Geopandas Overview

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Visualization Technique and Library Overview

The visualization technique that I will eventually build to throughout the demonstration is a chloropleth plot through use of the geopandas library (with intermediate steps and explanations throughout detailing the processes, functions, logic, etc. that can be utilized within the geopandas library, as well, in tandem with pandas and matplotlib). A chloropleth is a plot that displays a particular region of interest (in the demonstration, the US state of Maine) and assigns a color to particular sub-areas within the region depending on a value in a column of interest. This color pattern is a clear visual way of denoting both similarities and differences between areas as it relates to certain measurements, demographics, etc. For instance, if average age of a particular region was an area of focus and there were 3 sub-areas within the region with average ages of 45, 76, and 78 years old, respectively, the expectation within a chloropleth plot is that the regions with average ages of 76 and 78 would be a similar color and would differ sharply from the sub-area with an average age of 45 years old, allowing for conclusions to be drawn on a population visually.

While a chloropleth plot is the final figure that is generated from the below demonstration, the intermediate steps of the demonstration do display, more generally, how geographially-based plots can even be generated, as well, through use of the geopandas library. These geographically-based plots are perfect when shapefiles (.shp) and their necessary accompanying files (.cpg, .dbf, for example) are readily available for use. Geopandas, as can be discerned from its name, is closely related and can behave pretty similarly at times to the pandas library. Geopandas can read in .shp files and create GeoDataFrames (again similarly to the DataFrames that pandas can create). However, the major difference of a GeoDataFrame to a pandas DataFrame is that a geometry column is specified that is unique to when .shp files are read in. When a GeoDataFrame is plot (which can be done through the geopandas library, as well), the geometry is what is seen on the plot (an example of geometry may be a line or a polygon with varying values that define its space). Centroids of these geometries can also be identified through geopandas, allowing for annotation of the plots, as well. Geopandas' similarly to pandas is also ideal when there is other data of interest available that may not have come in through the .shp files. A GeoDataFrame can be joined to a DataFrame allowing for great flexibility when attempting to plot areas and values of interest.

In regards to the chloropleth and geographical-based plotting, this does, in a sense have similarities with a wide range of other types of plots, like scatter plots, bar graphs, etc. However, chloropleths go a step beyond these plots. While a scatter plot would just give an (x, y) point for a value for an area of interest, the chloropleth takes a scatter into consideration and clearly visually displays the relationship of a point to all other points. Those on the top right of a scatter can clearly be differentiated from those on the bottom left, and the added benefit of the chloropleth is that this relationship is now presented geographically when this is a need.

As noted above, the library that is being used for the demonstration is geopandas and is an extremely valuable library for chloropleths and geographical plotting in general as it has the capability of creating GeoDataFrames and plotting the geometry data needed to spatially arrange the data. Geopandas is open-source and a community-driven library. While created in 2013 by Kelsey Jordahl, there is now a team of both core developers and volunteer contributors that are responsible for the geopandas library. As will be seen below, conda can be used to install geopandas for use with the following command: `conda install geopandas` . When installed, geopandas does integrate well within the Jupyter Notebook environment. In researching the geopandas library, there did appear to be other options available that aid/thrive in geographically-based plotting, like geoplot, for instance. However, geopandas worked very well using its own plot function and paired well with matplotlib's subplot functionality, so this approach was used for the demonstration as there was familiarity already with the mechanics behind matplotlib's plotting to allow for plots overlayed over one another. In terms of declarative vs. procedural, geopandas is similar to pandas and is a declarative library. A simple function of read_file() or GeoDataFrame() can meet the needs of geographical plotting, requiring little need for procedures to be generated.

Geopandas Demonstration

Prior to beginning work with geopandas, the library will need to be installed on the Jupyter Notebook. This can be handled by utilizing conda and running the code below.

In [1]:
```
conda install geopandas
```

geopandas, along with pandas itself and pyplot from matplotlib can then be imported into the notebook for use.

In [2]:
```
import geopandas as gpd
import pandas as pd
import matplotlib.pyplot as plt
```

Read in Shapefile with geopandas and Discuss GeoDataFrame

As noted earlier, working with geopandas very closely resembles the processes and data structures seen with pandas itself. A major difference to note is that while pandas may utilize a "read_excel" or "read_csv" function to pull in data into a DataFrame or Series format, geopandas will utilize a "read_file" function and pull in a .shp or shapefile.

Note: while "read_file" only calls the .shp file itself, for the shapefile to be read in appropriately and successfilly, all other accompanying files (.dbf, .shx, etc.) must also be available in the same folder and play a role in generating the correct GeoDataFrame.

