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Spatiotemporal Patterns and Driving Factors on Crime Changing During Black Lives Matter Protests

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Abstract: The death of George Floyd has brought a new wave of 2020 Black Lives Matter (BLM) protests into U.S. cities. Protests happened in a few cities accompanied by reports of violence over the first few days. The protests appear to be related to rising crime. This study uses newly collected crime data in 50 U.S. cities/counties to explore the spatiotemporal crime changes under BLM protests and to estimate the driving factors of burglary induced by the BLM protest. Four spatial and statistic models were used, including the Average Nearest Neighbor (ANN), Hotspot Analysis, Least Absolute Shrinkage, and Selection Operator (LASSO), and Binary Logistic Regression. The results show that (1) crime, especially burglary, has risen sharply in a few cities/counties, yet heterogeneity exists across cities/counties; (2) the volume and spatial distribution of certain crime types changed under BLM protest, the activity of burglary clustered in certain regions during protests period; (3) education, race, demographic, and crime rate in 2019 are related with burglary changes during BLM protests. The findings from this study can provide valuable information for ensuring the capabilities of the police and governmental agencies to deal with the evolving crisis.

Keywords: crime; pandemic; statistical analyses; socioeconomic factors; burglary

1. Introduction

Investigating spatiotemporal distribution patterns and driving factors of crime are continuing concerns within the geography of crime and criminological research [1,2]. The general hypothesis is that social disorganization theory, low economic status, ethnic heterogeneity, residential instability, and family disruption lead to community social disorganization and lack of informal social control, which, in turn, increases crime and delinquency rates [3,4]. The routine activities theory argues that (macro-level) social changes introduce adjustments in people's lifestyles and, subsequently, contribute to the supply of crime opportunities (i.e., the agglomeration in space and time of motivated offenders, suitable targets, and the absence of capable guardians) [5,6]. These two foundational, place-based criminological theories relate socioeconomic factors (i.e., demographic, ethnicity, economic, social, family disruption, marital status, and urbanization) to criminal events [7–9].

Black Lives Matter (BLM) is a decentralized movement advocating for non-violent civil disobedience in protest against incidents of police brutality and all racially motivated violence against Black people [10]. The death of George Floyd sparked widespread protests in cities across the United States in support of BLM [11]. To record, the protests that sustained throughout June, July, and August, are the largest protests to take place in the United States. While many protests remained continuously peaceful, some instigated violence and crime. Protests happened in a few cities accompanied by reports of violence over the first few days [12], several robbings occurred and dozens of buildings were vandalized during protests periods. These events are usually centered around the gathering places of protests.

Unlike the former incidents (such as Trayvon Martin on 13 July 2013, Michael Brown on 9 August 2014, in Ferguson), the George Floyd protest happened in the context of the COVID-19 pandemic. Social distancing regulations, large-scale lockdown, and stay-at-home orders are designed to limit the spread of COVID-19 but may also alter and disrupt the contextual conditions under which crime may occur [13–16]. After these routine activities changed, a variety of evidence began to emerge indicating dramatic decreases in crime [17,18]. Felson et al. found burglaries increase in block groups with mixed land use, but not blocks dominated by residential land use during the COVID-19 pandemic [19]. Mohler et al. found a marginal decline in residential burglaries, a marginal increase in auto thefts, and an increase in domestic violence calls, pointing to shifts in crime patterns [13]. Dodd reported major crime declines in the UK, while Dutch news reported a 46% drop in burglary, a 43% decline in bike thefts, and a 74% drop in pickpocketing [20]. This research indicated that major declines in crime have been reported while those declines depend on crime type and may differ by parts of a city and land uses. However, many researchers are focusing on the impact of COVID-19 on different types of crime, yet few researchers have explored crime changes during the BLM protest period.

