Renewable_Energy_Technical_Potential

April 24, 2018

1 Dashboard of Renewable Energy in the U.S

```
In [1]: import pandas as pd
        import numpy as np
        import folium
        import os
        from branca.utilities import split_six
        state_geo = os.path.join('data', 'us-states.json')
        import matplotlib.pyplot as plt
        %matplotlib inline
        from IPython.display import Image
        from IPython.display import display_html
        from IPython.display import display
```

1.1 Import Data

- Data Source: https://catalog.data.gov/dataset/united-states-renewable-energy-technical-potential
- Reference: https://openei.org/doe-opendata/dataset/5346c5c2-be26-4be7-9663-b5a98cbb7527/resource/01fe78a8-77b6-4c59-bc36-cae177ee86c3/download/usretechpotential.pdf
- Goal: Create dashboard to visualize the data of renewable energy technical potential in the US.

```
In [2]: inputDF = pd.read_csv('usretechnicalpotential.csv')
```

```
In [3]: inputDF = inputDF.rename(columns = {'Unnamed: 0':'state'})
        # replacing NaN values with 0
        inputDF.fillna(0, inplace=True)
```

```
In [4]: inputDF.head()
```

```
Out[4]:         state  urbanUtilityScalePV_GWh  urbanUtilityScalePV_GW  \
        0     Alabama                    35850                      20
        1      Alaska                      166                       0
        2     Arizona                   121305                      52
        3    Arkansas                    28960                      15
        4  California                   246008                     111
```

```
     urbanUtilityScalePV_km2  ruralUtilityScalePV_GWh  ruralUtilityScalePV_GW  \
0                        426                  3706838                    2114
1                          2                  8282976                    9005
2                       1096                 11867693                    5147
3                        332                  4986388                    2747
4                       2320                  8855917                    4010

   ruralUtilityScalePV_km2  rooftopPV_GWh  rooftopPV_GW     CSP_GWh  \
0                    44058        15475.0            12           0
1                   187608            0.0             1           0
2                   107230        22736.0            14    12544333
3                    57239         8484.0             6           0
4                    83549       106411.0            75     8490916

              ...       biopowerGaseous_GWh  biopowerGaseous_GW  \
0             ...                      1533                   0
1             ...                        61                   0
2             ...                       837                   0
3             ...                      1063                   0
4             ...                     15510                   1

   biopowerGaseous_Tonnes-CH4  geothermalHydrothermal_GWh  \
0                      326186                           0
1                       13156                       15437
2                      178188                        8329
3                      226178                           0
4                     3300211                      130921

   geothermalHydrothermal_GW  EGSGeothermal_GWh  EGSGeothermal_GW  \
0                          0           535489.0              67.0
1                          1                0.0               0.0
2                          1          1239147.0             157.0
3                          0           628621.0              79.0
4                         16          1344179.0             170.0

   hydropower_GWh  hydropower_GW  hydropower_countOfSites
0            4102              0                     2435
1           23675              5                     3053
2            1303              0                     1958
3            6093              1                     3268
4           30023              6                     9692

[5 rows x 31 columns]

In [5]: inputDF.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
```

```
Data columns (total 31 columns):
state                          51 non-null object
urbanUtilityScalePV_GWh        51 non-null int64
urbanUtilityScalePV_GW         51 non-null int64
urbanUtilityScalePV_km2        51 non-null int64
ruralUtilityScalePV_GWh        51 non-null int64
ruralUtilityScalePV_GW         51 non-null int64
ruralUtilityScalePV_km2        51 non-null int64
rooftopPV_GWh                  51 non-null float64
rooftopPV_GW                   51 non-null int64
CSP_GWh                        51 non-null int64
CSP_GW                         51 non-null int64
CSP_km2                        51 non-null int64
onshoreWind_GWh                51 non-null int64
onshoreWind_GW                 51 non-null int64
onshoreWind_km2                51 non-null int64
offshoreWind_GWh               51 non-null float64
offshoreWind_GW                51 non-null float64
offshoreWind_km2               51 non-null float64
biopowerSolid_GWh              51 non-null int64
biopowerSolid_GW               51 non-null int64
biopowerSolid_BDT              51 non-null int64
biopowerGaseous_GWh            51 non-null int64
biopowerGaseous_GW             51 non-null int64
biopowerGaseous_Tonnes-CH4     51 non-null int64
geothermalHydrothermal_GWh     51 non-null int64
geothermalHydrothermal_GW      51 non-null int64
EGSGeothermal_GWh              51 non-null float64
EGSGeothermal_GW               51 non-null float64
hydropower_GWh                 51 non-null int64
hydropower_GW                  51 non-null int64
hydropower_countOfSites        51 non-null int64
dtypes: float64(6), int64(24), object(1)
memory usage: 12.4+ KB
```

1.2 Organize data

1.2.1 1. Utility-Scale Photovoltaics (Urban)

- Definition: large-scale photovoltaics(PV) deployed within urban boundaries on urban open space.
- State technical potential generation is expressed as:

$$StateMWh = State\Sigma[UrbanOpenSapce(km^2) * PowerDensity(48\frac{MW}{km^2}) * StateCapacityFactor(\%) * 8760(Hou$$

```
In [6]: urbanUtilityScalePV_DF = inputDF[['state','urbanUtilityScalePV_GWh','urbanUtilityScaleP
        urbanUtilityScalePV_sumDF = pd.DataFrame([['U.S Total',\
```

```
                      urbanUtilityScalePV_DF['urbanUtilityScalePV_
                      urbanUtilityScalePV_DF['urbanUtilityScalePV_
                      urbanUtilityScalePV_DF['urbanUtilityScalePV_
                  columns=['state','urbanUtilityScalePV_GWh','u
```

The total estimated annual technical potential in the United States for urban utility-scale PV

```
In [7]: urbanUtilityScalePV_sumDF

Out[7]:        state  urbanUtilityScalePV_GWh  urbanUtilityScalePV_GW  \
        0  U.S Total                  2231670                    1195

           urbanUtilityScalePV_km2
        0                     25343
```

Choropleth map of estimated technical potential for urban utility-scale photovoltaics in the U.S.:

```
In [8]: threshold_scale = split_six(urbanUtilityScalePV_DF['urbanUtilityScalePV_GWh'])

        m = folium.Map(location=[48, -102], zoom_start=3)
        m.choropleth(
            geo_data=state_geo,
            name='choropleth',
            data=urbanUtilityScalePV_DF,
            columns=['state', 'urbanUtilityScalePV_GWh'],
            key_on='feature.properties.name',
            fill_color='YlGn',
            fill_opacity=0.7,
            line_opacity=0.2,
            legend_name='Urban Utility Scale PV (Gigawatt Hours)',
            threshold_scale=threshold_scale,
            reset=True
        )


        folium.LayerControl().add_to(m)

        m.save(os.path.join('choroplethMap', 'urbanUtilityScalePV.html'))

        m

Out[8]: <folium.folium.Map at 0x1119fb8d0>
```

Note: GitHub preview cannot load the choropleth map directly, so I saved the map in html and screenshot the result for better visualizationon on GitHub preview.

```
In [9]: display(Image("choroplethMap/urbanUtilityScalePV.png", width=1000))
```
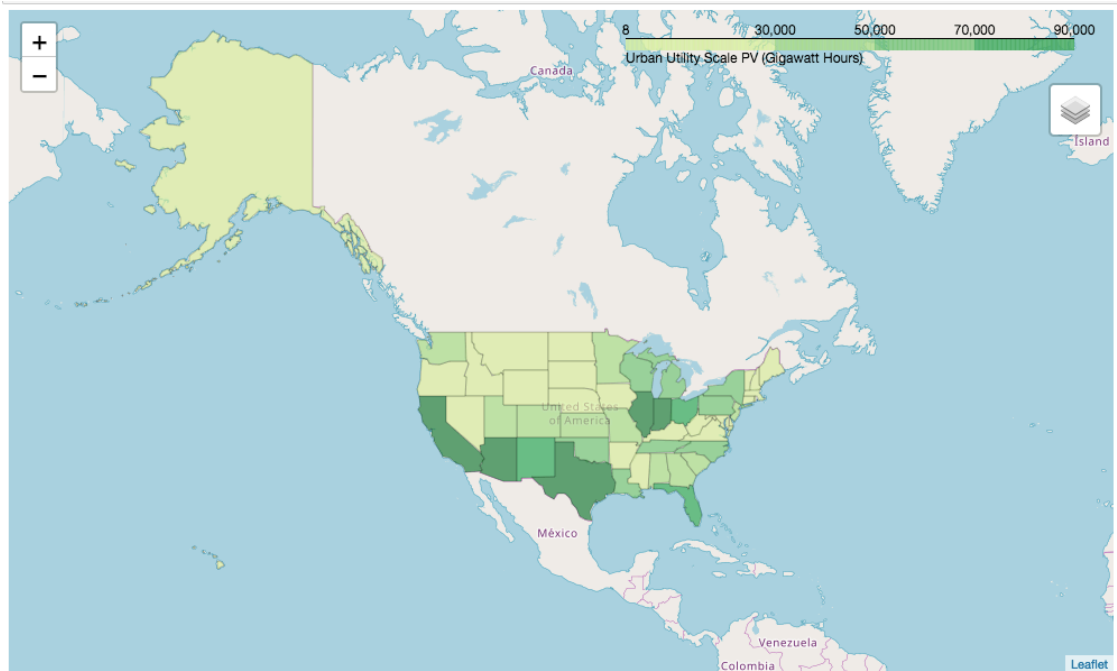
Table of estimated technical potential for urban utility-scale photovoltaics by state: Texas and California have the highest estimated technical potential, a result of a combination of good solar resource and large population

```
In [10]: urbanUtilityScalePV_DF.append(urbanUtilityScalePV_sumDF)
```

```
Out[10]:                    state  urbanUtilityScalePV_GWh  urbanUtilityScalePV_GW  \
         0               Alabama                    35850                      20
         1                Alaska                      166                       0
         2               Arizona                   121305                      52
         3              Arkansas                    28960                      15
         4            California                   246008                     111
         5              Colorado                    43470                      19
         6           Connecticut                     7716                       4
         7              Delaware                    14856                       9
         8   District of Columbia                        8                       0
         9               Florida                    72787                      39
         10              Georgia                    43166                      24
         11               Hawaii                     3725                       1
         12                Idaho                    23194                      12
         13             Illinois                   103551                      63
         14              Indiana                    98815                      61
         15                 Iowa                    27091                      15
         16               Kansas                    31705                      15
         17             Kentucky                    26514                      16
```

18	Louisiana	55669	32
19	Maine	3216	1
20	Maryland	28551	18
21	Massachusetts	17469	10
22	Michigan	50845	33
23	Minnesota	33370	20
24	Mississippi	26366	15
25	Missouri	30549	18
26	Montana	11370	6
27	Nebraska	12954	6
28	Nevada	24893	10
29	New Hampshire	3790	2
30	New Jersey	44307	25
31	New Mexico	71356	30
32	New York	52803	32
33	North Carolina	68346	37
34	North Dakota	4871	2
35	Ohio	86495	57
36	Oklahoma	50040	25
37	Oregon	25783	12
38	Pennsylvania	56161	36
39	Rhode Island	1787	1
40	South Carolina	33834	19
41	South Dakota	4573	2
42	Tennessee	50243	28
43	Texas	294684	154
44	Utah	30492	14
45	Vermont	1632	1
46	Virginia	27451	15
47	Washington	33690	19
48	West Virginia	3023	2
49	Wisconsin	54938	34
50	Wyoming	7232	3
0	U.S Total	2231670	1195

	urbanUtilityScalePV_km2
0	426
1	2
2	1096
3	332
4	2320
5	399
6	100
7	189
8	0
9	830
10	505
11	34