The data that is being pulled in is from 2017, at a State County level, and is from the US Census government website where they store yearly cartographic boundary files: [https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.2017.html (https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.2017.html)](https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.2017.html).

When running the print and .head() steps below, you will see that gpd.read_file will generate a GeoDataFrame and that the structure of the GeoDataFrame is very similar to a pandas DataFrame. The major difference is the geometry field, which dictates the shape and position of where the row's data can be displayed in a plot.

In [3]:
```
census = gpd.read_file('cb_2017_us_county_500k.shp')

print(type(census))
census.head(3)
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
```

Out[3]:

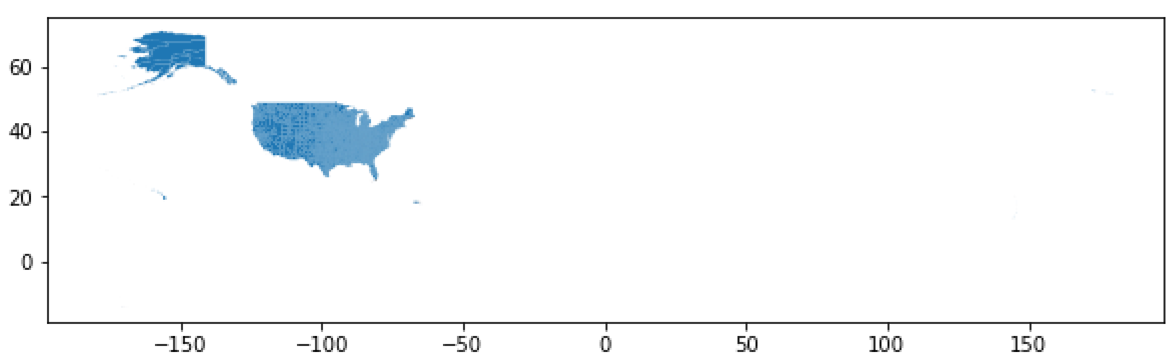
	STATEFP	COUNTYFP	COUNTYNS	AFFGEOID	GEOID	NAME	LSAD	ALAND	A
0	01	005	00161528	0500000US01005	01005	Barbour	06	2292144656	5(
1	01	023	00161537	0500000US01023	01023	Choctaw	06	2365869837	1(
2	01	035	00161543	0500000US01035	01035	Conecuh	06	2201948618	6

Plotting with GeoDataFrames

Similarly to how we can use a plot() function with matplotlib and specify figure size, the same can be done with a GeoDataFrame and geopandas. When a GeoDataFrame is plotted, the geometry is what is plotted on a figure. The geometry, again, being shapes at the US state county level, which is shown below.

