Strategic Optimization of Police Patrol Locations Using Spatial-Temporal Analysis of Crime Severity Distribution

ABSTRACT

This study optimizes police patrol locations using spatial-temporal analysis of crime severity in Philadelphia. Crime data were assigned severity scores based on federal standards. Two models were used: the Maximum Coverage Location Problem (MCLP) to maximize coverage of high-severity crimes within a response distance, and the P-Median model to minimize the total weighted distance to all crimes. The findings reveal spatial-temporal variations in crime severity, influencing resource allocation throughout the day. The analysis highlights trade-offs between maximizing coverage and minimizing response times, providing insights for strategic deployment of police resources to enhance public safety.

1. Introduction

This research aims to refine the police patrol location-allocation model by incorporating crime severity data, with a focus on high-severity offenses such as homicides, and by accounting for the spatial distribution of crimes at different times of the day. Using Philadelphia as the study area, it employs both the Maximum Coverage Location Problem (MCLP) and the P-Median models to analyze and compare their effectiveness in covering high-severity crime areas and optimizing police response times. Additionally, this research explores the impact of adjusting the number of patrol locations under various budgetary constraints.

The analysis will aid in identifying optimal resource distribution strategies, which can be tailored to scenarios that either maximize crime severity coverage or minimize total response times. By synthesizing the outcomes from both models (MCLP and P-Median), the study helps law enforcement agencies to balance cost-efficiency with rapid response to the most urgent incidents, especially under budget or personnel constraints. This ensures that patrol units, such as police cars, are strategically positioned to enhance public safety management.

2. Literature Review

Recent studies have increasingly focused on the severity and multiple dimensions of crime, rather than merely tallying crime incidents. This approach, which emphasizes crime harm scores over the counts of crime incidents, enhances both policy and environmental design by providing a more comprehensive understanding of crime's impact. Pyle (2019) discusses how socio-spatial variation in perceptions of crime location and severity can inform a more nuanced approach to crime analysis[1]. Harinam, Bavecivic, and Ariel (2022) further argue against abandoning count-based models in understanding the trajectories of crime severity and distribution[2].

To effectively manage risk, law enforcement agencies are adopting location-allocation models and network analysis to optimize the coverage of police stations. This strategic approach helps maximize the utility of resources by aligning them with areas of highest need. Jiang, Guo, and Yan (2022) explore multi-criterion spatial optimization for future police stations to account for urban expansion and criminal behavior characteristics[3]. Researchers have also developed spatially optimized strategies for police patrol allocations, aiming to minimize expected crime response times. Mukhopadhyay et al. (2016) discussed the optimal allocation of police patrol resources using a continuous-time crime model, which significantly improves response efficiency[4]. Curtin, Hayslett-McCall, and Qiu (2010) have demonstrated the efficacy of using Maximal Covering and Backup Covering Location Models to enhance police services across varying scenarios[5].

Integrating both spatial and temporal dimensions into crime analysis is crucial. This methodology not only aids in understanding crime patterns over different geographical locations but also across time, providing a dynamic framework for resource allocation and policy formulation. Spatial-temporal correlations for crime prediction have also been modeled to enhance the predictability of crime rates and locations[6].

3. Methodology and Data Preparation

The methodology begins with collecting different types of crime data in Philadelphia for the year 2022. These crime types are then assigned severity scores ranging from 0.5 to 7, based on federal standards, to quantify the negative impact of each crime type and to serve as weight values in subsequent modeling processes. This framework enables us to construct visual maps illustrating the spatial distribution of crime severity across the city. Additionally, crime data are aggregated into various time frames (daytime, evening, and nighttime) based on 8-hour intervals to identify spatial-temporal patterns and shifts in crime hotspots, which aids in deploying police patrols more effectively. To balance the precision of location selection with the computation time of model results, this study employs a fishnet grid of 1640 feet by 1640 feet as potential facility points.

During the model building process, the research employs two location-allocation models: the Maximum Coverage Location Problem (MCLP) and the P-median model, leveraging the ArcGIS Pro platform and the actual road network structure of Philadelphia to compute the model results. Each model has distinct objectives: the former aims to select locations within a given distance (in

