Quality of Life

- A Comprehensive Analysis of Regional Living Standards Focusing on Tri-States

Goergen Institute for Data Science
Graduate '24
Wonha Shin (wshin7@ur.rochester.edu)

1. Introduction

"Exploring Economic and Environmental Indicators in the Tri-State Area:
A Data-Driven Approach to Quality of Life Enhancement"

In our data-centric world, the intersection of economic and environmental indicators offers invaluable insights into the quality of life. This project delves into the heart of this nexus, with a concentrated focus on the Tri-State area of New York, New Jersey, and Connecticut. Leveraging a rich dataset from Kaggle, I would like to take insights to understand how these indicators not only reflect living standards but also influence them in this specific region.

I've found this dataset at Kaggle which is a rich compilation of data that reflects the multifaceted aspects of living standards across various regions. It's a treasure trove of data, ripe for analysis, offering a glimpse into how economic prosperity, environmental sustainability, and quality of life intertwine.

Through this project, I aim to decipher the meanings and implications of various indicators. What aspects of our economic environment most significantly affect our lives? How does our natural environment contribute to or detract from our sense of well-being? These are some of the questions I seek to address. The dataset is not just a collection of numbers and statistics; it's a mirror reflecting the multifaceted aspects of our lives, and a guide that can lead us to make more informed decisions for our collective future.

2. Dataset Overview

The "City, ZIP, County FIPS - Quality of Life" dataset from Kaggle offers a detailed overview of various quality of life indicators across different geographic areas. It could provide four different kinds of informations as follows :

1. Demographic Information: population statistics, age distribution, and other demographic characteristics of different regions.
2. Economic Indicators: detailed data on income levels, employment rates, and other economic factors provide insights into the financial well-being of communities.
3. Environmental Metrics: aspects such as air quality, green spaces, and other environmental conditions that affect the quality of life.
4. Geographical Diversity: from a diverse range of locations, offering a comparative view across different cities, ZIP codes, and counties.

By Analyzing this dataset, I would like to yield just a bit of insights that could be crucial for policy-making, urban planning, and community development, enhancing our understanding of the factors that influence quality of life in diverse areas.

(1) Initial Examination of the Dataset

Before diving into a detailed analysis, we will conduct an initial examination of the dataset, focusing on several key aspects. This preliminary review is as follows.

```
df.head()
```

	countyhelper	LSTATE	NMCNTY	FIPS	LZIP	ULOCALE	Overall Rank	2022 Population	2016 Crime Rate	Unemployment	2020PopulrVoteParty	2020 PopulrMajor%	AQI%Good
0	VACharles City County	VA	Charles City County	51036	23030	42-Rural: Distant	NaN	6,605	8/1000	3.21%	D	54.11%	93.76%
1	TXMcmullen County	TX	McMullen County	48311	78072	43-Rural: Remote	NaN	576	47/1000	1.81%	R	52.06%	75.33%
2	TXTerrell County	TX	Terrell County	48443	79848	43-Rural: Remote	NaN	693	20/1000	3.54%	R	52.06%	75.33%
3	AKSkagway Municipality	AK	Skagway Municipality	2230	99840	43-Rural: Remote	NaN	1,081	13/1000	7.19%	R	52.83%	87.86%
4	GABaker County	GA	Baker County	13007	39870	42-Rural: Distant	NaN	2,788	0	4.19%	D	49.50%	83.30%

```
df.columns
```

```
Index(['countyhelper', 'LSTATE', 'NMCNTY', 'FIPS', 'LZIP', 'ULOCALE', 'Overall Rank', '2022 Population', '2016 Crim
e Rate', 'Unemployment', '2020PopulrVoteParty', '2020 PopulrMajor%', 'AQI%Good', 'WaterQualityVPV', 'ParkScore2023
Rank', '%CvgCityPark', 'NtnlPrkCnt', '%CvgStatePark', 'Cost of Living', '2022 Median Income', 'AVG C2I', '1p0c', '1
p1c', '1p2c', '1p3c', '1p4c', '2p0c', '2p1c', '2p2c', '2p3c', '2p4c', 'Stu:Tea Rank', 'Diversity Rank (Race)', 'Div
ersity Rank (Gender)'], dtype='object')
```

```
df.isnull().sum()
```

```
countyhelper               0
LSTATE                     0
NMCNTY                     0
FIPS                       0
LZIP                       0
ULOCALE                    0
Overall Rank            3134
2022 Population            0
2016 Crime Rate            0
Unemployment               0
2020PopulrVoteParty        0
2020 PopulrMajor%          0
AQI%Good                   0
WaterQualityVPV            0
ParkScore2023 Rank         0
%CvgCityPark               0
NtnlPrkCnt                 0
%CvgStatePark              0
Cost of Living             0
```

```
df.describe().round(1)
```

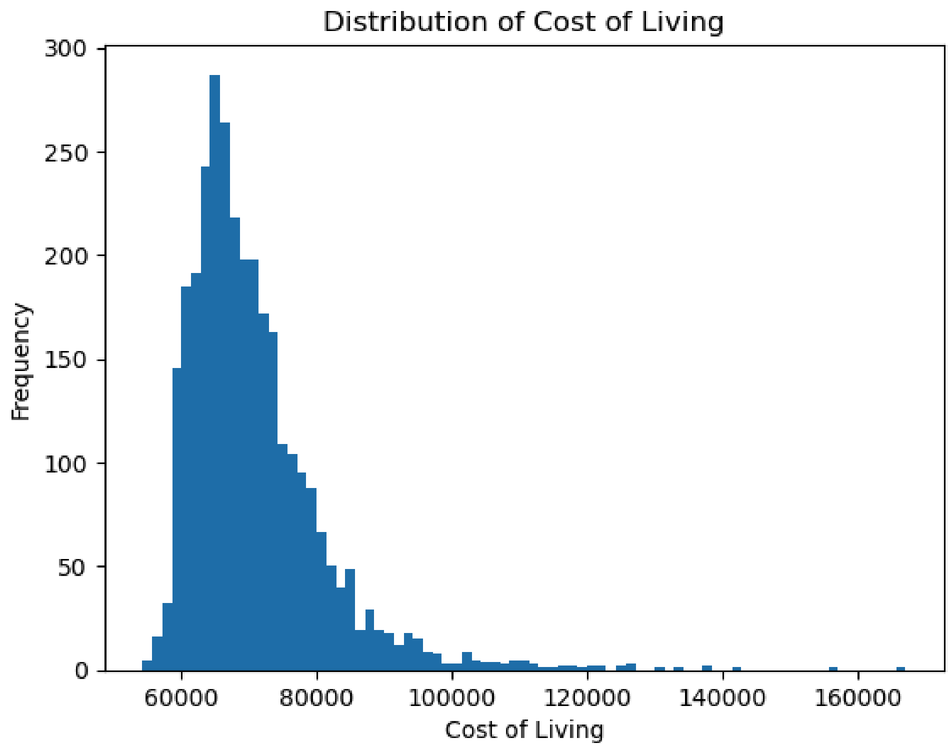
	FIPS	LZIP	Overall Rank	WaterQualityVPV	ParkScore2023 Rank	NtnlPrkCnt	Stu:Tea Rank	Diversity Rank (Race)	Diversity Rank (Gender)
count	3134.0	3134.0	0.0	3134.0	3134.0	3134.0	3134.0	3134.0	3134.0
mean	30393.0	53173.5	NaN	2.7	-0.9	1.2	1482.6	1567.5	1567.5
std	15162.1	23271.7	NaN	10.4	2.0	1.6	902.9	904.9	904.9
min	1001.0	1098.0	NaN	-1.0	-1.0	0.0	-1.0	1.0	1.0
25%	18179.5	34239.8	NaN	0.0	-1.0	0.0	698.2	784.2	784.2
50%	29178.0	54431.5	NaN	1.0	-1.0	1.0	1481.5	1567.5	1567.5
75%	45080.5	71727.5	NaN	3.0	-1.0	1.0	2264.8	2350.8	2350.8
max	56045.0	99929.0	NaN	456.0	52.0	9.0	3048.0	3134.0	3134.0

3. Geometrical Analysis

(1) Cost of Living

(a) Data Preparation

For the analysis for cost of living distribution, we will take a look from seeing the distribution for the datasets as below.

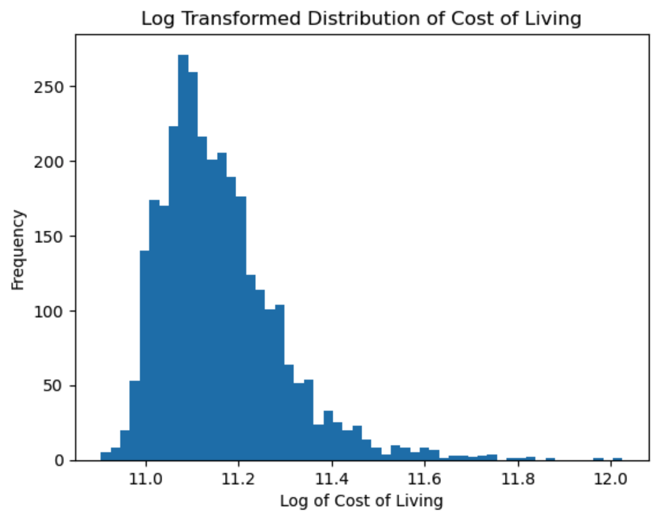


The dataset is left-skewed, which means that the bulk of the data is concentrated to the right. Since normal distribution is often a key assumption for parametric statistical tests, regression models, and other analyses, we will try to transform this with log transformation and box cox transformation respectively.

```
import numpy as np

# Apply log transformation
df['Cost of Living Log'] = np.log(df['Cost of Living'])

# Plot to see the distribution after transformation
plt.hist(df['Cost of Living Log'], bins='auto')
plt.title('Log Transformed Distribution of Cost of Living')
plt.xlabel('Log of Cost of Living')
plt.ylabel('Frequency')
plt.show()
```



Still, the log transferred distribution is left skewed. We will try with Box-Cox Transformation in the Scipy library. Code and the result as below.

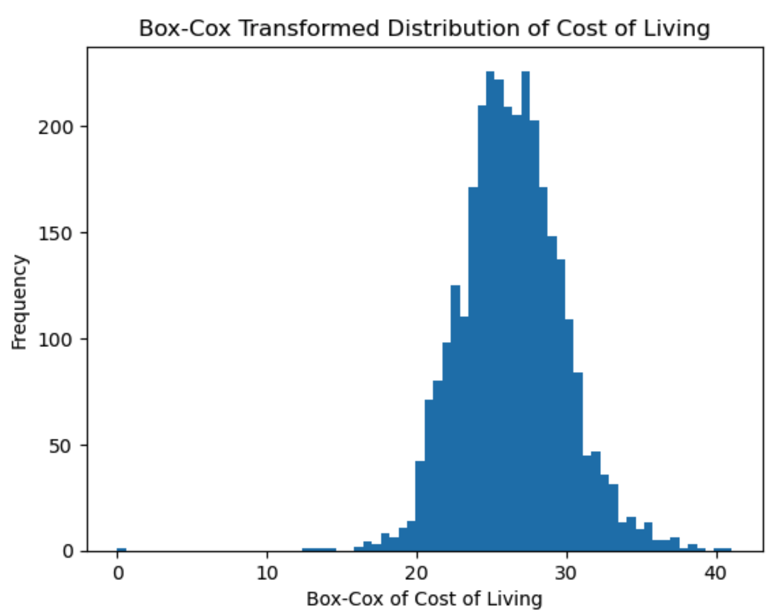
```
from scipy import stats

# The data must be positive for Box-Cox Transformation
df['Cost of Living Positive'] = df['Cost of Living'] + 1 - df['Cost of Living'].min()

# Apply Box-Cox Transformation
df['Cost of Living Box Cox'], fitted_lambda = stats.boxcox(df['Cost of Living Positive'])

# Plot to see the distribution after transformation
plt.hist(df['Cost of Living Box Cox'], bins='auto')
plt.title('Box-Cox Transformed Distribution of Cost of Living')
plt.xlabel('Box-Cox of Cost of Living')
plt.ylabel('Frequency')
plt.show()

print(f"Lambda used for Box-Cox Transformation: {fitted_lambda}")
```



* Lambda used for Box-Cox Transformation: 0.1849793087308169

So after box-cox transformation, the datasets look like a normal distribution. We will use the box-cox transformed datasets for further analysis.