12	251
13	1324
14	1274
15	324
16	317
17	338
18	674
19	40
20	378
21	228
22	699
23	419
24	317
25	376
26	127
27	141
28	224
29	48
30	527
31	645
32	682
33	789
34	57
35	1190
36	533
37	270
38	754
39	24
40	397
41	50
42	595
43	3213
44	292
45	22
46	326
47	402
48	41
49	727
50	75
0	25343

1.2.2 2. Utility-Scale Photovoltaics (Rural)

- Definition: large-scale PV deployed outside urban boundaries (the complement of urban utility-scale PV).
- State technical potential generation is expressed as:

$$StateMWh = State\Sigma[AvailableLand(km^2) * PowerDensity(48\frac{MW}{km^2}) * StateCapacityFactor(\%) * 8760(HoursI$$

```
In [11]: ruralUtilityScalePV_DF = inputDF[['state','ruralUtilityScalePV_GWh','ruralUtilityScale
         ruralUtilityScalePV_sumDF = pd.DataFrame([['U.S Total',\
                                          ruralUtilityScalePV_DF['ruralUtilityScalePV
                                          ruralUtilityScalePV_DF['ruralUtilityScalePV
                                          ruralUtilityScalePV_DF['ruralUtilityScalePV
                                     columns=['state','ruralUtilityScalePV_GWh','r
```

The total estimated annual technical potential in the United States for rural utility-scale PV

```
In [12]: ruralUtilityScalePV_sumDF

Out[12]:        state  ruralUtilityScalePV_GWh  ruralUtilityScalePV_GW  \
         0  U.S Total               280613190                  152950

            ruralUtilityScalePV_km2
         0                  3186931
```

Choropleth map of estimated technical potential for rural utility-scale photovoltaics in the U.S.:

```
In [13]: threshold_scale = split_six(ruralUtilityScalePV_DF['ruralUtilityScalePV_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=ruralUtilityScalePV_DF,
             columns=['state', 'ruralUtilityScalePV_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Rural Utility Scale PV (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'ruralUtilityScalePV.html'))


         m

Out[13]: <folium.folium.Map at 0x1119fb4a8>

In [14]: display(Image("choroplethMap/ruralUtilityScalePV.png", width=1000))
```
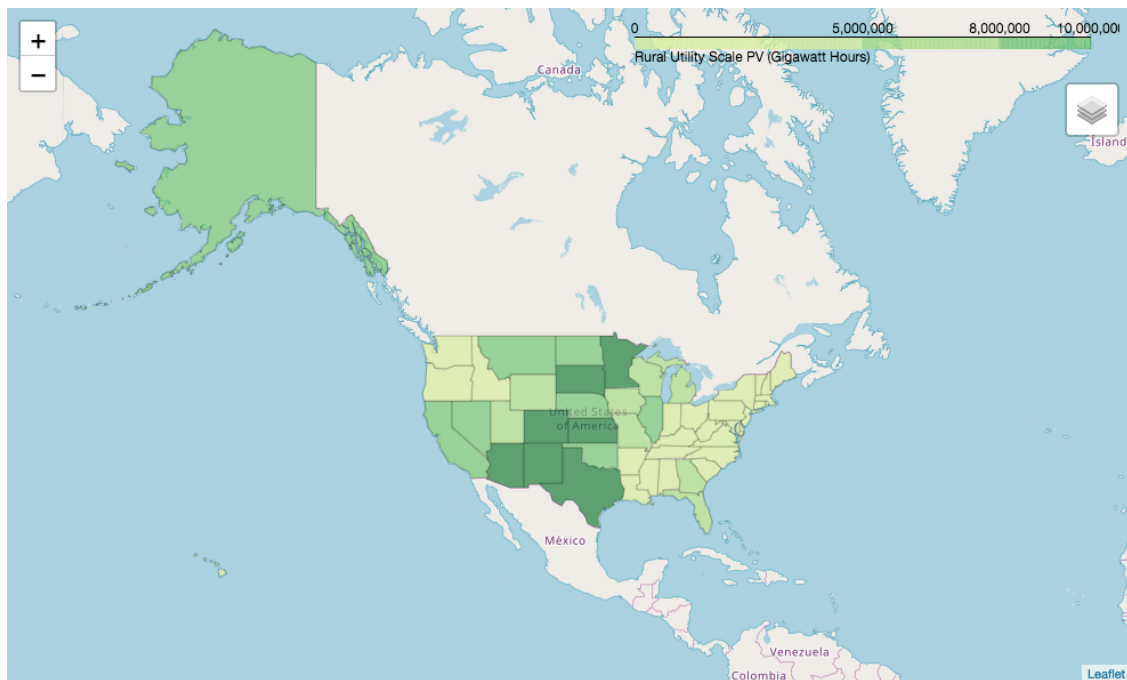
Table of estimated technical potential for rural utility-scale photovoltaics by state:

```
In [15]: ruralUtilityScalePV_DF.append(ruralUtilityScalePV_sumDF)
```

```
Out[15]:                    state  ruralUtilityScalePV_GWh  ruralUtilityScalePV_GW  \
         0               Alabama                  3706838                    2114
         1                Alaska                  8282976                    9005
         2               Arizona                 11867693                    5147
         3              Arkansas                  4986388                    2747
         4            California                  8855917                    4010
         5              Colorado                 10238083                    4514
         6           Connecticut                    19627                      12
         7              Delaware                   272332                     167
         8  District of Columbia                        0                       0
         9               Florida                  5137346                    2812
         10              Georgia                  5492183                    3088
         11               Hawaii                    38032                      20
         12                Idaho                  3936847                    2045
         13             Illinois                  8090985                    4969
         14              Indiana                  4876185                    3018
         15                 Iowa                  6994159                    4020
         16               Kansas                 14500149                    6959
         17             Kentucky                  1823976                    1119
         18            Louisiana                  4114605                    2394
         19                Maine                  1100327                     658
         20             Maryland                   585949                     373
```

21	Massachusetts	82204	51
22	Michigan	5215639	3443
23	Minnesota	10792814	6510
24	Mississippi	4981252	2879
25	Missouri	5335268	3156
26	Montana	8187341	4402
27	Nebraska	9266756	4869
28	Nevada	8614454	3732
29	New Hampshire	57363	35
30	New Jersey	439773	251
31	New Mexico	16318543	7087
32	New York	1492566	926
33	North Carolina	4232789	2346
34	North Dakota	9734447	5482
35	Ohio	3626181	2395
36	Oklahoma	9341920	4782
37	Oregon	3740478	1884
38	Pennsylvania	553356	356
39	Rhode Island	13636	8
40	South Carolina	2754973	1555
41	South Dakota	10008873	5344
42	Tennessee	2225989	1266
43	Texas	38993581	20411
44	Utah	5184878	2390
45	Vermont	54727	35
46	Virginia	1882467	1074
47	Washington	1738150	996
48	West Virginia	52693	35
49	Wisconsin	5042258	3205
50	Wyoming	5727224	2854
0	U.S Total	280613190	152950

	ruralUtilityScalePV_km2
0	44058
1	187608
2	107230
3	57239
4	83549
5	94046
6	256
7	3482
8	0
9	58596
10	64343
11	430
12	42612
13	103524
14	62890

```
15                      83762
16                     144995
17                      23319
18                      49876
19                      13722
20                       7772
21                       1074
22                      71740
23                     135627
24                      59996
25                      65766
26                      91724
27                     101456
28                      77751
29                        741
30                       5231
31                     147652
32                      19294
33                      48892
34                     114227
35                      49908
36                      99640
37                      39266
38                       7429
39                        184
40                      32398
41                     111350
42                      26395
43                     425230
44                      49797
45                        739
46                      22377
47                      20758
48                        729
49                      66788
50                      59463
0                     3186931
```

1.2.3 3. Rooftop Photovoltaics

- Definition: We obtained rooftop PV estimates from Denholm and Margolis (2008b), who obtained floor space estimates for commercial and residential buildings from McGraw-Hill and scaled these to estimate a building footprint based on the number of floors.

```
In [16]: rooftopPV_DF = inputDF[['state','rooftopPV_GWh','rooftopPV_GW']]
         rooftopPV_sumDF = pd.DataFrame([['U.S Total',\
                                         rooftopPV_DF['rooftopPV_GWh'].sum(),\
                                         rooftopPV_DF['rooftopPV_GW'].sum()]],\
```

11

```
                            columns=['state','rooftopPV_GWh','rooftopPV_(
```

The total estimated annual technical potential in the United States for Rooftop Photovoltaics

```
In [17]: rooftopPV_sumDF

Out[17]:        state  rooftopPV_GWh  rooftopPV_GW
         0  U.S Total       818711.0           639
```

Choropleth map of estimated technical potential for rooftop photovoltaics in the U.S.:

```
In [18]: threshold_scale = split_six(rooftopPV_DF['rooftopPV_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=rooftopPV_DF,
             columns=['state', 'rooftopPV_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Rooftop PV (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'rooftopPV.html'))


         m

Out[18]: <folium.folium.Map at 0x111c4fa90>

In [19]: display(Image("choroplethMap/rooftopPV.png", width=1000))
```
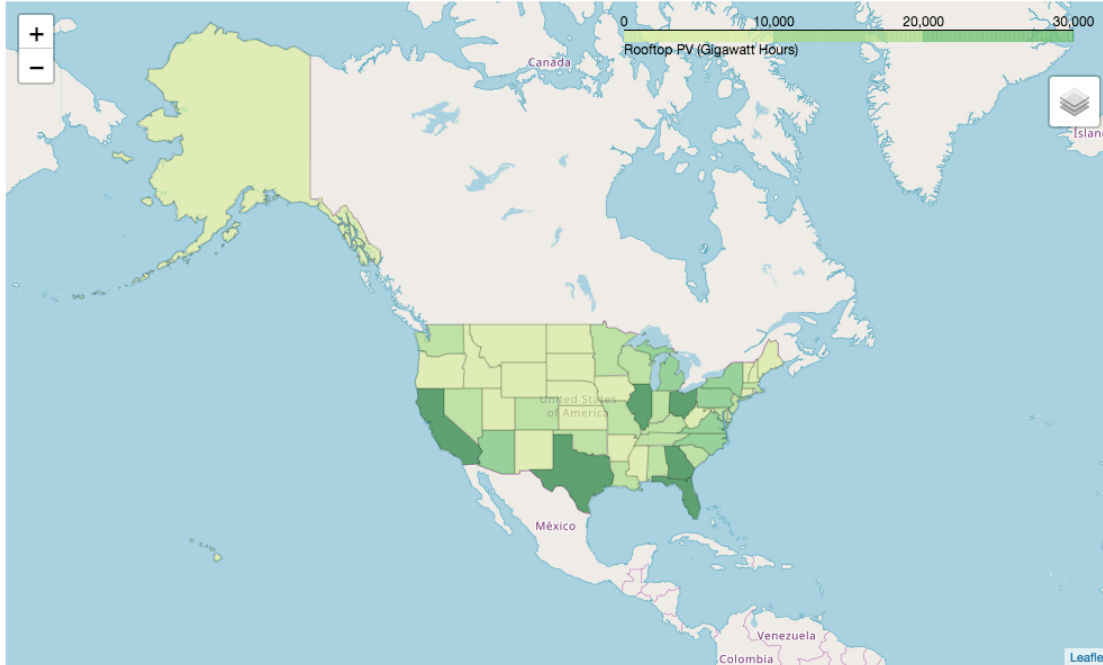
Table of estimated technical potential for rooftop photovoltaics by state: States with the largest technical potential typically have the largest populations. California has the highest technical potential of 106 TWh due to its mix of high population and relatively good solar resource.

```
In [20]: rooftopPV_DF.append(rooftopPV_sumDF)
```

```
Out[20]:                      state  rooftopPV_GWh  rooftopPV_GW
         0                    Alabama        15475.0            12
         1                     Alaska            0.0             1
         2                    Arizona        22736.0            14
         3                   Arkansas         8484.0             6
         4                 California       106411.0            75
         5                   Colorado        16162.0            11
         6                Connecticut         6616.0             5
         7                   Delaware         2185.0             1
         8       District of Columbia         2490.0             2
         9                    Florida        63986.0            49
         10                   Georgia        31116.0            24
         11                    Hawaii            0.0             2
         12                     Idaho         4051.0             3
         13                  Illinois        30086.0            26
         14                   Indiana        17151.0            14
         15                      Iowa         8646.0             7
         16                    Kansas         8962.0             6
         17                  Kentucky        12312.0            10
```

