Poster #474

Evaluation of the co-influence of green coverage, social factors, and neighborhood factors on crime rate - a case study of Baltimore City

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CHARMED Community Health: Addressing Regional Maryland Environmental Determinants of Disease

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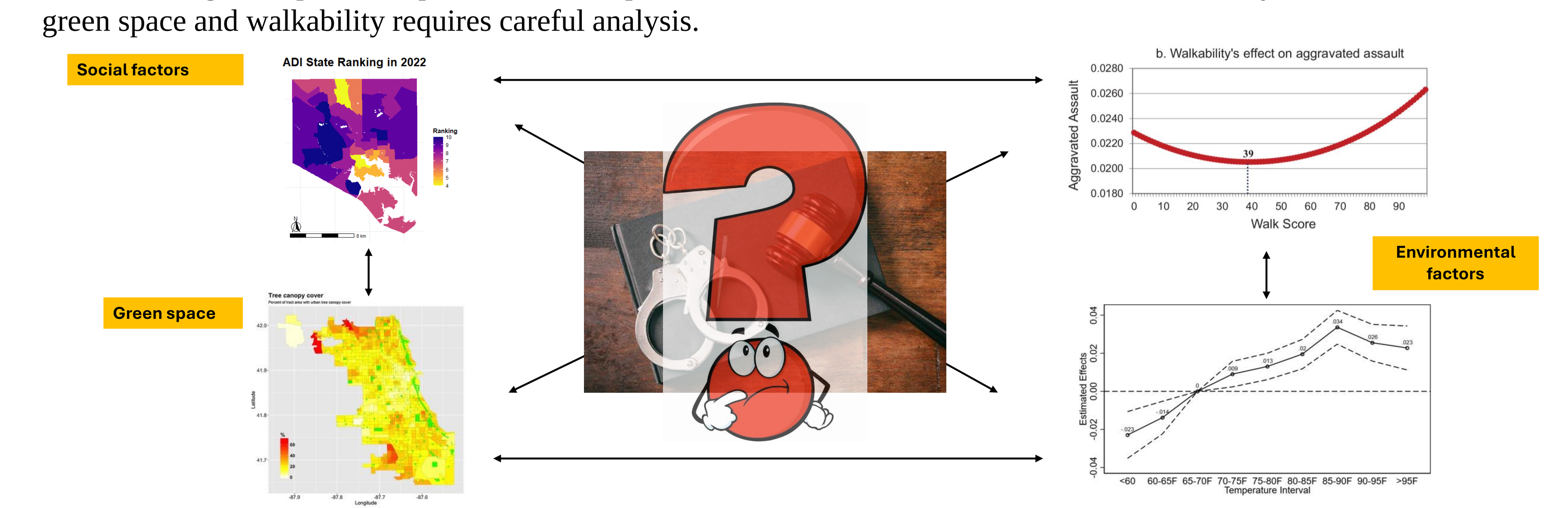
Introduction

- Baltimore's crime rate remains high, even during the pandemic. The "Black Butterfly" illustrates the racial and economic disparities, concentrated in vulnerable areas[1].
- A rise in extreme heat events in Baltimore from 2016 to 2022, with a peak in 2020. In 2022, multiple summer days exceeded 90°F, highlighting the increasing frequency of extreme heat[2].
- Factors like green space, temperature, and deprivation are linked to crime rates, but collinearity between variables like green space and walkability requires careful analysis.