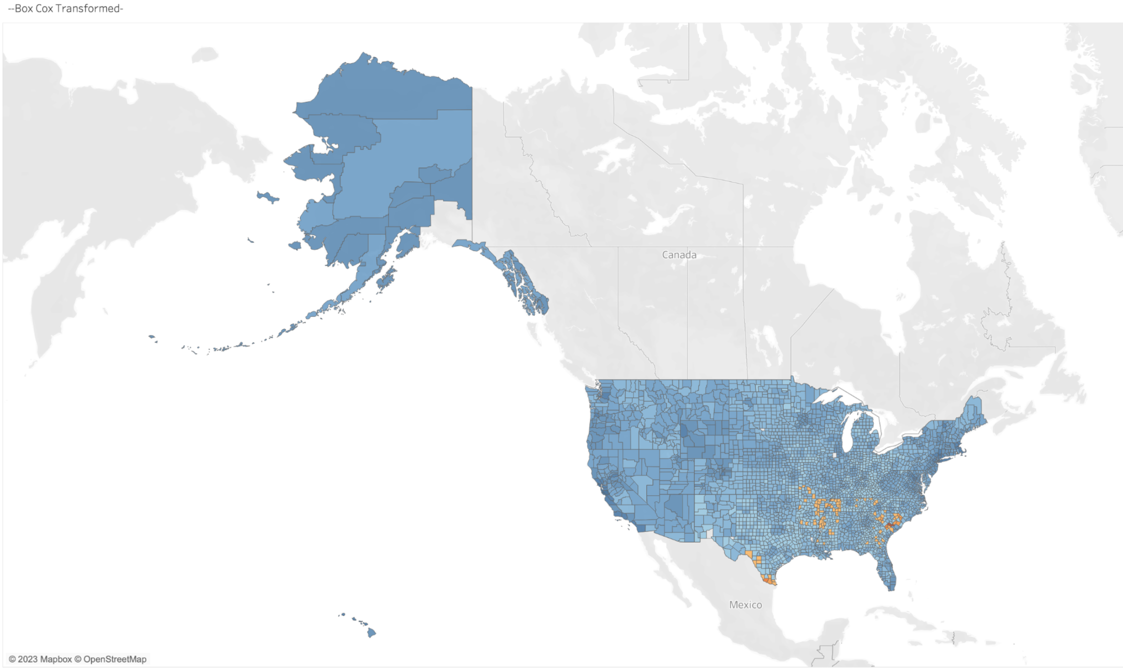
```
df.head()
```

2l	1p0c	1p1c	1p2c	1p3c	1p4c	2p0c	2p1c	2p2c	2p3c	2p4c	Stu:Tea Rank	Diversity Rank (Race)	Diversity Rank (Gender)	Cost of Living Log	Cost of Living Positive	Cost of Living Box Cox
%	51.54%	74.45%	91.51%	111.16%	119.90%	67.97%	90.07%	105.57%	123.82%	131.87%	135	1	25	11.232303	21101.35	28.696376
%	54.47%	73.72%	86.94%	105.46%	111.95%	72.03%	90.73%	104.21%	120.05%	127.11%	3	2	87	11.065282	9483.26	24.006475
%	67.29%	90.58%	106.09%	127.10%	135.84%	87.96%	110.73%	125.11%	145.91%	153.79%	12	3	47	11.072263	9931.00	24.258546
%	50.91%	79.00%	99.19%	121.39%	128.32%	69.18%	94.01%	113.02%	132.18%	139.30%	15	4	9	11.381783	33279.30	31.694980
%	63.61%	85.92%	103.34%	122.57%	131.91%	85.54%	108.73%	124.45%	141.99%	153.63%	26	5	60	10.991869	4959.27	20.682704

(b) Map Visualisation

The map below illustrates the Box-Cox transformed "Cost of Living" data across different locations in the United States. Areas with darker or more intense colors represent higher transformed cost of living values, while lighter colors indicate lower values. It seems that there is a concentration of higher cost of living scores in certain regions, potentially urban areas.

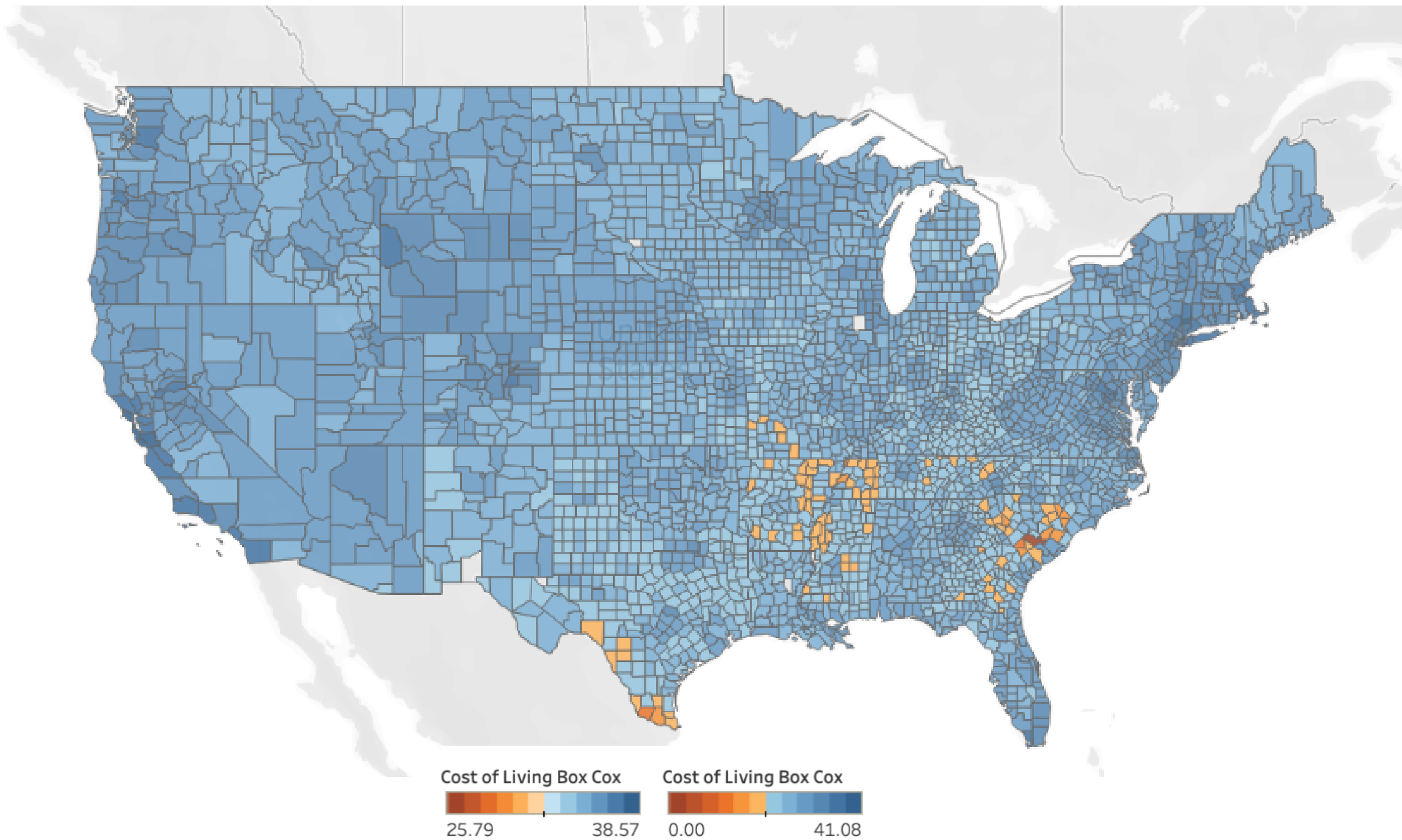
<Cost of Living Analysis- Whole Country>
--Box Cox Transformed-



Map based on Longitude (generated) and Latitude (generated). For marks layer Tri_state_datasets.csv.Nmcnty: Color shows sum of Cost of Living Box Cox. Details are shown for Lzip, Lstate and Nmcnty. For marks layer United States: Color shows sum of Cost of Living Box Cox. Details are shown for Nmcnty, Lzip and Lstate.

Cost of Living Box Cox 25.79 38.57

Cost of Living Box Cox 0.00 41.08



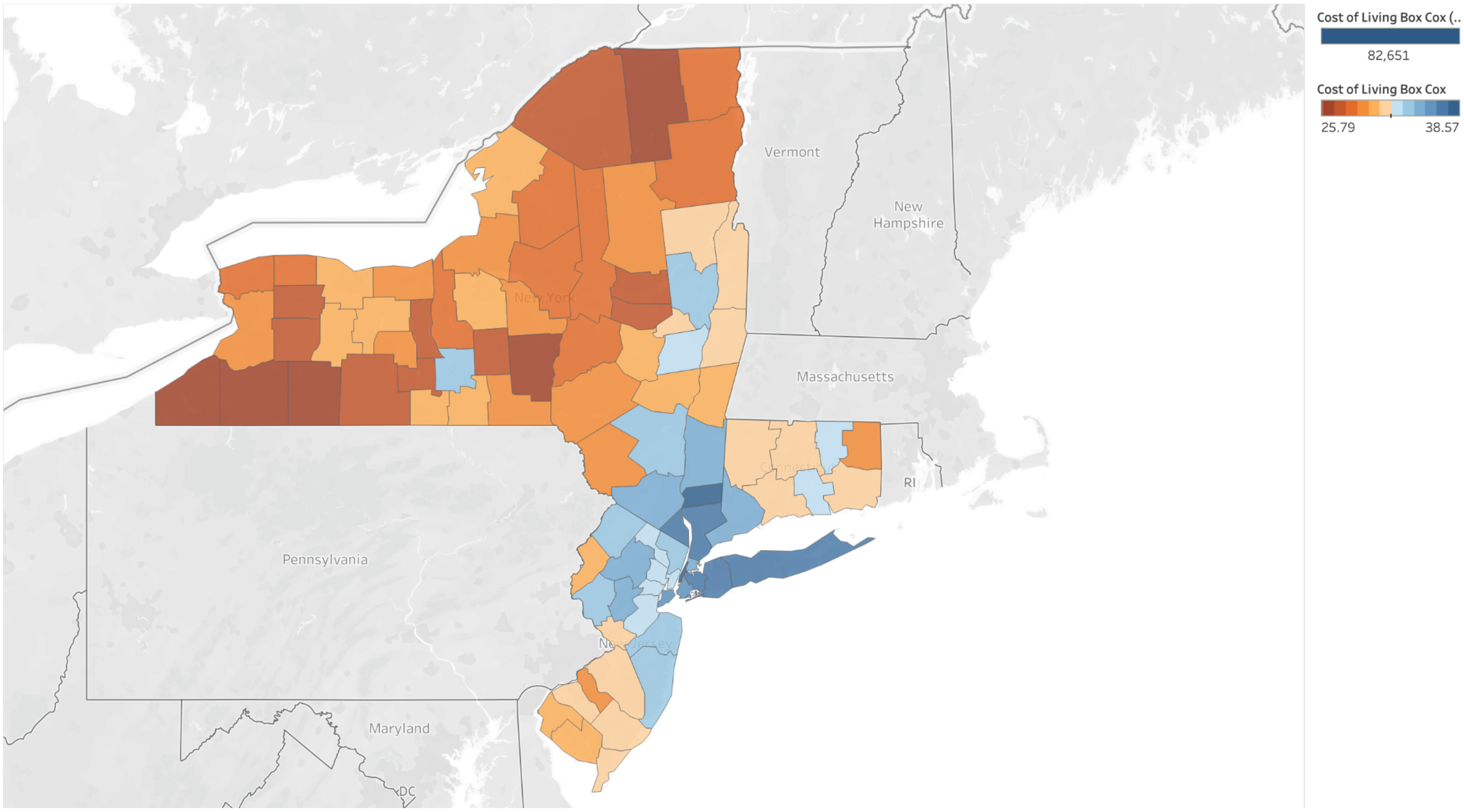
The geographic regions are divided into counties, with each county's color indicating its relative cost of living according to the transformed data. Darker shades would indicate a higher cost of living, while lighter shades represent a lower cost of living after the Box-Cox transformation.