18	Louisiana	14368.0	11
19	Maine	2443.0	2
20	Maryland	14849.0	12
21	Massachusetts	11722.0	10
22	Michigan	23527.0	21
23	Minnesota	14321.0	12
24	Mississippi	8614.0	6
25	Missouri	16159.0	13
26	Montana	2194.0	1
27	Nebraska	5336.0	4
28	Nevada	10767.0	7
29	New Hampshire	2298.0	2
30	New Jersey	15767.0	13
31	New Mexico	6513.0	4
32	New York	28779.0	25
33	North Carolina	28419.0	23
34	North Dakota	1916.0	1
35	Ohio	30064.0	27
36	Oklahoma	12442.0	9
37	Oregon	8322.0	7
38	Pennsylvania	22215.0	19
39	Rhode Island	1710.0	1
40	South Carolina	14412.0	11
41	South Dakota	2082.0	1
42	Tennessee	19685.0	16
43	Texas	78716.0	60
44	Utah	7513.0	5
45	Vermont	1115.0	1
46	Virginia	22266.0	18
47	Washington	13599.0	13
48	West Virginia	4220.0	3
49	Wisconsin	13939.0	12
50	Wyoming	1550.0	1
0	U.S Total	818711.0	639

1.2.4   4. Concentrating Solar Power (CSP)

- Definition: power from a utility-scale solar power facility in which the solar heat energy is collected in a central location.

- State technical potential generation is expressed as:

$$StateMWh = State\Sigma[AvailableLand(km^2) * PowerDensity(32.895\frac{MW}{km^2}) * StateCapacityFactor(\%) * 8760(Ho$$

```
In [21]: CSP_DF = inputDF[['state','CSP_GWh','CSP_GW','CSP_km2']]
         CSP_sumDF = pd.DataFrame([['U.S Total',\
                                                 CSP_DF['CSP_GWh'].sum(),\
                                                 CSP_DF['CSP_GW'].sum(),\
```

```
                                        CSP_DF['CSP_km2'].sum()]], \
                          columns=['state','CSP_GWh','CSP_GW','CSP_km2
```

The total estimated annual technical potential in the United States for Concentrating Solar Power

```
In [22]: CSP_sumDF

Out[22]:        state    CSP_GWh  CSP_GW  CSP_km2
         0  U.S Total  116146234    38057  1157199
```

Choropleth map of estimated technical potential for Concentrating Solar Power in the U.S.:

```
In [23]: threshold_scale = split_six(CSP_DF['CSP_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=CSP_DF,
             columns=['state', 'CSP_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Concentrating Solar Power (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'CSP.html'))


         m

Out[23]: <folium.folium.Map at 0x111c4fc18>

In [24]: display(Image("choroplethMap/CSP.png", width=1000))
```
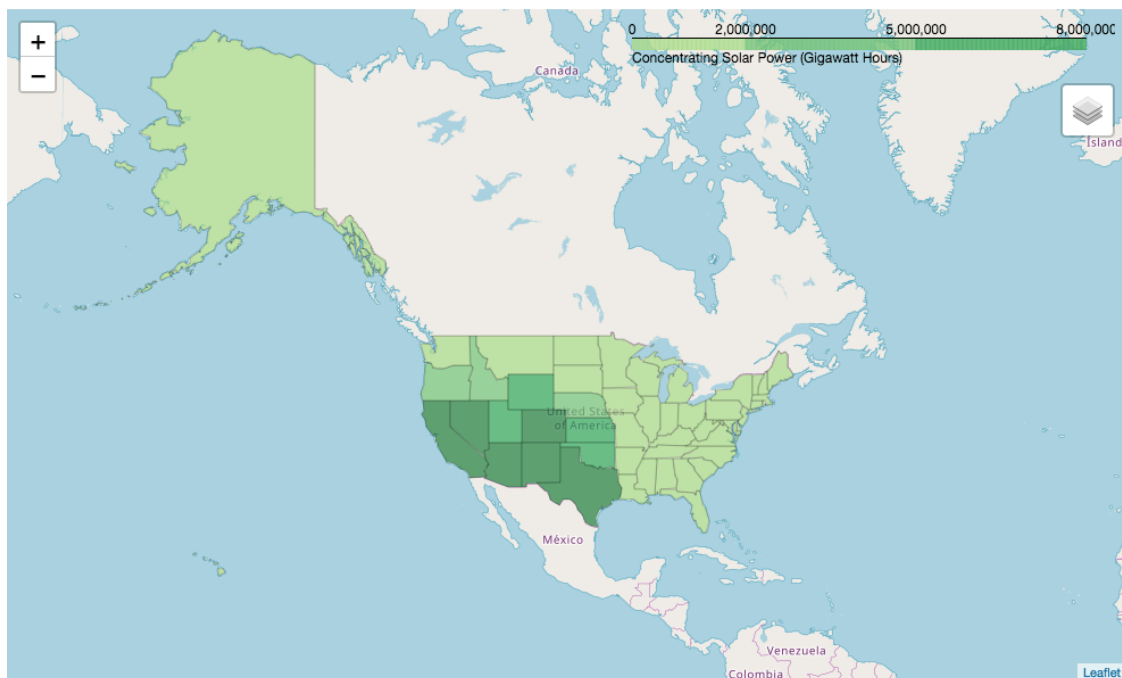
Table of estimated technical potential for Concentrating Solar Power by state: Technical potential for CSP exists predominately in the Southwest.

```
In [25]: CSP_DF.append(CSP_sumDF)
```

```
Out[25]:                     state    CSP_GWh   CSP_GW   CSP_km2
         0                  Alabama          0        0         0
         1                   Alaska          0        0         0
         2                  Arizona   12544333     3527    107238
         3                 Arkansas          0        0         0
         4               California    8490916     2725     82859
         5                 Colorado    9154524     3097     94173
         6              Connecticut          0        0         0
         7                 Delaware          0        0         0
         8     District of Columbia          0        0         0
         9                  Florida        358        0         3
         10                 Georgia          0        0         0
         11                  Hawaii      15369        5       168
         12                   Idaho    3502877     1267     38523
         13                Illinois          0        0         0
         14                 Indiana          0        0         0
         15                    Iowa          0        0         0
         16                  Kansas    7974255     2884     87697
         17                Kentucky          0        0         0
         18               Louisiana          0        0         0
```

19	Maine	0	0	0
20	Maryland	0	0	0
21	Massachusetts	0	0	0
22	Michigan	0	0	0
23	Minnesota	0	0	0
24	Mississippi	0	0	0
25	Missouri	0	0	0
26	Montana	1540287	557	16939
27	Nebraska	4846929	1753	53304
28	Nevada	8295752	2557	77759
29	New Hampshire	0	0	0
30	New Jersey	0	0	0
31	New Mexico	16812349	4860	147747
32	New York	0	0	0
33	North Carolina	0	0	0
34	North Dakota	36049	13	396
35	Ohio	0	0	0
36	Oklahoma	5068036	1812	55113
37	Oregon	2812126	1017	30926
38	Pennsylvania	0	0	0
39	Rhode Island	0	0	0
40	South Carolina	0	0	0
41	South Dakota	1629659	589	17922
42	Tennessee	0	0	0
43	Texas	22786749	7743	235398
44	Utah	5067546	1638	49799
45	Vermont	0	0	0
46	Virginia	0	0	0
47	Washington	161713	58	1778
48	West Virginia	0	0	0
49	Wisconsin	0	0	0
50	Wyoming	5406407	1955	59457
0	U.S Total	116146234	38057	1157199

1.2.5   5. Onshore Wind Power

- Definition: wind resource at 80 meters(m) height above surface that results in an annual average gross capacity factor of 30% (net capacity factor of 25.5%), using typical utility-scale wind turbine power curves.
- We estimate annual generation by assuming a power density of 5 MW/km^2(DOE EERE 2008)10 and 15% energy losses to calculate net capacity factor.

```
In [26]: onshoreWind_DF = inputDF[['state','onshoreWind_GWh','onshoreWind_GW','onshoreWind_km2
         onshoreWind_sumDF = pd.DataFrame([['U.S Total',\
                                                      onshoreWind_DF['onshoreWind_GWh'].sum(),\
                                                      onshoreWind_DF['onshoreWind_GW'].sum(),\
                                                      onshoreWind_DF['onshoreWind_km2'].sum()]],
                                                    columns=['state','onshoreWind_GWh','onshoreW
```

The total estimated annual technical potential in the United States for Onshore Wind Power

```
In [27]: onshoreWind_sumDF

Out[27]:         state  onshoreWind_GWh  onshoreWind_GW  onshoreWind_km2
         0  U.S Total         32783975           10937          2190929
```

