Income Inequality Data Analytics

This notebook visualizes income inequality data geospatially, comparing various years altogether.

In [ ]:
```
# This Python 3 environment comes with many helpful analytics libraries insi
# It is defined by the kaggle/python Docker image: https://github.com/kaggle
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import geopandas as gpd
import matplotlib.pyplot as plt

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will l

import os
for dirname, _, filenames in os.walk('./kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that
# You can also write temporary files to /kaggle/temp/, but they won't be sav
```

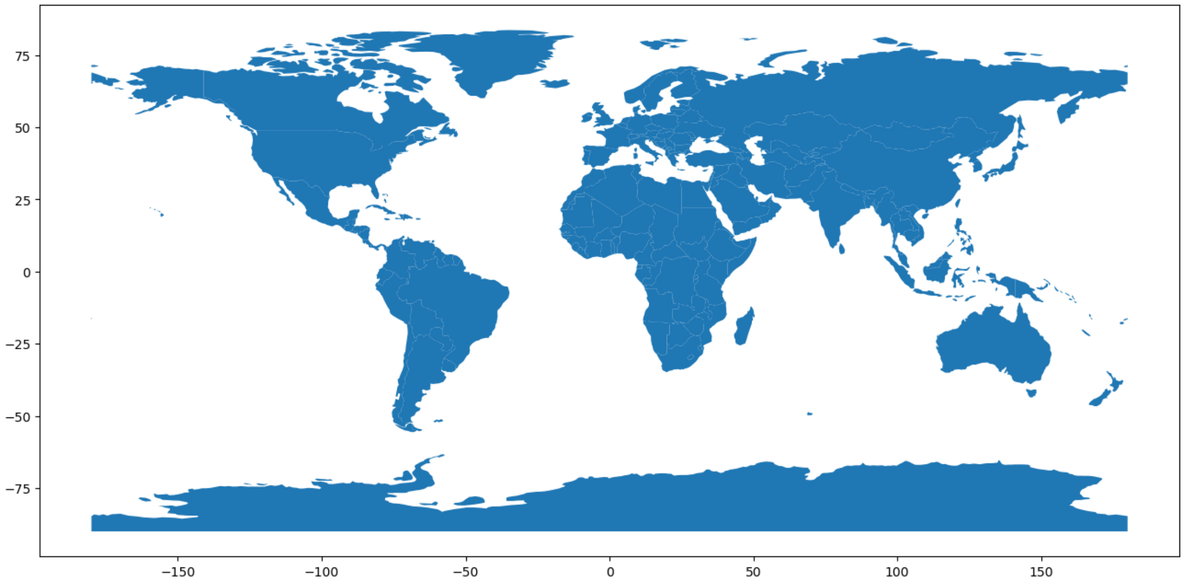
In [ ]:
```
world_data = gpd.read_file('../world-data.geojson', driver='geojson', crs=43
# Updates to names so merge finds as many countries as possible
world_data['name'] = np.where(world_data['name'].str.contains('United States
world_data['name'] = np.where(world_data['name'].str.contains('Dem. Rep. Con
world_data['name'] = np.where(world_data['name'].str.contains('Congo'), 'Con
world_data['name'] = np.where(world_data['name'].str.contains("Côte d'Ivoire
world_data['name'] = np.where(world_data['name'].str.contains("eSwatini"), '
world_data['name'] = np.where(world_data['name'].str.contains("Slovakia"), '
world_data['name'] = np.where(world_data['name'].str.contains("Bosnia and He
world_data['name'] = np.where(world_data['name'].str.contains("Laos"), "Lao'
world_data['name'] = np.where(world_data['name'].str.contains("Central Afric
world_data['name'] = np.where(world_data['name'].str.contains("Czechia"), "C
world_data['name'] = np.where(world_data['name'].str.contains("Kyrgyzstan"),
world_data['name'] = np.where(world_data['name'].str.contains("Macedonia"),
world_data['name'] = np.where(world_data['name'].str.contains("S. Sudan"), '
world_data['name'] = np.where(world_data['name'].str.contains("Eq. Guinea"),
world_data['name'] = np.where(world_data['name'].str.contains("Dominican Rep
world_data['name'] = np.where(world_data['name'].str.contains("Solomon Is.")
world_data['name'] = np.where(world_data['name'].str.contains("N. Cyprus"),
```

