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

Yixuan Zhao

University at Buffalo

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Dr. Li Yin

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Introduction

At the beginning of 2020, COVID-19 appeared in the United States, and the number of cases nationwide increased rapidly (CDC, 2020a; CDC, 2020b; Inserro, 2020; Keaten, et al, 2020). In response to the pandemic, many cities have implemented various mitigation policies to minimize the spread of the virus (Ortiz & Hauck, 2020). One of the main strategies to prevent the spread of the virus focuses on using stay-at-home orders to reduce contact between individuals. The order closed non-essential businesses, forced citizens to wear masks, and encouraged citizens to minimize all non-essential visits (Ortiz & Hauck, 2020). The implementation of such policies has led to tremendous changes in people's daily social patterns and behaviors. Now, people spend less time in the office, many employees work from home, children study at home, wearing masks and maintaining social distancing have become the new social order (Bergmann, 2020; Gorzelanny, 2021; Kessel, et al, 2021). According to a new survey based on 5,858 U.S. adults who are working part time or full time and who have only one job or have more than one job but consider one of them to be their primary job by the Pew Research Center, more than half of people expressed their desire to continue working remotely after the pandemic, and their employers are actively considering accepting this strategy (Parker, et al, 2020). This is because most employers claim that working from home does not reduce the work efficiency of employees, and that working from home also saves the company a lot of operating costs, such as cleaning fees, office rental fees, and various other expenses. (Deluxe, 2020; Shearmur, 2020; Silverman, 2020; URI, 2020). Therefore, the COVID-19 pandemic may permanently change the global social order and human daily life patterns. The impact of this change on urban life has attracted widespread attention from social scientists around the world.

Criminologists have discovered that crime is related to human behavior, and changes in human behavior can lead to changes in crime patterns (Fink, 1983; Savage & Kanazawa, 2002). Recent studies in North American and European cities have also confirmed this statement. Research results show that changes in daily life patterns have a significant impact on the number and distribution of crimes (Ashby, 2020; Campedelli, et al, 2020a; Campedelli, et al, 2020b; Drake, et al, 2021; Mohler et al, 2020; Park, et al, 2021; Payne& Morgan, 2020; Yang et al, 2021). According to a report by the National Insurance and Crime Bureau, there were more than 873,000 motor vehicle thefts across the country in 2020, an increase of 9.2% over 2019, and the highest number of motor vehicle thefts detected by NICB in the past ten years (2021). Some scholars believe that the cause of this situation may be during the COVID-19 pandemic, as people stay at home to reduce the spread of COVID-19, their cars, trucks and SUVs are parked on the street unattended, which making them easy targets for thieves (Ortiz& Hauck, 2020; Park, et al, 2021). Recent research has analyzed the timing impact of the COVID-19 pandemic on different types of crime. However, the impact of the COVID-19 pandemic on the temporal and spatial distribution of urban crime is unclear, especially the motor vehicle thefts. In addition, existing research mainly studies the impact of the COVID-19 pandemic on crimes across the city, and rarely analyzes its impact on crime on a relatively micro scale. After the start of the COVID-19 pandemic, motor vehicle thefts in Buffalo have increased dramatically. From 2020 to the first six months of 2021, motor vehicle thefts in Buffalo increased by nearly 72% (Becker, 2021; Proia, 2021). Understanding the temporal and spatial patterns of motor vehicle theft is important because law enforcement agencies have discovered that these stolen vehicles are mainly used for other crimes, including shootings and robberies (INTERPOL, 2018; Modelevsky, 2018). Through the understanding of it, other types of crimes can be prevented, the detection rate of law enforcement agencies can be improved, and the occurrence of other crimes can be reduced.

This work is a case study aimed at investigating the impact of COVID-19 on the temporal and spatial patterns of motor vehicle thefts in Buffalo through spatiotemporal crime analysis methods. Specifically, this study uses Seasonal and Trend decomposition using Loess (STL) to analyze the time pattern changes of motor vehicle thefts in seven-time dimensions. Then, using ArcGIS to draw visual crime maps explored the spatial pattern changes of motor vehicle thefts in 2020 compared to 2019, and used local Moran's I to identify local clusters and local spatial outliers. Finally, the Multi-scale Geographically Weighted Regression (MGWR) was used to identify factors related to changes in the number of motor vehicle thefts in the region after the COVID-19 pandemic. The research results can help answer the following questions: First, has the spatiotemporal pattern of motor vehicle thefts changed since the beginning of the COVID-19 pandemic; and if so, what has changed? Second, what are the factors related to the increase or decrease in motor vehicle thefts in various Buffalo city block groups after the beginning of the COVID-19 pandemic? This study fills the gap in the existing literature on the changes in the micro-level motor vehicle thefts in cities after the COVID-19 pandemic. Law enforcement in the Buffalo can use the results to assess whether and how the patrol strategy for dealing with motor vehicle thefts needs to be updated.

Literature Review

Crime Theoretical Framework

In order to help understand the changes in the spatiotemporal patterns of motor vehicle thefts in Buffalo after the COVID-19 pandemic began, the theoretical framework of this research is determined by the Routine Activities Theory (Cohen& Felson, 2003), General Strain Theory (Agnew& Brezina, 2019), and Social Disorganization Theory（Shaw& McKay, 1942). Routine Activities Theory points out that crime is most likely to occur when potential criminals converge with suitable criminal targets in space and time, and there is no capable criminal guardian (Cohen & Felson, 2003). In other words, the occurrence of a crime requires three essential elements: criminal motive, a suitable target, and lack of capable guardians. Without any of these, the crime is unlikely to occur. For example, a recent research based on Routine Activities Theory found that during the pandemic in Washington D.C. (i) vehicles were sitting on the street for longer periods, (ii) fewer people were around to act as a deterrent, and (iii) more home deliveries were leading to an increase of vehicles idling on the street. So, all of these reasons create more targets for criminals (Weise, 2021; McDonald& Balkin, 2020).

General Strain Theory pointed out that during the COVID-19 pandemic, individuals may be more likely to commit crimes due to excessive stress. This is because the uncertainty related to COVID-19 containment policy and economic rebound risk has (i) limited people's freedom of movement, and (ii) intensified social isolation. As a result, people faced serious financial difficulties, and their anxiety and stress have rapidly increased (Brodeur et al, 2021; Brooks et al, 2020). In this situation, individuals, especially young people, may be negatively influenced (for example, they may go through stress), which may cause them to experience a series of negative emotions, which can make them feel the urge to commit a crime (Agnew & Brezina, 2019; Campedelli rt al, 2021). A statistical report issued by the Buffalo law enforcement agency supports this theory. The police and prosecutors found that the number of stolen cars reported by the city of Buffalo has increased sharply in the past year and a half, and a large proportion of them are caused by teenagers because the COVID-19 pandemic has put pressure on some people' lives. In view of this, although interaction and reduced mobility will affect crime in the short term, long-term stay-at-home orders may trigger a surge in criminal activity in the medium and long term.

In addition, the economic impact of the COVID-19 pandemic on the United States is largely destructive. Starting in March 2020, unemployment has been rapid. In the three weeks ending April 4, there were approximately 16 million people who lost their jobs in the United States (Rushe & Sainato, 2020). Social Disorganization Theory believes that the crime level of a community is closely related to the local ecological characteristics (Shaw & McKay, 1942). The socio-economic pressure generated during the COVID-19 pandemic will reduce social organization. Communities with the chaotic social organization have a lower level of social control, which will lead to a lack of self-regulation in the community, and if external agencies' supervision is not perfect, some people will exercise their unrestricted freedom to express their temperaments and desires, which will/can often lead to illegal behavior. Therefore, economic recession and instability will lead to an increase in the crime rate in the region.