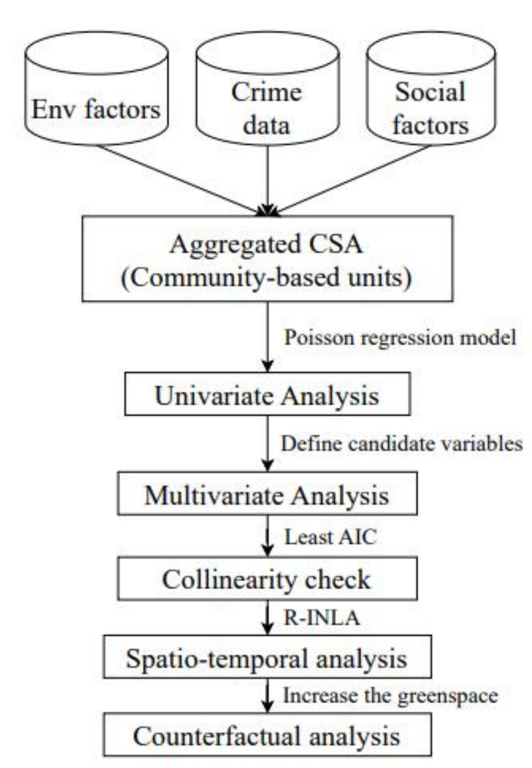


Method

Data

- Category
  - Green space percentage[3], temperature[2], crime[4], walkability[5], Percentage of sleep less than 7 hours[5], Area Deprivation Index (ADI) ranking[6], Lockdown week[7].
- Time
  - 2016-2022 (weekly)

Study framework



Statistical method

- Zero-Inflated Poisson Regression
  - $\Pr(Y=0)=\pi+(1-\pi)e^{-\lambda}$
  - $\Pr(Y=y_i)=(1-\pi)\frac{\lambda^{y_i}e^{-\lambda}}{y_i!}, y_i=1,2,3\ldots$

  where the outcome variable y_i has any non-negative integer value, λ is the expected Poisson count for the i^{th} individual; π is the probability of extra zeros.
- INLA approach[8]
  - A fast and accurate method for Bayesian inference in hierarchical models, particularly useful for spatial and spatiotemporal models.
  - $Y_{ij} \sim Poisson(E_{ij}\theta_{ij})$

  where Y_{ij} is the observed number of cases, E_{ij} is the expected number of cases, and θ_{ij} is the relative risk of CSA i and week j.
  - $Y_{ij} \sim a_{ij} + b_{ij} + f(CSA, model = "bym2", graph = g)$

Y_{ij} represents the crime incidents in CSA i and day j, a_{ij} and b_{ij} are the considered factors in CSA i and week j; g represents the adjacency matrix defining the neighborhood structure among the CSAs. The 'bym2' model delivered the unstructured random effect.

