Model Libraries / Data / Setup

1. Package Imports

In [1]:

```
import geopandas
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import math
import numpy as np
import pandas as pd
import random
import statsmodels.api as sm
import plotly.graph_objects as go

from scipy.spatial.distance import squareform, pdist
from pyproj import Proj, transform
from shapely.geometry import Point
from sklearn.linear_model import LinearRegression

pd.options.mode.chained_assignment = None  # default='warn'
```

2. Function Definition

In [2]:

```
def dist_calc(lat1,lat2,lon1,lon2):
    d = math.dist([lat1,lon1],[lat2,lon2])
    return d

######
def random_points_in_polygon(number, polygon):
    points = []
    min_x, min_y, max_x, max_y = polygon.bounds
    i= 0
    while i < number:
        point = Point(random.uniform(min_x, max_x), random.uniform(min_y, max_y))
        if polygon.contains(point):
            points.append(point)
            i += 1
    return points  # returns list of shapely point
######

def calculate_need(x,y):

    test_gdf = geopandas.GeoDataFrame()
    test_gdf['geometry'] = geopandas.points_from_xy([x],[y],crs="EPSG:26915")
    test_gdf['site_id'] = 'test_site'
    test_gdf['color'] = 2
    test_gdf = test_gdf.set_crs(26915)
    test_gdf['site_lat'] = test_gdf.geometry.centroid.y/1000
    test_gdf['site_lon'] = test_gdf.geometry.centroid.x/1000

    test_counties = counties[['COUNTY','county_lat','county_lon','POP2010']]
    test_counties['distance'] = np.sqrt((test_counties.county_lon-x/1000)**2 + (test_co
    test_counties['dist_wt'] = 1 / test_counties.distance**1.5
    test_counties['pop_wt'] = test_counties.dist_wt * test_counties.POP2010
```

```
    test_pop = test_counties.pop_wt.sum() / test_counties.dist_wt.sum()
    exp_closest = -0.00009192*test_pop+18.30715947
    exp_within_25 = 0.00009816*test_pop-0.99121985

    test_sites = sites[['site_id','site_lat','site_lon']]
    test_sites['distance'] = np.sqrt((test_sites.site_lon-x/1000)**2 + (test_sites.site

    within_25 = len(test_sites[test_sites.distance<25])
    closest = test_sites.distance.min()

    z_closest = ((closest-exp_closest) - test_df.closest_diff.mean())/test_df.closest_d
    z_within_25 = ((exp_within_25-within_25) - test_df.within_25_diff.mean())/test_df.w
    z_agg = (z_closest+z_within_25)/2
    closest_score = 50-10*z_closest
    within_25_score = 50-10*z_within_25
    need_score = 50-10*z_agg

    d1 = {'Site': 'test_site', 'Coordinates [x,y]' : [[x,y]],'Population (est)': [test_
    d2 = {'Class': ['Actual','Expected','Score (20-80)'], 'Distance (mi) to closest sit
    d3 = {'Score (20-80)': [need_score]}

    table1 = pd.DataFrame(data=d1).set_index('Site')
    table2 = pd.DataFrame(data=d2).set_index('Class')
    table3 = pd.DataFrame(data=d3).set_index('Score (20-80)')

    display(table1,table2,table3)

def plot_coordinate(x,y):
    sites2 = sites[['geometry','site_id']]
    sites2['color'] = 'k'

    site_add = geopandas.GeoDataFrame()
    site_add['geometry'] = geopandas.points_from_xy([x],[y],crs="EPSG:26915")
    site_add['site_id'] = 'test_site'
    site_add['color'] = 'w'
    site_add = site_add.set_crs(26915)
    combine = geopandas.overlay(sites2.append(site_add),counties)

    plot = combine
    #df = geopandas.overlay(plot,counties)
    cmap = mpl.cm.Blues(np.linspace(0,1,20))
    cmap = mpl.colors.ListedColormap(cmap[10:,:-1])

    fig_size = [7.5,7.5]
    plt.rcParams["figure.figsize"] = fig_size

    fig, ax = plt.subplots()
    ax.set_title('Arkansas NAD83 Projection (UTM Zone 15N)')
    counties.plot(ax=ax,column='POP2010', cmap=cmap, legend=True, legend_kwds={'label':
    plot.plot(ax=ax,color=plot.color)
    plt.grid(color='w', linestyle = '--')
    plt.show()

def state_plot():

    plot = sites
    df = geopandas.overlay(plot,counties)
    cmap = mpl.cm.Blues(np.linspace(0,1,20))
    cmap = mpl.colors.ListedColormap(cmap[10:,:-1])
```

```
    fig_size = [7.5,7.5]
    plt.rcParams["figure.figsize"] = fig_size

    fig, ax = plt.subplots()
    counties.plot(ax=ax,column='POP2010', cmap=cmap, legend=True, legend_kwds={'label':
    plot.plot(ax=ax,color='k')
    plt.grid(color='w', linestyle = '--')
    plt.show()

def heat_plot():

    fig_size = [7.5,7.5]
    plt.rcParams["figure.figsize"] = fig_size

    fig, ax = plt.subplots()
    ax.set_title('Counties Needing Sites')
    heat_df.plot(ax=ax,column='Needed_Sites', cmap='coolwarm', legend=True, legend_kwds
    sites.plot(ax=ax,color='k')
    plt.grid(color='w', linestyle = '--')
    plt.show()

def show_x_highest_need_locations(x):
    return_df = pd.merge(rp,test_df[['test_site','pop_wt','closest','exp_closest','with
    return return_df.sort_values('Score')[['test_site','geometry','pop_wt','closest','e

def grab_coordinates(x,y,zip_code,method):
    if method == 'zip':
        x = zip_df[zip_df.ZCTA == str(zip_code)]['x'].values[0]
        y = zip_df[zip_df.ZCTA == str(zip_code)]['y'].values[0]
    elif method == 'coo':
        x = x
        y = y
    else:
        x = None
        y = None
    return x,y
```

