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
```

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','urbanUtilityScale
        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
```

```
Out[8]: <folium.folium.Map at 0x111b10550>
```

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 [9]: urbanUtilityScalePV_DF.append(urbanUtilityScalePV_sumDF)
```

```
Out[9]:                  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:

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

```
In [10]: ruralUtilityScalePV_DF = inputDF[['state','ruralUtilityScalePV_GWh','ruralUtilityScale
         ruralUtilityScalePV_sumDF = pd.DataFrame([['U.S Total',\
                                           ruralUtilityScalePV_DF['ruralUtilityScaleP
                                           ruralUtilityScalePV_DF['ruralUtilityScaleP
                                           ruralUtilityScalePV_DF['ruralUtilityScaleP
                                         columns=['state','ruralUtilityScalePV_GWh','
```

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

```
In [11]: ruralUtilityScalePV_sumDF
```

```
Out[11]:        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 [12]: 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
```

Out[12]: <folium.folium.Map at 0x111c03240>

Table of estimated technical potential for rural utility-scale photovoltaics by state:

In [13]:
```
ruralUtilityScalePV_DF.append(ruralUtilityScalePV_sumDF)
```

Out[13]:

	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 [14]: 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()]],\
                                          columns=['state','rooftopPV_GWh','rooftopPV_(
```

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

```
In [15]: rooftopPV_sumDF

Out[15]:        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 [16]: 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
```

Out[16]: <folium.folium.Map at 0x111d63358>

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 [17]:
```
rooftopPV_DF.append(rooftopPV_sumDF)
```

Out[17]:

	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 [18]: 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 [19]:
```
CSP_sumDF
```

Out[19]:

	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 [20]:
```
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
```

Out[20]: <folium.folium.Map at 0x111e38978>

Table of estimated technical potential for Concentrating Solar Power by state: Technical potential for CSP exists predominately in the Southwest.

In [21]:
```
CSP_DF.append(CSP_sumDF)
```

Out[21]:

	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 [22]:
```
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 [23]:
```
onshoreWind_sumDF
```

Out[23]:

	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 [24]:
```
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
```

Out[24]: <folium.folium.Map at 0x111f0afd0>

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 [25]:
```
onshoreWind_DF.append(onshoreWind_sumDF)
```

Out[25]:

	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 [26]: 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','offshore
```

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

```
In [27]: offshoreWind_sumDF
```

```
Out[27]:        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 [28]: 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
```

Out[28]: <folium.folium.Map at 0x111f0aa90>

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 [29]:
```
offshoreWind_DF.append(offshoreWind_sumDF)
```

Out[29]:

	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
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 [30]: 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 [31]: biopowerSolid_sumDF
```

```
Out[31]:        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 [32]: 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
```

Out[32]: <folium.folium.Map at 0x111fd2c50>

Table of estimated technical potential for Biopower of Solid by state:

```
In [33]: biopowerSolid_DF.append(biopowerSolid_sumDF)
```

Out[33]:

	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
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 [34]: 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','biopo
```

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

In [35]:
```
biopowerGaseous_sumDF
```

Out[35]:
```
        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 [36]:
```
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
```

Out[36]:
```
<folium.folium.Map at 0x112129518>
```

Table of estimated technical potential for Biopower of Gaseous by state:

In [37]:
```
biopowerGaseous_DF.append(biopowerGaseous_sumDF)
```

Out[37]:
```
                     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
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 [38]:
```
geothermalHydrothermal_DF = inputDF[['state','geothermalHydrothermal_GWh','geothermalH
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 [39]:
```
geothermalHydrothermal_sumDF
```

Out[39]:
```
       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 [40]:
```
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
```

Out[40]:
```
<folium.folium.Map at 0x11206dac8>
```

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

```
In [41]: geothermalHydrothermal_DF.append(geothermalHydrothermal_sumDF)
```

```
Out[41]:                   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 [42]: 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','EGSGeo
```

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

```
In [43]: EGSGeothermal_sumDF

Out[43]:        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 [44]: 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
```

Out[44]: <folium.folium.Map at 0x11206d6d8>

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 [45]: EGSGeothermal_DF.append(EGSGeothermal_sumDF)
```

Out[45]:

	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 [46]:
```
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','hydropowe
```

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

In [47]:
```
hydropower_sumDF
```

Out[47]:
```
       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 [48]: 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

Out[48]: <folium.folium.Map at 0x112395080>
```

Table of estimated technical potential for Enhanced Geothermal Systems by state: Technical potential for hydropower exists predominately in the Northwest and Alaska.

```
In [49]: hydropower_DF.append(hydropower_sumDF)

Out[49]:                    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 [50]:
```
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 [51]:
```
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 [52]:
```
energy_df
```

Out[52]:

	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
```