In [ ]:
```
world_data[world_data['name'].str.contains('Congo')].head()
```

Out[ ]:

	iso_a3	name	continent	geometry
11	COD	Congo, Rep.	Africa	POLYGON ((29.34000 -4.49998, 29.51999 -5.41998...
67	COG	Congo, Rep.	Africa	POLYGON ((18.45307 3.50439, 18.39379 2.90044, ...

In [ ]:
```
world_data.plot(figsize=(16,8))
plt.show()
```



In [ ]:
```
continents = pd.read_csv('../CSV/continent_country.csv')
continents[continents['country'].str.contains('K')].head()
```

Out[ ]:

	continent	country
24	Africa	Kenya
79	Asia	Hong Kong, China
80	Asia	Korea, Dem. Rep.
81	Asia	Korea, Rep.
99	Asia	Kuwait

In [ ]:
```
gini_data = pd.read_csv('../CSV/gini.csv')
```

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

Out[ ]:

	country	1800	1801	1802	1803	1804	1805	1806	1807	1808	...	2031	2032
0	Afghanistan	30.5	30.5	30.5	30.5	30.5	30.5	30.5	30.5	30.5	...	36.8	36.8
1	Albania	38.9	38.9	38.9	38.9	38.9	38.9	38.9	38.9	38.9	...	29.0	29.0
2	Algeria	56.2	56.2	56.2	56.2	56.2	56.2	56.2	56.2	56.2	...	27.6	27.6
3	Andorra	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	...	40.0	40.0
4	Angola	57.2	57.2	57.2	57.2	57.2	57.2	57.2	57.2	57.2	...	42.6	42.6

5 rows × 242 columns

In [ ]:
```
gini_data = gini_data.melt(id_vars=['country'], var_name='year', value_name=
```

In [ ]:
```
#gini_data.query('country == "France"').head()
#gini_data[gini_data['country'].str.contains('State')].head()
#gini_data['country'].unique()
```

In [ ]:
```
gini_world_data = world_data.merge(gini_data, left_on='name', right_on='cour
```

In [ ]:
```
gini_world_data[gini_world_data['country'].isna()]
```

Out[ ]:

	iso_a3	name	continent	geometry	country	year	gini
482	ESH	W. Sahara	Africa	POLYGON ((-8.66559 27.65643, -8.66512 27.58948...	NaN	NaN	NaN
4580	FLK	Falkland Is.	South America	POLYGON ((-61.20000 -51.85000, -60.00000 -51.2...	NaN	NaN	NaN
4822	GRL	Greenland	North America	POLYGON ((-46.76379 82.62796, -43.40644 83.225...	NaN	NaN	NaN
4823	ATF	Fr. S. Antarctic Lands	Seven seas (open ocean)	POLYGON ((68.93500 -48.62500, 69.58000 -48.940...	NaN	NaN	NaN
9885	PRI	Puerto Rico	North America	POLYGON ((-66.28243 18.51476, -65.77130 18.426...	NaN	NaN	NaN
31094	NCL	New Caledonia	Oceania	POLYGON ((165.77999 -21.08000, 166.59999 -21.7...	NaN	NaN	NaN
32300	TWN	Taiwan	Asia	POLYGON ((121.77782 24.39427, 121.17563 22.790...	NaN	NaN	NaN
36639	ATA	Antarctica	Antarctica	MULTIPOLYGON (((-48.66062 -78.04702, -48.15140...	NaN	NaN	NaN
38327	ABV	Somaliland	Africa	POLYGON ((48.94820 11.41062, 48.94820 11.41062...	NaN	NaN	NaN
39774	OSA	Kosovo	Europe	POLYGON ((20.59025 41.85541, 20.52295 42.21787...	NaN	NaN	NaN