In [4]:
```
census.plot(figsize = (10,10))
```

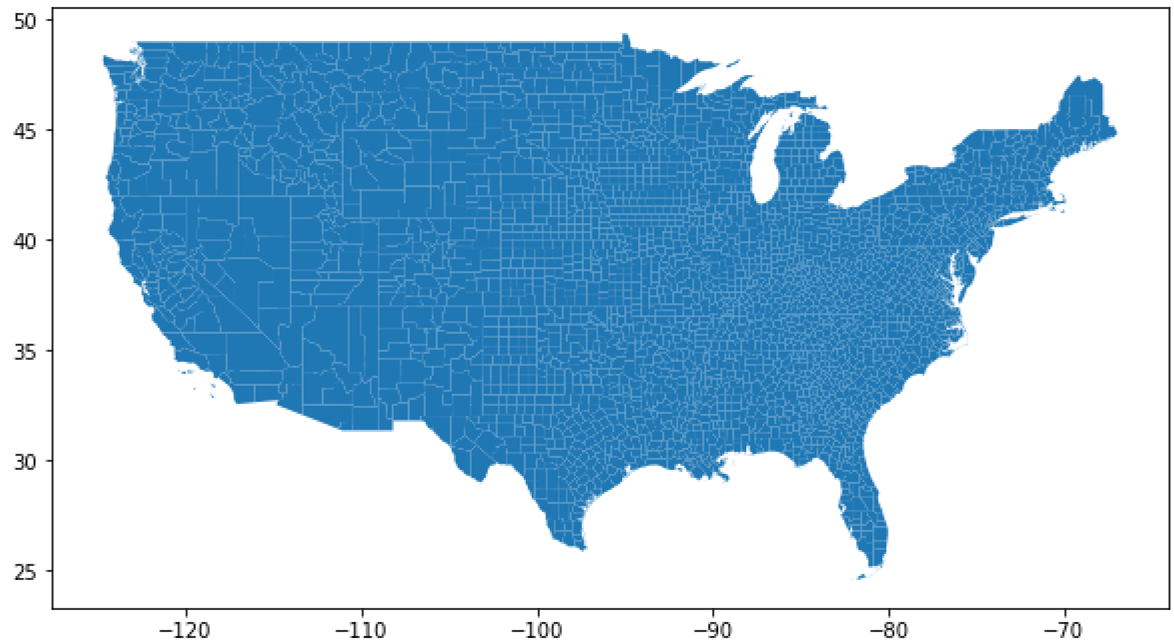
Out[4]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f452010ec50>
```



Currently, this is not super helpful for visualizing anything meaningful (especially at a county level) as Alaska, Hawaii, and a few United States territories are included in the dataset from the US census department. The process below cleans the dataset, to just include states on the mainland. This is done by combining the "isin" function with "~" which essentially acts as a "NOT" to remove US territories, Alaska, and Hawaii based on their State FIPS number. The cleaned GeoDataFrame is then again plotted.

In [5]:
```
census_clean = census[~census.STATEFP.isin(['60', '66', '69', '72', '78', '02'
, '15'])]
census_clean.plot(figsize = (10,10))
```

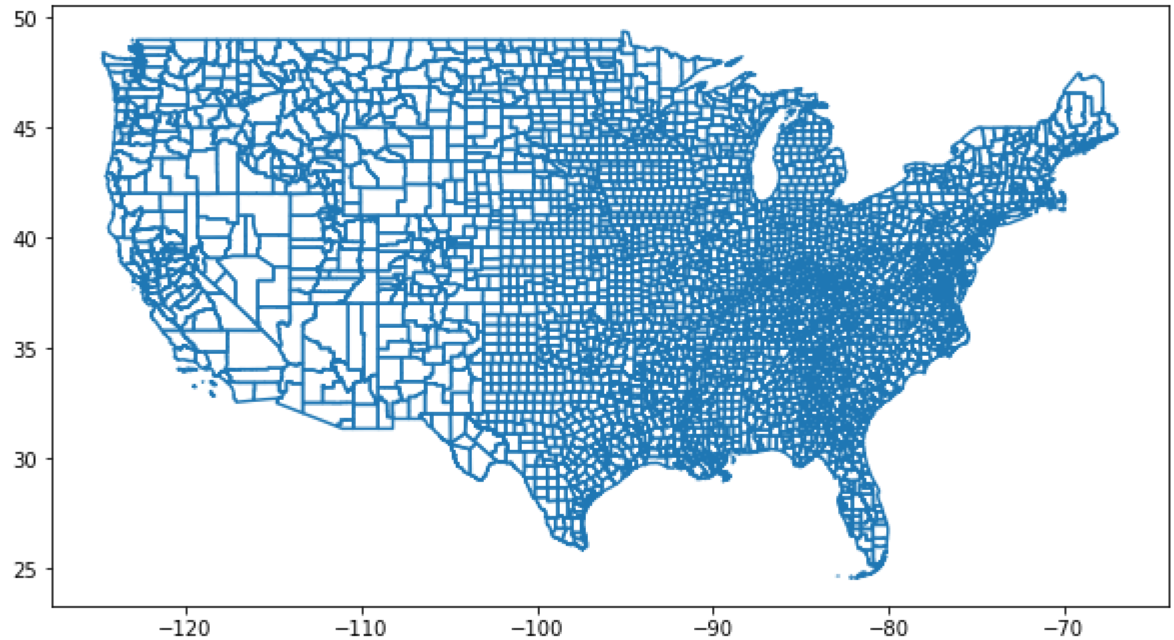
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7f451d848b00>



Another valuable tool that will be used later on in this demonstration that is a benefit of the GeoDataFrame geometry is that a plot of just boundaries can also be done (and again, as will be seen later, can be overlayed in a subplot). With the geometry of the file being at a county level, the boundaries of every county can be seen below.

In [6]:
```
census_clean.boundary.plot(figsize = (10,10))
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f451b1c5518>



