Visualizing Geospatial Data Using Geopandas Library

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1. Introduction

Geospatial Visualization Technique

Geospatial word comes from a combination of 'Geo' and 'Spatial' which could refers to geographic space. This space could be points or shapes which could represent cities, towns, generic locations, countries etc. Geospatial visualization can help make sense of positional data in space-time dimension. One can use this geospatial data in improving machine learning model with space data being incorporated into the model. One can use this geo-location data in predicting natural disasters in advance or improve agricultural activities based on climate pattern, terrain, or altitude. Policy maker can also use geospatial data in decision making regarding public policies. However, geospatial data can be a bit obscure without visualizing them only cartographic map that people are familiar with. Here, I want to guide you and get your hands wet on geospatial data manipulation, sources and visualization

Visualization Library

There are multiple geospatial visualization library in python including `Folium`, `Matplotlib`, `Rasterio`, `Geopandas` and many more, but the library to also work with the geometry or shape data of GIS format is `Geopandas`.

GIS data includes at least 4 parts, .SHP, .DBF, .PRJ, .SHX. .SHP file is a geometry of the features, .DBF database spreadsheet containing other data regarding features such as population, GDP etc., .SHX is the index file, and .PRJ is the projection and coordinate system the data uses. There are many public resources which you can download this type of files.

Why Geopandas is good for geospatial visualization?

- It works similar to normal `Pandas` Dataframe with addition of geometry column which contain geospatial information from the files mentioned above. This library can
- It can help pre-processing the GIS data into JSON which can be digest by other interactive visualization such as `Folium`
- Allows many geospatial operation such as merging data, splitting large geometry into smaller geometry, vice versa.
- Allows quick exploratory geospatial visualization with simple class function.

Difficulties with Geopandas

- Clash in library dependencies can occur during installation
- Cannot configure many chart features by itself, requires other library such as Matplotlib or Folium for more adjustments

Installation

Use the following command to install Geopandas using conda command

```
conda install -c conda-forge geopandas
```

Should there be any dependencies conflict, try the following installation after to manually includes required libraries

```
conda install pandas fiona shapely pyproj rtree
```

Or use pip to install via the following command

```
pip install geopandas
```

Then you should be able to import Geopandas Library into your code

2. Demonstration

Basic Geospatial Visualization

We will first need to import geopandas and if you have not already install the package, head back to the installation section

In [ ]:
```
import geopandas as gpd
import warnings
warnings.simplefilter("ignore")
```

For this basic demonstration of geospatial visualization, we will use Bangkok's districts shapefile which has already pre-downloaded into the folder using below

```
Geopandas.read_file(*arg,  **kwarg)
```

In [ ]:
```
# read shape file of Bangkok districts in this folder
gdf = gpd.read_file('Bangkok_shape/district.shp', encoding='TIS-620') # encoding 'TIS-620' is needed to read Thai characters in i
gdf.head(3)
```

Out[ ]:

	OBJECTID	AREA	dcode	dname	dname_e	pcode	no_female	pname	no_male	no_health	no_temple	no_commu	no_hos	no_sch
0	29	11804564.0	1025	เขต บางพลัด	Bang Phlat	10	53750	กรุงเทพมหานคร	46569	1	23	46	0	11
1	30	16319268.0	1017	เขต ห้วยขวาง	Huai Khwang	10	42026	กรุงเทพมหานคร	35694	2	3	25	0	3
2	31	17075578.0	1045	เขต วังทองหลาง	Wang Thong Lang	10	62158	กรุงเทพมหานคร	52925	0	1	19	0	3

From above `GeoDataFrame` we can see that there is this geometry column which contains the essential shape info for the visualization

In [ ]:
```
gdf.geometry.head()
```

Out[ ]:
```
0    POLYGON ((663924.794 1526162.057, 663895.856 1...
1    POLYGON ((671711.864 1526487.438, 671710.552 1...
2    POLYGON ((674358.118 1525633.939, 674369.430 1...
3    POLYGON ((650975.092 1526253.298, 651115.593 1...
4    POLYGON ((694058.076 1525667.706, 694060.576 1...
Name: geometry, dtype: geometry
```

One other important concept that we need to be aware of in geospatial referencing is CRS which stands for The Coordinate Reference System. This is important, as GeoDataFrame alone is just a coordinate in an arbitrary space. This CRS tells Geopandas how the data coordinates located on earth, according to difference referencing system.