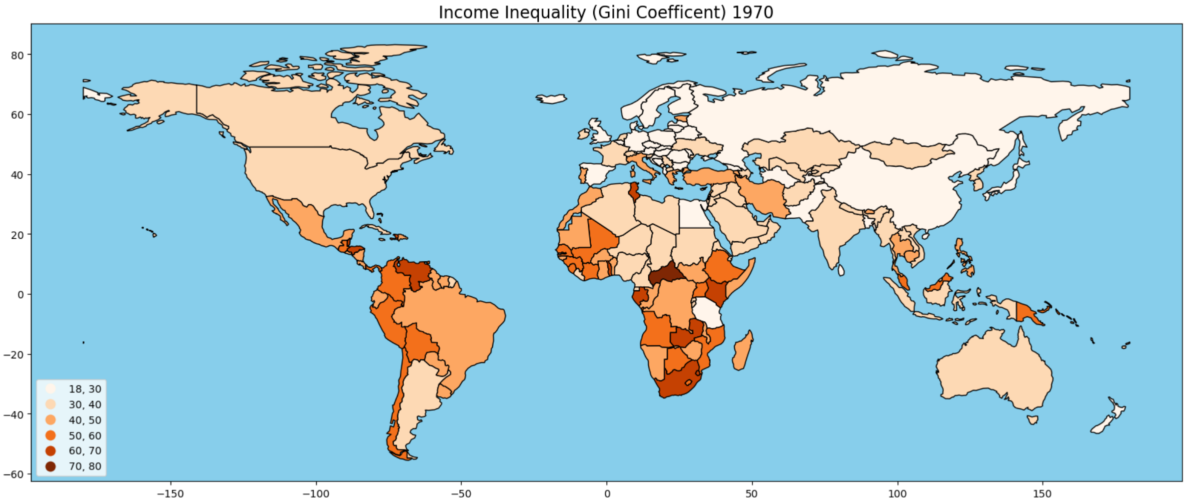
In [ ]:

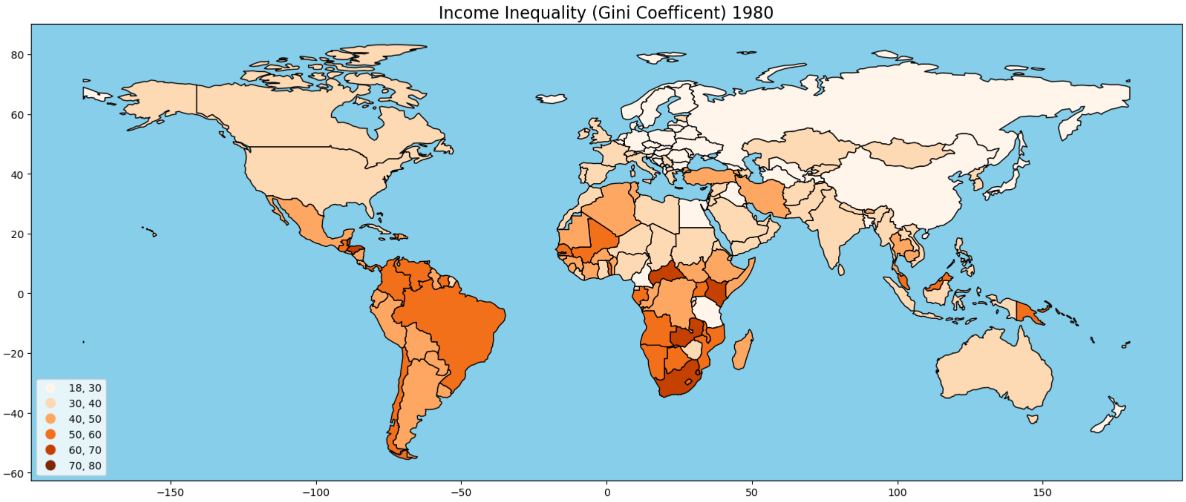
```
gini_world_data.query('year == "2002"').head()
#gini_world_data[gini_world_data['name'].str.contains('State')].head()
#gini_world_data.head()
```