Investigate Maine Population and Income Per Capita

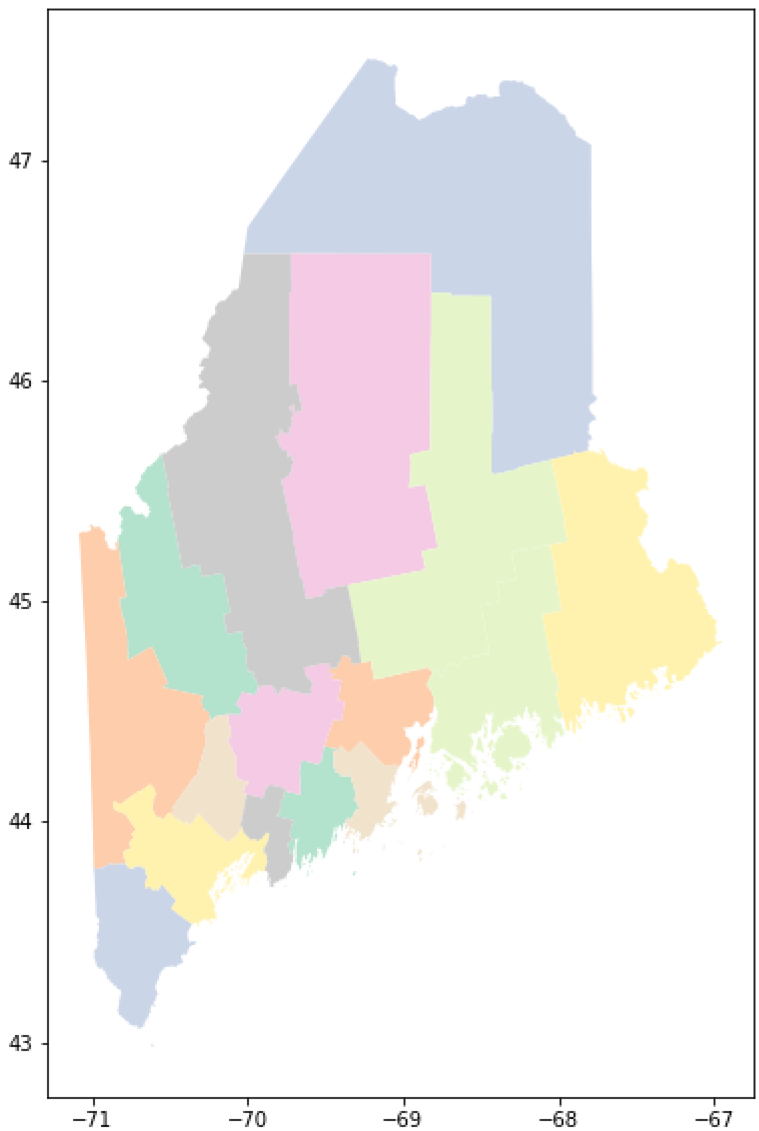
I'm currently living in Maine so, for the bulk of this demonstration, I wanted to create a visualization relevant to an area I'm most familiar with. To do so, I limited the cleaned census data set to just Maine counties (again through the State FIPS code field in the data). To differentiate between counties, cmap can be set to a wide range of color options, but I chose one of the pastel variations. The plot of Maine counties and the data itself can be seen below.

In [7]:
```
maine = census_clean[census_clean.STATEFP.isin(['23'])]
maine.plot(cmap = 'Pastel2', figsize = (10, 10))
maine
```

Out[7]:

	STATEFP	COUNTYFP	COUNTYNS	AFFGEOID	GEOID	NAME	LSAD	AL
108	23	015	00581293	0500000US23015	23015	Lincoln	06	118063
398	23	007	00581289	0500000US23007	23007	Franklin	06	439519
399	23	017	00581294	0500000US23017	23017	Oxford	06	537906
400	23	027	00581299	0500000US23027	23027	Waldo	06	189057
401	23	031	00581301	0500000US23031	23031	York	06	256623
741	23	003	00581287	0500000US23003	23003	Aroostook	06	1727803
1349	23	021	00581296	0500000US23021	23021	Piscataquis	06	1025901
1364	23	011	00581291	0500000US23011	23011	Kennebec	06	224680
1640	23	009	00581290	0500000US23009	23009	Hancock	06	411028
1641	23	019	00581295	0500000US23019	23019	Penobscot	06	879866
2469	23	029	00581300	0500000US23029	23029	Washington	06	663732
2604	23	005	00581288	0500000US23005	23005	Cumberland	06	216439

	STATEFP	COUNTYFP	COUNTYNS	AFFGEOID	GEOID	NAME	LSAD	AL
2656	23	013	00581292	0500000US23013	23013	Knox	06	94569
2926	23	001	00581286	0500000US23001	23001	Androscoggin	06	121196
3144	23	025	00581298	0500000US23025	23025	Somerset	06	1016412
3181	23	023	00581297	0500000US23023	23023	Sagadahoc	06	65780



However, if you aren't familiar with Maine, even a color-coded display of counties will not be particularly helpful. The code below (which is commented to help explain the approach) creates a subplot of 3 plots: the same plot as above, a boundary plot of Maine counties to allow for clear demarcation of the counties, and a plot that annotates the display with the name of each county.