Changes in the spatiotemporal patterns of vehicle theft

Many research literature containing vehicle theft crimes found large differences between the results. Most studies have found that vehicle thefts in cities have dropped significantly after the COVID-19 pandemic began (Alvarado et al, 2021; Andresen& Hodgkinson, 2020; De et al, 2021; Halford et al, 2020; Hodgkinson& Andresen, 2020; Kim& Leung, 2020; Payne et al, 2021; Rashid, 2021; Wang et al, 2021; Payne& Morgan, 2020). Some studies suggest that as more people stay at home and do not go to work, both motor vehicle theft and burglary will decrease because wider social distancing regulations keep residents at home and act as natural guardians of their property and vehicles (Payne et al., 2021). Some studies have found diametrically opposite results. These studies believe that the increase in vehicle thefts is due to the fact that cars are still parked in their normal positions. The reduced level of guardianship allows the vehicle to be easily stolen (Ashby, 2020; McDonald & Balkin, 2020). Some crime studies on multiple cities believe that the reason for this difference is that the crime is related to the intensity of the city's policy implementation. Compared with cities with less stringent lockdowns, the crime rate in cities with stricter lockdowns has decreased more (Ashby, 2020; McDonald& Balkin, 2020; Mohler et al, 2020; Nivette et al, 2021). In short, a large number of research results have found that vehicle theft has dropped significantly after COVID-19 became widespread popular. However, this result is quite different from the trend of vehicle theft in the national statistics. According to statistical data, the national vehicle theft rate has increased significantly after the COVID-19 pandemic began, which shows that the current research has a large deviation in choice of the study area.

The impact of the COVID-19 pandemic on the spatial distribution of urban vehicle thefts is unclear. The current study has only studied the spatial distribution of burglary and violent crime and found that these types of crime incidents have dropped significantly in the city center, while violent crime has increased in predominantly black communities (Campedelli et al, 2020; Moise& Piquero, 2021; Yang et al, 2021). In addition, existing research cannot determine whether the increase or decrease in crime is related to the socio-economic background and built environment of the area. To solve this problem, this study reviewed the previous literature that combined vehicle theft with the community environment. Many previous studies based on crime theory have found that crimes do not occur randomly in cities. The occurrence of crimes is related to the socio-economic characteristics and built environment of various areas of the city. In the past, some studies linking vehicle theft with community characteristics found that some demographic variables reflect the Economically Disadvantaged of the community (% African American;% Males 17-28; % unemployed) are positively correlated with vehicle theft (Musah et al, 2020; Passley, 2019; Brosnan, 2018; Narayan& Smyth, 2004; Park et al, 2019; Dao& Thill, 2021; Peterson& Krivo, 2010; Feng, 2021; Hipp et al, 2019; Hegerty, 2021; Chiavelli, 2019; Konkel et al, 2019; Wo, 2019). Because according to General Strain Theory, economically fragile communities usually face more pressure, and these pressures can cause people to commit crimes. In addition, other studies have found that vehicle theft is positively correlated with community housing quality (Housing units with more than one person per room; Owner Occupied Housing Units $300000 Or More), because high population density and house value indicates that there are more potential value targets for theft. (Musah et al, 2020; Passley, 2019; Brosnan, 2018; Narayan& Smyth, 2004; Park et al, 2019; Dao& Thill, 2021; Peterson& Krivo, 2010; Feng, 2021; Chiavelli, 2019; Konkel et al, 2019; Wo, 2019). Finally, some researchers found that some specific urban zoning (Vacant %; Commercial land %; Mixed land entropy) are positively correlated with vehicle crime (Musah et al, 2020; Wo, 2019; Hegerty, 2021; Dao& Thill, 2021; Hipp et al, 2019; Feng, 2021). Because these areas lack the necessary surveillance, they usually attract a lot of crime.

Spatiotemporal Analysis of Vehicle Theft

Some common time analysis methods can be used for crime analysis, such as ITSA, autoregressive integrated moving average (ARIMA) model, BSTS model, X11 decomposition, and seasonal extraction in ARIMA time series decomposition (SEATS). ITSA can be used to verify the impact of a policy on crime, based on crime trends before and after the policy (Nivette et al, 2021; Hodgkinson & Andresen, 2020). The ARIMA model and the BSTS model are often used to predict crime trends in 2020 without a pandemic or certain policies (Campedelli et al, 2021; Payne, 2021; Payne& Morgan, 2020; Rashid, 2021; Wang et al, 2021). However, ITSA, ARIMA models, and BSTS models cannot identify periodic changes or outliers in the distribution of prime time. X11 decomposition and seat decomposition only apply to quarterly and monthly data (Dagum& Bianconcini, 2016). STL decomposition is a commonly used algorithm in time series decomposition, which uses locally weighted scatter plot smoothing (Loess) as a smoothing method (Cleveland et al, 1990). It can identify different time trends, detect abnormal values of criminal incidents, and draw dynamic graphs of incidents over time with high precision and resolution. In addition, STL decomposition can handle any type of seasonality. We can also control the smoothness of the trend cycle in the STL decomposition. Therefore, we use STL decomposition to investigate the time changes of vehicle theft from seven dimensions.

The Local Moran statistic is a way to identify local clusters and local spatial outliers. This method has recently been used to analyze the impact of COVID-19 on the spatial pattern of crime (Yang et al, 2021; Park et al, 2020). This study will also use this method to identify whether there are spatial clusters of vehicle thefts in Buffalo before and after COVID-19, and whether the cluster location has changed. Once it is determined that there is a significant cluster Change, this study will use Multi-scale Geographically Weighted Regression to establish a formula to explore the elements related to vehicle theft. MGWR is often used to identify the relationship between crime and place (De Maria et al, 2019; Wang et al, 2017; Wang et al, 2019; Walker et al, 2014; Xu et al, 2017; Yan et al, 2010; Li et al, 2020). Since the local effect of the space object is considered, its advantage is higher accuracy.

