Geospatial Data Visualization Using python

January 1, 2022

1 Geospatial Data in Python: Software Preparation, Data Reading, and Displaying

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In this tutorial. I will layout necessary process to downoad the latest verion of `python`, package distribution system `anaconda`, install some extra packages and read `shapefile` data.

First let's begin by installing Python, I hope you already know how to install it.

1.1 Install Python

To install python visit Python Website and click on download. In this tutorial I am using Microsoft's Windows 10 Operating system. Therefore,This tutorial specifically focuses on Windows. Once you find the version of python you wish to install, simply click on it and wait until the download gets completed. When the download complets simply run the execution file and follow along with the subsequent pop-up windows.

When installation gets completed, you can check version of your python installed on your machine by opening `command prompt` (ctrl+Run, and type cmd). On the command prompt type

```
py --version
```

This will give you the inforamtion on current version of python installed on your machine.

1.2 Install Anaconda

To manages python packages I usually use `*conda*` distirbution than `*pip*`. When conda fails then I turned to pip. You can find more information on `conda` and `pip` in this Stack Overflow discussion

To download the `Anaconda` distribution, visit Anaconda website. Hover over **Products** tab and select **Individual Edition**. Hit the download button to begin the download process. Once the download gets completed install the software accepting all defaults. After anaconda installation, go to start icon of your machine, and find `Anaconda prompt` if required open it as an administrator.

First, lets update `conda` on your anaconda prompt type following:

1) `conda update conda`
2) `conda update --all`
3) `conda list` # this lists the packages installed, check pandas and matplotlib

To use the `geospatial` data we need **geopandas**, and **shapely** packages. Lets install `geopandas` which should also install `shapely` packages as a dependency.

conda install geopandas or conda install -c conda-forge geopandas

Basically, to install any packages you can type **conda install** `<Package name>`

You can find more infomation on **geopandas** , and **Shapely**

1.3 Load Library

[52]:
```
import shapely                                  # load shapely package
import matplotlib as plt                        # load matplotlib as plt
import geopandas as gpd                         # load geopandas as gpd
import os                                       # operating system
from IPython.display import Markdown as md      # markdown in cells
import geoplot as gplt
from matplotlib import pyplot as pplot
```

1.4 Read Geospatial Data

Geopandas library contains geospatial dataset e.g., `naturalearth_lowers`, which contains the geometry of each country in the world along with other attribute information. Usually, we have our own data and want to read it directly from our directory. Lets read the data from direcotry of my machine, you can change the path of your data depending on path of your data

If you have a file containing both data and geometry (e.g. GeoPackage, Shapefile), you can read it using `geopandas.read_file()`, which automatically detects the filetype and creates a `GeoDataFrame`. I have my `point shapefile` on my computer's directory. Lets read it first.

[53]:
```
pdata = gpd.read_file("./Data/c1s1.shp") #./ starts looking at file from␣
 ↪current working directory
```

[54]:
```
os.getcwd()
```

[54]:
```
'D:\\IntroSpatialData'
```

c1s1.shp data is threfore located in the **Data** folder which is nested within the **IntroSpatialData** folder

[55]:
```
# Print pdata
pdata.head(6)
```

[55]:

	sn	Tree_numbe	lat	lon	treeid	species	dbh	height	\
0	1.0	142.0	3068940.39	691125.84	1.0	Pyar	30.0	15.0	
1	2.0	145.0	3068946.55	691109.18	2.0	Sal	39.0	16.0	
2	3.0	141.0	3068938.55	691129.03	3.0	Sal	48.0	16.0	
3	4.0	144.0	3068945.74	691114.22	4.0	Sal	38.0	15.0	
4	5.0	143.0	3068943.58	691117.80	5.0	Sal	34.0	18.0	
5	6.0	146.0	3068950.75	691108.22	6.0	Sal	38.0	18.0	

```
   class remarks Compartmen                          geometry
0    2.0    None       C1S1  POINT (691125.840 3068940.390)
1    2.0    None       C1S1  POINT (691109.180 3068946.550)
2    2.0    None       C1S1  POINT (691129.030 3068938.550)
3    2.0    None       C1S1  POINT (691114.220 3068945.740)
4    1.0    None       C1S1  POINT (691117.800 3068943.580)
5    1.0    None       C1S1  POINT (691108.220 3068950.750)
```

