



# Stadia as risky places: The importance of context

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Leisure and  
fun

Large  
gatherings

Team  
Rivalry

Sports,  
concerts &  
others

After game  
celebration



- Financial services
- Construction
- Environment
- Social engagement
- Management
- Marketing
- Technical
- Insurance
- Business (e.g., Food & Drinks)
- 
- 
- 
- **Crime occurrences**



# Crime patterns associated with sporting events?



Time difference for fans:  
Local fans vs global fans vs **fluid fans**  
(new term in the sports industry)

# Agenda

- Stadia (or stadiums) in relationship with crime
- Crime – sporting events – social media
  - Understanding patterns
  - Prediction and biases
- New technologies, modern applications – adapting theory?

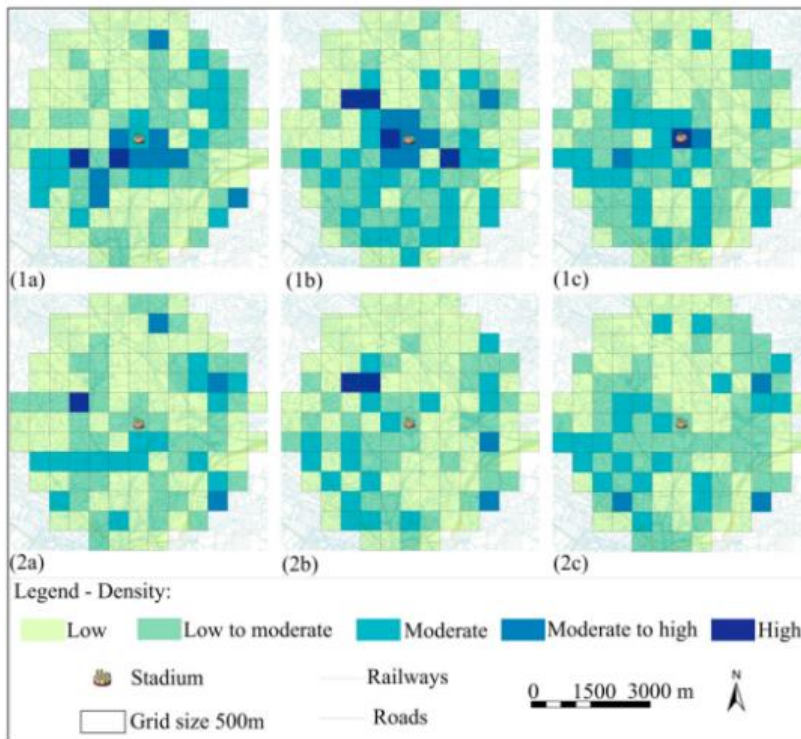




# Literature

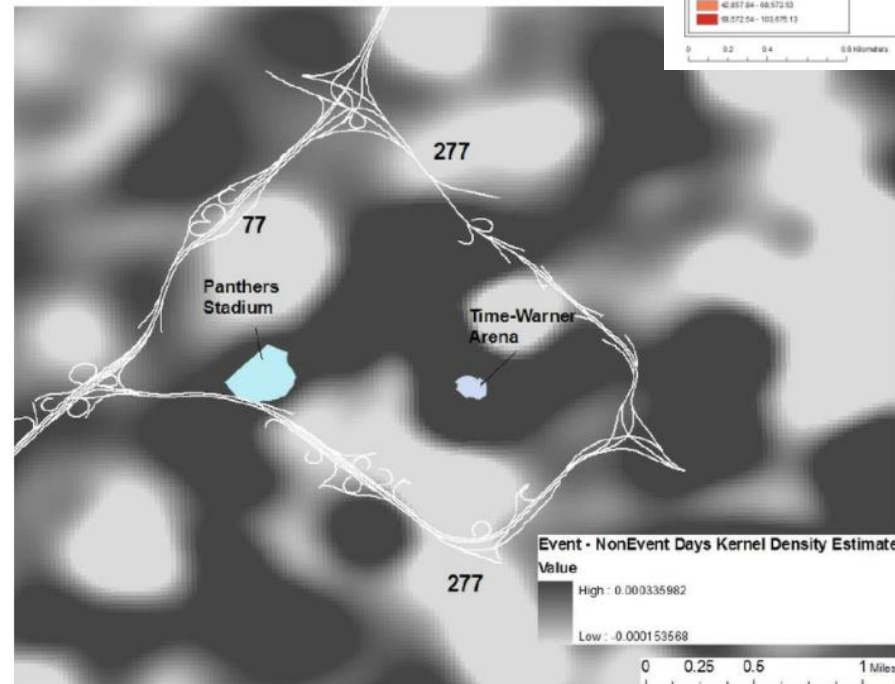
Ristea et al 2018

**Figure 7.** Density for each crime type (a) criminal damage, (b) theft and handling, and (c) violence against the person; (1) match days, (2) comparison days (using the Natural Jenks classification method).

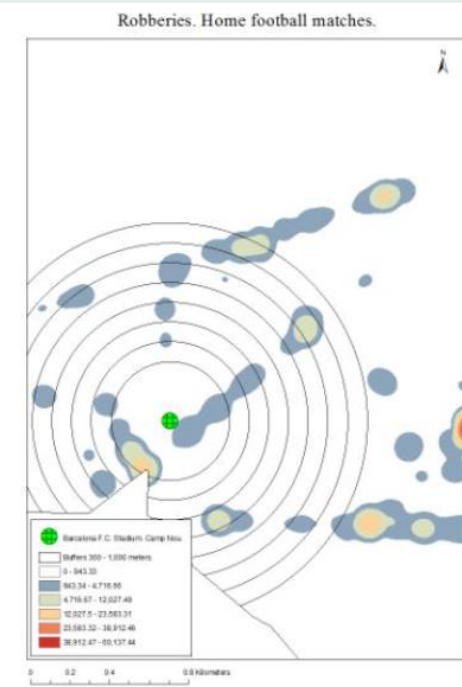
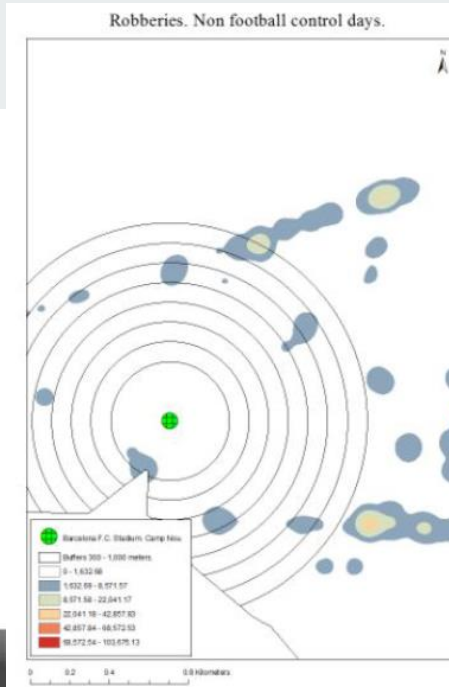


Game days  
vs  
comparison days

Billings & Depken 2012



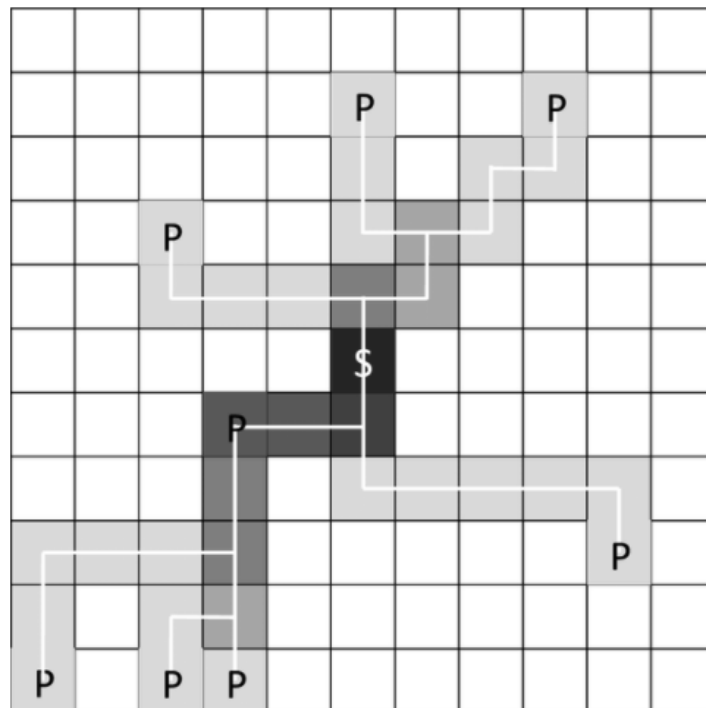
Kernel Density Estimator Depicting Distribution of Difference in Total Reported Crime in Charlotte NC on Event Days and Non-event Days from January 1, 2005 through December 31, 2008



Struse and Montolio (2014)

# Literature

Kurland & Johnson 2019



Example of the shortest network distance (SND) approach to estimating movement potential between "micro-facilities" (pubs in this example) and the relevant stadium

Game days  
vs  
comparison days

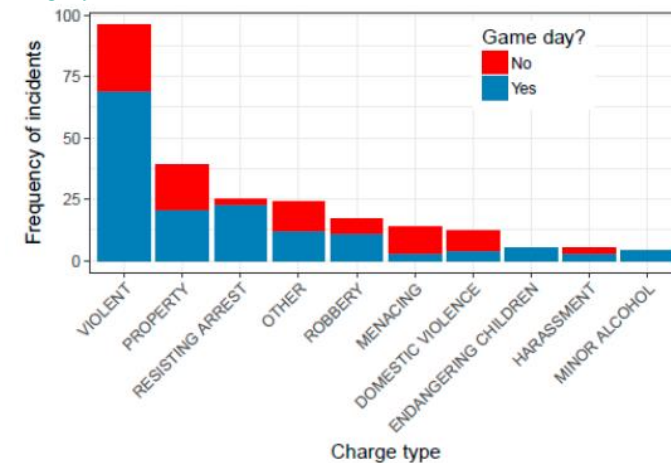
Klick & MacDonald 2021

**Table 4** Effect of extra innings on assaults

Before and After Xfinity Live! Opens

	Baseline extra innings effect	Additional pre-2012 extra innings effect	Observations
Extra innings*Home game*CBP coefficient	0.04*** (0.0004)	-0.05*** (0.0006)	2,029,384
Permutation <i>p</i> (t stat) 1-sided	<0.028	<0.022	
Permutation <i>p</i> (t stat) 2-sided	<0.064	<0.047	

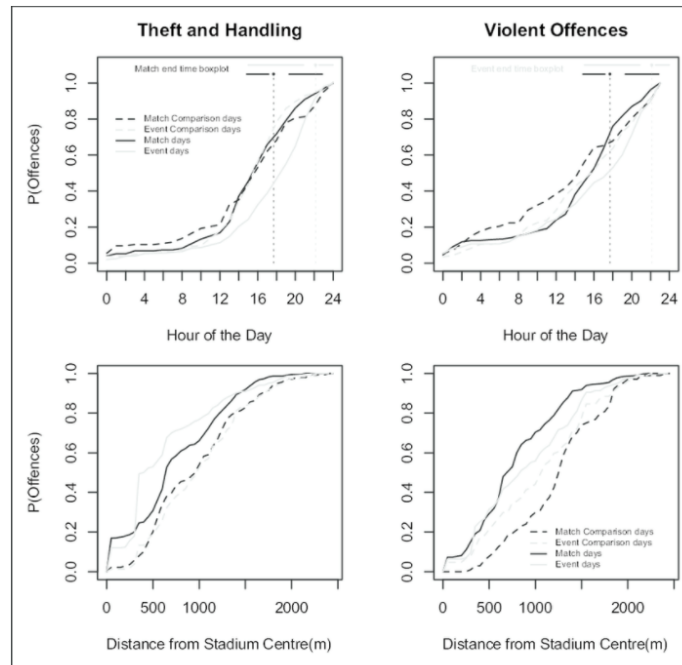
Menaker et al 2019



**Figure 1.** Frequency of 11 types of charges reported within 800 m of two professional sports venues in Cleveland, OH, January 2009 – February 2014. Charge frequency generally increased on game days (table 1) although the effect was limited to specific charges (figure 2).