Choropleth map of estimated technical potential for Onshore Wind Power in the U.S.:

```
In [28]: threshold_scale = split_six(onshoreWind_DF['onshoreWind_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=onshoreWind_DF,
             columns=['state', 'onshoreWind_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Onshore Wind Power (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'onshoreWind.html'))


         m

Out[28]: <folium.folium.Map at 0x111d45b38>

In [29]: display(Image("choroplethMap/onshoreWind.png", width=1000))
```
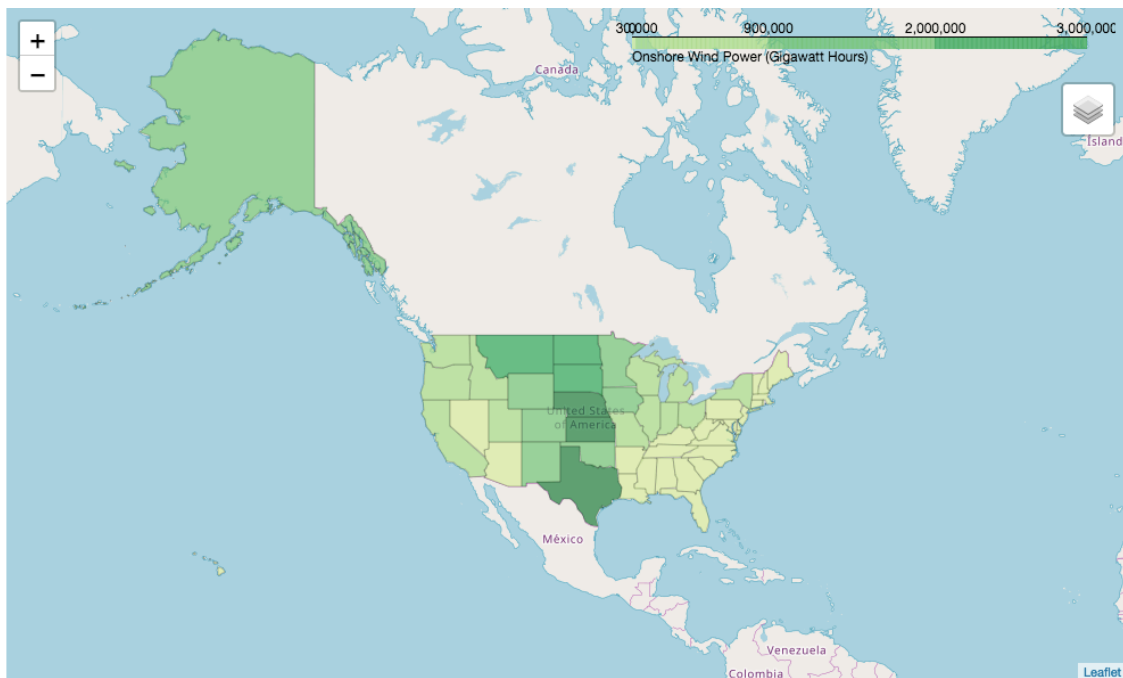
Table of estimated technical potential for Onshore Wind Power by state: Technical potential for onshore wind power is largest in the central Great Plains and lowest in the southeastern United States.

```
In [30]: onshoreWind_DF.append(onshoreWind_sumDF)
```

```
Out[30]:                     state   onshoreWind_GWh   onshoreWind_GW   onshoreWind_km2
         0                  Alabama              283                0                23
         1                   Alaska          1373433              493             98669
         2                  Arizona            26036               10              2180
         3                 Arkansas            22892                9              1840
         4               California            89862               34              6822
         5                 Colorado          1096035              387             77443
         6              Connecticut               61                0                 5
         7                 Delaware               21                0                 1
         8     District of Columbia                0                0                 0
         9                  Florida                0                0                 0
         10                 Georgia              322                0                26
         11                  Hawaii             7786                2               493
         12                   Idaho            44319               18              3615
         13                Illinois           649467              249             49976
         14                 Indiana           377603              148             29645
         15                    Iowa          1723587              570            114142
         16                  Kansas          3101575              952            190474
         17                Kentucky              147                0                12
```

18	Louisiana	934	0	81
19	Maine	28742	11	2250
20	Maryland	3631	1	296
21	Massachusetts	2827	1	205
22	Michigan	143907	59	11808
23	Minnesota	1428524	489	97854
24	Mississippi	0	0	0
25	Missouri	689519	274	54871
26	Montana	2746271	944	188800
27	Nebraska	3011252	917	183599
28	Nevada	17709	7	1449
29	New Hampshire	5706	2	427
30	New Jersey	317	0	26
31	New Mexico	1399156	492	98416
32	New York	63565	25	5156
33	North Carolina	2037	0	161
34	North Dakota	2537824	770	154039
35	Ohio	129142	54	10983
36	Oklahoma	1521651	516	103364
37	Oregon	68766	27	5420
38	Pennsylvania	8230	3	661
39	Rhode Island	129	0	9
40	South Carolina	427	0	37
41	South Dakota	2901858	882	176482
42	Tennessee	765	0	61
43	Texas	5552399	1901	380305
44	Utah	31552	13	2620
45	Vermont	7795	2	589
46	Virginia	4589	1	358
47	Washington	47249	18	3695
48	West Virginia	4951	1	376
49	Wisconsin	255266	103	20751
50	Wyoming	1653856	552	110414
0	U.S Total	32783975	10937	2190929

1.2.6 6. Offshore Wind Power

- Definition: annual average wind speed greater than or equal to 6.4 meters per second (m/s) at 90 m height above surface.
- Our annual generation estimates assume a power density of 5 MW/km^2 and capacity factors based on wind speed interval and depth-based wind farm configurations to account for anchoring and stabilization for the turbines as developed by NREL analysts for use in the ReEDS model (Musial and Ram 2010).

```
In [31]: offshoreWind_DF = inputDF[['state','offshoreWind_GWh','offshoreWind_GW','offshoreWind_
         offshoreWind_sumDF = pd.DataFrame([['U.S Total',\
                                             offshoreWind_DF['offshoreWind_GWh'].sum(),\
                                             offshoreWind_DF['offshoreWind_GW'].sum(),\
```

```
                                    offshoreWind_DF['offshoreWind_km2'].sum()]]
                            columns=['state','offshoreWind_GWh','offshor
```

The total estimated annual technical potential in the United States for Offshore Wind Power

```
In [32]: offshoreWind_sumDF

Out[32]:        state  offshoreWind_GWh  offshoreWind_GW  offshoreWind_km2
         0  U.S Total       16975788.0           4210.0          844688.0
```

Choropleth map of estimated technical potential for Offshore Wind Power in the U.S.:

```
In [33]: threshold_scale = split_six(offshoreWind_DF['offshoreWind_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=offshoreWind_DF,
             columns=['state', 'offshoreWind_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Offshore Wind Power  (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'offshoreWind.html'))


         m

Out[33]: <folium.folium.Map at 0x111fc6c50>

In [34]: display(Image("choroplethMap/offshoreWind.png", width=1000))
```
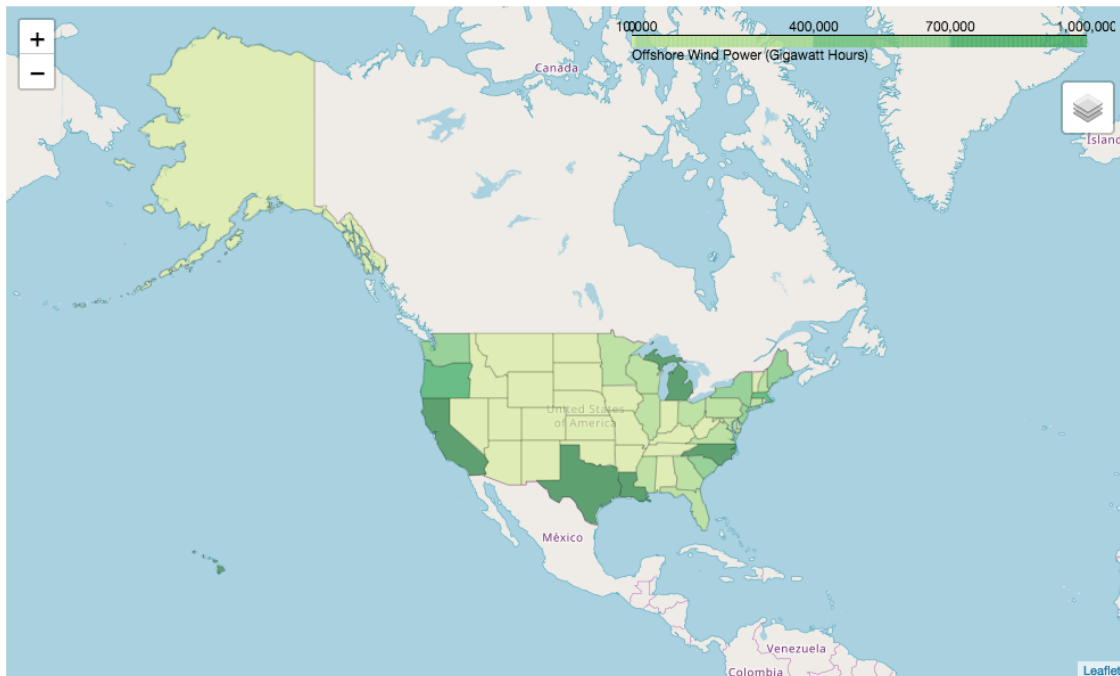
Table of estimated technical potential for Offshore Wind Power by state: Technical potential for offshore wind power is present in significant quantities in all offshore regions of the United States.

```
In [35]: offshoreWind_DF.append(offshoreWind_sumDF)
```

```
Out[35]:                    state  offshoreWind_GWh  offshoreWind_GW  offshoreWind_km2
         0                Alabama               0.0              0.0               0.0
         1                 Alaska               0.0              0.0               0.0
         2                Arizona               0.0              0.0               0.0
         3               Arkansas               0.0              0.0               0.0
         4             California         2662579.0            654.0          130966.0
         5               Colorado               0.0              0.0               0.0
         6            Connecticut           26545.0              7.0            1434.0
         7               Delaware           60654.0             15.0            3007.0
         8   District of Columbia               0.0              0.0               0.0
         9                Florida           34684.0              9.0            1929.0
         10               Georgia          220807.0             58.0           11725.0
         11                Hawaii         2836735.0            736.0          147389.0
         12                 Idaho               0.0              0.0               0.0
         13              Illinois           66070.0             15.0            3174.0
         14               Indiana             165.0              0.0               9.0
         15                  Iowa               0.0              0.0               0.0
         16                Kansas               0.0              0.0               0.0
         17              Kentucky               0.0              0.0               0.0
```

22

18	Louisiana	1200698.0	340.0	68122.0
19	Maine	631960.0	147.0	29483.0
20	Maryland	200852.0	51.0	10381.0
21	Massachusetts	799344.0	184.0	36815.0
22	Michigan	1739800.0	422.0	84515.0
23	Minnesota	100454.0	29.0	5842.0
24	Mississippi	10172.0	3.0	642.0
25	Missouri	0.0	0.0	0.0
26	Montana	0.0	0.0	0.0
27	Nebraska	0.0	0.0	0.0
28	Nevada	0.0	0.0	0.0
29	New Hampshire	14477.0	3.0	691.0
30	New Jersey	429807.0	101.0	20386.0
31	New Mexico	0.0	0.0	0.0
32	New York	614279.0	146.0	29215.0
33	North Carolina	1269626.0	306.0	61204.0
34	North Dakota	0.0	0.0	0.0
35	Ohio	170561.0	41.0	8360.0
36	Oklahoma	0.0	0.0	0.0
37	Oregon	962722.0	225.0	45001.0
38	Pennsylvania	23571.0	5.0	1134.0
39	Rhode Island	89114.0	20.0	4193.0
40	South Carolina	542218.0	133.0	26643.0
41	South Dakota	0.0	0.0	0.0
42	Tennessee	0.0	0.0	0.0
43	Texas	1101062.0	271.0	54288.0
44	Utah	0.0	0.0	0.0
45	Vermont	0.0	0.0	0.0
46	Virginia	361053.0	89.0	17814.0
47	Washington	488025.0	120.0	24192.0
48	West Virginia	0.0	0.0	0.0
49	Wisconsin	317754.0	80.0	16134.0
50	Wyoming	0.0	0.0	0.0
0	U.S Total	16975788.0	4210.0	844688.0

1.2.7 7. Biopower (Solid and Gaseous)

- Definition: We obtained county-level estimates of solid biomass resource for crop, forest, primary/secondary mill residues, and urban wood waste from Milbrandt (2005, updated in 2008) who reported the estimates in bone-dry tonnes (BDT) per year.