Crimes are most likely to occur when possible criminals converge in space and time with appropriate criminal targets in the absence of capable crime preventers [19]. For example, when people are located near businesses whose owners and customers are absent, those businesses become vulnerable targets for crime. As mentioned, the COVID-19 pandemic had some effects on routine activities and crimes because of the effect of measures taken by the government. Owners and customers of business locations moved away, leaving businesses highly vulnerable to burglary and trespassing. In particular, when dozens or hundreds of people gathered in support for BLM, the dense crowds, closed business stores, and the absence of police all provided opportunities to criminals. Rosenfeld et al. reported that the sharp rise of nonresidential burglaries is likely associated with the property damage and looting at the beginning of protests against police violence [21]. A paper tested for the "Ferguson Effect" on crime rates in 81 large U.S. cities, and revealed that robbery rates, declining before Ferguson, increased in the months after Ferguson [22]. However, the existing research has focused on metropolitan areas of large cities, and not many studies have examined suburban and rural areas.

In summary, protests are likely to trigger rises in crime while those rises depend on crime type. Locations where protests occur are more prone to crimes. Therefore, there are strong reasons to expect that both the volume and distribution of crime and disorder will be altered. However, the overall trend of crime cannot reflect all types of crime, and heterogeneity will exist across counties/cities in the U.S. This leads us to explore (1) changes in different types of crime; (2) the spatiotemporal variations of burglaries; and (3) the driving factors of burglary changes during BLM protest.

Despite the increased media attention, the Black Lives Matter protest has received comparatively less scholarly attention than that of COVID-19 [23]. Our study is one of the first to analyze the crime changes and its influencing factors induced by the BLM protest (in the background of COVID-19). In this study, we use comprehensively recorded crime data in 50 counties/cities of different scales to identify the spatiotemporal variations of crime and illustrate the relationship between burglary and social, economic, and demographic factors under the BLM protest in the U.S. These results make an important contribution not only to the government in dealing with emergencies and adjustment of policy instructions, but also to the prediction of crime during large-scale social events.

2. Materials and Methods

2.1. Workflow

Figure 1 shows the workflow of the entire analytical process. First, the collection and processing of the dataset are described in Sections 2.2.1 and 2.2.2. Next, methods are introduced from two aspects in Sections 2.3.1 and 2.3.2. Then, the research contents are divided into four parts: (1) an overall temporal trend of crime during the COVID-19 pandemic (Section 3.1); (2) an overall change in different crime types (Section 3.2); (3) spatiotemporal variations of burglary during BLM protects (Section 3.3), and (4) impacts of driving factors on burglary changing (Section 3.4). Note that based on the results of Sections 3.1 and 3.2, the change in burglary accurately reflects the change in crime during the BLM protest compared to other crime types or total crimes. Therefore, Sections 3.3 and 3.4 will also focus on burglary instead of total crime.

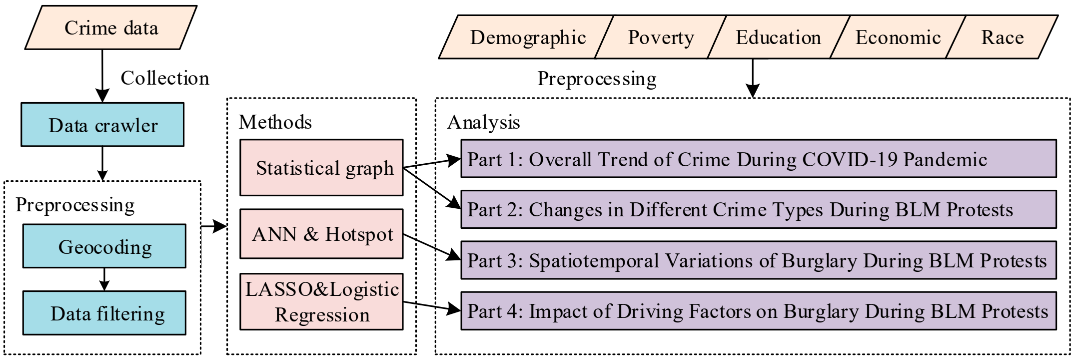


Figure 1. Workflow of the analytical process including datasets collected (yellow), data processing tools (blue), analyses methods (pink) and analytical results (purple).

The analysis time (from 15 May 2020 to 15 June 2020) encompasses the entirety of protests, including George Floyd's death (25 May 2020) and the outbreak of urban protests. In this paper, multiple spatial and statistical analysis methods were used in the research process. First, we created a simple descriptive graph to depict crime counts for the entirety of the data. To take account of the spatial nature of the data, Average Nearest Neighbor (ANN) [24] and hotspot analysis [25] were used to analyze the spatial distribution and its changes. Finally, to detect the impact of the influencing factors on the burglary changes during BLM protests, we made use of the Least Absolute Shrinkage and Selection Operator (LASSO) and Binary Logistic Regression model for feature selection and driving factors analysis. All the methods were accomplished through programs Python or R.

2.2. Dataset

2.2.1. Crime Dataset

The crime events data were obtained from the SpotCrime website [26], which is a crime incident aggregator and public crime visualization service. The SpotCrime website collects crime events data from police departments, verified news reports, user-generated content submissions, and other validated sources [27]. A comprehensive crime data scheme is provided in the SpotCrime dataset, including description, referral source, and spatiotemporal attributes, e.g., date, time, location address, and coordinates by latitude and longitude. Crime types are classified into 9 categories, including assault, arson, arrest, burglary, robbery, shooting, theft, vandalism, and others. The crime events data are organized and presented by a combination of county/city name and date under web pages. In this research, crime incidents between 1 January and 15 June 2019, and 2020 were collected by a customized web crawler and geocoded geocoder library in python. In addition to this, 50 counties/cities (including

12 cities and 38 counties) were selected from the overall 3370 regions in the SpotCrime website based on the following requirements.

- The crime events data missing days for each region should be less than 30 days in 2020 to maintain data consistency for long period time-series analysis.
- The average number of all crime events is higher than 15 each day in individual regions to avoid data noising by small samples.

The selected 50 counties/cities list and spatial distribution in the U.S. are shown in Table 1 and Figure 2, respectively. Fifty counties/cities are distributed in 20 states and cover over about 60,770 square miles. Thirteen counties/cities with a population of over one million people, and 4 counties with a population of fewer than 10,000 people. Additionally, the U.S. median household income was $63,179 in 2018. seven cities and twenty-one counties with a median household income in 2018 above average. Major, medium, and small counties/cities are all considered in this research. The research results thus will partly represent crime changes during BLM protest in the U.S.

Table 1. Selected 50 counties/cities list from the SpotCrime website.

ID	County/City Name	ID	County/City Name	ID	County/City Name
1	Tarrant County, TX	18	Suffolk County, NY	35	Boston, MA
2	Franklin County, OH	19	Ada County, ID	36	Washington, DC
3	Larimer County, CO	20	Miami-Dade County, FL	37	Montgomery County, TX
4	Travis County, TX	21	New York, NY	38	Baltimore County, MD
5	Bexar County, TX	22	Hamilton County, TN	39	Henrico County, VA
6	Sonoma County, CA	23	Skagit County, WA	40	Minneapolis, MN
7	Volusia County, FL	24	Riverside County, CA	41	Newport News, VA
8	Orange County, CA	25	Shelby County, AL	42	Chicago, IL
9	Pierce County, WA	26	Fairfax County, VA	43	Horry County, SC
10	Weld County, CO	27	Thurston County, WA	44	St. Paul, MN
11	El Paso County, CO	28	Collier County, FL	45	Denver, CO
12	Newberry County, SC	29	Ottawa County, MI	46	San Francisco, CA
13	Yakima County, WA	30	Frederick County, VA	47	Norfolk, VA
14	Sarasota County, FL	31	Anne Arundel County, MD	48	Harrison County, WV
15	Pinellas County, FL	32	Olmsted County, MN	49	Knox County, IL
16	Hillsborough County, FL	33	Escambia County, FL	50	Baltimore, MD
17	Los Angeles County, CA	34	Honolulu, HI		

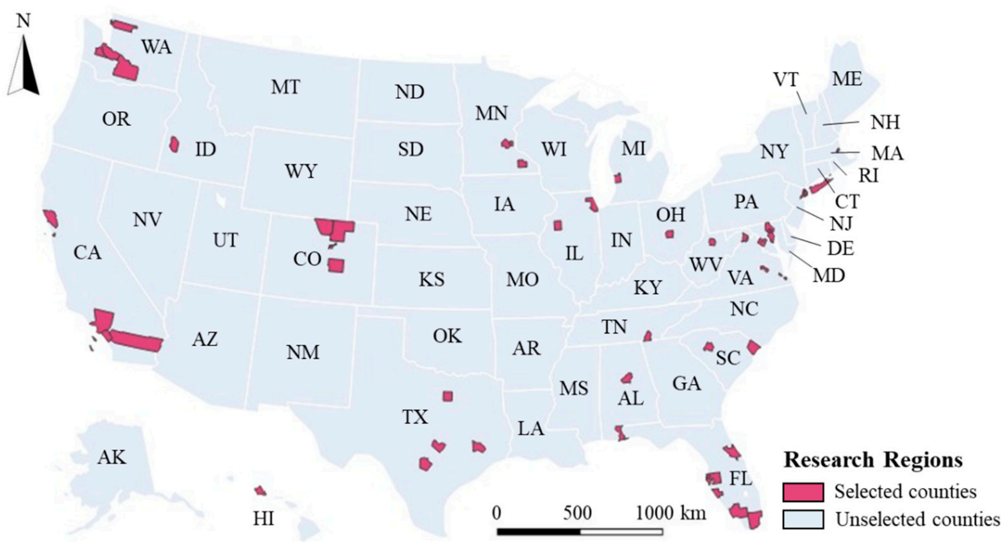


Figure 2. Selected 50 counties regions from SpotCrime website.

To validate the crime dataset collected from SpotCrime, we randomly selected and downloaded the available crime events data from publicly available official datasets. A quantitative comparison with the SpotCrime data collection and data sources was conducted from a statistical and spatiotemporal perspective. We found that the data match well in consistency and accuracy. Additionally, we checked the operationalizations of crime included in SpotCrime and found that "arrest" and "other" are not Part I index crimes according to the FBI's Uniform Crime Reporting (UCR) program [28]. Therefore, "arrest" and "other" categories are excluded from this research.

2.2.2. Driving Factors Datasets

Inspired by social disorganization theory and routine activities theory, relevant factors including demographic, education, poverty, race, and economic factors are collected in our study. As an estimated value, population, age, sex, race, education, and poverty were collected from U.S. Census Bureau reports. After the preprocessing, the factors of population density, population under 18 years, population over 60 years, age dependency ratio, males per 100 females, less than 9th grade, Bachelor's degree, median household income, below poverty level, White population, and Black or African American population were obtained. The diversity index captures the racial and ethnic diversity of a geographic area in a single number, from 0 to 100 [29], and is provided by Esri [30]. Additionally, the crime rate per 10,000 people from 1 January 2019, to 15 June 2019, is considered as a driving factor in our study. This is because the counties/cities with higher crime rates have environments that are more likely to cause crime. It is necessary to detect the relationship between the crime change during BLM protests with the crime rate in the same period last year. The descriptive statistics for these variables are provided in Table 2.

Table 2. Descriptive statistics for independent variables.

Category	Factors	Minimum	Mean	Median	Maximum	Standard Deviation
demographic	Population density	57.83	2671.15	796.24	27,903.88	4787.42
	Population under 18 years, %	13.44	21.88	22.19	29.85	3.09
	Population over 60 years, %	13.97	21.53	19.72	43.46	5.56
	Age dependency ratio, %	39.80	60.41	60.25	99.80	10.81
	Males per 100 females, %	88.60	96.75	97.05	109.40	3.94
education	Less than 9th grade, %	1.30	4.94	4.25	15.60	2.88
	Bachelor's degree, %	16.00	34.98	34.70	61.10	10.01
economic	Median household income, $	42,765.00	66,186.66	64,416.50	12,1133.00	15,779.62
poverty	Below poverty level, %	14.90	23.97	23.20	33.30	4.29
race	White, %	21.59	73.10	79.32	95.49	17.11
	Black or African American, %	1.12	14.59	9.36	62.73	13.38
	Diversity index	13.00	60.42	61.50	87.00	15.83
crime	2019 crime rate per 10,000	0.04	0.98	0.76	6.09	0.97

Source: U.S. Census Bureau, Esri and SpotCrime; calculations by the author.

2.3. Methods

2.3.1. Spatial Distribution Analysis

To identify the space concentration level and distribution of crime during BLM protests, we utilized the ANN model and hotspot mapping analysis. Here, the ANN method measures the distance between each crime point and its nearest neighbor's location [24]. It is used to quantify and compare the spatial distribution of crime within a county/city over time. If the ANN ratio is less than 1, the pattern exhibits clustering. If the value is greater than 1, the trend is toward dispersion. The ANN ratio of county/city c is defined as follows:

$$ANN_c = \frac{\overline{D}_O}{\overline{D}_E} = \frac{\sum\limits_{i=1}^{n} d_i/n_c}{0.5/\sqrt{n_c/A_c}}, \tag{1}$$

where $\overline{D}_O$ is the mean distance between each crime point and its nearest neighbor. $\overline{D}_E$ is the expected mean distance for n points given in a random pattern. d_i represents the distance between the point i and its nearest neighboring feature. n_c corresponds to the total number of points in county/city c. A_c represent the area of county/city c. Note that we use the great-circle distance as the calculation method of distance.

Hotspot mapping is a popular analytical technique in the geography of crime. KDE model, a hotspot mapping technique, is regarded as the most suitable spatial analysis technique for visualizing crime data. It can be used for visually identifying hotspots of crime, and spatially interpreting location, size, shape, and orientation of clusters of crime incidents [31]. The Folium package in Python was used in hotspot analysis.

2.3.2. Logistic Regression Model

The Logistic Regression model was used to estimate the effect of driving factors on the crime changing during BLM protests. Binary Logistic Regression is a statistical technique used to predict the relationship between predictors (independent variables) and a predicted variable (the dependent variable). In this section, we built the model from three steps: dependent variable definition, independent variables selection, and modeling building.

(1) Dependent variable definition

We calculated the changing rate of crime to represent the changing degree in crime during the BLM protests. The higher the growth rates, the higher the crime than the average. The changing rate is defined as follows:

$$r = \frac{avg^n_{after} - avg^n_{before}}{avg^n_{before}} * 100\%, \tag{2}$$

where, avg^n_{after} is the n days' average crime rate after the start date of protests, avg^n_{before} represents the n days' average crime rate before the start date of protests. n is decided based on the peak crime duration. The start dates of protests were collected from news reports.

It is not appropriate to directly use the changing rate as the dependent variable of the linear model, because we did not eliminate random fluctuations caused by seasonality and periodicity of crime. However, minor random fluctuations of crime will be ignored through classification. This is also the reason we selected the Logistic Regression model for our research. Therefore, we divided counties/cities into two categories based on the value of the changing rate, defined as follows:

$$y_c = \begin{cases} 0, if\ r < \sigma \\ 1, if\ r \geq \sigma \end{cases}, \tag{3}$$

where, r represents the changing rate during the BLM protests. σ is the threshold value. $y_c = 1$ means that crime in the city c has a big variation during BLM protests, $y_c = 0$ means the opposite. $y = \{y_1, y_2, \cdots, y_N\}$ is defined as the dependent variable, N is the number of counties and cities. The result of the classification is defined as the dependent variable.