# Literature

Kurland, Johnson & Tilly 2019

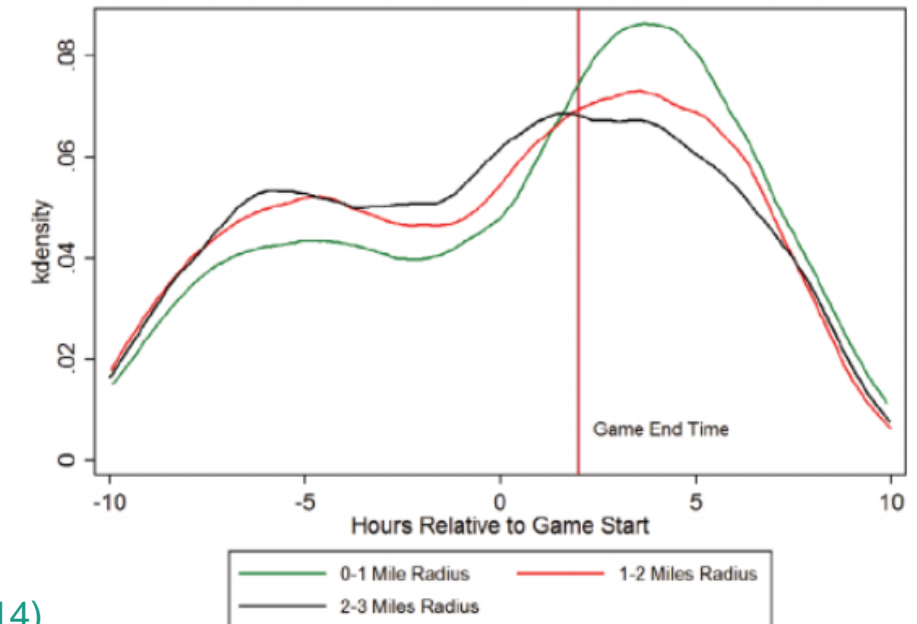


The empirical cumulative distribution function (ECDF) for the two categories of crime (and boxplots for the end times of matches and events).

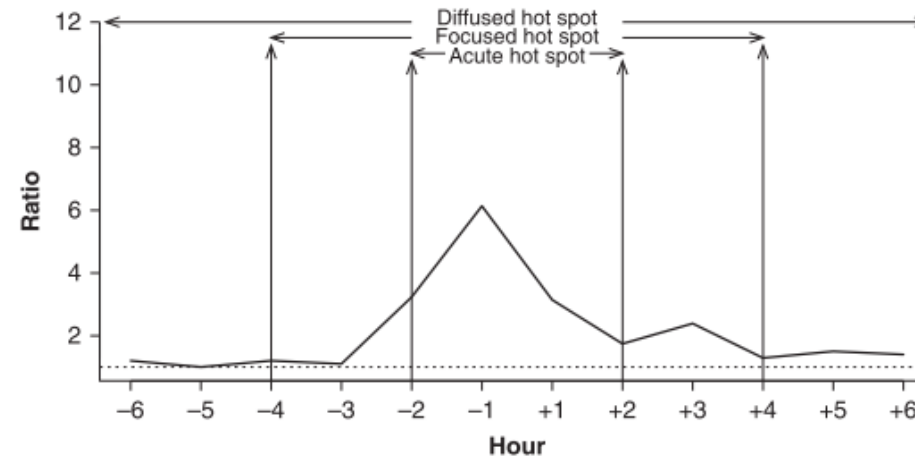
Game days  
vs  
comparison days

Ge, Barbieri & Schneider 2020

Density Distribution of Property Crimes.



Kurland, Tilley and Johnson (2014)



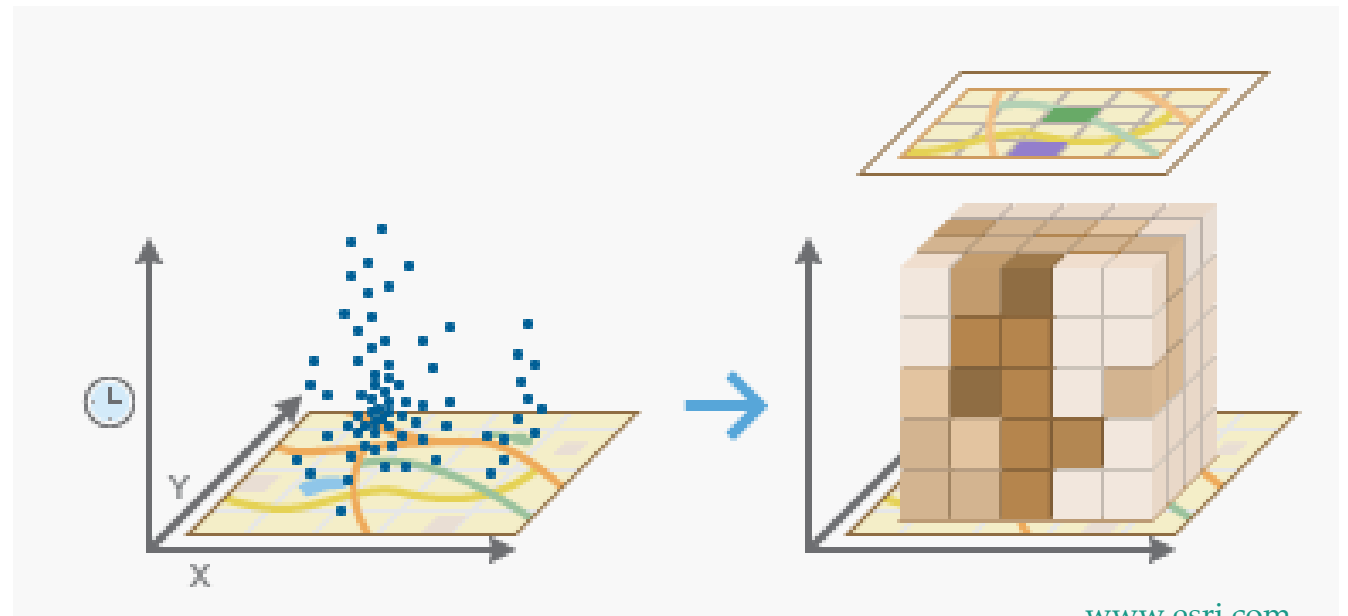


# Context

- Case studies for specific locations (Country/State specific)
- Built environment
- Type of fans
- Transportation mode - infrastructure
- Cultural differences
- Event characteristics: rival teams, friendly game, championship, timeline

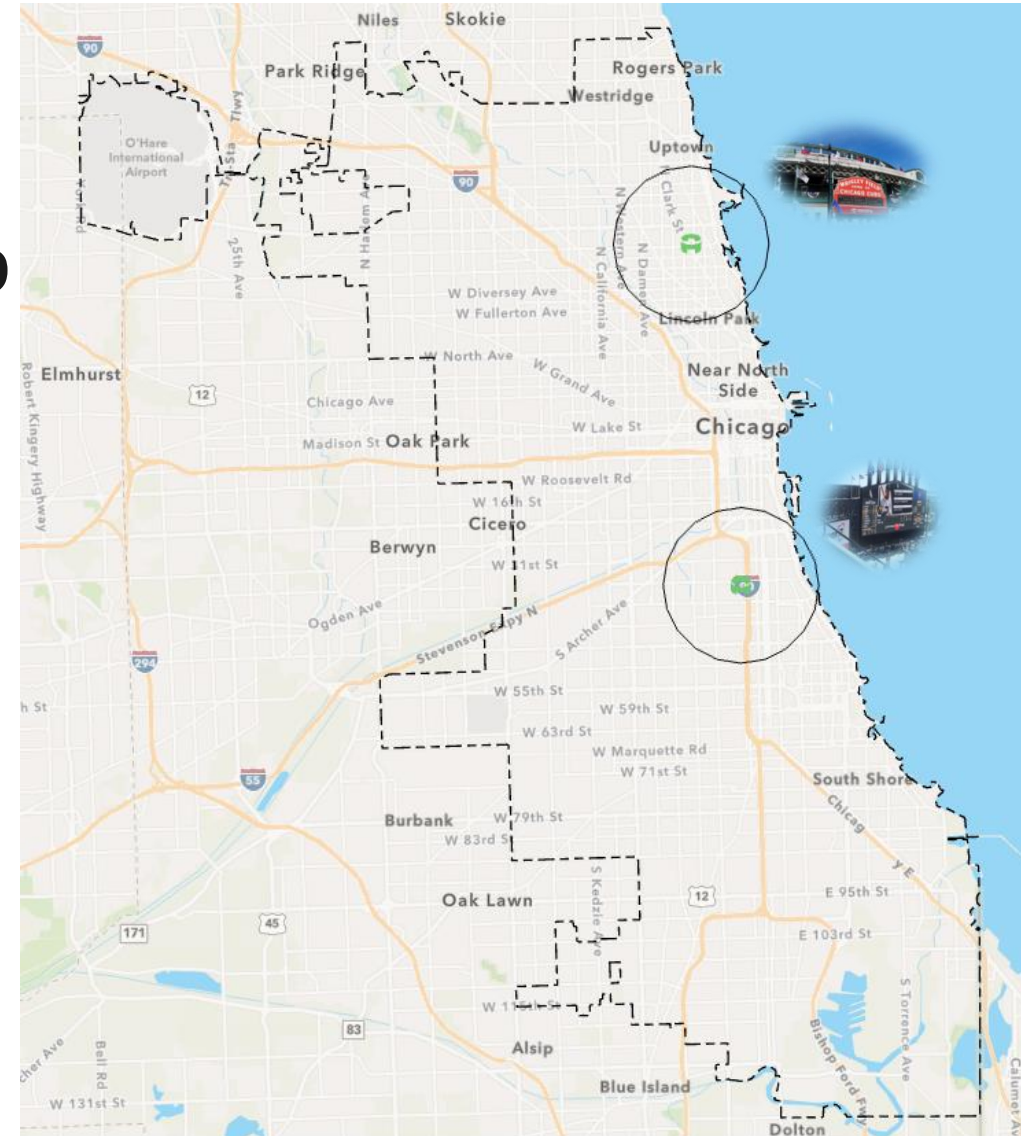


# Spatiotemporal Space-time cube

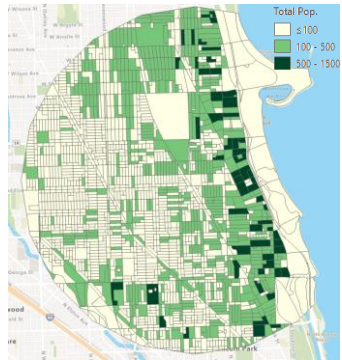


# Two baseball stadia in Chicago

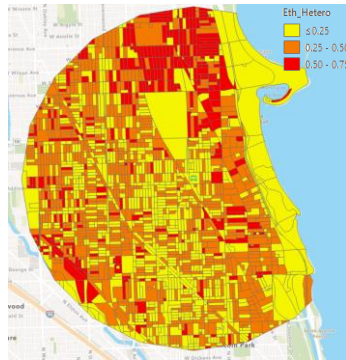
- Crime data: 2017 – 2019
- Methodology: game vs comparison days
- Spatial Unit: Census Block
- Temporal Unit: 2h before the game and 2h after the game (considering a game of 3h)



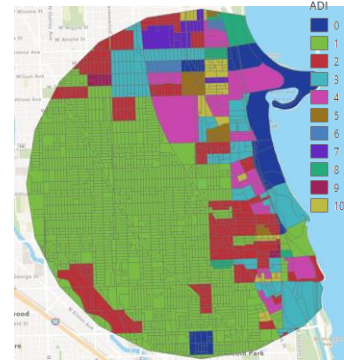
# Two baseball stadia in Chicago



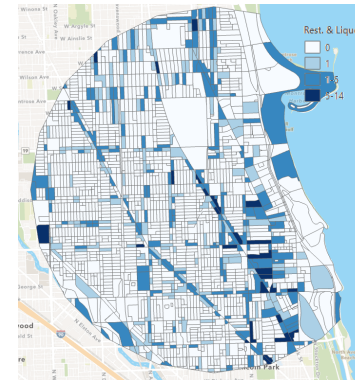
Total Population



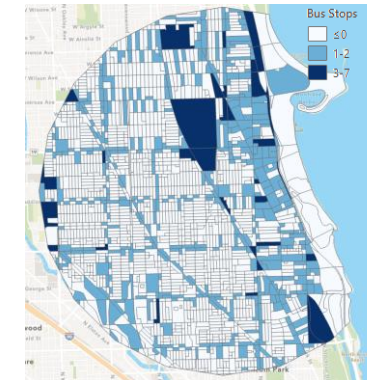
Ethnic  
Heterogeneity



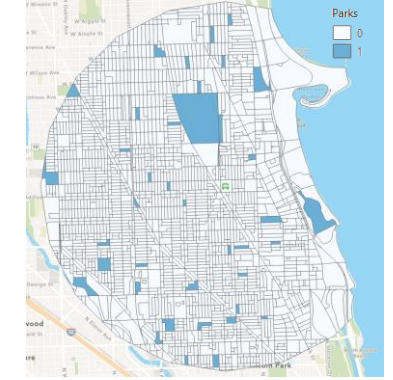
Area Deprivation  
Index (ADI)



