greg_nmbrlang

May 12, 2022

1 Appendix Part 2: GREG Database Wrangling

This notebook is included separately, because it contains the code used to transform the GREG dataset into values in a suitable format to swap in for the withheld WLMS data.

[1]:

```
import pandas as pd
import numpy as np
import geopandas as gpd

import matplotlib.pyplot as plt
import seaborn as sns
```

```
/opt/homebrew/lib/python3.9/site-packages/geopandas/_compat.py:111: UserWarning:
The Shapely GEOS version (3.10.2-CAPI-1.16.0) is incompatible with the GEOS
version PyGEOS was compiled with (3.10.1-CAPI-1.16.0). Conversions between both
will be slow.
  warnings.warn(
```

1.1 Import Shapefiles

[2]:

```
virtual = gpd.read_file('data_raw/Virtual_country')
virtual[['uniq_cnt25', 'point5_id', 'geometry']].head()
```

[2]:

```
   uniq_cnt25  point5_id                                           geometry
0          39   247867.0  POLYGON ((-86.00000 82.00000, -86.50000 82.000…
1          40   247868.0  POLYGON ((-85.50000 82.00000, -86.00000 82.000…
2          40   247869.0  POLYGON ((-85.00000 82.00000, -85.50000 82.000…
3          40   247870.0  POLYGON ((-84.50000 82.00000, -85.00000 82.000…
4          40   247871.0  POLYGON ((-84.00000 82.00000, -84.50000 82.000…
```

[3]:

```
greg = gpd.read_file('greg')
greg[['G1SHORTNAM', 'G2SHORTNAM', 'G3SHORTNAM', 'geometry']].head()
```

[3]:

```
                                          G1SHORTNAM G2SHORTNAM G3SHORTNAM  \
0                                  Curaçao Islanders       None       None
1  English-speaking population of the Lesser Anti…       None       None
2                                             Baloch     Brahui       None
3                                           Persians    Afghans       None
```

```
4                                             Afghans     Tajiks       None

                                             geometry
0  POLYGON ((-69.88223 12.41111, -69.94695 12.436…
1  MULTIPOLYGON (((-61.73889 17.54055, -61.75195 …
2  POLYGON ((64.03937 30.02453, 64.03937 30.11267…
3  POLYGON ((61.75456 30.78628, 61.75833 30.79028…
4  POLYGON ((61.62285 31.39536, 61.64841 31.46713…
```

Before proceeding must check that the two shapefiles follow the same coordinate reference system, in this case, WGS84.

[4]:

```
virtual.crs == greg.crs
```

[4]:

```
True
```

1.2 Transform GREG

The original GREG format is a number of regions, each of which has up to three ethnic groups attached to it. Ethnic groups may also be attached to different regions. This code chunk melts, and then dissolves, the original `greg` dataset, such that we have one entry per ethnic group.

[5]:

```
melted = pd.melt(greg, id_vars = ['geometry'], value_vars = ['G1SHORTNAM',␣
 ↪'G2SHORTNAM', 'G3SHORTNAM'], value_name = 'SHORTNAM')
ethnicGroups = melted[melted['SHORTNAM'].notna()].drop('variable', axis = 1).
 ↪dissolve(by = 'SHORTNAM', aggfunc = 'first', as_index = False)
ethnicGroups
```

[5]:

```
       SHORTNAM                                         geometry
0    Abazinians  MULTIPOLYGON (((41.83519 44.08370, 41.86445 44…
1        Abkhaz  MULTIPOLYGON (((41.73878 42.62086, 41.71329 42…
2      Achaguas  MULTIPOLYGON (((-74.02123 2.16973, -73.98634 2…
3        Achang  POLYGON ((97.84312 24.33767, 97.84467 24.36087…
4      Achinese  MULTIPOLYGON (((97.81446 2.77691, 97.86672 2.7…
..          …                                                …
923      Zagawa  MULTIPOLYGON (((25.88538 14.53904, 25.83321 14…
924   Zakhchins  POLYGON ((91.54557 47.36713, 91.54557 47.43751…
925    Zapotecs  POLYGON ((-94.96082 16.37316, -95.03084 16.322…
926       Zoque  MULTIPOLYGON (((-93.18895 16.87464, -93.13737 …
927       Zulus  POLYGON ((31.11778 -29.67945, 31.00972 -29.872…

[928 rows x 2 columns]
```

1.3 Perform Intersection

This cell intersects the imported dataset of cells with the dataset of ethnic groups, derived from GREG.