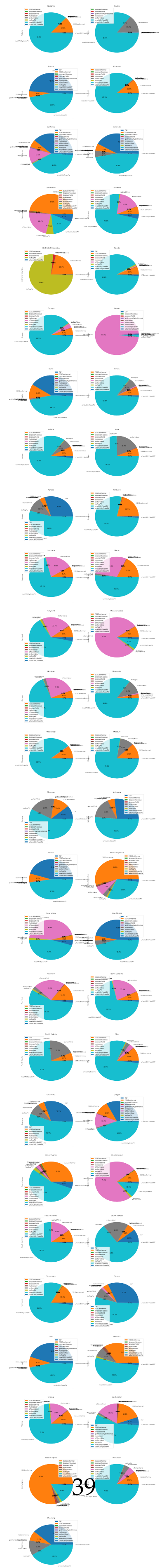
```
offshoreWind           317754.0        0.0
onshoreWind            255266.0  1653856.0
rooftopPV               13939.0     1550.0
ruralUtilityScalePV   5042258.0  5727224.0
urbanUtilityScalePV     54938.0     7232.0

[11 rows x 51 columns]
```

```
In [55]: energy_df.plot.pie(
                          figsize=(15,200),
                          fontsize = 10, autopct='%1.1f%%',
                          legend = True,
                          subplots=True,
                          layout=(26, 2),
                          title = state)
```

```
Out[55]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1188e8630>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11b55b518>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11b58a2e8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11b5b72b0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11b5f2208>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11b500a20>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11bdbceb8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11bdff080>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11be0e320>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11be6bda0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11be9f5f8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11bebd4a8>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11bf12438>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11bf4d240>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11bf60048>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11bfb1780>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11bfea6d8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c001c88>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c0604a8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c086e80>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c0c1208>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c0fdcc0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c135ac8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c158400>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c1a60b8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c1d3fd0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c1f89e8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c24cda0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c27e7b8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c29e1d0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x11c2f55f8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x11c32e470>],
```

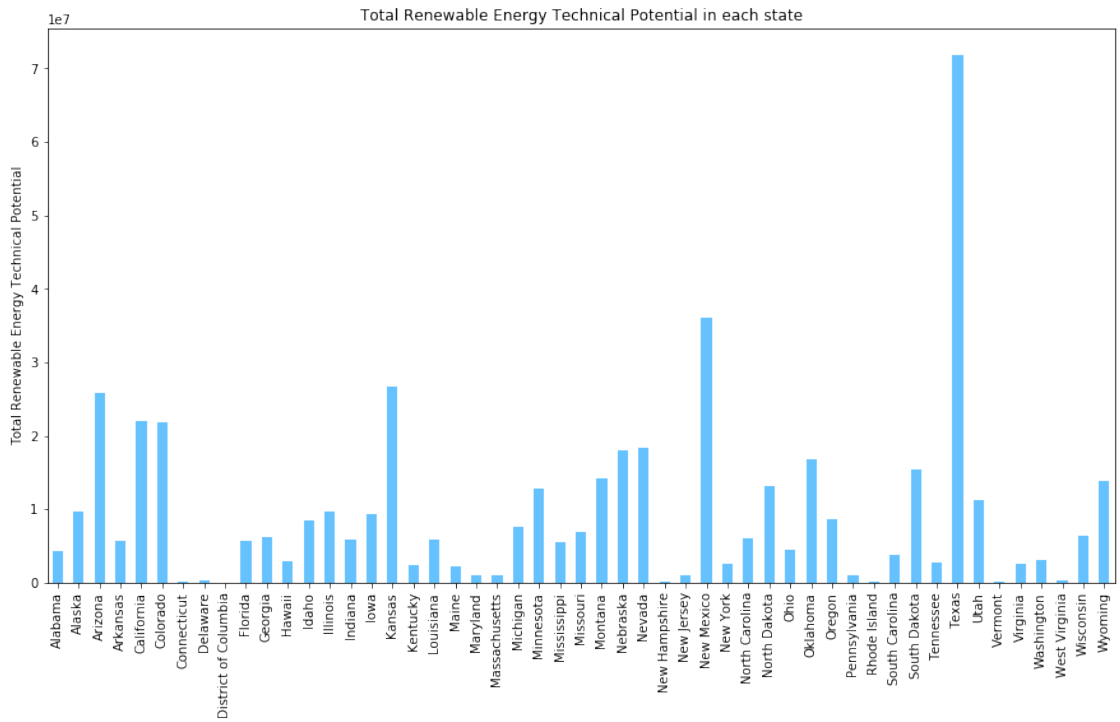
```
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c345e48>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c3939b0>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c3ce908>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c3edb70>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c5436d8>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c5780f0>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c5b3048>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c5e2ef0>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c618cf8>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c634278>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c68d2e8>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c6c3240>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c6dcb38>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c739080>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c764a58>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c79d9b0>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c7d7828>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c812630>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0x11c8287f0>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x11c875be0>]],
dtype=object)
```



1.4 Plotting the technical potential based on state

```
In [54]: 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[54]: Text(0,0.5,'Total Renewable Energy Technical Potential')
```



1.4.1 Conclusion

- Texas has the highest estimated technical potential.
- Rural Utility-Scale Photovoltaics is the predominant generation in most states.
- Connecticut, New Hampshire and West Virginia mainly depend on Enhanced Geothermal Systems.
- Hawaii, Massachusetts and Rhode Island mainly depend on Offshore Wind Power, as the result of geographic location