7.a. Biopower of Solid

- We calculate technical potential energy generation assuming 1.1 MWh/BDT, which represents an average solid biomass system output with an industry-average conversion efficiency of 20%, and a higher heating value (HHV) of 8,500 BTU/lb.

```
In [36]: biopowerSolid_DF = inputDF[['state','biopowerSolid_GWh','biopowerSolid_GW','biopowerSo
         biopowerSolid_sumDF = pd.DataFrame([['U.S Total',\
```

```
                        biopowerSolid_DF['biopowerSolid_GWh'].sum()
                        biopowerSolid_DF['biopowerSolid_GW'].sum()
                        biopowerSolid_DF['biopowerSolid_BDT'].sum()
                columns=['state','biopowerSolid_GWh','biopowe
```

The total estimated annual technical potential in the United States for Biopower of Solid

In [37]: biopowerSolid_sumDF

Out[37]:   state biopowerSolid_GWh biopowerSolid_GW biopowerSolid_BDT
         0   U.S Total   399750   30   363430992

Choropleth map of estimated technical potential for Biopower of Solid in the U.S.:

```
In [38]: threshold_scale = split_six(biopowerSolid_DF['biopowerSolid_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=biopowerSolid_DF,
             columns=['state', 'biopowerSolid_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Biopower of Solid (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'biopowerSolid.html'))


         m

Out[38]: <folium.folium.Map at 0x1120a9400>

In [39]: display(Image("choroplethMap/biopowerSolid.png", width=1000))
```
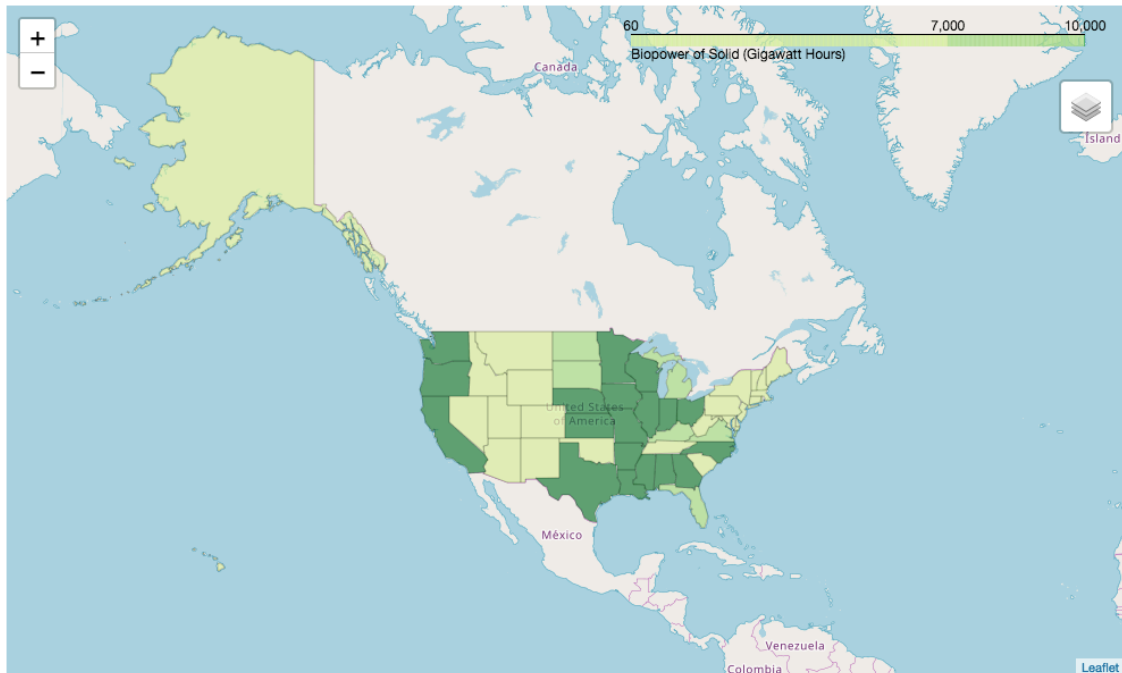
Table of estimated technical potential for Biopower of Solid by state:

```
In [40]: biopowerSolid_DF.append(biopowerSolid_sumDF)
```

```
Out[40]:                        state  biopowerSolid_GWh  biopowerSolid_GW  \
         0              Alabama              11193                 1
         1               Alaska                513                 0
         2              Arizona               1087                 0
         3             Arkansas              14381                 1
         4           California              12408                 1
         5             Colorado               2913                 0
         6          Connecticut                494                 0
         7             Delaware                512                 0
         8   District of Columbia               61                 0
         9              Florida               9664                 1
        10              Georgia              14682                 1
        11               Hawaii                524                 0
        12                Idaho               5775                 0
        13             Illinois              27738                 3
        14              Indiana              14941                 1
        15                 Iowa              27502                 3
        16               Kansas              12104                 1
        17             Kentucky               7048                 0
        18            Louisiana              14016                 1
        19                Maine               4273                 0
```

25

20	Maryland	2102	0
21	Massachusetts	1045	0
22	Michigan	9358	1
23	Minnesota	20361	2
24	Mississippi	14209	1
25	Missouri	11837	1
26	Montana	4924	0
27	Nebraska	16271	2
28	Nevada	288	0
29	New Hampshire	953	0
30	New Jersey	1212	0
31	New Mexico	595	0
32	New York	5558	0
33	North Carolina	12869	1
34	North Dakota	8186	1
35	Ohio	11009	1
36	Oklahoma	4128	0
37	Oregon	13793	1
38	Pennsylvania	6313	0
39	Rhode Island	143	0
40	South Carolina	6984	0
41	South Dakota	8380	1
42	Tennessee	6095	0
43	Texas	16077	2
44	Utah	433	0
45	Vermont	491	0
46	Virginia	7866	0
47	Washington	12311	1
48	West Virginia	2406	0
49	Wisconsin	11221	1
50	Wyoming	503	0
0	U.S Total	399750	30

	biopowerSolid_BDT
0	10175869
1	466797
2	988705
3	13074040
4	11280245
5	2648462
6	449775
7	465802
8	56180
9	8785824
10	13347586
11	476459
12	5250560
13	25216443

```
14          13583318
15          25002253
16          11004052
17           6407337
18          12741856
19           3884583
20           1911045
21            950308
22           8507307
23          18510689
24          12918114
25          10761509
26           4477082
27          14792723
28            262613
29            867153
30           1101910
31            541274
32           5053081
33          11699887
34           7441887
35          10008282
36           3753137
37          12539176
38           5739609
39            130452
40           6349820
41           7618309
42           5541359
43          14615951
44            394530
45            447268
46           7151120
47          11192456
48           2188057
49          10201440
50            457298
0          363430992
```

7.b. Biopower of Gaseous

- We obtained county-level estimates of gaseous biomass (methane emissions), from animal manure, domestic wastewater treatment plants, and landfills; all estimates were reported in tonnes of methane (CH4) per year.

```
In [41]: biopowerGaseous_DF = inputDF[['state','biopowerGaseous_GWh','biopowerGaseous_GW','biop
         biopowerGaseous_sumDF = pd.DataFrame([['U.S Total',\
                                         biopowerGaseous_DF['biopowerGaseous_GWh'].s
```

```
                                biopowerGaseous_DF['biopowerGaseous_GW'].su
                                biopowerGaseous_DF['biopowerGaseous_Tonnes-
                                columns=['state','biopowerGaseous_GWh','biop
```

The total estimated annual technical potential in the United States for Biopower of Gaseous

```
In [42]: biopowerGaseous_sumDF

Out[42]:          state  biopowerGaseous_GWh  biopowerGaseous_GW  \
         0  U.S Total                 88528                   1

            biopowerGaseous_Tonnes-CH4
         0                    18840706
```

Choropleth map of estimated technical potential for Biopower of Gaseous in the U.S.:

```
In [43]: threshold_scale = split_six(biopowerGaseous_DF['biopowerGaseous_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=biopowerGaseous_DF,
             columns=['state', 'biopowerGaseous_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name='Biopower of Gaseous (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'biopowerGaseous.html'))

         m

Out[43]: <folium.folium.Map at 0x107e18a90>

In [44]: display(Image("choroplethMap/biopowerGaseous.png", width=1000))
```
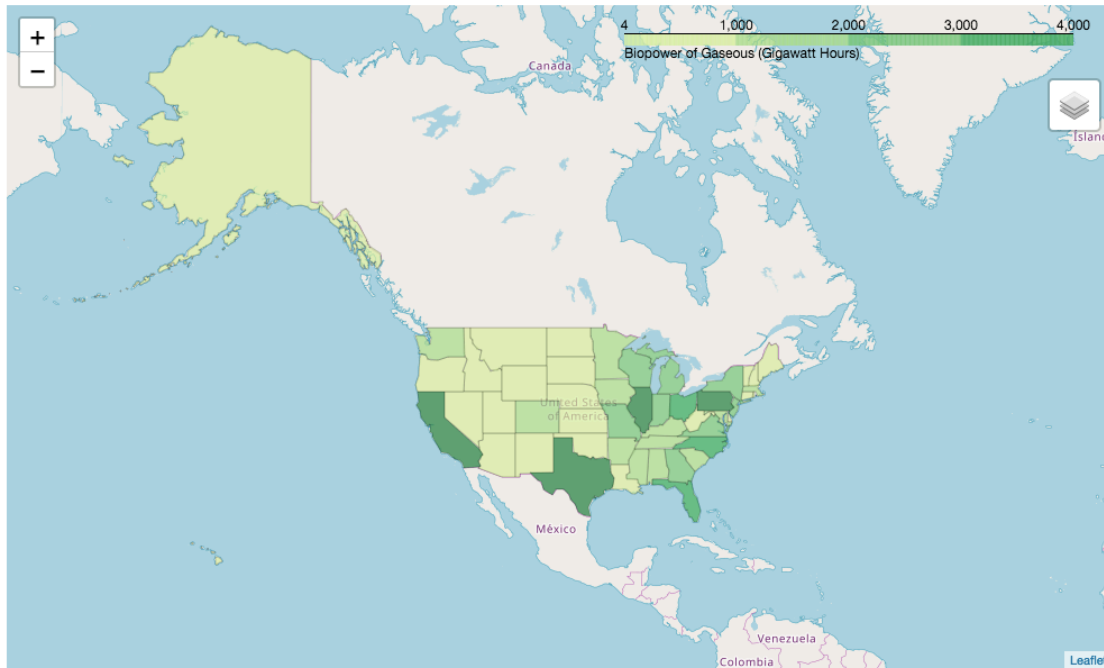
Table of estimated technical potential for Biopower of Gaseous by state:

```
In [45]: biopowerGaseous_DF.append(biopowerGaseous_sumDF)
```

```
Out[45]:                   state  biopowerGaseous_GWh  biopowerGaseous_GW  \
        0             Alabama                 1533                   0
        1              Alaska                   61                   0
        2             Arizona                  837                   0
        3            Arkansas                 1063                   0
        4          California                15510                   1
        5            Colorado                 1224                   0
        6         Connecticut                  414                   0
        7            Delaware                  385                   0
        8   District of Columbia                  4                   0
        9             Florida                 3693                   0
        10            Georgia                 2220                   0
        11             Hawaii                  200                   0
        12              Idaho                  182                   0
        13           Illinois                 4222                   0
        14            Indiana                 2978                   0
        15               Iowa                 1425                   0
        16             Kansas                  753                   0
        17           Kentucky                 1273                   0
        18          Louisiana                  857                   0
        19              Maine                  124                   0
        20           Maryland                 1226                   0
```