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[1] Gerald F. Pyle, "15. Systematic Sociospatial Variation in Perceptions of Crime Location and Severity," in Crime: A Spatial Perspective (Columbia University Press, 2019), 219–46, https://doi.org/10.7312/geor90788-022.
[2] Vincent Harinam, Zeljko Bavcevic, and Barak Ariel, "Spatial Distribution and Developmental Trajectories of Crime versus Crime Severity: Do Not Abandon the Count-Based Model Just Yet," Crime Science 11, no. 1 (November 29, 2022): 14, https://doi.org/10.1186/s40163-022-00176-x.
[3] Yuncheng Jiang, Baoyu Guo, and Zhigang Yan, "Multi-Criterion Spatial Optimization of Future Police Stations Based on Urban Expansion and Criminal Behavior Characteristics," ISPRS International Journal of Geo-Information 11, no. 7 (July 2022): 384, https://doi.org/10.3390/ijgi11070384.
[4] Ayan Mukhopadhyay et al., "Optimal Allocation of Police Patrol Resources Using a Continuous-Time Crime Model," in Decision and Game Theory for Security, ed. Quanyan Zhu et al. (Cham: Springer International Publishing, 2016), 139–58, https://doi.org/10.1007/978-3-319-47413-7_9.
[5] Kevin M. Curtin, Karen Hayslett-McCall, and Fang Qiu, "Determining Optimal Police Patrol Areas with Maximal Covering and Backup Covering Location Models," Networks and Spatial Economics 10, no. 1 (March 2010): 125–45, https://doi.org/10.1007/s11067-007-9035-6.
[6] "Modeling Temporal-Spatial Correlations for Crime Prediction," accessed May 9, 2024, https://doi.org/10.1145/3132847.3133024.

this study, a network distance of 4920 feet, which is a feasible rapid response distance for police vehicles) that maximize the total crime severity covered. The latter model aims to minimize the total weighted distance considering all crime points. For both models, we analyze how the results change with different numbers of selected locations. By analyzing and comparing the outcomes of these models, the research provides a foundation for strategic law enforcement resource allocation tailored to various objectives.

3.1. Crime Severity Data

The research utilizes 2022 crime data from Philadelphia city, sourced from OpenDataPhilly[7], which details each crime incident by specific types such as "Theft from Vehicle," "Vandalism," and "Burglary," among others. This data on crime types is aggregated into several main categories, and Table 1 provides a preview of these categories along with their corresponding counts.

To link these original crime types with severity scores, we refer to federal official standards to determine the severity of different crime types and assign values accordingly. According to 18 U.S. Code § 3559 - Sentencing classification of offenses[8], crimes are classified and fit into the structure shown in Table 2,[9] which assigns each crime a severity score ranging from 0.5 to 7, categorizing them from low to high severity. Following the assignment of severity scores, maps are generated to visually explore the patterns of crime severity across the city, providing direct insights for further analysis.

Aggregated Crime Types → **Crime Classification Table** → **Crime Severity Score**

text_gener	count
Thefts	33104
Other Assaults	25359
Theft from Vehicle	15546
Vandalism/Criminal Mischief	14372
All Other Offenses	11950
Motor Vehicle Theft	11820
Fraud	6922
Aggravated Assault No Firearm	4924
Burglary Residential	3724
Aggravated Assault Firearm	3405

Classification of Federal Offenses	Maximum Jail Term
Grade A Felony	Life imprisonment or the death penalty.
Grade B Felony	Twenty-five (25) years or more in prison.
Grade C Felony	Less than twenty-five (25) years, but ten (10) or more years in prison.
Grade D Felony	Less than ten (10) years, but five (5) or more years in prison.
Grade E Felony	Less than five (5) years, but more than one (1) year in prison.
Class A Misdemeanor	One (1) year or less, but more than six (6) months in jail.
Class B Misdemeanor (Petty Offense)	Six (6) months or less, but more than thirty (30) days in jail.
Class C Misdemeanor (Petty Offense)	Thirty (30) days or less, but more than five (5) days in jail.
Infraction (Petty Offense)	Five (5) days or less in jail. Or offenses with no authorized jail time

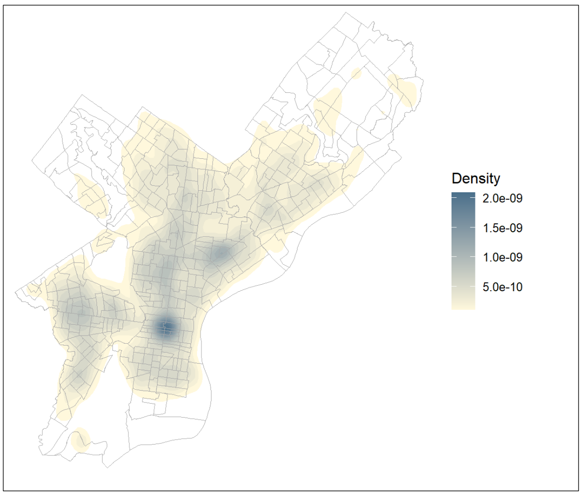
Severity Score
7.0
6.0
5.0
4.0
3.0
2.0
1.5
1
0.5
0.5

Table 1. Original Crime Types (Left). Table 2. 18 USC § 3559 Crime Classification Table (Middle). Table 3. Severity Score (Right)

[7] "Crime Incidents 2006 - Present," accessed May 8, 2024, https://data.phila.gov/visualizations/crime-incidents.
[8] "18 U.S. Code § 3559 - Sentencing Classification of Offenses," LII / Legal Information Institute, accessed May 8, 2024, https://www.law.cornell.edu/uscode/text/18/3559.
[9] GENARO CORTEZ, "Federal Classification of Crimes," Law Office of Genaro R. Cortez, PLLC., June 7, 2021, https://cortezdefense.com/federal-classification-of-crimes/.