3. Import Files

In [3]:

```
sites = geopandas.read_file(r"C:\Users\nastaja\Downloads\EMERG_MEDICAL_SERVICES_ADH\EME
sites = sites[sites.state=='AR']
sites['site_lat'] = sites.geometry.centroid.y/1000
sites['site_lon'] = sites.geometry.centroid.x/1000
sites['site_id'] = sites.index + 1

counties = geopandas.read_file(r"C:\Users\nastaja\Downloads\\COUNTY_BOUNDARY\\COUNTY_BO
counties['county_lat'] = counties.geometry.centroid.y/1000
counties['county_lon'] = counties.geometry.centroid.x/1000

zips = geopandas.read_file(r"C:\Users\nastaja\Downloads\\ZIPCODE_TABULATION_CENSUS_200
zip_df = zips[['ZCTA','geometry']].drop_duplicates(subset = 'ZCTA')
zip_df['x'] = zip_df.geometry.centroid.x
zip_df['y'] = zip_df.geometry.centroid.y

state = counties.geometry.unary_union
state = geopandas.GeoDataFrame(geometry=[state], crs=counties.crs)

### RANDOM POINT FILE IMPORT
rp = geopandas.read_file("rp.shp")
```

```python
## Read distance matrix from .csv's
test_to_county = pd.read_csv('test_to_county.csv')
test_to_site = pd.read_csv('test_to_site.csv')
```

Feature Engineering / Data Manipulation

1. Generate (x) random points to enable analysis

In [4]:

```python
### FOR MANUAL CALCULATION ONLY

'''
geodata = state

num_points = 150

# generate (x) points within the first county polygon in geodata
points = random_points_in_polygon(num_points, geodata.iloc[0].geometry)

rp = geopandas.GeoDataFrame(geometry=points).set_crs(26915)
rp['test_id'] = rp.index + 1
rp['test_lat'] = rp.geometry.centroid.y/1000
rp['test_lon'] = rp.geometry.centroid.x/1000
'''
```