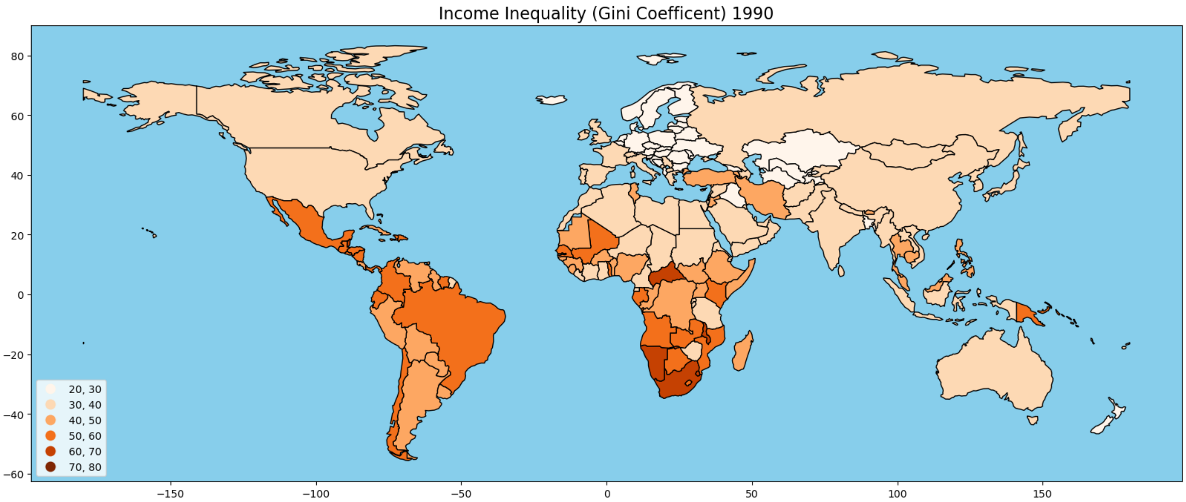
Out[ ]:

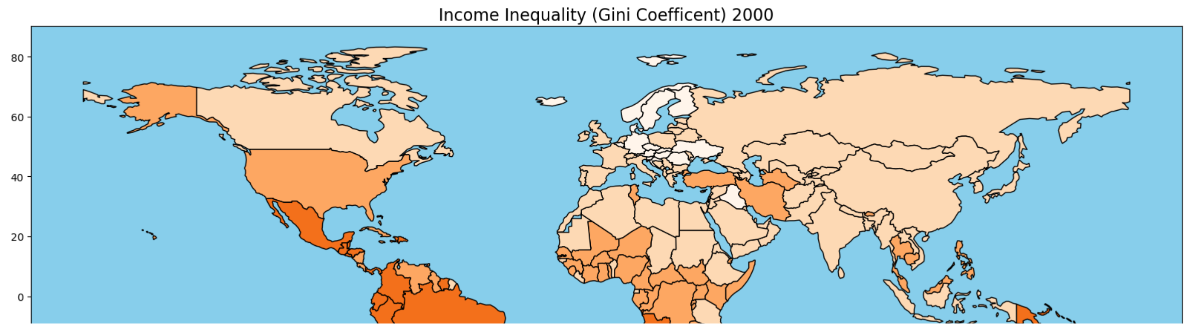
	iso_a3	name	continent	geometry	country	year	gini
202	FJI	Fiji	Oceania	MULTIPOLYGON (((180.00000 -16.06713, 180.00000...	Fiji	2002	38.2
443	TZA	Tanzania	Africa	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...	Tanzania	2002	37.9
685	CAN	Canada	North America	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...	Canada	2002	33.5
926	USA	United States	North America	MULTIPOLYGON (((-122.84000 49.00000, -120.0000...	United States	2002	40.5
1167	KAZ	Kazakhstan	Asia	POLYGON ((87.35997 49.21498, 86.59878 48.54918...	Kazakhstan	2002	34.5