Darker shades, indicating a higher transformed cost of living value, seem to be concentrated around certain areas.Typically, urban areas (like New York City) have a higher cost of living due to factors such as housing demand and the price of services. The map likely shows this, with darker shades potentially corresponding to metropolitan areas.

Also, areas with similar economic activities or characteristics might show similar colors on the map, indicating comparable costs of living. These clusters can be indicative of shared economic drivers, such as industry presence or economic policies - like New York City, Long Island, and Hudson County.

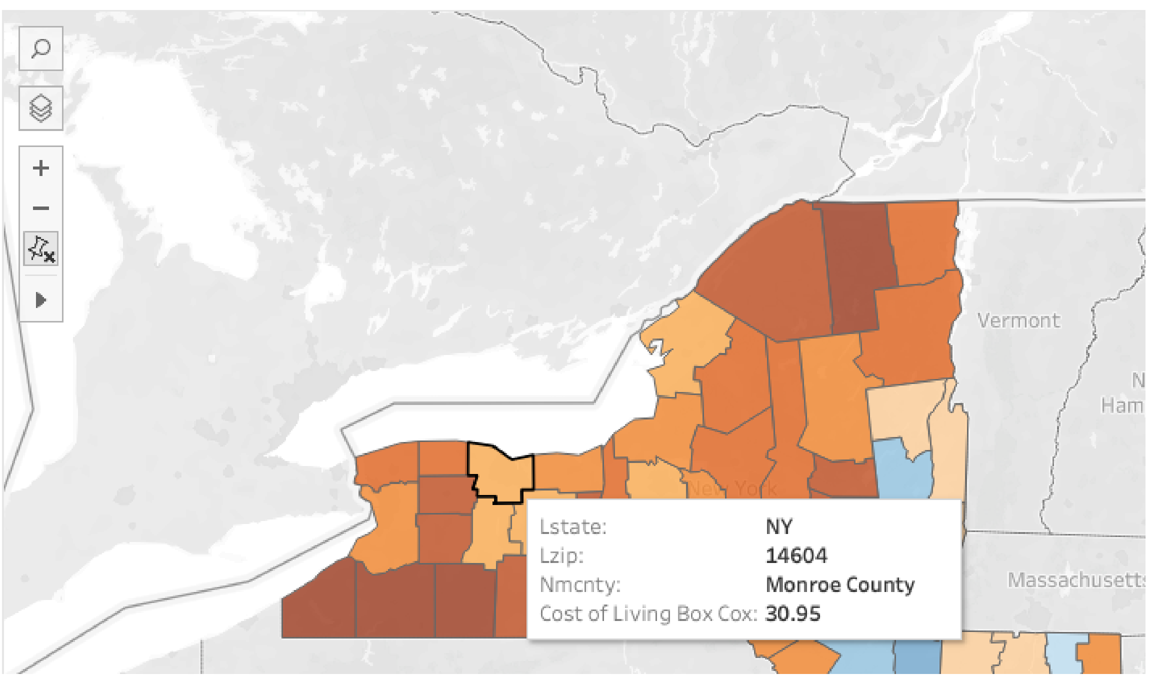
<Cost of Living Analysis- Tri States>

--Box Cox Transformed-

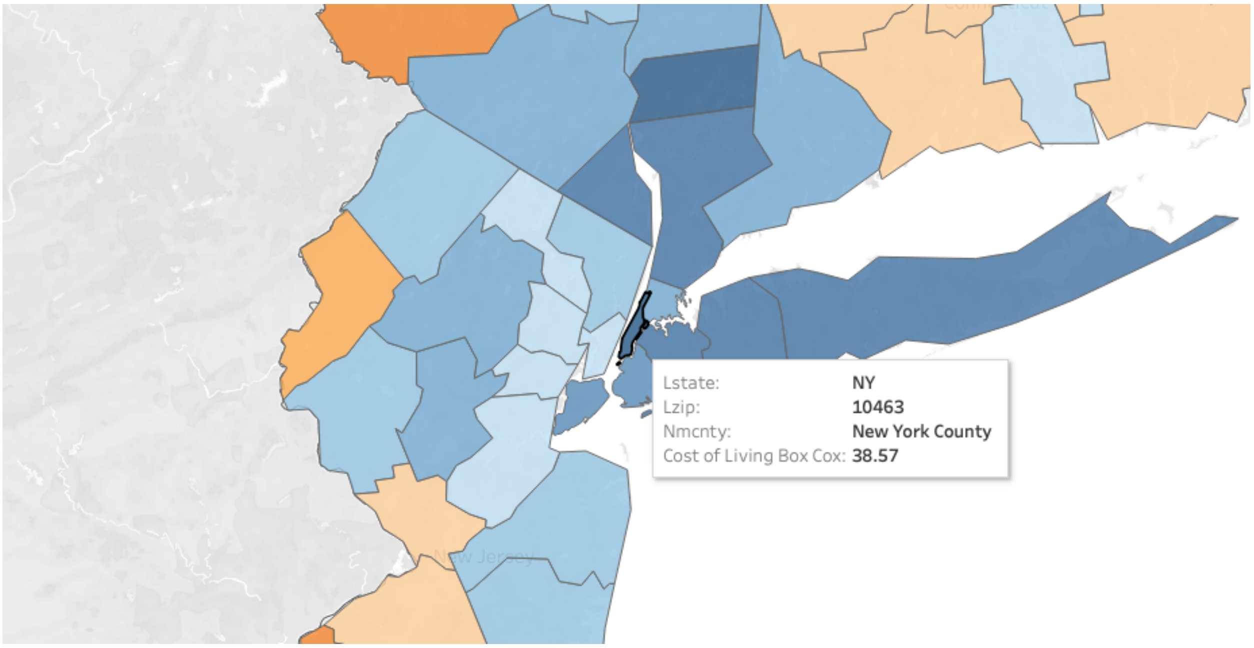


<Cost of Living Analysis- Tri States>

--Box Cox Transformed-



Monroe County is a relatively low living cost region amongst other counties in Tri-States regions. Meanwhile, New York City has the highest living cost.



(c) Analysis : Monroe County vs. New York City

1. **Monroe County Affordability**: Monroe County is depicted with lighter shades on the map, indicating it has a lower cost of living relative to other counties in the Tri-State area. This could be due to a variety of factors such as lower housing costs, a more affordable price for goods and services, or lower taxes.

2. **New York City's Premium**: Marked by darker tones, New York City stands out for its high living expenses. The city's premium cost of living is driven by intense economic activity, with a dense concentration of high-paying industries, corporate offices, and cultural hubs, which inflate expenses across the board.

3. **Underlying Factors**: After conducting research for the reason why this difference occurred, I have arranged the reasons as below.
   - <u>Economic Dynamics</u>: New York City's economy thrives on high-stakes finance and corporate sectors, necessitating expensive infrastructure and services. Conversely, Monroe County's diversified economic base leans on industries that sustain a more cost-effective living environment.
   - <u>Transportation Infrastructure</u>: The comprehensive public transit system in New York City, while efficient, demands significant investment, influencing the city's

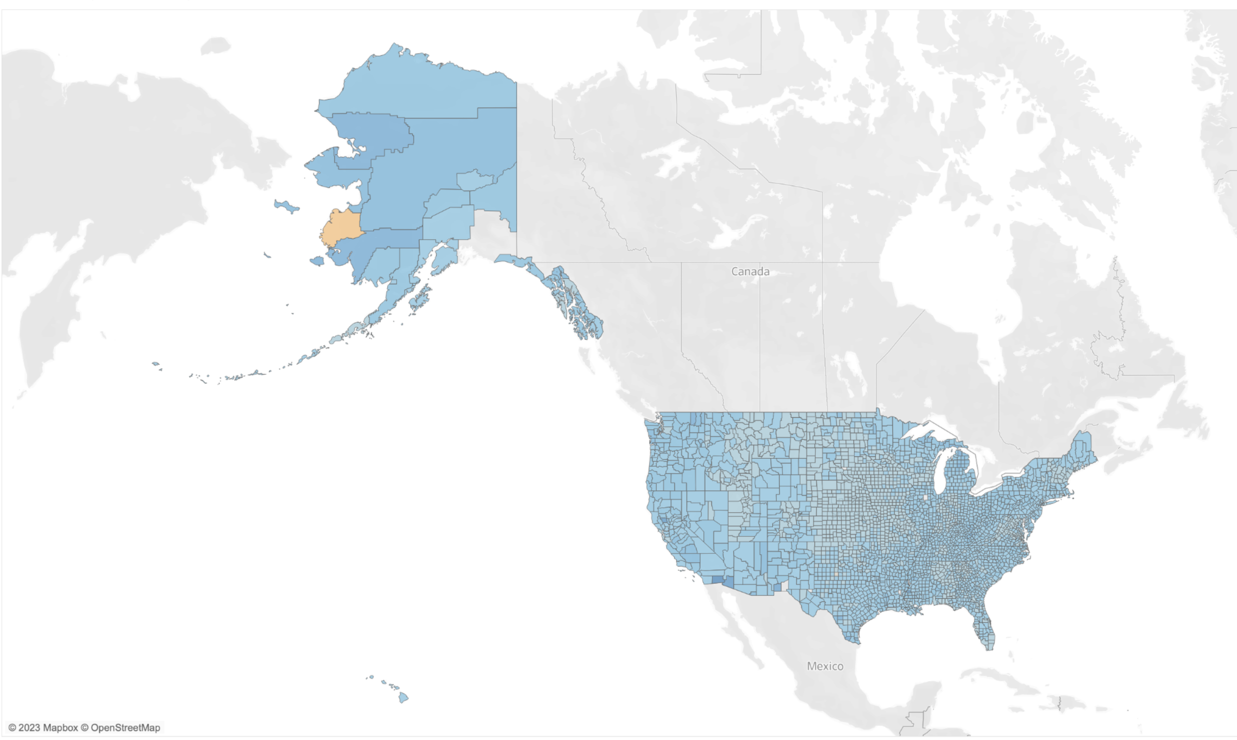
living costs. In Monroe County, personal vehicle use prevails, sparing the region from comparable public infrastructure expenses.

- Real Estate Market: NYC's real estate scene is fiercely competitive, inflating housing costs notably in central boroughs. Monroe County's more relaxed housing market benefits from greater land availability and reduced demand, offering residents more affordable living spaces.

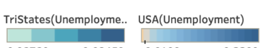
This analysis offers a snapshot of how economic structure, transportation, and housing dynamics shape living costs in these distinct regions, illuminating the stark contrast between urban and suburban living in the Tri-State area.

(2) Unemployment

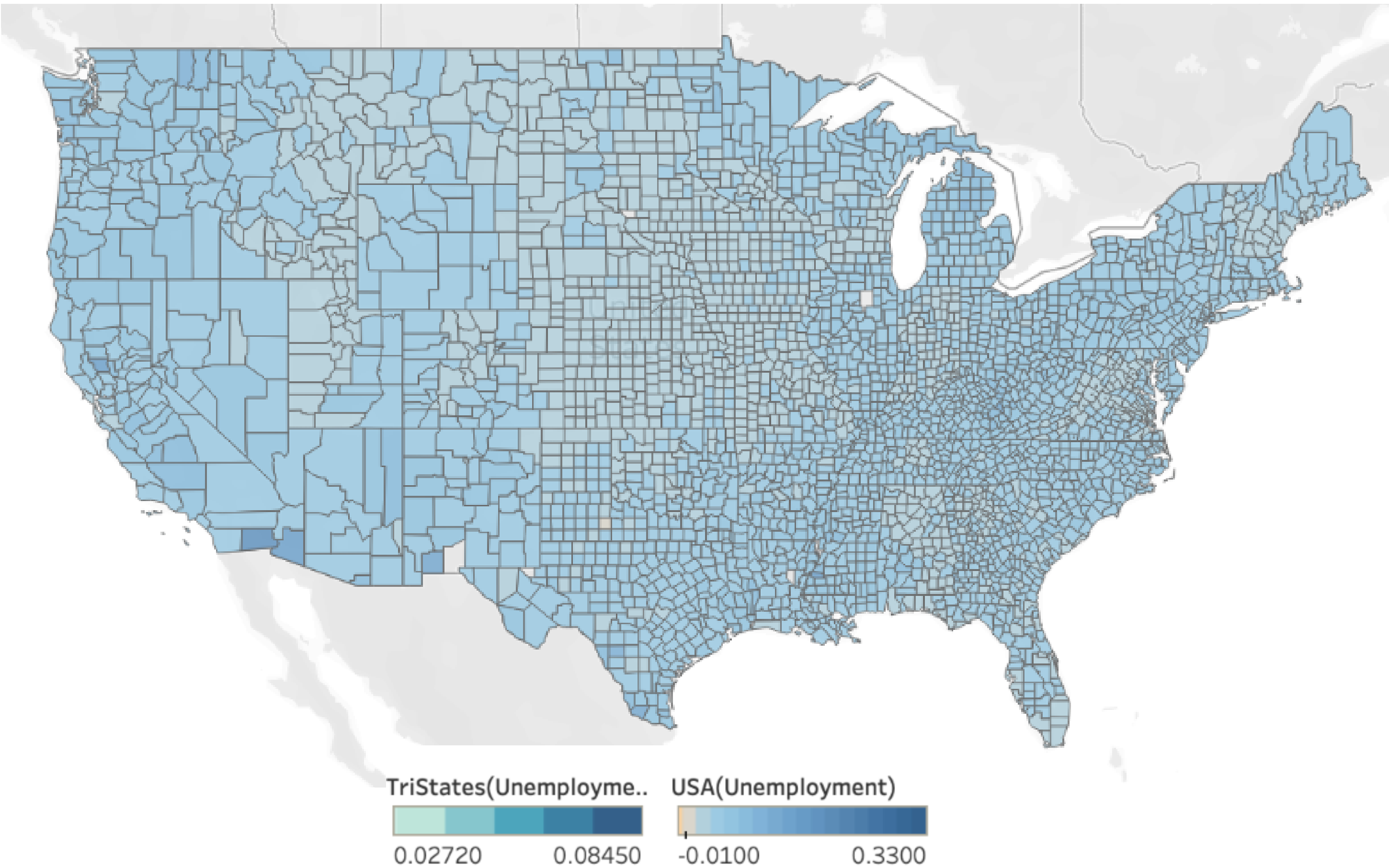
<Unemployment Analysis> - the United States



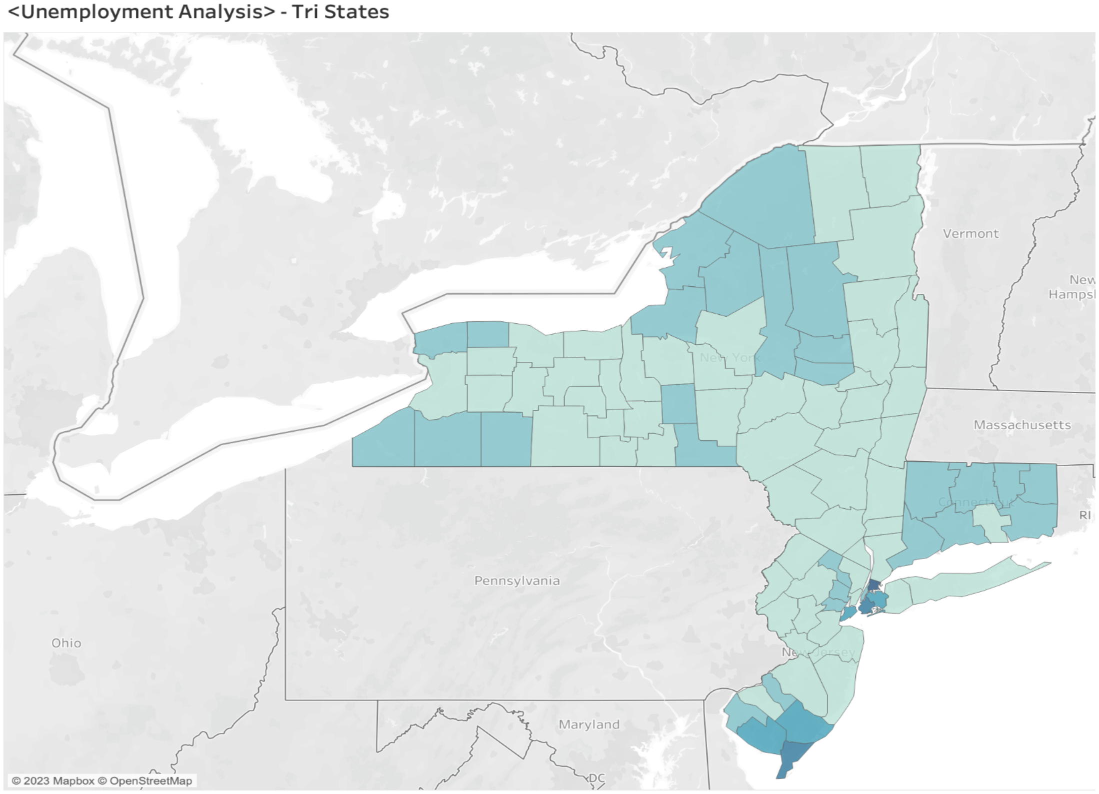
Map based on Longitude (generated) and Latitude (generated). For marks layer Tri_state_datasets.csv.Nmcnty: Color shows sum of Unemployment. Details are shown for Lzip, Lstate and Nmcnty. For marks layer United States: Color shows sum of Unemployment. Details are shown for Nmcnty, Lzip and Lstate.

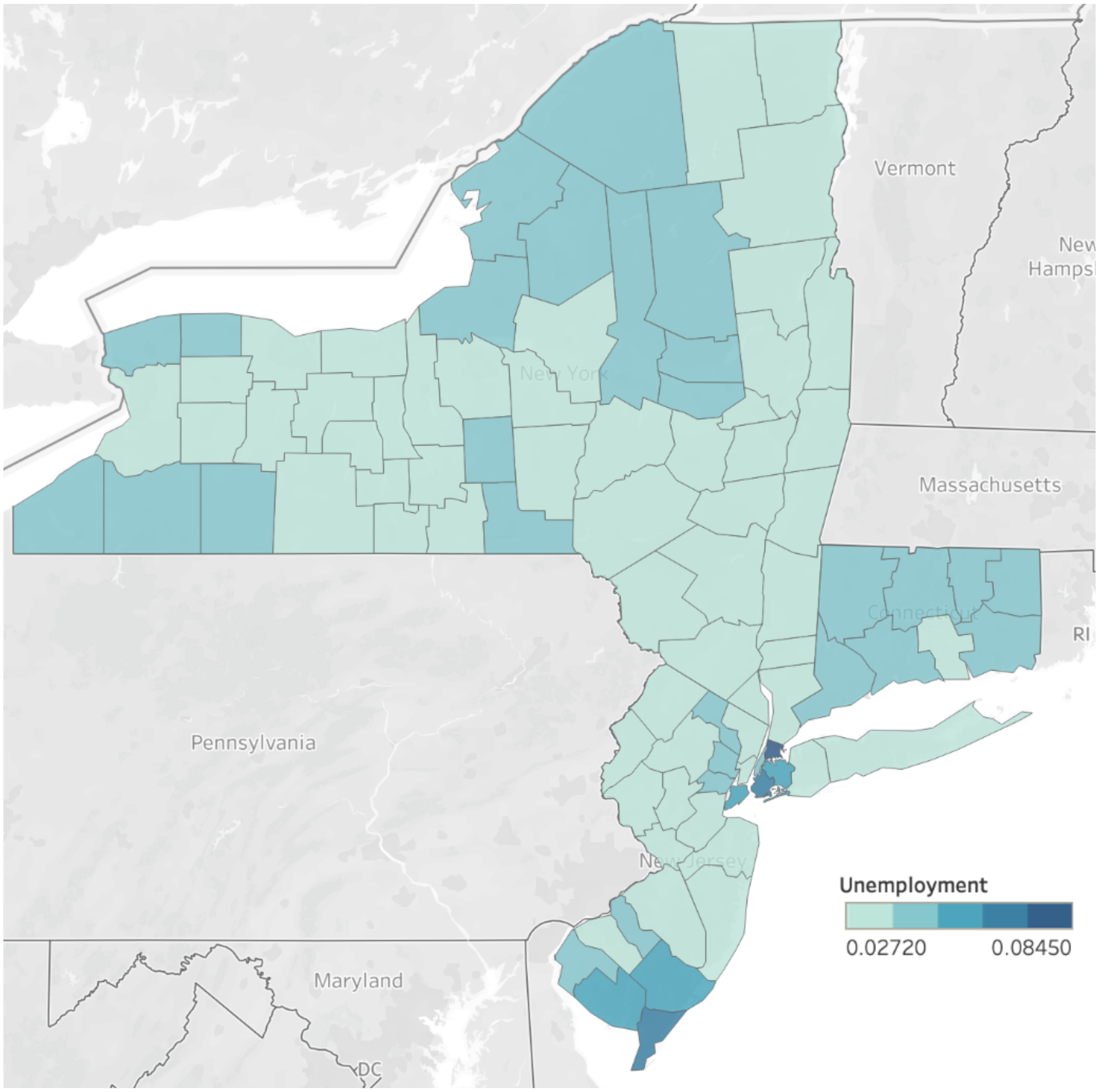


There are noticeable differences in unemployment rates across the country. Some areas are colored much darker than others, suggesting higher unemployment in those regions. Certain regions, particularly those in darker blue, might indicate economic distress or a lack of job opportunities. In contrast, lighter areas could point to more robust job markets.



<Unemployment Analysis> - Tri States





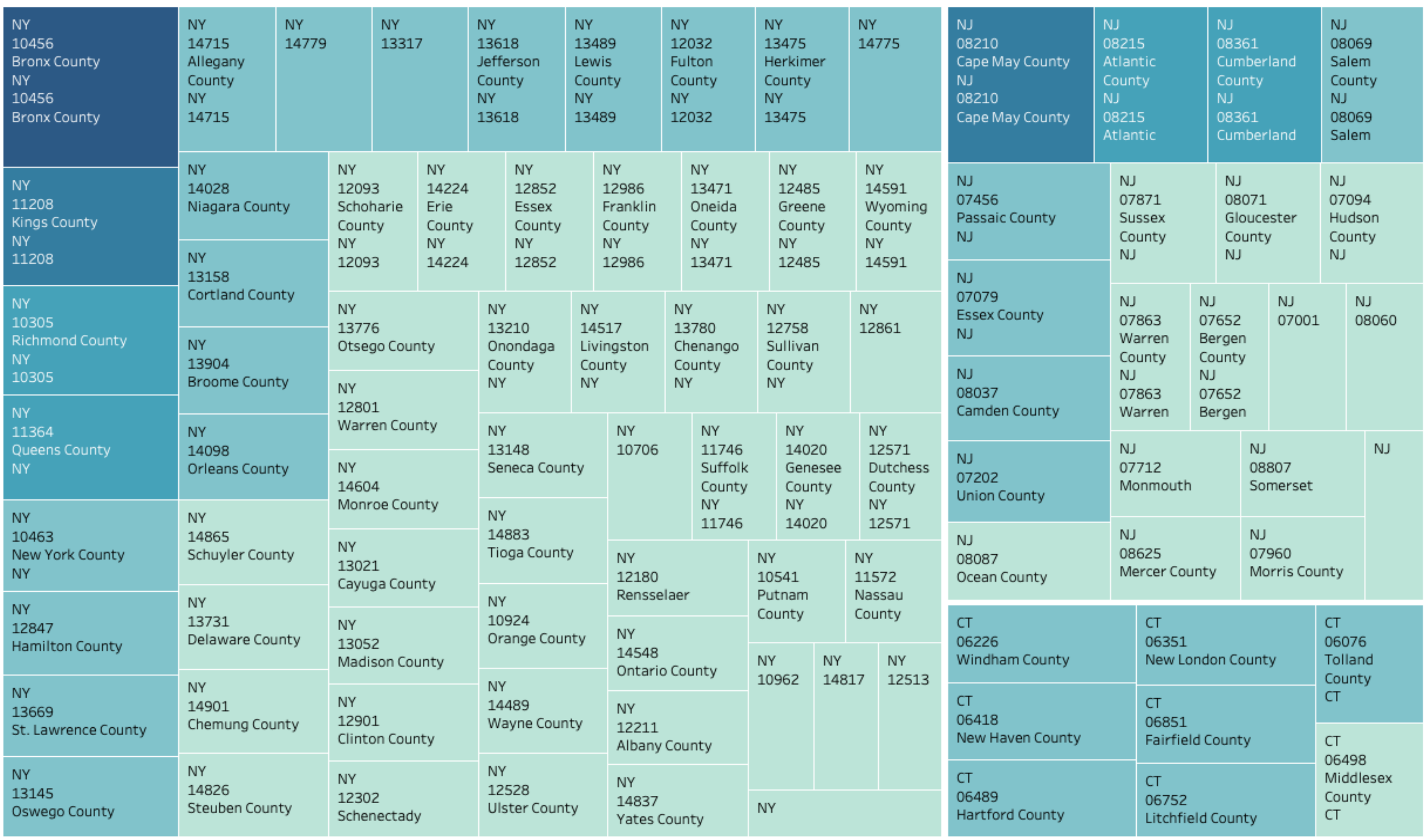
The overall ranking charts grouped by States are also next pages.

- New York State: In New York, the Bronx has the highest unemployment rates, with Kings (Brooklyn), Richmond (Staten Island), and Queens also reporting high numbers. This pattern suggests that urban counties, particularly within New York City, are experiencing the brunt of unemployment issues. Factors could include a high cost of living driving out businesses, automation, shifts in industry demands, or a mismatch between job seekers' skills and job availability.

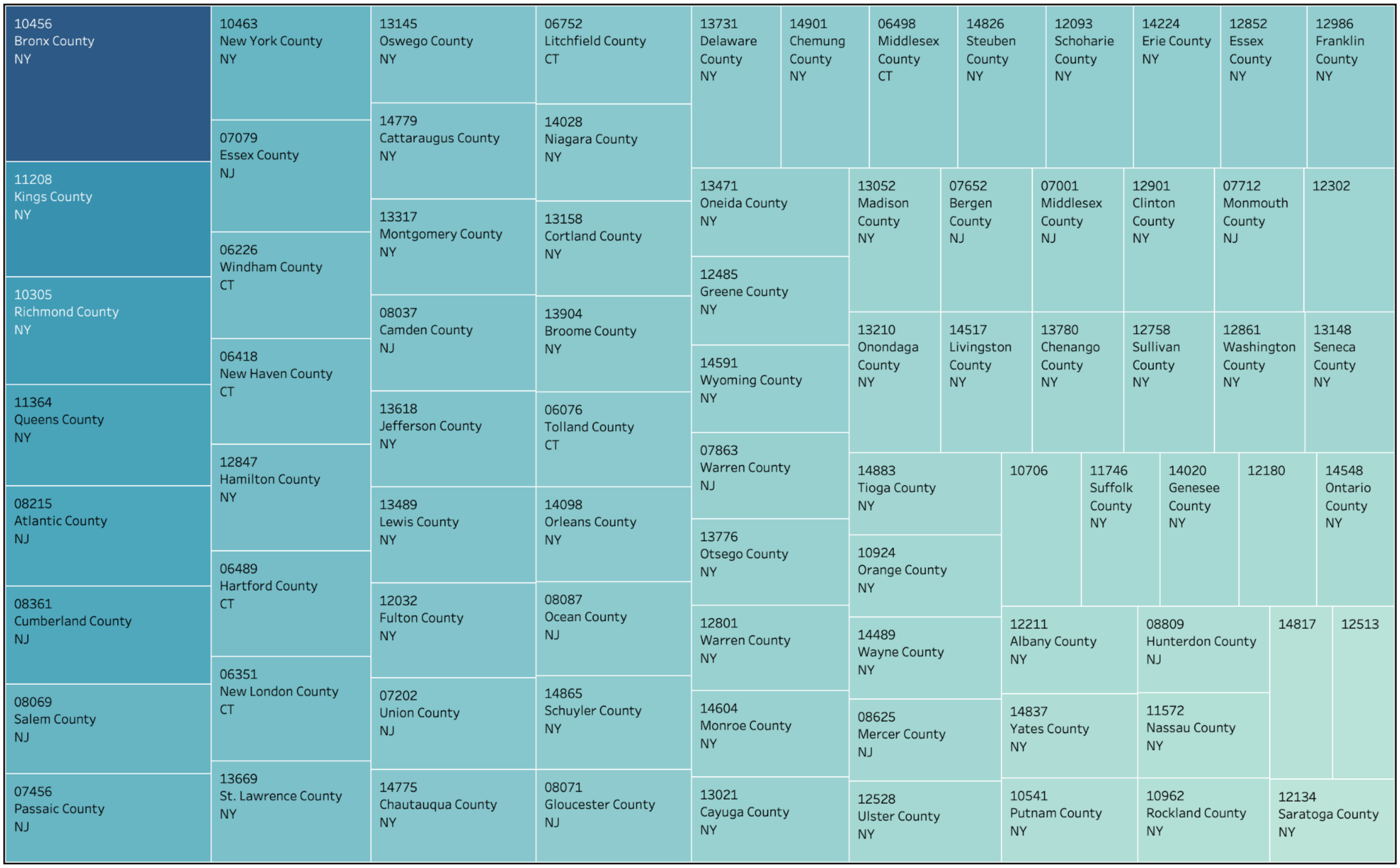
- New Jersey: Cape May and Atlantic City are highlighted for their high unemployment rates. These areas have economies heavily reliant on seasonal tourism, which can lead to significant employment fluctuations. Economic diversification in these regions may be limited, and job losses in key sectors like hospitality can disproportionately affect the local job market.

- Connecticut: Windham, New Haven, and Hartford in Connecticut show milder yet significant unemployment rates. These areas might be experiencing structural changes, such as the decline of manufacturing jobs, shifts to a service-based economy, or educational disparities that affect job opportunities.

<Unemployment Analysis> - Tri States



<Unemployment Analysis> - Tri States



Lzip, Nmcnty and Lstate. Color shows sum of Unemployment. Size shows sum of Unemployment. The marks are labeled by Lzip, Nmcnty and Lstate. The data is filtered on sum of Water Quality VPV (filtered_water+), which keeps non-Null values only.

Unemployment

0.02720 0.08450

(3) Crime Rate of 2016

(1) Data Preparation

For effective analysis and visualization, the format of the crime rate data is crucial. The original datasets have format as follows, I added a column “Crime Rate Per Capita”, a converted number, which is a more insightful method, the crime rates into a per capita basis, such as a crime rate per 1000 people.

```
In [6]: tri_state_data[['2016 Crime Rate']]
Out[6]:
```

	2016 Crime Rate
320	11/1000
542	19/1000
726	6/1000
757	13/1000
993	15/1000
1054	19/1000
1182	11/1000
1454	13/1000
1550	25/1000
1614	13/1000

```python
# Replace non-numeric values with NaN and convert to float
tri_state_data['2016 Crime Rate'] = pd.to_numeric(tri_state_data['2016 Crime Rate'].str.rstrip('/1000'),

# Calculate crime rate per capita
tri_state_data['2016 Crime Rate Per Capita'] = tri_state_data['2016 Crime Rate'] / 1000
```

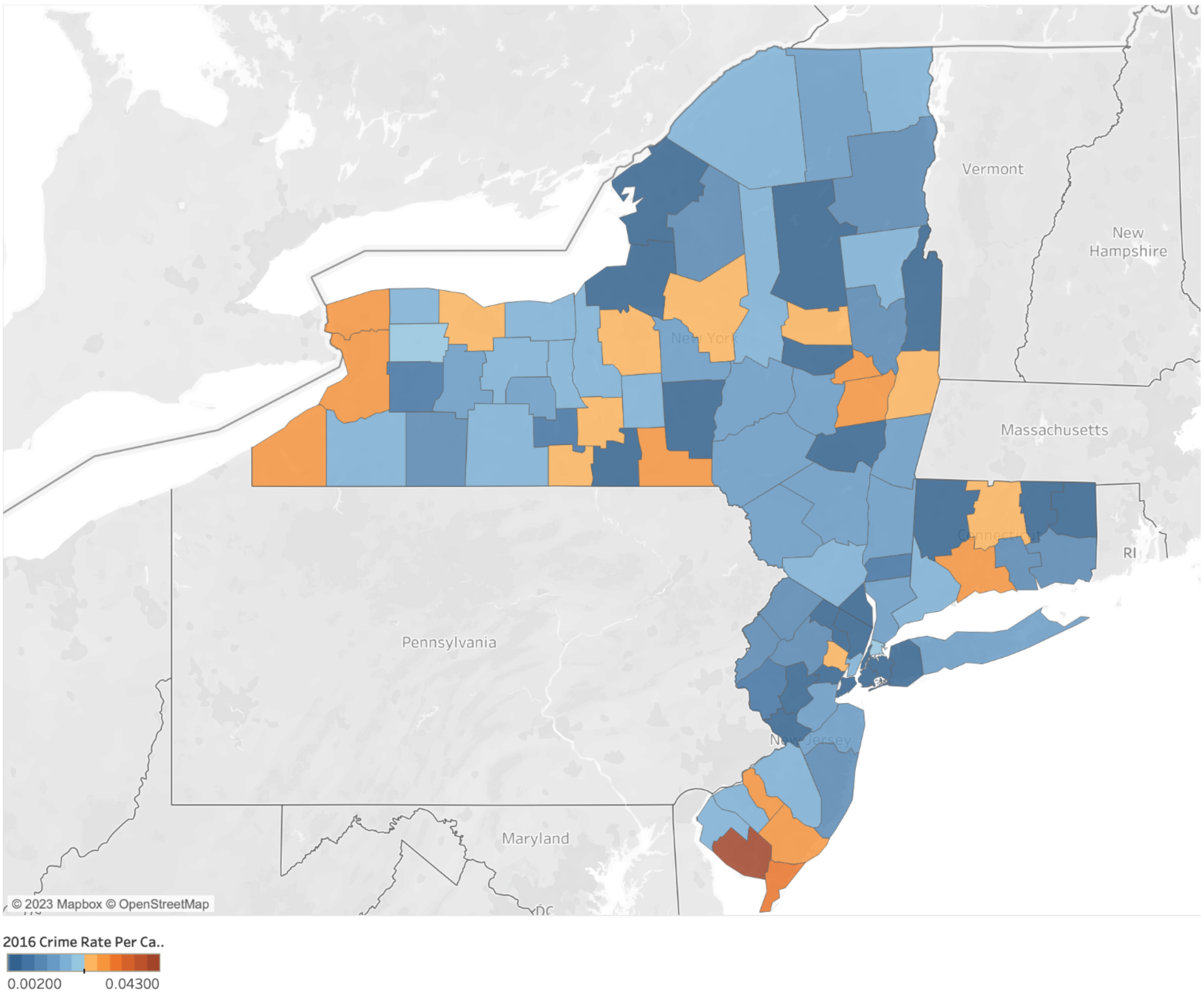
From the code above, the result is as follows.

```
In [8]: tri_state_data[['2016 Crime Rate']]
Out[8]:
```

	2016 Crime Rate
320	NaN
542	19.0
726	6.0
757	13.0
993	15.0
1054	19.0
1182	NaN
1454	13.0
1550	25.0
1614	13.0

<2016 Crime Rate Analysis> - Tri States

- 2016 Crime Rate Per Capita



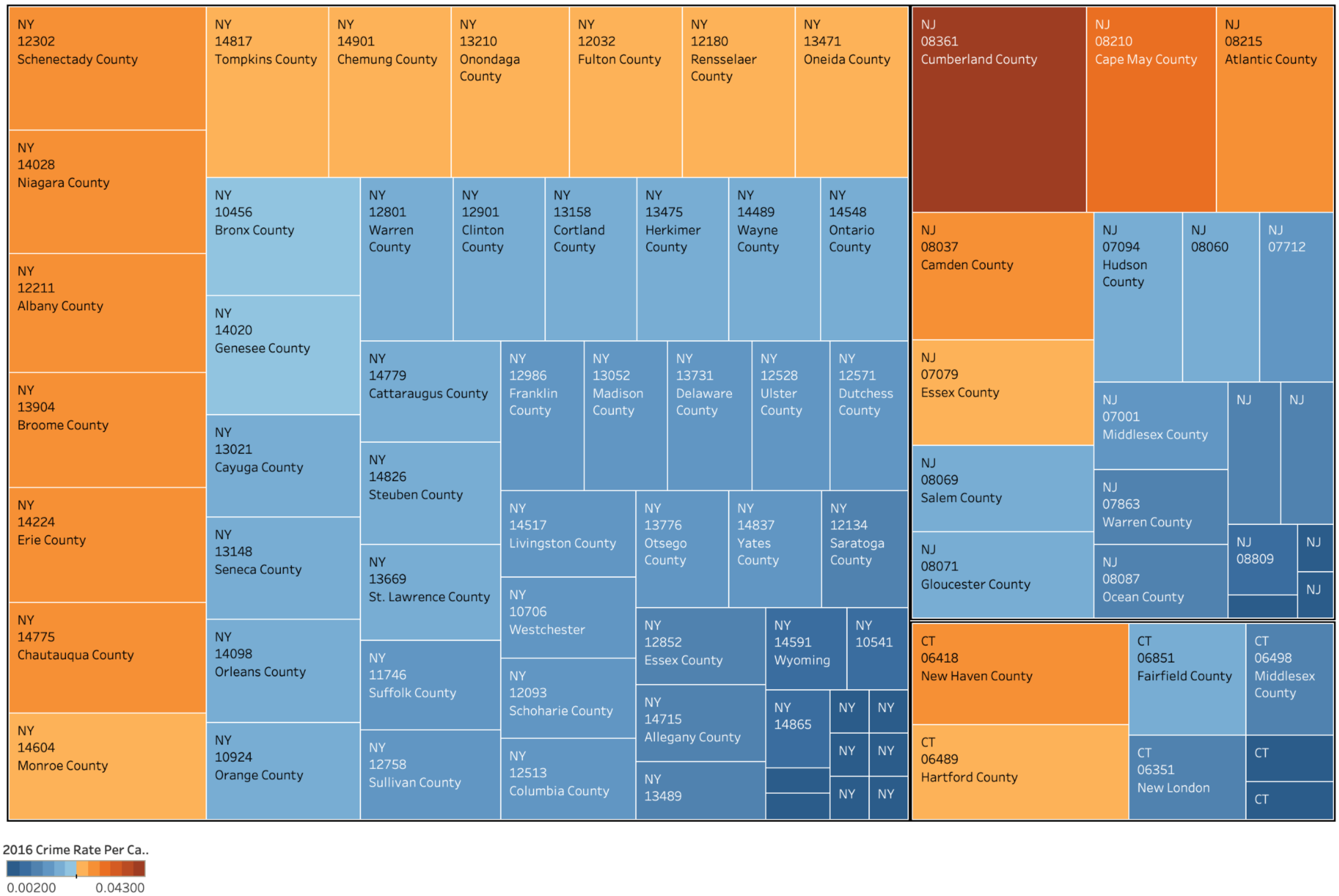
From the provided visualization, it seems that Cumberland, Cape May, Atlantic, and Camden Counties in New Jersey have higher crime rates. In New York, Schenectady, Niagara, and Albany Counties stand out, while in Connecticut, New Haven and Hartford Counties appear to have higher crime rates.

This suggests that certain urban or densely populated areas may experience higher crime rates, which could be due to a variety of socio-economic factors that often correlate with crime, such as poverty levels, unemployment rates, and population density. For a deeper analysis, one would typically look at the root causes, the types of crimes contributing to these rates, and how these rates have changed over time to develop a comprehensive understanding of the crime dynamics within these regions.

The overall ranking grouped by States is as follows.

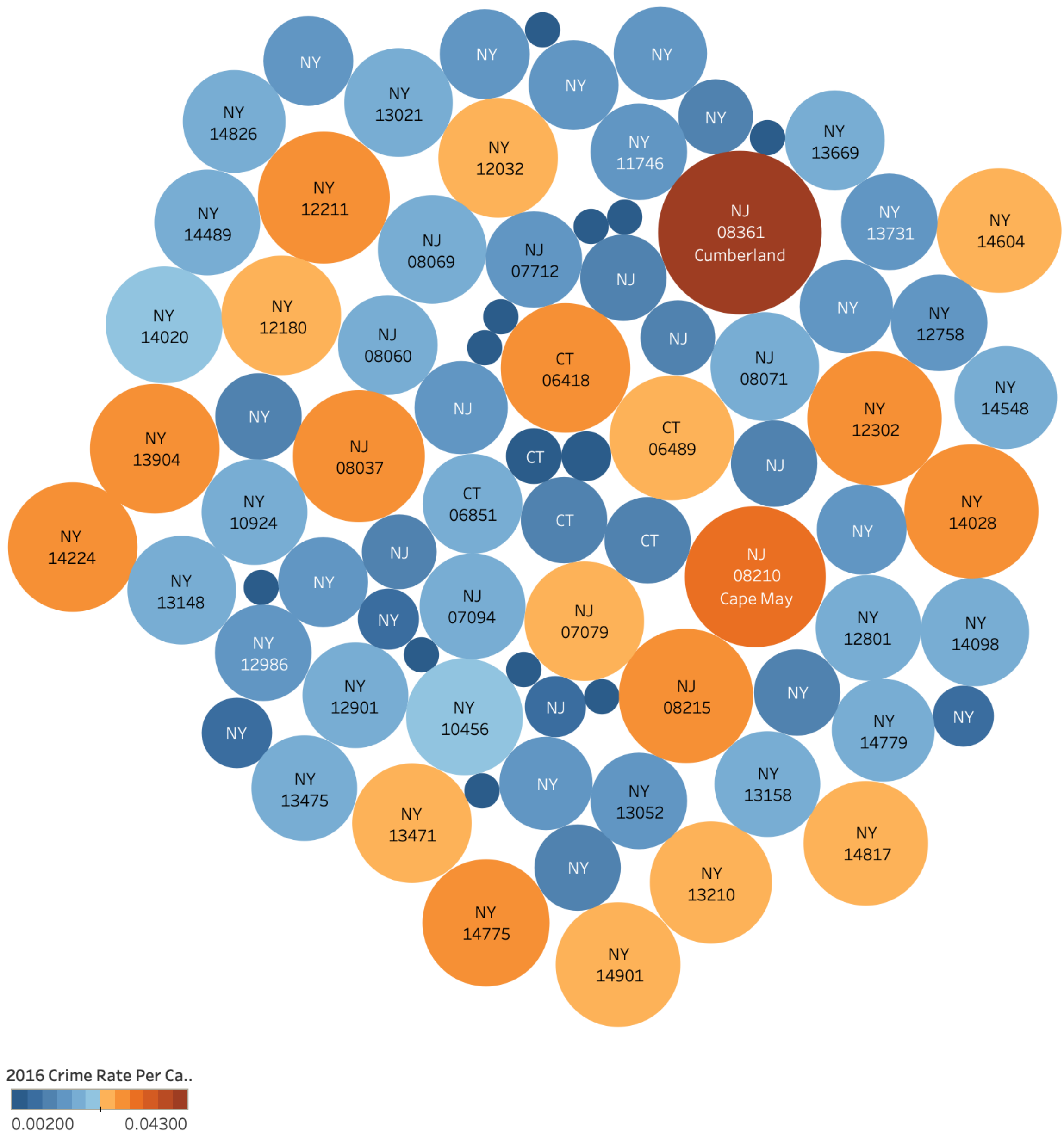
<2016 Crime Rate Analysis> - Tri States

- 2016 Crime Rate Per Capita per each States



<2016 Crime Rate Analysis> - Tri States

- 2016 Crime Rate Per Capita all states



4. Water Quality Analysis

(1) Data Preparation

Prior to the analysis, I assessed the distribution of the Quality of Life dataset and identified the presence of outliers. To address this, I will utilize the Interquartile Range (IQR) method to detect and trim these outliers, ensuring a robust dataset that will yield more accurate insights and facilitate a clearer understanding of the underlying trends and patterns. This process will help in mitigating the impact of extreme values that could skew the results and potentially lead to misleading conclusions.

```
df['WaterQualityVPV'].describe()
```

```
count    3134.000000
mean        2.689215
std        10.376495
min        -1.000000
25%         0.000000
50%         1.000000
75%         3.000000
max       456.000000
Name: WaterQualityVPV, dtype: float64
```

```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = df['WaterQualityVPV'].quantile(0.25)
Q3 = df['WaterQualityVPV'].quantile(0.75)
IQR = Q3 - Q1

# Define bounds for what is considered an outlier
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
filtered_df = df[(df['WaterQualityVPV'] >= lower_bound) & (df['WaterQualityVPV'] <= upper_bound)]
```

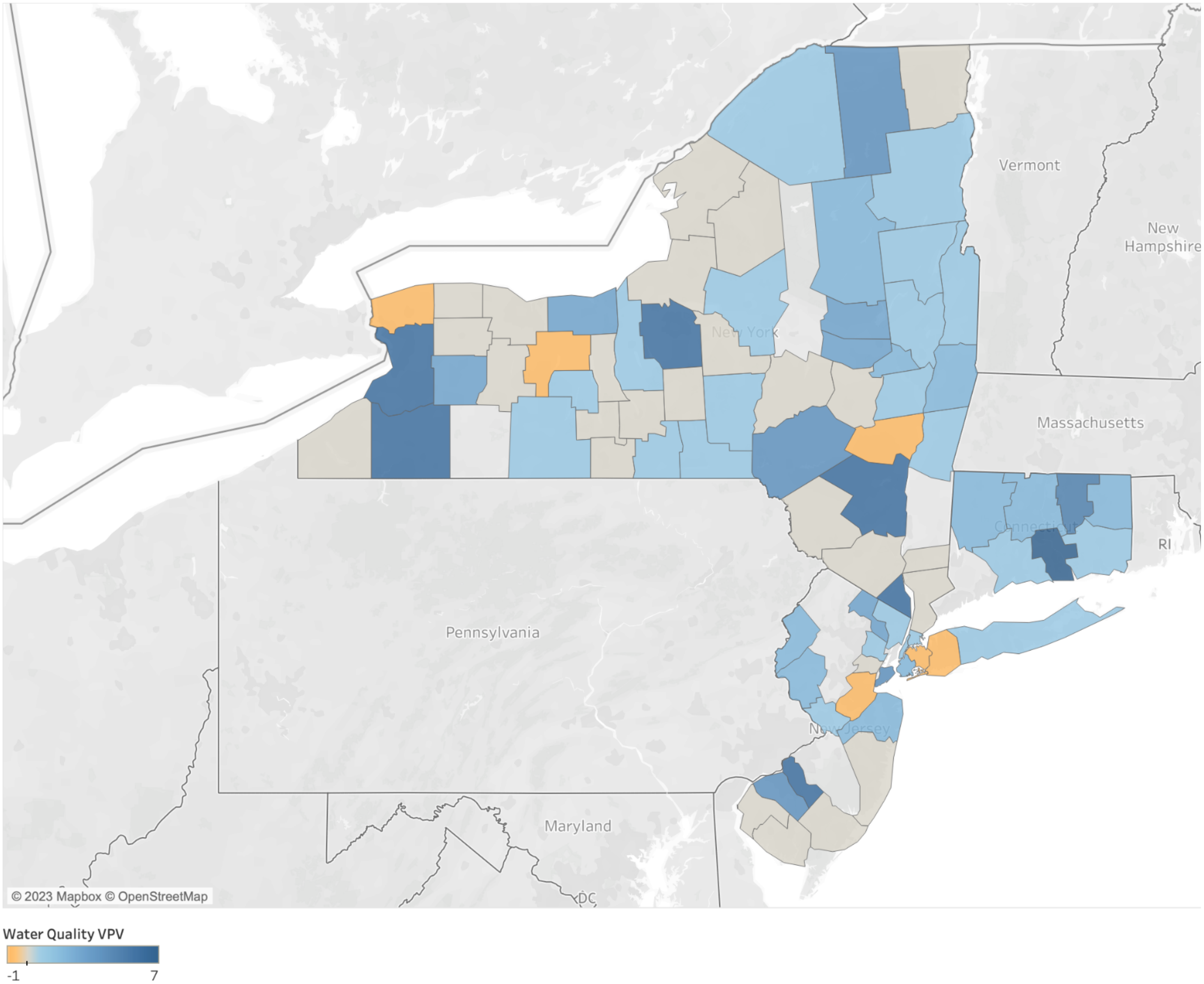
(2) WaterQualityVPV

The map represents the water quality in the Tri-State area after addressing outliers through IQR trimming, with varying shades indicating different levels of quality.