Out[4]:

```
"\ngeodata = state\n\nnum_points = 150\n\n# generate (x) points within the first county polygon in geodata\npoints = random_points_in_polygon(num_points, geodata.iloc[0].geometry)\n\nrp = geopandas.GeoDataFrame(geometry=points).set_crs(26915)\nrp['test_id'] = rp.index + 1\nrp['test_lat'] = rp.geometry.centroid.y/1000\nrp['test_lon'] = rp.geometry.centroid.x/1000\n"
```

2. Simulate point-to-point distances to estimate population, metrics at individual sites

In [5]:

```python
### FOR MANUAL SIMULATION ONLY: OTHERWISE READ FILE IN NEXT CELL

'''
test_county_matrix = []
for i in rp['test_id'].unique():
    for j in counties['COUNTY'].unique():
        lat1 = rp[rp['test_id']==i]['test_lat'].values[0]
        lat2 = counties[counties['COUNTY']==j]['county_lat'].values[0]
        lon1 = rp[rp['test_id']==i]['test_lon'].values[0]
        lon2 = counties[counties['COUNTY']==j]['county_lon'].values[0]
        distance = dist_calc(lat1,lat2,lon1,lon2)
        test_county_matrix.append([i,j,distance])
test_to_county = pd.DataFrame(test_county_matrix,columns=['test_site','COUNTY','Distanc
test_to_county.to_csv("test_to_county.csv")

test_site_matrix = []
for i in rp['test_id'].unique():
    for j in sites['site_id'].unique():
        lat1 = rp[rp['test_id']==i]['test_lat'].values[0]
        lat2 = sites[sites['site_id']==j]['site_lat'].values[0]
        lon1 = rp[rp['test_id']==i]['test_lon'].values[0]
        lon2 = sites[sites['site_id']==j]['site_lon'].values[0]
```

```
        distance = dist_calc(lat1,lat2,lon1,lon2)
        test_site_matrix.append([i,j,distance])
test_to_site = pd.DataFrame(test_site_matrix,columns=['test_site','site_id','Distance']
test_to_site.to_csv("test_to_site.csv")
'''
```

Out[5]:

```
'\ntest_county_matrix = []\nfor i in rp[\'test_id\'].unique():\n    for j in counties
[\'COUNTY\'].unique():\n        lat1 = rp[rp[\'test_id\']==i][\'test_lat\'].values[0]\n
lat2 = counties[counties[\'COUNTY\']==j][\'county_lat\'].values[0]\n        lon1 = rp[rp
[\'test_id\']==i][\'test_lon\'].values[0]\n        lon2 = counties[counties[\'COUNTY\']=
=j][\'county_lon\'].values[0]\n        distance = dist_calc(lat1,lat2,lon1,lon2)\n
test_county_matrix.append([i,j,distance])\ntest_to_county = pd.DataFrame(test_county_mat
rix,columns=[\'test_site\',\'COUNTY\',\'Distance\']).drop_duplicates(subset=[\'test_site
\',\'COUNTY\'])\ntest_to_county.to_csv("test_to_county.csv")\n\ntest_site_matrix = []\nf
or i in rp[\'test_id\'].unique():\n    for j in sites[\'site_id\'].unique():\n        la
t1 = rp[rp[\'test_id\']==i][\'test_lat\'].values[0]\n        lat2 = sites[sites[\'site_i
d\']==j][\'site_lat\'].values[0]\n        lon1 = rp[rp[\'test_id\']==i][\'test_lon\'].va
lues[0]\n        lon2 = sites[sites[\'site_id\']==j][\'site_lon\'].values[0]\n        di
stance = dist_calc(lat1,lat2,lon1,lon2)\n        test_site_matrix.append([i,j,distance])
\ntest_to_site = pd.DataFrame(test_site_matrix,columns=[\'test_site\',\'site_id\',\'Dist
ance\']).drop_duplicates(subset=[\'test_site\',\'site_id\'])\ntest_to_site.to_csv("test_
to_site.csv")\n'
```

Model Training

```
1. Estimate Population based on proximity to other counties (Weighted
Average)
2. Estimate distance to closest site based on population density (Linear
Regression)
3. Estimate number of sites within 25 miles based on population density
(Linear Regression)
4. Generate "Score" on a (20-80) scale, where 20 is most in need of a new
site (Weighted Z-Score Aggregation)
```