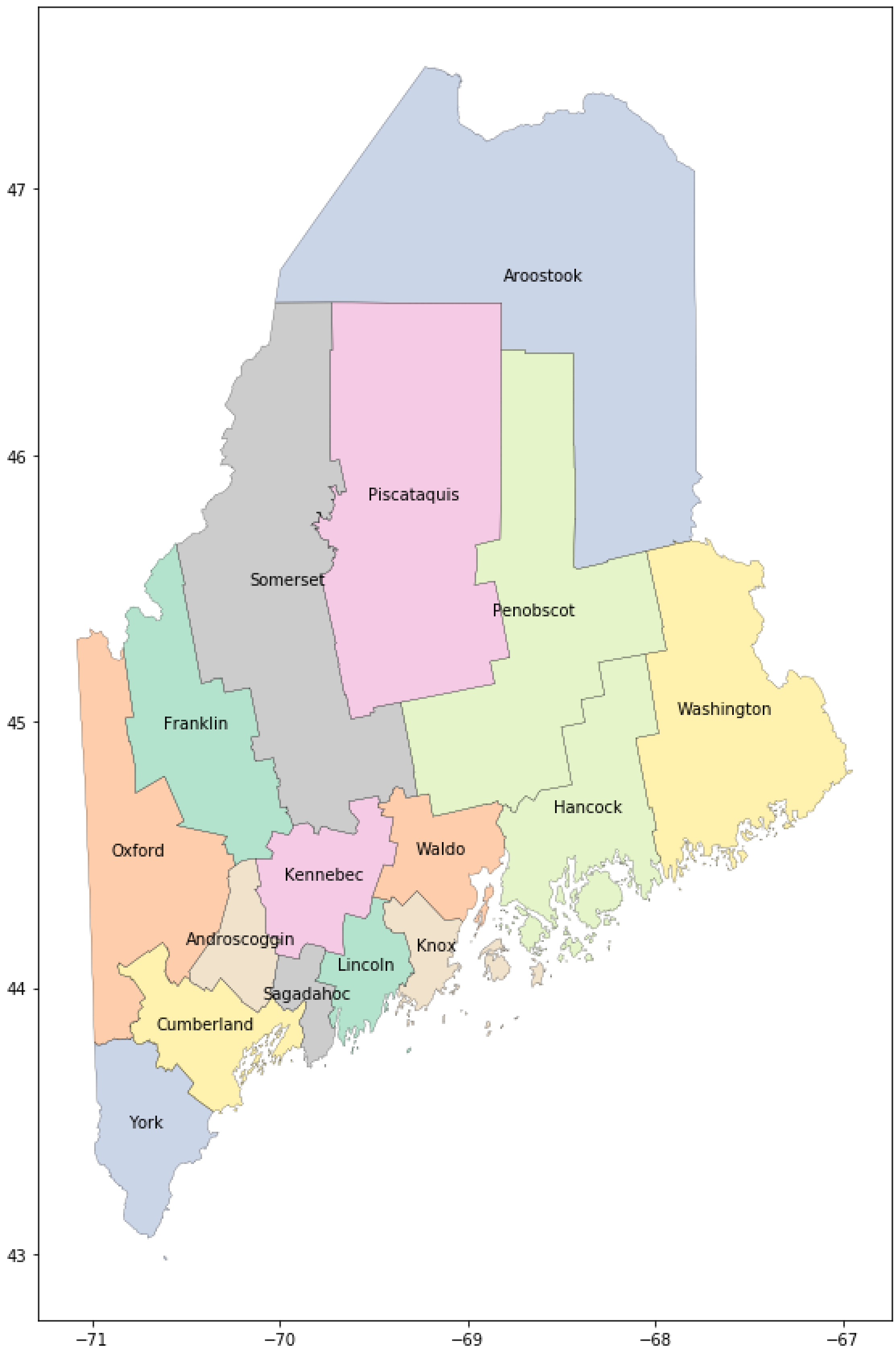
In [8]:
```
#Create a figure through matplotlib operations
fig = plt.figure(figsize = (15,15))
#maine_plot will be a subplot within the figure created above
maine_plot = fig.add_subplot(111)

#This code goes through each row (axis = 1) of the Maine data set, and while d
oing so annotates the maine_plot with county name (NAME)
#The geometry.centroid.coords[0] logic gives x and y points that are in the ce
nter of the geometry specified in the .shp file
#Horizontal alignment and font size can then also be specified
maine.apply(lambda x: maine_plot.annotate(x.NAME, xy=x.geometry.centroid.coord
s[0], ha='center', fontsize= 10), axis=1)

#Boundary plot in the subplot that gives the boundary of the Maine counties, s
ets the lines to black and
#the line width controls how bold the line will be
maine.boundary.plot(ax = maine_plot, color = 'black', linewidth = 0.2)

#This plot takes the Maine dataset same as before and plots it in the subplot
maine.plot(ax = maine_plot, cmap = 'Pastel2')
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f451b2690f0>



With the 16 counties now all labelled, I was interested in displaying meaningful demographic information on top of the plot, as well. For this, I decided to use the total population data already available in the GeoDataFrame and pull in other 2017 county data available through Kaggle that gives additional demographics around the population, with one being Income per capita (https://www.kaggle.com/muonneutrino/us-census-demographic-data?select=acs2017_county_data.csv (https://www.kaggle.com/muonneutrino/us-census-demographic-data?select=acs2017_county_data.csv)).

To pull in this data from Kaggle, pandas was used to read in the .csv file. The file was limited to Maine counties only again and a regex was used to set the County columns from "Waldo County", for example, to just "Waldo" to allow for the join between the DataFrame and GeoDataFrame. Once the data was cleaned, the Kaggle dataset was inner joined to the census data by County name and now there was one table that had all the data combined.

However, there was one problem with this. Following a merge through pandas, the combined dataset maine_demo was made into a DataFrame. An additional step was needed following this merge to convert the DataFrame into a GeoDataFrame and reset the geometry that would be used for plotting.

In [9]:
```
demographics = pd.read_csv('acs2017_county_data.csv')
demographics = demographics[demographics['State'] == 'Maine'].reset_index()
demographics['County'].replace(' [\w]*', '', regex = True, inplace = True)