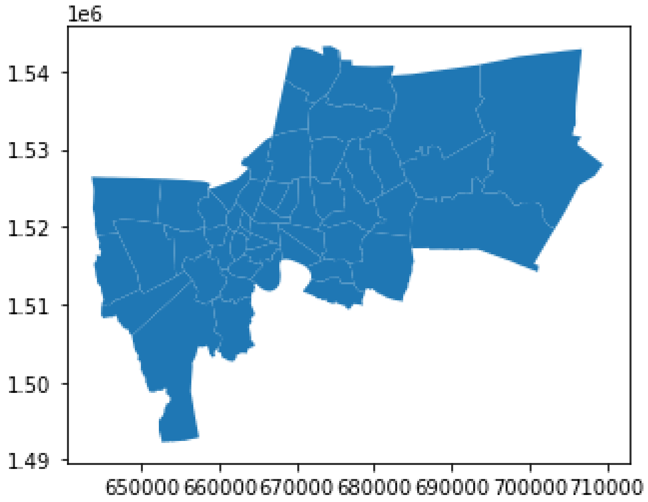
In [ ]:
```
gdf.crs
```

Out[ ]:
```
<Projected CRS: EPSG:32647>
Name: WGS 84 / UTM zone 47N
Axis Info [cartesian]:
- E[east]: Easting (metre)
- N[north]: Northing (metre)
Area of Use:
- name: World - N hemisphere - 96°E to 102°E - by country
- bounds: (96.0, 0.0, 102.0, 84.0)
Coordinate Operation:
- name: UTM zone 47N
- method: Transverse Mercator
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

Above shows that this Bangkok's district data rely on CRS: EPSG32647. This concept will be useful in the next section. Next we will plot our first geospatial plot using `plot()` method on GeoSeries or GeoDataFrame

In [ ]:
```
gdf.plot()
```

Out[ ]:
```
<AxesSubplot:>
```



Advance Choropleth Map Visualization

In this advance Geopandas visualization we will explore 24-hour fire data in Southeast Asia collected through NASA satellites which we can download from Fire Information for Resource Management System and Southeast Asia GIS file. Due to recent year, countries in Southeast Asia has been suffering from small air particles (PM2.5 and PM10) which is hazardous, we want to visualize active fire in the region to see where we should aim our effort in curbing the issue.

In [ ]:
```
import geopandas as gpd
```

Download all the files in the package

In [ ]:
```
fire_data_modis = gpd.read_file('MODIS_C6_1_SouthEast_Asia_24h/MODIS_C6_1_SouthEast_Asia_24h.shp')
fire_data_suomi = gpd.read_file('SUOMI_VIIRS_C2_SouthEast_Asia_24h/SUOMI_VIIRS_C2_SouthEast_Asia_24h.shp')
fire_data_j1 = gpd.read_file('J1_VIIRS_C2_SouthEast_Asia_24h/J1_VIIRS_C2_SouthEast_Asia_24h.shp')
sea_shape = gpd.read_file('Southeast_Asia/cntry_3m.shp') # Source from databasin.org
```

In [ ]:
```
fire_data_modis.sample(5) # initial look at what does the GeoDataFrame look like
```

Out[ ]:

	LATITUDE	LONGITUDE	BRIGHTNESS	SCAN	TRACK	ACQ_DATE	ACQ_TIME	SATELLITE	CONFIDENCE	VERSION	BRIGHT_T31	FRP	DAYNIGHT
1276	19.58138	94.50745	315.07	2.53	1.53	2022-03-20	0345	T	28	6.1NRT	297.74	28.65	D
1826	20.28148	100.58868	318.70	1.49	1.20	2022-03-20	0659	A	69	6.1NRT	298.34	16.74	D
3171	25.26454	93.12051	324.37	1.08	1.04	2022-03-20	0701	A	49	6.1NRT	303.57	11.76	D
46	24.96776	117.95325	307.41	1.35	1.15	2022-03-19	0300	T	54	6.1NRT	297.28	6.38	D
1319	12.43535	121.29708	330.85	1.05	1.02	2022-03-20	0518	A	83	6.1NRT	298.34	22.97	D

In [ ]:

```
fire_data_modis.crs
```

Out[ ]:

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

Above we can see that the active fire data is in point coordinates, as indicated in column `geometry`, which is expected since the satellite collect coordinates of fire data. Then we want to take a look at the Southeast Asia GIS GeoDataFrame.

In [ ]:

```
sea_shape.sample(5) # shape file for Southeast Asia
```

Out[ ]:

	AREA	PERIMETER	CTRY3M_	CTRY3M_ID	COUNTRY	CNTRY_NAME	REGION	CONTINENT	LAND_OCEAN	geometry
261	0.000	0.089	5798	4756	CH	China	Eastern Asia	Asia	Island	POLYGON ((13538390.562 3295418.530, 13538148.5...
2201	0.000	0.079	9045	6863	RP	Philippines	Southeastern Asia	Asia	Island	POLYGON ((13534716.489 738673.452, 13533913.05...
1382	0.000	0.024	7936	11776	RP	Philippines	Southeastern Asia	Asia	Island	POLYGON ((13435487.637 1255425.321, 13435054.4...
2074	0.001	0.113	8894	6728	TH	Thailand	Southeastern Asia	Asia	Island	POLYGON ((11054701.819 823594.610, 11055695.50...
188	0.000	0.096	5623	4586	JA	Japan	Eastern Asia	Asia	Island	POLYGON ((14518129.816 3607954.338, 14518934.9...

We can see that the GeoDataFrame actually contain other region nearby such as Oceanea and Australia. We can filter out only the `REGION` that we want as we would filter DataFrame. Another point to notice in this GeoDataFrame is that country such as the Philippines may have more than one geometry. That is because there are a lot of islands in the country. This is also true for many other countries as well. Geopandas provides a simple method call `dissolve()` to collapes multiple polygon shape based on a grouping column.

In [ ]:
```
sea_shape = sea_shape.dissolve('CNTRY_NAME') #collapse multiple polygon together based on `CNTRY_NAME`, this multiple polygon may
```

Here in this next step, I filter the GeoDataFrame to only show Southeast Asia region and you will also notice that I use method `to_crs()` to convert the CRS of the GeoDataFrame to EPSG4326 to be the same as that of the fire GeoDataFrame.

In [ ]:
```
sea = sea_shape[sea_shape['REGION'] == 'Southeastern Asia'].to_crs(epsg=4326).reset_index()
```

In [ ]:
```
sea.head()
```

Out[ ]:

	CNTRY_NAME	geometry	AREA	PERIMETER	CTRY3M_	CTRY3M_ID	COUNTRY	REGION	CONTINENT	LAND_OCEAN
0	Brunei	MULTIPOLYGON (((115.01843 4.89579, 115.01250 4...	0.363	3.627	9380	6972	BX	Southeastern Asia	Asia	Island
1	Burma	MULTIPOLYGON (((97.97078 9.62723, 97.97276 9.6...	57.580	90.616	5792	10984	BM	Southeastern Asia	Asia	Continent
2	Cambodia	MULTIPOLYGON (((102.91138 9.90555, 102.90721 9...	15.115	25.704	7173	11291	CB	Southeastern Asia	Asia	Continent
3	Indonesia	MULTIPOLYGON (((122.87543 -10.99916, 122.86665...	0.011	0.581	9199	6921	ID	Southeastern Asia	Asia	Island
4	Laos	POLYGON ((101.14824 21.57264, 101.14993 21.570...	19.677	42.783	6365	11079	LA	Southeastern Asia	Asia	Continent

Now that we have clean Southeast Asia polygon shape file, we want to take know which fire data coordinates belongs to which country. This may seem near impossible, but with GeoDataFrame, these coordinates can be map onto the shapefile via merging with `sjoin()` method, short for Spatial Join.

In [ ]:

```
fire_country = gpd.sjoin(fire_data_suomi, sea, how='left') # how='left' indicating that we want to keep the geometry of the left
fire_country.head()
```

Out[ ]:

	LATITUDE	LONGITUDE	BRIGHT_TI4	SCAN	TRACK	ACQ_DATE	ACQ_TIME	SATELLITE	CONFIDENCE	VERSION	...	index_right	CNTRY_NAME	ARE
0	-5.92812	151.00734	331.31	0.62	0.71	2022-03-19	0236	N	nominal	2.0NRT	...	NaN	NaN	Na
1	-5.93187	151.00490	331.20	0.62	0.71	2022-03-19	0236	N	nominal	2.0NRT	...	NaN	NaN	Na
2	-5.79133	150.91014	325.10	0.63	0.72	2022-03-19	0236	N	nominal	2.0NRT	...	NaN	NaN	Na
3	-4.38546	153.06689	328.80	0.43	0.62	2022-03-19	0236	N	nominal	2.0NRT	...	NaN	NaN	Na
4	-0.88132	133.21754	347.29	0.50	0.41	2022-03-19	0417	N	nominal	2.0NRT	...	3.0	Indonesia	0.0

5 rows × 24 columns

Now, we have multiple fire GeoDataFrame map onto country and region. We then dissolve this GeoDataFrame based on `CNTRY_NAME` as before.

In [ ]:
```
fire_density = fire_country[['CNTRY_NAME', 'BRIGHT_TI4', 'geometry']].dissolve('CNTRY_NAME', aggfunc=['count','mean']) #dissolve
fire_density.rename(columns={('BRIGHT_TI4', 'count'):'fire_count', ('BRIGHT_TI4', 'mean'):'brightness_avg' }, inplace=True)
```

In [ ]:
```
fire_density
```

Out[ ]:

CNTRY_NAME	geometry	fire_count	brightness_avg