Now, the returned information seems familiar, right? **Geopandas** essentially is an extentiono of **pandas** packages to handle geospatial data. For each observation there is an geometry information associated with it along with other fields and records. One of the important information associated with geospatial data is "Coordinate Reference System" or `CRS`. Lets look find out

[56]:
```
# print coordinate system of point data
pdata.crs
```

[56]:
```
<Projected CRS: EPSG:32644>
Name: WGS 84 / UTM zone 44N
Axis Info [cartesian]:
- E[east]: Easting (metre)
- N[north]: Northing (metre)
Area of Use:
- name: Between 78°E and 84°E, northern hemisphere between equator and 84°N,
onshore and offshore. China. India. Kazakhstan. Kyrgyzstan. Nepal. Russian
Federation. Sri Lanka.
- bounds: (78.0, 0.0, 84.0, 84.0)
Coordinate Operation:
- name: UTM zone 44N
- method: Transverse Mercator
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

Now, it is evident that the `pdata` is projected data with EPSG (European Petroleum Survey Group):32644 or Universal Transverse Mercator (UTM) zone 44N. `data.crs` function results three information about the data a) Name of projection system, b) area of projection system used /area of data's location, and 3) Datum of the tranformation.

What if this is not the correct projection sytem of the data. How do we change it? this is simple, we can invoke `data.to_crs` function to change projection information.

What if there was no coordinate system associated with the geographic data? you can try `data.set_crs` function to set your data. If you are familiar with ESRI's ArcGIS Desktop or ArcGIS Pro; `.set_crs`, and `.to_crs` are equivalent to `define projection`, and `project` function, respectively.

For the sake of practice lets change the coordinate system of data to UTM web mercator projection i.e., **(EPSG:3857)**

[57]:
```
pwmdata = pdata.to_crs("EPSG:3857")
```

print coordinate system of re-projected data **pwmdata**.

[58]:
```
pwmdata.crs   # check what has changed
```

[58]:
```
<Projected CRS: EPSG:3857>
Name: WGS 84 / Pseudo-Mercator
Axis Info [cartesian]:
- X[east]: Easting (metre)
- Y[north]: Northing (metre)
Area of Use:
- name: World between 85.06°S and 85.06°N.
- bounds: (-180.0, -85.06, 180.0, 85.06)
Coordinate Operation:
- name: Popular Visualisation Pseudo-Mercator
- method: Popular Visualisation Pseudo Mercator
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

1.5 Make Map

GeoPandas can also plot maps. To plot the active geometry, call `GeoDataFrame.plot()`. To color code by another field, pass in that column as the first argument. In the present dataset (point) I will plot the active geometry column and color code by the "species" column.

[59]:
```
#pwmdata.species.head()

#pwmdata.species = pwmdata.species.astype('category')

pwmdata.loc[:, 'species'] = pwmdata['species'].astype('category')
```