maine_demo = pd.merge(demographics, maine, how = 'inner', left_on = 'County',
right_on = 'NAME')
maine_demo = gpd.GeoDataFrame(maine_demo, geometry = 'geometry')

maine_demo.head(2)
```

Out[9]:

	index	CountyId	State	County	TotalPop	Men	Women	Hispanic	White	Black	...
0	1177	23001	Maine	Androscoggin	107317	52550	54767	1.8	91.1	1.6	...
1	1178	23003	Maine	Aroostook	68840	34006	34834	1.1	94.5	0.9	...

2 rows × 48 columns

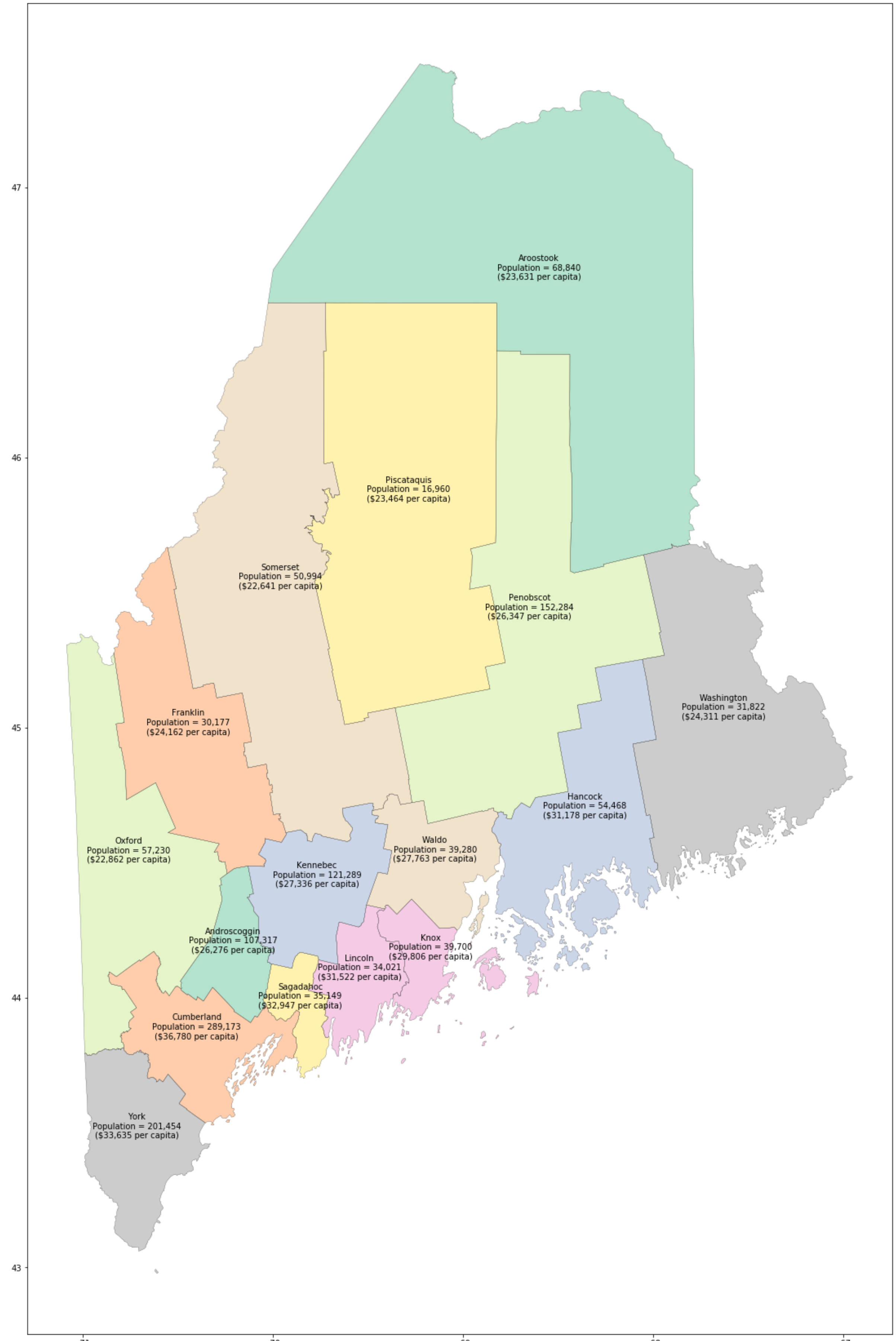
With this new combined table now available, the GeoDataFrame can again be plotted use a similar approach to the first subplot that was created. The difference for this round revolves around the annotation itself. TotalPop and IncomePerCap are formatted as strings with commas every third digit, and a long concatenation across 3 lines (using the '\n' to add a line) is performed to display this demographic information.

In [10]:
```
fig2 = plt.figure(figsize = (30, 30))
maine_plot2 = fig2.add_subplot(111)