In [6]:

```
## Weighted population average based on distance
test_to_county['dist_wt'] = 1 / test_to_county.Distance**1.5
test_to_county = pd.merge(test_to_county,counties[['COUNTY','POP2010']],on='COUNTY')
test_to_county['pop_wt'] = test_to_county.dist_wt * test_to_county.POP2010
test_pop = pd.DataFrame(test_to_county.groupby('test_site')['pop_wt'].sum()/test_to_cou

## Add count of sites within 25 miles of each point
counts_df = test_to_site[test_to_site.Distance<25].groupby('test_site').count().reset_i
test_to_site['within_25'] = test_to_site.merge(counts_df,on='test_site',how='left')['co

## Add distance of closest site
closest_df = test_to_site.groupby('test_site')['Distance'].min().reset_index().rename(c
test_to_site['closest'] = test_to_site.merge(closest_df,on='test_site',how='left')['clo
test_df = pd.merge(test_to_site.drop_duplicates(subset='test_site')[['test_site','withi

## Calculate expected closest distance, number of sites within 25 miles
test_df['exp_closest'] = -0.00009192*test_df.pop_wt+18.30715947
test_df['exp_within_25'] = 0.00009816*test_df.pop_wt-0.99121985

## Compute a score to demonstrate how well a location is covered for this type of build
test_df['closest_diff'] = test_df.closest - test_df.exp_closest
test_df['within_25_diff'] = test_df.exp_within_25 - test_df.within_25
test_df['z_closest'] = (test_df.closest_diff - test_df.closest_diff.mean())/test_df.clo
test_df['z_within'] = (test_df.within_25_diff - test_df.within_25_diff.mean())/test_df.
```

```
test_df['z_agg'] = (test_df.z_closest + test_df.z_within)/2
test_df['Score'] = 50-10*test_df.z_agg
```

5. Create Heat Map DataFrame

In [7]:

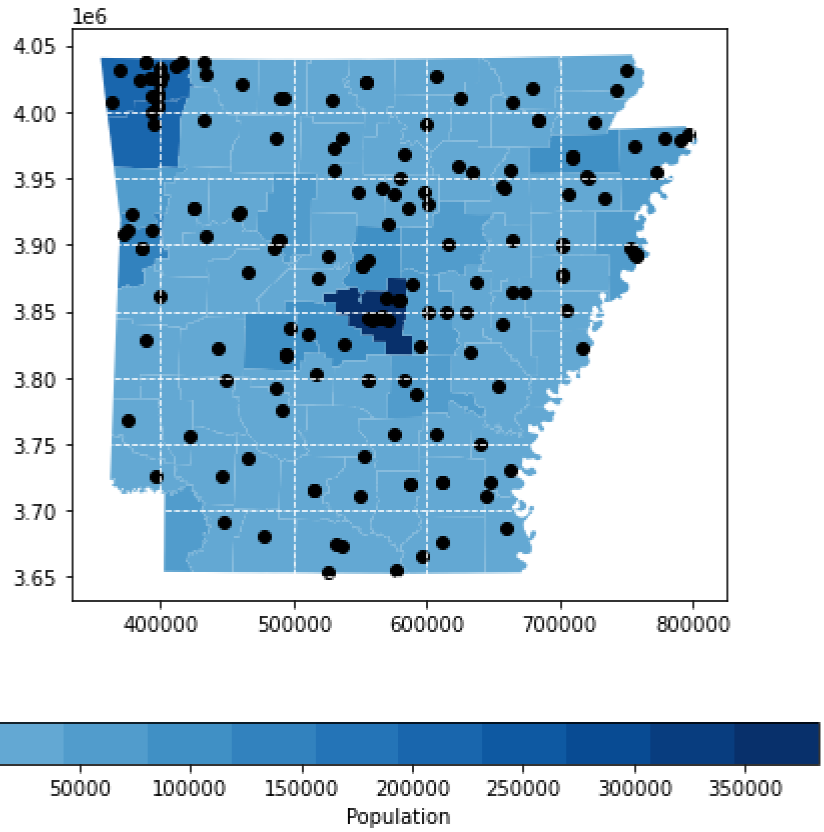
```
heat_df = geopandas.overlay(sites,counties)
heat_df = pd.merge(counties,sites.groupby('county')['site_id'].count().reset_index().re
heat_df.site_count = heat_df.site_count.fillna(0)
heat_df['exp_sites'] = 0.00003759*heat_df.POP2010 + 0.87172343
heat_df['Needed_Sites'] = heat_df.exp_sites - heat_df.site_count
```