[6]:

```
joined = gpd.overlay(virtual, ethnicGroups, how = 'intersection')
joined.head()
```

[6]:

```
   uniq_cnt25  point5_id   pop95  maize  pasture  suit_new  sorghum  allcrops  \
0         211   247281.0  0.0301    0.0      0.0    0.0000      0.0       0.0
1         211   247282.0  0.0300    0.0      0.0    0.0000      0.0       0.0
2         335   241416.0  0.0271    0.0      0.0    0.0001      0.0       0.0
3         335   242134.0  0.0195    0.0      0.0    0.0001      0.0       0.0
4         335   242135.0  0.0330    0.0      0.0    0.0001      0.0       0.0

  SHORTNAM                                           geometry
0  Eskimos  MULTIPOLYGON (((-19.00000 81.71801, -19.14417 …
1  Eskimos  MULTIPOLYGON (((-19.00000 81.80707, -18.99083 …
2  Eskimos  POLYGON ((-72.00000 78.00000, -71.87679 78.000…
3  Eskimos  MULTIPOLYGON (((-73.00000 78.17449, -72.99834 …
4  Eskimos  POLYGON ((-72.34038 78.00000, -72.34695 78.003…
```

1.4 Coverage

These cells reduce each virtual country to *only contain cells in which the cell is completely covered by an ethnic group from GREG*, similar to our interpretation of the procedure described in Michalopolous.

First, we calculate the "area" of each small cell after it has been intersected with the transformed GREG dataset. Then we compare this area to the area of the full cell, and equaivalent areas indicate that the cell is completely covered.

[7]:

```
dissolved = joined[['point5_id', 'geometry']].dissolve('point5_id')
areasCell = dissolved.area.to_frame().rename(columns = {0: 'overlay'})
areasCell['full'] = virtual.set_index('point5_id').area
areasCell['complete'] = np.isclose(areasCell['overlay'], areasCell['full'])
areasCell
```

```
/opt/homebrew/lib/python3.9/site-packages/pygeos/set_operations.py:388:
RuntimeWarning: divide by zero encountered in unary_union
  result = lib.unary_union(collections, **kwargs)
/var/folders/l7/_yl1rg512jv095gql7v0v5r00000gn/T/ipykernel_50548/310672282.py:2:
UserWarning: Geometry is in a geographic CRS. Results from 'area' are likely
incorrect. Use 'GeoSeries.to_crs()' to re-project geometries to a projected CRS
before this operation.

  areasCell = dissolved.area.to_frame().rename(columns = {0: 'overlay'})
/var/folders/l7/_yl1rg512jv095gql7v0v5r00000gn/T/ipykernel_50548/310672282.py:3:
UserWarning: Geometry is in a geographic CRS. Results from 'area' are likely
incorrect. Use 'GeoSeries.to_crs()' to re-project geometries to a projected CRS
before this operation.

  areasCell['full'] = virtual.set_index('point5_id').area
```

```
[7]:             overlay  full  complete
     point5_id
     49903.0    0.040962  0.25     False
     49904.0    0.111268  0.25     False
     49905.0    0.112302  0.25     False
     49906.0    0.006557  0.25     False
     50621.0    0.006873  0.25     False
     …               …     …        …
     242136.0   0.185729  0.25     False
     242137.0   0.013326  0.25     False
     242857.0   0.033278  0.25     False
     247281.0   0.013842  0.25     False
     247282.0   0.060065  0.25     False

     [58073 rows x 3 columns]
```

This cell merges the overlay dataset calculated earlier with the coverage dataset, to determine whether each cell-ethnic group combination is of a cell with complete coverage.

```
[8]: joinedCoverage = joined.merge(areasCell, left_on = 'point5_id', right_index =␣
       ↪True)
     joinedCoverage[['uniq_cnt25', 'point5_id', 'complete']].head()
```

```
[8]:    uniq_cnt25  point5_id  complete
     0         211   247281.0     False
     1         211   247282.0     False
     2         335   241416.0     False
     3         335   242134.0     False
     4         335   242135.0     False
```

Finally, we group by the virtual country ID, and count the number of unique ethnic groups (SHORTNAM), along with the number of complete cells (point5_id).