Burma	MULTIPOINT (92.30754 21.10724, 92.30966 21.199...	5015	337.464913
Cambodia	MULTIPOINT (102.81477 13.78349, 102.81548 13.7...	132	337.557045
Indonesia	MULTIPOINT (99.48875 1.28786, 99.48997 1.29118...	112	334.342500
Laos	MULTIPOINT (100.24541 20.72566, 100.37011 20.7...	773	338.649715
Malaysia	MULTIPOINT (101.60513 2.82193, 102.35706 3.945...	7	318.010000
Philippines	MULTIPOINT (117.93797 9.07269, 117.98032 9.060...	77	333.808831
Thailand	MULTIPOINT (97.61864 18.34098, 97.61930 18.335...	256	325.310977
Vietnam	MULTIPOINT (102.38753 22.32460, 102.39021 22.3...	566	337.123180

With fire GeoDataFrame of points collapsed based on country, now the geometry is a `MULTIPOINT`. However, to plot the chart onto a map, we need polygon geometry of country, hence, we `sjoin()` the geometry back in again.

In [ ]:
```
fire_density_plot = gpd.sjoin(fire_density, sea, how='right').dropna()
```

In [ ]:
```
fire_density_plot
```

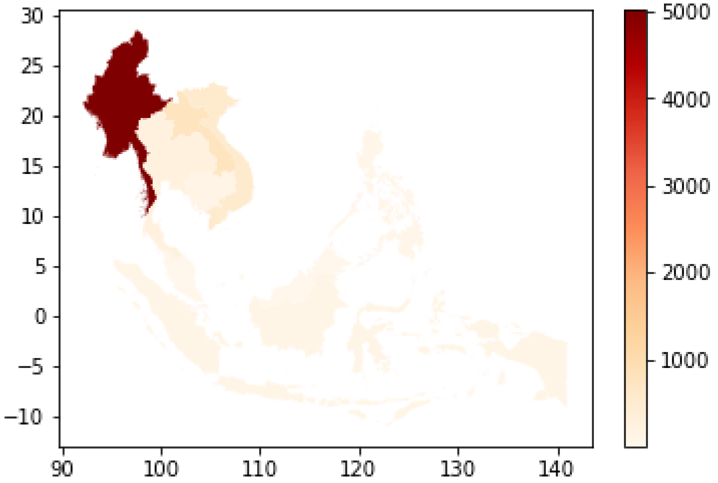
Out[ ]:

	index_left	fire_count	brightness_avg	CNTRY_NAME	geometry	AREA	PERIMETER	CTRY3M_	CTRY3M_ID	COUNTRY	REGION	CONTIN
1	Burma	5015.0	337.464913	Burma	MULTIPOLYGON (((97.97078 9.62723, 97.97276 9.6...	57.580	90.616	5792	10984	BM	Southeastern Asia	
