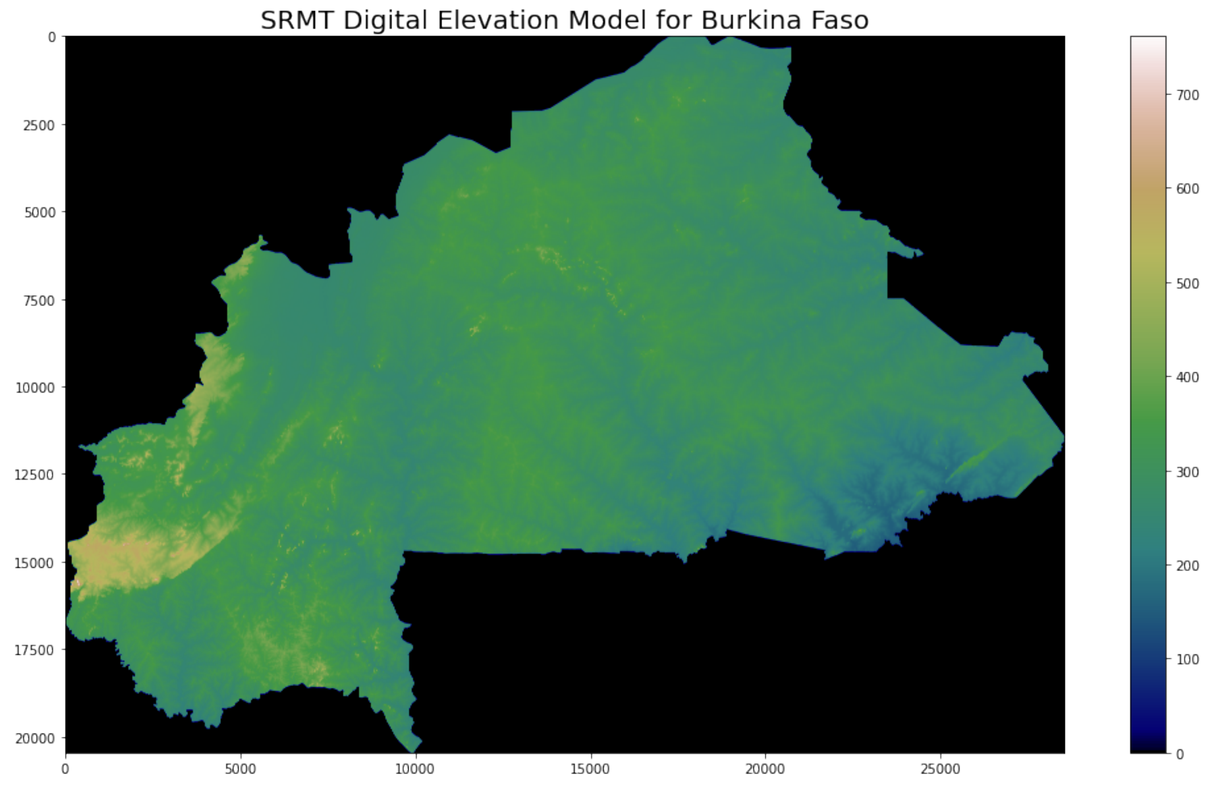


We can seee the value of R^2 is 0.86. This means the output is accurate at 86%.

2.2 Comparison of the created continuous elevation raster with the SRMT Digital Elevation Model for Burkina Faso.

[7]:
```
my_raster=rasterio.open("../../SDA_Project_Files/Burkina/bfa_srtm.tif")
f, ax=plt.subplots(1,2, figsize=(16,6), gridspec_kw=dict(width_ratios=(7,10)))
#cbar = plt.colorbar()
spline_cliped.scalars.plot(ax=ax[0])
ax[0].set_title(label="Spline Interpolation : Continuous elevation raster",␣
  ↪size=17)
im=ax[1].imshow(my_raster.read(1))
ax[1].set_title(label="SRMT Digital Elevation Model for Burkina Faso",␣
  ↪size=17)
plt.colorbar(im)
plt.show()
```





We can see from the two plots that the values are similar. But even they are similar, we can notice some differences between the rasters object. The Shuttle Radar Topography Mission (SRTM) digital elevation dataset was originally produced to provide consistent, high-quality

elevation data at near global scope.[9]
In fact, interpolation continuous value are in the range of 0 and 700 of SRTM30mBur. Wheras, the value of the SRTMT Digital Elevation Model are out of the range 0 and 700. Also we can notice the higher quality of the raster from the SRMT Digital Model.

References

[1] https://rspatial.org/raster/analysis/

[2] https://mgimond.github.io/Spatial/introGIS.html

[3] https://mgimond.github.io/Spatial/introGIS.html

[4] https://github.com/WZBSocialScienceCenter/geovoronoi

[5] https://github.com/rosskush/skspatial

[6] https://github.com/fatiando/verde

[7] https://wikipedia.org/wiki/Spline_interpolation

[8] Spatial Autocorrelation and Statistical Tests: Some Solutions, https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwi_-6O79enwAhVZShUIHYO4DC4QFjAAegQIAhAD&url=https%3A%2F%2Fwww.jstor.org%2Fstable%2F20696567&usg=AOvVaw0oJPUCAXSuwaNUccih85Q-

[9] https://developers.google.com/earth-engine/datasets/catalog/CGIAR_SRTM90_V4