maine_demo.apply(lambda x: maine_plot2.annotate(
    x.NAME + '\n' + 'Population = ' + str("{:,}".format(x.TotalPop)) + '\n'
'($' + str("{:,}".format(x.IncomePerCap)) + ' per capita)',
    xy=x.geometry.centroid.coords[0], ha='center', fontsize= 10), axis=1)

maine_demo.boundary.plot(ax = maine_plot2, color = 'black', linewidth = 0.2)
maine_demo.plot(ax = maine_plot2, cmap = 'Pastel2')
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f451b2524e0>
```



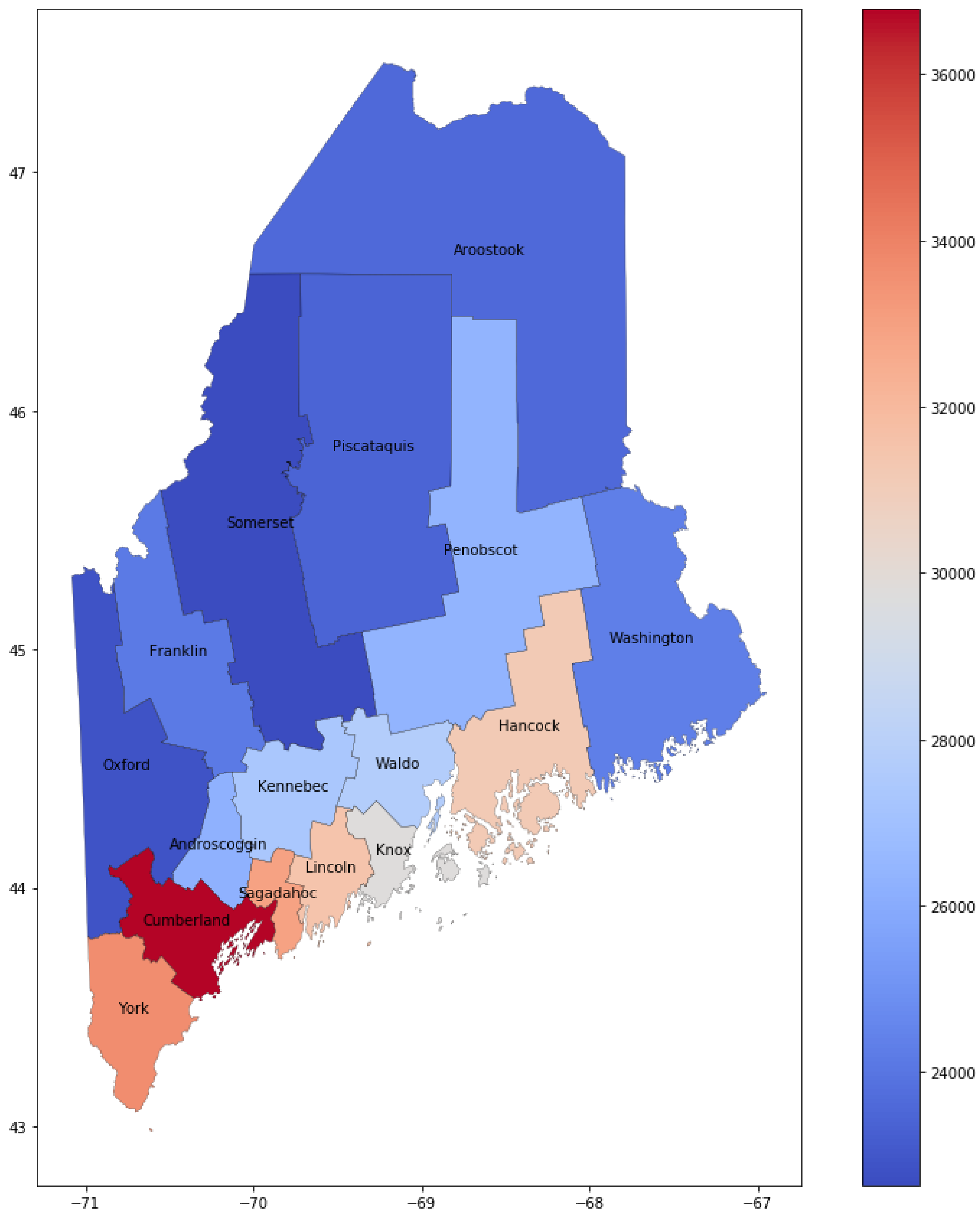
While this is definitely a valuable and meaningful way to display demographics, even expanding the figure to 15x15 lead to a very crowded and messy display when annotations run longer than a couple of lines. Geopandas does also allow for differences to be displayed in certain regions through a wide range of other clearer ways. The approach I'll focus on for this demonstration will be a chloropleth.

In [11]:
```
fig3 = plt.figure(figsize = (15, 15))
maine_plot3 = fig3.add_subplot(111)

maine_demo.apply(lambda x: maine_plot3.annotate(x.NAME, xy=x.geometry.centroid
.coords[0], ha='center', fontsize= 10), axis=1)

maine_demo.boundary.plot(ax = maine_plot3, color = 'black', linewidth = 0.2)
maine_demo.plot(ax = maine_plot3, column = 'IncomePerCap', legend = True, cmap
= 'coolwarm',
               legend_kwds = {'label': 'Income Per Capita'})
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4520036908>