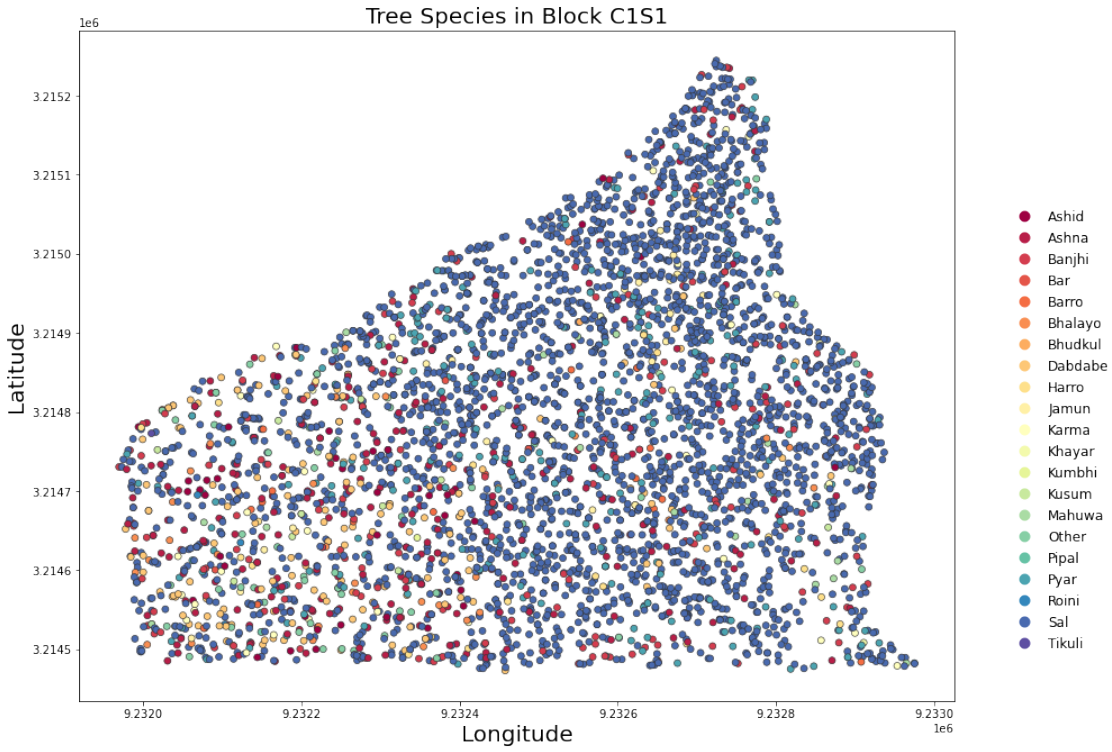
[60]:
```
from matplotlib import pyplot as plt

fig, ax = plt.subplots(1, figsize=(14,14))

pwmdata.plot(column='species', categorical=True,
             cmap='Spectral', linewidth=.6, edgecolor='0.2',
             legend=True,
             legend_kwds={'bbox_to_anchor':(1.05, 0.75),'fontsize':12,'frameon':
 ↪False}, ax=ax)
ax.set_xlabel("Longitude", fontsize = 20)

ax.set_ylabel("Latitude", fontsize = 20)
ax.set_title('Tree Species in Block C1S1',fontsize=20)
```

```
plt.tight_layout()
```



[ ]:

[61]:
```
#Install scale bar module
#conda install -c conda-forge matplotlib-scalebar
# layout
from matplotlib_scalebar.scalebar import ScaleBar
scale1 = ScaleBar(
dx=1, label='',
    location='lower left',  # in relation to the whole plot
    label_loc='left', scale_loc='bottom'  # in relation to the line
)
```

[62]:
```
# Which specie has th most count in the file

pwmdata.groupby(['species']).size().reset_index(name='counts').
 ↪sort_values('counts')

# counts by species
counts = pwmdata['species'].value_counts()
```

```
counts[counts>100]

fildata = pwmdata[pwmdata['species'].isin(counts[counts > 99].index)]
```

2 Manipulate Data

[63]:
```
# counts by species
counts = pwmdata['species'].value_counts()
```

[64]:
```
counts
```

[64]:
```
Sal        2951
Ashna       267
Pyar        263
Banjhi      180
Dabdabe     142
Other        55
Ashid        44
Bhalayo      40
Karma        36
Mahuwa       25
Jamun        24
Harro        22
Barro        18
Kusum        11
Bar           5
Roini         3
Khayar        1
Kumbhi        1
Bhudkul       1
Pipal         1
Tikuli        1
Name: species, dtype: int64
```