29

21	Massachusetts	1103	0
22	Michigan	2539	0
23	Minnesota	1029	0
24	Mississippi	1076	0
25	Missouri	2147	0
26	Montana	147	0
27	Nebraska	750	0
28	Nevada	325	0
29	New Hampshire	389	0
30	New Jersey	2310	0
31	New Mexico	353	0
32	New York	2950	0
33	North Carolina	3780	0
34	North Dakota	30	0
35	Ohio	3363	0
36	Oklahoma	965	0
37	Oregon	890	0
38	Pennsylvania	7132	0
39	Rhode Island	474	0
40	South Carolina	1430	0
41	South Dakota	235	0
42	Tennessee	1984	0
43	Texas	5898	0
44	Utah	427	0
45	Vermont	203	0
46	Virginia	2498	0
47	Washington	1514	0
48	West Virginia	281	0
49	Wisconsin	2072	0
50	Wyoming	50	0
0	U.S Total	88528	1

	biopowerGaseous_Tonnes-CH4
0	326186
1	13156
2	178188
3	226178
4	3300211
5	260470
6	88227
7	82013
8	977
9	785787
10	472546
11	42602
12	38830
13	898345
14	633660

```
           15                  303277
           16                  160219
           17                  271052
           18                  182404
           19                   26542
           20                  260965
           21                  234811
           22                  540282
           23                  219074
           24                  229076
           25                  456990
           26                   31324
           27                  159729
           28                   69248
           29                   82889
           30                  491691
           31                   75228
           32                  627734
           33                  804301
           34                    6383
           35                  715603
           36                  205359
           37                  189571
           38                 1517540
           39                  100888
           40                  304312
           41                   50072
           42                  422220
           43                 1254999
           44                   91018
           45                   43248
           46                  531592
           47                  322155
           48                   59811
           49                  441053
           50                   10670
            0                18840706
```

1.2.8   8. Hydrothermal Power Systems (Geothermal Energy Technologies)

- Definition: For identified hydrothermal and undiscovered hydrothermal, we used estimates from Williams et al.   (2008), who estimated electric power generation potential of conventional geothermal resources (hydrothermal), both identified and unidentified in the western United States, Alaska, and Hawaii.
- In all cases, exclusions included public lands, such as national parks, that are not available for resource development.

```
In [46]: geothermalHydrothermal_DF = inputDF[['state','geothermalHydrothermal_GWh','geothermal
```

```
geothermalHydrothermal_sumDF = pd.DataFrame([['U.S Total',\
                                    geothermalHydrothermal_DF['geothermalHydrot
                                    geothermalHydrothermal_DF['geothermalHydrot
                            columns=['state','geothermalHydrothermal_GWh
```

The total estimated annual technical potential in the United States for Hydrothermal Power Systems

In [47]: geothermalHydrothermal_sumDF

Out[47]:   state geothermalHydrothermal_GWh geothermalHydrothermal_GW
         0 U.S Total   301376   32

Choropleth map of estimated technical potential for Hydrothermal Power Systems in the U.S.:

In [48]: threshold_scale = split_six(geothermalHydrothermal_DF['geothermalHydrothermal_GWh'])

```
m = folium.Map(location=[48, -102], zoom_start=3)
m.choropleth(
    geo_data=state_geo,
    name='choropleth',
    data=geothermalHydrothermal_DF,
    columns=['state', 'geothermalHydrothermal_GWh'],
    key_on='feature.properties.name',
    fill_color='YlGn',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='Hydrothermal Power Systems (Gigawatt Hours)',
    threshold_scale=threshold_scale,
    reset=True
)


folium.LayerControl().add_to(m)
m.save(os.path.join('choroplethMap', 'geothermalHydrothermal.html'))


m
```

Out[48]: <folium.folium.Map at 0x105b53f98>

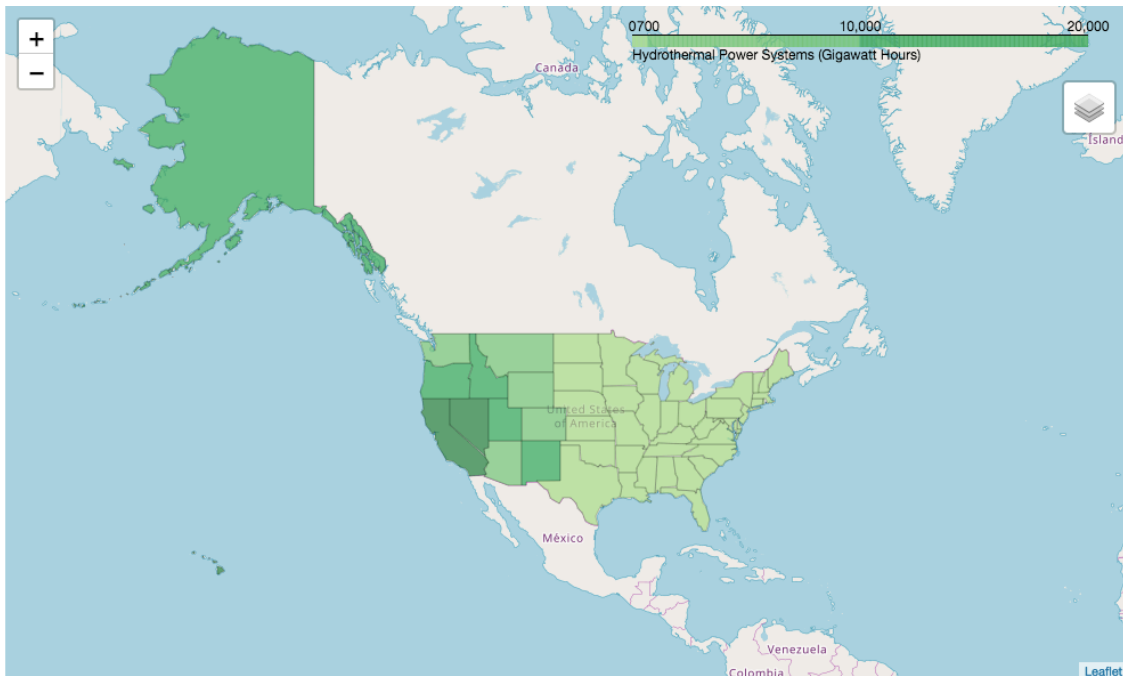In [49]: display(Image("choroplethMap/geothermalHydrothermal.png", width=1000))

Table of estimated technical potential for Hydrothermal Power Systems by state:

```
In [50]: geothermalHydrothermal_DF.append(geothermalHydrothermal_sumDF)
```

```
Out[50]:                       state  geothermalHydrothermal_GWh  \
         0                    Alabama                           0
         1                     Alaska                       15437
         2                    Arizona                        8329
         3                   Arkansas                           0
         4                 California                      130921
         5                   Colorado                        8953
         6                Connecticut                           0
         7                   Delaware                           0
         8       District of Columbia                           0
         9                    Florida                           0
         10                   Georgia                           0
         11                    Hawaii                       20632
         12                     Idaho                       17205
         13                  Illinois                           0
         14                   Indiana                           0
         15                      Iowa                           0
         16                    Kansas                           0
         17                  Kentucky                           0
         18                 Louisiana                           0
         19                     Maine                           0
         20                  Maryland                           0
```

21	Massachusetts	0
22	Michigan	0
23	Minnesota	0
24	Mississippi	0
25	Missouri	0
26	Montana	6547
27	Nebraska	0
28	Nevada	45320
29	New Hampshire	0
30	New Jersey	0
31	New Mexico	12933
32	New York	0
33	North Carolina	0
34	North Dakota	0
35	Ohio	0
36	Oklahoma	0
37	Oregon	18199
38	Pennsylvania	0
39	Rhode Island	0
40	South Carolina	0
41	South Dakota	0
42	Tennessee	0
43	Texas	0
44	Utah	12981
45	Vermont	0
46	Virginia	0
47	Washington	2546
48	West Virginia	0
49	Wisconsin	0
50	Wyoming	1373
0	U.S Total	301376

	geothermalHydrothermal_GW
0	0
1	1
2	1
3	0
4	16
5	1
6	0
7	0
8	0
9	0
10	0
11	2
12	2
13	0
14	0

15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	5
29	0
30	0
31	1
32	0
33	0
34	0
35	0
36	0
37	2
38	0
39	0
40	0
41	0
42	0
43	0
44	1
45	0
46	0
47	0
48	0
49	0
50	0
0	32

1.2.9   9. Enhanced Geothermal Systems

- Definition: We derive technical potential estimates for enhanced geothermal systems (EGS) from temperature at depth data obtained from the Southern Methodist University's (SMU) Geothermal Laboratory
- Electric generation potential calculations summarize the technical potential (MW) at all depth intervals, electric generation potential (GWh) at all depth intervals with a 90% capacity factor, and annual electric generation potential (GWh) only at optimum depth.

```
In [51]: EGSGeothermal_DF = inputDF[['state','EGSGeothermal_GWh','EGSGeothermal_GW']]
```

```
EGSGeothermal_sumDF = pd.DataFrame([['U.S Total',\
                                    EGSGeothermal_DF['EGSGeothermal_GWh'].sum()
                                    EGSGeothermal_DF['EGSGeothermal_GW'].sum()]
                            columns=['state','EGSGeothermal_GWh','EGSGeot
```

The total estimated annual technical potential in the United States for Enhanced Geothermal Systems

In [52]: EGSGeothermal_sumDF

Out[52]:   state EGSGeothermal_GWh EGSGeothermal_GW
        0 U.S Total   31344671.0   3948.0

Choropleth map of estimated technical potential for Enhanced Geothermal Systems in the U.S.:

In [53]: threshold_scale = split_six(EGSGeothermal_DF['EGSGeothermal_GWh'])

```
m = folium.Map(location=[48, -102], zoom_start=3)
m.choropleth(
    geo_data=state_geo,
    name='choropleth',
    data=EGSGeothermal_DF,
    columns=['state', 'EGSGeothermal_GWh'],
    key_on='feature.properties.name',
    fill_color='YlGn',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='Enhanced Geothermal Systems (Gigawatt Hours)',
    threshold_scale=threshold_scale,
    reset=True
)


folium.LayerControl().add_to(m)
m.save(os.path.join('choroplethMap', 'EGSGeothermal.html'))


m
```