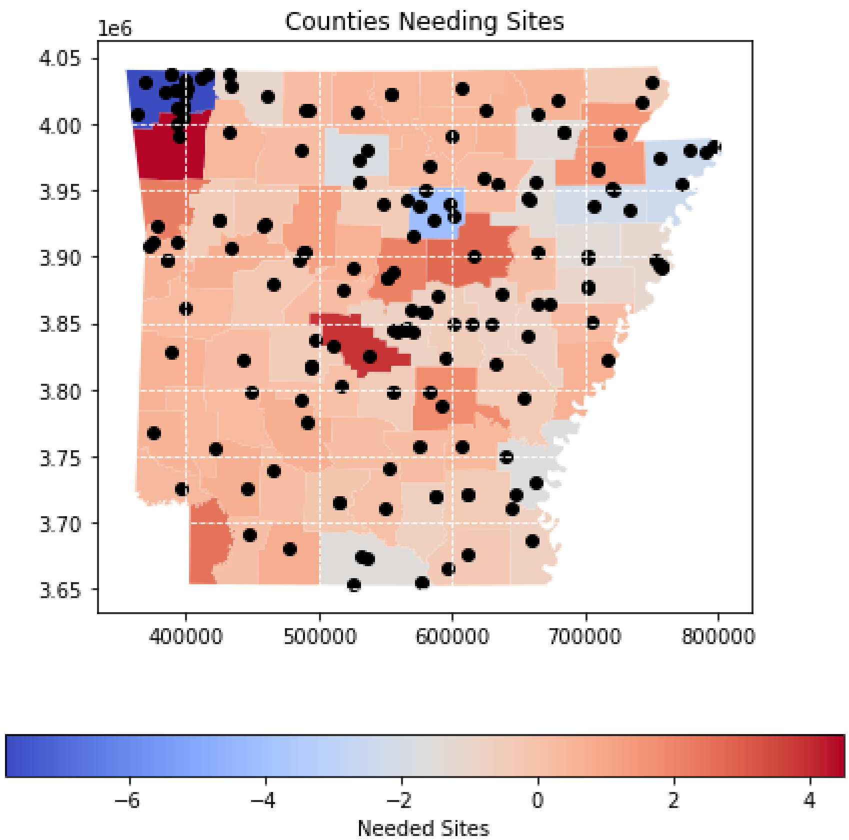
State Plots

1. PLOT: Entire State
2. PLOT: Heat Map (Sites needed per county)

In [8]:

```
state_plot()
heat_plot()
```





Enter Hypothetical Building Location for Location Score

```
    MULTIPLE (TABLE/PLOT): Show need-based metrics and Score for a
HYPOTHETICAL BUILDING LOCATION:
     - Adjust (x,y) if using coordinates (NAD83 / UTM Zone 15N)
     - Adjust (zip_code) if using zip
     - Set (method) to 'coo' for (x,y) or 'zip' for zip codes

    TABLE:
     - Shows distance to closest site vs. expected
     - Shows number of sites within 25 miles vs. expected
     - Shows overall Score (lower needs a building more)

    PLOT:
     - Shows plot of all building type in the state (in black)
     - Shows hypothetical location of new building (in white)
```