This plot followed a similar approach to the other subplots in how the boundaries and labels were plotted, but the difference for this display is that a particular demographic column was specified in the plot function. A chloropleth was thus created based on the value within this field and by specifying legend = True, the viewer now has a very clear and easy way to evaluate income per capita across Maine. From this graph, it is immediately clear that Southern Maine typically has higher earners relative to Northern Maine. While a chloropleth is one option that can be used, I saw in my research that cartograms and heat maps are also options through the geopandas and the GeoDataFrame. It's clear that geopandas is a very powerful tool in intaking .shp files and generating meaningful insights from demographics, etc. at a geographical level.

Resources and References

https://jcutrer.com/python/learn-geopandas-plotting-usmaps (https://jcutrer.com/python/learn-geopandas-plotting-usmaps)

https://github.com/shotleft/how-to-python/blob/master/How%20it%20works%20-%20labelling%20districts%20in%20GeoPandas.ipynb (https://github.com/shotleft/how-to-python/blob/master/How%20it%20works%20-%20labelling%20districts%20in%20GeoPandas.ipynb)

https://medium.com/@erikgreenj/mapping-us-states-with-geopandas-made-simple-d7b6e66fa20d (https://medium.com/@erikgreenj/mapping-us-states-with-geopandas-made-simple-d7b6e66fa20d)

Multiple Sections within the documentation itself:

https://geopandas.org/index.html (https://geopandas.org/index.html)

https://geopandas.org/docs/user_guide/mapping.html (https://geopandas.org/docs/user_guide/mapping.html)

https://geopandas.org/gallery/plotting_with_geoplot.html (https://geopandas.org/gallery/plotting_with_geoplot.html)

https://geopandas.org/about/team.html (https://geopandas.org/about/team.html)