Out[53]: <folium.folium.Map at 0x105c1c4e0>

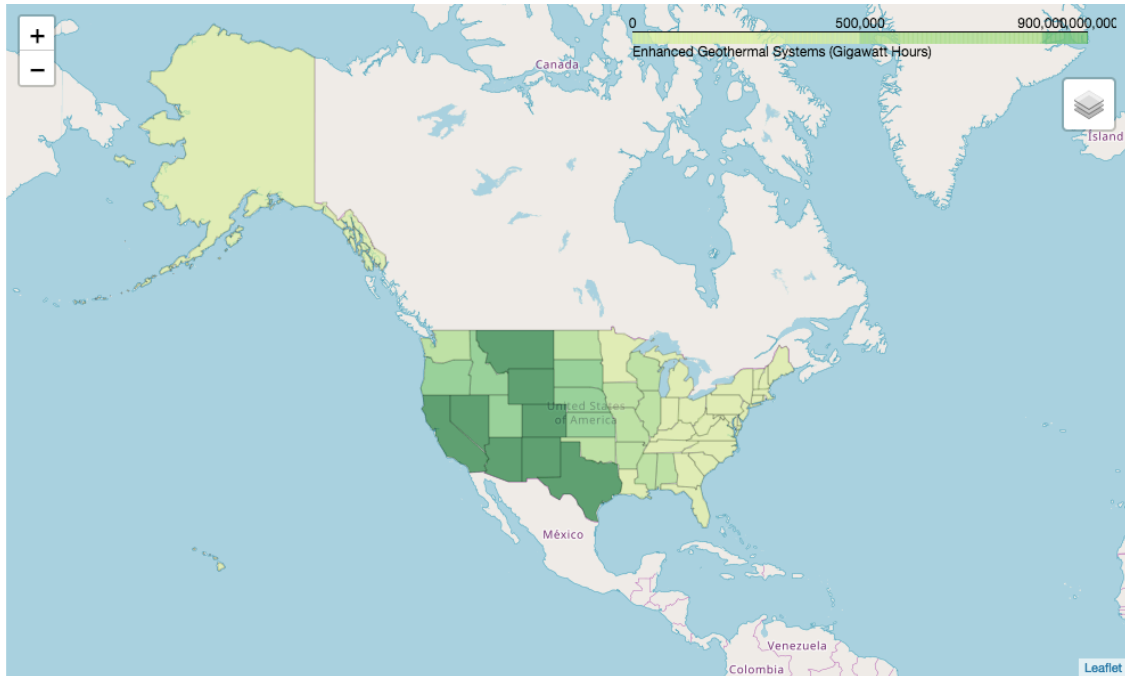In [54]: display(Image("choroplethMap/EGSGeothermal.png", width=1000))

Table of estimated technical potential for Enhanced Geothermal Systems by state: The vast majority of the geothermal potential for EGS(31,344 TWh) within the contiguous United States is located in the westernmost portion of the country.

```
In [55]: EGSGeothermal_DF.append(EGSGeothermal_sumDF)
```

```
Out[55]:                      state  EGSGeothermal_GWh  EGSGeothermal_GW
         0                 Alabama           535489.0              67.0
         1                  Alaska                0.0               0.0
         2                 Arizona          1239147.0             157.0
         3                Arkansas           628621.0              79.0
         4              California          1344179.0             170.0
         5                Colorado          1251657.0             158.0
         6             Connecticut            56078.0               7.0
         7                Delaware            22813.0               2.0
         8    District of Columbia              697.0               0.0
         9                 Florida           374161.0              47.0
         10                Georgia           353206.0              44.0
         11                 Hawaii                0.0               0.0
         12                  Idaho           993257.0             125.0
         13               Illinois           676055.0              85.0
         14                Indiana           434258.0              55.0
         15                   Iowa           606390.0              76.0
         16                 Kansas           989675.0             125.0
         17               Kentucky           484658.0              61.0
```

18	Louisiana	484271.0	61.0
19	Maine	377075.0	47.0
20	Maryland	86649.0	10.0
21	Massachusetts	92227.0	11.0
22	Michigan	457850.0	58.0
23	Minnesota	369784.0	46.0
24	Mississippi	559056.0	70.0
25	Missouri	835444.0	105.0
26	Montana	1647303.0	208.0
27	Nebraska	927996.0	117.0
28	Nevada	1262174.0	160.0
29	New Hampshire	104314.0	13.0
30	New Jersey	35230.0	4.0
31	New Mexico	1417978.0	179.0
32	New York	375400.0	47.0
33	North Carolina	420741.0	53.0
34	North Dakota	820226.0	104.0
35	Ohio	495921.0	62.0
36	Oklahoma	779667.0	98.0
37	Oregon	914105.0	115.0
38	Pennsylvania	327340.0	41.0
39	Rhode Island	11491.0	1.0
40	South Carolina	364104.0	46.0
41	South Dakota	921972.0	116.0
42	Tennessee	428380.0	54.0
43	Texas	3030250.0	384.0
44	Utah	939380.0	119.0
45	Vermont	35616.0	4.0
46	Virginia	290736.0	36.0
47	Washington	563023.0	71.0
48	West Virginia	261376.0	33.0
49	Wisconsin	647173.0	82.0
50	Wyoming	1070078.0	135.0
0	U.S Total	31344671.0	3948.0

1.2.10   10. Hydropower

- Definition: Source point locations of hydropower estimates were provided by the Idaho National Laboratory and were taken from Hall et al. (2006).

- The feasibility study included additional economic potential criteria such as site accessibility, load or transmission proximity, along with technical potential exclusions of land use or environmental sensitivity.

```
In [56]: hydropower_DF = inputDF[['state','hydropower_GWh','hydropower_GW','hydropower_countOfS
         hydropower_sumDF = pd.DataFrame([['U.S Total',\
                                           hydropower_DF['hydropower_GWh'].sum(),\
                                           hydropower_DF['hydropower_GW'].sum(),\
```

```
                                hydropower_DF['hydropower_countOfSites'].su
                          columns=['state','hydropower_GWh','hydropower
```

The total estimated annual technical potential in the United States for Hydropower

```
In [57]: hydropower_sumDF
```

```
Out[57]:        state  hydropower_GWh  hydropower_GW  hydropower_countOfSites
         0  U.S Total          258929             38                   128126
```

Choropleth map of estimated technical potential for Hydropower in the U.S.:

```
In [58]: threshold_scale = split_six(hydropower_DF['hydropower_GWh'])

         m = folium.Map(location=[48, -102], zoom_start=3)
         m.choropleth(
             geo_data=state_geo,
             name='choropleth',
             data=hydropower_DF,
             columns=['state', 'hydropower_GWh'],
             key_on='feature.properties.name',
             fill_color='YlGn',
             fill_opacity=0.7,
             line_opacity=0.2,
             legend_name=' Hydropower (Gigawatt Hours)',
             threshold_scale=threshold_scale,
             reset=True
         )


         folium.LayerControl().add_to(m)
         m.save(os.path.join('choroplethMap', 'hydropower.html'))

         m
```

```
Out[58]: <folium.folium.Map at 0x112185c50>
```

```
In [59]: display(Image("choroplethMap/hydropower.png", width=1000))
```
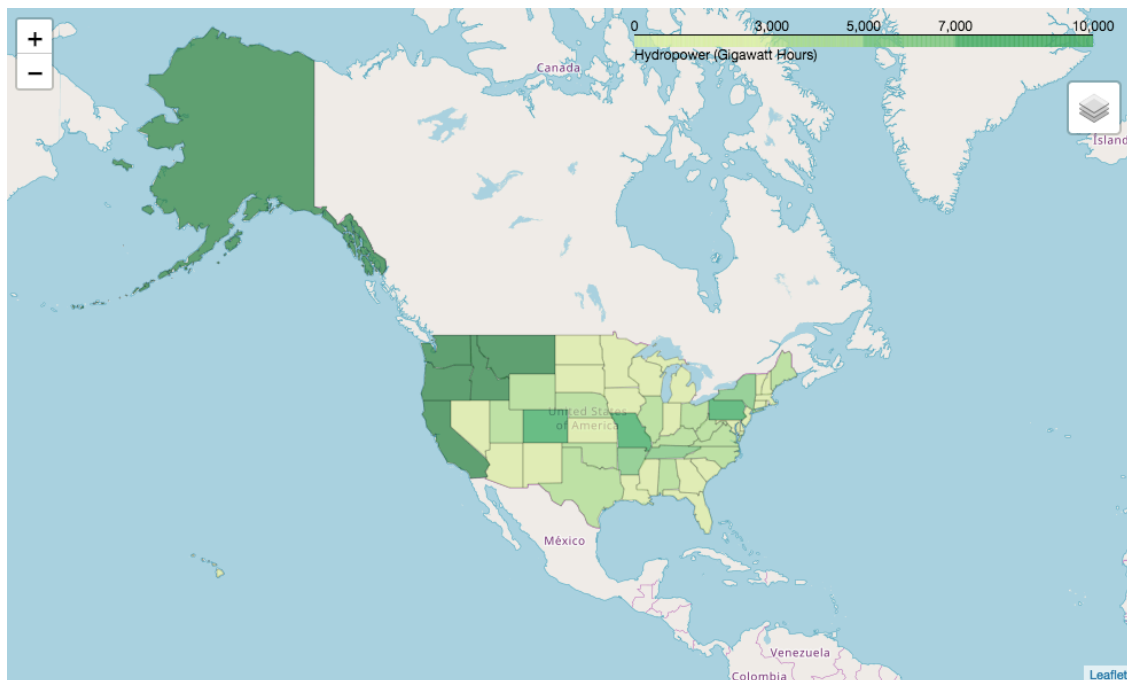
Table of estimated technical potential for Enhanced Geothermal Systems by state: Technical potential for hydropower exists predominately in the Northwest and Alaska.

```
In [60]: hydropower_DF.append(hydropower_sumDF)
```

```
Out[60]:                     state  hydropower_GWh  hydropower_GW  \
         0                 Alabama            4102              0
         1                  Alaska           23675              5
         2                 Arizona            1303              0
         3                Arkansas            6093              1
         4              California           30023              6
         5                Colorado            7789              1
         6             Connecticut             922              0
         7                Delaware              30              0
         8    District of Columbia               0              0
         9                 Florida             682              0
         10                Georgia            1988              0
         11                 Hawaii            2602              0
         12                  Idaho           18757              4
         13               Illinois            4882              1
         14                Indiana            2394              0
         15                   Iowa            2818              0
         16                 Kansas            2507              0
         17               Kentucky            4255              0
         18              Louisiana            2423              0
```

19	Maine	3916	0
20	Maryland	814	0
21	Massachusetts	1196	0
22	Michigan	1180	0
23	Minnesota	1254	0
24	Mississippi	2211	0
25	Missouri	7198	1
26	Montana	14546	3
27	Nebraska	3142	0
28	Nevada	845	0
29	New Hampshire	1740	0
30	New Jersey	549	0
31	New Mexico	1362	0
32	New York	6711	1
33	North Carolina	3036	0
34	North Dakota	347	0
35	Ohio	3045	0
36	Oklahoma	3015	0
37	Oregon	18184	4
38	Pennsylvania	8368	1
39	Rhode Island	59	0
40	South Carolina	1888	0
41	South Dakota	1047	0
42	Tennessee	5744	1
43	Texas	3006	0
44	Utah	3528	0
45	Vermont	1710	0
46	Virginia	3656	0
47	Washington	27248	6
48	West Virginia	4408	1
49	Wisconsin	2286	1
50	Wyoming	4445	1
0	U.S Total	258929	38

	hydropower_countOfSites
0	2435
1	3053
2	1958
3	3268
4	9692
5	5060
6	659
7	25
8	2
9	493
10	2100
11	437
12	6706

```
13                    1330
14                    1142
15                    2398
16                    3201
17                    1394
18                     934
19                    1373
20                     491
21                     560
22                    1942
23                    1391
24                    1536
25                    5089
26                    6859
27                    2880
28                    1489
29                     810
30                     402
31                    1810
32                    4839
33                    2131
34                     572
35                    1791
36                    2824
37                    7993
38                    4466
39                      86
40                     889
41                    1712
42                    2610
43                    4366
44                    3394
45                    1207
46                    2601
47                    7310
48                    1711
49                    1863
50                    2842
0                   128126
```