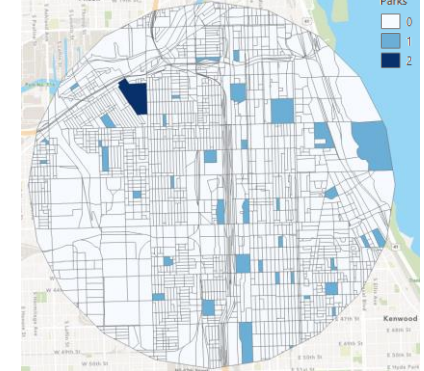
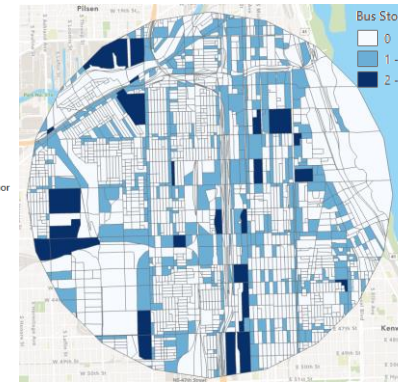
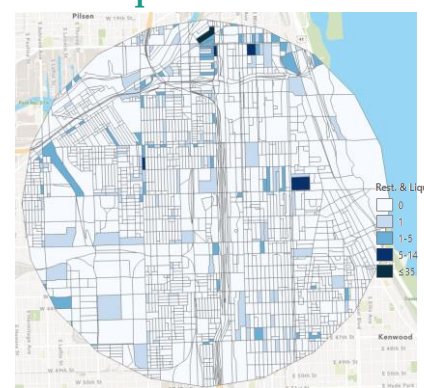
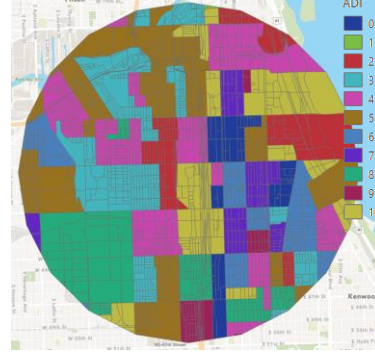
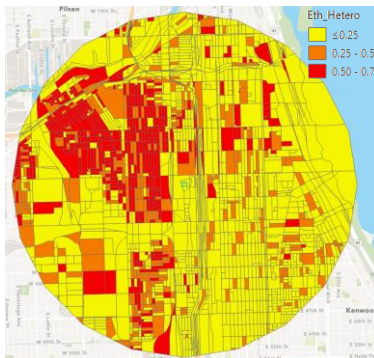
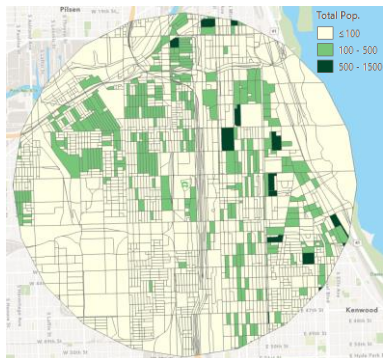
Restaurants and  
Liquor Stores



Bus Stops



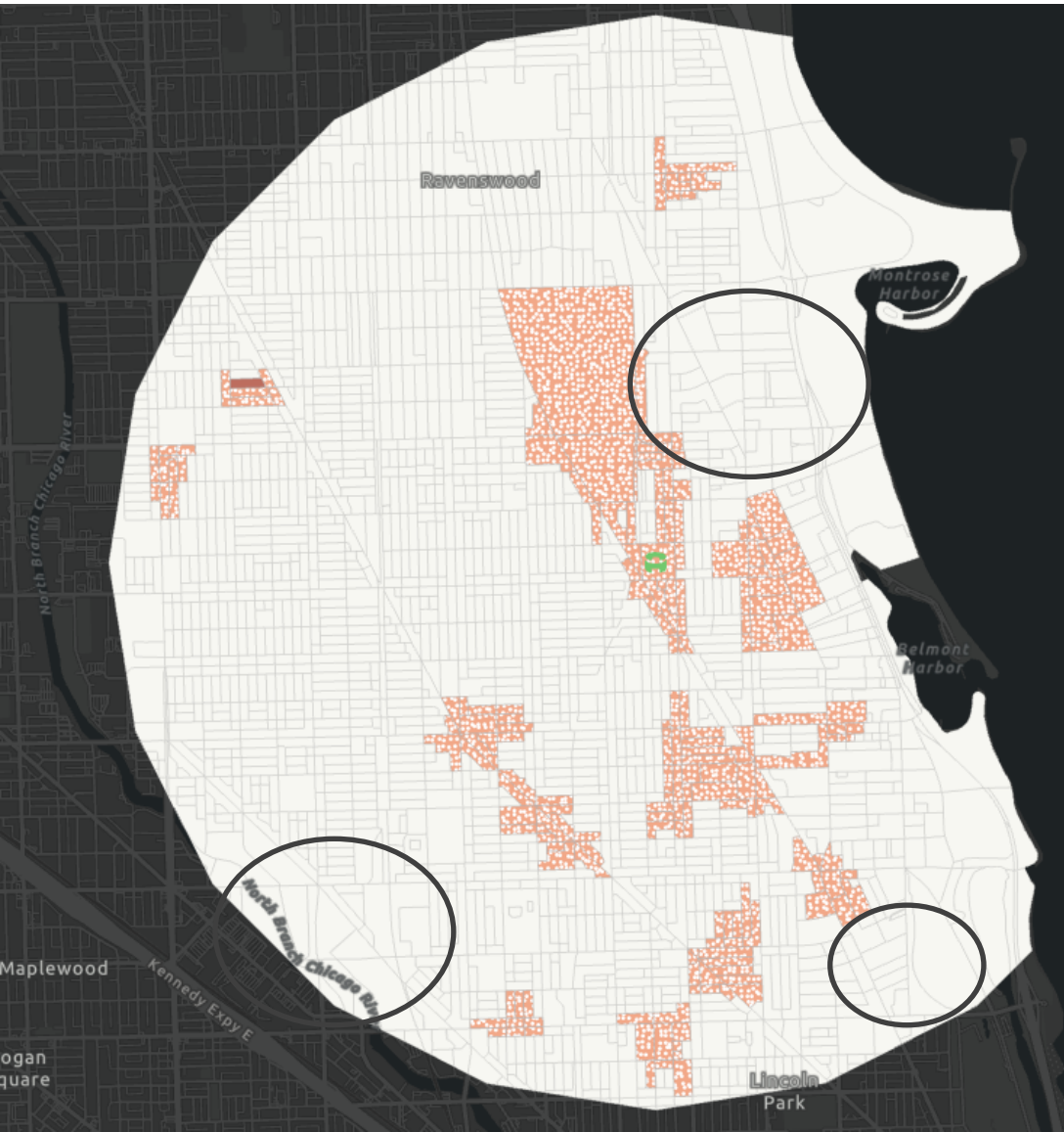
Parks





# Burglary, Robbery, Vehicle Theft, Assault, Theft – Wrigley Field

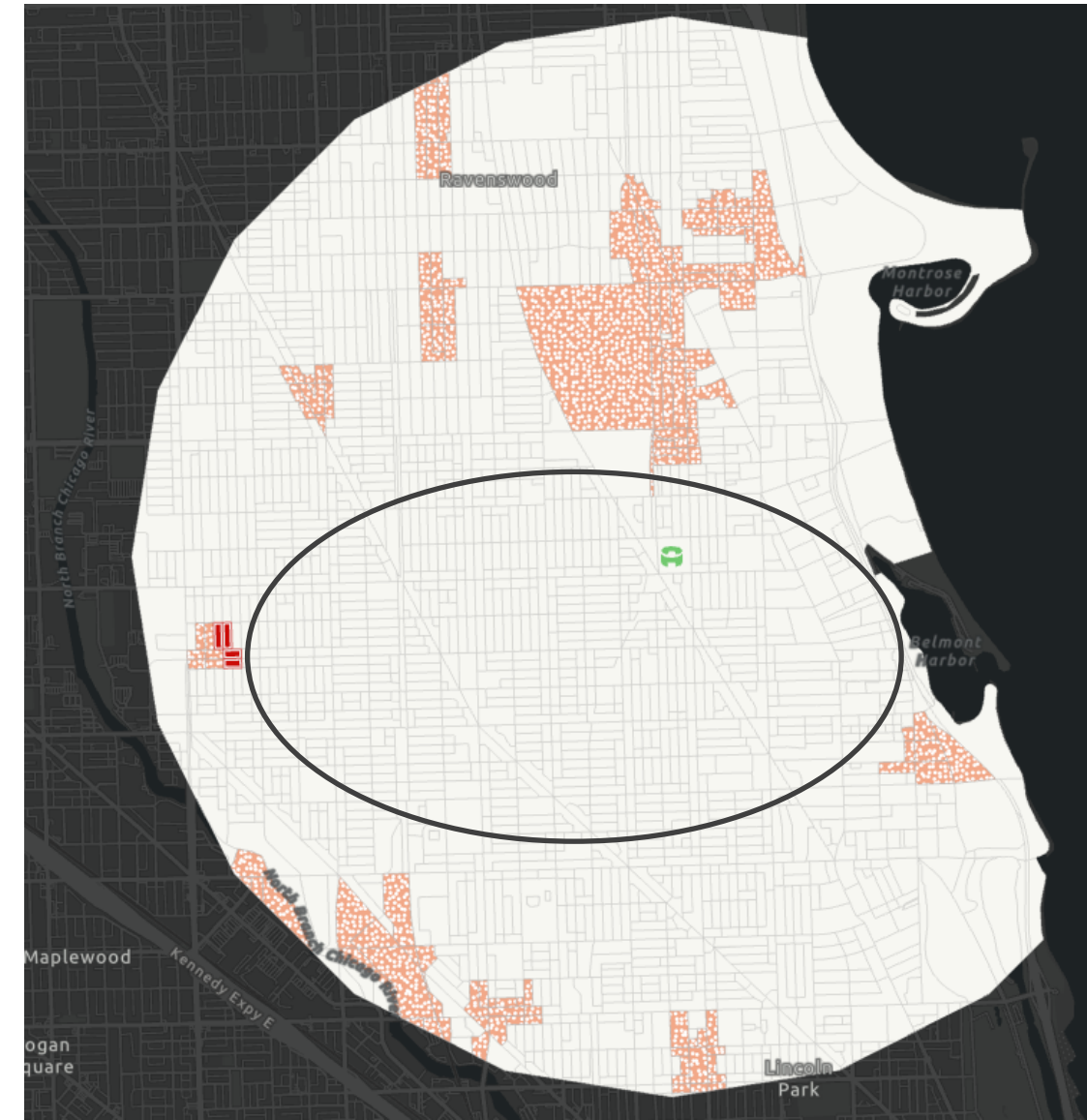
## Game



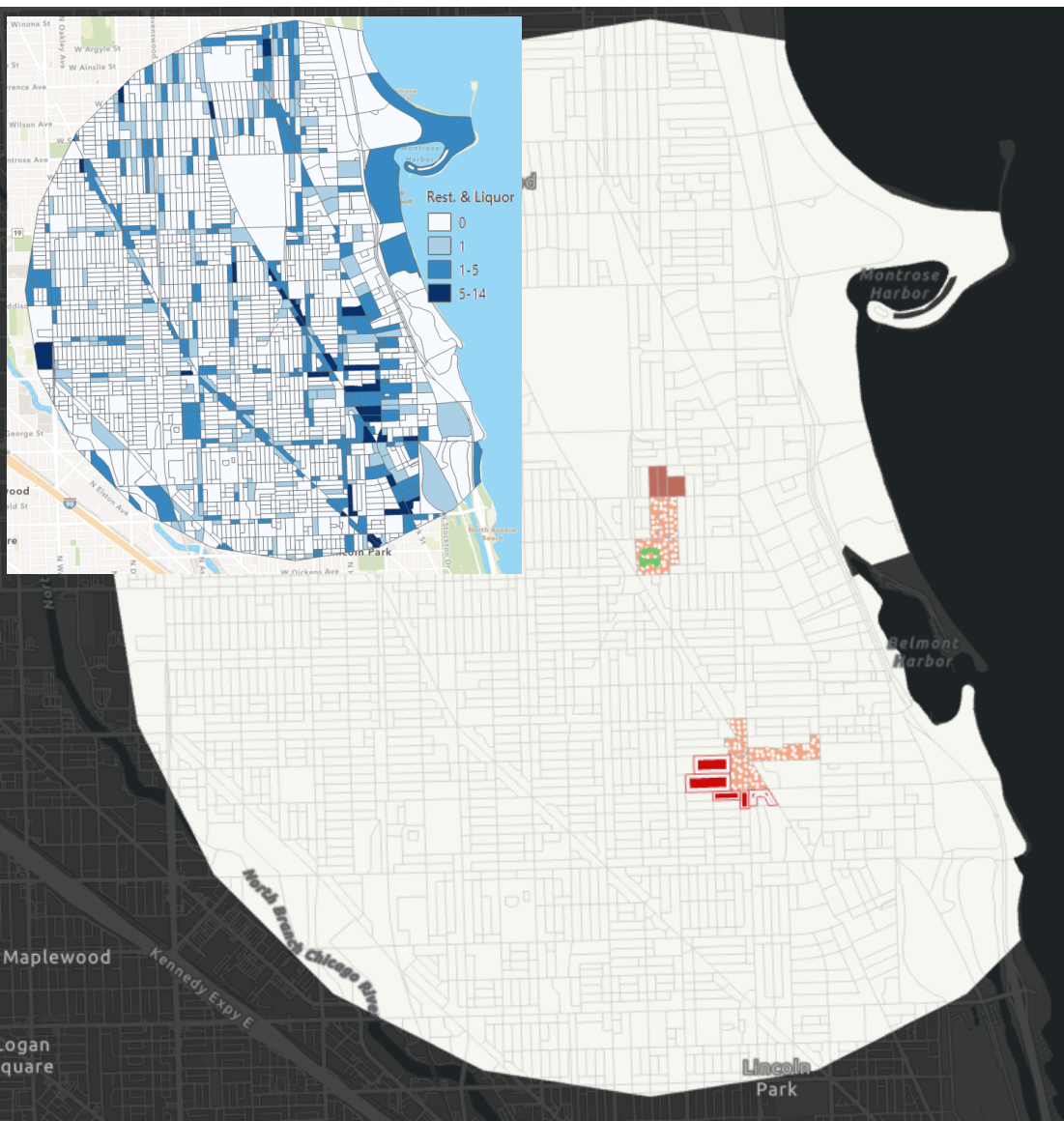
### PATTERN

- New Hot Spot
- Consecutive Hot Spot
- Intensifying Hot Spot
- Persistent Hot Spot
- Diminishing Hot Spot
- Sporadic Hot Spot
- Oscillating Hot Spot
- Historical Hot Spot
- New Cold Spot
- Consecutive Cold Spot
- Intensifying Cold Spot
- Persistent Cold Spot
- Diminishing Cold Spot
- Sporadic Cold Spot
- Oscillating Cold Spot
- Historical Cold Spot
- No Pattern Detected