2	Cambodia	132.0	337.557045	Cambodia	MULTIPOLYGON (((102.91138 9.90555, 102.90721 9...	15.115	25.704	7173	11291	CB	Southeastern Asia	
3	Indonesia	112.0	334.342500	Indonesia	MULTIPOLYGON (((122.87543 -10.99916, 122.86665...	0.011	0.581	9199	6921	ID	Southeastern Asia	
4	Laos	773.0	338.649715	Laos	POLYGON ((101.14824 21.57264, 101.14993 21.570...	19.677	42.783	6365	11079	LA	Southeastern Asia	
5	Malaysia	7.0	318.010000	Malaysia	MULTIPOLYGON (((100.53688 3.98749, 100.53609 3...	0.000	0.022	8849	6686	MY	Southeastern Asia	
7	Philippines	77.0	333.808831	Philippines	MULTIPOLYGON (((119.27054 4.50056, 119.26639 4...	0.000	0.042	6616	5273	RP	Southeastern Asia	
10	Thailand	256.0	325.310977	Thailand	MULTIPOLYGON (((100.79854 12.71930, 100.80498 ...	43.032	72.237	6703	11286	TH	Southeastern Asia	
11	Vietnam	566.0	337.123180	Vietnam	MULTIPOLYGON (((104.83992 8.42555, 104.83998 8...	27.474	80.153	6269	10997	VM	Southeastern Asia	

From this GeoDataFrame, we can try to plot choropleth map showing the density of fire count in the region.

In [ ]:
```
fire_density_plot.plot(column='fire_count', cmap='OrRd', legend=True) # default bin scheme
```

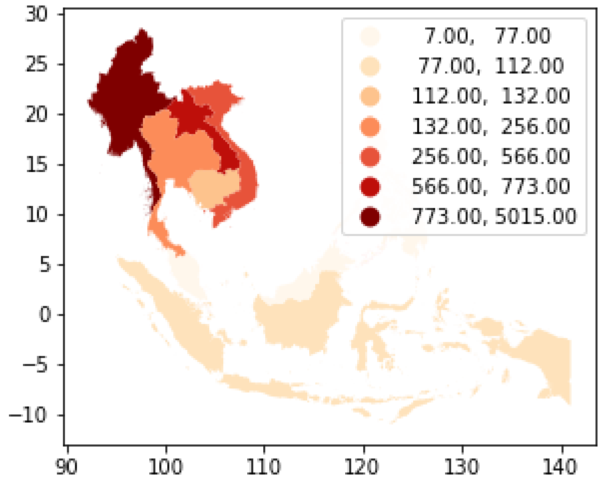
Out[ ]: <AxesSubplot:>



