Baltimore Crime Intensity: A Spatial Analysis

MATH 536 Final Project
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I. Problem Statement

In Baltimore, major crimes against persons—such as homicide, assault, and robbery—pose significant challenges to public safety and resource allocation. Understanding the spatial distribution and severity of these crimes is essential for targeted interventions and effective policymaking.

This analysis aims to answer the question: *How can I predict the spatial distribution and severity of major crimes against persons in Baltimore for the year 2024 to identify crime hotspots across the city?* By leveraging historical crime data, I seek to model and visualize crime intensity patterns using geospatial statistical methods.

II. Data Description

The data used for this analysis is sourced from Open Baltimore, a publicly accessible website that provides detailed records of crimes reported across the city. The dataset includes information on crime type, offender details, time, and geographic coordinates, making it well-suited for spatial modeling and prediction. For this study, the dataset is filtered to include crime occurrences between January 1, 2024, and December 2, 2024.

As part of the data preprocessing, a crime severity scale is defined and the following severity ratings are assigned to each corresponding observation:

Crime	Severity Rating
Homicide	10
Rape	9
Aggravated Assault	8
Common Assault	7
Shooting	7
Robbery - Carjacking	6
Robbery - Commercial	6
Robbery	5
Burglary	4
Arson	4

Auto Theft	3
Larceny from Auto	2
Larceny	1

Since there is a very large number of observations (about 40,000), crime locations are discretized onto a 40x40 grid covering the city of Baltimore. Within each grid location, the total crime severity is computed as the sum of the severity ratings of all crimes occurring within that grid cell. **Figure 1** illustrates the spatial distribution of crime locations overlaid onto this grid on a map of Baltimore, highlighting the geographic extent of the data and its aggregation into grid cells for analysis. This discretization provides a structured representation of crime data, enabling the application of spatial modeling techniques.

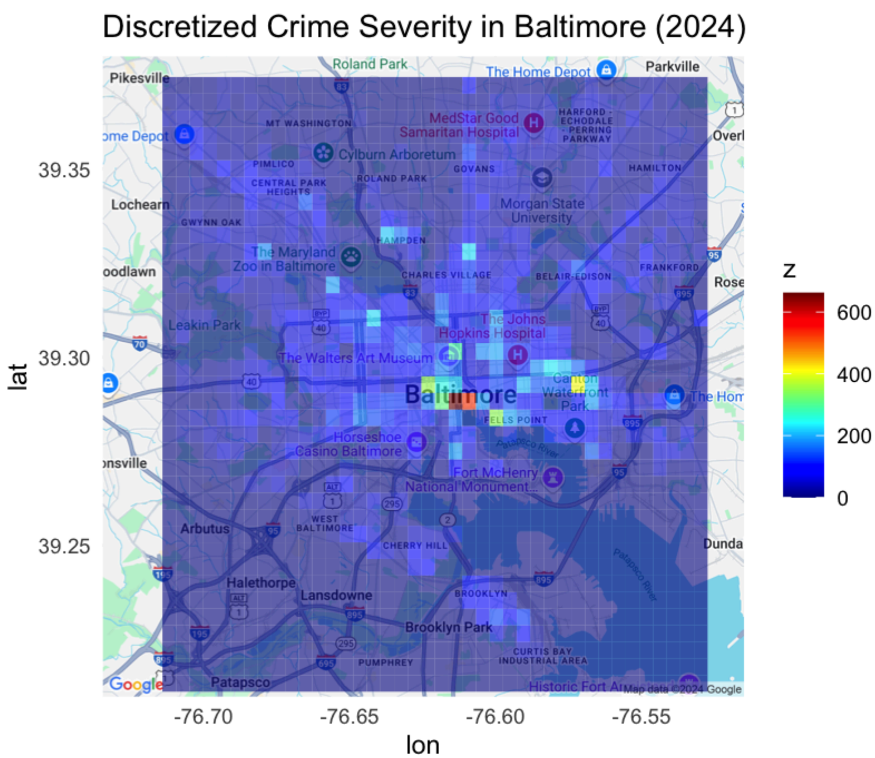

Figure 1

III. Statistical and Graphical Methods

A Poisson regression model with Gaussian process-based Kriging is used to estimate the log intensity surface of crime severity. The model parameters (λ and θ), which control spatial smoothness and scaling, are optimized through a grid search. A log-likelihood surface is generated over the parameter space to identify the maximum likelihood estimates (MLEs) for λ and θ, providing the best-fitting parameters for the model. The model is then evaluated at the

MLEs for λ and θ and a log crime severity surface is predicted from this fit. The log crime severity surface is then transformed back to its original scale.

IV. Results

The MLE parameter estimates for λ and θ are 48.3293 and 0.0058, respectively. The log-likelihood surface can be seen in **Figure 3** in the Appendix. Also, a summary of the model for log crime is included as **Figure 5** in the Appendix.

The estimated crime severity surface for Baltimore in 2024 is shown in **Figure 2**, where the intensity of predicted crime severity is represented spatially across the city. Areas with higher crime severity are highlighted using a color gradient, ranging from blue (lower severity) to red (higher severity).

Contours outline regions with the top 5% and 1% highest predicted crime severity values. The top 5% regions, depicted by lighter red contours, primarily cluster around downtown Baltimore and extend toward nearby neighborhoods. These areas include densely populated regions and zones associated with high commercial or social activity, suggesting concentrated hotspots of major crimes. The top 1% severity regions, marked with darker red contours, are confined to smaller, more localized areas including central downtown Baltimore, further emphasizing specific high-severity zones.

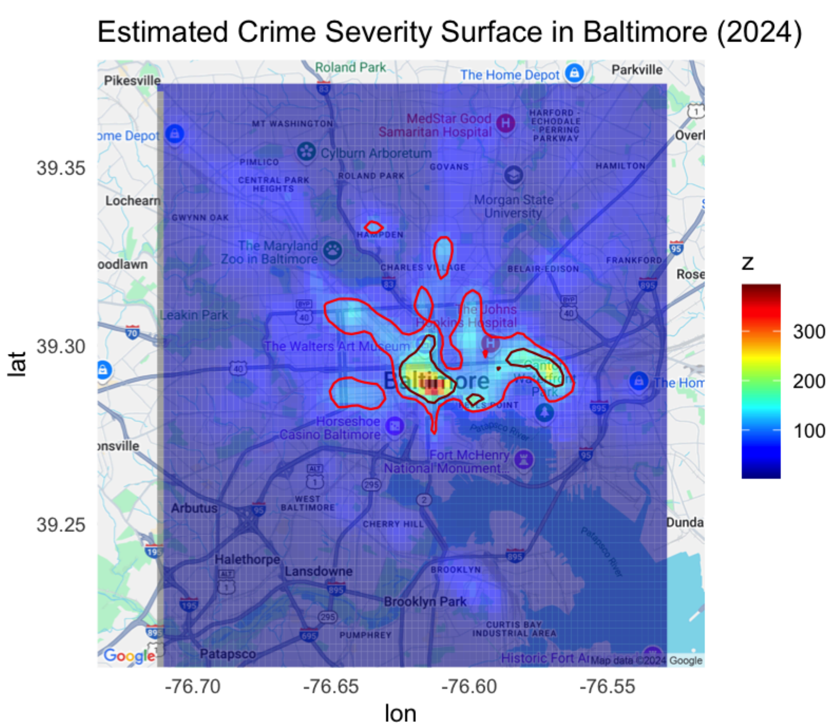

Figure 2

V. Conclusion

This analysis focused on predicting the spatial distribution and severity of major crimes against persons in Baltimore for 2024. The results identified significant hotspots of crime severity within central Baltimore. By integrating spatial modeling techniques with historical crime data, a more nuanced understanding of high-severity crime areas was developed, which has implications for resource allocation and public safety strategies. The predictive framework provides actionable insights that can support data-driven decision-making for law enforcement and policymakers.

VI. Future Work

Future work could expand the model to incorporate temporal dynamics by integrating seasonality or socioeconomic variables, such as poverty rates or unemployment statistics, to capture broader influences on crime patterns. Additionally, analyzing spatial crime trends over time would provide valuable insights into the evolution of crime hotspots and the effectiveness of interventions.

Appendix: Additional Figures

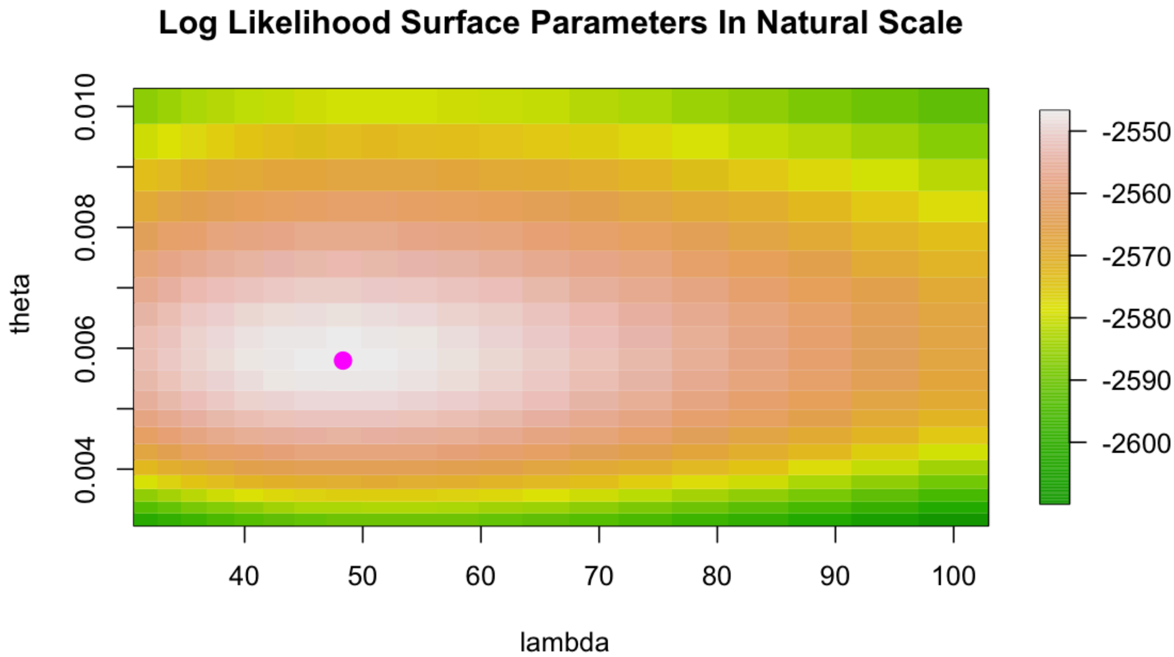

Figure 3

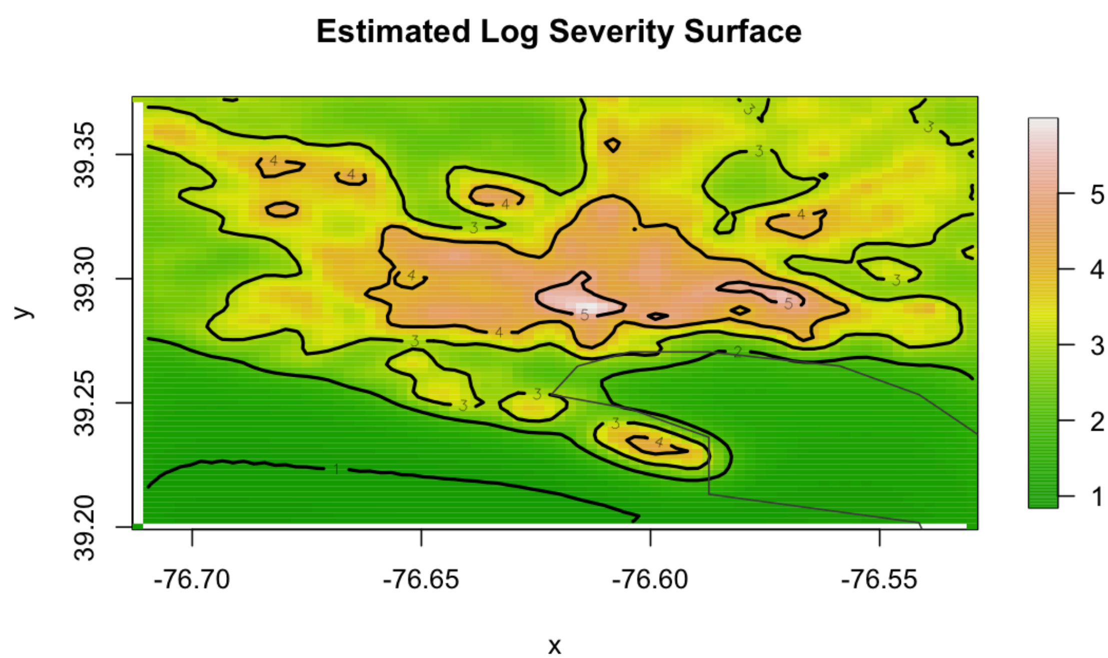

Figure 4

```r
summary(objFit)
```

```
## [1] -416.901263    1.753878   14.097139
```

```
## Call:
## mKrig(x = s, y = yPS, weights = mu.old, lambda = lambda, theta = theta)
##
##  Number of Locations:                             1600
##  Degree of polynomial null space ( base model): 1
##  Total number of parameters in base model       3
##   Estimate Eff. degrees of freedom              360.7
##      Standard Error of Eff. Df                  4.128
##  Smoothing parameter                            48.33
##  tau (nugget sd)                                3.75
##  sigma (process sd)                             0.5395
##  Nonzero entries in covariance                  2560000
##
##
## Summary of fixed effects
##    estimate      SE    pValue
## d1 -416.900 82.0700 3.773e-07
## d2    1.754  0.9316 5.974e-02
## d3   14.100  1.0530 6.612e-41
##
## Covariance Model: stationary.cov
##    Covariance function:   Exponential
##    Non-default covariance arguments and their values
##    Argument: theta  has the value(s):
## [1] 0.005796394
##    Argument: onlyUpper  has the value(s):
## [1] FALSE
##    Argument: distMat  has the value(s):
## [1] NA
```

Figure 5