[65]:
```
#fildata.info()
counts
counts[counts>99]
```

[65]:
```
Sal        2951
Ashna       267
Pyar        263
Banjhi      180
Dabdabe     142
Name: species, dtype: int64
```

2.1 Subset by species count

One approach would be to count values `value_counts` to create an aggregate series, which we used before is: `counts` We can now use this information to filter the dataset

[66]:
```
# Filter by aggregate series
fildata = pwmdata[pwmdata['species'].isin(counts[counts > 99.0].index)]
fildata.info
```

[66]:
```
<bound method DataFrame.info of           sn  Tree_numbe         lat        lon
treeid  species   dbh  \
0         1.0       142.0  3068940.39  691125.84     1.0     Pyar  30.0
1         2.0       145.0  3068946.55  691109.18     2.0      Sal  39.0
2         3.0       141.0  3068938.55  691129.03     3.0      Sal  48.0
3         4.0       144.0  3068945.74  691114.22     4.0      Sal  38.0
4         5.0       143.0  3068943.58  691117.80     5.0      Sal  34.0
…       …          …          …         …       …    …
4086   5577.0       626.0  3068503.35  690624.41  5806.0      Sal  30.0
4087   5578.0       198.0  3068678.81  690872.16  5807.0      Sal  42.0
4088   5579.0       285.0  3068744.32  690837.30  5808.0     Pyar  32.0
4089   5580.0       360.0  3068696.09  690631.54  5809.0  Dabdabe  51.0
4090   5581.0       372.0  3068660.31  690604.69  5810.0  Dabdabe  37.0

       height  class remarks Compartmen                          geometry
0        15.0    2.0    None       C1S1  POINT (9232712.329 3215136.148)
1        16.0    2.0    None       C1S1  POINT (9232693.633 3215143.436)
2        16.0    2.0    None       C1S1  POINT (9232715.897 3215134.004)
3        15.0    2.0    None       C1S1  POINT (9232699.308 3215142.427)
4        18.0    1.0    None       C1S1  POINT (9232703.310 3215139.912)
…       …    …      …         …                                 …
4086     12.0    1.0    None       C1S1  POINT (9232138.589 3214649.193)
4087     10.0    2.0    None       C1S1  POINT (9232421.343 3214843.865)
4088     10.0    3.0    None       C1S1  POINT (9232383.158 3214918.821)
4089     12.0    1.0    None       C1S1  POINT (9232150.055 3214867.765)
4090     12.0    1.0       M       C1S1  POINT (9232119.114 3214827.644)

[3803 rows x 12 columns]>
```

[67]:
```
#The data has `fildata.shape[0]`
#from IPython.display import Markdown as md
md(f"The filtered data, i.e. `fildata`,  consists of {fildata.shape[0]}␣
↪records")
```

[67]: The filtered data, i.e. `fildata`, consists of 3803 records

filter by groupby I prefer to use `groupby` appraoch as this is similar to `R:dplyr`

[68]:
```
fildatag = pwmdata.groupby('species').filter(lambda x: len(x) >= 99)
```

[69]:
```
md(f"The filtered data using `groupby` function shows that the data has same␣
 ↪number of records as given by aggretaing series approach:  {fildatag.
 ↪shape[0]} records")
```

[69]:

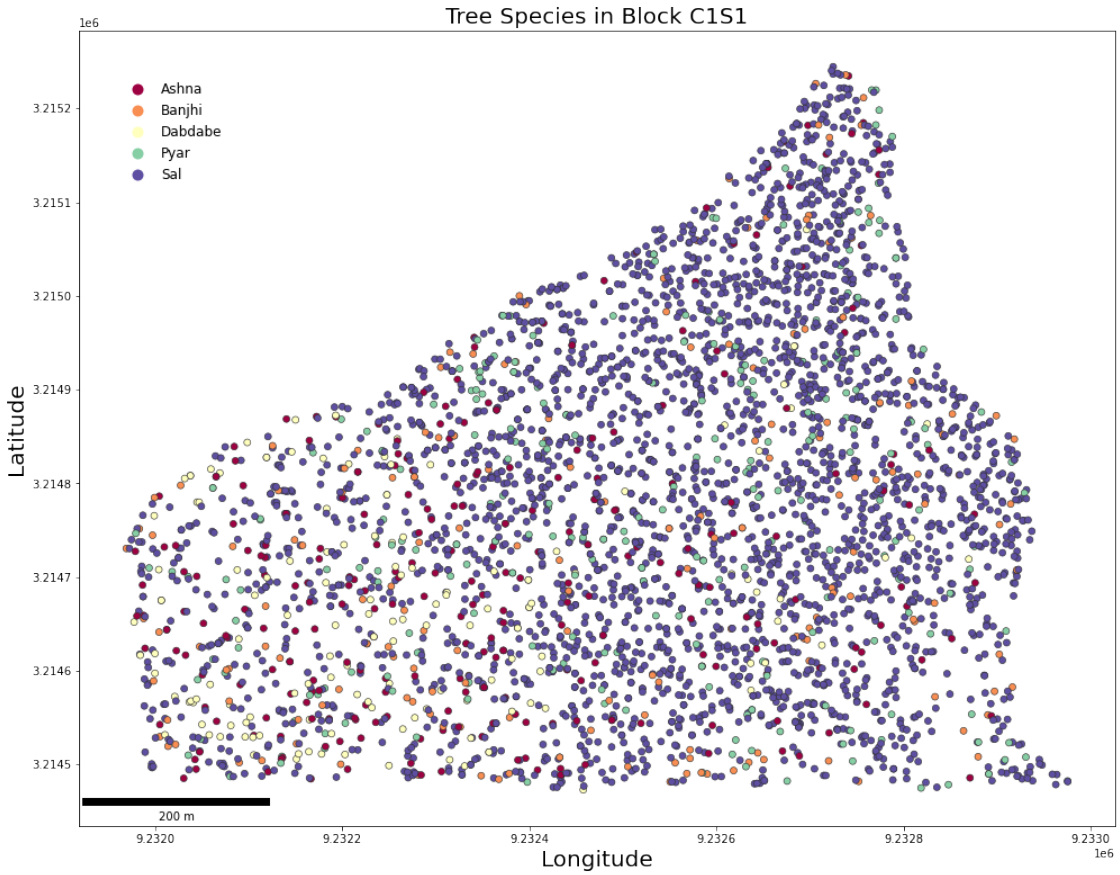
The filtered data using `groupby` function shows that the data has same number of records as given by aggretaing series approach: 3803 records

[70]:
```
#pwmdata.species.head()

fildatag.loc[:, 'species'] = pwmdata['species'].astype('string')
```

[71]:
```
fig, ax = plt.subplots(1, figsize=(14,14))

fildatag.plot(column='species', categorical=True,
              cmap='Spectral', linewidth=.6, edgecolor='0.2',
              legend=True,
              legend_kwds={'bbox_to_anchor':(0.15, 0.95),'fontsize':12,'frameon':
 ↪False}, ax=ax)
ax.set_xlabel("Longitude", fontsize = 20)
ax.set_ylabel("Latitude", fontsize = 20)
ax.set_title('Tree Species in Block C1S1',fontsize=20)
ax.add_artist(scale1)
plt.tight_layout()
```


Tree Species in Block C1S1
1e6
Ashna
Banjhi
Dabdabe
Pyar
Sal
3.2152
3.2151
3.2150
3.2149
3.2148
3.2147
3.2146
3.2145
Latitude
200 m
9.2320
9.2322
9.2324
9.2326
9.2328
9.2330
1e6
Longitude

#—— The End ———-#

[ ]: