Team_17_code

February 12, 2023

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from scipy.stats import linregress
```

Loading in datasets

[ ]:
```
# mapping dataset
ct_to_id_data = "fips_codes.csv"
# analysis datasets|
ineq_treecover_data = "urban_tree_canopy.csv" # income inequality - tree cover
#https://www.countyhealthrankings.org/explore-health-rankings/
↪rankings-data-documentation/national-data-documentation-2010-2019
health_data = "2010nationalhealth.csv" # health data
park_cover_data = "percent_cover_county.txt"
```

[ ]:
```
# Dataset for MAPPING ONLY
# getting state + county ids for mapping with other datasets
# =================================================================
ct_to_id = pd.read_csv(ct_to_id_data, dtype=str)
ct_to_id["county_id"] = ct_to_id["state_code"] + ct_to_id["county_code"] # new␣
↪column
ct_to_id["county"] = ct_to_id["county"].str.replace(' County','')
ct_to_id["state_county"] = ct_to_id["county"] + "," + " " +␣
↪ct_to_id["state_name"]
ct_to_id.index = ct_to_id.index + 1
```

[ ]:
```
ct_to_id
```

[ ]:
```
     state state_code                    state_name county_code  \
1       AL         01                       Alabama         001
2       AL         01                       Alabama         003
3       AL         01                       Alabama         005
4       AL         01                       Alabama         007
5       AL         01                       Alabama         009
…     …          …                       …          …
3243    PR         72                   Puerto Rico         153
```

```
3244     UM          74  U.S. Minor Outlying Islands         300
3245     VI          78          U.S. Virgin Islands         010
3246     VI          78          U.S. Virgin Islands         020
3247     VI          78          U.S. Virgin Islands         030

                  county county_id                              state_county
1                Autauga     01001                           Autauga, Alabama
2                Baldwin     01003                           Baldwin, Alabama
3                Barbour     01005                           Barbour, Alabama
4                   Bibb     01007                              Bibb, Alabama
5                 Blount     01009                            Blount, Alabama
…                    …       …                                          …
3243     Yauco Municipio     72153               Yauco Municipio, Puerto Rico
3244      Midway Islands     74300  Midway Islands, U.S. Minor Outlying Islands
3245    St. Croix Island     78010        St. Croix Island, U.S. Virgin Islands
3246     St. John Island     78020         St. John Island, U.S. Virgin Islands
3247   St. Thomas Island     78030       St. Thomas Island, U.S. Virgin Islands

[3247 rows x 7 columns]
```

0.0.1 Data exploration & Feature Selection

Urban canopy dataset (Income inequality & tree cover gap)

[ ]:
```
# load inequality to tree cover dataset
# ================================================================
ineq_tc = pd.read_csv(ineq_treecover_data, dtype=str) # read as string to not␣
 ↪lose leading 0s
ineq_tc = ineq_tc.drop(columns=[ "city_name"])
ineq_tc.index = ineq_tc.index + 1
# extract country codes
ineq_tc["census_block"] =  np.array(ineq_tc["census_block"]).astype('U5')
ineq_tc = ineq_tc.astype({col: float for col in ineq_tc.columns[1:]})     #␣
 ↪convert remaining columns back to numerical data
```

[ ]:
```
# drop irrelevant data
ineq_tc = ineq_tc.drop(columns=["surface_temp"])
# filtering
ineq_tc = ineq_tc[ineq_tc["pop_dens_group"] >= 3]  # focus on medium to high␣
 ↪density urban centres
ineq_tc.describe() # describe to see an overview of the data
```

[ ]:
```
       mean_percent_tree_cover       tree_gap  income_percent   income_group  \
count            397998.000000  397998.000000   397998.000000  397998.000000
mean                  0.172264       0.188614    30261.959517       2.138506
std                   0.140353       0.091758    18905.542880       1.086566
min                   0.000000       0.015537      -99.000000       1.000000
25%                   0.062626       0.103041    17644.250000       1.000000
```

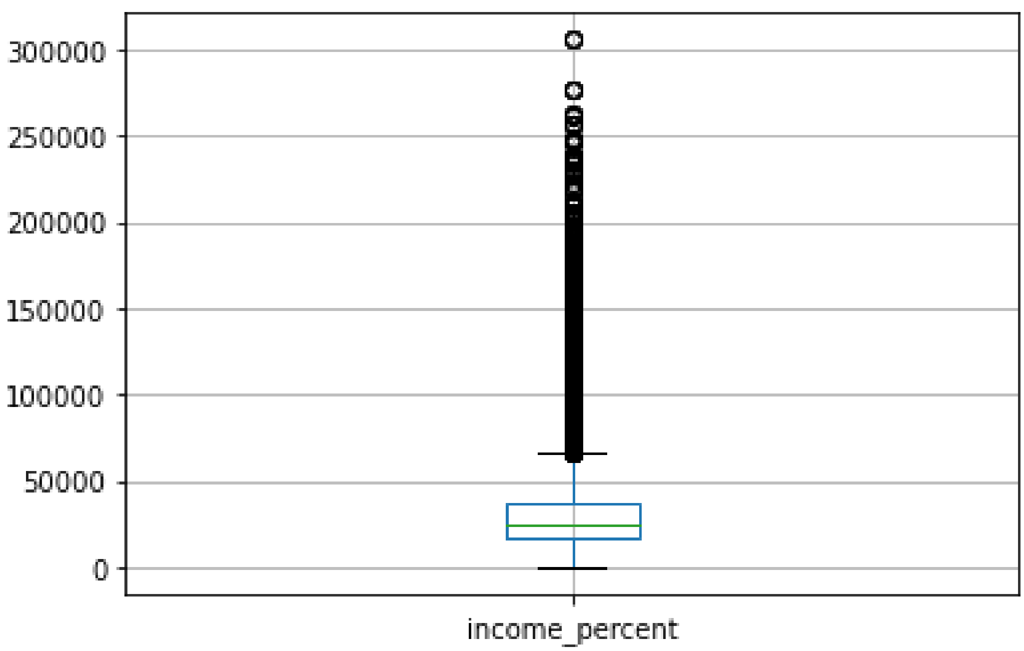
```
50%                     0.143673        0.194592    25340.000000         2.000000
75%                     0.249009        0.250564    36939.000000         3.000000
max                     1.000000        0.700332   305700.000000         4.000000

       pop_dens_group
count   397998.000000
mean         3.344560
std          0.475225
min          3.000000
25%          3.000000
50%          3.000000
75%          4.000000
max          4.000000
```

Outlier filtering and Visualization

[ ]:
```
# clean up obvious data mistakes & visualize distribution with box plots
ineq_tc = ineq_tc[ineq_tc["income_percent"] >= 0]
```

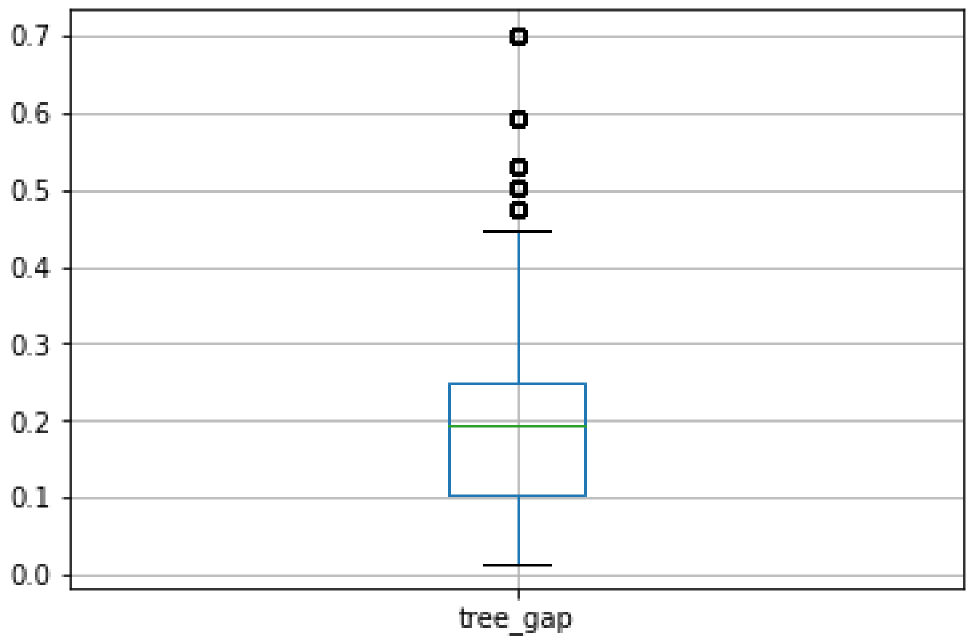
[ ]:
```
income_percent = pd.DataFrame(ineq_tc["income_percent"])
income_percent.boxplot()  # note that this plot shows a lot of data that are␣
 ↪"outliers" if IQR is applied, so it wasn't adjusted via IQR
```

[ ]: <AxesSubplot:>



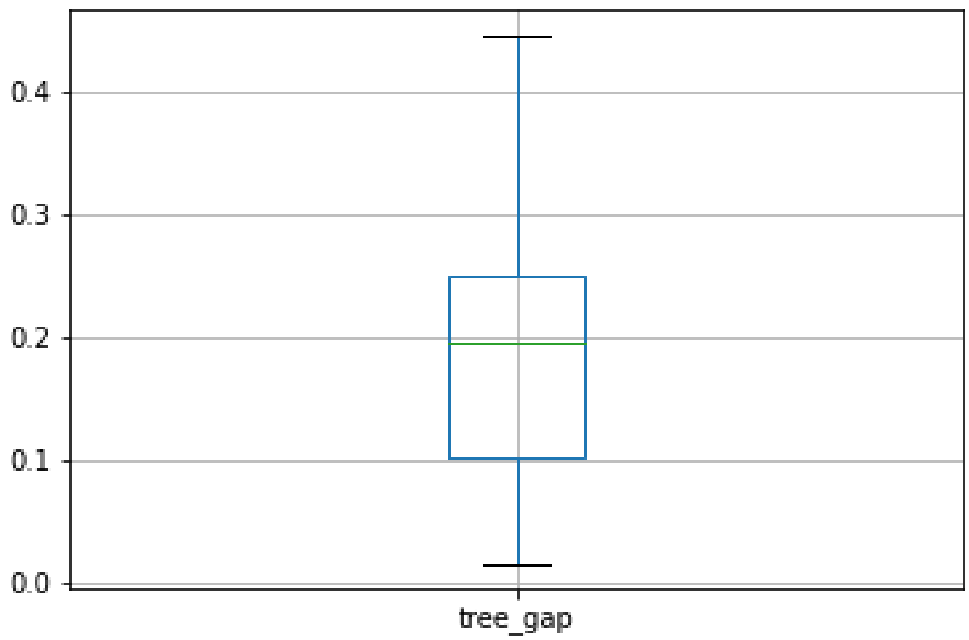
```
[ ]: tree_gap = pd.DataFrame(ineq_tc["tree_gap"])
     tree_gap.boxplot()
```

```
[ ]: <AxesSubplot:>
```



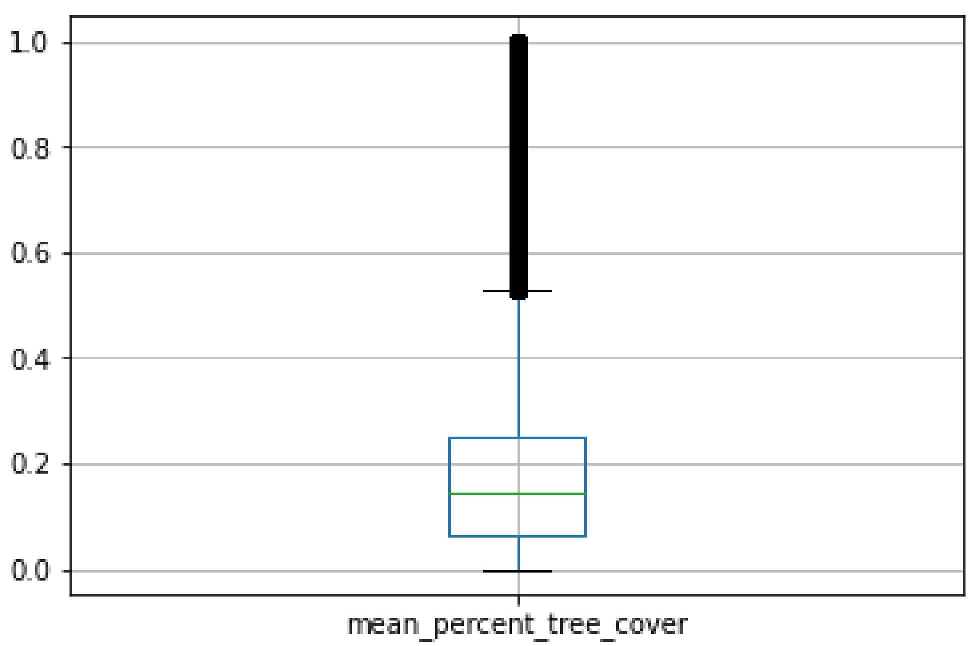

```
[ ]: # apply IQR to remove tree_gap
     q1 = tree_gap.quantile(0.25)
     q3 = tree_gap.quantile(0.75)
     iqr = q3-q1
     tree_gap = tree_gap[~((tree_gap<(q1-1.5*iqr)) | (tree_gap>(q3+1.5*iqr)))]
     tree_gap.boxplot()
```

```
[ ]: <AxesSubplot:>
```



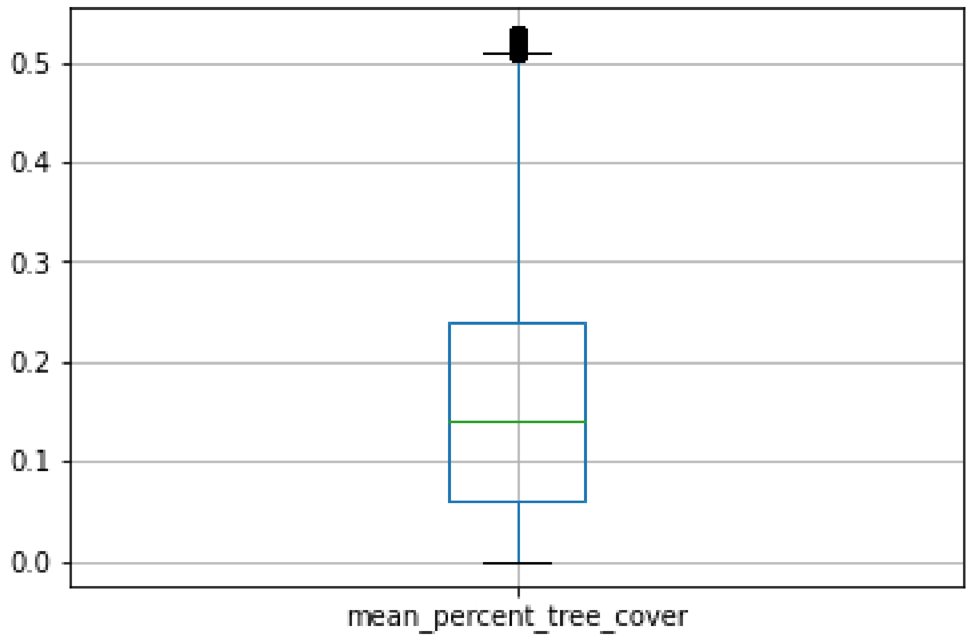

```
[ ]: mean_tree_cover = pd.DataFrame(ineq_tc["mean_percent_tree_cover"])
     mean_tree_cover.boxplot()
```

```
[ ]: <AxesSubplot:>
```



[ ]:
```python
# apply IQR to remove mean_percent_tree_cover outliers
q1 = mean_tree_cover.quantile(0.25)
q3 = mean_tree_cover.quantile(0.75)
iqr = q3-q1
mean_tree_cover = mean_tree_cover[~((mean_tree_cover<(q1-1.5*iqr)) |␣
↪(mean_tree_cover>(q3+1.5*iqr)))]
mean_tree_cover.boxplot()
```

[ ]: <AxesSubplot:>



[ ]:
```python
# add outlier adjusted data back into the datatset
ineq_tc["tree_gap"] = tree_gap
ineq_tc["mean_percent_tree_cover"] = mean_tree_cover
ineq_tc = ineq_tc.dropna() # drop no data entries
ineq_tc.describe()
```

[ ]:

	mean_percent_tree_cover	tree_gap	income_percent	income_group \
count	387167.000000	387167.000000	387167.000000	387167.000000
mean	0.161327	0.184206	30177.441913	2.131279
std	0.121952	0.086534	18841.869457	1.082733
min	0.000000	0.015537	118.000000	1.000000
25%	0.060791	0.096380	17616.000000	1.000000
50%	0.139279	0.194592	25285.000000	2.000000
75%	0.239496	0.244978	36772.000000	3.000000
max	0.528582	0.445957	305700.000000	4.000000

```
       pop_dens_group
count   387167.000000
mean         3.349604
std          0.476845
min          3.000000
25%          3.000000
50%          3.000000
75%          4.000000
max          4.000000
```

Skew and Kurt Analysis

```
[ ]: # calculate the skewness for tree_gap, mean_percent_tree_cover and␣
      ↪income_percent
     # Skewness = 0: Then normally distributed.
     # Skewness > 0: Then more weight in the left tail of the distribution.
     # Skewness < 0: Then more weight in the right tail of the distribution.
     income_percent_skew = income_percent.skew()
     tree_gap_skew = tree_gap.skew()
     mean_tree_cover_skew = mean_tree_cover.skew()
```

```
[ ]: # calculate the kurtosis  for tree_gap, mean_percent_tree_cover and␣
      ↪income_percent
     # kurtosis for normal distribution is equal to 3.
     # For a distribution having kurtosis < 3: It is called playkurtic.
     # For a distribution having kurtosis > 3, It is called leptokurtic and it␣
      ↪signifies that it tries to produce more outliers rather than the normal␣
      ↪distribution.
     income_percent_kurt = income_percent.kurt()
     tree_gap_kurt = tree_gap.kurt()
     mean_tree_cover_kurt = mean_tree_cover.kurt()
```

```
[ ]: print("income_percent skew: " + str(income_percent_skew))
     print("---------------------------------------")
     print("tree_gap_skew: " + str(tree_gap_skew))
     print("---------------------------------------")
     print("mean_tree_cover_skew: " + str(mean_tree_cover_skew))
     print("---------------------------------------")
     print("income_percent_kurt: " + str(income_percent_kurt))
     print("---------------------------------------")
     print("tree_gap_kurt: " + str(tree_gap_kurt))
     print("---------------------------------------")
     print("mean_tree_cover_kurt:" + str(mean_tree_cover_kurt))
     print("---------------------------------------")
```

```
income_percent skew: income_percent    2.373856
dtype: float64
```

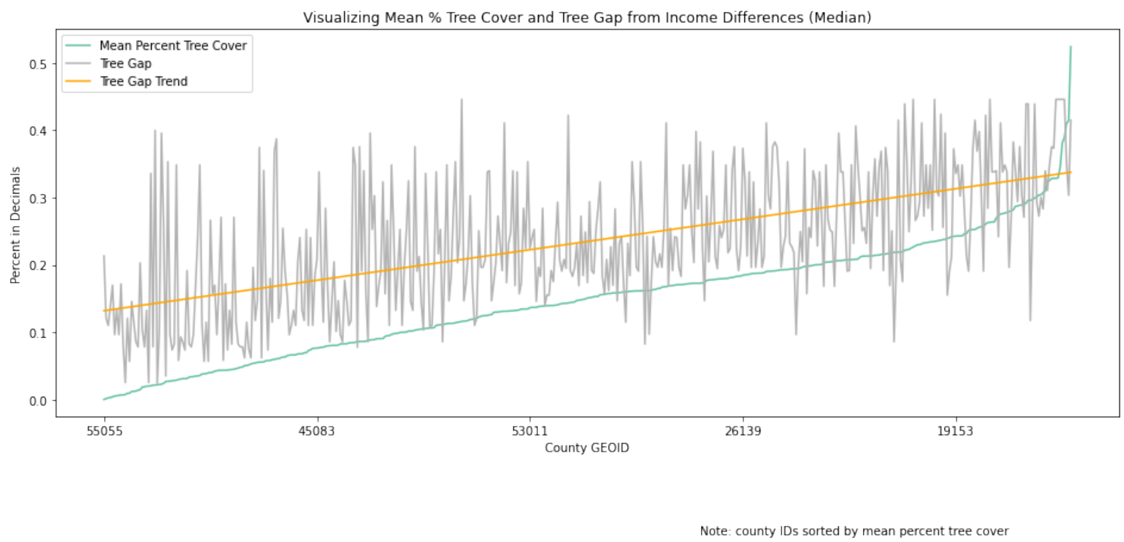
```
---------------------------------------
tree_gap_skew: tree_gap    0.222618
dtype: float64
---------------------------------------
mean_tree_cover_skew: mean_percent_tree_cover    0.724803
dtype: float64
---------------------------------------
income_percent_kurt: income_percent    10.376055
dtype: float64
---------------------------------------
tree_gap_kurt: tree_gap   -0.224469
dtype: float64
---------------------------------------
mean_tree_cover_kurt:mean_percent_tree_cover   -0.184217
dtype: float64
---------------------------------------
```

[ ]:

```
# visualizing relationship between mean percent tree cover in a county vs %␣
↪tree cover gap between high income / low income areas sorted by tree_gap
plt.figure()
# sort_bytreegap = ineq_tc.copy()
# sort_bytreegap = sort_bytreegap.drop(columns=["income_percent",␣
↪"income_group", "pop_dens_group"])
# sort_bytreegap = sort_bytreegap.groupby("census_block").median()
# sort_bytreegap = sort_bytreegap.sort_values(by=["tree_gap"])

# # other quantiles
# sort_bytreegap_75 = sort_bytreegap.groupby("census_block").quantile(0.75)
# sort_bytreegap_25 = sort_bytreegap.groupby("census_block").quantile(0.25)
# sort_bytreegap_75 = sort_bytreegap_75.sort_values(by=["tree_gap"])
# sort_bytreegap_25 = sort_bytreegap_25.sort_values(by=["tree_gap"])

# # sort_bytreegap.plot(figsize=(16,6), colormap='Set2') # note the scale is␣
↪from 0 - 50%

# sort by mean percent tree cover
sort_bytc = ineq_tc.copy()
sort_bytc = sort_bytc.drop(columns=["income_percent", "income_group",␣
↪"pop_dens_group"])
sort_bytc = sort_bytc.groupby("census_block").median()
sort_bytc = sort_bytc.sort_values(by=["mean_percent_tree_cover"])

sort_bytc.plot(figsize=(16,6), colormap='Set2') # note the scale is from 0 - 50%

X = np.array(range(0, len(sort_bytc))).reshape(-1, 1) # values converts it into␣
↪a numpy array
```

```
Y = sort_bytc.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate the␣
↪dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='orange')

plt.title("Visualizing Mean % Tree Cover and Tree Gap from Income Differences␣
↪(Median)")
plt.legend(["Mean Percent Tree Cover", "Tree Gap", "Tree Gap Trend"])
plt.xlabel('County GEOID')
plt.ylabel('Percent in Decimals')
plt.text(280, -0.2, 'Note: county IDs sorted by mean percent tree cover')
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```




```
[ ]: sort_bytreegap_75.plot(figsize=(16,6), colormap='Set2') # note the scale is␣
↪from 0 - 50%

plt.title("Visualizing Mean % Tree Cover and Tree Gap from Income Differences␣
↪(75th Percentile)")
plt.legend(["Mean Percent Tree Cover", "Tree Gap"])
plt.xlabel('County GEOID')
plt.ylabel('Percent in Decimals')
plt.text(280, -0.2, 'Note: county IDs sorted by tree gap')
plt.show()
```

```
[ ]: sort_bytreegap_25.plot(figsize=(16,6), colormap='Set2') # note the scale is␣
     ↪from 0 - 50%

     plt.title("Visualizing Mean % Tree Cover and Tree Gap from Income Differences␣
     ↪(25th Percentile)")
     plt.legend(["Mean Percent Tree Cover", "Tree Gap"])
     plt.xlabel('County GEOID')
     plt.ylabel('Percent in Decimals')
     plt.text(280, -0.2, 'Note: county IDs sorted by tree gap')
     plt.show()
```

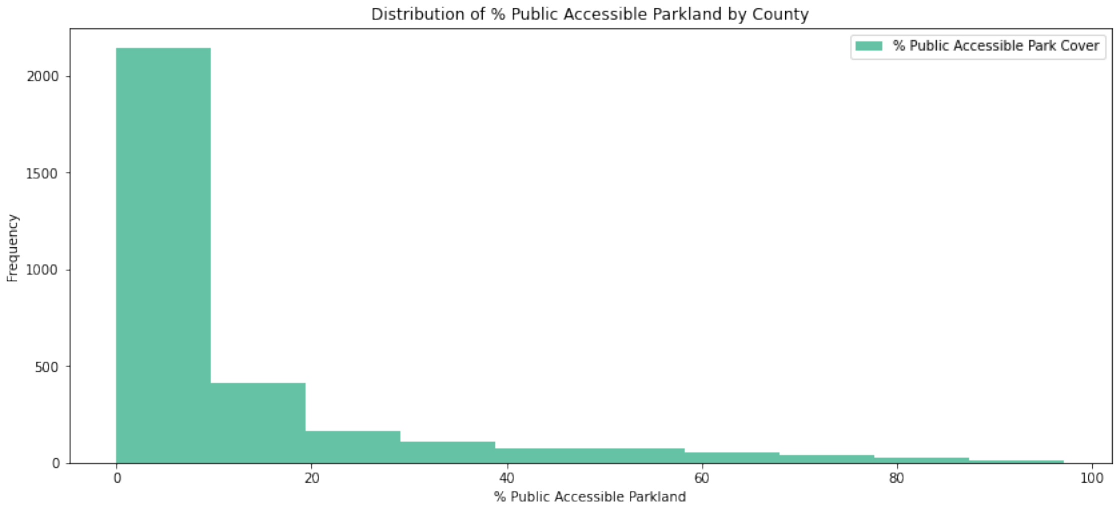
Park Cover Dataset

```
[ ]: # load percent park cover by county data
     # ================================================================
     park_cov = pd.read_csv(park_cover_data, sep=",", dtype=str)
     park_cov = park_cov.astype({col: float for col in park_cov.columns[2:]})
     park_cov = park_cov.drop(columns="NAME")
     park_cov = park_cov.dropna()
     park_cov = park_cov.drop_duplicates(subset=['GEOID'])
     park_cov.head()
```

[ ]:

	GEOID	pc_park
0	01027	18.777
1	01091	0.665
2	01049	2.205
3	01019	7.050
4	01065	8.659

```
[ ]: park_cov.plot.hist(figsize=(14,6), title="Distribution of % Public Accessible␣
     ↪Parkland by County",  colormap='Set2')
     plt.legend(["% Public Accessible Park Cover"])
     plt.xlabel('% Public Accessible Parkland')
     plt.show()
```



2010 Health dataset

[ ]:
```
health_data = pd.read_excel("2010 County Health Rankings National Data_v2.xls",␣
↪sheet_name = "Ranked Measure Data", header = [1], usecols = [0, 1, 2, 15,␣
↪16, 17, 18, 19, 20, 21, 22, 23, 24])
health_data.rename(columns = {'Sample Size.2':'Sample Size'}, inplace = True)
health_data.drop('FIPS', axis = 1, inplace = True)
health_data.index = health_data.index + 1
```

[ ]:
```
health_data.dropna(axis = 0, how = 'all', inplace = True)
health_data.dropna(axis = 1, how = 'all', inplace = True)
```

[ ]:
```
health_data
```

[ ]:
```
        State      County  Sample Size.1  Physically Unhealthy Days  \
1     Alabama     Autauga          255.0                       5.48
2     Alabama     Baldwin          960.0                       3.57
3     Alabama     Barbour          187.0                       6.11
4     Alabama        Bibb          182.0                       4.22
5     Alabama      Blount          247.0                       5.62
…         …          …             …                          …
3137  Wyoming  Sweetwater         2300.0                       3.61
3138  Wyoming       Teton         1180.0                       2.65
3139  Wyoming       Uinta         1351.0                       4.13
3140  Wyoming    Washakie          646.0                       3.02
3141  Wyoming      Weston          580.0                       3.12

      95% CI - Low.2  95% CI - High.2 Quartile.2  Sample Size  \
1               4.16             6.80          4        258.0
2               2.86             4.28          1        964.0
```

```
3              3.86             8.36          4        186.0
4              2.82             5.62          2        180.0
5              3.94             7.30          4        249.0
…              …                …             …        …
3137           3.24             3.98          4       2331.0
3138           2.16             3.13          1       1172.0
3139           3.57             4.68          4       1347.0
3140           2.42             3.62          2        654.0
3141           2.46             3.79          2        581.0

      Mentally Unhealthy Days  95% CI - Low.3  95% CI - High.3 Quartile.3
1                        4.14            2.78             5.49          2
2                        4.06            3.23             4.89          2
3                        3.84            2.39             5.30          2
4                        5.31            3.40             7.22          4
5                        4.47            2.76             6.19          3
…                        …               …                …             …
3137                     3.99            3.57             4.42          4
3138                     2.25            1.84             2.66          1
3139                     3.44            2.99             3.89          4
3140                     2.44            1.92             2.97          1
3141                     3.14            2.31             3.98          3

[3141 rows x 12 columns]
```

[ ]:
```
# add county id to health data
health_data["state_county"] = health_data["County"] + ", " +␣
 ↪health_data["State"]
health_data["county_id"] = health_data['state_county'].map(ct_to_id.
 ↪set_index('state_county')['county_id'])
health_data.head()

# note for unhealthy days:
# Average number of reported physically unhealthy days per month
```

[ ]:
```
     State   County  Sample Size.1  Physically Unhealthy Days  95% CI - Low.2  \
1  Alabama  Autauga          255.0                       5.48            4.16
2  Alabama  Baldwin          960.0                       3.57            2.86
3  Alabama  Barbour          187.0                       6.11            3.86
4  Alabama     Bibb          182.0                       4.22            2.82
5  Alabama   Blount          247.0                       5.62            3.94

   95% CI - High.2 Quartile.2  Sample Size  Mentally Unhealthy Days  \
1             6.80          4        258.0                     4.14
2             4.28          1        964.0                     4.06
3             8.36          4        186.0                     3.84
4             5.62          2        180.0                     5.31
```

```
5             7.30          4        249.0                     4.47

   95% CI - Low.3  95% CI - High.3 Quartile.3      state_county county_id
1           2.78             5.49          2  Autauga, Alabama     01001
2           3.23             4.89          2  Baldwin, Alabama     01003
3           2.39             5.30          2  Barbour, Alabama     01005
4           3.40             7.22          4     Bibb, Alabama     01007
5           2.76             6.19          3   Blount, Alabama     01009
```

[ ]:
```
health_data['Physically Unhealthy Days'].corr(health_data['Mentally Unhealthy␣
↪Days'])
```

[ ]:
```
0.6261356817720176
```

0.0.2 Combining Health, Income, Tree Cover Datasets

[ ]:
```
health_byct = pd.DataFrame(sort_bytreegap.index)
health_byct = health_byct.drop_duplicates(subset=['census_block'])
health_data = health_data.drop_duplicates(subset=['county_id'])

health_byct['PUD/month'] = health_byct['census_block'].map(health_data.
↪set_index('county_id')['Physically Unhealthy Days'])
health_byct['MUD/month'] = health_byct['census_block'].map(health_data.
↪set_index('county_id')['Mentally Unhealthy Days'])
health_byct = health_byct.dropna()
health_byct
```

[ ]:
```
    census_block  PUD/month  MUD/month
0          42101       4.14       4.38
1          35043       3.70       3.13
2          35001       3.60       3.46
7          35013       3.66       3.15
8          48141       4.17       3.16
..           …          …          …
441        26049       4.02       4.18
442        47187       1.58       1.47
443        47165       3.47       3.76
444        47037       2.97       3.00
445        47149       3.42       3.37

[359 rows x 3 columns]
```

Income and Health

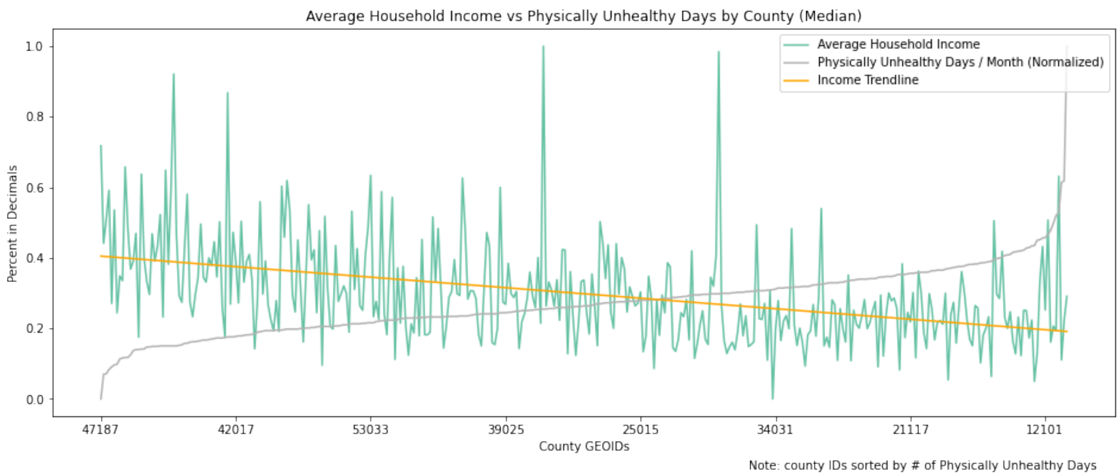
[ ]:
```
# plot income and unhealthy days
income_ud = ineq_tc.copy()
income_ud = income_ud.drop(columns=["mean_percent_tree_cover", "tree_gap",␣
↪"pop_dens_group", "income_group"])
```

[ ]:
```python
def plot_income_health(ud, col, quantile, input):
    data = input.copy()
    data = data.groupby("census_block").quantile(quantile)
    data[ud] = data.index.map(health_byct.set_index('census_block')[ud])
    data= data.sort_values(by=[ud])

    data = data.dropna()

    # normalize income_percent, and PUD/month
    min = data[col].min()
    max = data[col].max()
    data[col] = (data[col] - min)/(max - min)
    min = data[ud].min()
    max = data[ud].max()
    data[ud] = (data[ud]-min)/(max - min)

    return data
```

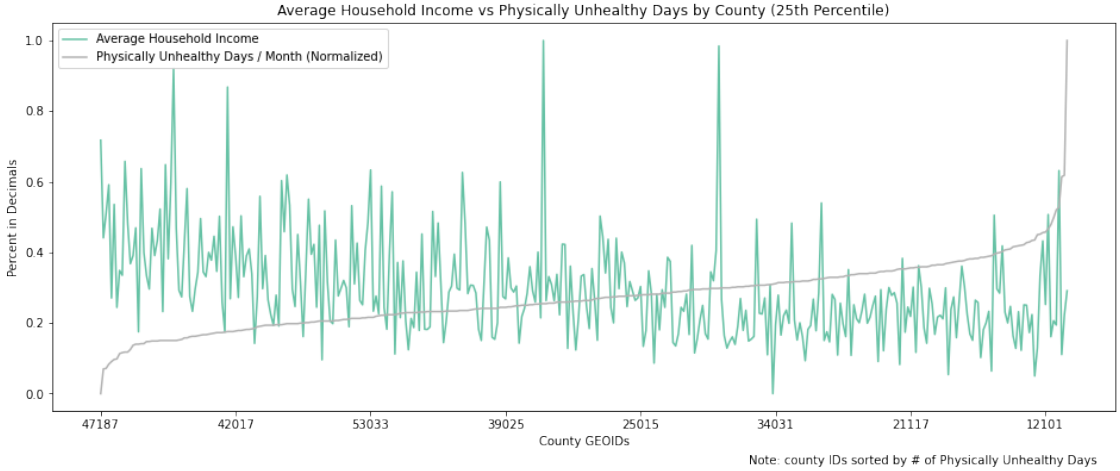
[ ]:
```python
def plot_income_health_v2(ud, ud2, col, quantile, input):
    data = input.copy()
    data = data.groupby("census_block").quantile(quantile)
    data[ud] = data.index.map(health_byct.set_index('census_block')[ud])
    data= data.sort_values(by=[ud])

    data = data.dropna()

    # normalize income_percent, and PUD/month
    min = data[col].min()
    max = data[col].max()
    data[col] = (data[col] - min)/(max - min)
    min = data[ud].min()
    max = data[ud].max()
    data[ud] = (data[ud]-min)/(max - min)

    return data
```

[ ]:
```python
income_ud_median_pud = income_ud.copy()
income_ud_median_pud = plot_income_health('PUD/month', 'income_percent', 0.5,␣
 ↪income_ud_median_pud)
income_ud_median_pud.plot(figsize=(16,6), colormap='Set2')

X = np.array(range(0, len(income_ud_median_pud))).reshape(-1, 1) # values␣
 ↪converts it into a numpy array
Y = income_ud_median_pud.iloc[:, 0].values.reshape(-1, 1)  # -1 means that␣
 ↪calculate the dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
```

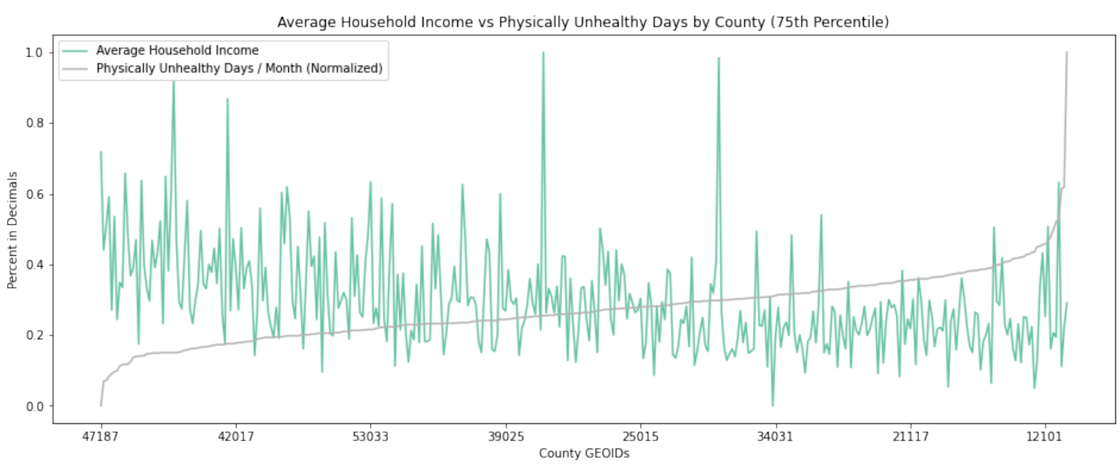
```
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='orange')

plt.title("Average Household Income vs Physically Unhealthy Days by County␣
↪(Median)")
plt.legend(["Average Household Income", "Physically Unhealthy Days / Month␣
↪(Normalized)", "Income Trendline"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(240, -0.2, 'Note: county IDs sorted by # of Physically Unhealthy Days')
plt.show()
```



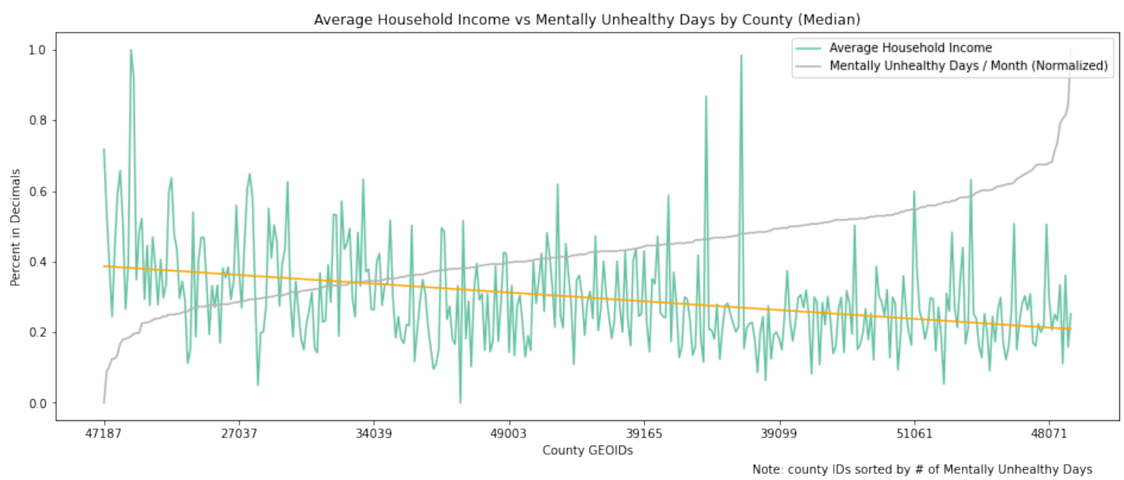
[ ]:
```
income_ud_25_pud = income_ud.copy()
income_ud_25_pud = plot_income_health('PUD/month', 'income_percent', 0.25,␣
↪income_ud_median_pud)
income_ud_25_pud.plot(figsize=(16,6), colormap='Set2')
plt.title("Average Household Income vs Physically Unhealthy Days by County␣
↪(25th Percentile)")
plt.legend(["Average Household Income", "Physically Unhealthy Days / Month␣
↪(Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(240, -0.2, 'Note: county IDs sorted by # of Physically Unhealthy Days')
plt.show()
```



[ ]:
```
income_ud_75_pud = income_ud.copy()
income_ud_75_pud = plot_income_health('PUD/month', 'income_percent', 0.75,␣
 ↪income_ud_median_pud)
income_ud_75_pud.plot(figsize=(16,6), colormap='Set2')



plt.title("Average Household Income vs Physically Unhealthy Days by County␣
 ↪(75th Percentile)")
plt.legend(["Average Household Income", "Physically Unhealthy Days / Month␣
 ↪(Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(240, -0.2, 'Note: county IDs sorted by # of Physically Unhealthy Days')
plt.show()
```

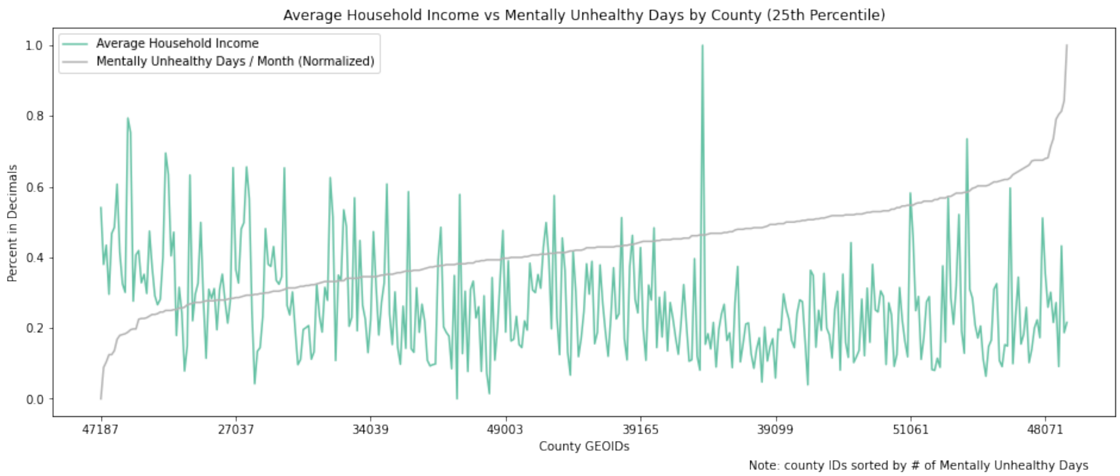


[ ]:
```
income_ud_median_mud = income_ud.copy()
income_ud_median_mud = plot_income_health('MUD/month', 'income_percent', 0.5,␣
↪income_ud_median_mud)
income_ud_median_mud.plot(figsize=(16,6), colormap='Set2')

X = np.array(range(0, len(income_ud_median_mud))).reshape(-1, 1) # values␣
↪converts it into a numpy array
Y = income_ud_median_mud.iloc[:, 0].values.reshape(-1, 1)  # -1 means that␣
↪calculate the dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='orange')

plt.title("Average Household Income vs Mentally Unhealthy Days by County␣
↪(Median)")
plt.legend(["Average Household Income", "Mentally Unhealthy Days / Month␣
↪(Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(240, -0.2, 'Note: county IDs sorted by # of Mentally Unhealthy Days')
plt.show()
```

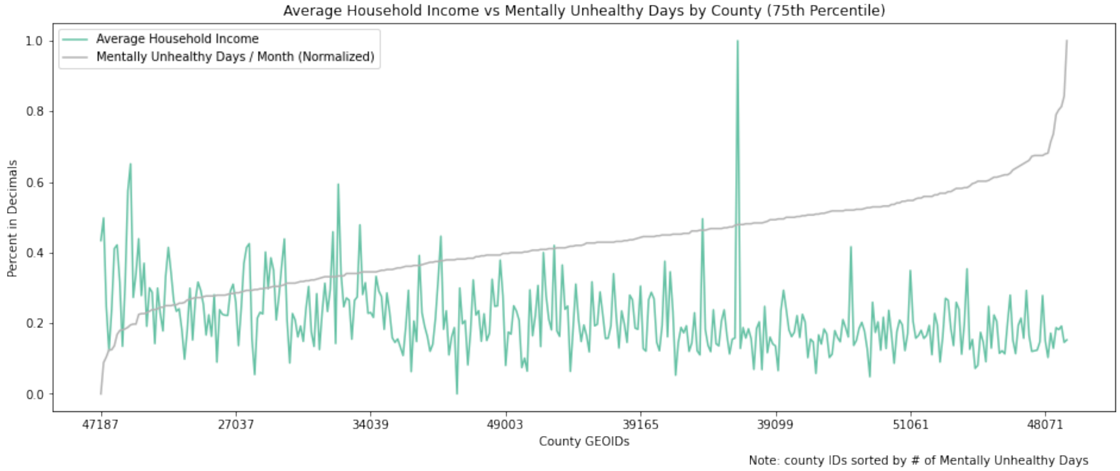


[ ]:
```
income_ud_25_mud = income_ud.copy()
income_ud_25_mud = plot_income_health('MUD/month', 'income_percent', 0.25,␣
↪income_ud_25_mud)
income_ud_25_mud.plot(figsize=(16,6), colormap='Set2')
```

```
plt.title("Average Household Income vs Mentally Unhealthy Days by County (25th␣
↪Percentile)")
plt.legend(["Average Household Income", "Mentally Unhealthy Days / Month␣
↪(Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(240, -0.2, 'Note: county IDs sorted by # of Mentally Unhealthy Days')
plt.show()
```



[ ]:
```
income_ud_75_mud = income_ud.copy()
income_ud_75_mud = plot_income_health('MUD/month', 'income_percent', 0.75,␣
↪income_ud_75_mud)
income_ud_75_mud.plot(figsize=(16,6), colormap='Set2')
plt.title("Average Household Income vs Mentally Unhealthy Days by County (75th␣
↪Percentile)")
plt.legend(["Average Household Income", "Mentally Unhealthy Days / Month␣
↪(Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(240, -0.2, 'Note: county IDs sorted by # of Mentally Unhealthy Days')
plt.show()
```

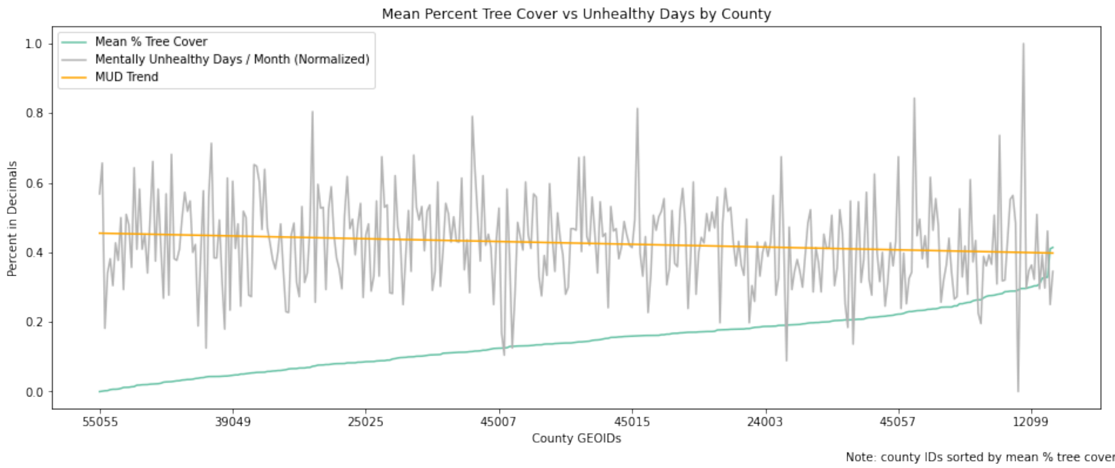


Mean Percent Tree Cover & Health

```
[ ]: # combine tree_gap with PUD
ud_meantc = sort_bytreegap.copy()
ud_meantc = ud_meantc.drop(columns=['tree_gap'])
ud_meantc = ud_meantc.sort_values(by=['mean_percent_tree_cover'])
ud_meantc['PUD/month'] = ud_meantc.index.map(health_byct.
 ↪set_index('census_block')['PUD/month'])
ud_meantc['MUD/month'] = ud_meantc.index.map(health_byct.
 ↪set_index('census_block')['MUD/month'])
ud_meantc= ud_meantc.dropna()
# normalize for plot
ud_meantc['PUD/month'] = (ud_meantc['PUD/month'] -  ud_meantc['PUD/month'].
 ↪min()) / (ud_meantc['PUD/month'].max()- ud_meantc['PUD/month'].min())
ud_meantc['MUD/month'] = (ud_meantc['MUD/month'] -  ud_meantc['MUD/month'].
 ↪min()) / (ud_meantc['MUD/month'].max()- ud_meantc['MUD/month'].min())
```

```
[ ]: ud_meantc_mud = ud_meantc.copy()
ud_meantc_mud = ud_meantc_mud.drop(columns=['PUD/month'])

ud_meantc_mud.plot(figsize=(16,6), colormap='Set2')

X = np.array(range(0, len(ud_meantc_mud))).reshape(-1, 1) # values converts it␣
 ↪into a numpy array
Y = ud_meantc_mud.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate␣
 ↪the dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='orange')
```

```
plt.title("Mean Percent Tree Cover vs Unhealthy Days by County")
plt.legend(["Mean % Tree Cover", "Mentally Unhealthy Days / Month␣
 ↪(Normalized)", "MUD Trend"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: county IDs sorted by mean % tree cover')
plt.show()
```

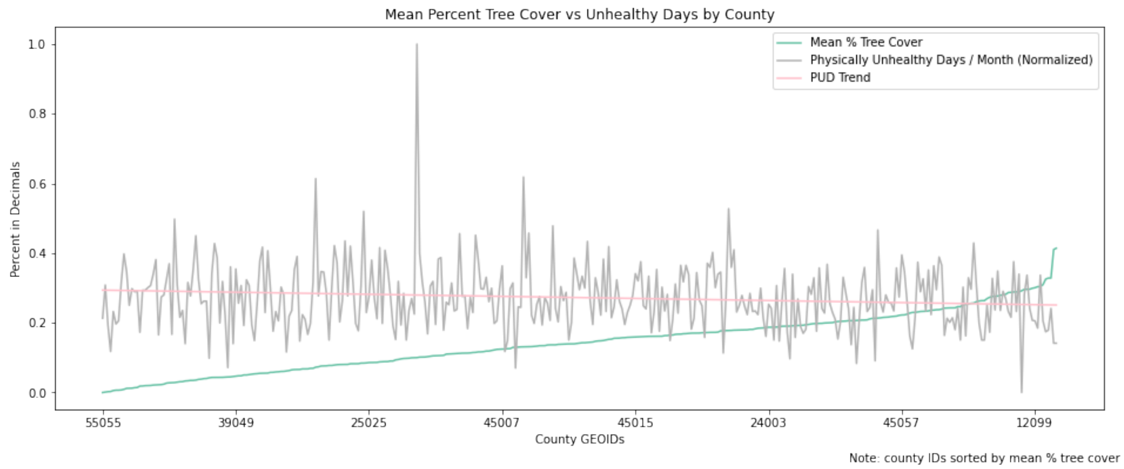


[ ]:
```
print(Y_pred.max())
print(Y_pred.min())
print(Y_pred.max() - Y_pred.min())
```

```
0.4551822191272052
0.3980717692242762
0.05711044990292902
```

[ ]:
```
ud_meantc_pud = ud_meantc.copy()
ud_meantc_pud = ud_meantc_pud.drop(columns=['MUD/month'])

ud_meantc_pud.plot(figsize=(16,6), colormap='Set2')

X = np.array(range(0, len(ud_meantc_pud))).reshape(-1, 1) # values converts it␣
 ↪into a numpy array
Y = ud_meantc_pud.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate␣
 ↪the dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='pink')

plt.title("Mean Percent Tree Cover vs Unhealthy Days by County")
```

```
plt.legend(["Mean % Tree Cover", "Physically Unhealthy Days / Month␣
↪(Normalized)", "PUD Trend"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: county IDs sorted by mean % tree cover')
plt.show()
```

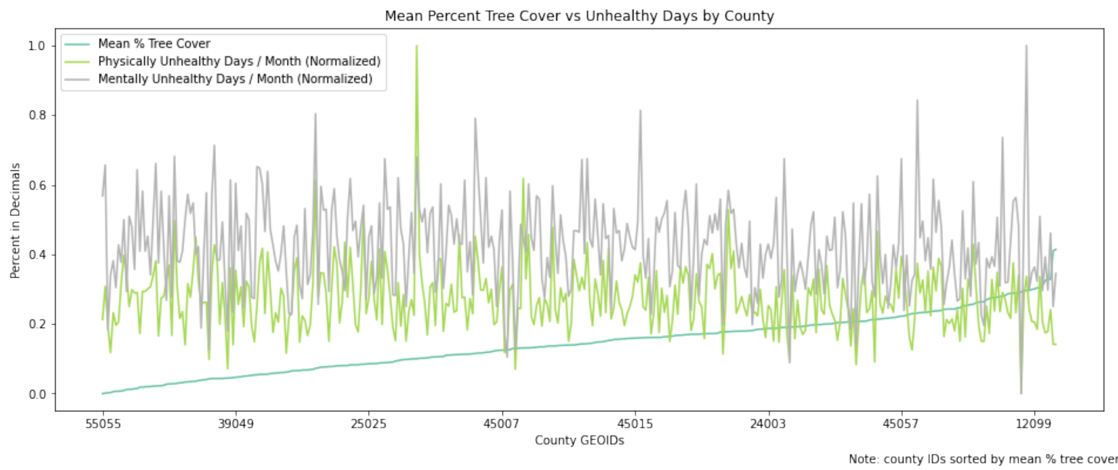



```
[ ]: print(Y_pred.max())
     print(Y_pred.min())
     print(Y_pred.max() - Y_pred.min())
```

```
0.2938761559611827
0.2511798656919439
0.042696290269238824
```

```
[ ]: ud_meantc.plot(figsize=(16,6), colormap='Set2')

     # X = np.array(range(0, len(ud_meantc))).reshape(-1, 1) # values converts it␣
     ↪into a numpy array
     # Y = ud_meantc.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate the␣
     ↪dimension of rows, but have 1 column
     # linear_regressor = LinearRegression()  # create object for the class
     # linear_regressor.fit(X, Y)  # perform linear regression
     # Y_pred = linear_regressor.predict(X)  # make predictions
     # plt.plot(X, Y_pred, color='orange')

     # X = np.array(range(0, len(ud_meantc))).reshape(-1, 1) # values converts it␣
     ↪into a numpy array
     # Y = ud_meantc.iloc[:, 2].values.reshape(-1, 1)  # -1 means that calculate the␣
     ↪dimension of rows, but have 1 column
     # linear_regressor = LinearRegression()  # create object for the class
```

```
# linear_regressor.fit(X, Y)  # perform linear regression
# Y_pred = linear_regressor.predict(X)  # make predictions
# plt.plot(X, Y_pred, color='pink')

plt.title("Mean Percent Tree Cover vs Unhealthy Days by County")
plt.legend(["Mean % Tree Cover", "Physically Unhealthy Days / Month␣
↪(Normalized)", "Mentally Unhealthy Days / Month (Normalized)", "MUD Trend",␣
↪"PUD Trend"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: county IDs sorted by mean % tree cover')
plt.show()
```

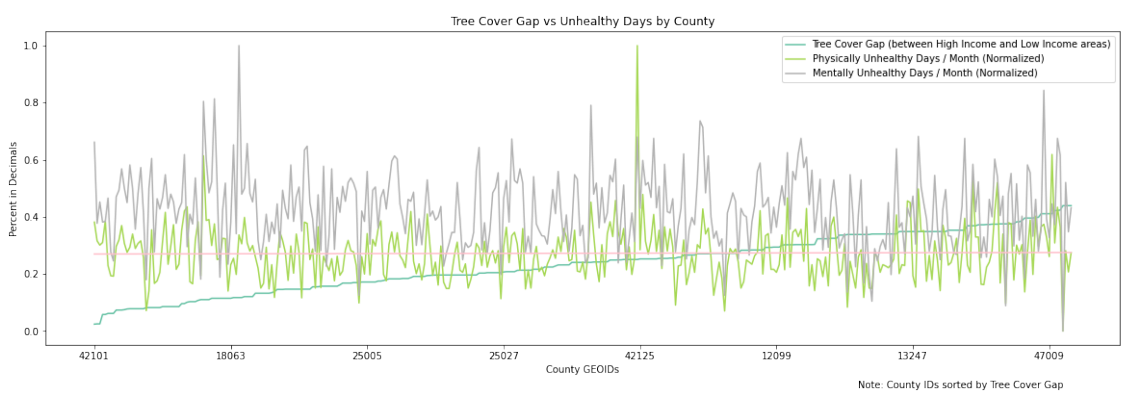


Tree Gap and Health

```
[ ]: # combine tree_gap with PUD
pud_treegap = sort_bytreegap
pud_treegap = pud_treegap.drop(columns=['mean_percent_tree_cover'])
pud_treegap['PUD/month'] = pud_treegap.index.map(health_byct.
↪set_index('census_block')['PUD/month'])
pud_treegap['MUD/month'] = pud_treegap.index.map(health_byct.
↪set_index('census_block')['MUD/month'])
pud_treegap = pud_treegap.dropna()
# normalize for plot
pud_treegap['PUD/month'] = (pud_treegap['PUD/month'] -  pud_treegap['PUD/
↪month'].min()) / (pud_treegap['PUD/month'].max()-pud_treegap['PUD/month'].
↪min())
pud_treegap['MUD/month'] = (pud_treegap['MUD/month'] -  pud_treegap['MUD/
↪month'].min()) / (pud_treegap['MUD/month'].max()- pud_treegap['MUD/month'].
↪min())
```

```
[ ]: print(pud_treegap['PUD/month'].corr(pud_treegap['tree_gap']))
print(pud_treegap['MUD/month'].corr(pud_treegap['tree_gap']))
pud_treegap.plot(figsize=(20, 6), colormap='Set2')

X = np.array(range(0, len(pud_treegap))).reshape(-1, 1) # values converts it␣
 ↪into a numpy array
Y = pud_treegap.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate the␣
 ↪dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='pink')


plt.title("Tree Cover Gap vs Unhealthy Days by County")
plt.legend(["Tree Cover Gap (between High Income and Low Income areas)",␣
 ↪"Physically Unhealthy Days / Month (Normalized)", "Mentally Unhealthy Days /␣
 ↪Month (Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: County IDs sorted by Tree Cover Gap')
plt.show()

print(Y_pred.max())
print(Y_pred.min())
print(Y_pred.max() - Y_pred.min())
```

```
0.010499745427257982
-0.11540414403595992
```




```
0.2752436461053293
0.2698123755477973
0.005431270557532009
```

```
[ ]: # # combine tree_gap with MUD
# mud_treegap = sort_bytreegap
# mud_treegap = mud_treegap.drop(columns=['mean_percent_tree_cover'])
# mud_treegap['MUD/month'] = mud_treegap.index.map(health_byct.
 ↪set_index('census_block')['MUD/month'])
# mud_treegap = mud_treegap.dropna()
# # normalize for plot
# mud_treegap['MUD/month'] = (mud_treegap['MUD/month'] -  mud_treegap['MUD/
 ↪month'].min()) / (mud_treegap['MUD/month'].max()- mud_treegap['MUD/month'].
 ↪min())
```

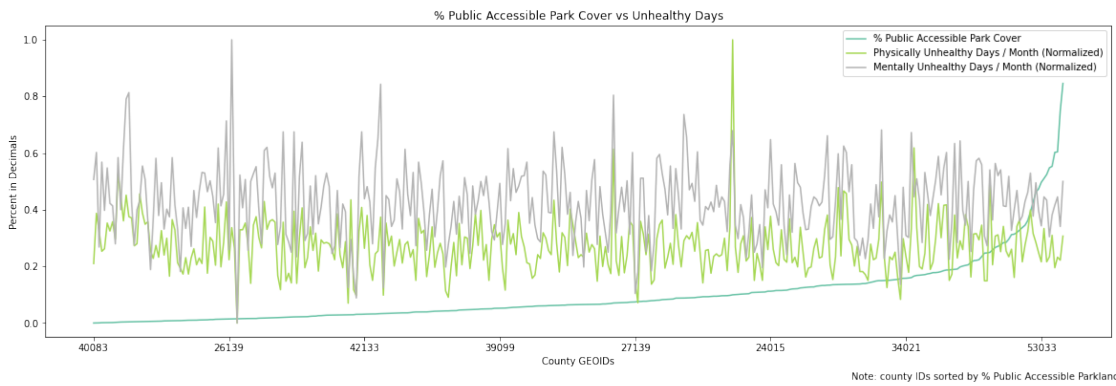
```
[ ]: # print(pud_treegap['PUD/month'].corr(pud_treegap['tree_gap']))
# mud_treegap.plot(figsize=(20, 6), colormap='Set2')
# plt.title("Tree Cover Gap vs Unhealthy Days by County")
# plt.legend(["Tree Cover Gap (between High Income and Low Income areas)",␣
 ↪"Mentally Unhealthy Days / Month (Normalized)"])
# plt.ylabel('Percent in Decimals')
# plt.xlabel('County GEOIDs')
# plt.text(280, -0.2, 'Note: county IDs sorted by tree cover gap')
# plt.show()
```

% Public Accessible Parkland Cover vs Health

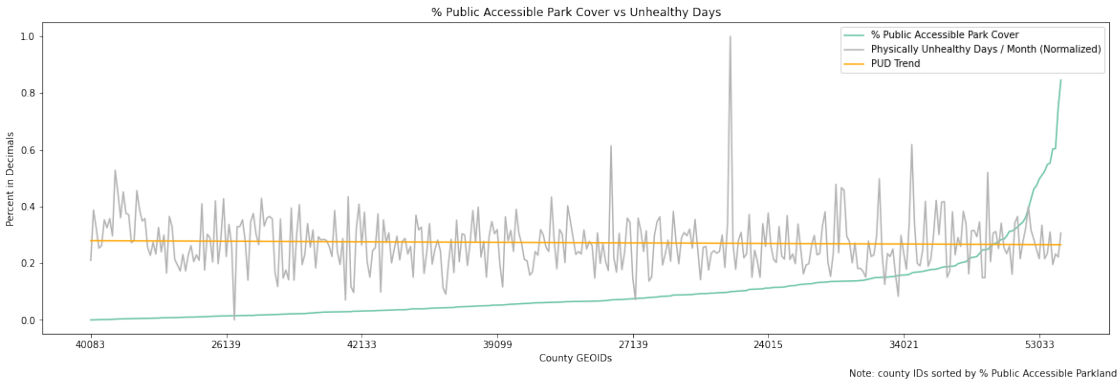
```
[ ]: # combine park cover with PUD / MUD
pud_park = park_cov.copy()
pud_park = pud_park.sort_values(by=['pc_park'])
pud_park['pc_park'] = pud_park['pc_park']/100
pud_park['PUD/month'] = pud_park["GEOID"].map(health_byct.
 ↪set_index('census_block')['PUD/month'])
pud_park['MUD/month'] = pud_park["GEOID"].map(health_byct.
 ↪set_index('census_block')['MUD/month'])
pud_park = pud_park.dropna()
# normalize for plot
pud_park['PUD/month'] = (pud_park['PUD/month'] -  pud_park['PUD/month'].min()) /
 ↪ (pud_park['PUD/month'].max()- pud_park['PUD/month'].min())
pud_park['MUD/month'] = (pud_park['MUD/month'] -  pud_park['MUD/month'].min()) /
 ↪ (pud_park['MUD/month'].max()- pud_park['MUD/month'].min())

pud_park = pud_park.set_index('GEOID')
```

```
[ ]: pud_park = pud_park.copy()

pud_park.plot(figsize=(20,6), colormap='Set2')


plt.title("% Public Accessible Park Cover vs Unhealthy Days")
```

```
plt.legend(["% Public Accessible Park Cover", "Physically Unhealthy Days / Month (Normalized)", "Mentally Unhealthy Days / Month (Normalized)"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: county IDs sorted by % Public Accessible Parkland')
plt.show()
```

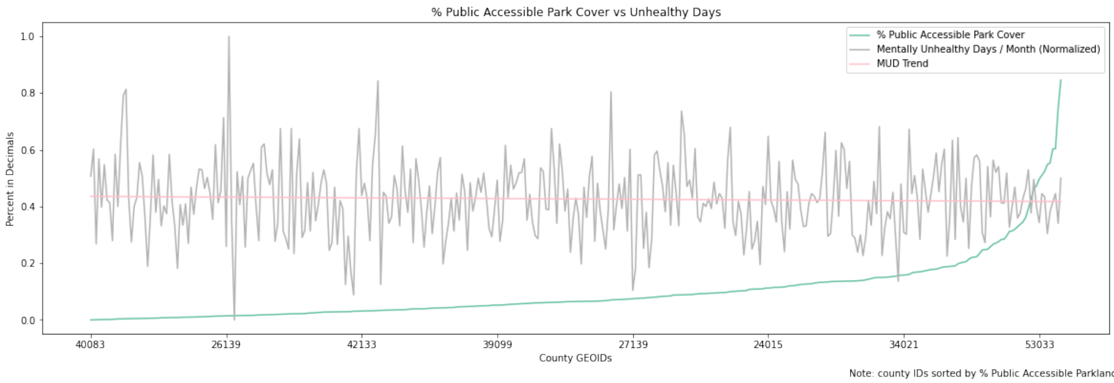


[ ]:
```
pud_park_pud = pud_park.copy()
pud_park_pud = pud_park_pud.drop(columns=['MUD/month'])

pud_park_pud.plot(figsize=(20,6), colormap='Set2')

X = np.array(range(0, len(pud_park_pud))).reshape(-1, 1) # values converts it into a numpy array
Y = pud_park_pud.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate the dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='orange')

plt.title("% Public Accessible Park Cover vs Unhealthy Days")
plt.legend(["% Public Accessible Park Cover", "Physically Unhealthy Days / Month (Normalized)", "PUD Trend"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: county IDs sorted by % Public Accessible Parkland')
plt.show()

print(Y_pred.max())
print(Y_pred.min())
print(Y_pred.max() - Y_pred.min())
```




```
0.2796044374518278
0.26545158420129883
0.014152853250528952
```

[ ]:
```python
pud_park_mud = pud_park.copy()
pud_park_mud = pud_park_mud.drop(columns=['PUD/month'])

pud_park_mud.plot(figsize=(20,6), colormap='Set2')

X = np.array(range(0, len(pud_park_mud))).reshape(-1, 1) # values converts it␣
↪into a numpy array
Y = pud_park_mud.iloc[:, 1].values.reshape(-1, 1)  # -1 means that calculate␣
↪the dimension of rows, but have 1 column
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, Y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions
plt.plot(X, Y_pred, color='pink')

plt.title("% Public Accessible Park Cover vs Unhealthy Days")
plt.legend(["% Public Accessible Park Cover", "Mentally Unhealthy Days / Month␣
↪(Normalized)", "MUD Trend"])
plt.ylabel('Percent in Decimals')
plt.xlabel('County GEOIDs')
plt.text(280, -0.2, 'Note: county IDs sorted by % Public Accessible Parkland')
plt.show()

print(Y_pred.max())
print(Y_pred.min())
print(Y_pred.max() - Y_pred.min())
```



0.4357102008947413
0.4175437874567401
0.018166413438001183