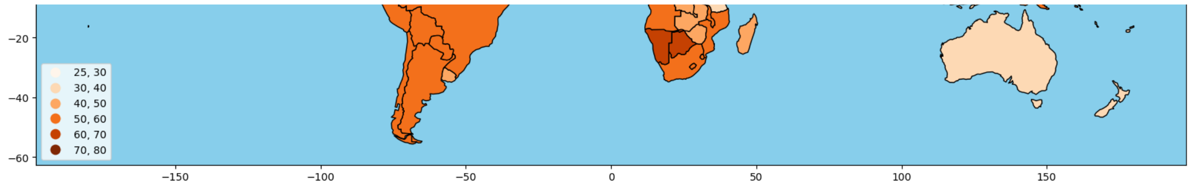
In [ ]:
```
years = [1970, 1980, 1990, 2000, 2010]
classifications = dict(bins=[30,40,50,60,70,80])

fig, axs = plt.subplots(len(years), 1, figsize=(20, 10*len(years)))

for ndx, yr in enumerate(years):
    ax1 = axs[ndx]
    ax1.set_facecolor('skyblue')
    ax1.set_title(f'Income Inequality (Gini Coefficent) {yr}', fontsize=16)
    gini_world_data.query(f'year == "{yr}"').plot(
        ax=ax1,
        column='gini',
        edgecolor='black',
        categorical=False,
        scheme='User_Defined',
        classification_kwds=classifications,
        #k=6,
        #scheme='fisher_jenks',
        cmap='Oranges',
        legend=True,
        legend_kwds={'loc': 'lower left', 'fmt': '{:,.0f}'}
        #,
        #missing_kwds={'color':'red','edgecolor': 'brwon', 'hatch': '///',
    )
plt.show()
```

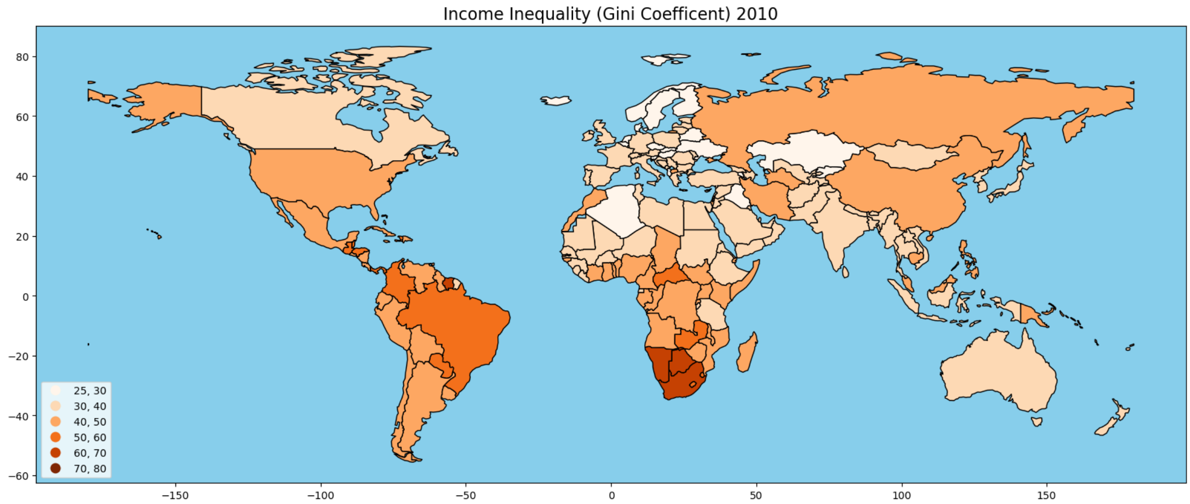

Income Inequality (Gini Coefficent) 1970
18, 30
30, 40
40, 50
50, 60
60, 70
70, 80


Income Inequality (Gini Coefficent) 1980
18, 30
30, 40
40, 50
50, 60
60, 70
70, 80


Income Inequality (Gini Coefficent) 1990
20, 30
30, 40
40, 50
50, 60
60, 70
70, 80


Income Inequality (Gini Coefficent) 2000


25, 30
30, 40
40, 50
50, 60
60, 70
70, 80


Income Inequality (Gini Coefficent) 2010
25, 30
30, 40
40, 50
50, 60
60, 70
70, 80

```
In [ ]:
```