The map color is hard to discern since large number of count is in Myanmar, top left while the rest of the count are below 1,000. We adjust this by adding scheme for binning of the data using `scheme='quantiles', k=7`

In [ ]:
```
fire_density_plot.plot(column='fire_count',scheme='quantiles', k=7, cmap='OrRd', legend=True)
```

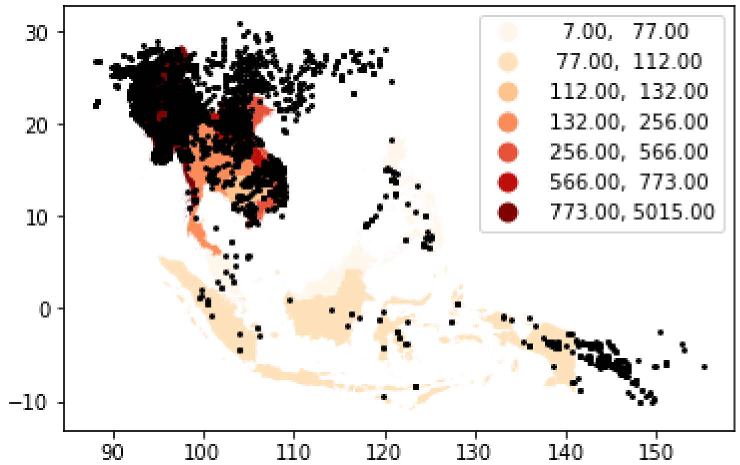
Out[ ]: <AxesSubplot:>



We can also layer points onto the map as below using `ax=` argument

In [ ]:
```
# layering data on top of map
base = fire_density_plot.plot(column='fire_count',scheme='quantiles', k=7, cmap='OrRd', legend=True)
fire_data_suomi.plot(ax=base, marker='x', color='black', markersize=4)
```

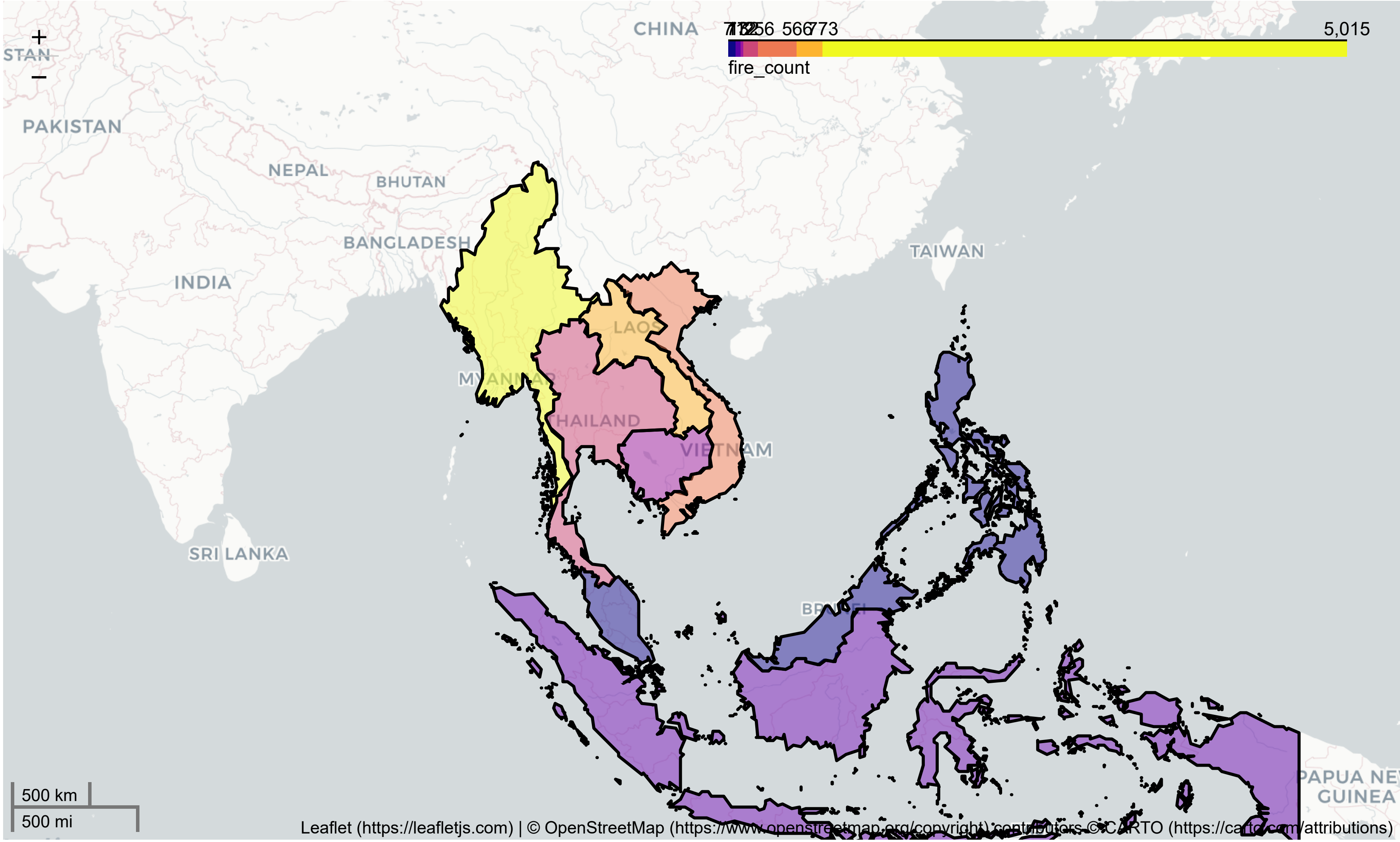
Out[ ]: <AxesSubplot:>



We can also create a simple exploratory interactive choropleth map with `Geopandas.GeoDataFrame.explore()`

In [ ]:
```
# create interactive plot using geopandas.GeoDataFrame.explore
fire_density_plot[['index_left', 'geometry', 'fire_count', 'brightness_avg']].explore(column='fire_count', # make choropleth base
     scheme='quantiles', k=7,
     tooltip="index_left", # show value in tooltip (on hover)
     highlight=True,
     popup=True, # show all values in popup (on click)
     tiles="CartoDB positron",
     cmap='plasma', # use matplotlib colormap