Data

Study area

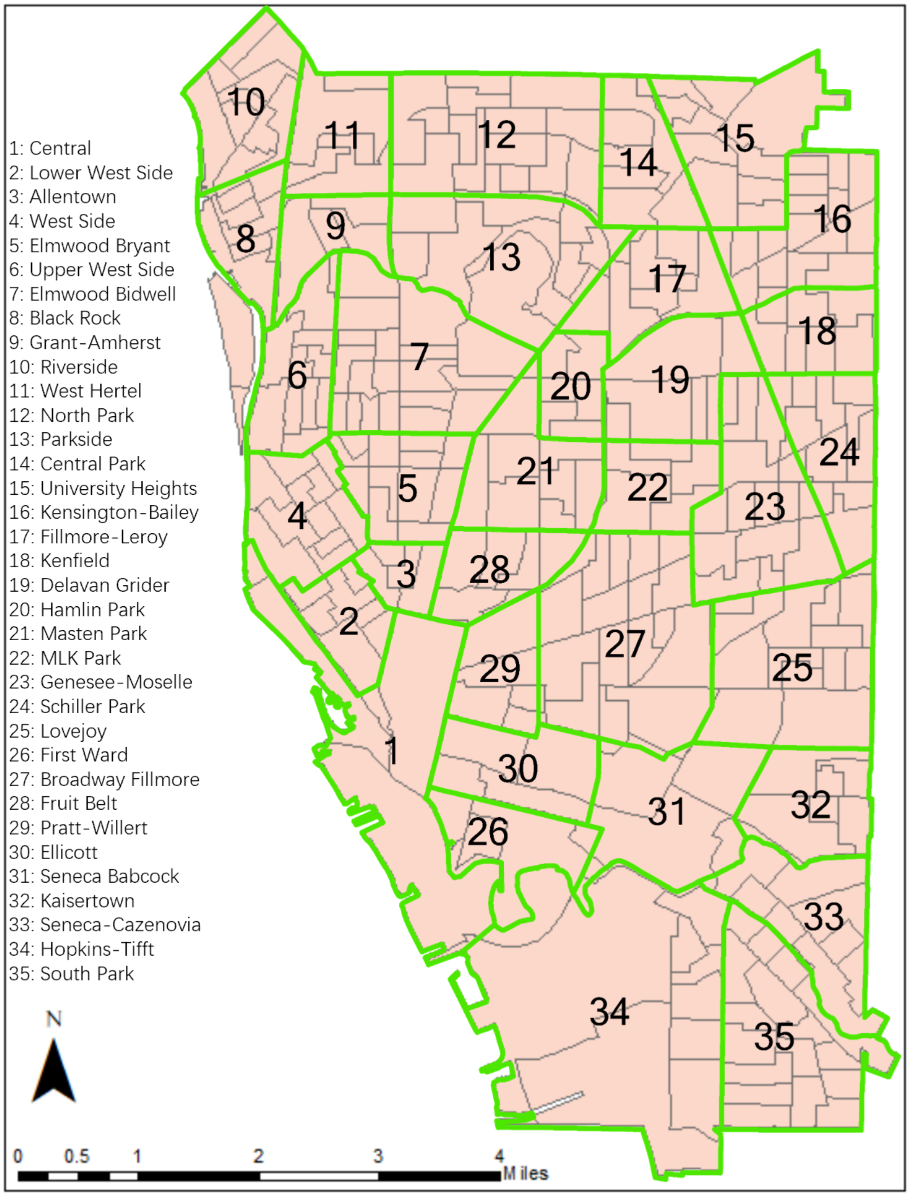


Figure 1. Case study area

Buffalo is the second-largest city in New York State and a typical shrinking city with a population of about 250,000 and shrinking continuously (Silverman, Yin & Patterson, 2015; World Population Review, 2021). The U.S. Census divides Buffalo's 35 neighborhoods into 278 block groups (Figure. 1). Buffalo reported its first COVID-19 case on March 15, 2020 (Spectrum

News Staff, 2020). In order to curb the spread of COVID-19, New York Governor Cuomo announced a statewide stay-at-home order on March 22, 2020 (Cuomo, 2020a). Then the four-phase reopening plan was launched after the daily number of new infections decreased, and the plan entered the final phase on July 10, 2020 (Cuomo, 2020b). However, the number of COVID-19 infections increased rapidly after the complete reopening. Until September 26, 2020, the state recorded more than 1,000 COVID-19 cases every day. This is the first time the state has seen such a high number since its reopening (Bloomberg News, 2020). Based on this, the governor issued a new stay-at-home order on November 12, 2020, requiring residents to stay at home as much as possible to control the spread of the virus (Cuomo, 2020c). The cumulative number of COVID-19 cases in Buffalo City had exceeded 200,000 until the first phase of the COVID-19 vaccination started on January 12, 2021. With the remaining vaccination schedule on February 15, 2021, and March 17, 2021, the spread of COVID-19 was significantly controlled (Cuomo, 2021). Therefore, when the time distribution of vehicle theft in Buffalo changes drastically, this study uses these seven-time points in the following analysis to subdivide crime trends.

Research variables

In order to study the temporal and spatial changes of vehicle theft after the COVID-19 pandemic and the relationship between this change and the characteristics of the community, this study first collected data on vehicle theft during the same period of one year before and after the start of the home order in New York State. Then based on the literature review, the factors related to the increase in vehicle theft were obtained from the U.S. Census Bureau and Buffalo open data. In order to control the error caused by the area, this study standardized all the independent variables. Finally, this study uses the land-use mixing degree calculation method proposed by Wo, and generates a mixed land entropy (2019) for each Block Group according to the ratio of different land-use variables in the land zoning map of Buffalo City. Its form is as follows:

$$H = 1 - \sum_{j=1}^{J} G_j^2$$

Among them, G represents the proportion of the plot group (area) of the land use category j in the J categories. Therefore, values close to 1 are close to perfect heterogeneity, and values close to 0 are close to perfect homogeneity. The data is shown in the following table:

Dataset	**Source**	**Time Span**	**Type of data**	**Data unit**
Buffalo Black Group 2019	City of Buffalo	2019	Polygon	Buffalo Black Group 2019
Crime Incidents	City of Buffalo	2019/MAR/22 - 2021/MAR/21	Point	Number of Motor Vehicle Thefts incidents
Total Population: Male: between 18-25 Years	ACS	2015-2019	Block group	% of Males 18-25 population
Total Population: Black or African American Alone	ACS	2015-2019	Block group	% of African American population
Employment Status for Total Population 16 Years and Over	ACS	2015-2019	Block group	% of population unemployed
OwnerOccupiedHousingUnits$300000 OR MORE	ACS	2015-2019	Block group	%House Units value $300000 of more
Occupied Housing Units: 1.01 or More Occupants Per Room	ACS	2015-2019	Block group	% of population living in crowded housing units
Vacant Housing Units Other Vacant	ACS	2015-2019	Block group	% Abandoned
Vacant Housing Units for Sale Only	ACS	2015-2019	Block group	% of Vacant Sale

Vacant Housing Units for Rent	ACS	2015-2019	Block group	% of Vacant Rent
Commercial land zoning	City of Buffalo	2021	Polygon	% of commercial land in Block Group
Mixed land entropy	City of Buffalo	2021	Polygon	% of land mixed in Block Group

Table 1. Data Collection

Method

Seasonal and Trend decomposition using Loess (STL)

In order to investigate the trends and cyclical changes of different types of crimes from March 2020 to March 2021, this study used STL decomposition to decompose the distribution of crimes (Yv) at each moment into the seasonal component (Sv), trend component (Tv), and remainder component (Rv). Since the periodic fluctuation of crimes is relatively stable, the model used by STL is an additive model whose formula is as follows:

$$\mathbf{Y\nu = T\nu + S\nu + R\nu \quad \nu = 1, \cdots, N}$$

Where Yν is the daily number of stolen vehicles from March 22, 2019, to March 21, 2021, in Buffalo, NY. Sν is the seasonal component which represents the periodic variation of crimes in each month from March 22, 2019, to March 21, 2021. Tν is after trend smoothing, the overall trend of crimes within two years is shown in the trend component. The number of crimes fluctuates around this trend. Rν, the remainder component, is the random noise in the time series obtained by eliminating the seasonal component and the trend component. It can reflect the robust outliers of crime events.

Spatial analysis

First, to investigate the spatial distribution and clustering patterns of crime, this study uses local Moran's I to explore the spatial autocorrelation of local changes to observe the impact of the pandemic on local areas. Local Moran I can be used to identify statistically significant hot spots, cold spots, and spatial outliers (Moran, 1962). In crime research, this method can help mark clusters of different types of crimes. It is a mature space technology that has been used to explore clusters of various criminal offenses, such as drug offenses and violent crimes (Cohen & Tita, 1999; Murray et al, 2001; Quick & Law, 2013). The method identifies where high or low values are clustered spatially and reveals features with very different values from surrounding features. Through these clusters, it is obvious that the distribution characteristics of the vehicle theft in Buffalo have changed. In this work, the local Moran's I was realized by the function of GeoDa (a spatial analysis software). The weight of Moran's I is calculated by the queen adjacency, which is considered to define the neighbor relationship through the common vertices and common edges of the polygon (Anselin & Rey, 1991).