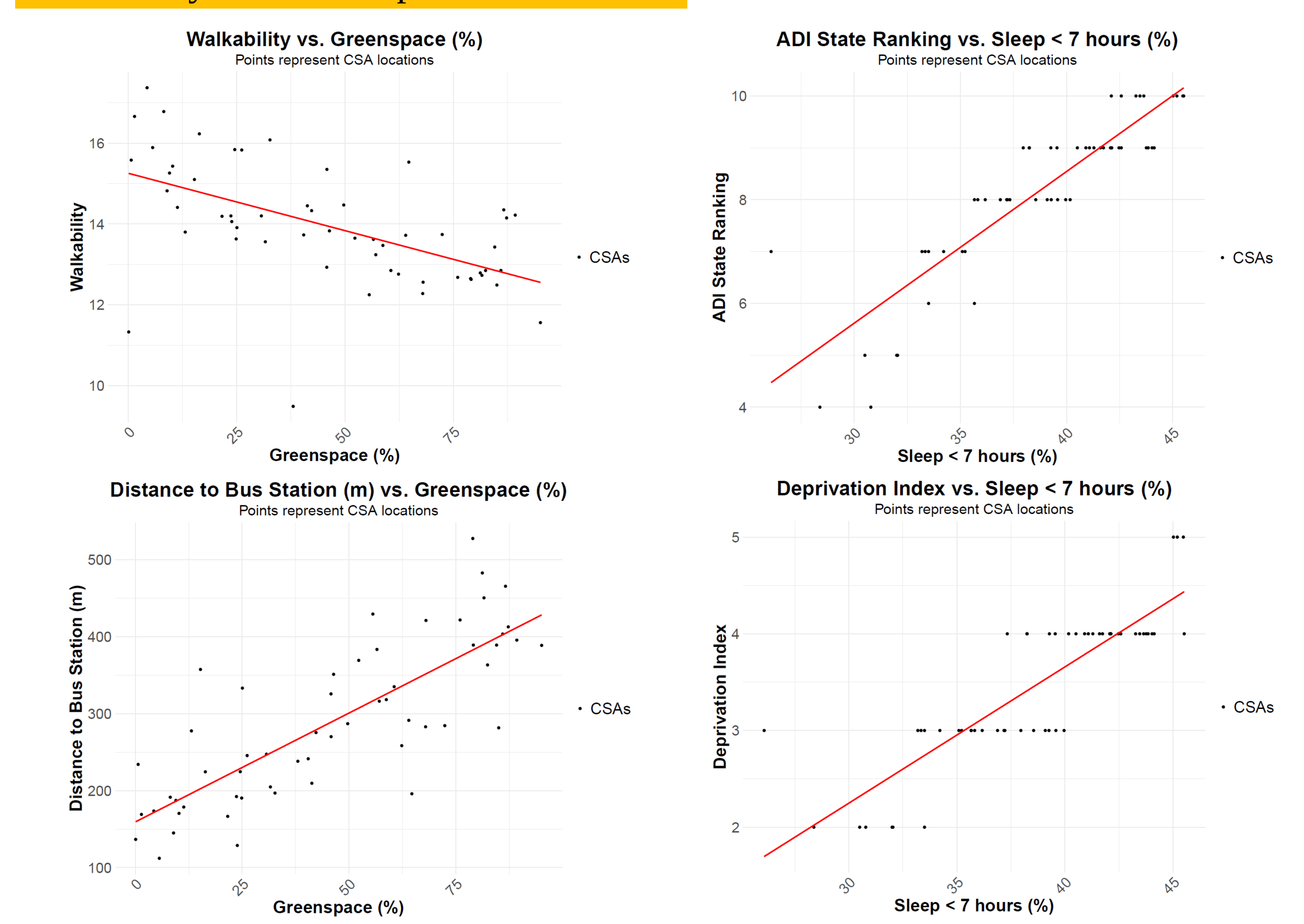
General Regression

Univariate analysis

Table 1. The RR of each variable in univariate analyses

Description	Per unit change	Relative Risk (RR)	Lower	Upper
Greenspace	1 %	0.280	0.274	0.286
Deprivation ranking	1	1.615	1.601	1.629
Walkability	1	1.101	1.097	1.106
Percentage of sleep less than 7 hours	1 %	1.105	1.103	1.107
Distance to bus station	1 m	0.996	0.996	0.996
Temperature	1 °F	1.006	1.005	1.006
Lockdown week	Binary	0.867	0.838	0.896
ADI state ranking	1	1.415	1.407	1.423
ADI national ranking	1	1.032	1.032	1.033

Collinearity between important covariates



Spatio-Temporal (ST) Analysis

Result

- The factors influencing crime align with general regression findings, with risk concentrated in the central, east, west, and north areas

