

Quantitative Spatial Analysis Project Final Results

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This project sought to examine whether the proximity to police stations in Los Angeles has a significant influence on local crime rates. By leveraging ArcGIS Pro, a combination of spatial and statistical analyses was performed to assess this relationship. The study normalized crime data by population to ensure accurate comparisons and evaluated whether crime rates were notably lower within a one-mile radius of police stations compared to more distant areas. The report outlines the comprehensive methodology and analysis, including data preprocessing, spatial joins, population normalization, and statistical testing using t-tests to identify significant patterns. Additional insights into geographic trends and population density impacts were also explored to strengthen the findings.

Research Question

Is there a statistically significant reduction in crime rates in Los Angeles neighborhoods that are within a specific proximity (e.g., within 1 mile) to police stations, when compared to neighborhoods located farther away?

Null Hypothesis

In the city of Los Angeles, the proximity of neighborhoods to police stations (within 1 mile) does not significantly affect the crime rate. Specifically, neighborhoods within a 1-mile radius of police stations experience similar average crime rates to those located farther than 1 mile, indicating that proximity alone does not lead to a measurable difference in crime reduction.

Alternative Hypothesis

In the city of Los Angeles, neighborhoods located within a 1-mile radius of police stations experience significantly lower crime rates compared to neighborhoods located farther away. This suggests that closer proximity to police stations correlates with improved crime reduction, implying a potentially greater deterrent effect in these closer neighborhoods.

Data Preparation and Buffer Creation

The analysis began by acquiring the necessary datasets:

- **Crime Data:** Geocoded crime incidents in Los Angeles. The crime data that was specifically used was from data.gov, a government entity providing accurate data for the past four fiscal years, from 01/01/2020 to mid-October of 2024. The first dataset was every single logged arrest by local (LAPD), county (LASD), and state agencies (CHP) that operate within the city boundaries. The second data was general crime reports, most likely from 911 call centers, reported over the past four years. After selecting and removing the unnecessary 2021, 2022, 2023, and 2024 datasets, I had the following results (Almost 450,000 individual incidents, including arrests and crime incidents: inside and outside buffer zones):

Arrest Data

Inside Buffer (1-Mile): 34,521

Outside Buffer: 69,218

Total Arrests: 103,739

Crime Data

Within Buffer: 87,233

Outside Buffer: 231,866

Total Incidents: 319,099

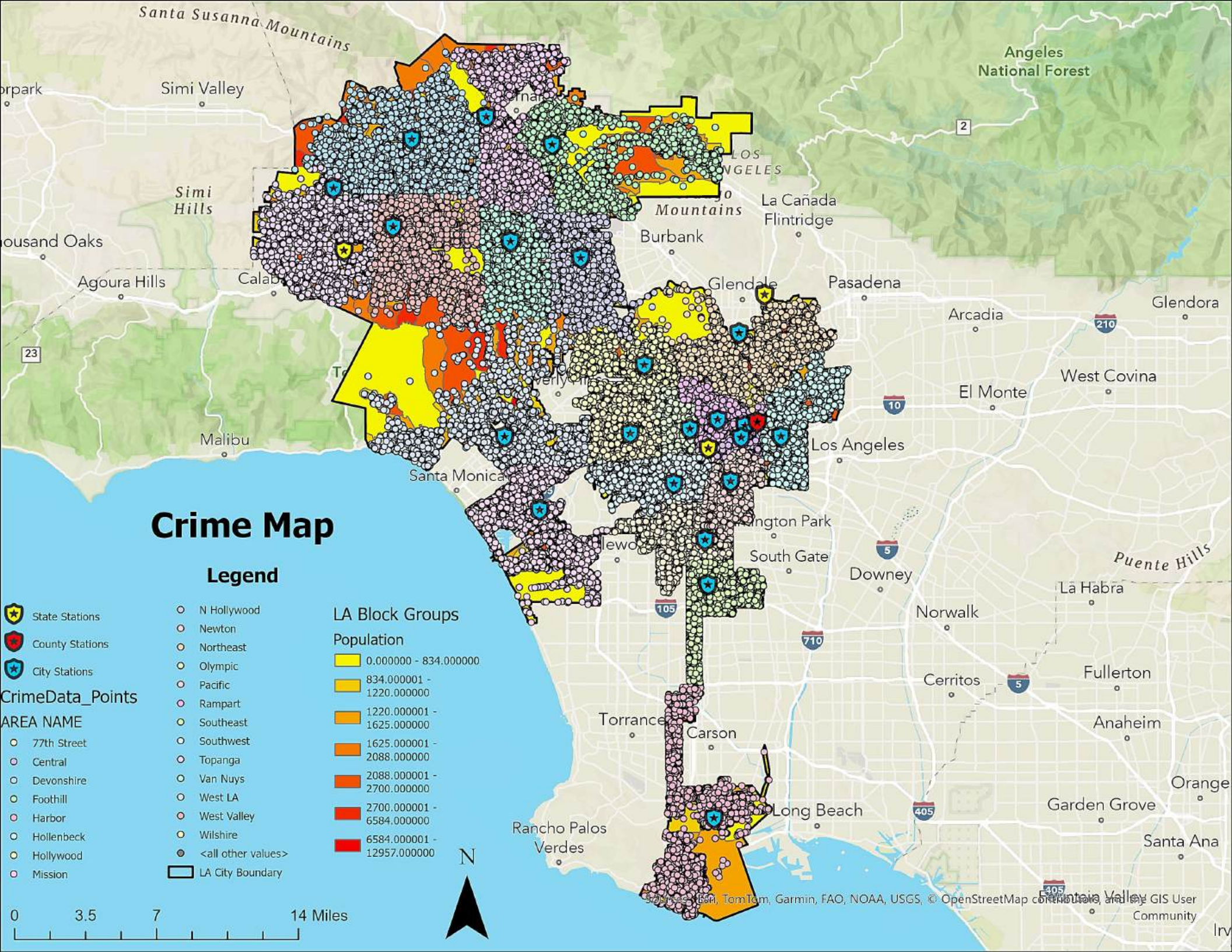
Inside Buffer Incidents (Arrest and Crime): 121,754

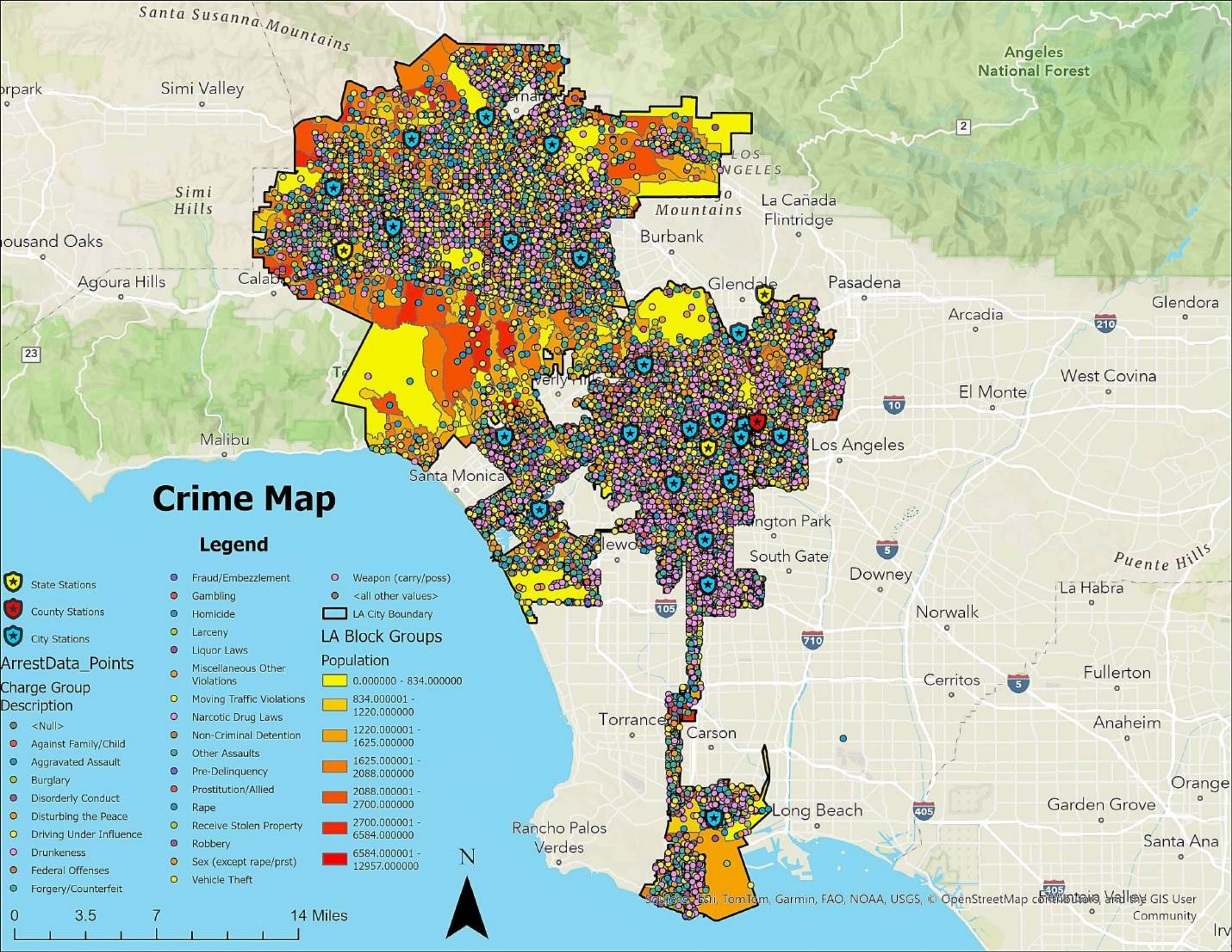
Outside Buffer Incidents (Arrest and Crime): 301,104

- Police Stations (Point Data): Locations of law enforcement stations. (Stations include LAPD, LASD, and CHP)
- Population Data (Quantitative): Census block group data from the 2020 TIGER/Line dataset, joined with demographic data from the Decennial Census.
- The geographic extent of the analysis was confined to the City of Los Angeles. (City of LA Polygon Data)
- Census block group population data was joined to the block groups and eventually spatially joined to the buffer zones.
- Point Data was created for each crime data set along with the law enforcement stations.

Buffer Creation

A 1-mile buffer was generated around each police station using the Buffer tool. This buffer represented the area of potential influence of police presence. A 2-mile radius around each police station was then created and the one mile buffer zone was erased from the 2-mile zone, creating a 1-mile buffer around the original buffer. This allows us to showcase incidents within a 1-mile zone and at least 1-mile away from the police stations.





Spatial Join of Crime Data: The Spatial Join tool was used to associate each crime incident with the nearest buffer zone. The "Have Their Center In" match option ensured only crimes occurring entirely within the buffer were considered.

Population Normalization

To account for variations in population density:

Join Population Data to Block Groups:

Population data was joined through the figures listed above.

Aggregate Population Data:

The Spatial Join tool was applied to intersect block groups with buffer zones. Using the "Sum" option for population fields, the total population within each buffer zone was calculated.

Calculate Outside Buffer Population: Areas outside the buffers were generated using the Erase tool, and a similar Spatial Join was performed to calculate populations outside the buffer zones.

The tables from the arrest and crime data within and outside the buffer zones were imported to Google Sheets, where I combined the data for each group. Outside of the buffer accounted for 2,569 buffer groups within the city of Los Angeles. Inside accounted for 28 buffer zones, which are 26 different law enforcement stations within LA. With population counts assigned, the crime rates (crimes per 1,000 residents) for both areas were calculated:

$$\text{Crime Rate} = \text{Total Incident Count (Merged Arrest and Crime Data)} \times (\text{Block Population} / 1000)$$

The spatial join confined the population to the area of the buffer zone, so the numbers remain accurate to the total amount of block groups that fall within a buffer area.

Statistical Analysis

T-Test Overview

A two-sample t-test was selected to evaluate whether the mean crime rates differed significantly between the areas inside and outside the 1-mile buffers.

Null Hypothesis: Crime rates inside the buffer zones are equal to those outside the buffer zones.

Alternative Hypothesis: Crime rates inside the buffer zones are lower than those outside the buffer zones.

Given the independent nature of the datasets and expected differences in variances, the two-sample t-test with unequal variances was used.

Conducting the T-Test

After compiling the crime rates for inside and outside buffer zones:

The T.TEST function was used with the following parameters:

Array1: Crime rates inside buffer zones.

Array2: Crime rates outside buffer zones.

Tails: 1 (for a one-tailed test, testing for lower crime rates inside buffers).

Type: 3 (two-sample t-test with unequal variances).

The output provided the p-value for comparison against the significance threshold

Calculating the T-Statistic (Google Sheets)

E3:E28: Inside Buffer Zones Crime Rate

J3:J28: Outside Buffer Zones Crime Rate

$$=(AVERAGE(E3:E28) - AVERAGE(J3:J28)) / SQRT((VAR.S(E3:E28)/COUNT(E3:E28)) + (VAR.S(J3:J28)/COUNT(J3:J28)))$$

Result Interpretation

T-Statistic: Indicates the difference between the two means relative to the variability of the data.

P-value: Determines statistical significance. (90% Confidence Interval)

More than 0.1 would lead to rejection of the null hypothesis, suggesting that police station proximity reduces crime rates.

T-Statistic

$$t = -1.677$$

The t-statistic remains the same, indicating a notable difference between the crime rates inside and outside the 1-mile police station buffers.

P-Value

$$p = 0.0502$$

A smaller p-value further strengthens the evidence against the null hypothesis.

At a significance level of $\alpha = 0.1$

Since $p = 0.0502 < 0.1$, the null hypothesis is rejected.

Hypothesis Test Conclusion

There is strong statistical evidence that crime rates differ significantly between the areas inside and outside the 1-mile buffers. For a one-tailed test, this result strongly supports the hypothesis that crime rates are lower within the buffer zones. The lower p-value reinforces the conclusion that police station proximity has a significant effect on reducing crime rates within a 1-mile

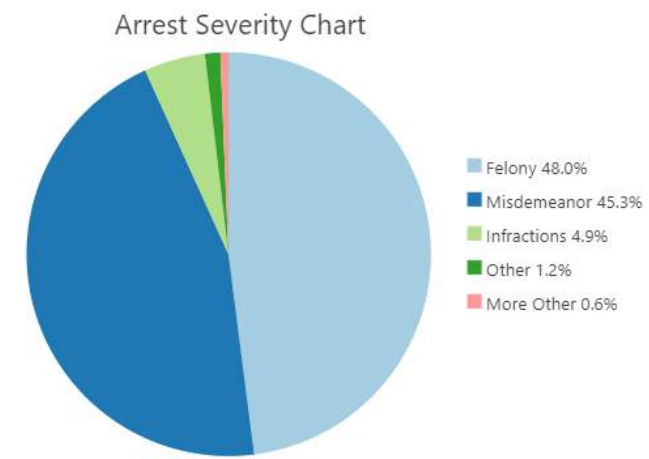
radius. This finding is particularly valuable for city planners and law enforcement agencies, providing a strong argument for strategic placement of police stations to maximize crime deterrence.

Google Sheets Analysis

<https://docs.google.com/spreadsheets/d/1cUU6APJLxTzhp45TqAABuM0mtxeEaYSKQ1vAEd7s5kI/edit?usp=sharing>

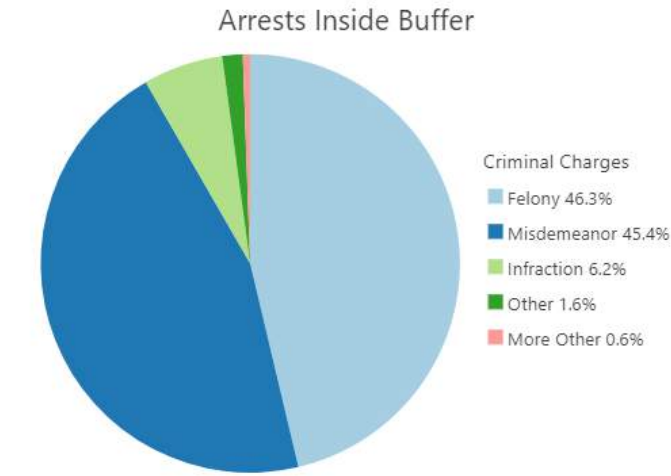
LA Arrest and Crime Data Distribution Charts

Arrests Outside Buffer



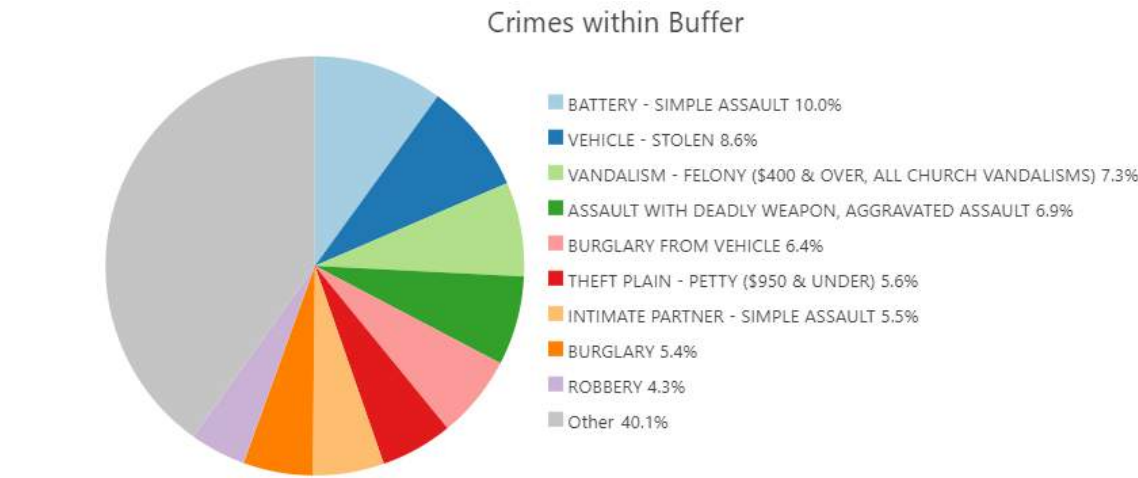
(Highest Percentage Felony)

Arrests Inside Buffer



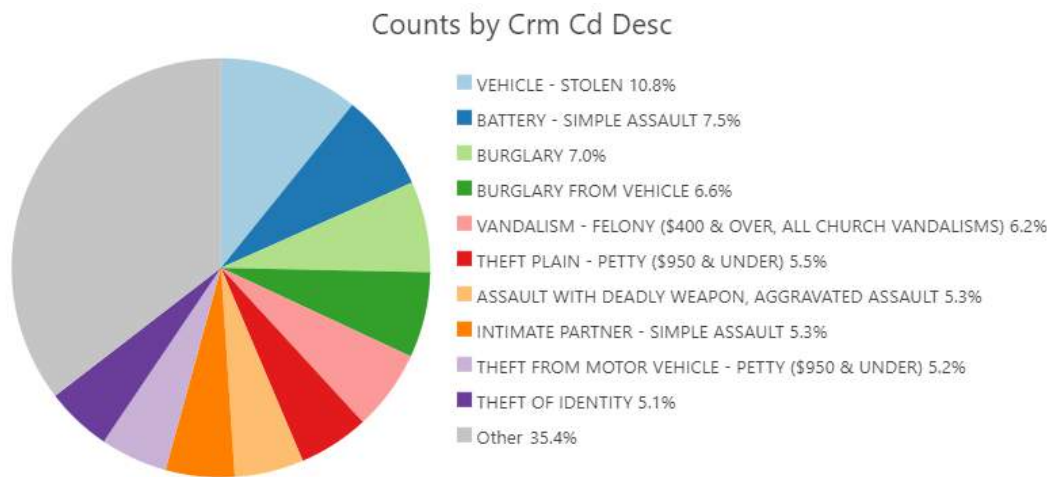
(Highest Percentage Felony)

Crimes Inside Buffer



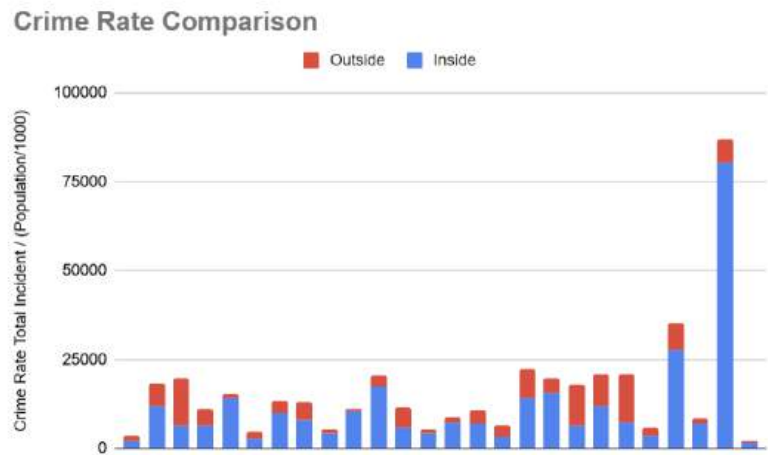
(Highest Percentage is Battery: 10%)

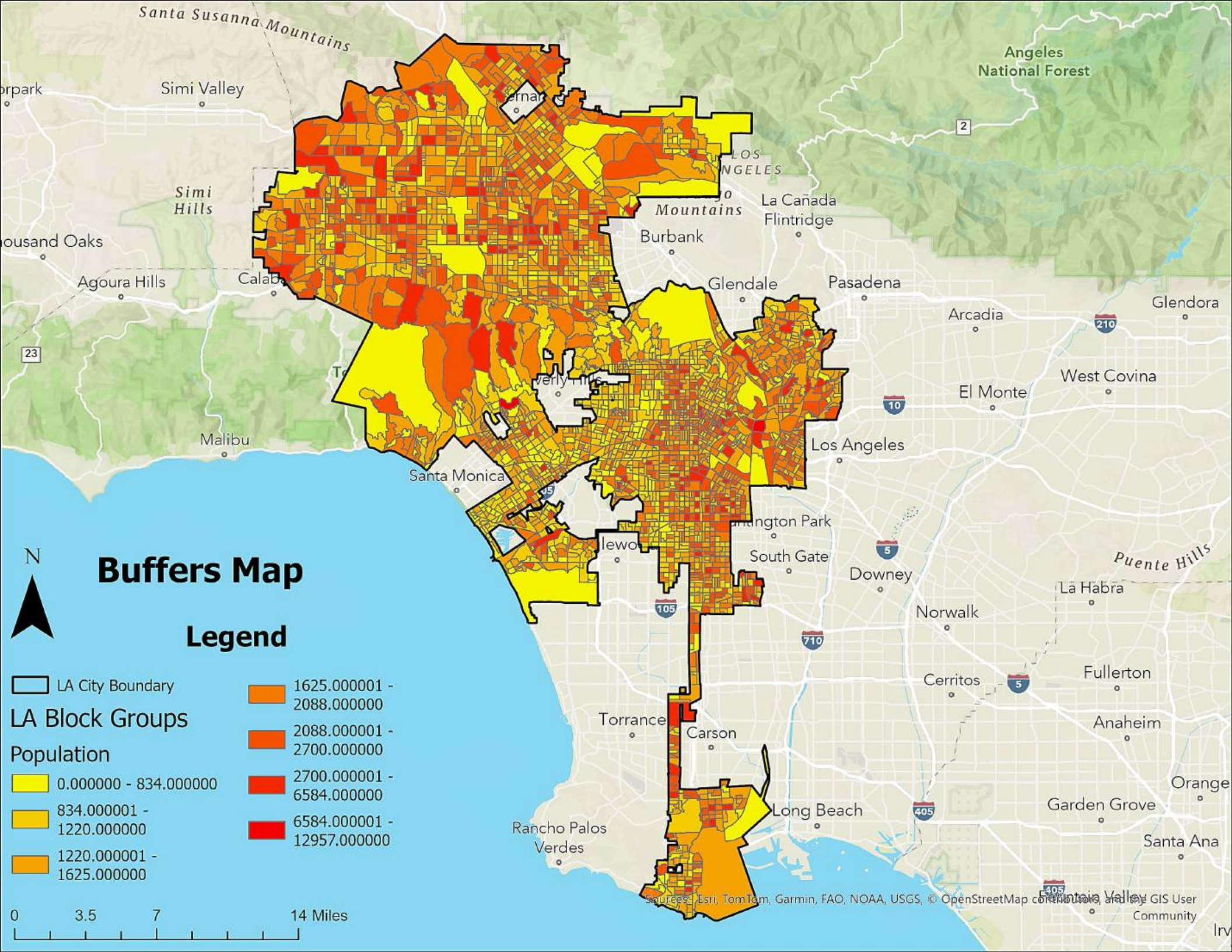
Crimes Outside Buffer

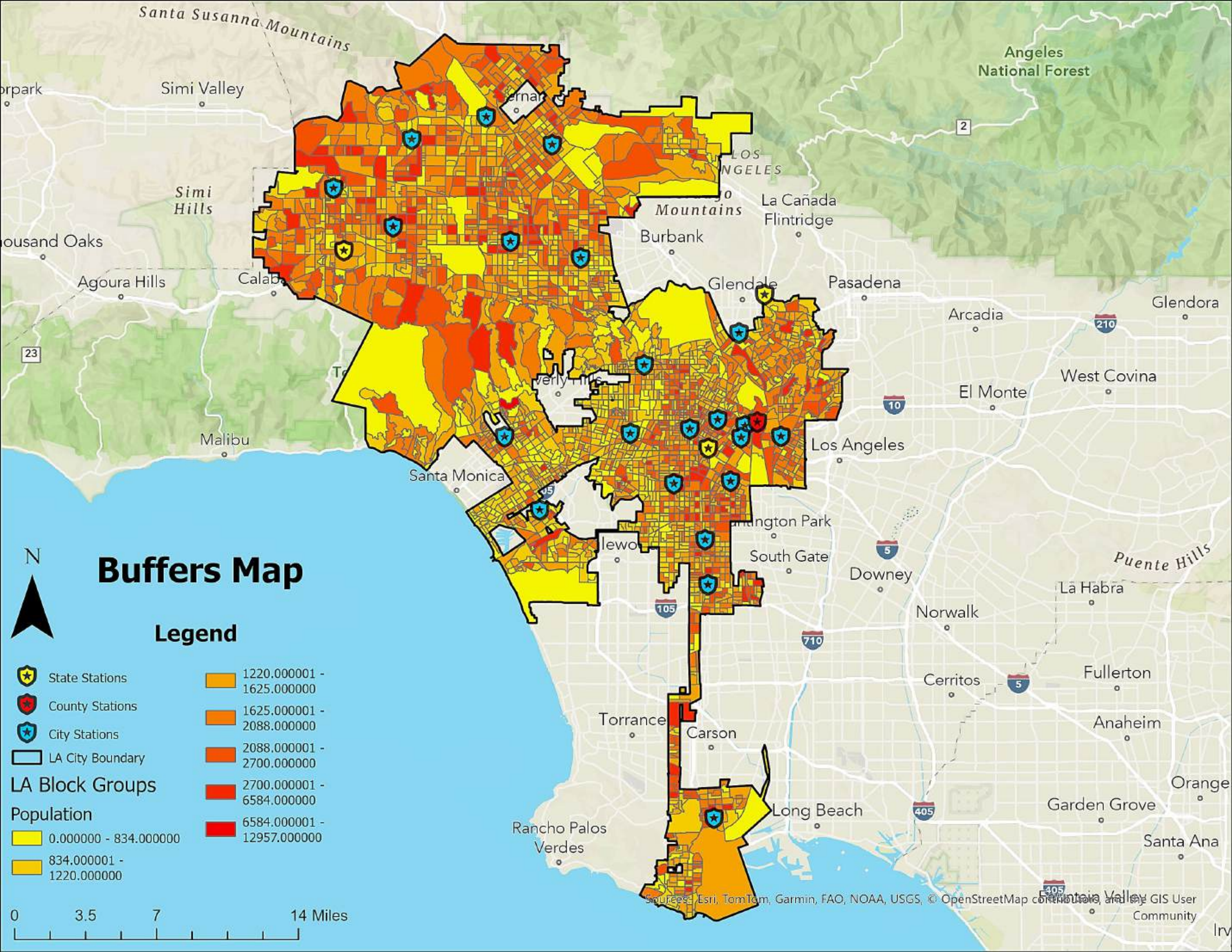


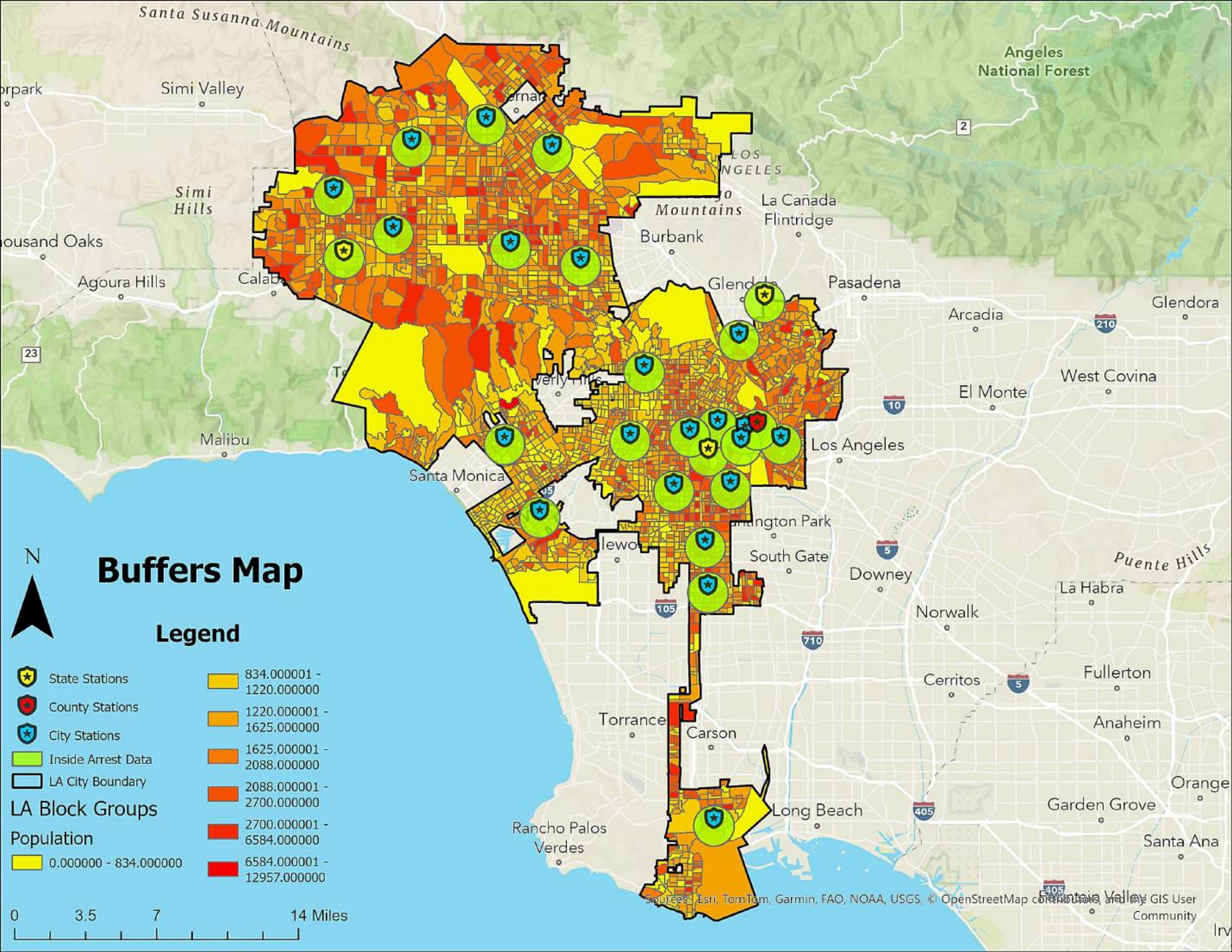
(Highest Percentage is Vehicle Theft: 10.8%)

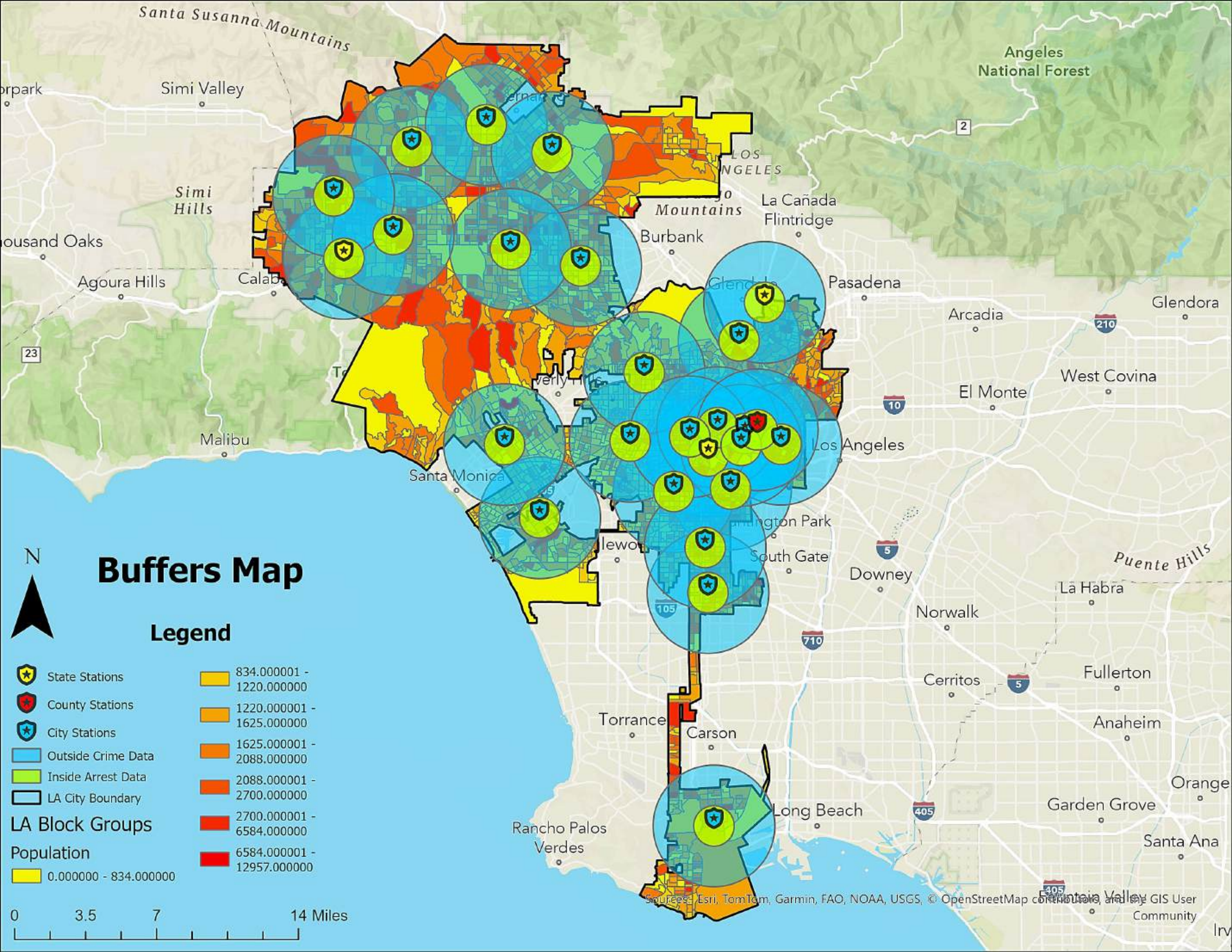
Crime Rate Comparison (Inside vs. Outside Buffer Zones)