Multi-scale Geographically Weighted Regression (MGWR) will be used to analyze which urban variables are related to the increase in vehicle theft after COVID-19 pandemic. The regression coefficient estimated value obtained through the traditional global regression model is the average value in the entire study area and cannot reflect the true spatial characteristics of the regression parameters. In order to solve this problem, Fortheringham and others summarized the local regression analysis and variable parameter research based on the idea of local smoothing and proposed the Geographically Weighted Regression Model (MGWR) (1996). At present, Geographically Weighted Regression (MGWR) has been widely used in various fields to simulate spatial non-fixed relationships. Multi-scale Geographically Weighted Regression (MGWR) is the latest development of the classic MGWR model, which was first proposed by Fotheringham and others in 2017 (2017). By using different bandwidths for each covariation, MGWR has an advantage in capturing multi-stage processes that are better than traditional single-scale MGWR models. This less restrictive expansion minimizes overfitting and reduces the deviation in parameter estimation and reduces concurrency (2017). The MGWR 2.2 software package was adopted as the core calculation module to calculate the geographic relationship between the number of vehicle thefts in the dependent variable and the independent variables in Block Group. This model is used to measure the local changing nature of vehicle theft changes. Using Gaussian model and Adaptive as the kernel space, an adaptive kernel controls for an optimal number of k neighbors to be included in the model fitting (Li et al, 2019). For the choice of bandwidth, the Golden Section method is used to determine the optimal size of the bandwidth, the Golden Section search finds the optimal value for the bandwidth by successively narrowing the range of values inside which the optimal value exists and comparing the optimization score of the model for each returning the value which has the lowest score (Li et al, 2019).

Finding and discussion

Temporal Analysis of Vehicle Theft

In order to analyze the changes in the time pattern of vehicle theft crimes, this work uses STL to disaggregate time crime data from 2019 to 2021, and sets the number of seasonal cycles to 7 observations to capture monthly cycles. Then, we compared the vehicle theft time patterns from 2019 to 2021 from the three dimensions of trend, seasonality, and remaining components (Figure 2).

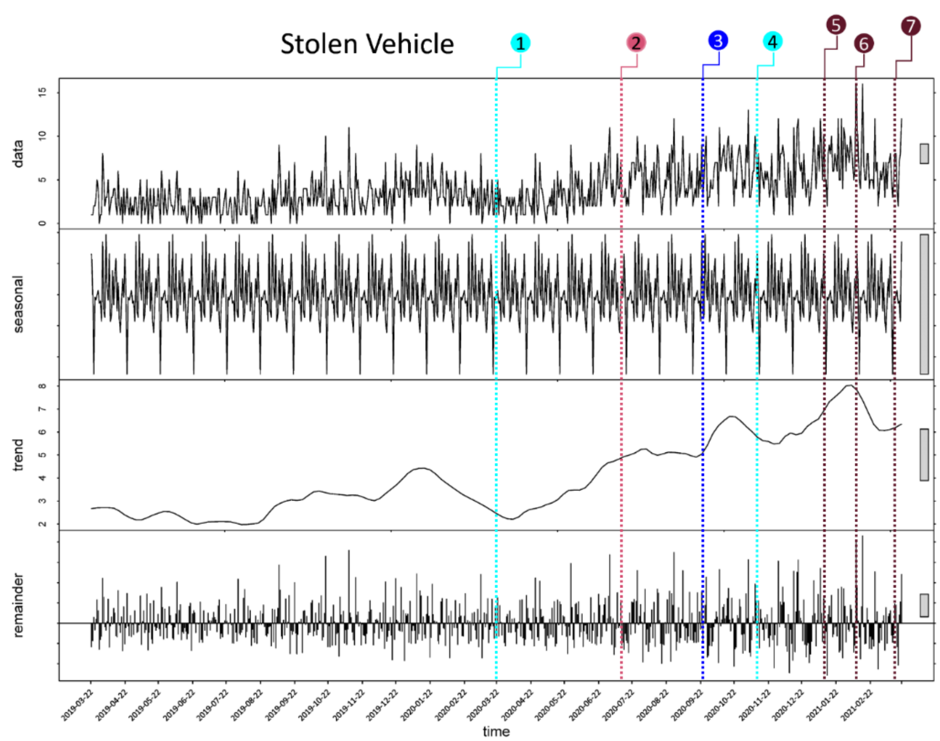


Figure 2. STL time series decomposition results

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 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.

According to the results of the STL in Figure 2, the trend component shows that the overall trend of crime in 2019 and 2020 is different. Compared with the growing trend of vehicle theft in 2019, vehicle theft has been increasing substantially in 2020. This study uses colored vertical lines to divide the trend components in Figure 2 into seven stages, based on the COVID-19 suppression policy and the time of vaccination. The first cyan vertical line was on March 22 (when the first mandatory stay-at-home order was issued), and the second red vertical line was on July 10 (when cautious reopening was issued). The third blue vertical line was on September 26 (when it was recommended to avoid unnecessary outings), and the fourth cyan vertical line was on November 12 (when the second mandatory stay-at-home order was issued). The fifth to seventh purple vertical lines represent the gradual unfolding of the vaccination plan. After excluding periodic effects, this study found that the number of vehicle thefts significantly increased after the issuance of an order recommending residents to avoid going out. The number of vehicle thefts gradually stabilized after the mandatory home order was revoked. After popularization, the number of vehicle thefts has dropped significantly, even during the stay-at-home order. The outliers reflect the abnormal changes in vehicle theft patterns. When Yang et al. used this method to study the changes in COVID-19 violent crimes and theft crimes in Chicago, they found that the outliers of these two crimes had the largest values on May 31, 2020. Outliers, which are closely related to the breakdown of the George Floyd protests. However, this phenomenon has not been observed in Buffalo. The uniform distribution of outliers indicates that the vehicle theft time in Buffalo has not been affected by a short-term special event on a certain day.

In order to show the time distribution of vehicle theft more intuitively, this study performed a descriptive statistical analysis of vehicle theft data for each year before and after the occurrence of COVID-19, summarizing each hour and week. Among them, Figure 3 reflects the periodic frequency of vehicle thefts in Buffalo City before and after the COVID-19 pandemic summarized by the hour, and Figure 4 reflects the periodic frequency of vehicle thefts in Buffalo City before and after the COVID-19 pandemic summarized by the week.

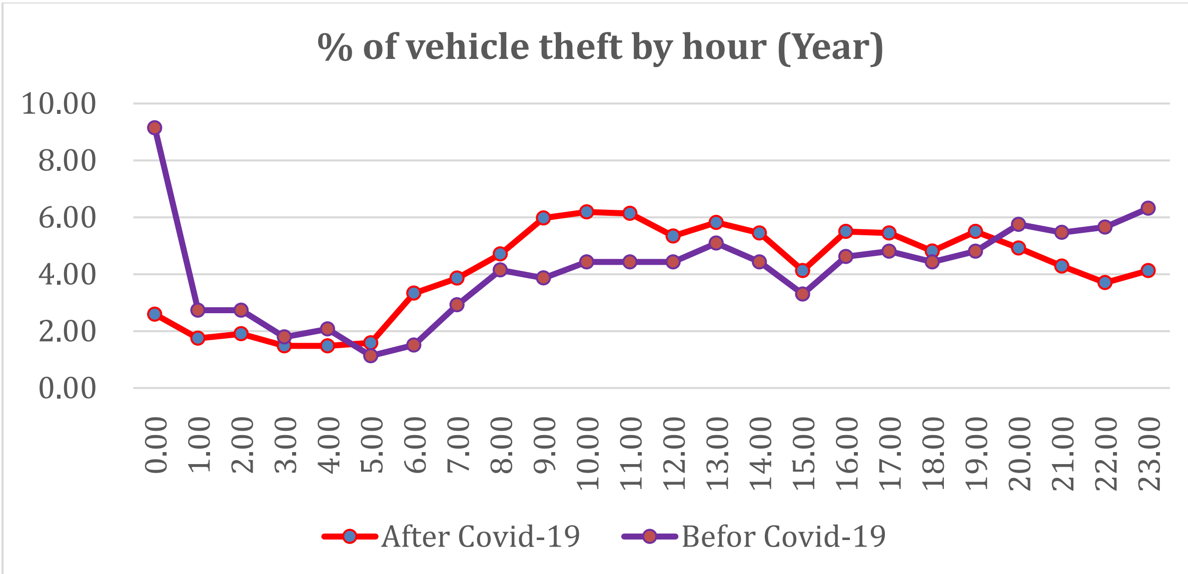


Figure 3. Percentage of vehicle theft by hour (Year)

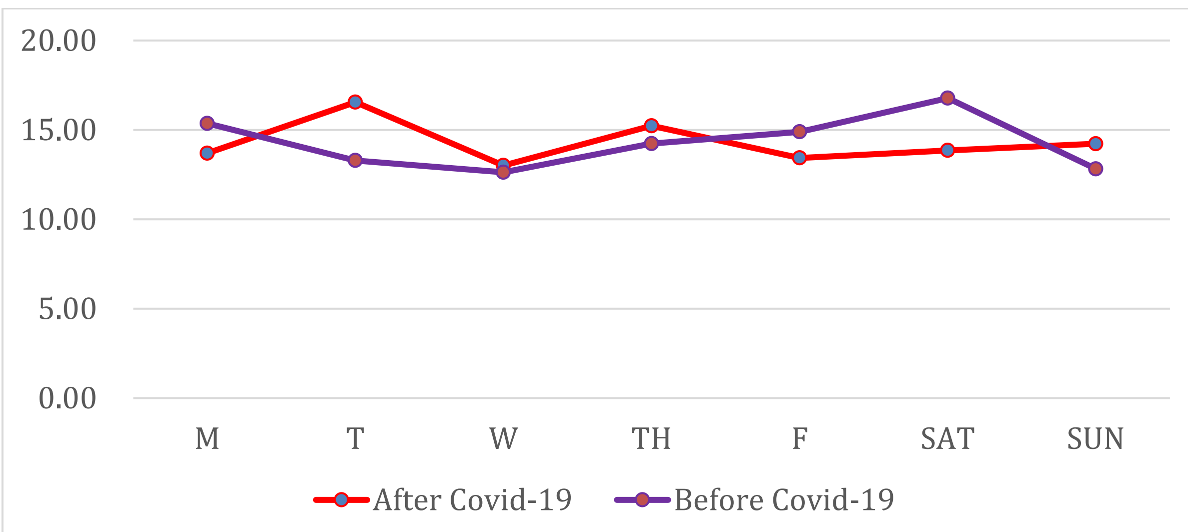


Figure 4. Percentage of vehicle theft by week (Year)

The study found that after Covid-19 became widespread, the time pattern of vehicle theft changed significantly. Weekly statistics show that after the COVID-19 pandemic began, the peak of vehicle theft occurred mostly on working days. Hourly statistics show that compared with before COVID-19, the pattern of vehicle theft has shifted from night to day after COVID-19.

Spatial analysis of Vehicle Theft

Figure 5 Local Moran's I result show different clusters (including high-high clustering, low-low clustering, low-high spatial outliers, and high-low spatial outliers) before and after COVID-19 pandemic.

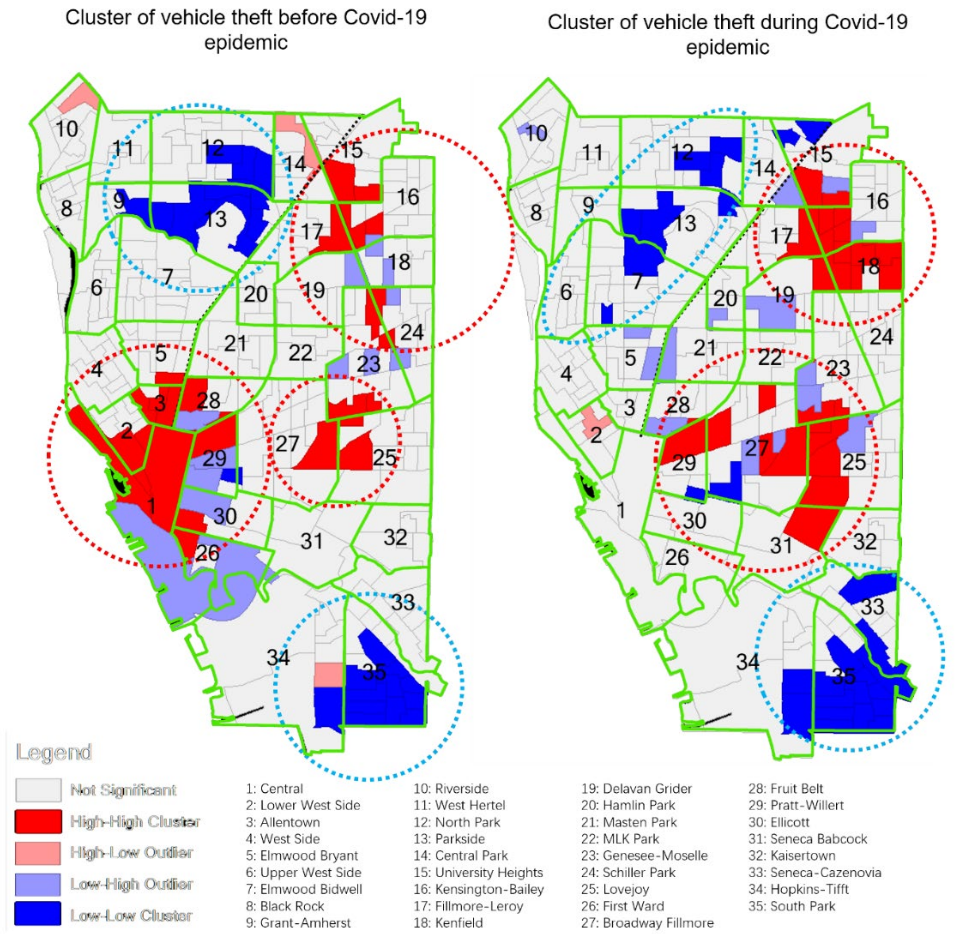


Figure 5. Cluster of vehicle theft before and after Covid-19 epidemic

According to image 5, the study found that vehicle theft moved from urban areas to the East Side of Buffalo after the COVID-19 pandemic began. This work suggests that Buffalo's police resources should be transferred to East Side. Local clusters of vehicle thefts in Buffalo also provide useful information on police prevention and crime-fighting practices.

Since previous research has found that the relationship between specific community characteristics and the number of vehicle thefts is inseparable. Asked to verify this relationship, this study used OLS and MGWR to build a regression model combining 10 factors that are most likely to be related to the increase in the number of vehicle thefts.

Tables 2 and 4 show that the adjusted R2 of the MGWR model before and after the COVID-19 epidemic is 35.7% and 52.5%, which are 25.8% and 28.6% higher than the OLS regressions in Tables 3 and 5, respectively. MGWR also produced reduced AICc. These model statistics suggest that MGWR is a more appropriate model, explaining 35.7% of the observed change in vehicle theft crime rates between different neighborhood groups in Buffalo before the COVID-19 epidemic and, 52.5% of the observed Changes in vehicle theft crime rates between different neighborhood groups in Buffalo after the COVID-19 epidemic began. Finally, the model explained changes in vehicle theft crime rates between different neighborhood groups in Buffalo to a greater extent after the onset of COVID-19 than before the onset of COVID-19.

Diagnostic	Information			
Residual sum of squares:	163.266			
Effective number of parameters (trace(S)):	33.024			
Degree of freedom (n - trace(S)):	253.976			
Sigma estimate:	0.802			
Log-likelihood:	-326.287			
Degree of Dependency (DoD):	0.806			
AIC:	720.621			
AICc:	730.08			
BIC:	845.13			
R2:	0.431			
Adj. R2:	**0.357**			
Variable	Bandwidth	ENP_j	Adj t-val(95%)	DoD_j
Intercept	286	1.345	2.094	0.948
% of Males 18-25 population	250	1.982	2.25	0.879
% of African American population	199	2.399	2.324	0.845
% of population unemployed	286	1.398	2.11	0.941
%House Units value $300000 or more	43	14.344	2.946	0.529
% of population living in crowded housing units	286	1.643	2.175	0.912
% Abandoned	282	1.659	2.179	0.911
% of Vacant Sale	286	1.421	2.116	0.938
% of Vacant Rent	286	1.083	2.002	0.986
% of land mixed in Block Group	248	2.366	2.318	0.848
% of commercial land in Block Group	188	3.383	2.453	0.785

Table 2. MGWR Result before COVID-19 pandemic.

Global	Regression Results			
Residual sum of squares:	249.645			
Log-likelihood:	-387.225			
AIC:	796.451			
AICc:	799.59			
R2:	0.13			
Adj. R2:	**0.099**			
Variable	Est.	SE	t(Est/SE)	p-value
Intercept	0	0.056	0	1
% of Males 18-25 population	-0.021	0.057	-0.37	0.711
% of African American population	0.183	0.065	2.836	0.005
% of population unemployed	0.122	0.069	1.777	0.076
%House Units value $300000 or more	0.18	0.061	2.966	0.003
% of population living in crowded housing units	0.007	0.057	0.119	0.905

% Abandoned	0.154	0.059	2.6	0.009
% of Vacant Sale	-0.01	0.059	-0.175	0.861
% of Vacant Rent	-0.017	0.062	-0.281	0.779
% of land mixed in Block Group	0.105	0.061	1.721	0.085
% of commercial land in Block Group	0.068	0.061	1.112	0.266

Table 3. OLS Result before COVID-19 pandemic.

Diagnostic	Information			
Residual sum of squares:	140.991			
Effective number of parameters (trace(S)):	52.462			
Degree of freedom (n - trace(S)):	234.538			
Sigma estimate:	0.775			
Log-likelihood:	-305.238			
Degree of Dependency (DoD):	0.689			
AIC:	717.4			
AICc:	742.442			
BIC:	913.043			
R2:	0.55			
Adj. R2:	**0.525**			
Variable	Bandwidth	ENP_j	Adj t-val(95%)	DoD_j
Intercept	78	7.06	2.713	0.655
% of Males 18-25 population	258	1.754	2.201	0.901
% of African American population	285	1.242	2.061	0.962
% of population unemployed	286	1.406	2.112	0.94
%House Units value $300000 or more	47	11.932	2.887	0.562
% of population living in crowded housing units	64	10.433	2.843	0.586
% Abandoned	75	8.014	2.755	0.632
% of Vacant Sale	286	1.418	2.115	0.938
% of Vacant Rent	138	2.554	2.348	0.834
% of land mixed in Block Group	195	3.114	2.422	0.799
% of commercial land in Block Group	45	13.325	2.922	0.542

Table 4. MGWR Result after COVID-19 pandemic.

Global	Regression Results			
Residual sum of squares:	240.127			
Log-likelihood:	-381.647			
AIC:	781.294			
AICc:	784.092			
R2:	0.163			
Adj. R2:	**0.139**			
Variable	Est.	SE	t(Est/SE)	p-value
Intercept	0	0.055	0	1
% of Males 18-25 population	-0.084	0.055	-1.52	0.129
% of African American population	0.259	0.06	4.325	0

% of population unemployed	-0.174	0.06	-2.912	0.004
%House Units value $300000 or more	0.062	0.058	1.056	0.291
% of population living in crowded housing units	-0.041	0.055	-0.746	0.456
% Abandoned	0.171	0.06	2.857	0.004
% of Vacant Sale	0.004	0.059	0.071	0.943
% of Vacant Rent	-0.072	0.06	-1.21	0.226
% of land mixed in Block Group	0.138	0.059	2.337	0.019
% of commercial land in Block Group	0.024	0.059	0.399	0.69

Table 5. OLS Result after COVID-19 pandemic.

1. The relationship between vehicle theft and mixed land use before and after the COVID-19 pandemic

According to Figure 6, the estimated value of the correlation coefficient between mixed land and vehicle theft incidents was between -0.03 and 0.022 before the COVID-19 pandemic, and the strength of the positive correlation between them gradually decreased from the city center to the city edge, and there is a completely negative relationship near several neighborhoods on the eastern edge of Buffalo. The relationship flipped after the COVID-19 pandemic, with estimated correlation coefficients for mixed land use and vehicle theft ranging from 0.001 to 0.361, with the strength of the positive relationship increasing from near the eastern boundary of Buffalo to Several neighborhoods gradually dwindled toward the city center. From the mixed land use map (Figure 7), those communities with high mixed land use are basically in the city center, and the population density is relatively dense. Previous research has found that mixed-use land can attract people outside the community to use its services, resulting in frequent use by residents and non-residents, causing local residents to be less wary of strangers, and the resulting overwhelming sense of anonymity that may undermine residents. ability to detect suspicious crime-related activity (Browning et al., 2010; Stucky and Ottensmann, 2009). This effect makes these types of lands more prone to lack of an effective system of social control: "eyes on the street" (Jacobs, 1961). This leads to high vehicle theft rates in areas with high mixed land use. However, the various changes in store closures during the COVID-19 pandemic and lower urban footfalls leading to fewer vehicles available for theft in urban areas have resulted in a change in the strength of their relationship, with areas that used to be negatively correlated in COVID- The post-COVID-19 epidemic turned into a strong positive correlation, which is consistent with the findings in Figure 5. Cluster of vehicle theft before and after Covid-19 epidemic, where vehicle theft shifted from urban to suburban areas.

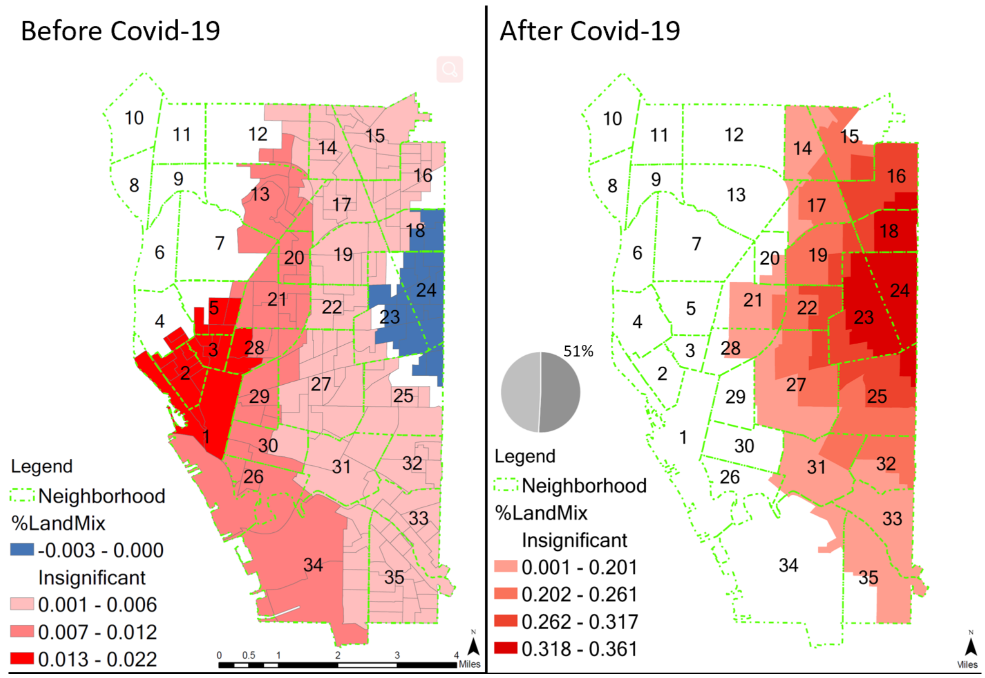


Figure 6. Spatial distribution map of vehicle theft and mixed land use

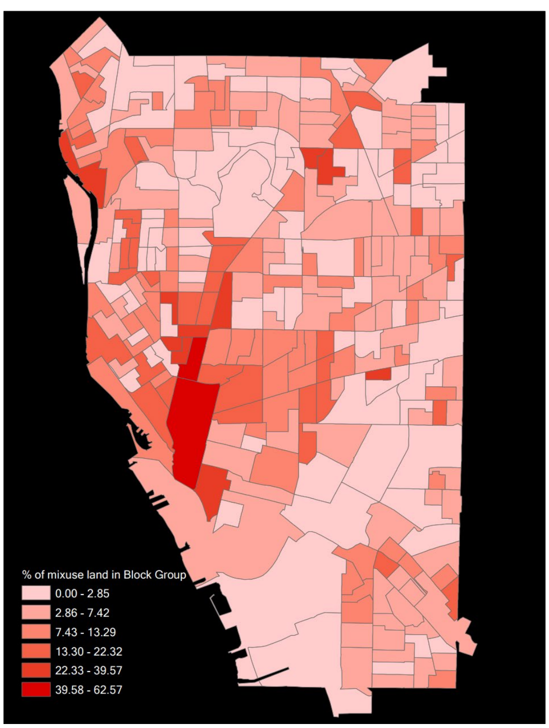
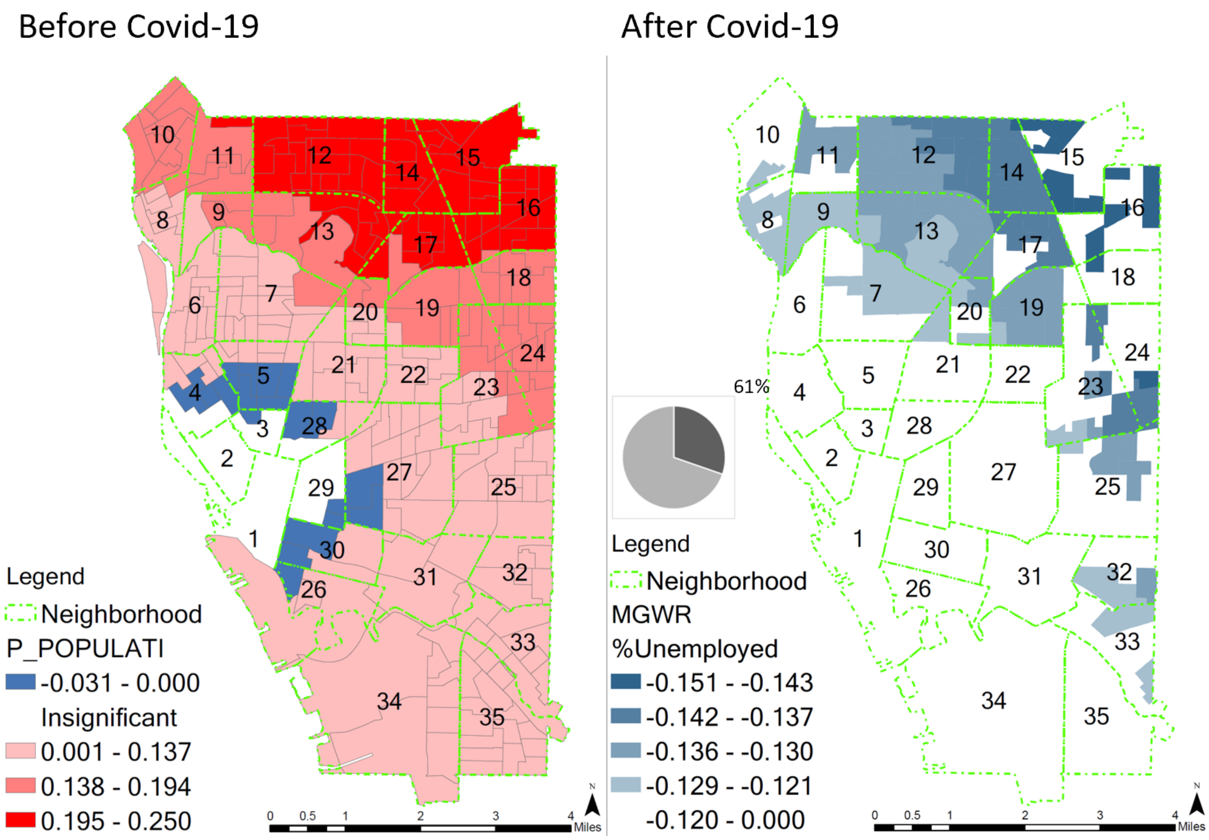
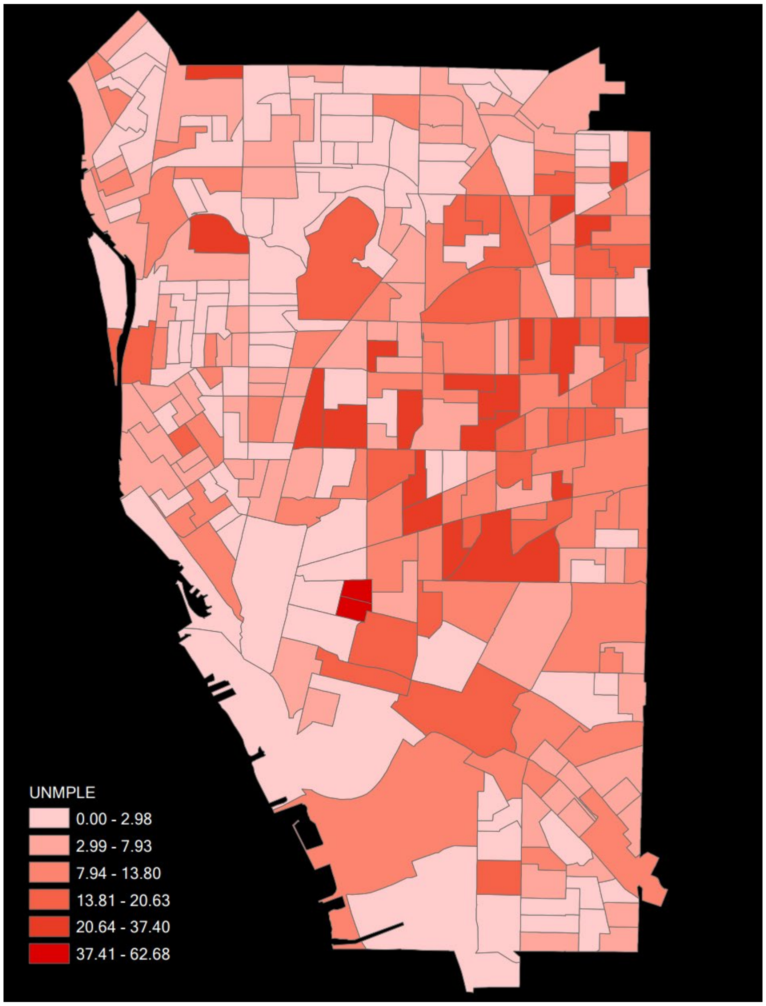


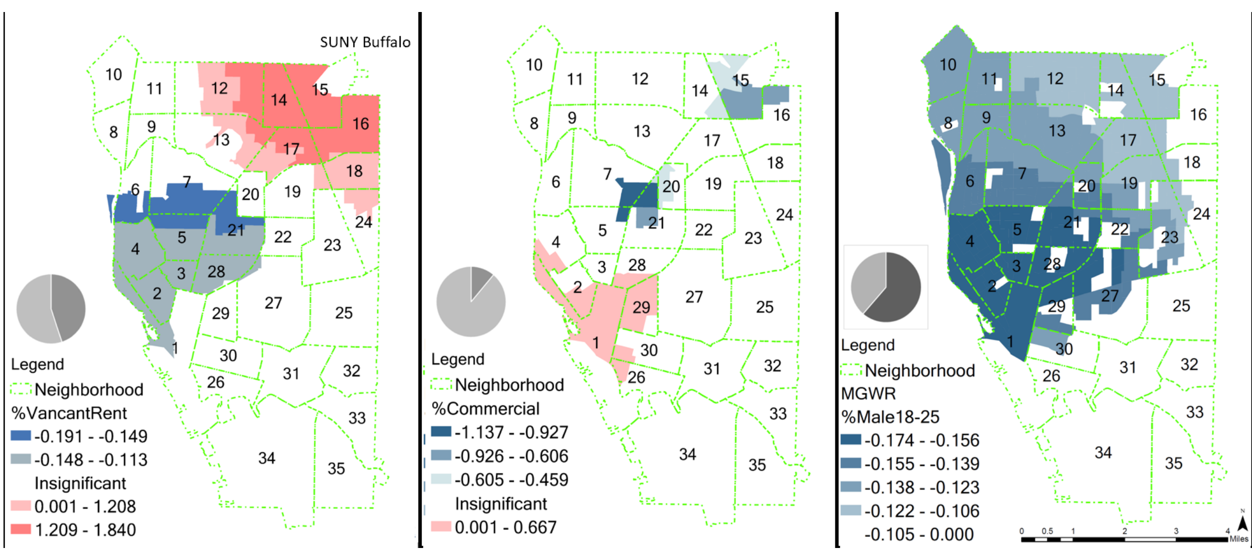
Figure 7. Spatial distribution map of mixed land

2. The relationship between vehicle theft and unemployment before and after the COVID-19 pandemic


Before Covid-19
After Covid-19
Legend
Neighborhood
P_POPULATI
-0.031 - 0.000
Insignificant
0.001 - 0.137
0.138 - 0.194
0.195 - 0.250
61%
Legend
Neighborhood
MGWR
%Unemployed
-0.151 - -0.143
-0.142 - -0.137
-0.136 - -0.130
-0.129 - -0.121
-0.120 - 0.000
Miles

398


UNMPLE
0.00 - 2.98
2.99 - 7.93
7.94 - 13.80
13.81 - 20.63
20.64 - 37.40
37.41 - 62.68


SUNY Buffalo
Legend
Neighborhood
%VancantRent
-0.191 - -0.149
-0.148 - -0.113
Insignificant
0.001 - 1.208
1.209 - 1.840
Legend
Neighborhood
%Commercial
-1.137 - -0.927
-0.926 - -0.606
-0.605 - -0.459
Insignificant
0.001 - 0.667
Legend
Neighborhood
MGWR
%Male18-25
-0.174 - -0.156
-0.155 - -0.139
-0.138 - -0.123
-0.122 - -0.106
-0.105 - 0.000

Conclusion

The temporal of vehicle theft has changed dramatically during the COVID-19 pandemic

First, this study takes the city of Buffalo as an example to investigate the impact of COVID-19 on vehicle theft and the changes in the Spatio-temporal pattern of vehicle theft at the micro-level of the city, which has never been studied before. First, this study found that the time patterns of vehicle theft in Buffalo have changed dramatically. Among them, the vehicle theft case in Buffalo was not affected by short-term events (such as George Floyd protests) and fluctuated significantly on a certain day, but various long-term incidents had an impact on the vehicle theft in Buffalo. Specifically, the stay-at-home order has had a beneficial effect on the theft of vehicles in Buffalo. The substantial increase in vehicle theft during the COVID-19 pandemic occurred after the stay-at-home order was implemented. After the stay-at-home order was lifted and the vaccinations were gradually implemented, vehicle thefts dropped significantly. In addition, the vehicle theft in Buffalo City has shifted over time. Vehicle thefts are now mainly concentrated in the daytime, and peak crimes were detected on Tuesday and Thursday. According to the weekly and daily distribution characteristics of crimes (Figure 3), the public security department should formulate corresponding preventive measures for the theft of units in different periods, such as strengthening the number of patrols during the working day during the implementation of the home order.

The spatial distribution of vehicle theft has changed during the COVID-19 pandemic

Second, this study found that the spatial distribution of vehicle theft in Buffalo has also changed dramatically. Specifically, the spatial cluster of vehicle thefts in Buffalo disappeared near the city center. During the COVID-19 pandemic, a large number of vehicle theft clusters were concentrated on the East Side of Buffalo. Based on this, Buffalo's law enforcement agencies should strengthen their investigations and patrol intensity of Buffalo's East Side.

The specific community environment significantly affects the probability of vehicle theft

Finally, there are two interesting findings that require special attention. First, the greater the number of high-value houses in a vulnerable area with poor security, the more vehicle thefts will be experienced in the area. Therefore, the head of household living in such a property should be their houses are equipped with additional anti-theft devices. Second, the greater the number of vacant homes for rent near the University at Buffalo which in Buffalo northeastern, the greater the probability that the area will experience vehicle theft. This is because most of the tenants in these areas are students, so the area usually has a high moving rate. The high moving rate means that community residents will be less vigilant towards strangers. In addition, during the COVID-19 epidemic, a large number of students returned to their hometowns, but their cars were still parked in vacant houses near the school. The combination of these results in an increase in the number of targets available for theft in this area, but there are no effective guardianship measures.

In short, this study found that changes in social patterns and human behavior after the COVID-19 pandemic did have an impact on the temporal and spatial patterns of vehicle theft. The research results can help us further understand the changes in crime patterns in the post-pandemic era. In addition, Buffalo's law enforcement agencies can adjust their security patrol strategies in a timely manner based on the results.

Limitation

The research has several unavoidable limitations, but it is of great significance for future research. First, as of now, the Census Bureau has not released the 2020 census statistics, so the census data used in this study are estimates for 2019. However, the COVID-19 pandemic has changed the structure of society. The socio-economic background of the region may also undergo major changes. This study will also be updated in a timely manner after the future census data is updated. Second, not all crimes are reported to the police. Common factors for non-reporting include public dissatisfaction with the police, police misconduct, fear, and socio-economic factors that may cause individuals not to report to the police. The third problem is related to the MGWR method used, which produces the best results when applied to large data sets. Therefore, future research can consider larger research areas to increase the sample size of using MGWR to simulate crime factors. Fourth, the study area is bounded by the administrative boundary between the city and the suburbs of Buffalo. There is no data for areas outside of Buffalo City. This suggests that there are limitations, as features outside the artificial boundaries may explain the frequency and hotspots of crime in certain communities located on the periphery of the city. Future research should investigate crime. Finally, many studies have used census data from different geographic levels to contextualize communities in an attempt to understand criminal activities. However, it is questionable whether these regional units truly represent the neighborhoods that influence criminal behavior in a meaningful way. Offenders may have personal activity spaces and unique travel patterns that exceed the boundaries of administrative regulations, which may lead to differences between their measured and actual communities. In future research, work should focus on collecting qualitative information from interviews with offenders and/or victims and incorporating personalized behavior data into crime clusters. This approach may solve some "uncertain geographic environments" and clarify the impact of neighborhood environments on crime. Or, in future research, the difference in crime rates calculated based on the surrounding population and the resident population should be compared and their impact on crime patterns and spatial analysis.

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