

Changes in Motor Vehicle Thefts Patterns during the Covid-19 Epidemic in Buffalo, New York

Reported: Yixuan Zhao

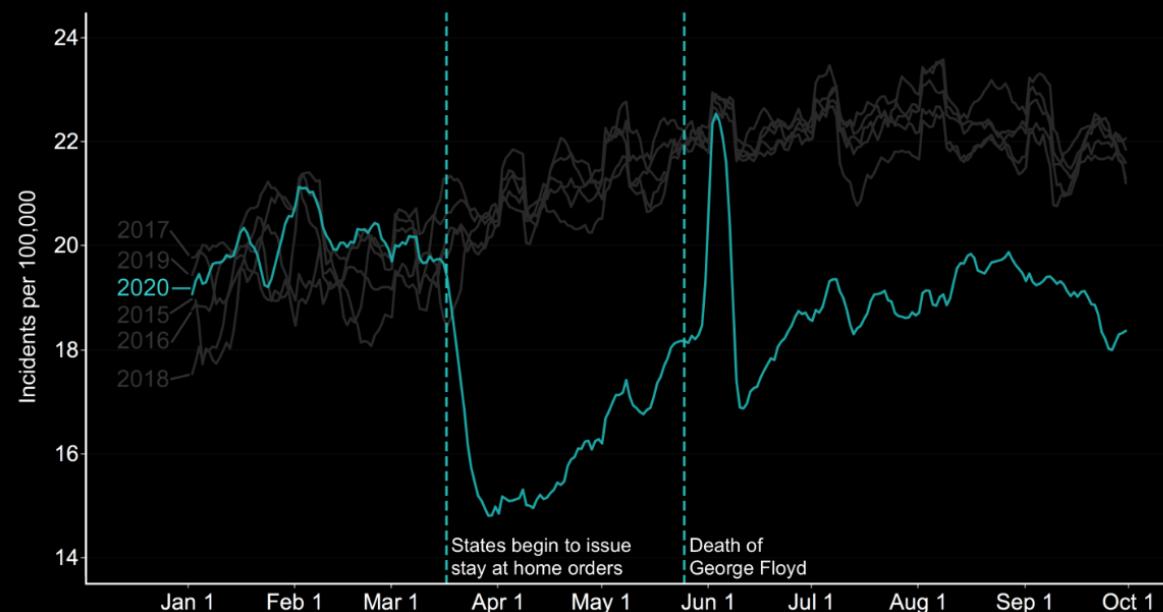
Professor: Li Yin

Date: AUG/26/2021

Crime in the Time of COVID

By David S. Abrams · March 30, 2021
 University of Pennsylvania

OVERALL CRIME INCIDENTS PER CAPITA FOR 25 OF THE LARGEST U.S. CITIES, 2015-2020

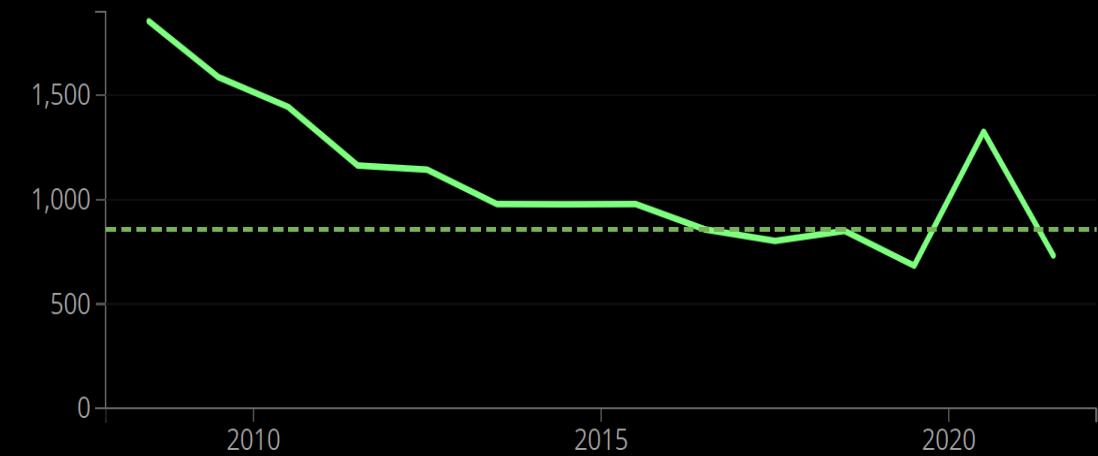


Source: CityCrimeStats.com, University of Pennsylvania
<https://econofact.org/crime-in-the-time-of-covid>

EconoFact econofact.org

Buffalo Police Department

From 2008 to 2020, there were 14,651 motor vehicle thefts in the City of Buffalo. Since the 13-year high in 2008 (1,855), there has been a substantial decrease in motor vehicle thefts with a spike in 2020.



<https://data.buffalony.gov/stories/s/CitiStat-Buffalo-Buffalo-Police-Department/hugq-2uun>

LITERATURE REVIEW

Recent study crime change during covid-19

Study Area	Method	Finding	Trend	Sources
Mexico City	After studying the changes in crime trends in Mexico City, they found that after a pandemic or a nationwide lockdown, most types of crime have decreased significantly	Auto Regressive Integrated Moving Average (ARIMA)	↓	3Estévez-Soto, P. R.
16 large cities or urban counties in the United States	Predicted the crime trend when there is no pandemic in 2020, and obtained the change in crime trend by comparing with the actual frequency of crime. They found that motor vehicle thefts have declined in some cities, but motor vehicle thefts have committed crimes. The model is differentiated. [A seasonal autoregressive integrated moving average (SARIMA)	↓	13Ashby, M. P. J.. (2020)
77 communities of Chicago	Researchers in Chicago found that criminals may decide to specifically target people with weaker resistance, because the reduction in robbery is negatively correlated with the presence of elderly people in specific communities, and the population in urban communities is stable and positively correlated with a significant reduction in crime The only factor.	Firth's Logistic Regression	↓	2Campedelli, G.M., Favarin, S., Aziani, A. et al.
9 types of crime in Los Angeles	In Los Angeles, researchers found that the overall crime rate in the area has dropped significantly, especially robbery, shoplifting, theft and batteries. However, burglaries, domestic violence, car thefts and homicides remain unchanged.	Firth's Logistic Regression& Bayesian Structural Time Series	↓	10Campedelli, G. M., Aziani, A. et Favarin, S.. (2020)
Violent crime data from the Miami-Dade Central Records Bureau were analyzed.	They found that during the pandemic, arrests for violent crimes were concentrated in disadvantaged communities in the north, mostly black, and the arrests were mostly black men.	Local Moran's I	↓	12Moise, I. K., & Piquero, A. R. (2021)
77 communities of Chicago	Significant changes have taken place in the distribution of crime in 2020. Local changes such as theft, assault, burglary, and fraud present a cluster of clusters in the city center.	Seasonal and Trend decomposition using Loess (STL) & local Moran's I	↓	5Yang, M., Chen, Z., Zhou, M., Liang, X., & Bai, Z.

Economic and demographic background and crime

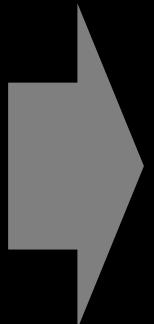
Criminology Theory

Social disorganization theory

The theory of social disintegration believes that the level of crime in a community is closely related to the local ecological characteristics. Socioeconomic pressure will reduce social organization. Communities with chaotic social organizations have a lower level of social control, which will reduce the monitoring of criminal activities, which will lead to crimes.

Routine activity theory

The conventional activity theory has determined three necessary elements of crime: motivated criminals, suitable targets and lack of capable guardians. If any of these are missing, crime is unlikely to occur.



Socioeconomic demographic characteristics that may lead to crime

Motivated criminals

1. Poverty - population living below Federal poverty level
2. Unemployment - age 16 and over seeking work
3. Per capita income - (2019 inflation-adjusted \$)
4. Education - age 25+ without a high school diploma

Law, J., & Quick, M. (2013); Schulenberg, J. (2003); Schulenberg, J. L., Jacob, J. C., & Carrington, P. J. (2007); Jacob, J. (2006)

Suitable targets

1. Large apt. bldgs. - 10 or more housing units per building
2. Crowding - housing units with more than one person per room
3. Group quarters - population living in group quarters

Li, J., & Rainwater, J. (2000, June); Berry, H. L. (2007); MacDonald, J. (2015)

Lack of capable guardians

1. Elderly - population age 65 and over
2. Disability - age 5 or more with a disability
3. Limited English - age 5 and over who speak English less than "Well"

Adler, F., Adler, F., & Coston, C. T. M. (2004); Toseland, R. W. (1982); Hövermann, A., Groß, E. M., Zick, A., & Messner, S. F. (2015)

Neighborhood Environment and Crime

Variable	Method	Finding	Sources	P
Number of intersections in the community	negative binomial models	The study found a positive correlation between the number of intersections and crime rates.	4Stucky, T., Smith, S.	+
	descriptive statistics, correlations, regression and discriminant analyses, and matched pair analysis	High-crime bus stops (at the top of the Table) have many more negative environmental attributes in their vicinity than low-crime bus stops.	Loukaitou-Sideris, A., Liggett, R., Iseki, H., & Thurlow, W. (2001)	+
	nonparametric spatial point pattern test	Property crime in Vancouver is highly concentrated in a small percentage of street segments and intersections, as few as 5 percent of street segments and intersections in 2013 depending on the crime type.	Andresen, M. A., Lining, S. J., & Malleson, N. (2017)	X
Number of bus stops in the community	negative binomial models	In commercial and industrial areas, bus stops have a greater impact on crime, but in areas with high residential densities, it has been weakened.	4Stucky, T., Smith, S. (2005;2010)	+
Number of vehicles towed away due to illegal parking in the community	Descriptive statistics	Since illegal parking is easier to escape from surveillance, illegal parking is more likely to lead to theft of vehicles.	Webb, B. (1994)	*
Population density	Visual descriptive statistical analysis based on GIS	High population density will lead to a drop in crime rates.	Li, J., & Rainwater, J. (2000, June)	-
	Multiple linear regression	Analysis demonstrated that both property and violent crimes were moderately correlated with population density, and these crimes largely affected the same blocks. It was concluded that at the block level of geography, no evidence of a differential between property and violent crimes based on population density could be detected.	Harries, K. (2006)	X
	Johansen cointegration method	The outcomes reveal that the population densty have a negative and significant impact on crime rate among the districts of Punjab.	Kassem, M., Ali, A., & Audi, M. (2019)	+
	Firth logistic regression	More populated communities are more prone to experience significant reductions. The higher the number of people at home, the higher the levels of capable guardianship, the lower the opportunities for crime.	2Campedelli, G.M., Favarin, S., Aziani, A. et al.	-

Land Used and Crime

Variable	Method	Finding	Sources	P
% vacant parcels in the community	linear and Poisson regression models	The crime rate around the open space is usually higher, but the green open space can significantly reduce the crime rate.	Kondo, M., Hohl, B., Han, S., & Branas, C. (2016).	+
	multilevel Poisson models	The presence of more vacant units on the block that is associated with higher aggravated assaults, robberies and homicides.	Boessen, A., & Hipp, J. R. (2015).	+
%Residential land use	Movement Pattern Analysis base on GIS	Findings of the study also indicated that, there was a strong relationship between petty crimes, drug abuse and land use patterns. These criminal activities tend to concentrate in residential and commercial areas of the study area.	Ludin, A. N. M., Aziz, N. A., Yusoff, N. H., & Abd Razak, W. J. W. (2013)	+
	multilevel Poisson models	Studies have found that the crime rate is higher in shopping places and near bars than in other places.	Boessen, A., & Hipp, J. R. (2015)	+
%Recreation and entertainment land use	“crime location quotient (LQC)	with the highest concentration shown by commercial crimes and by the theft of property other crime type.	Sypion-Dutkowska, N., & Leitner, M. (2017)	+
	Ordinary Least Squares	In grid cells with retail shops , the average number of P1V crime, P1P crime and all types of crime is about five times greater than the averageof all 6975 rids	SooHyun, O., & Lee, Y. (2016)	+
	multilevel Poisson models	There is no significant relationship between crime and residential land.	Boessen, A., & Hipp, J. R. (2015)	X

Insufficient

- Previous studies seldom paid attention to changes over a period of time and lacked the capture of temporal details or spatial details.
- In most of the correlation analysis for crimes, traditional linear regression models are usually used to analyze spatial data, and it is generally difficult to obtain satisfactory results. Because the global model assumes that the relationship between variables has "spatial homogeneity" before analysis. The results obtained are only a certain "average" within the study area, which may produce unreliable risk estimates. Therefore, it is necessary to adopt a new local regression method to deal with this attribute of spatial data itself.

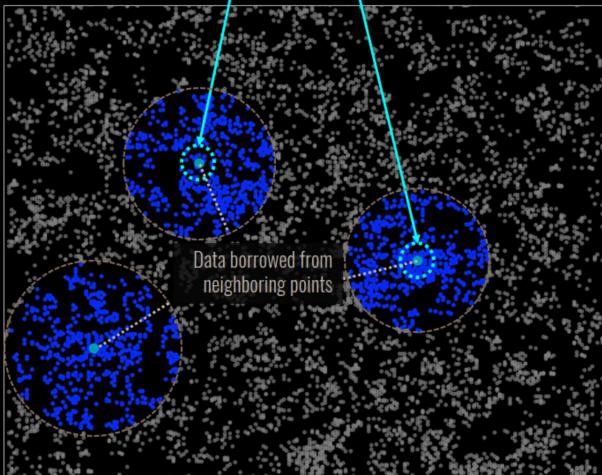
Control spatial heterogeneity

Finding	Sources
Study the risk of robbery in big cities in Brazil. The result model estimated by geographically weighted regression shows that there is a reasonable amount of spatial heterogeneity following the urban socio-economic spatial distribution characteristics.	De Maria André and Carvalho (2019)
Use geographic weighted regression models to better understand the spatial relationship between socioeconomic outcomes and policy investment. Geographically weighted regression results reveal the spatial mismatch of socially disadvantaged groups (such as the black population, other ethnic minorities, single-parent families, and zero-car families) who often live-in disadvantaged communities.	Wang and Chen (2017)
Use GWR and Local Moran's I to determine the spatial relationship between crime rates and demographic characteristics.	Wang et al. (2019)
It studied the impact of natural disasters on the temporal and spatial behavior of crime patterns, using local data, and highlighted various aspects of the changes in crime patterns as a response to Hurricane Wilma in Miami, Florida in 2005. The results show that using GWR can more accurately predict crimes of a specific type of crime in a specific city.	Walker et al. (2014)
Use GWR and mapping techniques to model the correlation between the Airbnb cluster and the crime index. The results showed that crime types (ie, robbery and motor vehicle theft) were significantly positively correlated, and violent crimes (ie, murder/rape) were negatively correlated, and a spatial relationship was found throughout the study area.	Xu et al. (2017)
Use GWR to construct a local model, analyze the impact of population density, road network density, and distance from the police station on the crime rate at the census district level, and analyze the relationship between the spatial distribution of crimes and geographic factors to find the reasons for the spatial distribution of crimes. The analysis results show that the spatial relationship between crime and geographic factors is a spatially non-stationary process, and the GWR model helps to improve the accuracy of parameter estimation.	Yan et al. (2010)
The original GWR program has recently been improved. Multi-scale Geographically Weighted Regression (MGWR) is the latest development of the classic GWR model. By using different bandwidths for each covariate, MGWR outperforms traditional single-scale GWR models in capturing multi-scale processes.	Li et al (2020)

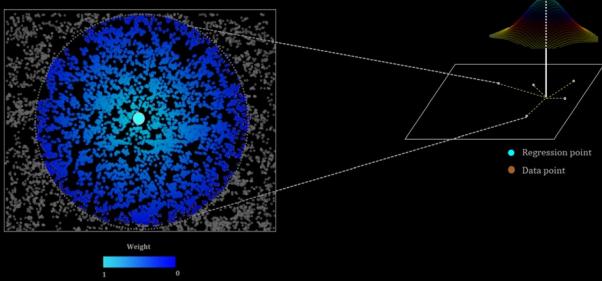
MGWR: Multi-scale Geographically Weighted Regression

GWR

$$y_i = \sum_j \beta_{ij} (u_i, v_i) X_{ij} + \epsilon_i$$

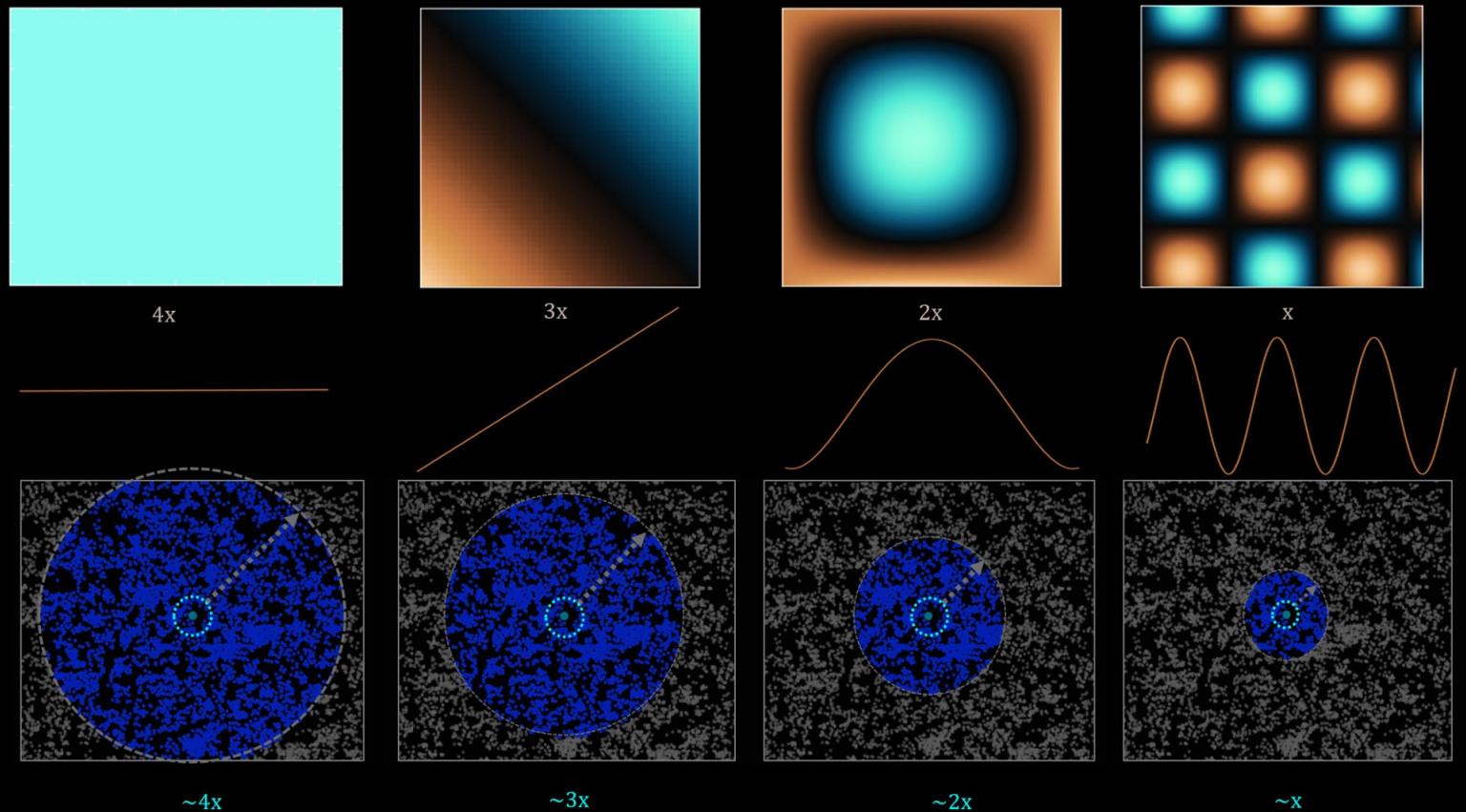


Bandwidth - Indicator of Scale



MGWR

$$y_i = \beta_0(u_i, v_i) + \sum_j \beta_{bj} (u_i, v_i) X_{ij} + \epsilon_i$$

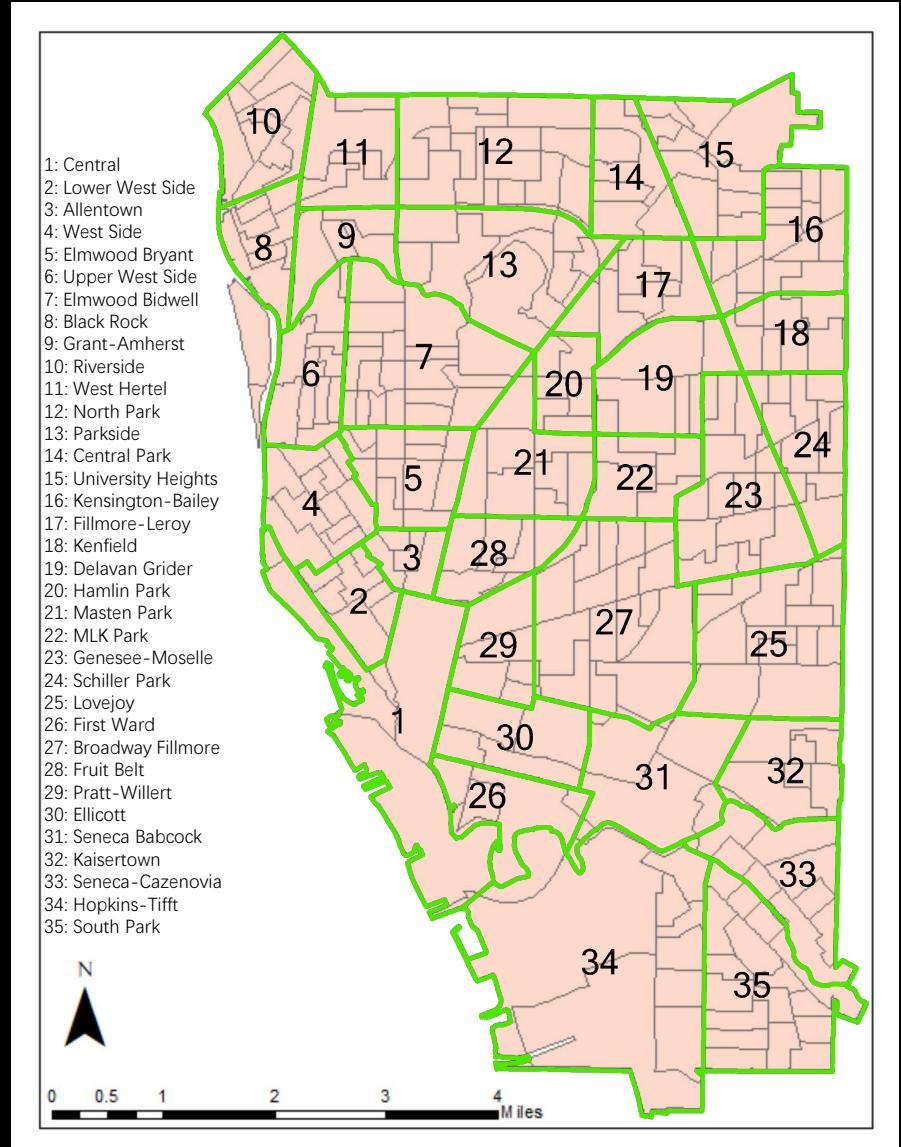
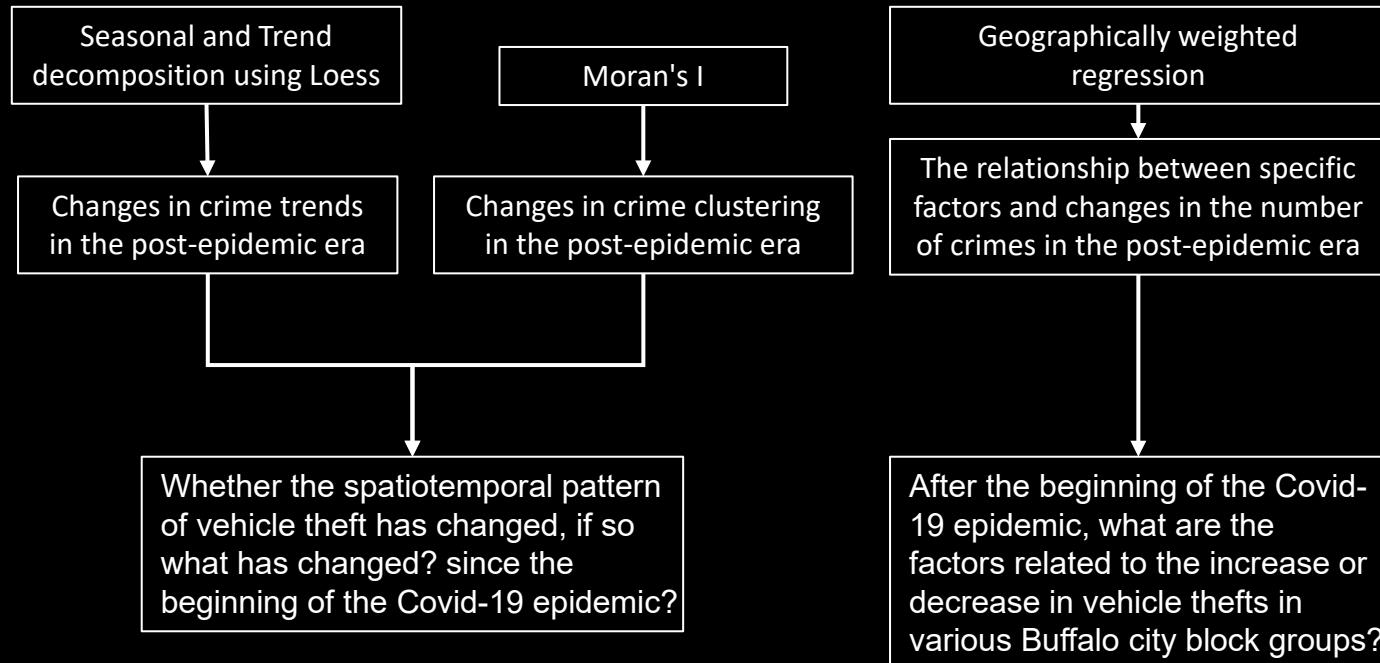


Where $\beta_0(u_i, v_i)$ is the intercept, x_{ij} is the j th predictor variable, $\beta_j (u_i, v_i)$ is the j th coefficient, ϵ_i is the error term, and y_i is the response variable.

Where bw_j in β_{bj} indicates the bandwidth used for calibration of the j th conditional relationship.

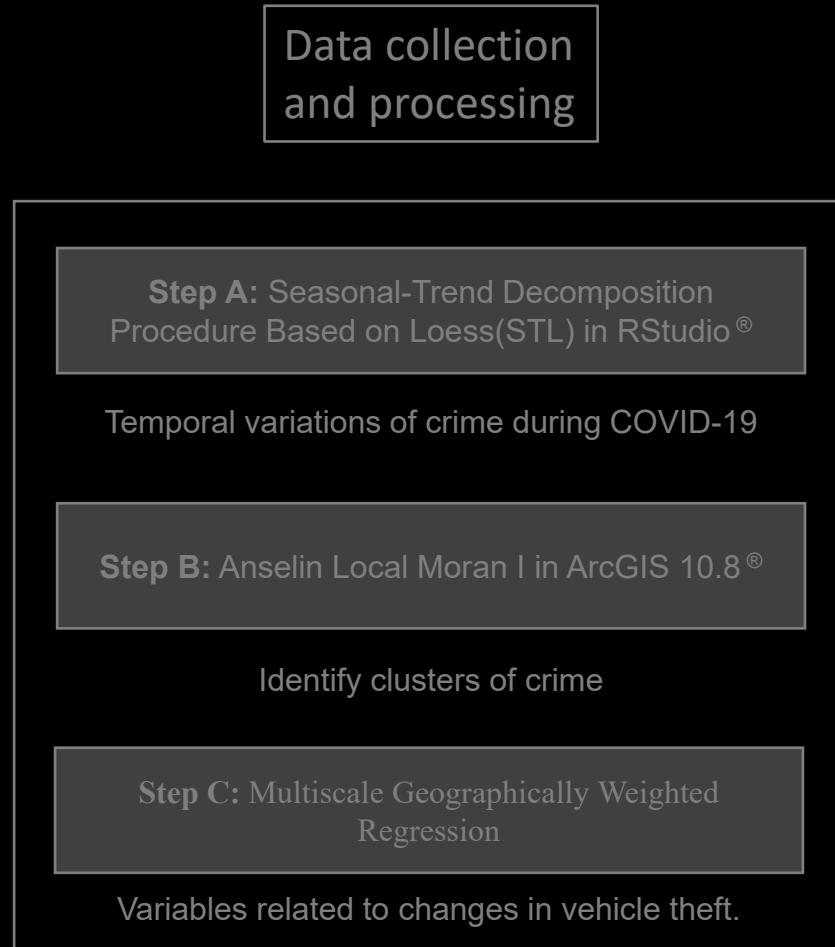
Study Area

278 Block Groups in 35 Neighborhoods in Buffalo, NY →



DATA COLLECTION AND PROCESSING

RESEARCH PROCESS



STL: Seasonal and Trend decomposition using Loess

Season-Trend decomposition procedure based on Loess (STL) is a common algorithm in time series decomposition. Based on LOESS, the data Y_v at a certain moment is decomposed into trend component(T_v), seasonal component(S_v) and remainder component(R_v)*.

$$Y_v = T_v + S_v + R_v \quad v = 1, \dots, N$$

Y_v : Daily Number of Stolen Vehicle from January 1, 2018, to July 1, 2021, in Buffalo, NY.

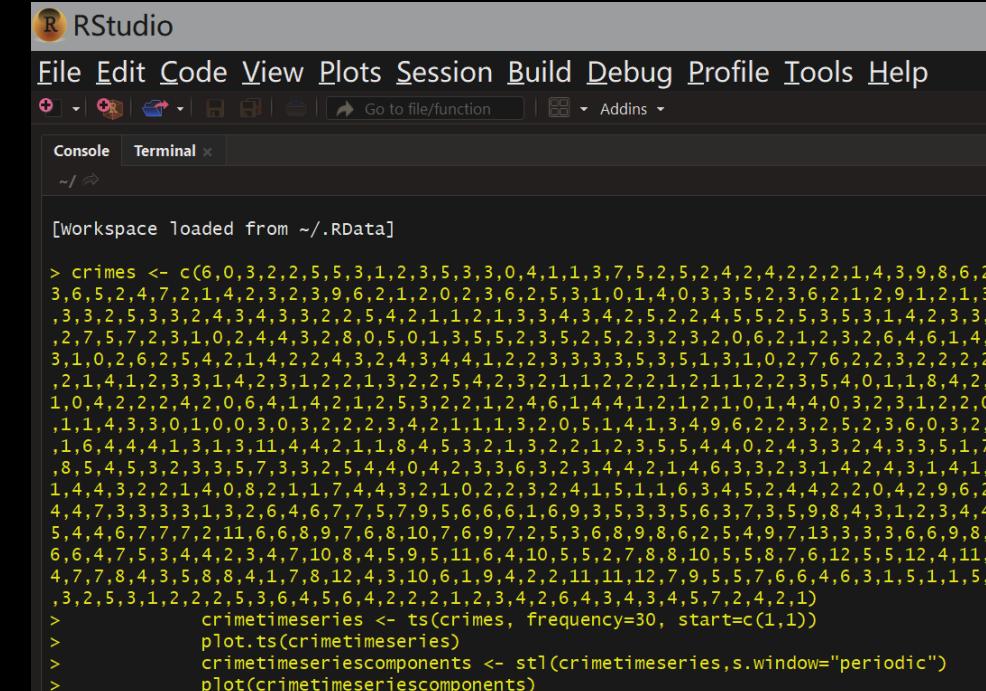
S_v : The seasonal component represents the periodic variation of crimes in month from January 1, 2018, to July 1, 2021.

T_v : After trend smoothing, the overall trend of crimes within three and half years is shown in the trend component. The number of crimes fluctuates around this trend.

R_v : The remainder component is the random noise in the time series obtained by eliminating the seasonal component and trend component. It can reflect the robust outliers of crime events.

STL decomposition was implemented by the “stl” function in R.

Variable	Span	Type	Source
Number of Motor Vehicle Thefts	Buffalo JAN 1, 2018 – JUL 1, 2021	EXCEL	Buffalo Police Department

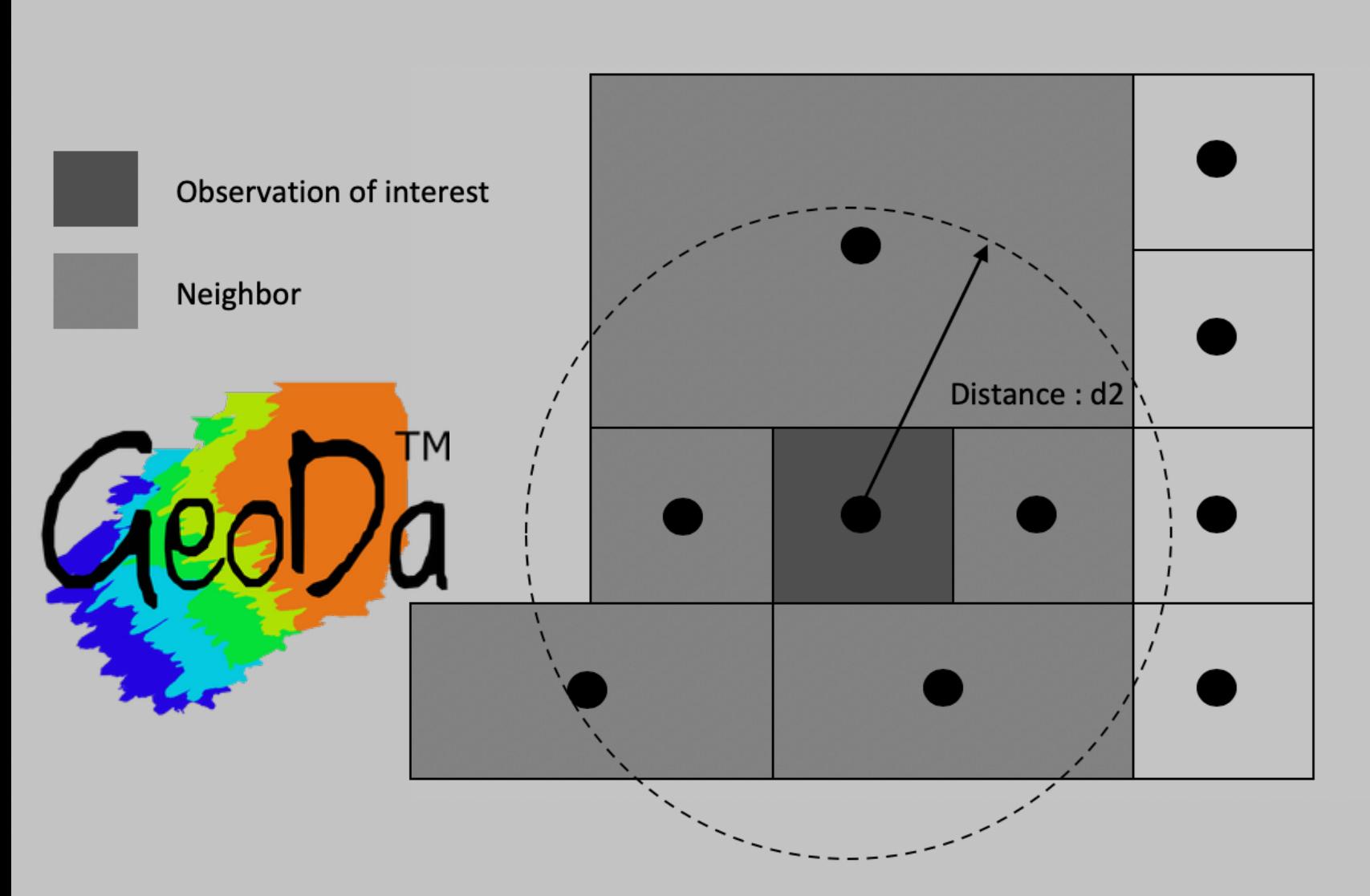


The screenshot shows the RStudio interface with the console tab active. The workspace has been loaded from `./.RData`. The R code in the console is as follows:

```
> crimes <- c(6,0,3,2,2,5,5,3,1,2,3,5,3,3,0,4,1,1,3,7,5,2,5,2,4,2,4,2,2,2,1,4,3,9,8,6,2  
3,6,5,2,4,7,2,1,4,2,3,2,3,9,6,2,1,2,0,2,3,6,2,5,3,1,0,1,4,0,3,3,5,2,3,6,2,1,2,9,1,2,1,  
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,4,4,7,3,3,3,3,1,3,2,6,4,6,7,7,5,7,9,5,6,6,1,6,9,3,5,3,3,5,6,3,7,3,5,9,8,4,3,1,2,3,4,4  
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,3,2,5,3,1,2,2,5,3,6,4,5,6,4,2,2,2,1,2,3,4,2,6,4,3,4,3,4,5,7,2,4,2,1)  
> crimetimeseries <- ts(crimes, frequency=30, start=c(1,1))  
> plot.ts(crimetimeseries)  
> crimetimeseriescomponents <- stl(crimetimeseries, s.window="periodic")  
> plot(crimetimeseriescomponents)
```

*. Cleveland, Robert B., William S. Cleveland, and Irma Terpenning. "STL: A seasonal-trend decomposition procedure based on loess." Journal of Official Statistics 6.1 (1990): 3.

Spatial cluster analysis – Local Moran's I



The Local Moran statistic was suggested in Anselin (1995) as a way to identify local clusters and local spatial outliers.

Spatial cluster analysis

Variable	Span	Type	Source
Number of Motor Vehicle Thefts	Buffalo JAN 1, 2018 – JUL 1, 2021	SHP(POINT)	Buffalo Police Department

Join data from another layer based on spatial location

Variable	Span	Type	Source
Buffalo Block Group	2021	SHP(POLYGON)	U.S. Census Bureau

Field calculator

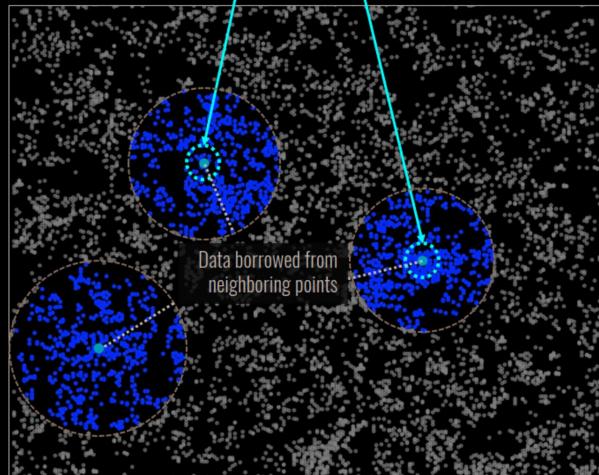
Variable	Span	
Vehicle theft rate before Covid-19 epidemic (per 1000)	March 15, 2019 to March 14, 2020	$\text{Vehicle theft rate} = \frac{\text{Vehicle thefts in Block Group}}{\text{total population in Block Group}} * 1000$
Vehicle theft rate during Covid-19 epidemic (per 1000)	March 15, 2020 to March 14, 2021	
Changes in vehicle theft rate during Covid-19 epidemic (per 1000)	March 15, 2020 to March 14, 2021	$\begin{aligned} &\text{Changes in vehicle theft rate} \\ &= \left(\frac{\text{Vehicle thefts in Block Group in 2020}}{\text{total population in block group}} * 1000 \right) \\ &- \left(\frac{\text{Vehicle thefts in Block Group in 2019}}{\text{total population in block group}} * 1000 \right) \end{aligned}$

- Analyzing Patterns
- Spatial Autocorrelation (Morans I)
- Mapping Clusters
- Cluster and Outlier Analysis (Anselin Local Morans I)

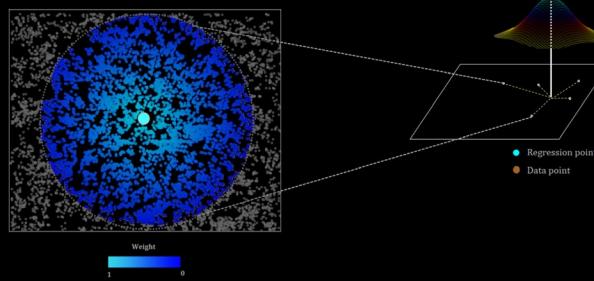
MGWR: Multi-scale Geographically Weighted Regression

GWR

$$y_i = \sum_j \beta_{ij} (u_i, v_i) X_{ij} + \epsilon_i$$

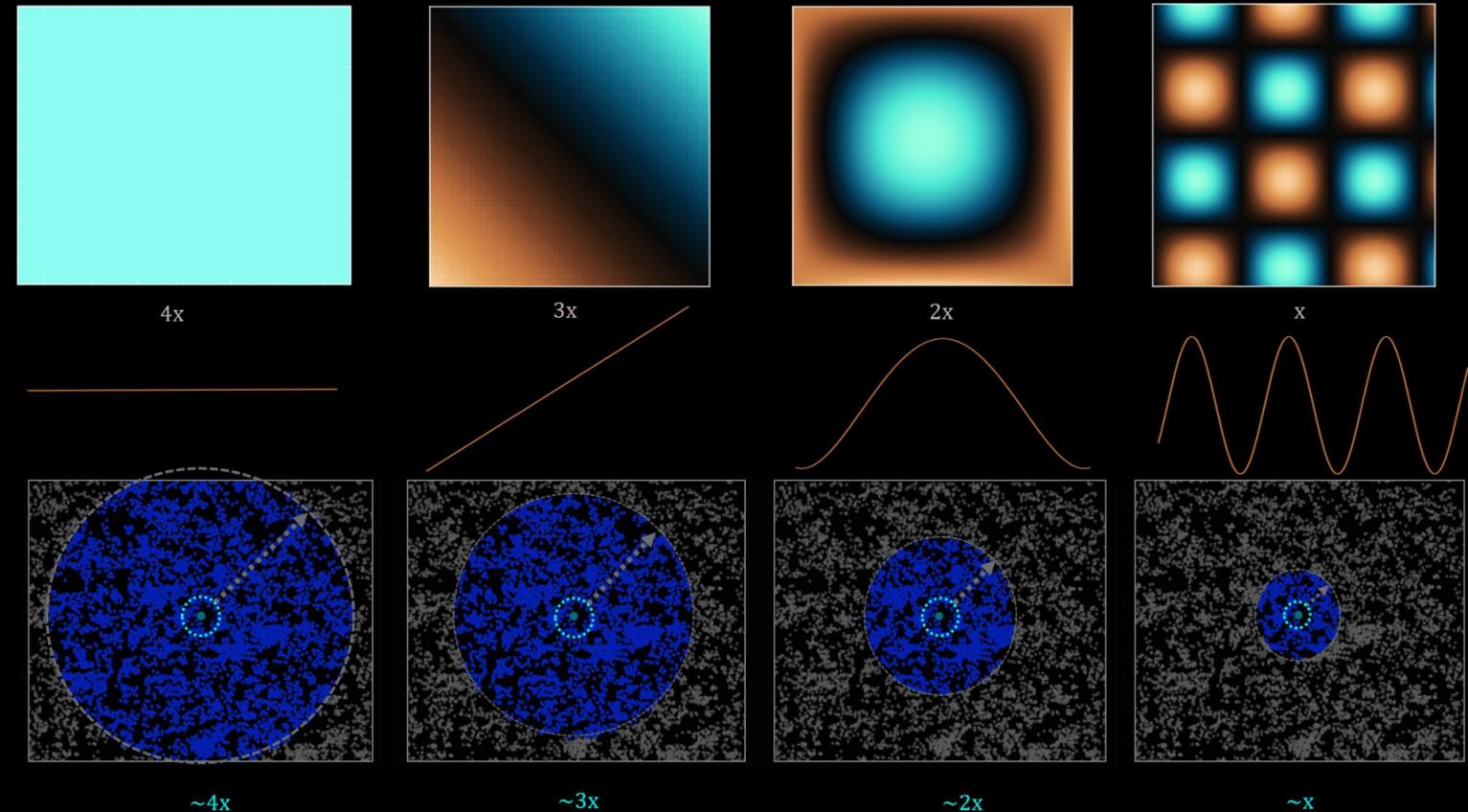


Bandwidth - Indicator of Scale



MGWR

$$y_i = \beta_0(u_i, v_i) + \sum_j \beta_{bj} (u_i, v_i) X_{ij} + \epsilon_i$$



Where $\beta_0(u_i, v_i)$ is the intercept, x_{ij} is the j th predictor variable, $\beta_j (u_i, v_i)$ is the j th coefficient, ϵ_i is the error term, and y_i is the response variable.

Where bw_j in β_{bj} indicates the bandwidth used for calibration of the j th conditional relationship.

PART TWO: Correlation analysis

Socio-economic vulnerability index

1. Poverty - population living below Federal poverty level
2. Unemployment - age 16 and over seeking work
3. Per capita income - (2019 inflation-adjusted \$)
4. Education - age 25+ without a high school diploma

Housing environment vulnerability index

1. Large apt. bldgs. - 10 or more housing units per building
2. Crowding - housing units with more than one person per room
3. Group quarters - population living in group quarters

Population vulnerability index

1. Elderly - population age 65 and over
2. Disability - age 5 or more with a disability
3. Limited English - age 5 and over who speak English less than "Well"

INDEX CALCULATION FORMULA

$$\left(\frac{\text{variable in block group}}{\text{total population/housing in block group}} \right) * \left(\frac{\text{variable in buffalo}}{\text{total population/housing in buffalo}} \right) * 100$$

Haque, A., 1998. Use of Geographic Information Systems in Mapping Distressed Areas of Cities. Journal of Urban Technology 5, 47–59.
<https://doi.org/10.1080/10630739883831>

Data From: American Community Survey (ACS) 2015--2019 (5-Year Estimates)

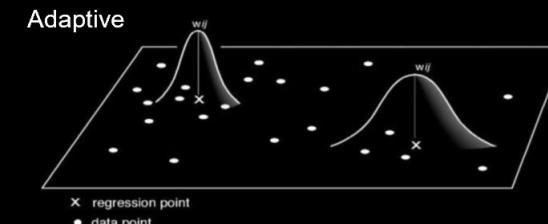
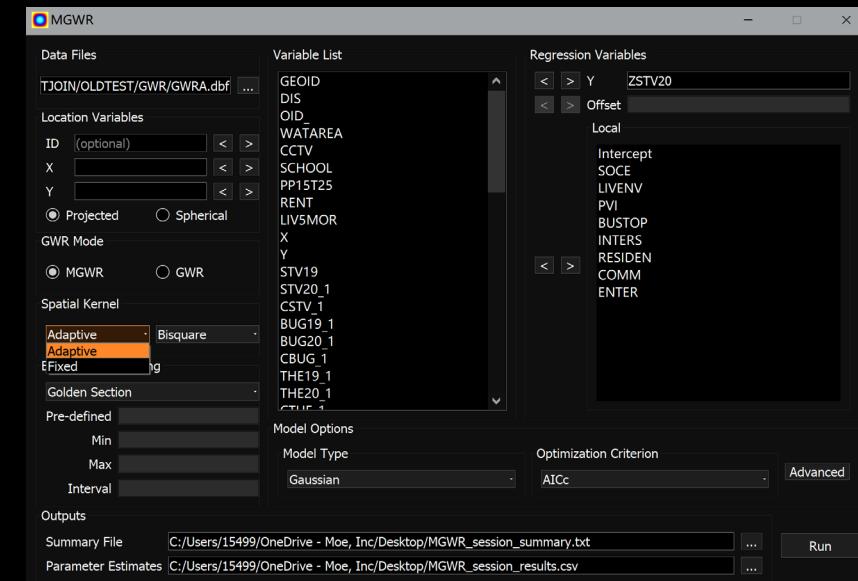
MGWR: Multi-scale Geographically Weighted Regression

Dependent Variable	Span	Source
Changes in vehicle theft rate	2020/03/15-2021/03/15	Buffalo Police Department
Independent Variable	Span	Source
Socio-economic vulnerability index	2015-2019	American Community Survey (ACS) 2015--2019 (5-Year Estimates)
Housing environment vulnerability index	2015-2019	American Community Survey (ACS) 2015--2019 (5-Year Estimates)
Population vulnerability index	2015-2019	American Community Survey (ACS) 2015--2019 (5-Year Estimates)
Population density	2015-2019	American Community Survey (ACS) 2015--2019 (5-Year Estimates)
Number of intersections in block groups	2021	Department of Public Works
Number of bus stops in block groups	2021	Niagara Frontier Transportation Authority
Number of vehicles towed away due to illegal parking in block groups	2020/03/15-2021/03/15	Parking Violations Bureau
%Rental housing in block groups	2015-2019	American Community Survey (ACS) 2015--2019 (5-Year Estimates)
% vacant parcels in block groups	2021	GIS.NY.GOV
% Recreation land use in block groups	2021	GIS.NY.GOV
% Resident land use in block groups	2021	GIS.NY.GOV

Part 2: Correlation analysis

Step 2.1: Step 2.1: Multiscale Geographically Weighted Regression

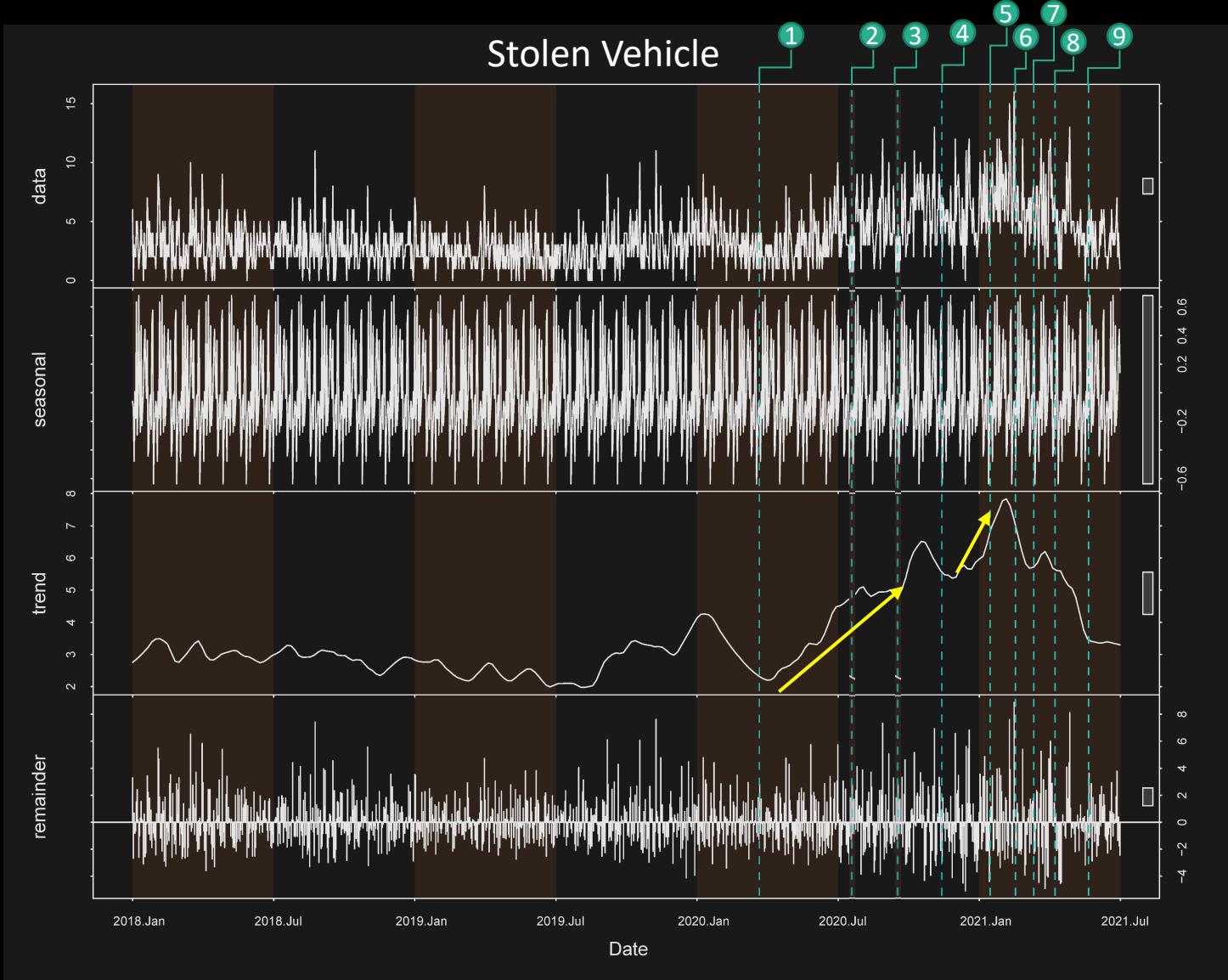
Variables related to changes in vehicle theft.



Conceptual diagrams explaining fixed (top) and adaptive (bottom) weighting schemes

RESULTS AND FINDINGS

STL: Seasonal and Trend decomposition using Loess



Covid-19 suppression measures

1. Cuomo announced the statewide stay-at-home order, also known as the NYS on Pause Program, with a mandate that all non-essential workers work from home beginning at 8 p.m. on **March 22, 2020**.
2. On **July 10, 2020**, the last stage of the opening plan allows the shopping mall to open at 25% of its capacity.
3. On **September 26, 2020**, the state recorded more than 1,000 COVID-19 cases every day, which is the first time the state has seen such a high number since June 5.
4. On **November 12, 2020**, Cuomo announced new statewide restrictions which took effect the next day.
5. People between 65 and 74 years old are eligible for vaccination from **January 12, 2021**
6. People with chronic diseases and some essential workers are eligible for vaccination from **February 15, 2021**
7. All essential workers are eligible for vaccination from **March 17, 2021**.
8. Since **April 6, 2021**, people aged 16 and above can schedule appointments and get vaccinated in New York State.
9. On **May 19, 2021**, most capacity restrictions were removed statewide

Descriptive Statistics

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	WeekTotal
Monday	14	5	2	0	4	3	2	6	6	13	11	11	9	5	3	6	3	12	4	5	7	14	3	12	160
Tuesday	14	3	3	3	2	1	1	7	6	5	9	7	4	6	5	3	4	3	8	9	8	5	15	9	140
Wednesday	13	7	5	2	2	1	1	4	9	4	7	5	6	2	7	4	8	3	6	6	5	6	7	8	128
Thursday	10	1	5	2	1	1	4	2	9	4	4	7	10	10	11	6	6	5	10	8	6	11	7	9	149
Friday	13	4	4	1	3	3	0	7	5	7	3	8	4	8	4	9	8	13	9	6	10	9	7	9	154
Saturday	22	4	6	8	6	1	5	4	8	2	4	3	6	10	8	6	9	7	6	8	14	4	12	10	173
Sunday	12	4	2	2	4	1	2	1	2	6	8	5	8	9	6	1	8	7	4	7	9	8	9	9	134
HourTotal	98	28	27	18	22	11	15	31	45	41	46	46	47	50	44	35	46	50	47	49	59	57	60	66	1038

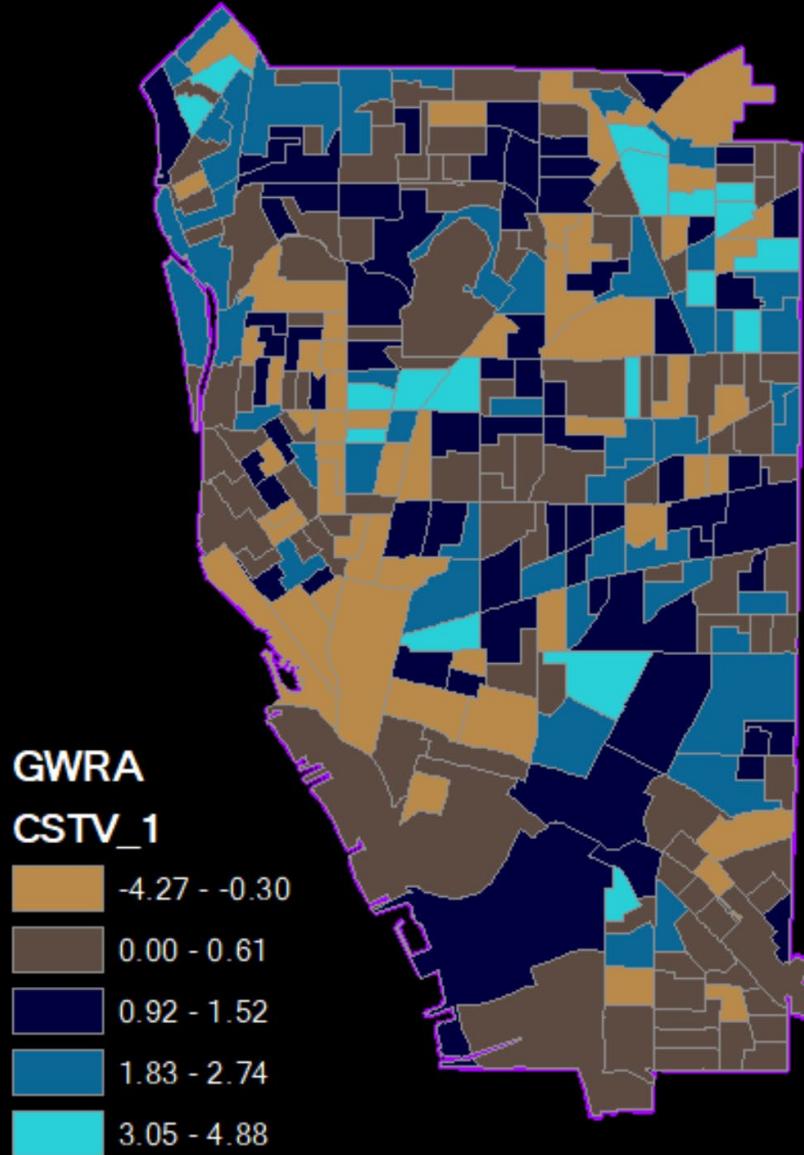
N	366
Min	0
Max	11
Total	1038
Ave	2.83
Std	1.845

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	WeekTotal
Monday	3	5	4	4	6	4	10	9	15	10	12	16	16	19	17	14	12	14	16	11	12	5	5	13	252
Tuesday	7	4	6	5	6	5	9	12	14	15	25	15	12	20	24	14	20	16	11	20	11	10	10	9	300
Wednesday	7	4	4	3	3	4	11	10	18	17	10	14	11	11	12	8	11	6	16	14	16	7	7	12	236
Thursday	8	6	7	2	4	5	10	12	10	13	15	16	15	11	15	16	12	22	12	14	17	12	10	11	275
Friday	6	3	7	4	2	1	11	9	7	20	15	14	14	14	16	5	14	15	9	13	8	15	11	11	244
Saturday	4	4	3	4	4	3	5	9	14	16	17	21	19	11	8	12	19	12	8	12	9	10	13	13	250
Sunday	11	4	3	6	2	5	6	10	8	16	19	15	12	17	10	8	13	16	12	11	17	13	10	7	251
HourTotal	46	30	34	28	27	27	62	71	86	107	113	111	99	103	102	77	101	101	84	95	90	72	66	76	1808

N	366
Min	0
Max	16
Total	1808
Ave	4.94
Std	2.822

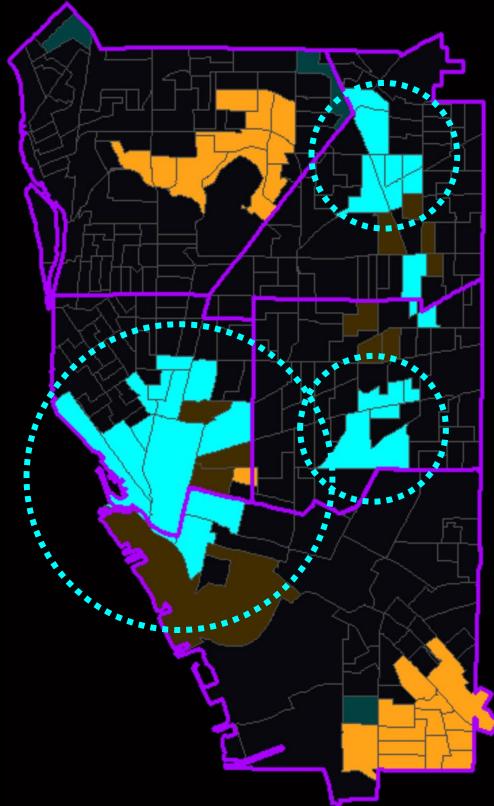
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	WeekTotal
Monday	-11	0	2	4	2	1	8	3	9	-3	1	5	7	14	14	8	9	2	12	6	5	-9	2	1	92
Tuesday	-7	1	3	2	4	4	8	5	8	10	16	8	8	14	19	11	16	13	3	11	3	5	-5	0	160
Wednesday	-6	-3	-1	1	1	3	10	6	9	13	3	9	5	9	5	4	3	3	10	8	11	1	0	4	108
Thursday	-2	5	2	0	3	4	6	10	1	9	11	9	5	1	4	10	6	17	2	6	11	1	3	2	126
Friday	-7	-1	3	3	-1	-2	11	2	2	13	12	6	10	6	12	-4	6	2	0	7	-2	6	4	2	90
Saturday	-18	0	-3	-4	-2	2	0	5	6	14	13	18	13	1	0	6	10	5	2	4	-5	6	1	3	77
Sunday	-1	0	1	4	-2	4	4	9	6	10	11	10	4	8	4	7	5	9	8	4	8	5	1	-2	117
HourTotal	-52	2	7	10	5	16	47	40	41	66	67	65	52	53	58	42	55	51	37	46	31	15	6	10	770

N	366
Min	-6
Max	15
Total	772
Ave	2.11
Std	3.199

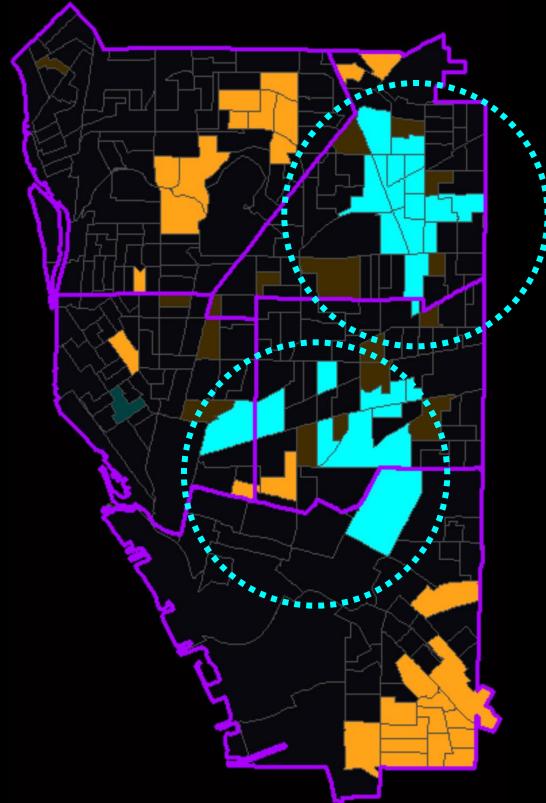


Correlation & Cluster Analysis

Cluster of vehicle theft rate before Covid-19 epidemic



Cluster of vehicle theft rate during Covid-19 epidemic



Cluster of changes in vehicle theft rate during Covid-19 epidemic



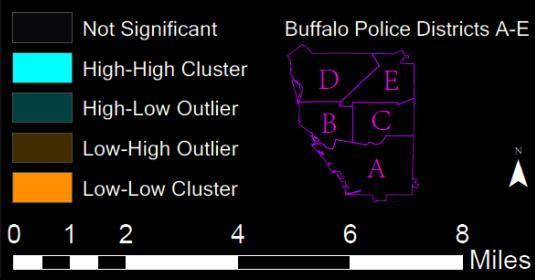
Global Moran's I

Data	Global Moran's I	Z-Score	p-Value	Typ	Sig
Vehicle theft rate before Covid-19 epidemic (per 1000)	0.169613	5.3862	0.00	C	***
Vehicle theft rate during Covid-19 epidemic (per 1000)	0.223486	6.7181	0.00	C	***
Changes in vehicle theft rate during Covid-19 epidemic (per 1000)	0.068881	2.1433	0.0321	C	**

*** P < 0.01, Z > 2.58, Very strong spatial clustering distribution.

** P < 0.05, Z = 1.95 ~ 2.58, Strong spatial clustering distribution.

Legend



MGWR: Multi-scale Geographically Weighted Regression

Changes in vehicle theft rates before
and after the COVID-19 epidemic

Global-Regression-Results				
Residual-sum-of-squares:				265.26
Log-likelihood:				-395.931
AIC:				813.863
AICc:				817.002
R2:				0.076
Adj.-R2:				0.042
Variable	Est.	SE	t(Est/SE)	p-value
Intercept	0	0.058	0	1
SOCE	-0.086	0.073	-1.182	0.237
LIVENV	-0.025	0.093	-0.274	0.784
PVI	0.079	0.067	1.179	0.238
BUSTOP	-0.117	0.091	-1.276	0.202
INTERS	-0.262	0.084	-3.108	0.002
RESIDEN	-0.092	0.093	-0.987	0.324
TC20T21	0.194	0.076	2.562	0.01
PVANC	-0.014	0.069	-0.208	0.835
RE	0.010	0.062	0.169	0.866
PS	0.041	0.065	0.631	0.528
POPDENS	-0.08	0.085	-0.942	0.346

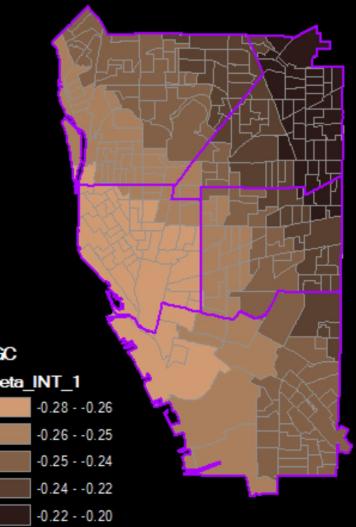
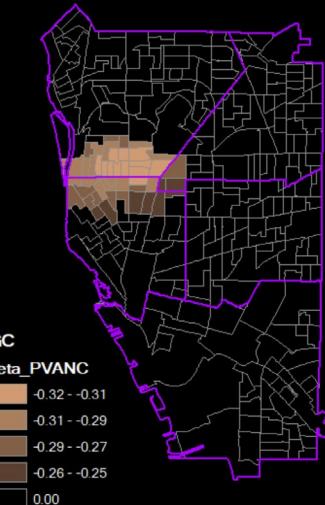
Multiscale-Geographically-Weighted-Regression (MGWR) Results					
Diagnostic-Information					
Residual-sum-of-squares:					194.448
Effective-number-of-parameters-(trace(S)):					37.398
Degree-of-freedom-(n- trace(S)):					249.602
Sigma-estimate:					0.883
Log-likelihood:					-351.369
Degree-of-Dependency-(DoD):					0.784
AIC:					779.533
AICc:					791.752
BIC:					920.049
R2:					0.389
Adj.-R2:					0.275
Variable		Bandwidth	ENP_j	Adj t-val(95%)	DoD_j
Intercept	Y	259	1.757	2.202	0.9
SOCE	Y	111	5.553	2.63	0.697
LIVENV					
PVI	Y	169	3.687	2.484	0.769
BUSTOP					
INTERS	Y	285	1.278	2.072	0.957
RESIDEN					
TC20T21	Y	49	13.299	2.922	0.543
PVANC	Y	144	4.054	2.518	0.753
RE	Y	129.000	4.974	2.591	0.717
POPDENS					

MGWR: Multi-scale Geographically Weighted Regression

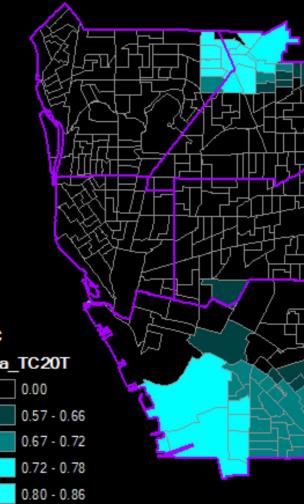
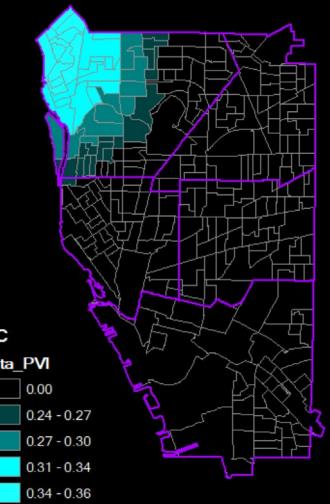
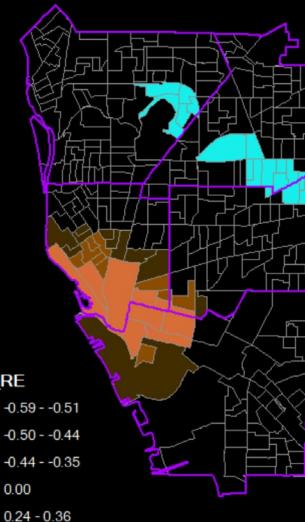
Changes in vehicle theft rates before and after the COVID-19 epidemic

Summary-Statistics-For-MGWR-Parameter-Estimates

Variable	Mean	STD	Min	Median	Max
Intercept	0.094	0.058	-0.03	0.094	0.198
SOCE	-0.112	0.141	-0.478	-0.071	0.096
LIVENV					
PVI	0.069	0.144	-0.131	0.053	0.363
BUSTOP					
INTERS	-0.244	0.019	-0.279	-0.245	-0.198
RESIDEN					
TC20T21	0.315	0.312	-0.443	0.349	0.855
PVANC	-0.106	0.113	-0.325	-0.086	0.092
RE	-0.011	0.232	-0.590	0.036	0.357
POPDENS					



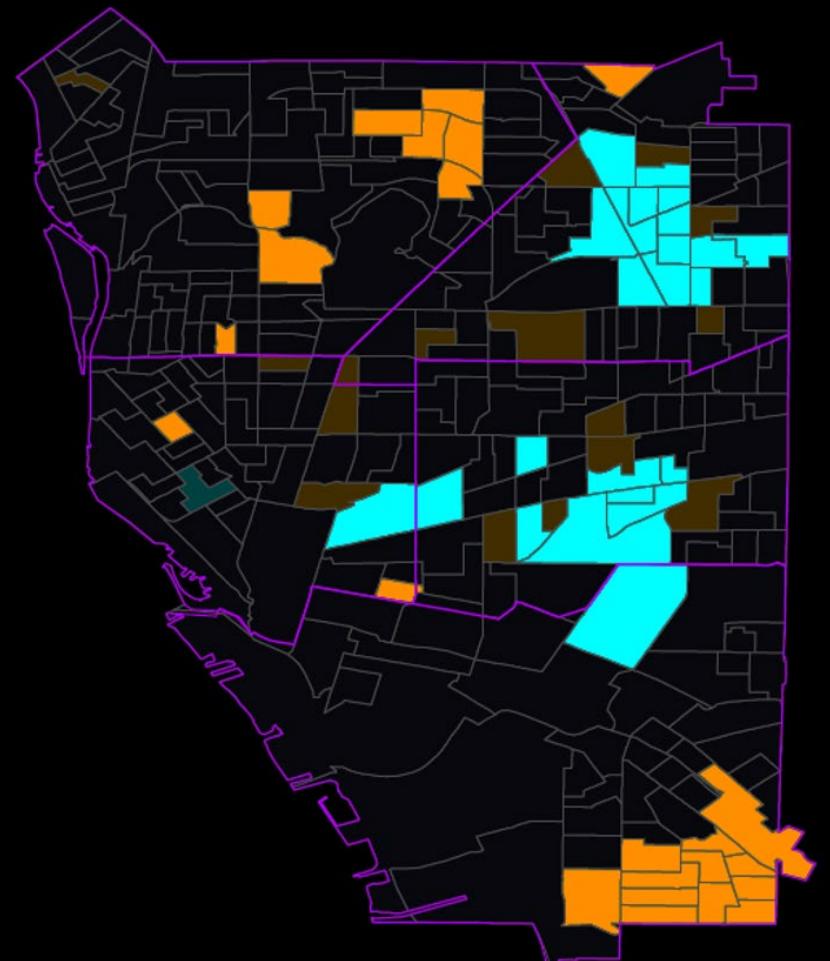
Buffalo Police Districts A-E



Discuss

1. The government's epidemic prevention department promotes the implementation of vaccination work as soon as possible.
2. During the social ban, the frequency of police patrols during the day should be increased, especially near recreational sites in the Eastern District of Buffalo.
3. People who are less resistant to crime should avoid living in the northwestern part of the city.
4. Criminals are more likely to pay attention to vehicles parked at illegal parking spots, because these illegal parking spots usually lack surveillance, and illegal parking should be avoided in order to ensure property safety.

StolenVehicle clusters
during the pandemic



Conclusion

In summary, the study found that:

1. Under the new crown pneumonia epidemic, the temporal and spatial distribution of vehicle theft crimes in Buffalo is not random.
2. Vehicle thefts occur more frequently during the day on working days.
3. After the implementation of the stay-at-home order and the social ban, the theft of vehicles will increase significantly.
4. The increase in the universal vaccination rate has a positive impact on curbing the crime of vehicle theft.
5. During the new crown pneumonia epidemic, the spatial distribution of vehicle theft was concentrated in the eastern suburbs of Buffalo City.
6. The increase in the rate of vehicle theft has nothing to do with the quality of the housing environment, population density, public transportation sites, the proportion of residential land, and the proportion of rental housing.
7. The increase in the rate of vehicle theft is negatively correlated with the socio-economic vulnerability index and the proportion of vacant housing in some parts of the city.
8. The number of intersections is also negatively correlated with the increase in vehicle theft rates, and this impact continues to weaken as the distance from the city center increases.
9. The higher the proportion of recreational land in downtown Buffalo, the lower the possibility of increased vehicle theft. This effect has the opposite effect in the economically fragile Eastern District.
10. The increase in the rate of vehicle theft in the northwest of the city is positively correlated with the proportion of groups with weaker crime resistance.
11. In the northeast and south of the city, the number of vehicles towed due to illegal parking is positively correlated with the increase in vehicle theft rates.

These conclusions are of great significance to the prevention and control of vehicle theft crimes when a large-scale public health crisis erupts in Buffalo in the future. For example, what time period and areas should be focused on should increase the number of patrols, and people who are less resistant to crimes Which areas should be moved out.