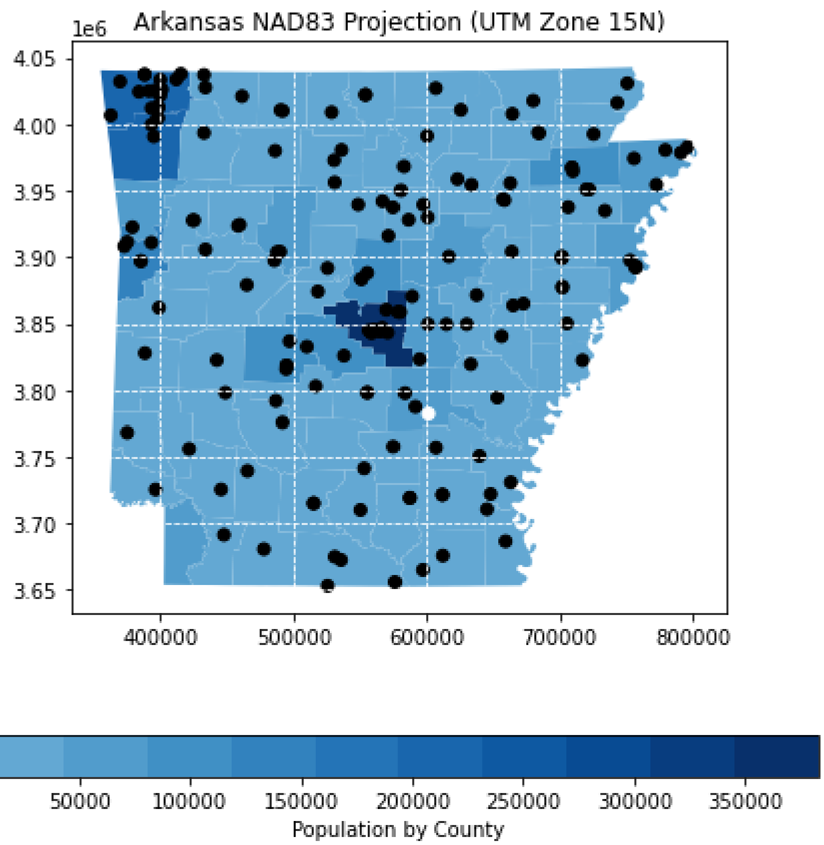
In [9]:

```
# Enter x,y coordinates OR zip code here
x = 525000
y = 3850000
zip_code = 71601
method = 'zip' ## Use 'coo' or 'zip'

x,y = grab_coordinates(x,y,zip_code,method)

calculate_need(x,y)
plot_coordinate(x,y)
```

Site	Coordinates [x,y]	Population (est)
test_site	[601168.1274699278, 3782296.929099404]	49844.914869

Class	Distance (mi) to closest site	Sites within 25 miles
Actual	11.091275	2.000000
Expected	13.725415	3.901557
Score (20-80)	53.615240	39.711348

Score (20-80)
46.663294



Show list of simulated sites with highest need of building type

In [10]:
```
show_x_highest_need_locations(10)
```

Out[10]:

test_site	Coordinates (x,y)	pop_wt	closest	exp_closest	within_25	exp_within_25	Score