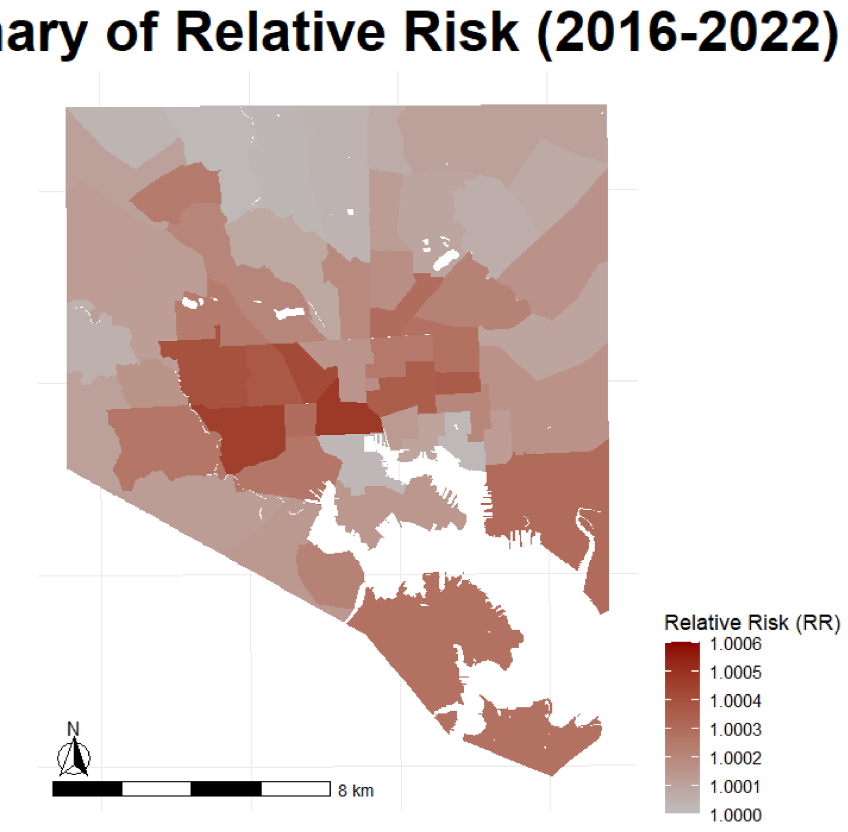
Table 2. Result of ST analysis before 2020

Term	RR	Lower	Upper
Greenspace	0.111	0.067	0.186
Temperature	1.005	1.004	1.005
Sleep less than 7 hours	1.134	1.095	1.176
Phi for CSA	0.143	0.009	0.504

Table 3. Result of ST analysis after 2020

Term	RR	Lower	Upper
Greenspace	0.115	0.067	0.199
Temperature	1.004	1.004	1.005
Lockdown	0.857	0.827	0.887
Sleep less than 7 hours	1.145	1.103	1.189
Phi for CSA	0.173	0.011	0.581

Summary of Relative Risk (2016-2022)



Counterfactual Analysis

Scenario setting

- Greenspace boost

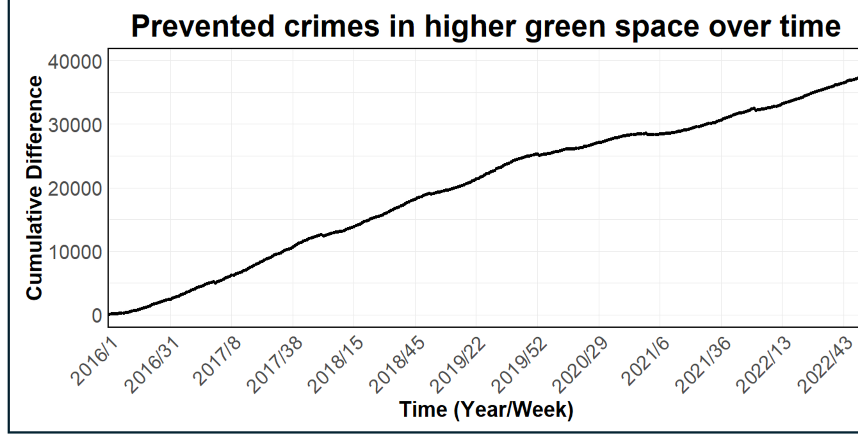
Increase the percentage of green space in each CSA to at least the 75[th] percentile based on the current level.
- Health co-benefit

Assess the number of prevented crimes using the fixed parameters for each factor from the ST analysis.