The crime severity dot map reveals that the most severe crimes occur in the northern and northeast parts of the city. West Philadelphia, the central city, and North Philadelphia show higher crime concentrations, while the far northeast and far north suburban areas report fewer incidents. From the crime severity density map, it is evident that the central city experiences a higher density of less severe crimes, despite appearing lighter on the dot map, which indicates fewer severe crimes like homicides. This suggests that a high volume of less severe incidents contributes to the overall intense crime density in this area.

Map 1. Crime Severity Dot Map (Left)

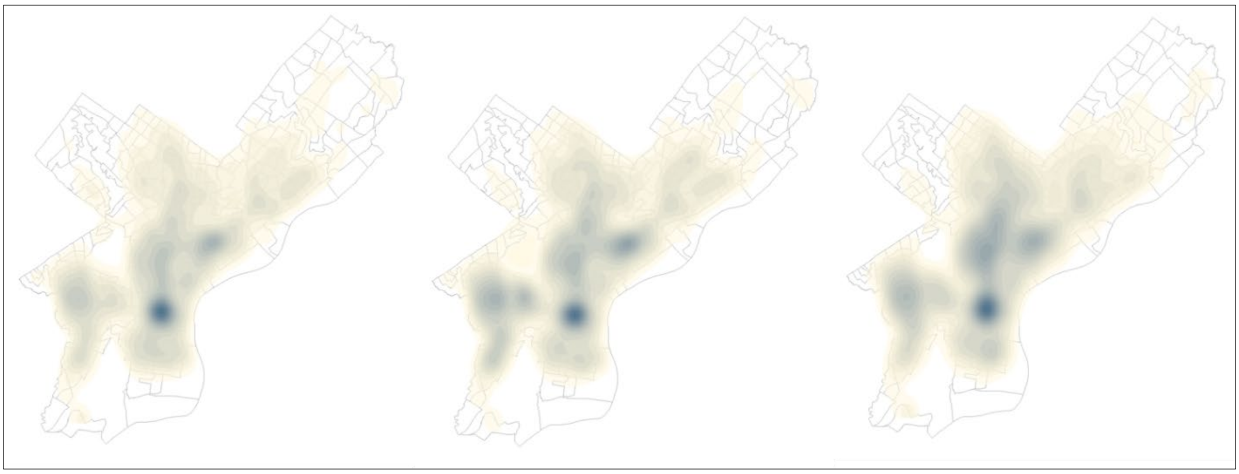


Map 2. Crime Severity Density Map (Right)

3.2. Time-based Analysis

The next step in data preparation is to aggregate the crime data into different time frames to explore the spatial-temporal changes in the crime hotspot areas and to deploy the police patrol force there more targetedly and precisely. Based on the same 8-hour time spans, crime data points are extracted for “8 AM to 4 PM”, “4 PM to 12 AM”, and “12 AM to 8 AM” to represent the distribution of crimes during the “daytime”, “evening”, and “nighttime” periods, respectively, within Philadelphia.

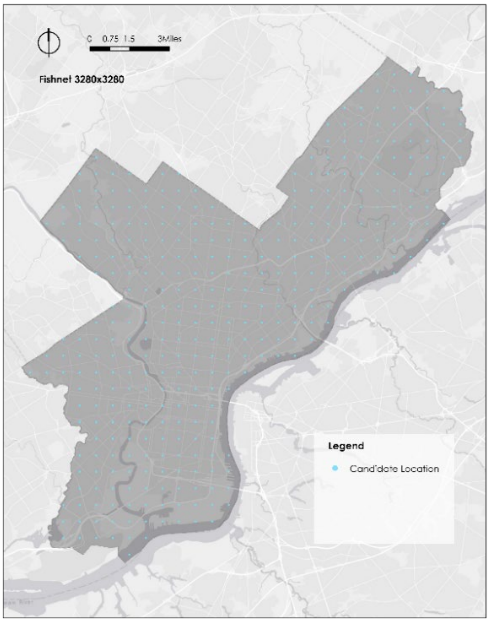
Following this aggregation, the overall number of crimes is observed to decrease progressively from daytime to evening and into nighttime. During the daytime, crime is predominantly concentrated in the central city, with other areas experiencing less activity. However, as the day progresses into the afternoon and evening, the western and northeastern parts of the city begin to show a higher intensity of crime. By nighttime, the trend shifts northwards, with northern Philadelphia demonstrating a notable increase in crime severity. This pattern underscores the temporal and spatial shifts in crime distribution throughout the day.