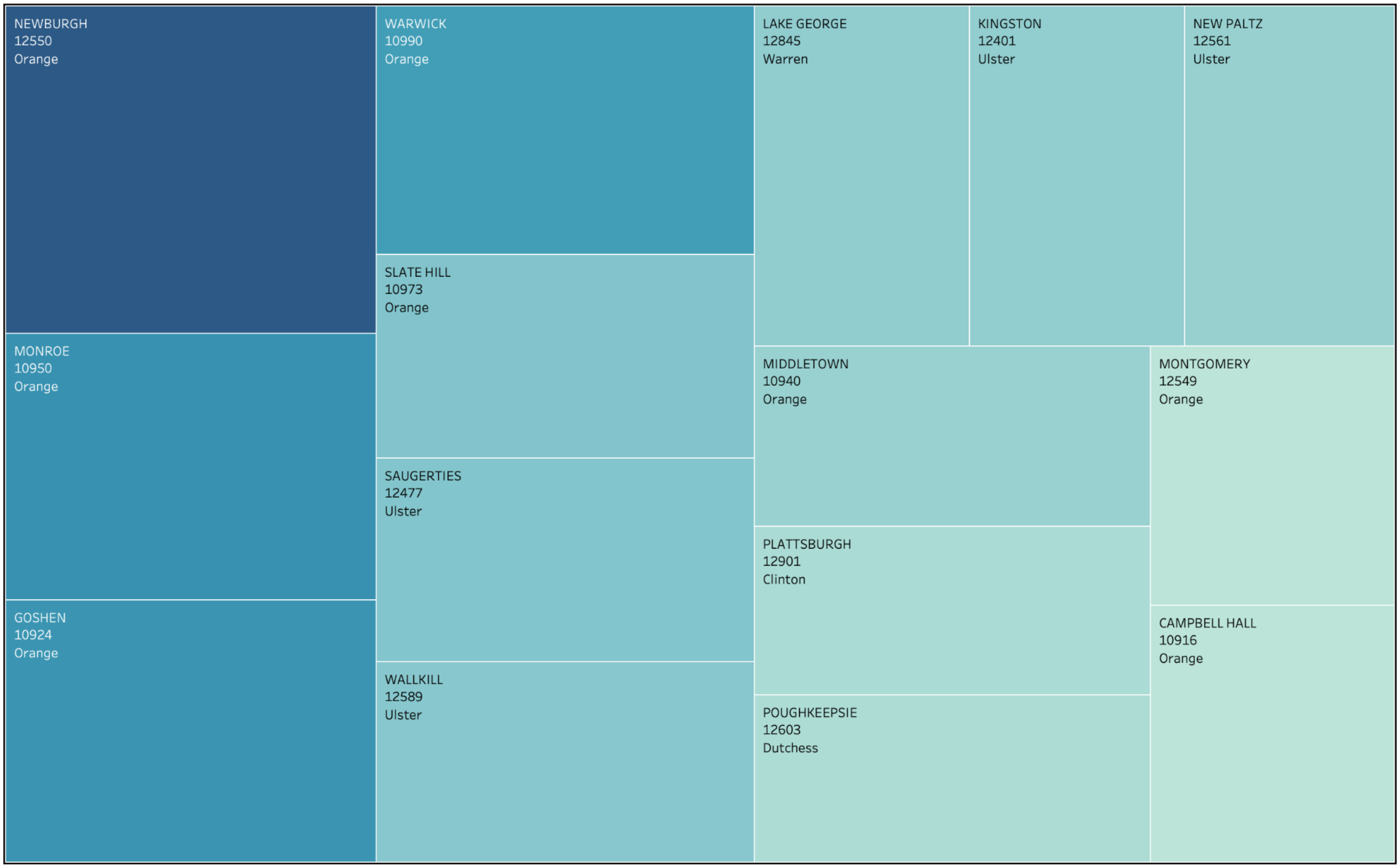
But due to numerous outliers and missing values, I plan to examine the 2022 datasets for more accurate and current insights.

<Water Quality> - Tri States

- After trimming with IQR method



<2022 Water Quality Analysis> - New York



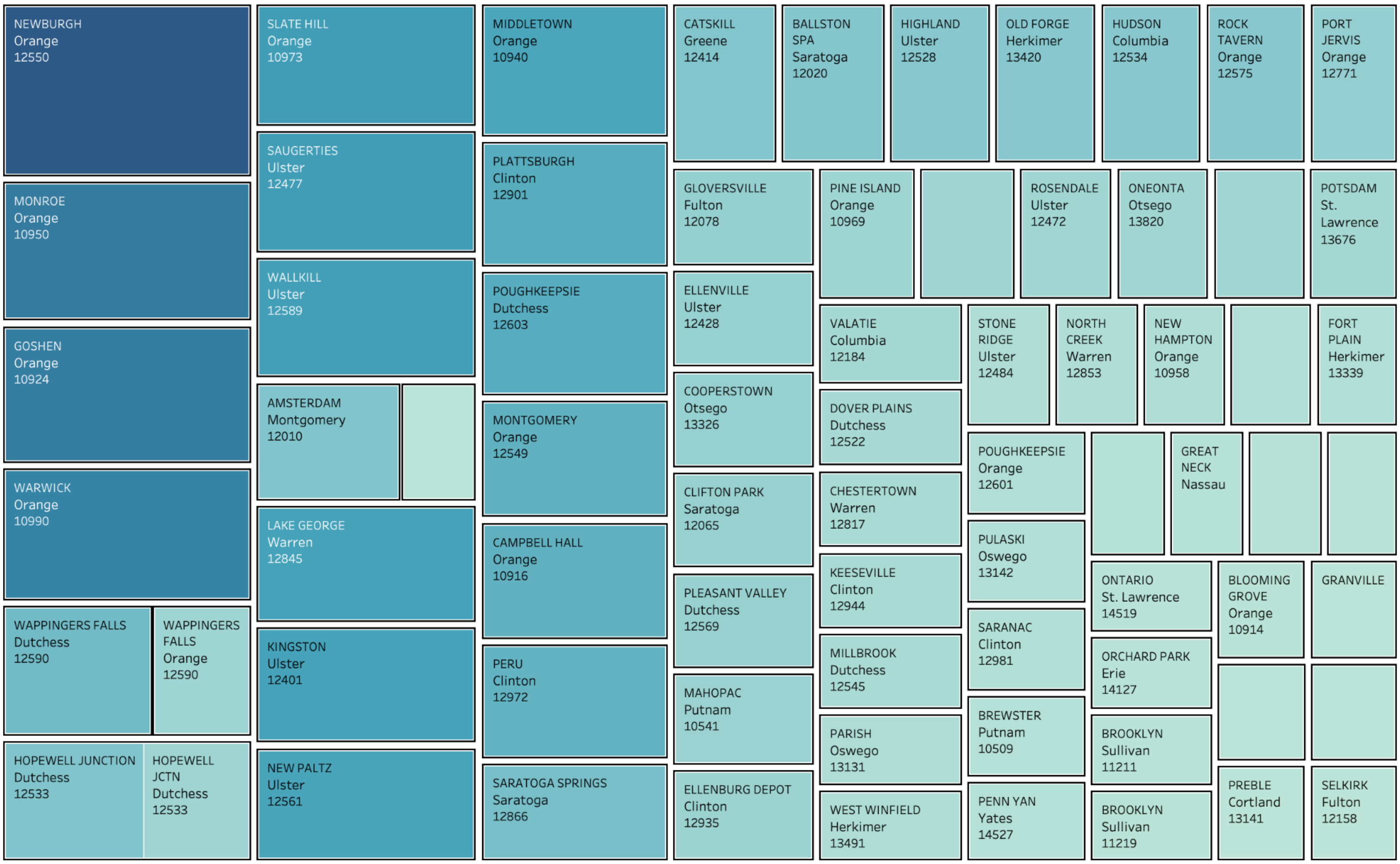
City Name, Zip Code and Counties Served. Color shows sum of # of Violations. Size shows sum of # of Violations. The marks are labeled by City Name, Zip Code and Counties Served. The view is filtered on sum of # of Violations, which ranges from 3,500 to 7,053.

# of Violations

3,513 6,819

(3) Water Quality 2022 Analysis in NYS

<2022 Water Quality Analysis> - Cities in NYS



Zip Code, Counties Served and City Name. Color shows sum of # of Violations. Size shows sum of # of Violations. The marks are labeled by Zip Code, Counties Served and City Name. The view is filtered on sum of # of Violations, which ranges from 1,400 to 7,053.

# of Violations

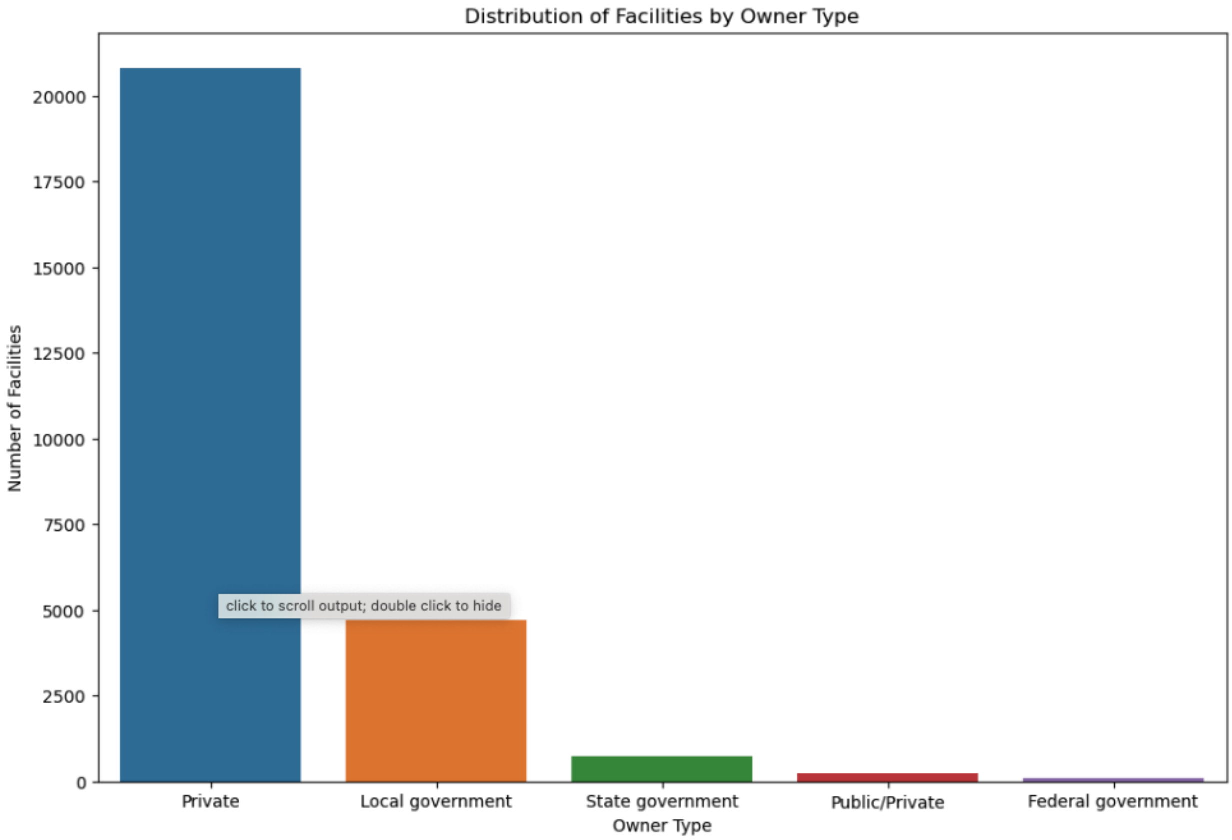
1,400 6,819

I've compiled the 2022 water system maintenance violation data over 22,000 from the EPA's Water System Summary for New York State cities, correlating each with its respective ZIP code and additional details. The dataset underwent rigorous scrutiny and preprocessing, including data trimming, to ensure accuracy and relevance for analysis.