Law Enforcement Articles

The quantitative spatial analysis of 1-mile buffer zones around police stations in Los Angeles reveals a strong connection between proximity to law enforcement and reduced crime rates. This result aligns with environmental criminology principles, which posit that crime is not randomly distributed but influenced by spatial factors, such as the presence of police (Cueva & Cabrera-Barona, 2024). By establishing these buffer zones, the study highlights a marked difference in crime rates, as evidenced by the t-statistic ($t = -1.677$), indicating significantly lower crime within the buffers compared to outside. This finding resonates with prior research, which emphasizes that spatial interventions like police station placement can act as deterrents to crime by limiting opportunities and increasing perceived risks for offenders (Kinney et al., 2008). Such interventions disrupt crime patterns and align with the broader "ecology of crime" framework, which seeks to explain how urban spatial arrangements and socioeconomic conditions influence crime dynamics (Cueva & Cabrera-Barona, 2024).

The statistical significance of the findings is further supported by a p-value of 0.0502, which falls below the 0.1 threshold, allowing for the rejection of the null hypothesis. This reinforces the hypothesis that crime rates differ significantly inside and outside the 1-mile buffers, further validating the role of police proximity as a crime deterrent. This observation also reflects established patterns in criminological research, where crime tends to cluster in specific micro-places, and targeted interventions often yield measurable reductions in criminal activity (Walter, Tillyer, & Acolin, 2023). For instance, the concept of "hotspot policing" aligns with this study's findings, as it demonstrates how focusing resources on high-crime areas or near police stations significantly impacts local crime rates (Sherman et al., 1989). Moreover, the results indicate that such spatial interventions are not only effective but also stable over time,

reinforcing the value of strategic law enforcement placement to maximize community safety (Walter et al., 2023).

This spatial analysis also supports broader discussions on geographic disparities in crime reduction and policing. For example, the findings in Los Angeles echo those from studies analyzing spatial patterns of violent crime in other U.S. cities, which reveal the importance of policing density in mitigating crime (Boylan, 2024). Boylan's research highlights how disparities in law enforcement resources can significantly impact regional crime rates, a phenomenon that was mitigated in Los Angeles through well-placed police stations and proactive spatial interventions. This analysis also demonstrates consistency with historical trends showing that police density correlates strongly with crime reduction, particularly in urban environments characterized by concentrated economic and social challenges (Boylan, 2024). These findings reinforce the importance of integrating geographic insights into urban safety planning and resource allocation.

Finally, the broader implications of this analysis extend to urban planning and law enforcement strategy. By incorporating these findings, policymakers can optimize resource distribution to prioritize high-risk areas and strengthen the spatial deterrent effect of police presence. Furthermore, studies like these challenge the misconception that crime reduction is primarily a matter of increasing police numbers. Instead, they emphasize the critical role of spatial arrangements and urban design in shaping crime outcomes. As Cueva and Cabrera-Barona (2024) note, "Urban zones with increased police unit density demonstrate significantly lower crime rates, irrespective of socioeconomic inequalities." Similarly, research on micro-places suggests that the deliberate clustering of law enforcement resources can prevent crimes at both street and neighborhood levels (Walter et al., 2023). In essence, this study underscores the

importance of spatial analysis as a tool for effective urban crime prevention, reinforcing the need for evidence-based policymaking that integrates criminological and geographic perspectives.

GIS Datasets

Data Type	Data Source	Organization	Link	Year	Description
Point / Polygon	City of Los Angeles	Federal Government	LA Data	2020	LA Crime Data, Arrest Data
Point / Polygon	TIGER/Line	U.S. Census	TIGER/Line	2020	Urban Areas, Population, State Boundaries, City Boundaries, etc.
Point / Polygon	FBI Crime Explorer	Federal Bureau of Investigation	FBI Explorer	2020	Local / Violent Crime Data
Point	LASD	Los Angeles County	LA County	Current	Police / Sheriff Stations
Point / Polygon	State of California	California Department of Health	Violent Crime	Current	Violent Crime Rate
Point / Polygon	HIFLD Explorer	Department of Homeland Security	DHS HIFLD	Current	Area Statistics (Population)

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