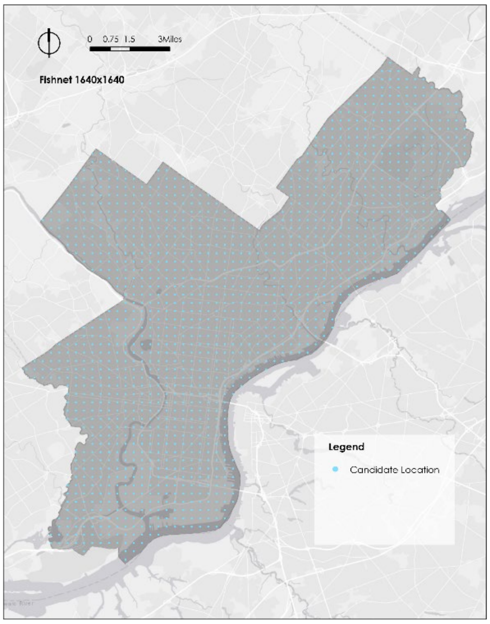


Map 3. Daytime Severity (8 AM-4 PM) Map 4. Evening Severity (4 PM-12 AM) Map 5. Nighttime Severity (12 AM-8AM)

3.3. Potential Allocation Locations

In the research, a fishnet grid is used to create potential locations for patrol police cars (the intersection points of the grid) with the boundaries of Philadelphia defining the limits of the fishnet creation[10]. During the research process, two different scales of fishnet are tested to balance the precision of site selection against the time required to compute model results: a finer scale of 1,640 feet by 1,640 feet and a coarser scale of 3,280 feet by 3,280 feet. The test results show that using a 1,640-foot grid requires a relatively longer solution time, especially when calculating results for the P-Median model. The 3,280-foot grid, due to its inability to select more precise locations, performs worse in terms of objective value compared to the 1,640-foot grid. Therefore, the finer scale grid of 1,640 feet by 1,640 feet is used in model building as the potential facility locations.





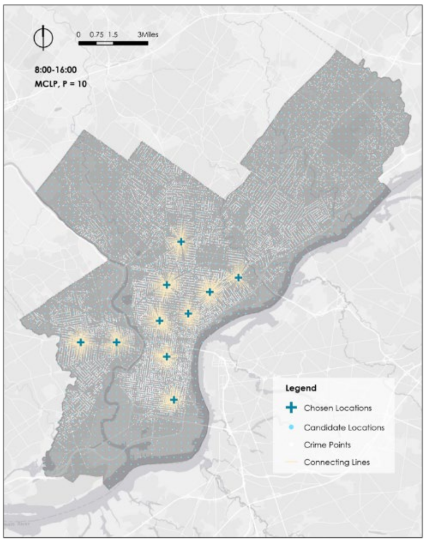
Map 6. 3280 ft * 3280 ft Fishnet (Left) Map 7. 1640 ft * 1640 ft Fishnet (Right)

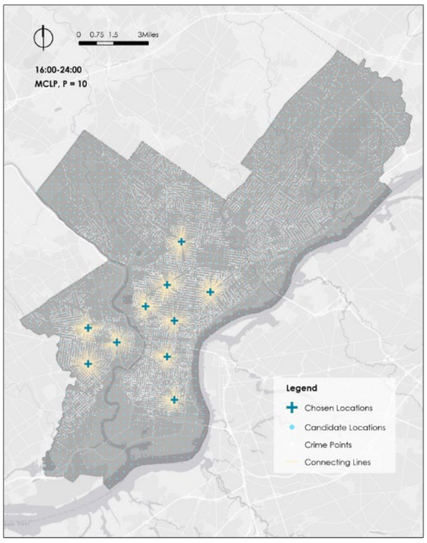
[10] "Census Tracts," OpenDataPhilly, accessed May 9, 2024, https://opendataphilly.org/datasets/census-tracts/.