The treemap based on EPA's Water System Summary data for 2022 indicates that within New York State, certain cities in Orange County, such as Newburgh, Monroe, Goshen, and Warwick, have reported higher water quality violations. This is followed by notable numbers in Wappingers Falls, Hopewell Junction, and Slate Hill.

(4) Exploratory Data Analysis with 2022 Water System report

(a) Facilities by Owner Type



The bar chart provided appears to illustrate the distribution of facilities by ownership type. Here is a breakdown of the information presented in the chart:

(1) **Private**: This category has the highest number of facilities by a significant margin, as indicated by the tallest bar on the chart. This suggests that the private sector owns the majority of facilities in this dataset.

(2) **Local Government**: Represented by the second bar, local government ownership is markedly less than private but still substantial. This shows that a considerable number of facilities are managed at the municipal or local level.

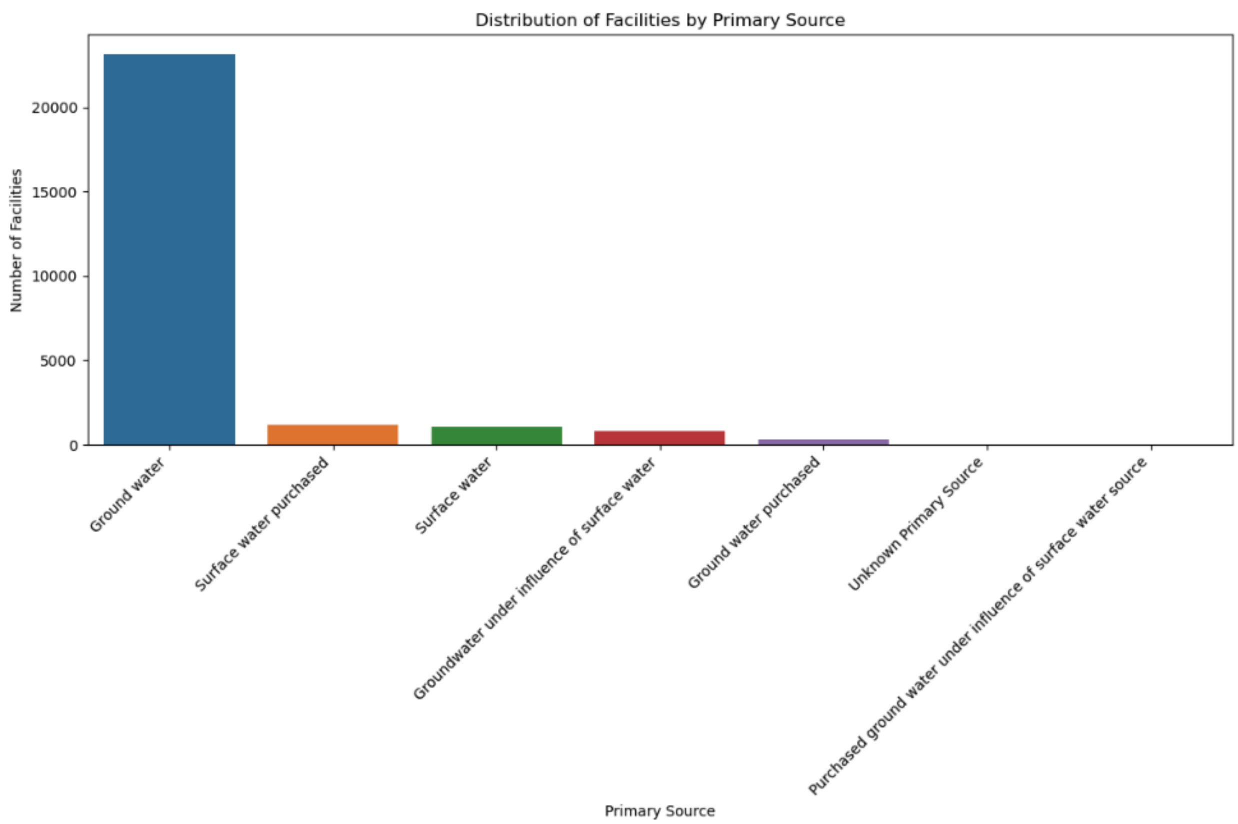
(3) **State Government**: The state government owns the fewest facilities among the categories shown, as indicated by the small size of the bar. This suggests that state-level ownership or operation of facilities is relatively uncommon in comparison to the other types of ownership.

(4) **Public/Private**: This category indicates facilities that have a mixed ownership or partnership between public and private entities. The bar here is very small, suggesting that this type of ownership is relatively rare.

(5) **Federal Government**: The federal government ownership is represented by the last bar, which is also quite small. This indicates that, like the state government, the federal government does not own a large number of facilities compared to the private sector.

The chart suggests that local governments play a more significant role than state or federal governments in facility ownership, which could be due to the local nature of many services (such as water, schools, and parks).

(b) Facilities by Owner Type



The bar chart illustrates the distribution of facilities according to their primary source of water. Each bar represents a different water source category, with the height of the bar indicating the number of facilities using that particular source.

- Ground Water: The tallest bar represents facilities that primarily use groundwater. This category has by far the largest number of facilities, indicating that groundwater is the most common source among the listed options.

- Surface Water Purchased: The second bar, much shorter than the first, signifies facilities that purchase surface water. This indicates that while some facilities rely on surface water, it is less common than groundwater.

- Surface Water: The third bar represents facilities that source water directly from surface water. This category has even fewer facilities compared to purchased surface water, suggesting that direct utilization of surface water is less common.

(c) Future work

Upon reviewing the dataset, I would like to conduct a comprehensive study on water contamination and various factors on it, which could exert influence on everyday life.

- Trend Analysis: Analyzing the data for trends over time would be a key area of focus. This could involve looking at changes in water source usage, shifts in ownership patterns, or the emergence of new sources.

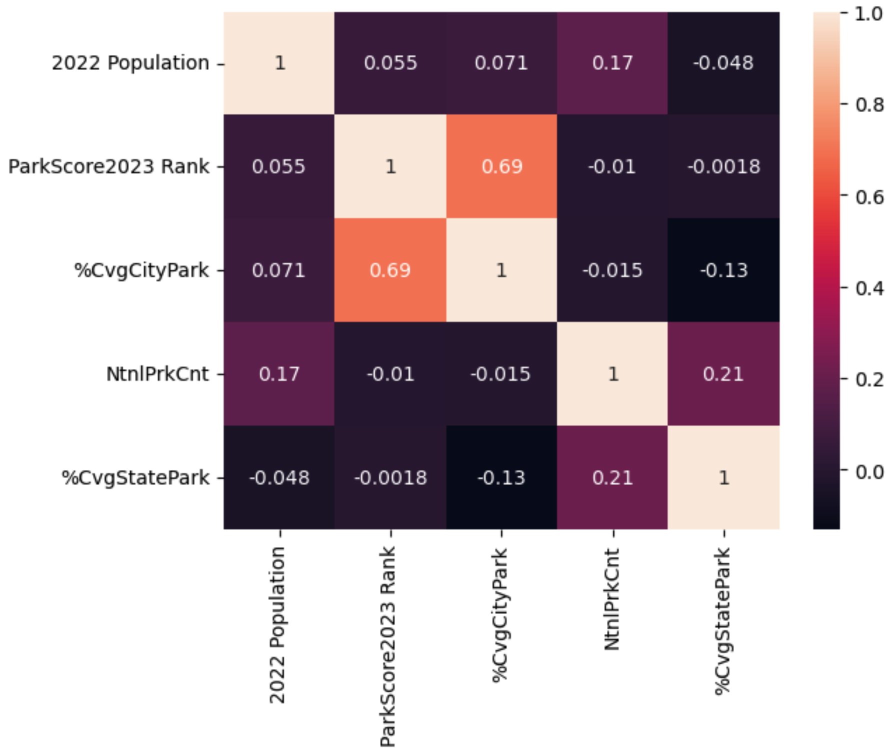
- Comparative Studies: Comparing the data from this dataset with other related datasets, such as population growth, climate change data, or industrial growth figures, could provide insights into how external factors influence water sourcing and facility distribution.

- Policy Impact Analysis: Examining the impact of current policies on the distribution and operation of water facilities and using this data to inform policy revisions or the development of new regulations.

5. Conclusion

My initial foray into this dataset analysis has revealed potential metrics that might significantly influence daily living standards within the Tri-State area. Regrettably, certain states are characterized by high unemployment rates, low median incomes, and high crime rates, all of which could adversely affect the quality of life.

The dataset also encompasses a diverse array of indicators that warrant a more multifaceted analytical approach. These include Park Scores Ranking, which evaluates the accessibility and quality of local parks; City Parking availability, which could affect urban mobility; and the proportions of land dedicated to National and State Parks, which reflect on a community's commitment to conservation and public recreation spaces.



In pursuit of a detailed understanding, forthcoming analyses could be expected to investigate the interplay between these environmental and infrastructural indicators and broader socioeconomic conditions. For instance, the availability and quality of parklands within a community may be indicative of higher real estate values, serving not only as a gauge for fiscal health but also for the well-being of its residents. The scarcity of parking provisions in city centers, on the other hand, could be symptomatic of a transition towards greener transportation methods or highlight potential shortcomings in urban planning.

Further, the proportion of land designated for National and State Parks could be emblematic of a region's dedication to preserving natural landscapes, which, in turn, might shed light on local investment in recreational spaces and the tourism sector.

By broadening the analytical framework to encompass these variables, it is conceivable to unearth subtle correlations between the availability of environmental resources and the economic and social fabric of a community. This holistic approach promises to enrich our comprehension of the myriad elements that contribute to the overall quality of life, facilitating informed decision-making aimed at enhancing communal living standards.

[1] Z. Vaughan, "City, ZIP, County, FIPS - Quality of Life," Kaggle, 2023. [Online]. Available: https://www.kaggle.com/datasets/zacvaughan/cityzipcountyfips-quality-of-life. [Accessed: Dec. 22, 2023].

[2] U.S. Environmental Protection Agency, "Safe Drinking Water Information System Federal Reports," U.S. Environmental Protection Agency. [Online]. Available: https://ordspub.epa.gov/ords/sfdw_rest/r/sfdw/sdwis_fed_reports_public/21?clear=RIR. [Accessed: Dec. 22, 2023].