## Comparison



## Game

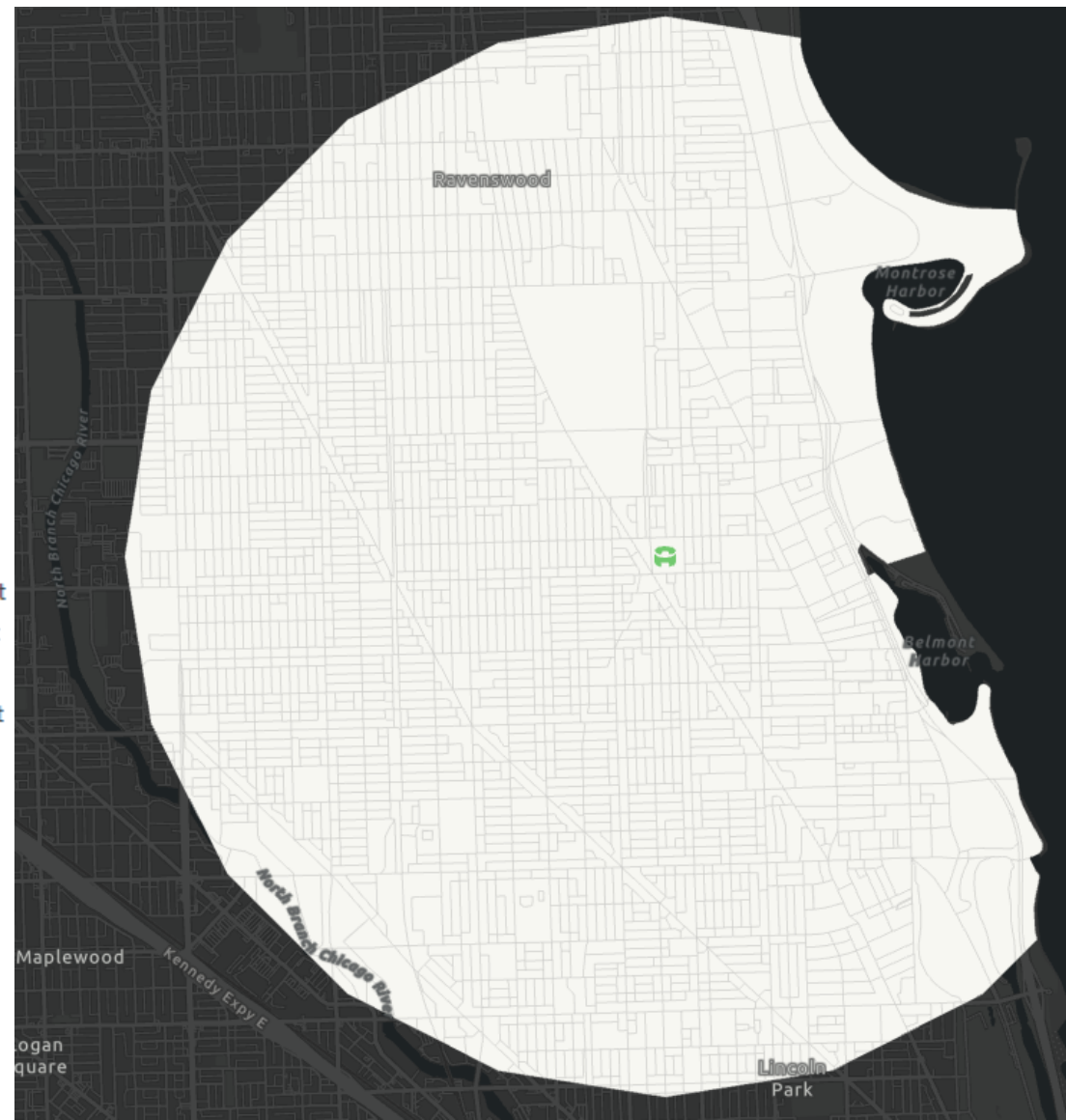


## Robbery

## Comparison

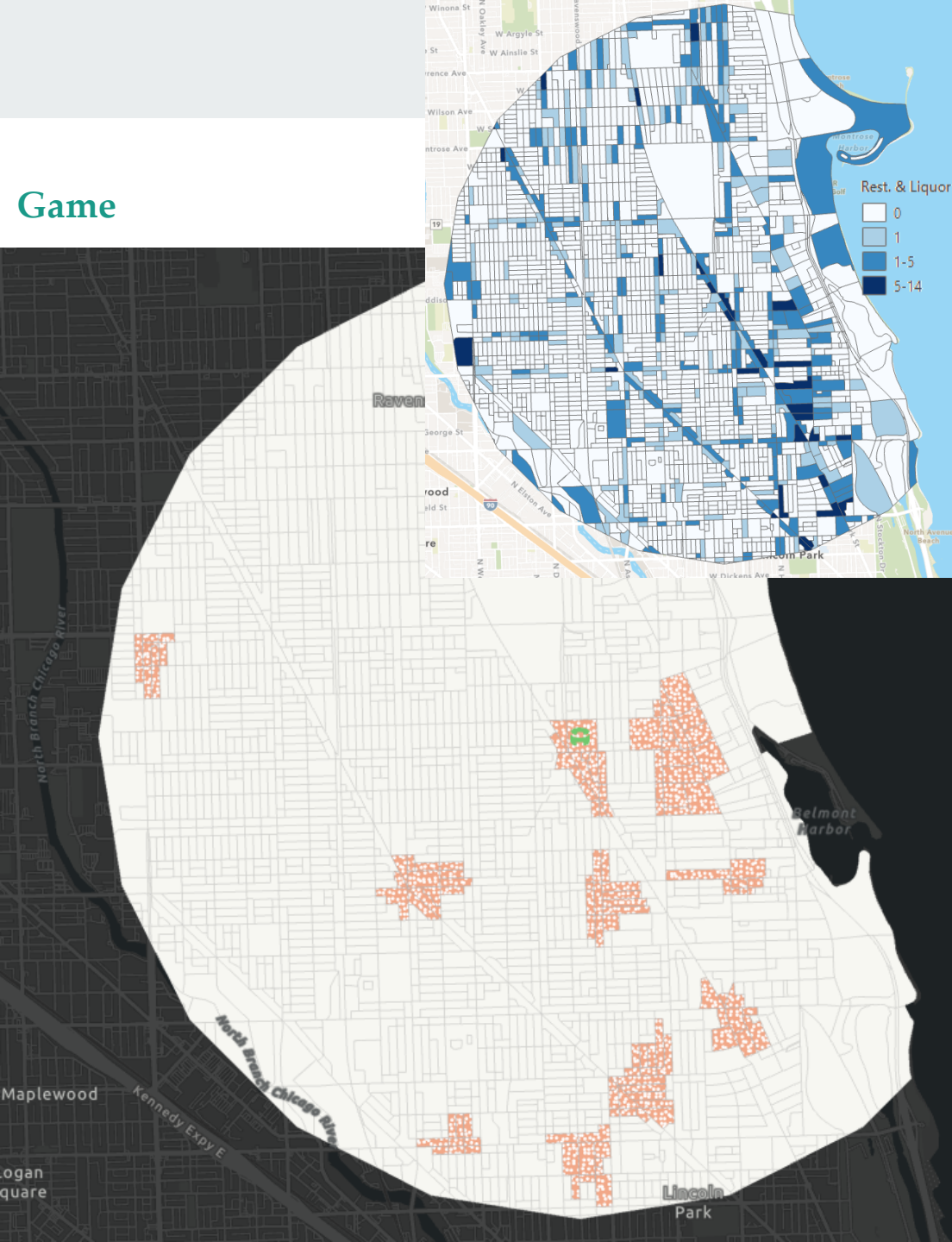
### PATTERN

- New Hot Spot
- Consecutive Hot Spot
- Intensifying Hot Spot
- Persistent Hot Spot
- Diminishing Hot Spot
- Sporadic Hot Spot
- Oscillating Hot Spot
- Historical Hot Spot
- New Cold Spot
- Consecutive Cold Spot
- Intensifying Cold Spot
- Persistent Cold Spot
- Diminishing Cold Spot
- Sporadic Cold Spot
- Oscillating Cold Spot
- Historical Cold Spot
- No Pattern Detected





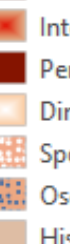
## Game

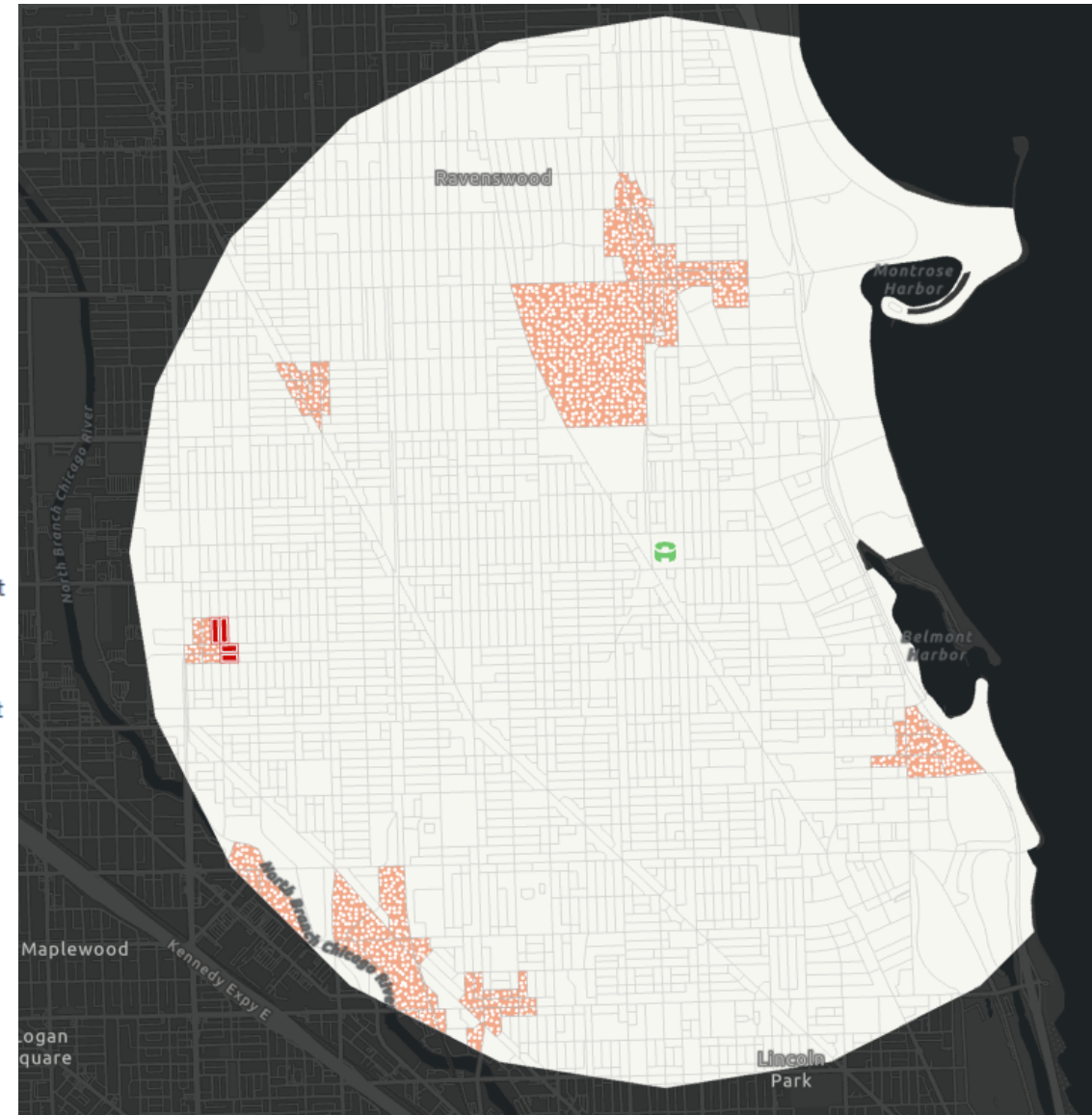


## Theft

## Comparison



- 
- Legend for Hot Spot and Cold Spot patterns:
- New Hot Spot
  - Consecutive Hot Spot
  - Intensifying Hot Spot
  - Persistent Hot Spot
  - Diminishing Hot Spot
  - Sporadic Hot Spot
  - Oscillating Hot Spot
  - Historical Hot Spot
  - New Cold Spot
  - Consecutive Cold Spot
  - Intensifying Cold Spot
  - Persistent Cold Spot
  - Diminishing Cold Spot
  - Sporadic Cold Spot
  - Oscillating Cold Spot
  - Historical Cold Spot
  - No Pattern Detected



# Burglary, Robbery, Vehicle Theft, Assault, Theft – Guaranteed Field

## Game



### PATTERN

- New Hot Spot
- Consecutive Hot Spot
- Intensifying Hot Spot
- Persistent Hot Spot
- Diminishing Hot Spot
- Sporadic Hot Spot
- Oscillating Hot Spot
- Historical Hot Spot
- New Cold Spot
- Consecutive Cold Spot
- Intensifying Cold Spot
- Persistent Cold Spot
- Diminishing Cold Spot
- Sporadic Cold Spot
- Oscillating Cold Spot
- Historical Cold Spot
- No Pattern Detected

## Comparison





Game

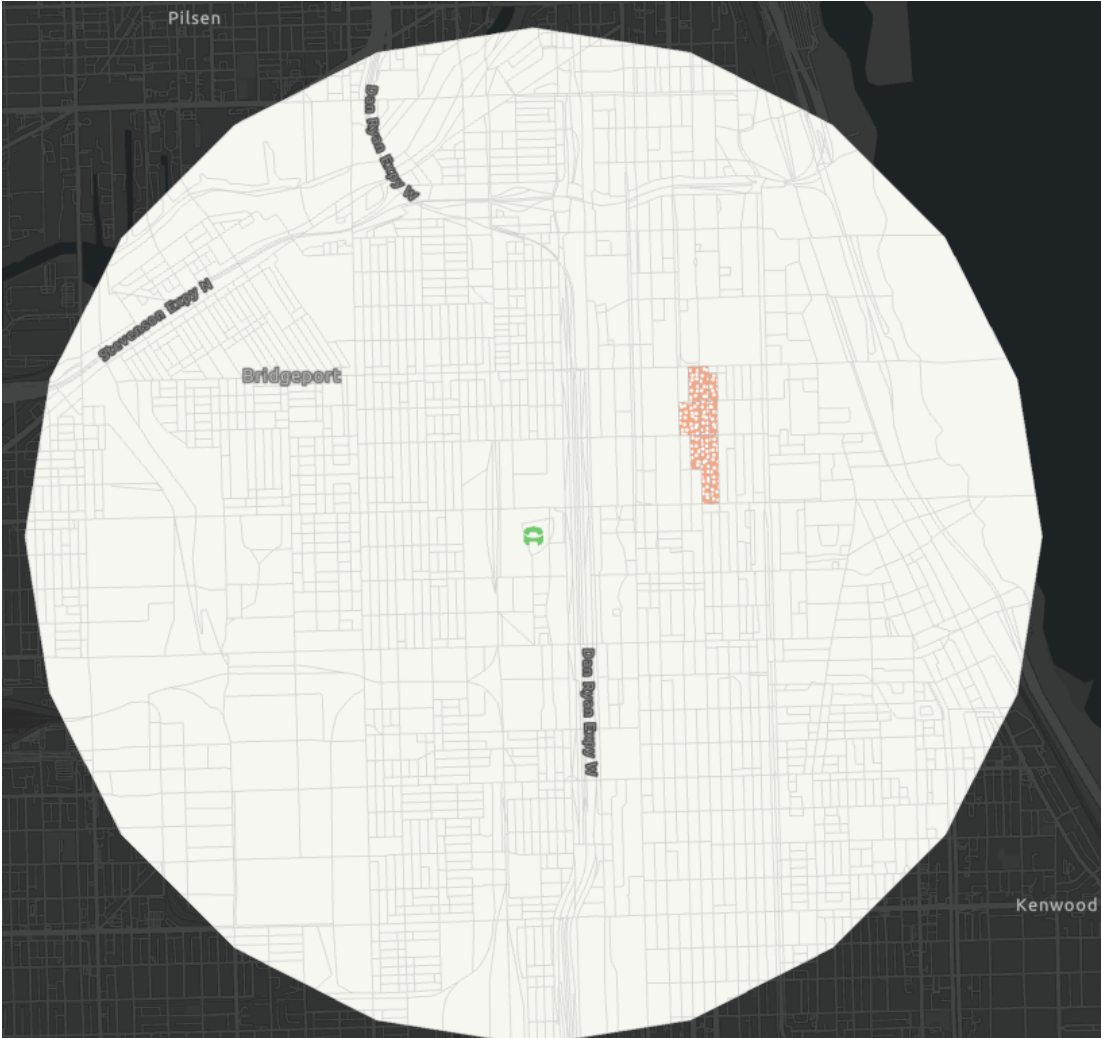


Robbery

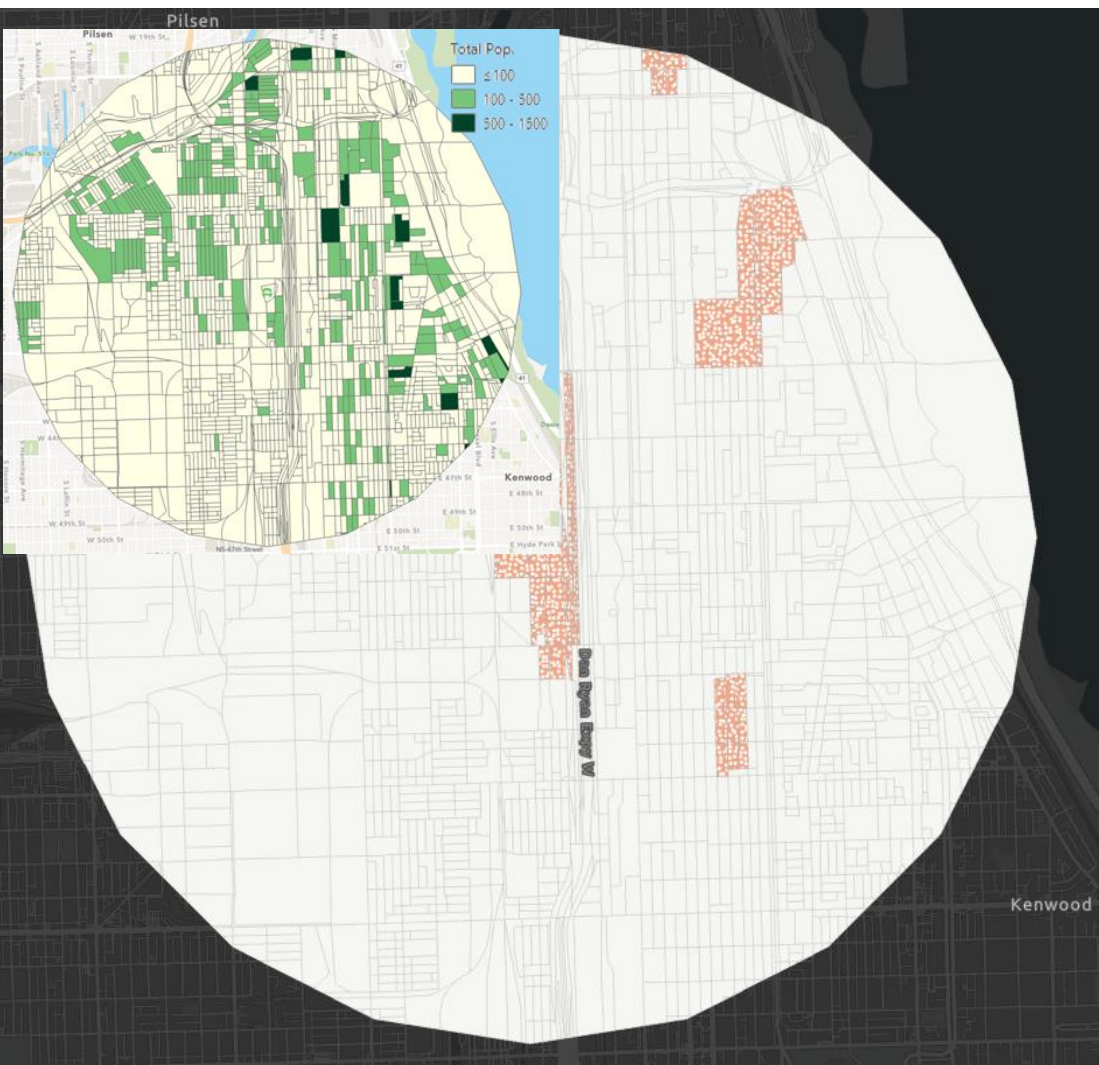
Comparison



- PATTERN
- New Hot Spot
  - Consecutive Hot Spot
  - Intensifying Hot Spot
  - Persistent Hot Spot
  - Diminishing Hot Spot
  - Sporadic Hot Spot
  - Oscillating Hot Spot
  - Historical Hot Spot
  - New Cold Spot
  - Consecutive Cold Spot
  - Intensifying Cold Spot
  - Persistent Cold Spot
  - Diminishing Cold Spot
  - Sporadic Cold Spot
  - Oscillating Cold Spot
  - Historical Cold Spot
  - No Pattern Detected



## Game

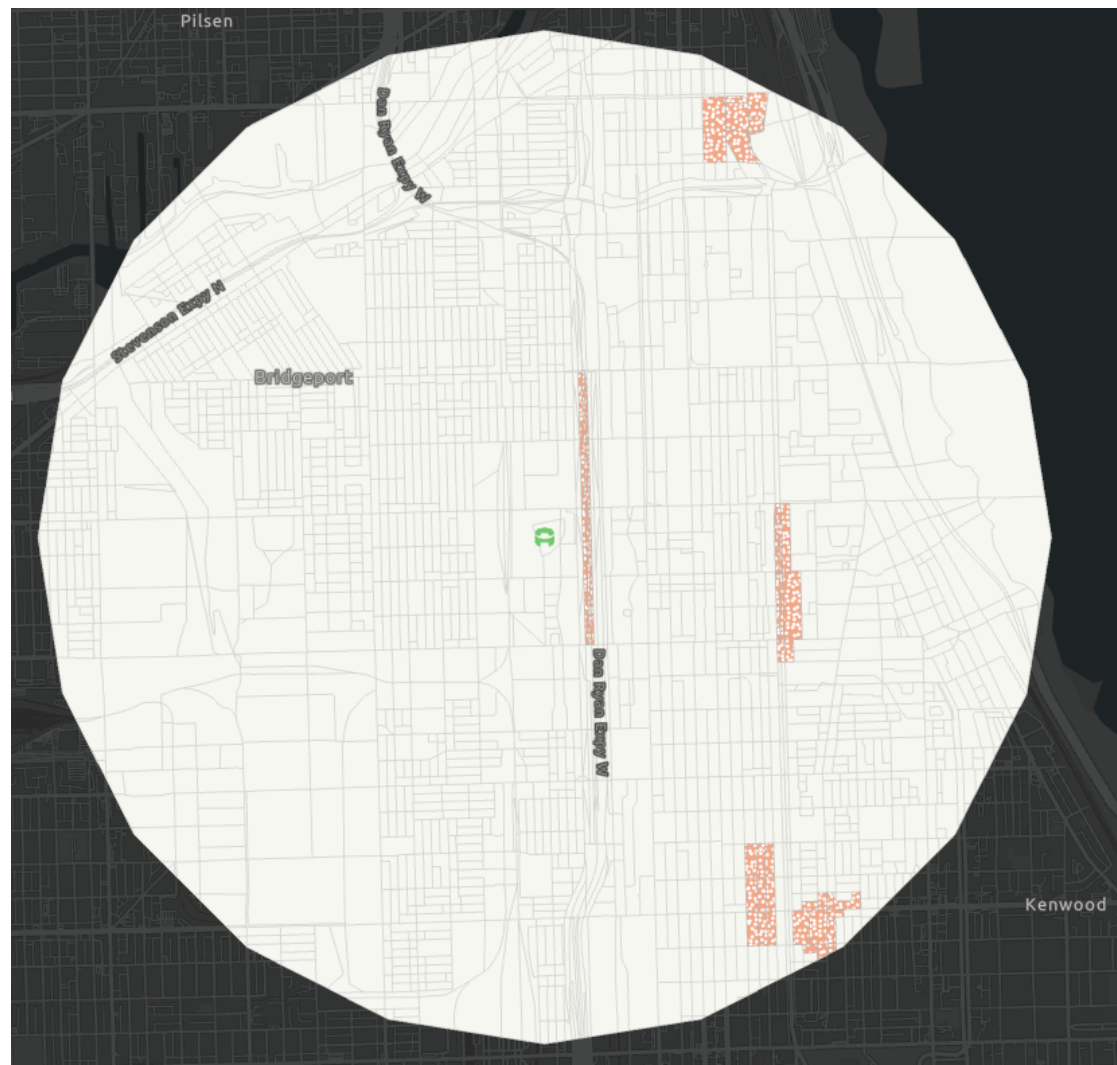


## Theft

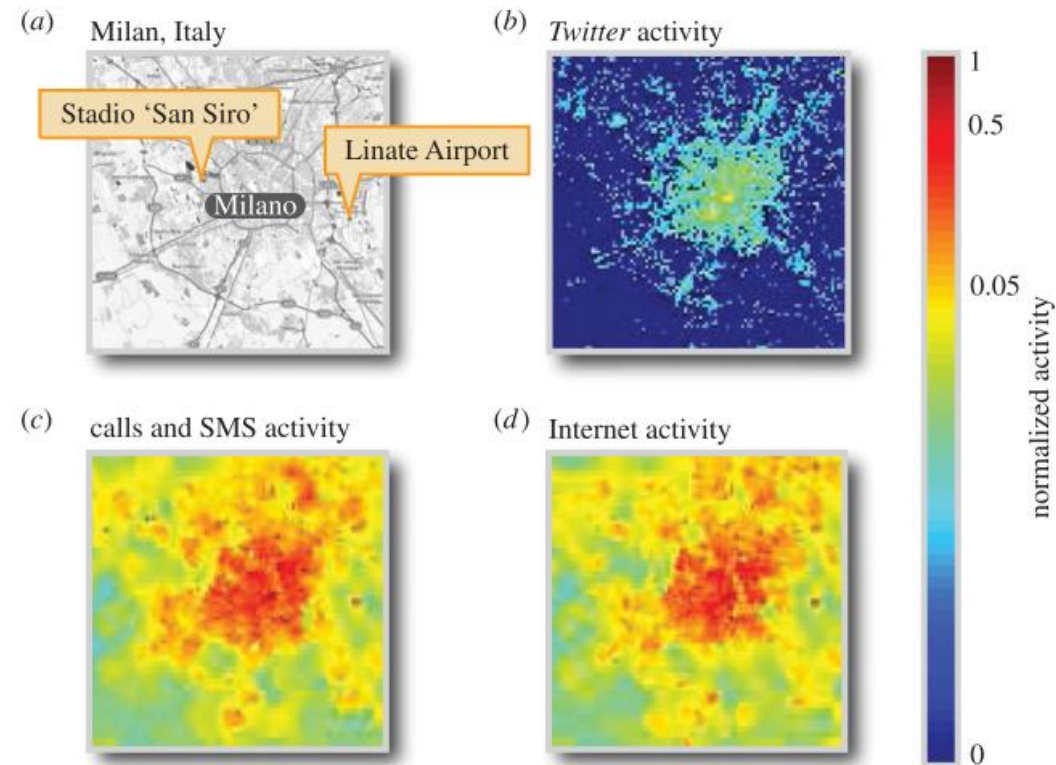
## Comparison

### PATTERN

- New Hot Spot
- Consecutive Hot Spot
- Intensifying Hot Spot
- Persistent Hot Spot
- Diminishing Hot Spot
- Sporadic Hot Spot
- Oscillating Hot Spot
- Historical Hot Spot
- New Cold Spot
- Consecutive Cold Spot
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- Persistent Cold Spot
- Diminishing Cold Spot
- Sporadic Cold Spot
- Oscillating Cold Spot
- Historical Cold Spot
- No Pattern Detected



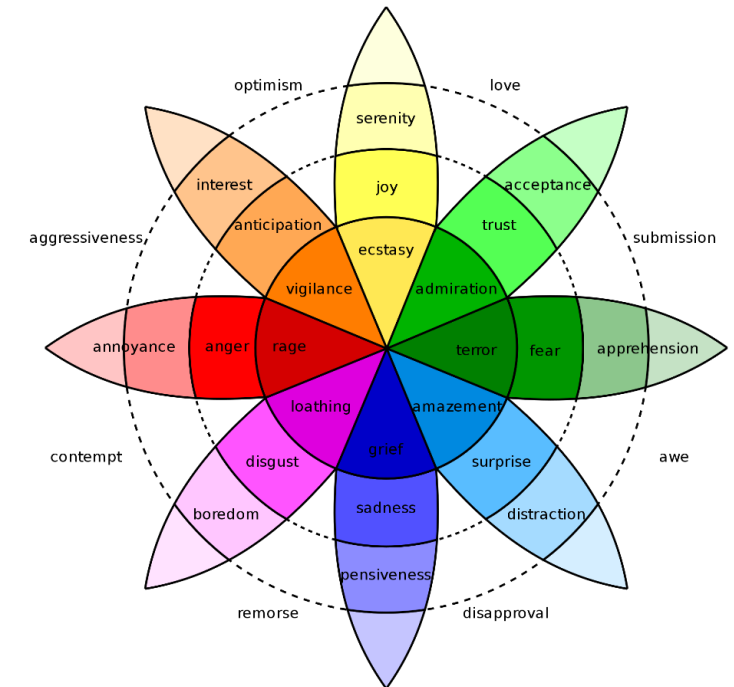
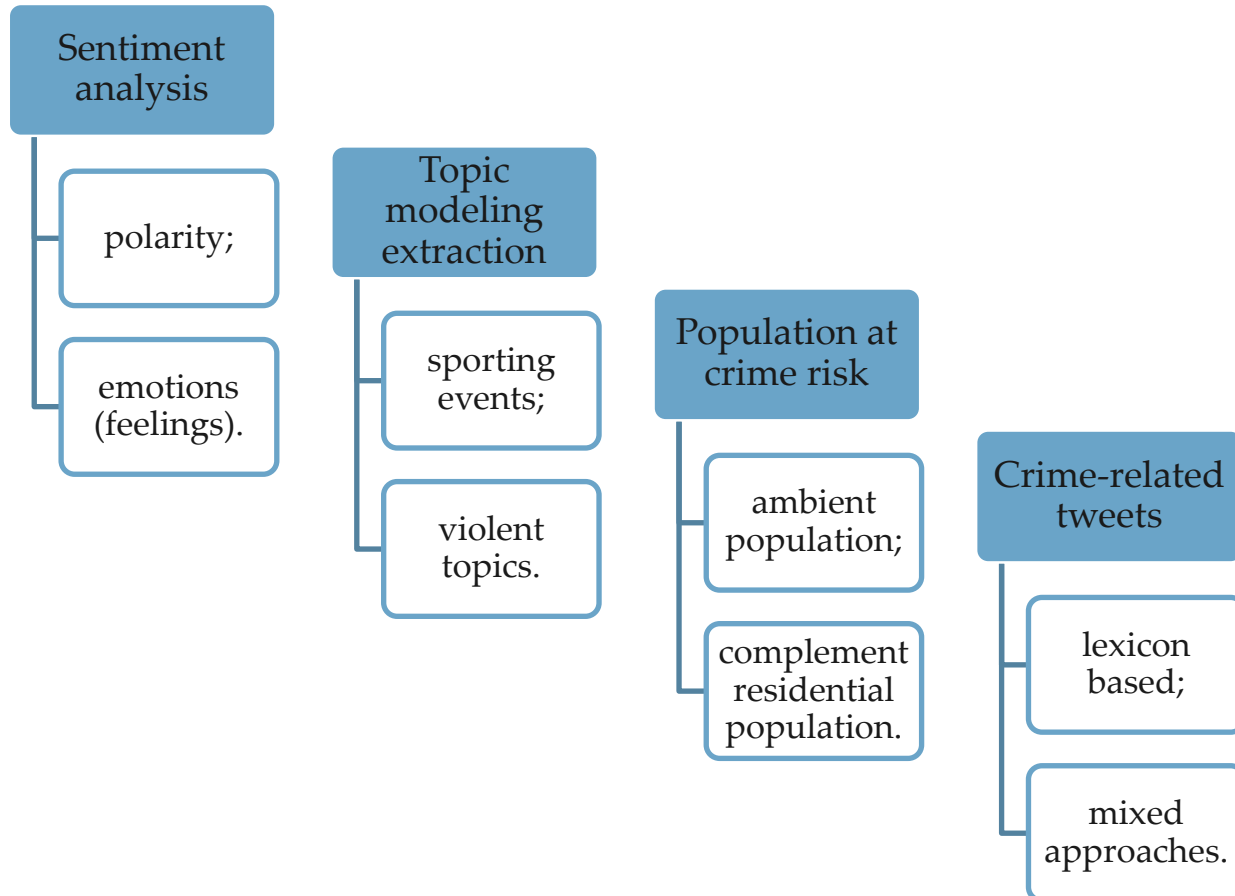
# Crime – Sporting Events – Social Media



Botta, Moat and Preis (2015)

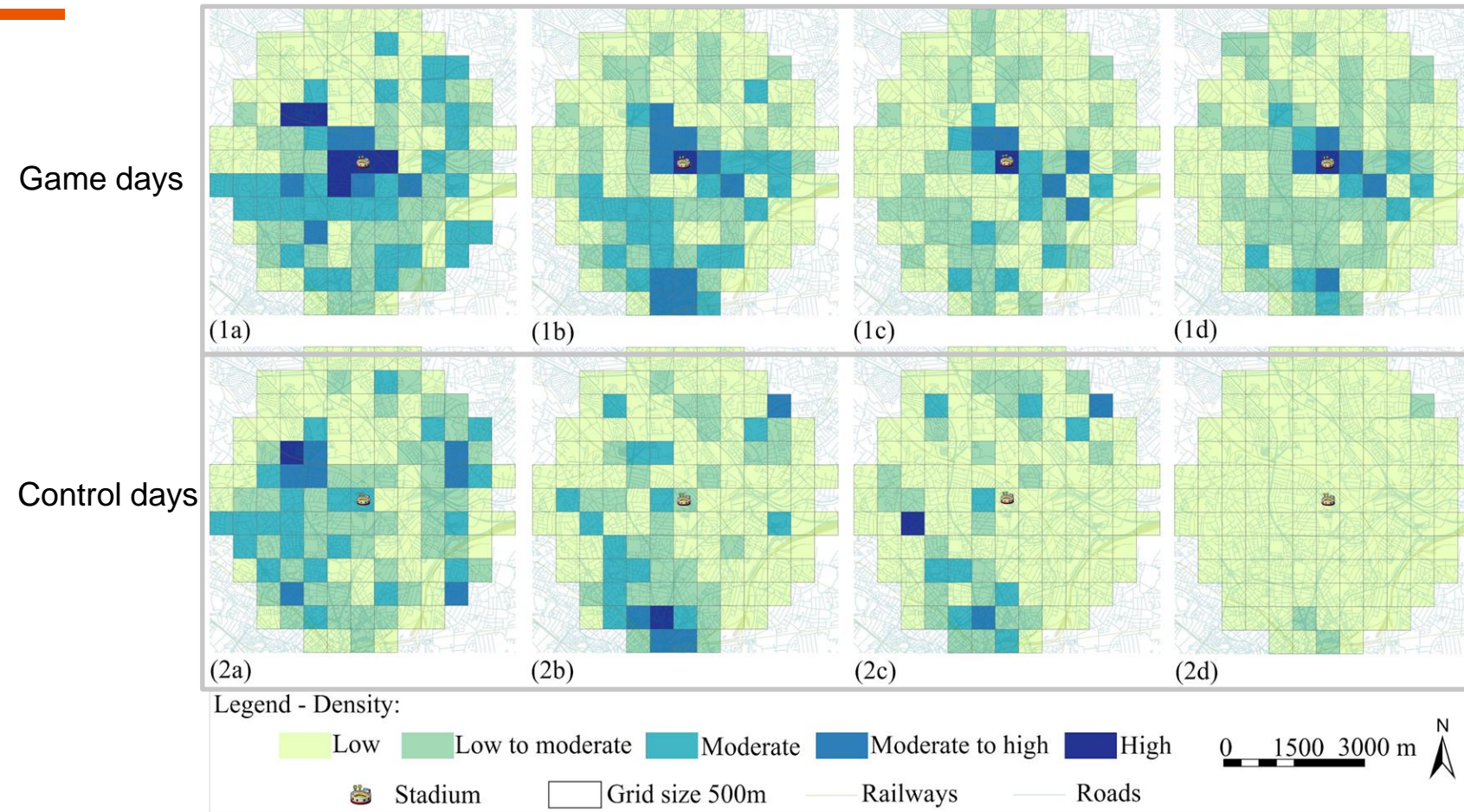


# Social Media related features



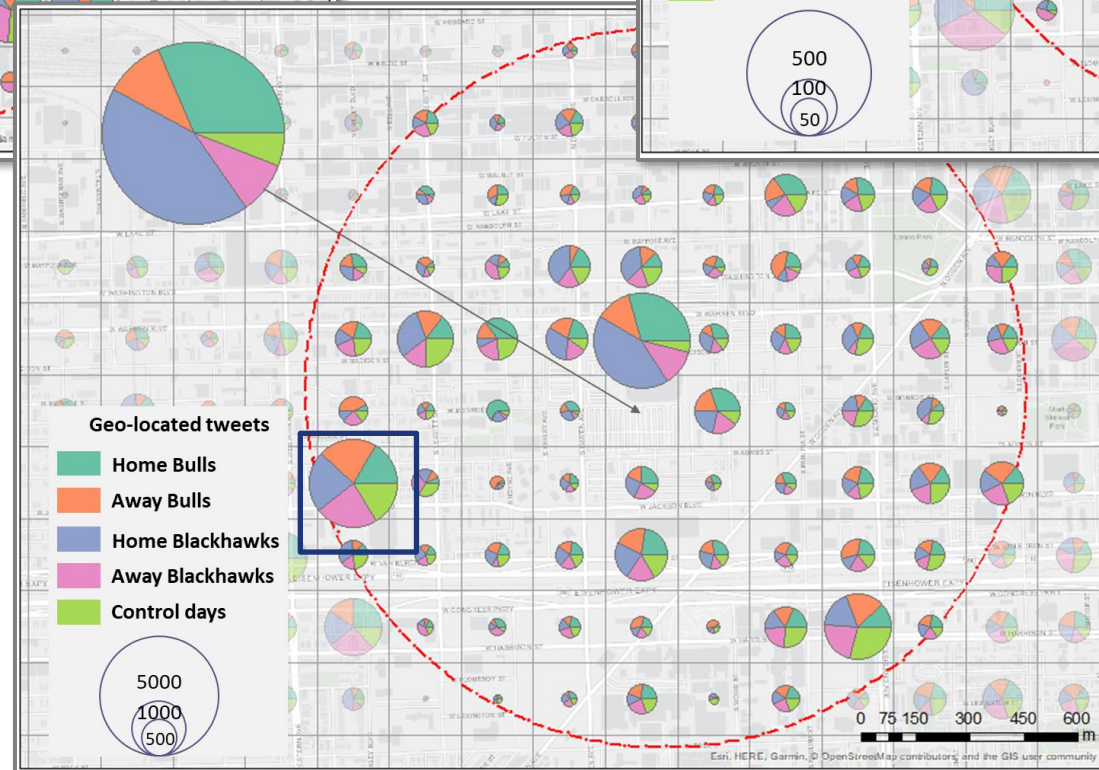
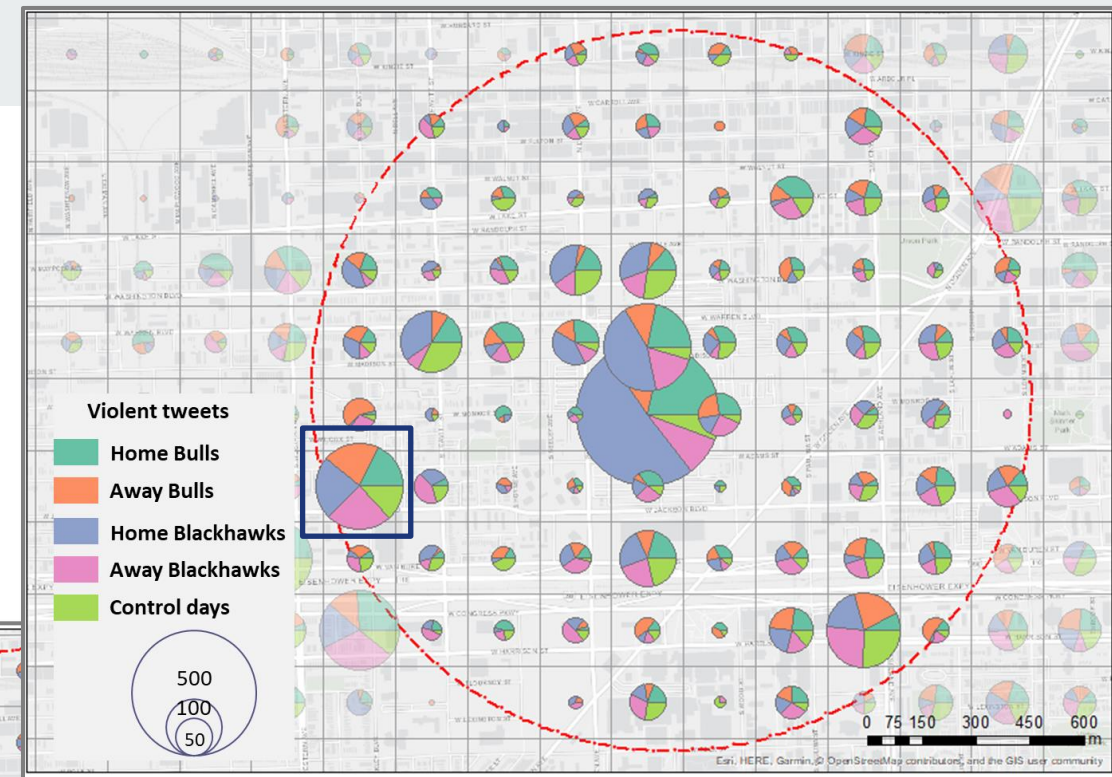
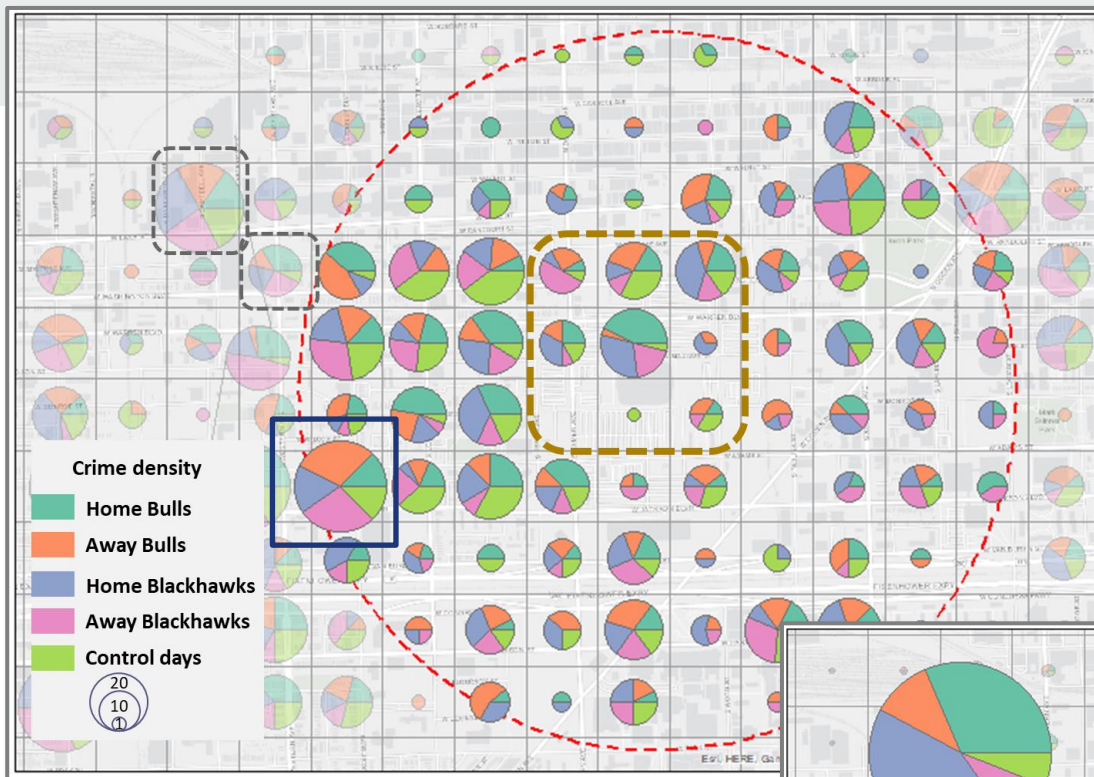
Plutchik's wheel of emotions

Plutchik  
(2001)



Density maps Aston Villa stadium (a) amalgamated crimes, (b) geotagged tweets, (c) violent tweets, and (d) football-related tweets








# Notes

- **geometry of crime** changes during sporting (home) game days
- **place composition** is highly connected with criminal behavior
- **positive correlation** between crimes and tweets on game days
- various **sporting events at a venue** -> various crime types increase
- **similar temporal patterns**
- **shifted vs stable** crime and social media hot spots – stadium proximity
- correlation **crime-related tweets** and **attitudes on disorder**.



Prediction

# A systematic review on spatial crime forecasting

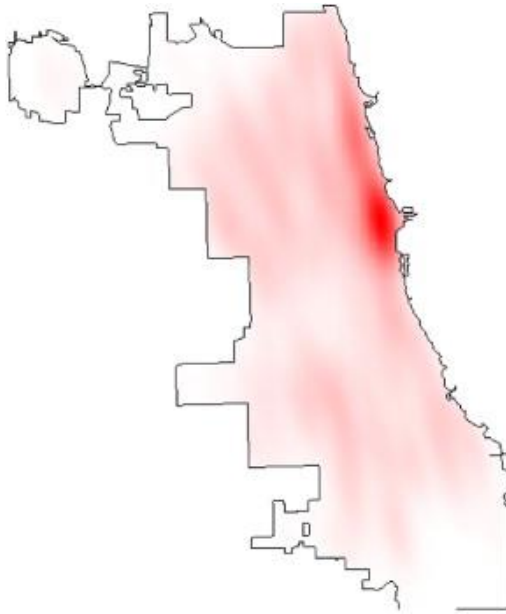
[Ourania Kounadi](#), [Alina Ristea](#) , [Adelson Araujo Jr.](#) & [Michael Leitner](#)

[Crime Science](#) **9**, Article number: 7 (2020) | [Cite this article](#)

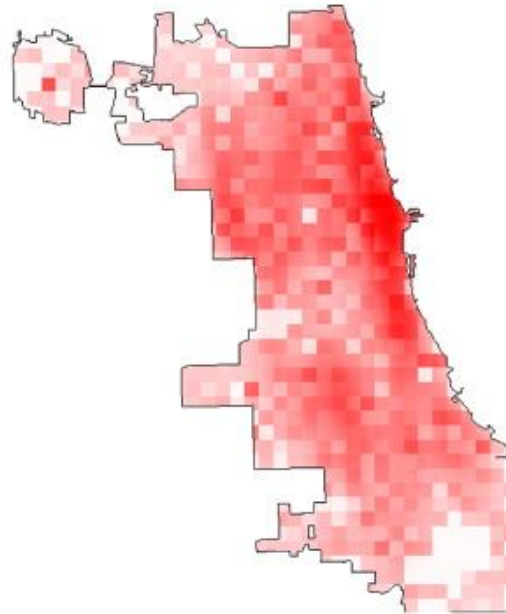
**6523** Accesses | **7** Citations | **11** Altmetric | [Metrics](#)

## Prediction: base + dynamic features in space-time

Gerber (2014)



(a) Predicted threat surface using only the KDE feature.

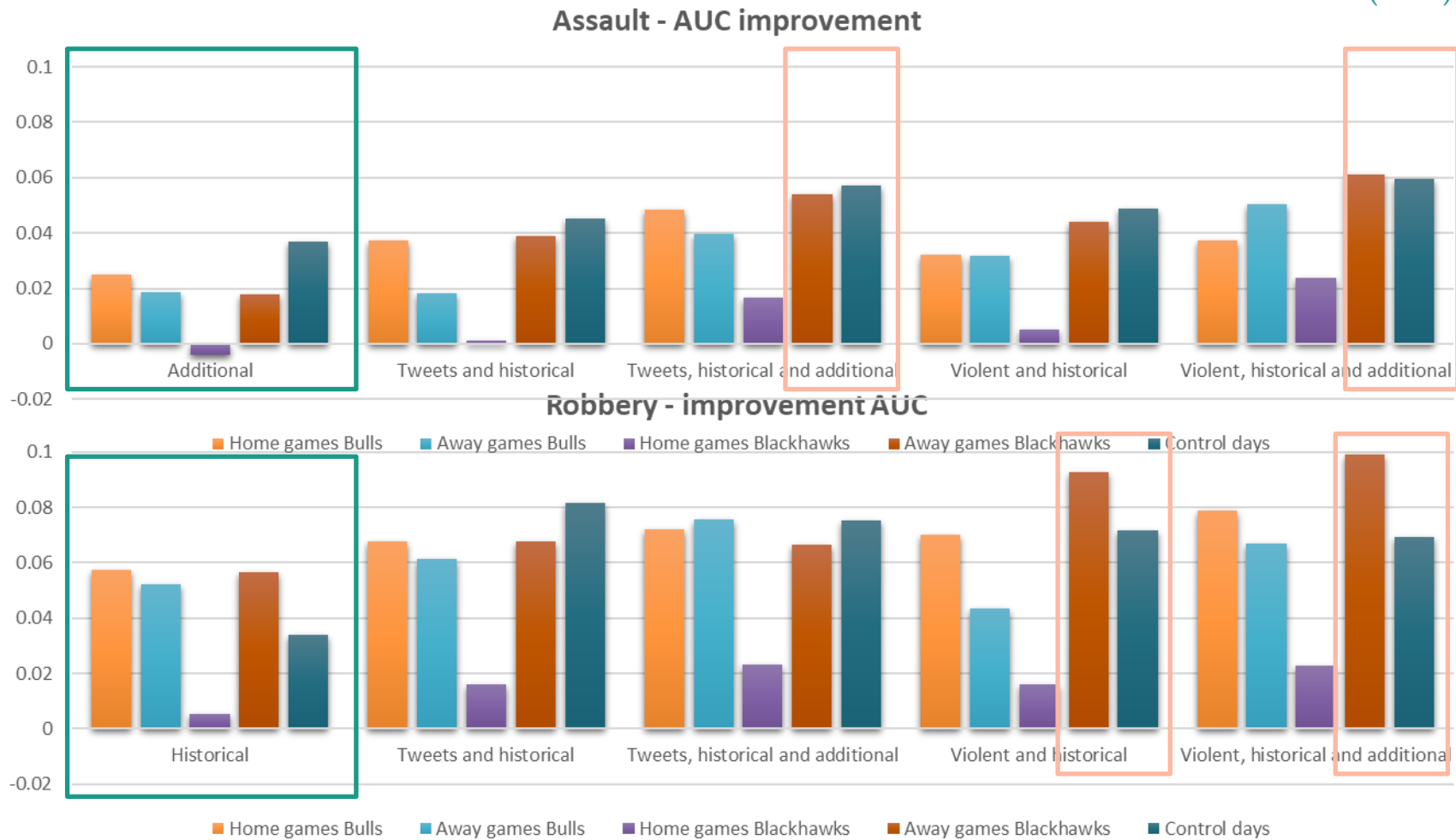


(b) Predicted threat surface using the KDE feature and the Twitter features.



# Prediction crime types

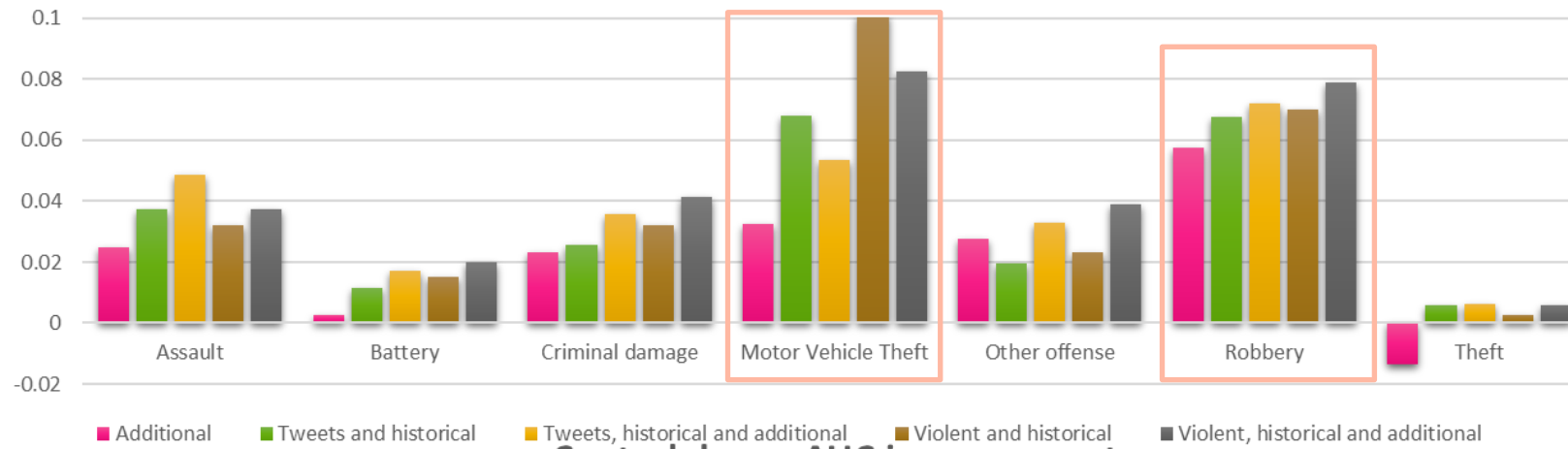
Ristea et al (2020)



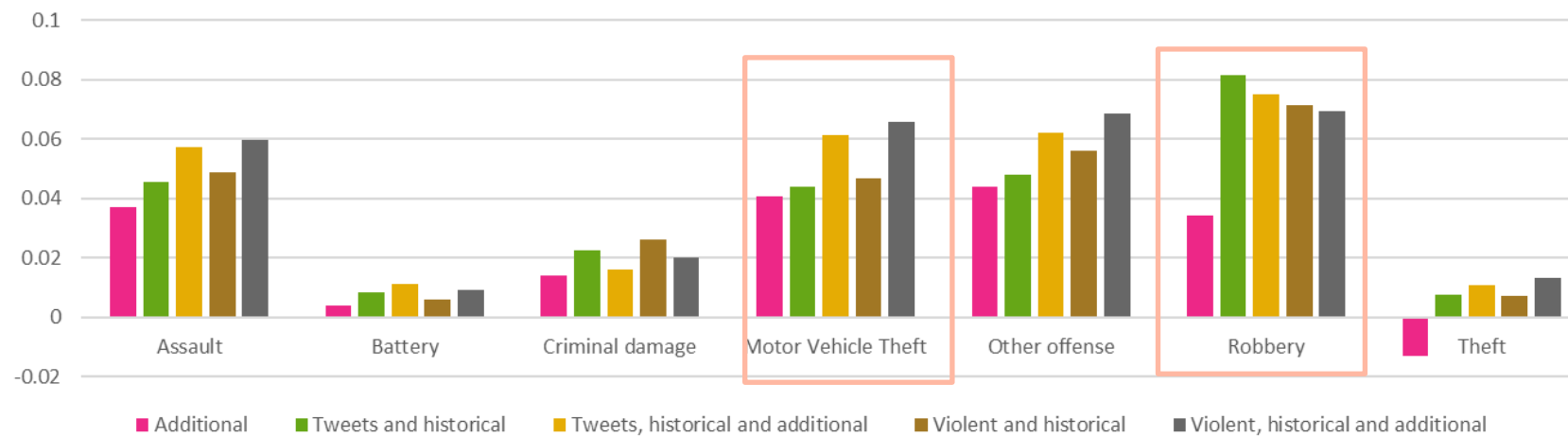
# Prediction game days vs control days

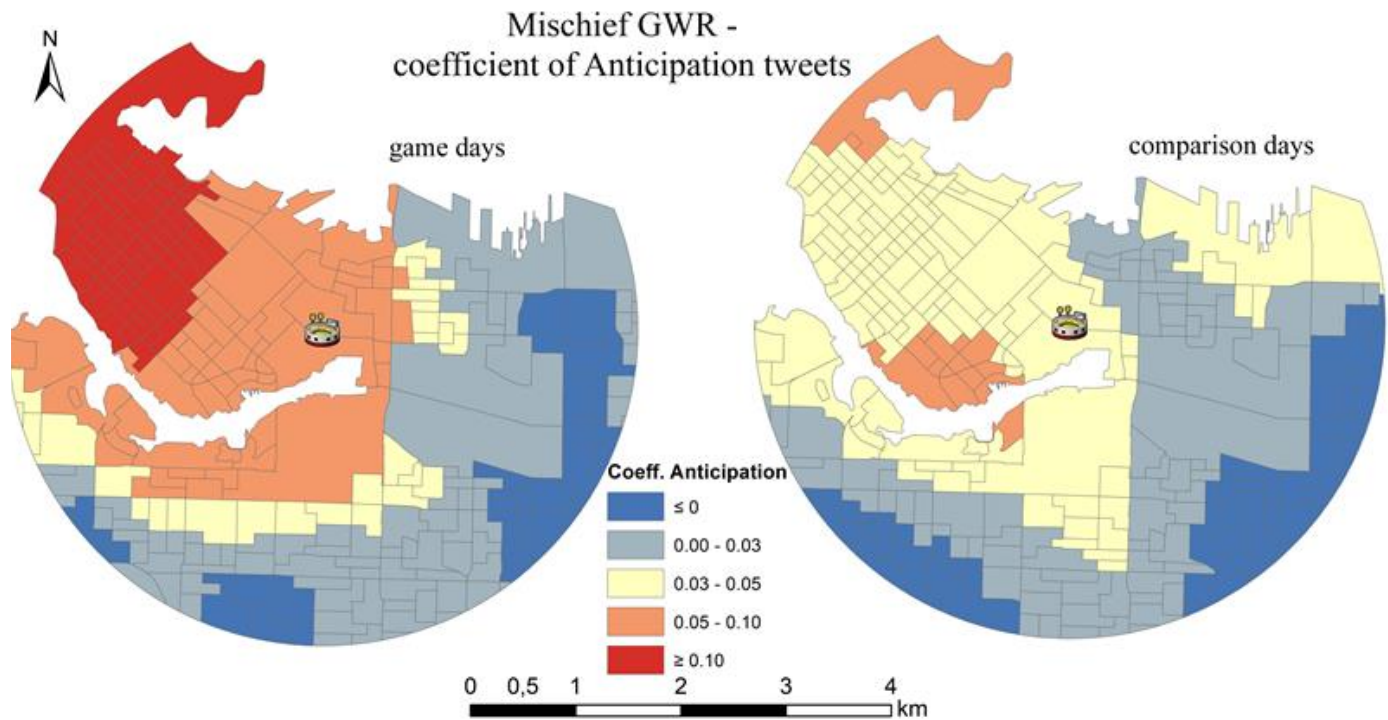
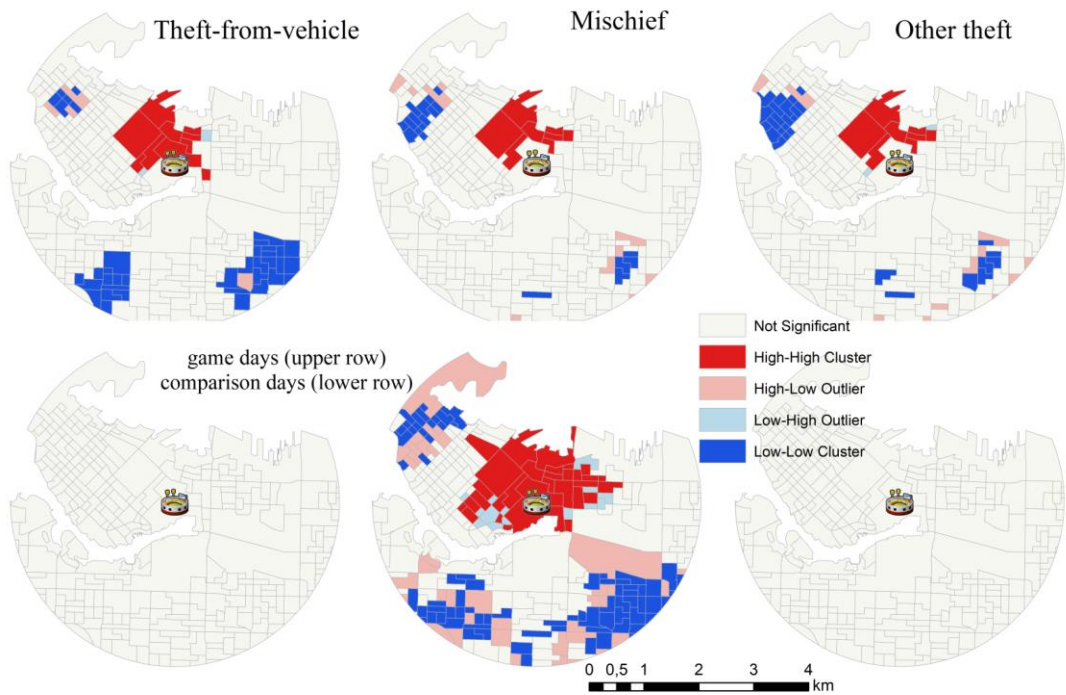
Ristea et al (2020)

Home games Chicago Bulls – AUC improvement



Control days – AUC improvement





3km area around Rogers Arena, Canucks team (hockey),  
Vancouver, Canada

Mischief Adj. R <sup>2</sup>	Game days GWR	Comparison days GWR
Tweets	0,83	0,78
Anticip.	0,85	0,79
Surprise	0,82	0,78
Trust	0,85	0,78
Positive	0,84	0,79



# Data quality

- data quality: social media bias (age, gender, semantics, study area etc) and geo-location information;
- crime data quality and geo-privacy aggregation;
- data aggregation in space and time: Modifiable Areal Unit Problem (MAUP) and temporal unit selection;
- data sparsity: negative-positive ratio in prediction;
- transferability of the results beyond the selected study areas;
- different crime types in different countries.

# Prediction bias

- It usually starts from the **data input**: missingness, not representative, too skewed
- If the training data includes **inequalities**, the algorithm can keep propagating those inequalities
- **Location-based algorithms** and individual targeting algorithms are different, but they can both be biased based on historical data
- A **diverse team** is recommended to review the work.



# Notes

- **proxy for crime** occurrences -> **potential value** subset depending on analysis purpose; **models tailored** to the characteristic of a crime type
- **social media subsets** - greater impact in prediction models
- statistically significant **social media subsets** (mostly crime-related tweets)
- tweets can be highly correlated with crimes, but the **estimated influence** varies across crime categories
- an increase in social media when **crime is stable** can deviate the prediction
- strong spatial and temporal patterns -> **historical data** may be enough to predict immediate future



# New technologies, modern applications – adapting theory?

- Environmental criminology, criminology of place
- Integration of new data: location data availability, social media
- Fans behavior
- Stadia restructuring based on needs – new crimes emerging?
- More collaboration between fields of study and between researchers and practitioners

Times are  
changing.  
Everywhere. In  
every field.

Thank you!



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