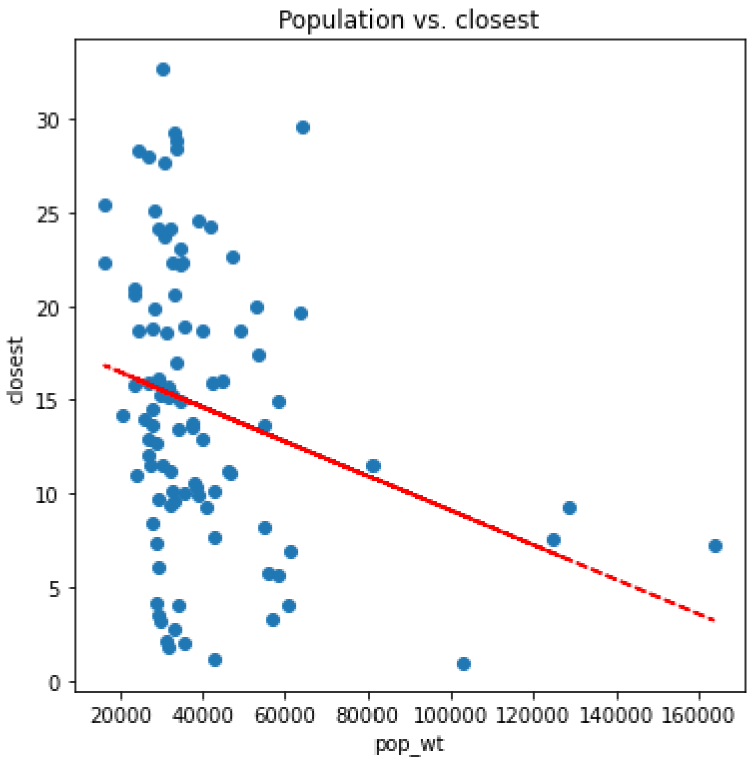
	test_site	Coordinates (x,y)	pop_wt	closest	exp_closest	within_25	exp_within_25	Score
67	68	POINT (368845.098 3950277.504)	64321.229578	29.552927	12.394752	0.0	5.322552	23.826540
13	14	POINT (511587.548 3747574.284)	30124.740959	32.622252	15.538093	0.0	1.965825	32.958098
11	12	POINT (415922.777 3837708.716)	33046.189325	29.271610	15.269554	0.0	2.252594	34.297356
5	6	POINT (710458.432 4018941.413)	33722.305154	28.761107	15.207405	0.0	2.318962	34.425491
93	94	POINT (546816.585 3771044.802)	33430.707750	28.419183	15.234209	0.0	2.290338	34.755957
1	2	POINT (516096.811 3762598.581)	30754.348439	27.638948	15.480220	0.0	2.027627	36.170898
91	92	POINT (580131.459 3888069.967)	63711.353044	19.668784	12.450812	2.0	5.262687	36.220268
0	1	POINT (549027.070 3912752.072)	47114.033015	22.653971	13.976438	1.0	3.633494	36.920790
3	4	POINT (488510.998 3723332.271)	26628.197177	27.921812	15.859496	0.0	1.622604	37.332745
52	53	POINT (621930.826 3797904.304)	41848.515600	24.228569	14.460444	1.0	3.116630	37.570632

Analysis / Model Steps

1. Population vs. Distance to Closest Site

In [11]:

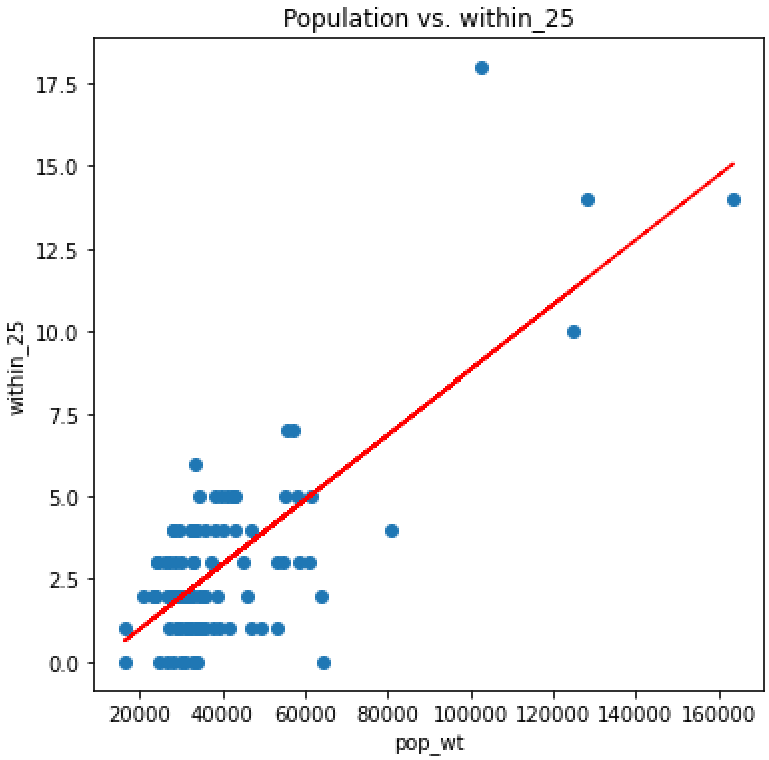
```
fig_size = [6,6]
plt.rcParams["figure.figsize"] = fig_size

x, y = test_df.pop_wt, test_df.closest
z = np.polyfit(x,y,1)
p = np.poly1d(z)

plt.scatter(x,y)
plt.plot(x,p(x),"r--")
plt.title("Population vs. "+y.name)
plt.xlabel(x.name)
plt.ylabel(y.name)
plt.show()
```