     style_kwds=dict(color="black") # use black outline
)
```

Out[ ]:



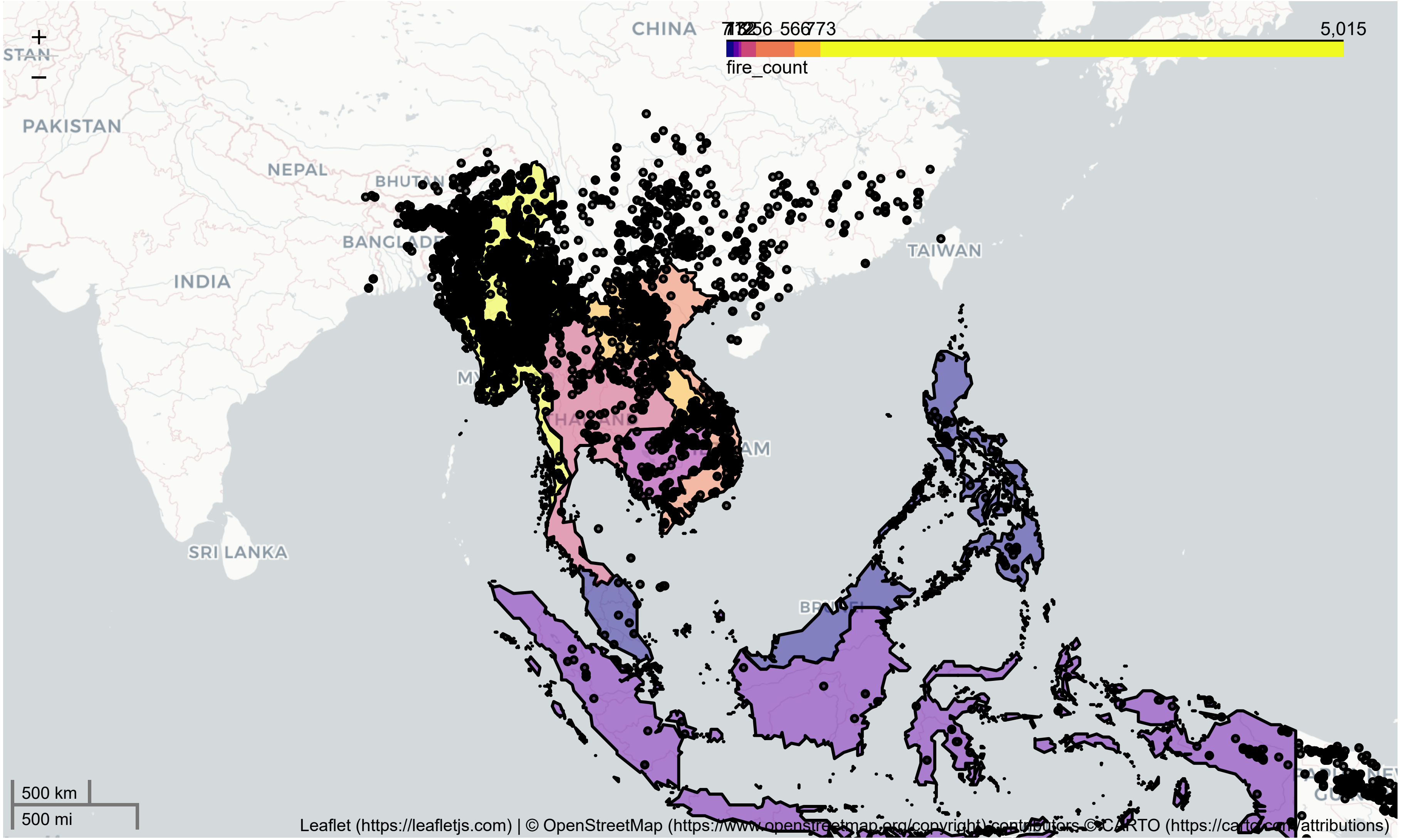
Similar to `Geopandas.GeoDataFrame.plot()`, we can layer with `explore()` method using `m=` argument

In [ ]:

```
# add layer to interactivity
map = fire_density_plot[['index_left', 'geometry', 'fire_count', 'brightness_avg']].explore(column='fire_count', # make choroplet
     scheme='quantiles', k=7,
     tooltip="index_left", # show value in tooltip (on hover)
     highlight=True,
     popup=True, # show all values in popup (on click)
```

```
    tiles="CartoDB positron",
    cmap='plasma', # use matplotlib colormap
    style_kwds=dict(color="black") # use black outline
)
fire_data_suomi.explore(m=map, color='black')
```

Out[ ]:



3. Resources

1. https://geopandas.org/en/stable/index.html
2. https://firms.modaps.eosdis.nasa.gov/active_fire/#firms-shapefile
3. https://towardsdatascience.com/geopandas-hands-on-building-geospatial-machine-learning-pipeline-9ea8ae276a15
4. https://towardsdatascience.com/interactive-geographical-maps-with-geopandas-4586a9d7cc10
5. https://geographicdata.science/book/intro.html#
6. https://databasin.org/datasets/59c48c37d74e4a2db4dbc6997c8eba3b/
7. http://www.bangkokgis.com/modules.php?m=download_shapefile