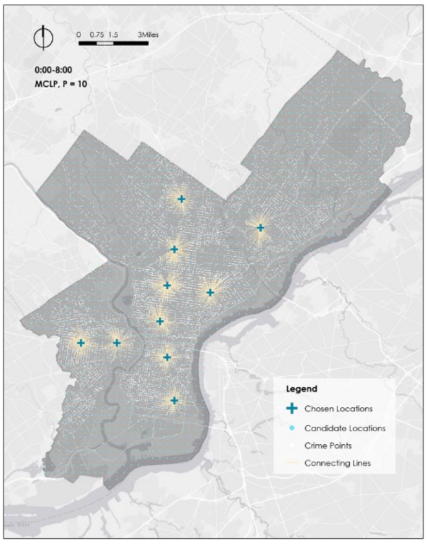
4. Model Results and Findings

4.1. Maximum Coverage Location Problem Model

When P is set to 10, the results of the MCLP model show notable distribution changes across different times of the day (Map 8, Map 9, Map 10). From daytime to evening, an increased number of police cars has been assigned to West Philly in response to the higher concentration of crime there. Despite a rise in severe crimes, Northeastern Philly has seen a smaller allocation of police cars due to the significant surge in crime severity within West Philly. From evening to nighttime, the selected police car patrol locations become more distributed towards the far north and far northeastern areas of the city. Although the central city also experiences increased severity at night, other parts show greater increases, so police are allocated to the areas with more severe crime.

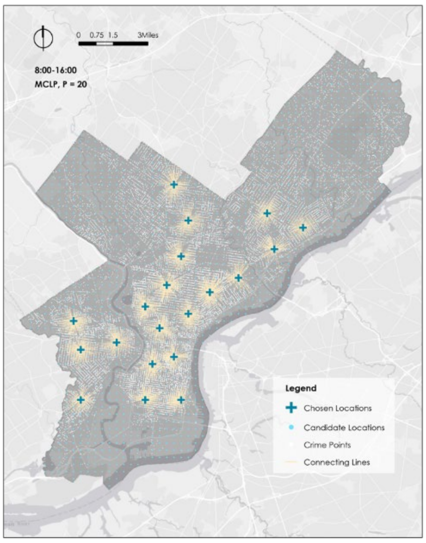


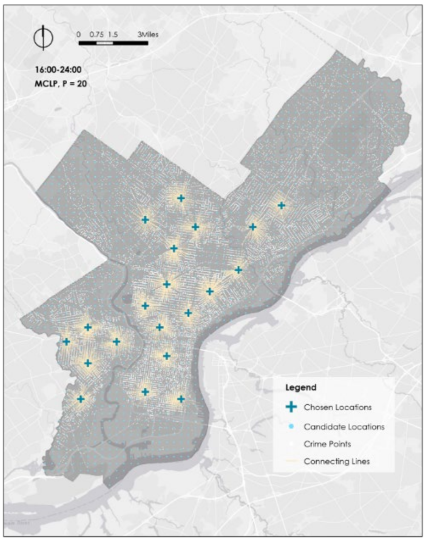


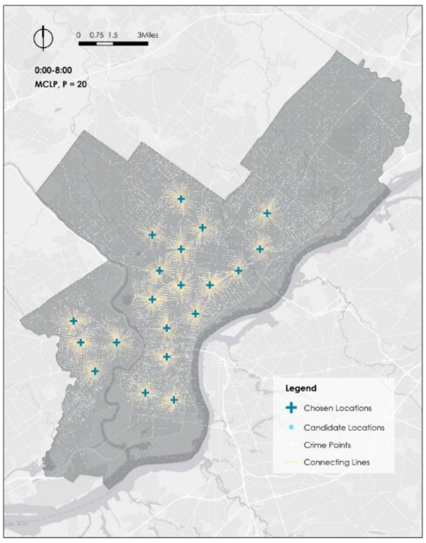


Map 8. Daytime MCLP, P = 10 (Left). Map 9. Evening MCLP, P = 10 (Middle). Map 10. Nighttime MCLP, P = 10 (Right).

When P equals 20, the site selections across the three different time periods are more similar compared to when P is 10, yet some variations still exist, reflecting the spatiotemporal dynamics of crime patterns and corresponding adjustments in police deployment strategies (Map 11, Map 12, Map 13). From daytime to evening, more police forces are deployed to West Philly and North Philly, areas where crime rates may rise due to increased evening activities. From evening to nighttime, aside from West Philly, there are no significant changes. This indicates that with an increased number of deployable police resources, most areas with high crime density and severity are already covered, and therefore, although there are some fluctuations in site selections over time, the overall changes are not pronounced.







Map 11. Daytime MCLP, P = 20 (Left). Map 12. Evening MCLP, P = 20 (Middle). Map 13. Nighttime MCLP, P = 20(Right)

4.2. Objective Value of MCLP

Table 5 illustrates the variations in the objective function values for two levels of patrol police car deployment, P = 10 and P = 20, throughout different times of the day: 8AM - 4PM, 4PM - 12AM, and 12AM - 8AM. For both deployment levels, the objective function value - which measures the total covered crime severity within a range of 4920 feet - is highest during the daytime period (8AM - 4PM) and decreases in subsequent time periods. However, the percentage of coverage consistently increases, which is attributed to the fact that the total crime severity during the daytime is the highest among the three time periods. The scenario with P = 20 consistently starts with a higher objective function value across all time periods compared to P = 10. This indicates that deploying more patrol police cars results in greater coverage and effectiveness.

Time Frame	Total Severity
8 AM - 4 PM	174400.5
4 PM - 12 AM	141531.5
12 AM - 8 AM	44732.5

Table 4. Total Crime Severity by Time Frame

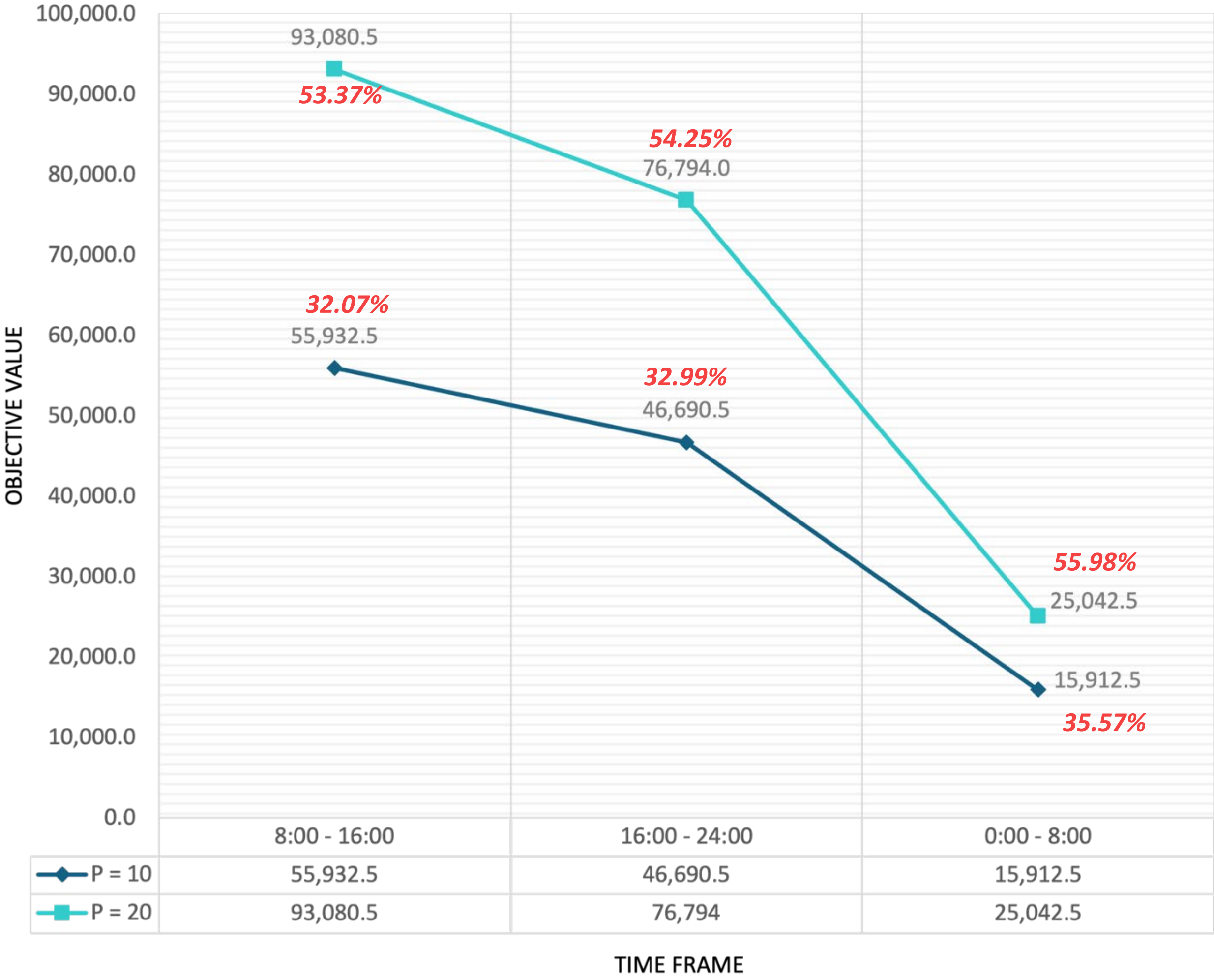
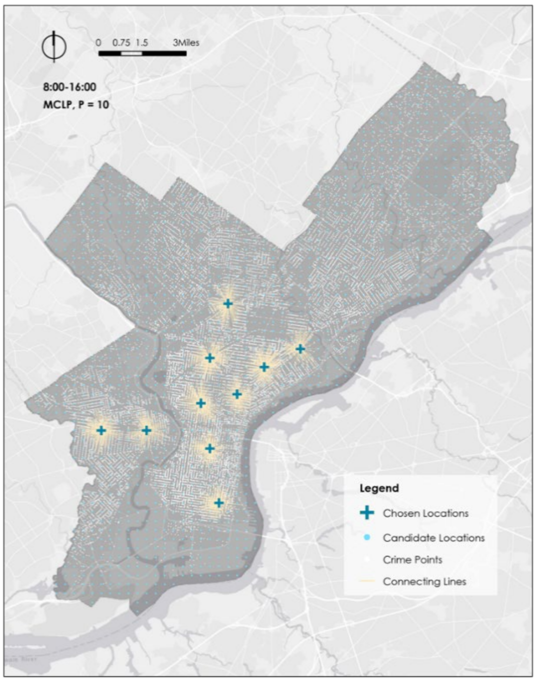
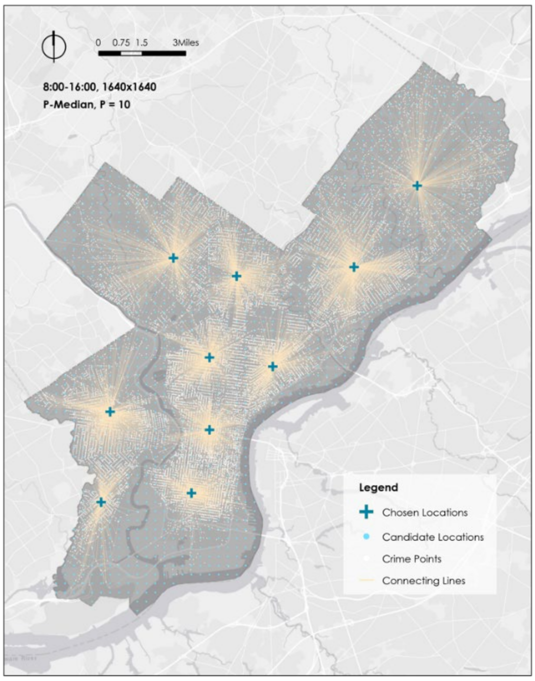