1.3 Visualizing distribution of renewable energy in each state

```
In [61]: state = []
         energy_list = []
         for idx, row in inputDF.iterrows():
             state.append(row.state)
             energy_dist = {}
             energy_dist['urbanUtilityScalePV'] = row['urbanUtilityScalePV_GWh']
```

```
         energy_dist['ruralUtilityScalePV'] = row['ruralUtilityScalePV_GWh']
         energy_dist['rooftopPV'] = row['rooftopPV_GWh']
         energy_dist['CSP'] = row['CSP_GWh']
         energy_dist['onshoreWind'] = row['onshoreWind_GWh']
         energy_dist['offshoreWind'] = row['offshoreWind_GWh']
         energy_dist['biopowerSolid'] = row['biopowerSolid_GWh']
         energy_dist['biopowerGaseous'] = row['biopowerGaseous_GWh']
         energy_dist['geothermalHydrothermal'] = row['geothermalHydrothermal_GWh']
         energy_dist['EGSGeothermal'] = row['EGSGeothermal_GWh']
         energy_dist['hydropower'] = row['hydropower_GWh']
         energy_list.append(energy_dist)
```

In [62]:
```
energy_df = pd.DataFrame.from_dict(energy_list[0], orient='index').sort_values(by=0)
for i in range(1,len(state)):
    energy_df_tmp = pd.DataFrame.from_dict(energy_list[i], orient='index').sort_values
    energy_df = pd.concat([energy_df, energy_df_tmp], axis=1)
energy_df.columns = state
```

In [63]: energy_df

Out[63]:
```
                            Alabama      Alaska      Arizona    Arkansas  \
CSP                             0.0         0.0   12544333.0        0.0
EGSGeothermal              535489.0         0.0    1239147.0   628621.0
biopowerGaseous              1533.0        61.0        837.0     1063.0
biopowerSolid               11193.0       513.0       1087.0    14381.0
geothermalHydrothermal          0.0     15437.0       8329.0        0.0
hydropower                   4102.0     23675.0       1303.0     6093.0
offshoreWind                    0.0         0.0          0.0        0.0
onshoreWind                   283.0   1373433.0      26036.0    22892.0
rooftopPV                   15475.0         0.0      22736.0     8484.0
ruralUtilityScalePV       3706838.0   8282976.0   11867693.0  4986388.0
urbanUtilityScalePV         35850.0       166.0     121305.0    28960.0

                          California    Colorado  Connecticut  Delaware  \
CSP                        8490916.0   9154524.0          0.0       0.0
EGSGeothermal              1344179.0   1251657.0      56078.0   22813.0
biopowerGaseous              15510.0      1224.0        414.0     385.0
biopowerSolid                12408.0      2913.0        494.0     512.0
geothermalHydrothermal      130921.0      8953.0          0.0       0.0
hydropower                   30023.0      7789.0        922.0      30.0
offshoreWind               2662579.0         0.0      26545.0   60654.0
onshoreWind                  89862.0   1096035.0         61.0      21.0
rooftopPV                   106411.0     16162.0       6616.0    2185.0
ruralUtilityScalePV        8855917.0  10238083.0      19627.0  272332.0
urbanUtilityScalePV         246008.0     43470.0       7716.0   14856.0

                          District of Columbia    Florida    ...        \
```

```
CSP                                    0.0       358.0    ...
EGSGeothermal                        697.0    374161.0    ...
biopowerGaseous                        4.0      3693.0    ...
biopowerSolid                         61.0      9664.0    ...
geothermalHydrothermal                 0.0         0.0    ...
hydropower                             0.0       682.0    ...
offshoreWind                           0.0     34684.0    ...
onshoreWind                            0.0         0.0    ...
rooftopPV                           2490.0     63986.0    ...
ruralUtilityScalePV                    0.0   5137346.0    ...
urbanUtilityScalePV                    8.0     72787.0    ...

                        South Dakota   Tennessee        Texas        Utah  \
CSP                        1629659.0         0.0   22786749.0   5067546.0
EGSGeothermal               921972.0    428380.0    3030250.0    939380.0
biopowerGaseous                235.0      1984.0       5898.0       427.0
biopowerSolid                 8380.0      6095.0      16077.0       433.0
geothermalHydrothermal           0.0         0.0          0.0     12981.0
hydropower                    1047.0      5744.0       3006.0      3528.0
offshoreWind                     0.0         0.0    1101062.0         0.0
onshoreWind                2901858.0       765.0    5552399.0     31552.0
rooftopPV                     2082.0     19685.0      78716.0      7513.0
ruralUtilityScalePV       10008873.0   2225989.0   38993581.0   5184878.0
urbanUtilityScalePV           4573.0     50243.0     294684.0     30492.0

                        Vermont   Virginia   Washington   West Virginia  \
CSP                         0.0        0.0     161713.0             0.0
EGSGeothermal           35616.0   290736.0     563023.0        261376.0
biopowerGaseous           203.0     2498.0       1514.0           281.0
biopowerSolid             491.0     7866.0      12311.0          2406.0
geothermalHydrothermal      0.0        0.0       2546.0             0.0
hydropower               1710.0     3656.0      27248.0          4408.0
offshoreWind                0.0   361053.0     488025.0             0.0
onshoreWind              7795.0     4589.0      47249.0          4951.0
rooftopPV                1115.0    22266.0      13599.0          4220.0
ruralUtilityScalePV     54727.0  1882467.0    1738150.0         52693.0
urbanUtilityScalePV      1632.0    27451.0      33690.0          3023.0

                        Wisconsin    Wyoming
CSP                           0.0  5406407.0
EGSGeothermal            647173.0  1070078.0
biopowerGaseous            2072.0       50.0
biopowerSolid             11221.0      503.0
geothermalHydrothermal        0.0     1373.0
hydropower                 2286.0     4445.0
offshoreWind             317754.0        0.0
onshoreWind              255266.0  1653856.0
rooftopPV                 13939.0     1550.0
```

```
          ruralUtilityScalePV      5042258.0  5727224.0
          urbanUtilityScalePV        54938.0     7232.0

          [11 rows x 51 columns]

In [64]: energy_df.plot.pie(
                    figsize=(15,200),
                    fontsize = 10, autopct='%1.1f%%',
                    legend = True,
                    subplots=True,
                    layout=(26, 2),
                    title = state)

Out[64]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x112644e48>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x1126d8748>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x108e11630>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112848d68>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112886748>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112886780>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x1128fa278>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x11291acf8>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112957748>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112995128>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x1129c3c88>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x1129ec940>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112a24ef0>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112a61dd8>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112a9ccc0>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112ad1b38>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112b09400>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112b412e8>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112b780f0>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112ba7f98>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112bdee10>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112c12c18>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112c4ab00>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112c80a58>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112cbda20>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112c55860>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x111f3b320>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112d00588>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112d430f0>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112d6eeb8>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112d894a8>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112de14a8>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112e17400>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x112e2d588>],
               [<matplotlib.axes._subplots.AxesSubplot object at 0x112e8b240>,
```
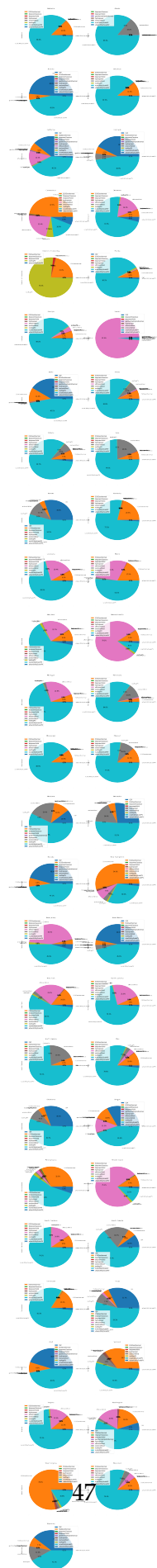
```
       <matplotlib.axes._subplots.AxesSubplot object at 0x112eb0ba8>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x112ed35c0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x112f269e8>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x112f5f7f0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x112f76710>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x112fc2da0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x112ffbcf8>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x113037c50>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x113070b38>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x1130a3550>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x1130b8f28>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x113115390>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x113150208>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x113166320>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x1131b26d8>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x1131ec630>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x1132027f0>]],
     dtype=object)
```

1.4 Plotting the technical potential based on state

```
In [65]: energy_df.sum().plot(kind='bar',
                    x='state',
                    y='Total Renewable Energy Technical Potential',
                    color = '#66c2ff',
                    figsize =(15,8),
                    title = 'Total Renewable Energy Technical Potential in each state',
                    legend = False)
         plt.ylabel('state')
         plt.ylabel('Total Renewable Energy Technical Potential')
```

```
Out[65]: Text(0,0.5,'Total Renewable Energy Technical Potential')
```
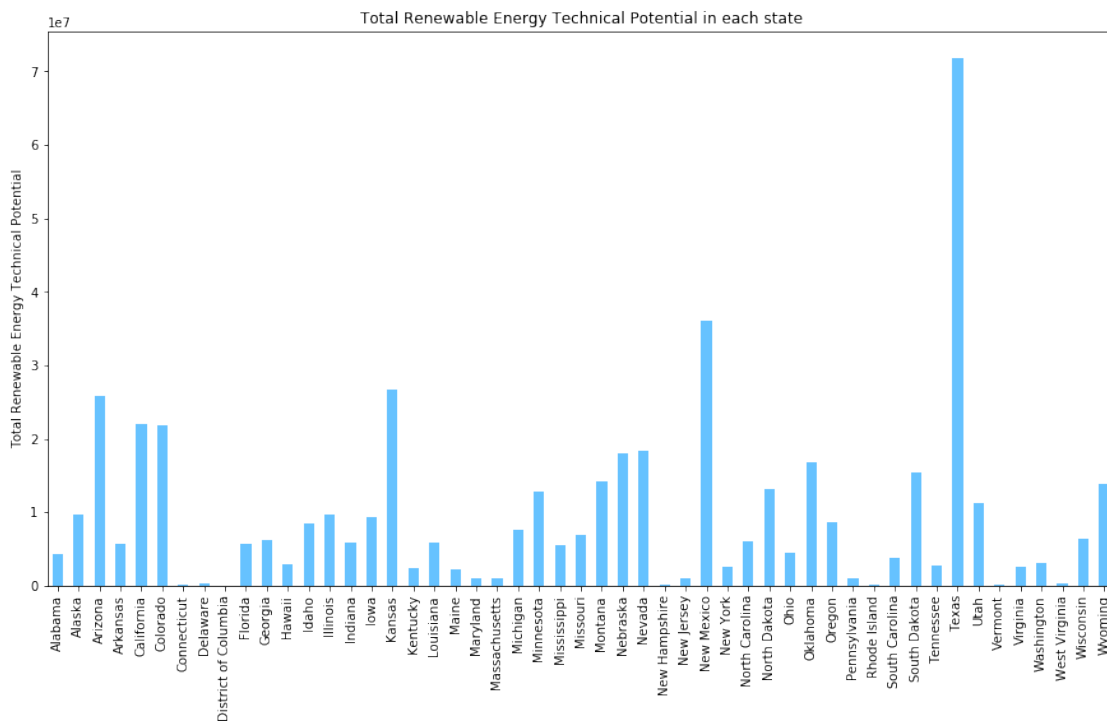

1.4.1 Conclusion

- Texas has the highest total estimated technical potential
- The biggest proportion of estimated technical potential in most state is Utility-Scale Photovoltaics which relats to the solar resource and population.
- Technical potential for offshore wind power is present in significant quantities in all offshore regions of the United States such as Hawaii, Massachusetts and Rhode Island.

- The vast majority of the geothermal potential for EGS within the contiguous United States is located in the westernmost portion of the country.