2. Population vs. Number of sites within 25 miles

In [12]:

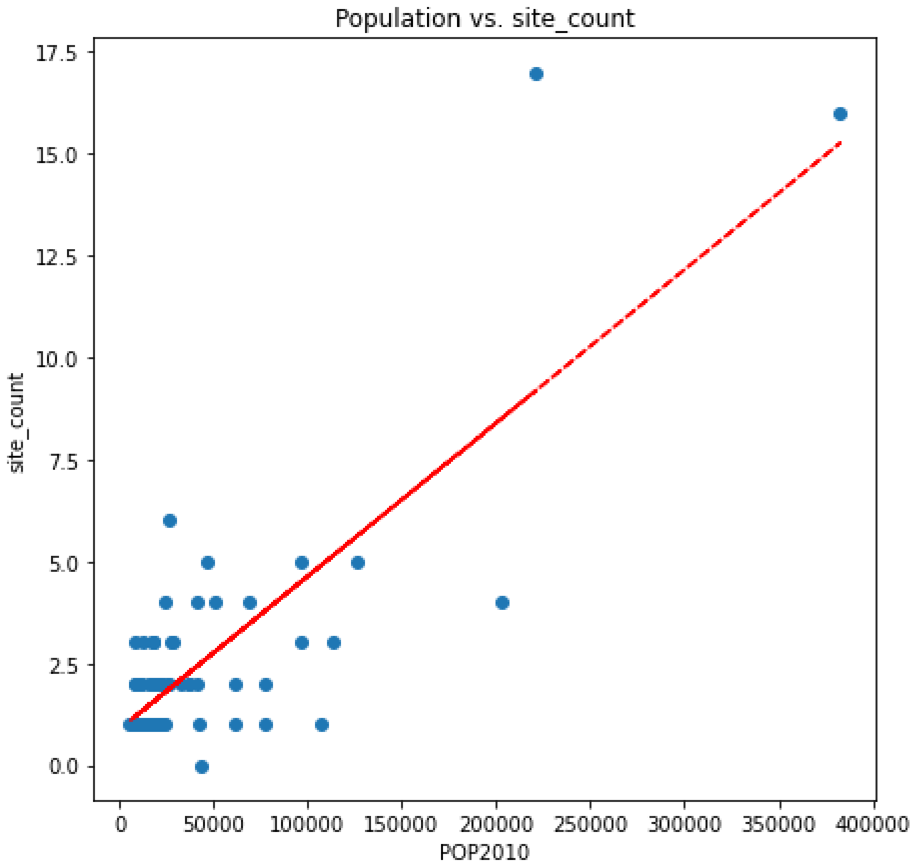
```
fig_size = [6,6]
plt.rcParams["figure.figsize"] = fig_size

x, y = test_df.pop_wt, test_df.within_25
z = np.polyfit(x,y,1)
p = np.poly1d(z)

plt.scatter(x,y)
plt.plot(x,p(x),"r--")
plt.title("Population vs. "+y.name)
plt.xlabel(x.name)
plt.ylabel(y.name)
plt.show()
```



3. By County: Population by Number of Sites

In [13]:

```
fig_size = [7,7]
plt.rcParams["figure.figsize"] = fig_size

x, y = heat_df.POP2010, heat_df.site_count
z = np.polyfit(x,y,1)
p = np.poly1d(z)

plt.scatter(x,y)
plt.plot(x,p(x),"r--")
plt.title("Population vs. "+y.name)
plt.xlabel(x.name)
plt.ylabel(y.name)
plt.show()
```


Population vs. site_count
site_count
POP2010
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
50000
100000
150000
200000
250000
300000
350000
400000

In [ ]: