The Impact of COVID-19 on Crime: A Study from the Spatial-temporal Perspective in the Montgomery County, AL

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Abstract: The policies curbing the spread of COVID-19 can influence the chance of committing a crime. This study aimed to investigate the impacts of COVID-19 on the spatial and temporal patterns of crime in Montgomery City, AL, by wavelet analysis, spatial point test, and machine learning tools. We obtained the crime case records between January 1, 2015 to March 12, 2021 from the police department in the City of Montgomery, and we downloaded demographical data from the U.S. Census. Results show that the overall crime rate in Montgomery decreased during the COVID-19 pandemic. However, crime rates would increase in a shorter time than COVID-19 confirmed cases when the social activities increased. Meanwhile, spatial distributions of simple assault, burglary, and vehicle theft had clustered in Montgomery business and shopping areas. These findings are helpful for the police institution in preventing and minimizing crimes as new COVID-19 variants emerge in the future.

1 INTRODUCTION

The COVID-19 pandemic has spread globally and impacts every aspect of people's daily life (Boman & Mowen, 2021). Governments have implemented stay-at-home orders and social distancing requirements to curb the spread of the COVID-19 virus within communities (Piquero, et al., 2021). People have been requested to limit social contacts, avoid social gatherings, close schools, and stop unnecessary business activities (Koh, 2020). Crimes, therefore, have been changed. For instance, overall crimes are reported to drop sharply, with approximate 37% worldwide (Boman & Mowen, 2021), 35% in the United States (Abrams, 2021), 41% in the United Kingdom (Halford, et al., 2020) during the COVID-19 pandemic. However, the impacts are varied on different types of crimes. For instance, some crimes decreased (e.g., burglary and robbery), some crimes increased (e.g., domestic violence), some crimes had no changes (e.g., assault-battery) in Los Angeles and Indianapolis (Mohler et al., 2020).

This study aims to investigate the impacts that COVID-19 has had on the spatial and temporal patterns of crime in Montgomery City, AL, through spatial and temporal crime analysis approaches. Specifically, we analyzed the temporal pattern between COVID-19 and crimes through wavelet analysis. Then, we explored the spatial pattern changes of different crimes on March 13, 2020 (the date with the first COVID-19 confirmed case reported) through March 12, 2021 (one year after the first confirmed case) by using the spatial point pattern test (SPPT) and utilized the local Moran's I to identify regional clusters and local spatial outliers.

2 RELATED WORKS

Some studies have analyzed the impact of the COVID-19 pandemic on the spatial and temporal distributions of crimes. For instance, Yang, Chen, Zhou, Liang, and Bai (2021) found that the distributions of crime in Chicago significantly changed in 2020, with local changes in theft, battery, burglary, and fraud displaying an aggregative cluster in the downtown area. However, because of the geographical variation, whether their results in a big city like Chicago can be applied to a middle-sided city like Montgomery is unknown. Additionally, existing studies have mainly considered the crime and COVID-19 data a few months after the COVID-19 occurred in February and March 2020 (Mohler et al., 2020). The holiday months at the end of 2020 with

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the highest numbers of confirmed cases occurred in many states, and the months when many people got vaccinated are not considered.

3 MATERIAL AND METHODS

3.1 Study Area and Data

Montgomery is the second-largest city in Alabama, with a population of 205,764 according to the 2010 census. Montgomery was divided into 199 block groups, the smallest geographic area for which the U.S. Census collects and tabulates decennial census data. In Montgomery, the first case of COVID-19 was reported on March 13, 2020. The number of confirmed cases increased and reached 22,232, of whom 526 had died in its county as of March 12, 2021. During the COVID-19 period, the Stay-at-Home order was issued on April 3, 2020, which was canceled on April 30, 2020. The Safer-at-Home order, which required wearing a mask and social distancing, was issued on April 30, 2020 and withdrawn on April 4, 2021.

We obtained the crime case records with date, time, location (X and Y), crime description, and type between January 1, 2015 to March 12, 2021 in Montgomery City from the police department from the City of Montgomery. Demographical data (including income and race) at the block group level used in the analysis were downloaded from U.S. Census. A block group is a subdivision of a census tract and consists of blocks. One block group usually has between 250 and 550 housing units (The United States. Bureau of the Census, 1994). We used block groups in the spatial analysis because they are the smaller geographic areas than census tracts and Zip codes, and they have a higher number of housing units for the sample size than blocks.

3.2 Proposed Methods

3.2.1 Wavelet Analysis

The wavelet approach is a proper statistical method that has been applied in various academic fields (Wu & Loo, 2017). Because crime and climate data are constantly varying time series variables influenced by factors, such as changes in the physical environment, related laws and policies, and criminal demographics, we applied wavelet coherency analysis to examine the possible non-linear and non-stationary connection between environmental factors and crime rates. Wavelet coherence allows us to explore the correlation between two non-stationary signals at a given time and frequency. Also, we conduct phase analyses to figure out how the signals are associated. The phase difference [i.e., in-phase (positively correlated) or out of phase (negatively correlated)] indicates their association. Before the wavelet analysis, we normalize the time-series data by using the formula:

$$\breve{X} = \frac{X - \mu}{\sigma}$$

which X is the time-series data, μ is the mean of X, and σ is the standard deviation of X.

3.2.2 Spatial Point Pattern Test

This study used SPPT to exam changes or differences in two different spatial patterns of points based on the unit area (Andresen, 2009), and SPPT GUI is an open source software in GitHub (https://github.com/nickmalleson/spatialtest, accessed on March 6, 2021). This study applied SPPT to compare the similarity of spatial distribution patterns of crime in 2020, 2019, 2018, 2017, and 2016 and investigated the local changes in crime on the level of block groups to explore whether the pandemic had affected the spatial distribution of crime. The global S-index (the index of similarity used to confirm the similar degree of two spatial point patterns) value of census tracts is larger than community areas. The global S-index value of blocks is the largest, yet it needs too much computing time. Therefore, we took the Montgomery block groups as the unit area of SPPT.

SPPT includes three parameters: the number of iterations, sample size, and confidence interval. The number of iterations is the number of repeated samplings of the test dataset. The sample size is the percent size of the test dataset randomly sampling, and confidence interval based on the test dataset is used to determine the similarity significance of the two samples. According to existing spatial analysis (Andresen, et al., 2017), the number of iterations was set to 200, the sample size to 85 percent, and the confidence interval to 95 percent in the analysis. SPPT identifies the spatial point patterns that diverge in areas and aggregates the similarities at the local level into a global index (Wheeler, et al., 2018). Taking the calculation of the global S-index of crimes in 2020 compared with 2019 as an example, the test can be described as follows: 1) Adopt crimes in 2020 as the base dataset and crimes in 2019 as the test dataset (the test detects spatial pattern variations of the base dataset relative to the test dataset); 2) Randomly sample 85% of the test dataset 200 times, and then calculate the percentage of crimes in census tracts to generate a 95%

confidence interval, and 3) Determine whether the percentage of the primary data in the census tracts falls into the confidence interval, obtain the value of the local S-index, and calculate the global S-index.

There are two critical values. One of them is the global S-index. Another is the local index, which is applied to identify statistically significant changes on the micro-scale (local changes). The local S-index has three values (−1, 0, 1), which means the base dataset is lower than, similar, or higher than the test dataset in a spatial unit, respectively. The global S-index value is the count of the local S-index, which equals zero, and then divides the number of all spatial units. The value of the global S-index ranges from 0 (no similarity) to 1 (perfect similarity), and 0.80 is used as the threshold to indicate that two spatial point patterns are similar. Furthermore, we used Moran's I to explore the spatial autocorrelation of local changes to observe the epidemical impact on local areas.

3.2.3 Crime Trend Discovery

As the continuing pandemic of the COVID-19, many of us face a long-term impact on our lives. Since the COVID-19 pandemic and the resulting economic recession have negatively affected many people's financial situation and mental health, people's lives and relations have dramatically changed over the past years. Our research expects to discover the local crime trends in Montgomery during the COVID-19.

As a branch of artificial intelligence, machine learning is used in many areas that enable a computer to learn without being explicitly programmed. Machine learning has already been applied to COVID-19 related research in these years; however, few research studies are focused on criminal justice. Thaipisutikul, et al., in 2021 proposed a framework to classify the illegal and violent activities from online Thai news during the COVID-19 pandemic. In our research, the hidden correlations between crime trends and the effect of the pandemic are challenging to disclose; therefore, we apply machine learning to reveal the relationships between the number of reporting crimes and the number of COVID-19 cases in Montgomery from March 13, 2020 to March 13, 2021. We rely on two types of COVID-19 cases in Montgomery; one is the number of confirmed cases, and the other is the number of deaths caused by COVID-19.

Our research adopts one of the most widely used machine learning methods, supervised learning. Under supervised learning, the data set is well labeled; every data instance is tagged with a pre-defined category. Therefore, each data example is a pair that consists of an input (X) and corresponding output (Y). During the training phase, labeled data has been fed into a machine learning algorithm, which produces a mapping function to map the input data with the output value. The generated mapping function can map the unseen examples to a label in the test step. Some widely used metrics can be applied to evaluate the performance of the inferred function used in the test data. In a word, supervised learning aims to learn a mapping function from the labeled data and discover the relationship between the input and data output. Supervised learning can further be categorized into classification and regression. Because our data output is continuous, we will apply the regression to our research.

To investigate the relationship between the crime trends and the COVID-19 pandemic, we examine how the confirmed cases or/and deaths affect the number of total crimes and the number of individual crime types in Montgomery. In our research study, the number of crimes in Montgomery is used as the output (Y); the number of confirmed cases or/and deaths is used as input of data (X). We use two state-of-art machine learning algorithms to fulfill our tasks, the Support Vector Regression (SVR) and the Linear Regression. SVR uses the same strategy as Support Vector Machine (SVM) but is used for regression tasks. Linear regression models a linear relationship between input variables and the single output. Additionally, we use the Root Mean Square Error (RMSE) method to evaluate the regression performance of machine learning models.

4 RESULTS AND DISCUSSION

There were 22,944 criminal cases in Montgomery County from March 13, 2020 to March 13, 2021. Compared to the pre-pandemic year of 2019 (i.e., March 13, 2019 to March 12, 2020), total crime fell by around 8.26%. For different types of crime, the numbers of burglary, larceny, traffic violations, vehicle theft, simple assault, and suicide decreased by 27.47%, 25.30%, 19.72%, 13.43%, 2.91%, and 1.52%, while the numbers of manslaughter, aggravated assault, robbery, murder, domestic crime, and rape increased by 42.24%, 38.36%, 18.86%, 14.43%, 6.02%, and 4.41% (Table 1). The number of crimes of different crime types and the rate of crime change one year after (March 13, 2020 to March 12, 2021) and before (March 13, 2019 to March 12, 2020) the first COVID-19 confirmed case are illustrated in Table 1. The symbol " + " means an increment, and the symbol " − " refers to a decrement.

Table 1: The number of crimes of different crime types and the rate of crime change.

Crime Type	Number of Crimes in one year before (March 13, 2019 to March 12, 2020)	Number of Crimes in one year after (March 13, 2020 to March 12, 2021)	Rate of Change
Murder	970	1,110	+14.43%
Manslaughter	490	697	+42.24%
Rape	68	71	+4.41%
Aggravated Assault	73	101	+38.36%
Simple Assault	3784	3674	-2.91%
Robbery	350	416	+18.86%
Burglary	5101	3700	-27.47%
Larceny	4249	3174	-25.30%
Vehicle Theft	1117	967	-13.43%
Domestic Crime	5120	5428	+6.02%
Suicide	261	257	-1.53%
Traffic Violations	71	57	+19.72%

Table 2: The means and standard deviations of crime rates (per 1,000 people) in the communities with different population density and races in one year after (March 13, 2020 to March 12, 2021) and before (March 13, 2019 to March 12, 2020) the first COVID-19 confirmed case.

Year	**Popu_Density**	**Mean (SD)**	**P-value**	**Race**	**Mean (Sd)**	**P-value**
One year after	Low	0.199 (0.073)	<0.001	White	0.166(0.055)	<0.001
	High	0.326 (0.079)		Africa America	0.351(0.070)	
Five years before	Low	0.237 (0.055)	<0.001	White	0.185(0.058)	<0.001
	High	0.373(0.087)		Africa America	0.412(0.082)	

In Table 2, when we grouped the crime cases by the population density of the block groups they located in, the results show that block groups with a low population density would have a significantly lower crime rate than the ones with a high population density [i.e., 0.199 (SD=0.073) vs. 0.326 (0.079). p<0.001]. The crime rate in the white community was significantly lower than the rate in the Africa American communities [i.e., 0.166 (SD=0.055) vs. 0.351 (0.070). p<0.001], even though similar findings can be found in the past five years.

Table 3 shows the results of the global Moran's I, which is generally used to indicate the global spatial autocorrelation. Values of the global Moran's I range from -1 to +1. Values above zero indicate positive spatial autocorrelation, and values below zero indicate negative spatial autocorrelation. Moreover, the significance of the global Moran's I values can be transformed to the p-value and Z-score. The p-value is the significance level of Moran's I, and the Z-value is the Moran's I statistic standard deviation. Table 3 also displays that the p-values of rape, simple assault, and burglary were less than 0.05. The Z-scores are greater than 1.96, indicating that crimes' spatial distributions were significantly autocorrelated. The global Moran's I value of simple assault and burglary were larger than 0, proving that local changes in these two crime types display a positive spatial autocorrelation. In contrast, the global Moran's I value of rape was smaller than 0, suggesting that local changes in these two crime types exhibit a negative spatial autocorrelation. The significant autocorrelations of rape, simple assault, and burglary

Table 3: Global Moran's I of local changes between 2020 and 2019 in different crimes.

Crime Types	Global Moral's I	p-Value	Z-Score
Murder	-0.055	0.222	-1.222
Manslaughter	-0.086	0.052	-1.941
Rape	-0.104	0.018	-2.358
Aggravated Assault	0.015	0.635	0.475
Simple Assault	0.094	0.020	2.325
Robbery	-0.055	0.243	-1.167
Burglary	0.101	0.012	2.499
Larceny	-0.006	0.974	-0.032
Vehicle Theft	-0.015	0.810	-0.241
Domestic Crime	0.063	0.113	1.584
Suicide	0.064	0.106	1.617
Traffic Violations	0.033	0.355	0.924

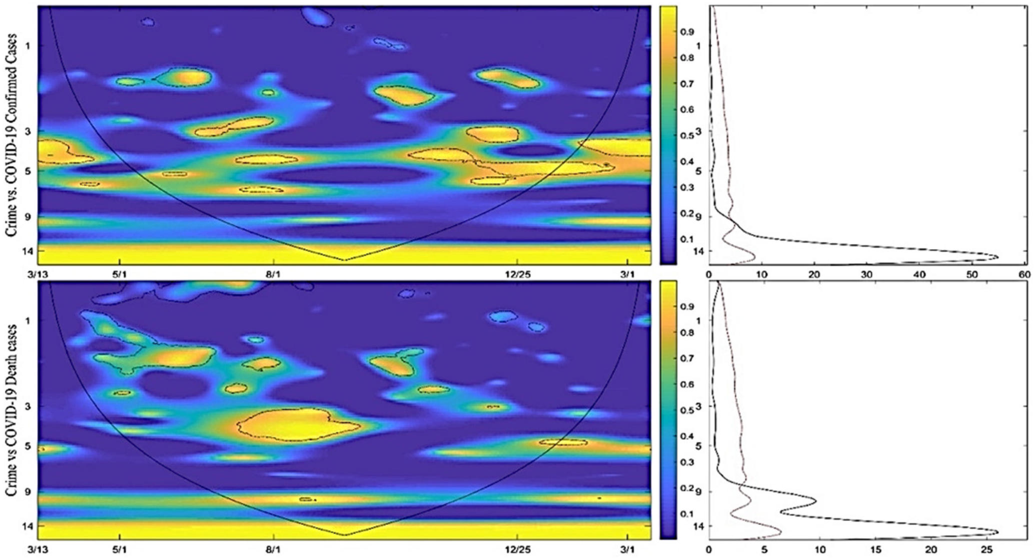

Figure 1: Continuous wavelet power spectra (left) and global wavelet spectrum (right) of the time series.

verified that the spatial distributions of some types of crimes are associated with the COVID-19 pandemic.

Turning to wavelet analysis, we first present the wavelet power spectra of the time series in Figure 1 after minimizing the red-noise bias by dividing the wavelet power by the period. In our crime rates time series, there is a 3 to 5-day periodicity band in the panels of COVID-19 confirmed cases, particularly during the holiday season (November 2020 to January 2021). A similar band in 3 to 5 days also can be found from August to November 2020 in the panel of COVID-19 death cases. In Figure 1, Blue represents lower power values, while yellow represents high values. The red curve shows the influence cone delimiting the region from the edge effect. The dashed black line indicates the 95% confidence interval based on 10,000 Markov bootstrapped series.

We compute the phases of criminal cases and COVID-19 cases (e.g., confirmed and death cases) and their phase difference to obtain additional information about the linkage between COVID-19 and crime. Figure 2 reveals that the number of COVID-19 confirmed cases was out of phase with the number of crime cases, with a delay of ½ of a quasi-cycle in the holiday season in 2020. The number of crime cases leads the number of COVID-19 death cases by ¼ quasi-cycle between July and October 2020. Blue represents lower power values, while yellow represents high values. The red curve shows the influence cone delimiting the region from the edge effect. The dashed black line indicates the 95% confidence interval based on 10,000 Markov bootstrapped series. The number of crime cases, with a delay of ½ of a quasi-cycle in the holiday season in 2020. The number of crime cases leads the number of COVID-19 death cases by ¼ quasi-cycle between July and October 2020.

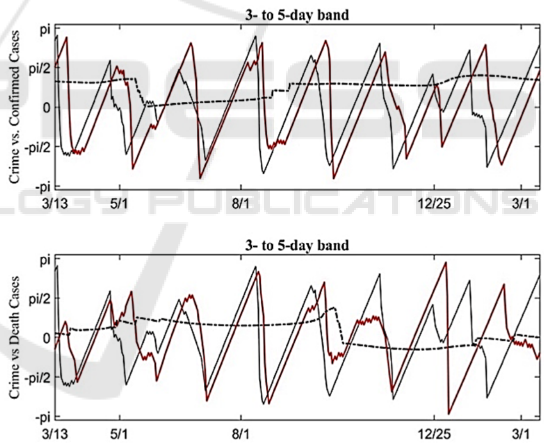

Figure 2: Phases of crime and COVID-19 cases were computed in the 3- to 5-day periodic band (cf. Figure 1).

After the SPPT test, all crime types (except traffic violations) had a global S-index value of less than 0.8. These values are low between 2019 (base dataset) and 2018 (test dataset), similar to the values between 2020 (base dataset) and 2019 (test dataset). The global S-index values described that the spatial distribution trend of crimes is not stable and usually changes significantly every year. We cannot determine whether the COVID-19 pandemic has impacted the spatial distributions of crimes with the global S-index values. However, results of the local S-index showed that changes in some regional areas are relatively stable. Andresen et al. observed the spatial characteristics of crimes based on local changes and proved the importance of smaller spatial units of analysis before our research. Thus, we investigated the variation of crimes in local spatial units in the following part. We subdivided the percentage difference of spatial units between 2020 and 2019 into several classes when local S-index values are not equal to zero. Then, we used gradation color symbols to display the percentage differences in Figure 3.

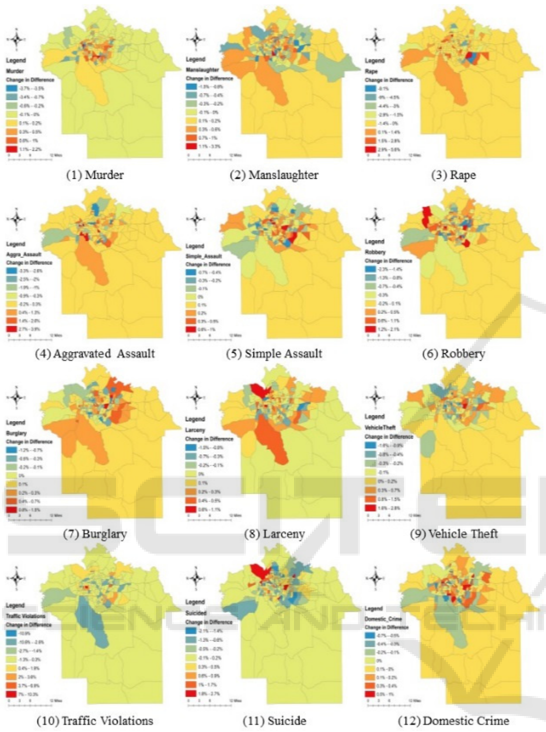

Figure 3: Differences in the percentages between 2020 and 2019 of different crimes' spatial distributions based on the spatial unit when SPPT results are significant.

There is an aggregation region of simple assault, suicide, domestic crime in the eastern business district. The aggregation regions of simple assault and domestic display much growth in crimes in 2020 compared with 2019, and suicide shows a decline in crimes in 2020 compared with 2019. These results indicated a significant difference in the spatial pattern of crimes during the pandemic, and the differences in space are mainly reflected on the microscopic scale.

The local Moran's I result displays different clusters (including high-high clusters, low-low clusters, low-high spatial outliers, and high-low spatial outliers). In Figure 4, there are high-high clusters of simple assault, burglary, and vehicle theft in east-central Montgomery. We also found that suicide contains high-high clusters in western Montgomery. The high-low spatial outliers representing the higher level of this region than surrounding areas should be noted.

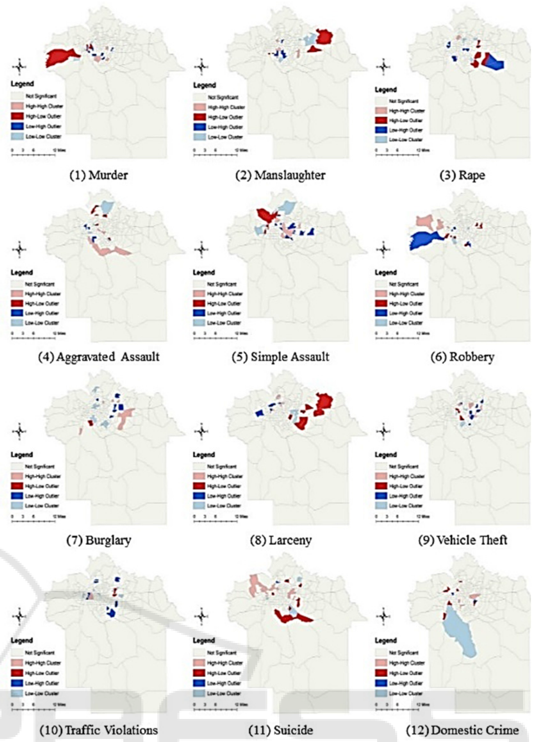

Figure 4: The local Moran's I for theft, battery, burglary, and fraud.

Table 4: RMSE scores for evaluating the performance of predicting the number of all individual crime types by utilizing the confirmed cases or/and deaths in Montgomery.

	Combined Cases		Confirmed Cases Only		Deaths Only	
	SVR	**LR**	**SVR**	**LR**	**SVR**	**LR**
Murder	3.73	3.59	3.78	3.6	3.73	3.6
Manslaughter	1.29	1.29	1.29	1.28	1.29	1.3
Rape	0.44	0.44	0.44	0.44	0.44	0.44
Aggravated Assault	0.68	0.66	0.68	0.66	0.68	0.65
Simple Assault	3.42	3.43	3.41	3.44	3.44	3.43
Robbery	1.63	1.57	1.63	1.57	1.63	1.57
Burglary	4.96	5.02	4.95	5.02	4.91	5.03
Larceny	3.61	3.61	3.61	3.62	3.61	3.61
Vehicle theft	1.77	1.74	1.71	1.74	1.88	1.77
Domestic Crime	5.05	5.1	5.07	5.15	5	5.08
Suicided-related Crime	0.98	0.97	0.97	0.97	0.98	0.98
Traffic Violations	1.19	1.11	1.19	1.12	1.19	1.11
Others	4.81	4.75	4.81	4.75	4.78	4.62

Table 4 illustrates the RMSE scores calculated for each crime type, such as murder, robbery, rape, and so forth. We group and count the same crime type every day in Montgomery from March 13, 2020 to March 12, 2021. Next, we build machine learning models to predict the number of individual crime types via using combined cases or/and deaths on a specific date. The machine learning algorithms SVR with kernel "Linear" and Linear Regression are also adopted in this experiment.

5 DISCUSSIONS

The ongoing COVID-19 pandemic has made a significant impact on people's activities and daily lives. This study investigated the changes of 12 types of crime in Montgomery, AL, over one year after the first COVID-19 confirmed case reported (from March 13, 2020 to March 12, 2021) based on spatial and temporal crime analyses.

Compared with one year before the first COVID-19 confirmed case, the general crime fell by around 8.26% numbers of some specific crime types increased, such as manslaughter (42.24%), aggravated assault (38.36%), robbery (18.86%), murder (14.43%), domestic crime (6.02%), and rape (4.41%). These results are similar but different from the findings in existing research. For instance, Yang et al. (2021) found that total crime fell by 23.7% in Chicago from February to June in 2020 (with -34.21% in theft, -29.11% decrease in fraud, -18.97% in the assault, -18.15% in battery, -7.53% in robbery, -6.54% in criminal damage, and 3.13% in the burglary). Nivette et al. (2021) found that overall crime declined by 37% following stay-at-home restrictions due to COVID-19 in 27 cities across 23 countries in the Americas, Europe, the Middle East, and Asia.

One of the contributions this study makes is investigating the impact of COVID-19 on crime from the spatial perspective. For instance, we grouped crime cases based on the population density of the block group. We found that the crime rate in high populated block groups was significantly higher than in low populated block groups. However, their difference became smaller than their difference in the past years. Meanwhile, when the criminal cases were grouped by race, we found that the crime rate in the block groups dominated by Africa America was significantly higher than that in the white-dominated block groups. The difference in crime rates between African America and white-dominated block groups also narrowed down compared with the rate difference in the past five years. These results suggest that the crime rates decreased in different communities in the COVID-19 pandemic.

Our wavelet analysis results show a 3 to 5-day periodicity band in the panels of COVID-19 confirmed cases during the holiday season (November 2020 to January 2021). Moreover, the number of crime cases leads to the number of COVID-19 confirmed cases by 1/2 quasi-cycle. This result suggests that crime rates would increase in a shorter time than COVID19 confirmed cases when the social activities increased (such as stay at home order ended, reopened economy, back-to-school, presidential election, holidays). It might be possible that when the social activities decreased, the virus-prone environment would be clean. When social activities resumed, the crime-related actions would occur immediately, but the virus would take time to spread in a cleaned environment.

There is an aggregation region of simple assault, burglary, and vehicle theft in east-central Montgomery. This location coincides with the business and shopping mall areas, including famous shopping malls (e.g., The Shoppers at Eastchase, Dillard's, Costco, and Target) and restaurants. It is the most crowded area in Montgomery and is usually a hot spot for crimes. As the wave of the COVID-19 pandemic poured in, senior centers, libraries, parks, and other city services were forced to close. Moreover, this region contains many commercial buildings with many employees who began to work at home during this period. The stay-at-home orders urged most people to quarantine at home, resulting in an insufficient flow of visitors here. Previous works have shown that the contextual characteristics of different areas would impact some crimes, such as the fact that the busy streets of the city center can attract more cases of robbery and theft, and the commercial land can attract more violence. Unlike these crime types, the aggregation region of burglaries shows significant growth, resulting from many closed business districts and the lack of regulators. The aggregation region of burglaries suggested that the police department prevent these crimes from increasing in this region again in the future.

Through looking into the machine learning performance in Table 5, the crime trend analysis reveals the confirmed cases or/and deaths in the COVID-19 pandemic have noticeable relations with a few certain crime types, e.g., rape and aggravated assault. Existing research discovers a rise in sexual violence during the COVID-19 pandemic in Bangladesh (Sifat, 2020). Another research study conducted by Roesch et al., devised violence against women during pandemic restriction.

6 CONCLUSIONS

In sum, we obtained the following conclusions: 1) The overall crime rate decreased in Montgomery during the COVID-19 pandemic, but some crimes were very sensitive to some policies or events during the pandemic, like the number of manslaughters, aggravated assault, robbery, and murder; 2) crime rates would increase in a shorter time compared with COVID19 confirmed cases when the social activities increased; 3) spatial distributions of simple assault, burglary, and vehicle theft had clustered in Montgomery business and shopping areas. These conclusions are significant for preventing and controlling crimes when the second wave of the COVID-19 outbreak in Montgomery, such as which types of crimes should be focused on, and which regions should be concerned with crime.

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