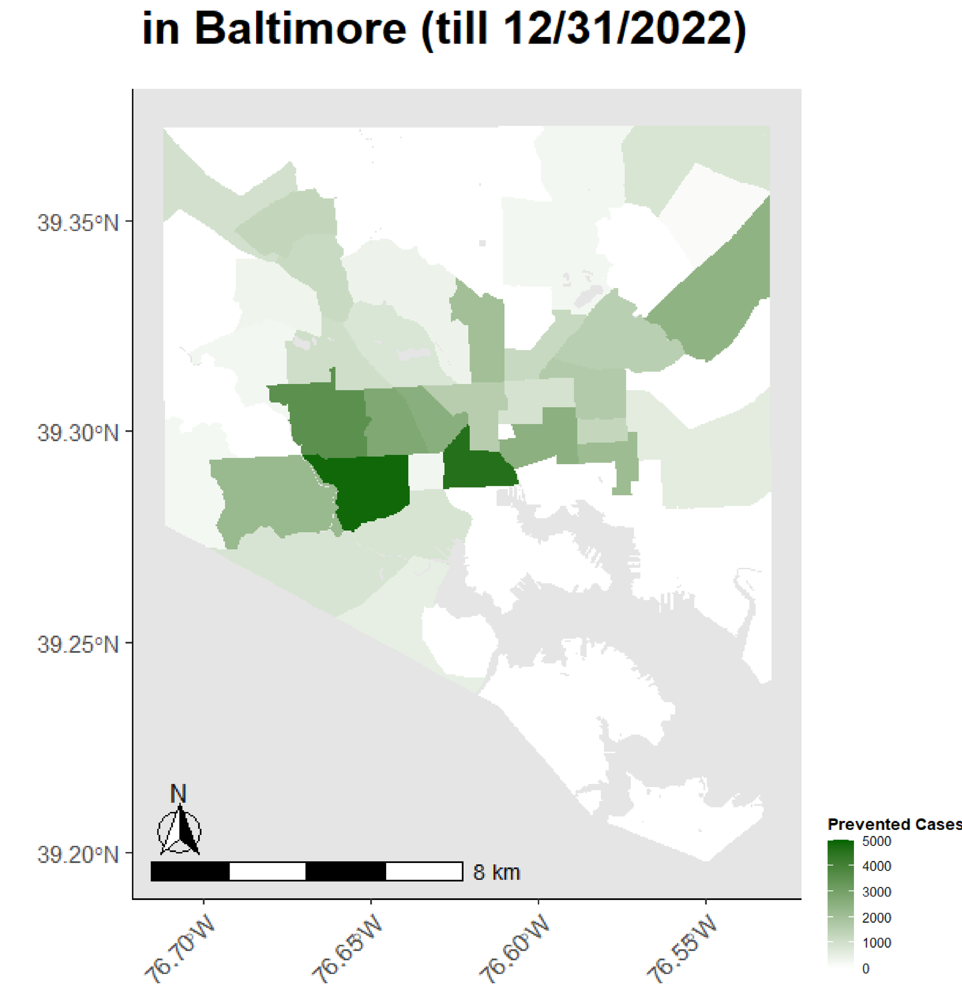
Results

Between 2016 and 2022, increasing green coverage could have prevented 37,365 crimes in total, with Southwest Baltimore seeing the greatest benefit (4,869 crimes), followed by Downtown/Seton Hills (4,603 crimes) and Greater Rosemont (3,526 crimes).

Prevented crimes in higher green space over time



Cumulative Prevented Crime Incidents in Baltimore (till 12/31/2022)



Discussion

- **Limitation**
  - Limited by secondary data and study design, can't define causality. These variables interact each other in complex ways, making it difficult to determine if any single variable is causing the crime.
  - Many of the criminal records don't have reliable location information.
  - Population structure changes dramatically around COVID-19.
- **Strength**
  - Integrate spatial and temporal analysis for detailed insights.
  - Assessing the relationship between social and environmental factors and crime together.
  - Offers empirical evidence supporting policy and intervention strategies.

Conclusion

- Our preliminary results suggest environmental and social factors affect crime in a complex ways, and that crime risk is concentrated in specific areas.
- The protective effect of green space is significant to crime rate in Baltimore City, the RR is 0.28 (95% CI [0.27-0.29]).
- The ADI ranking is positively correlated with crime rates.
- High walkability may be positively related to crime rates.
- Lockdown decreased the crime rate, but the greenspace show a stronger effect.
- Raising the green space in each CSA to the 75[th] percentile could prevent nearly 40,000 crimes over 7 years.

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