Table 5 Changes in MCLP Objective Value Under Varying Conditions

4.3. Model Comparison - MCLP and P-Median

For the comparative analysis of the MCLP and P-Median models, crime data from the “daytime” period, specifically “8 AM to 4 PM”, are chosen. This time frame is selected because it has the highest number of crimes, making the results more representative. With a value of P equal to 10, meaning only 10 police cars can be deployed within Philadelphia, the results of the two models show significant differences (Map 14, Map 15). The MCLP model’s selected locations are concentrated near Center City and University City, with some points extending northward and southward, but overall, the locations are compactly arranged around central areas. This distribution aligns well with the highly concentrated high crime severity areas, as the objective of the MCLP is to maximize the coverage of high-demand points within a fixed range. In contrast, the chosen locations in the P-Median model are not clustered in high-density or high-severity areas but are more evenly distributed across the map. This is because the P-Median model aims to minimize the total weighted distance to all crime points. Therefore, compared to the MCLP model, which is very sensitive to changes in crime severity, the P-Median is more responsive to spatial distance changes and is less affected by the weight value of crime severity.

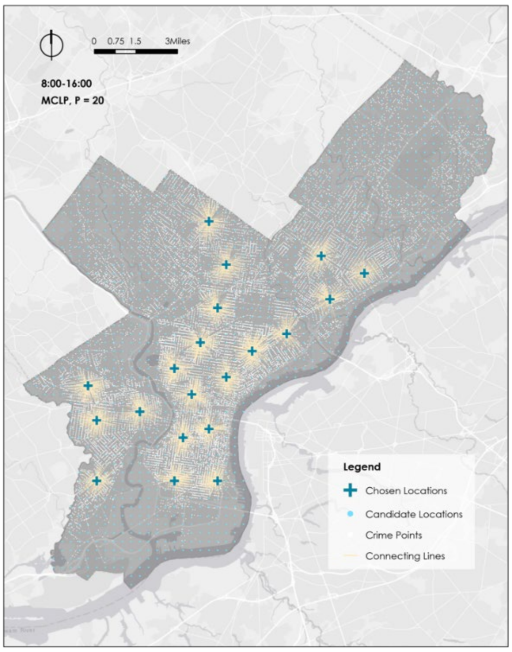


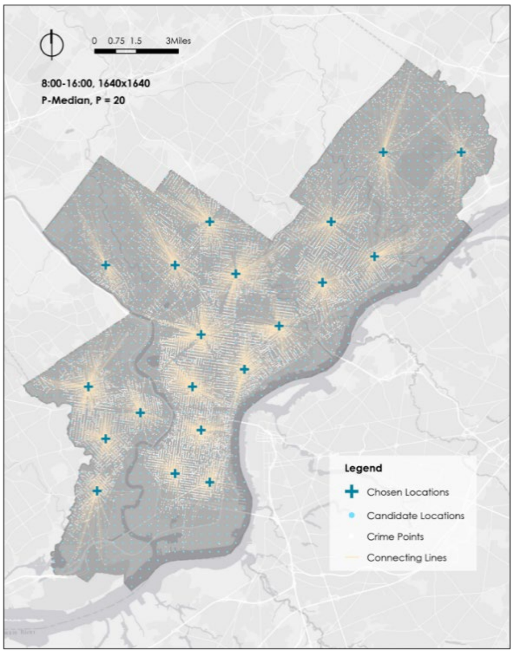


Map 14. Daytime MCLP, P = 10 (Left)

Map 15. Daytime P-Median, P = 10 (Right)

When P is set to 20, allowing for a relatively larger number of police cars to be deployed within Philadelphia, the overall site selection results of the two models still show differences (Map 16, Map 17). For instance, the MCLP model's locations remain relatively concentrated and do not include sites in the far northeast and far northwest, unlike the P-Median Model. However, the results of both models are closer compared to when P equals 10. This is because as the number of potential facility points increases, the sensitivity to spatial distance changes decreases, while the sensitivity to crime severity increases. This trend continues as the value of P further increases.





Map 16. Daytime MCLP, P = 20 (Left)

Map 17. Daytime P-Median, P = 20 (Right)

5. Policy Implications

Flexible Application of Model Results Based on Decision Objectives:

Choosing between different location-allocation models yields varying results, especially when police resources or budgets are limited (i.e., when there are fewer potential facility points). The choice between using the MCLP and the P-Median model can significantly differ: if the goal is to efficiently allocate limited resources, one might choose the MCLP model results to patrol and cover more severe crime locations; however, if fairness is a consideration, such as preventing some neighborhoods from severely lacking police resources or experiencing prolonged response times, the P-Median model might be selected to minimize the total response time across all areas. Thus, the actual decision-making process involves a trade-off, and the choice of which model to use, or whether to integrate results from both models, depends on the specific decision objectives.

Improving Police Deployment in High Crime Severity Areas:

By identifying areas and times with relatively high crime severity within the city, law enforcement can increase patrol frequencies and police presence during these periods in the affected areas. Moreover, a more detailed analysis of specific crime types can determine which crimes are more prevalent in particular areas, thereby enabling targeted preventive measures. This approach could involve dispatching specialized teams to different locations based on the predominant crime types identified.

Optimizing Emergency Response Strategies:

Research on the spatial distribution of crime severity can be utilized to optimize the allocation of police and emergency response resources. On one hand, establishing a dynamic system for data monitoring, analysis, and prediction would allow for the rapid response to spatiotemporal changes in crime through continuous collection of the latest crime data, enabling timely interventions for crime prevention. On the other hand, considering the establishment of rapid response centers in areas where crime severity is significantly higher could effectively manage emergency situations.

6. Conclusion

This study comprehensively analyzes and compares the distribution and differences of results when different numbers of facility points are selected using the MCLP and P-Median models. It demonstrates that the overall crime severity indeed shows varying spatial distribution patterns over time, thus providing feasible suggestions for the efficient allocation of police resources in Philadelphia based on different decision objectives.

The research recognizes certain limitations. The police patrol location problem can be viewed as a cost-benefit multi-objective model that aims to maximize benefits while minimizing costs as much as possible. Due to algorithmic constraints, the study primarily focuses on how to maximize benefits, namely, covering as much total crime severity as possible. However, it gives less consideration to costs, such as the distance from selected police car locations to police stations, and could further include factors like road congestion to calculate actual response times, which would add complexity to the final model. Additionally, considering the similarities between the police patrol location problem and the location-allocation problems for fire services and ambulances, future research could explore integrating the Backup Coverage Location Problem (BCLP) model with the current models to address situations where high-risk areas may have multiple response demands simultaneously.

7. References:

Gerald F. Pyle, "15. Systematic Sociospatial Variation in Perceptions of Crime Location and Severity," in Crime: A Spatial Perspective (Columbia University Press, 2019), 219–46, https://doi.org/10.7312/geor90788-022.

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