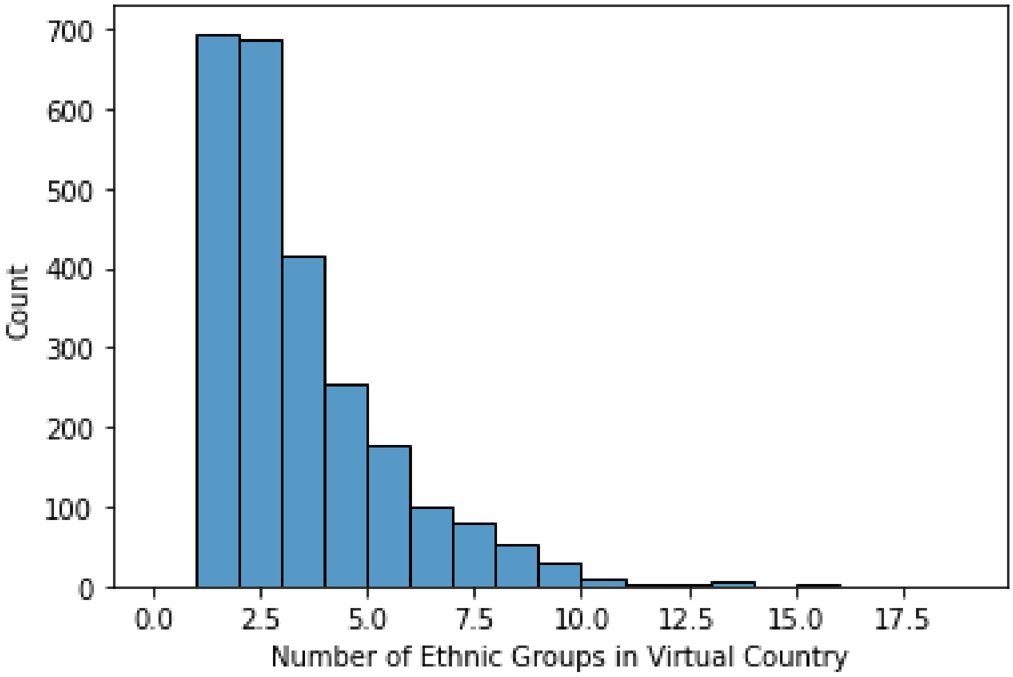
```
[9]: countries = joinedCoverage[joinedCoverage['complete'] == True].
       ↪groupby('uniq_cnt25')[['point5_id', 'SHORTNAM']].nunique()
     countries.to_csv('greg.csv')
```

```
[10]: len(countries)
```

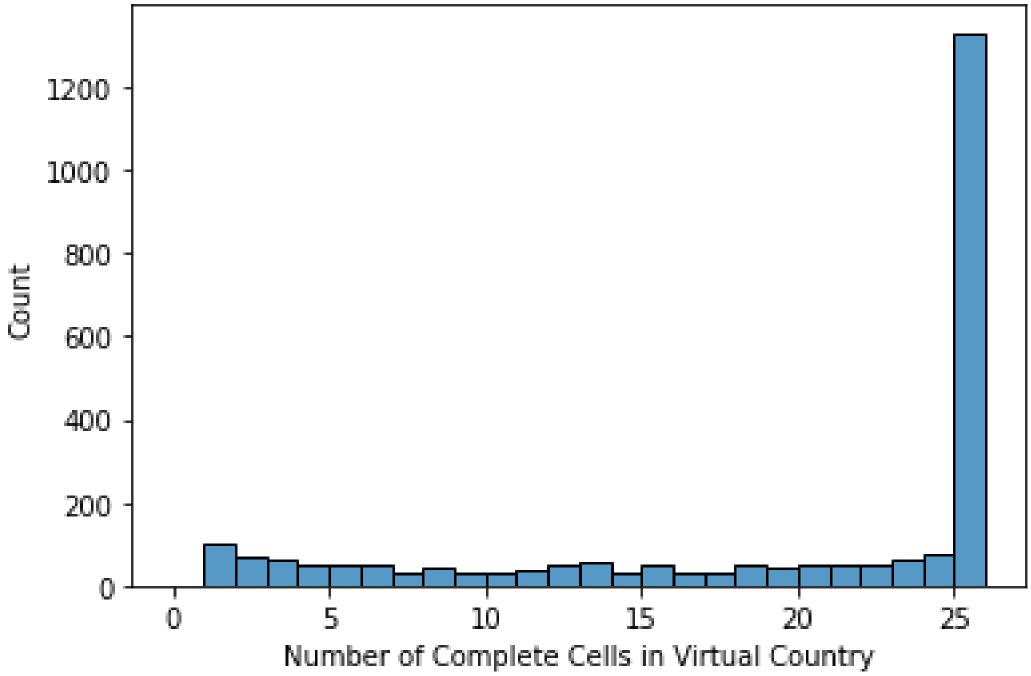
```
[10]: 2521
```

```
[11]: ax = sns.histplot(x = countries['SHORTNAM'], bins = np.arange(0, 20))
      ax.set_xlabel('Number of Ethnic Groups in Virtual Country')
```

```
[11]: Text(0.5, 0, 'Number of Ethnic Groups in Virtual Country')
```



```
[13]: ax = sns.histplot(x = countries['point5_id'], bins = np.arange(27))
      ax.set_xlabel('Number of Complete Cells in Virtual Country');
```



1.5 Comparison to WLMS

When calculating number of ethnic groups per virtual country, we obtained 2521 countries with full coverage in at least one of its 25 cells. 1857 of these countries are included in the dataset derived from WLMS provided in the data download. 31 of the countries included in the data downloaded are *not* included in the 2521 countries we obtained.

```
[14]: df = pd.read_stata('data_raw/Tables4-7b.dta')
      df['uniq_cnt25'] = df['uniq_cnt25'].astype(int)
```

```
[15]: len(df)
```

```
[15]: 1888
```

```
[16]: countries.index.isin(df['uniq_cnt25']).sum()
```

```
[16]: 1857
```

```
[17]: df['uniq_cnt25'].isin(countries.index).sum()
```

```
[17]: 1857
```