(2) Independent variables selection

Independent variable selection is one of the main techniques for selecting an important subset of features as a specific factor in model development, particularly for variables with collinearity. Variable selection methods target removing excess or insignificant variables [32]. LASSO is a regression analysis method that performs variable selection while in regression analysis, to enhance the interpretability of the statistical model it produces [33,34]. Lasso regularization is easily extended to Generalized

Linear Models (GML). When the response variable is binary, the optimization objective for a Logistic regression model is defined as [35]:

$$\hat{\beta}(\lambda) = \arg_{\beta}\min\left\{\frac{1}{N}\sum_{i=1}^{N}\rho_{(\beta)}(X_i, Y_i) + \lambda\|\beta\|_1\right\}, \tag{4}$$

where Y represents the outcome, consisting of N cases. $X = (x_1, x_2, \cdots, x_m)$ is the covariate. λ is a prespecified free parameter in Constant that multiplies the L1 term. The larger the value of λ, the greater the amount of shrinkage. R glmnet function has been used in experiments.

(3) Modeling building

Finally, the binary logistic regression model is defined as follows [36]:

$$\text{logit}(p) = \ln\frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n, \tag{5}$$

where p is the probability of the event occurring, $p = P(y_c = 1)$. $x_i := (x_1, x_2, \cdots, x_n)$ is the independent variable selected by the LASSO model. $\beta_0, \beta_1, \cdots, \beta_n$ are regression coefficients of variables.

3. Results

3.1. Overall Trend of Crime during COVID-19 Pandemic

This subsection tends to offer overall analytics on crime trend during the COVID-19 crisis and provide a background that BLM protests took place. In Figure 3, we display the distribution of the total crime rate per 10,000 people from January 1, 2020, to June 15, 2020, based on a boxplot. Each box represents a county/city, plotted by county/city id (Table 1) on the horizontal axis and crime rate per 10,000 people on the vertical. The boxes are sorted by a median of the crime rates (shown as the orange line). The overall trend of crime rate in Figure 3 illustrates the counties/cities with lower crime rates are tighter than counties/cities with higher crime rates, and counties/cities with higher crime rates have more outliers (shown as red circles).

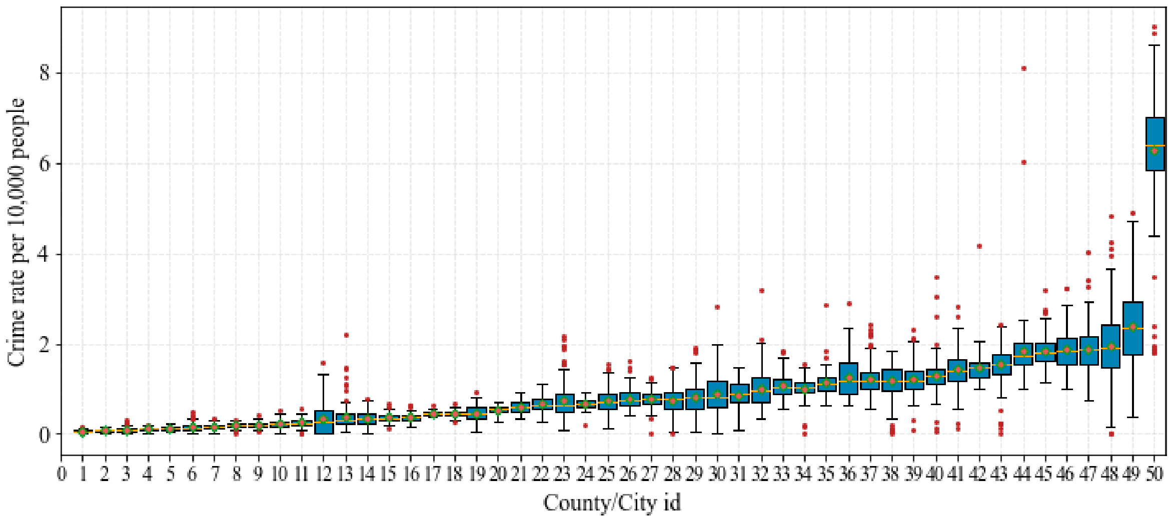


Figure 3. Boxplot of the total crime rate per 10,000 people including outliers (red circles), mean values of crime rates (orange circles), and median value of crime rates (yellow lines inside boxes).

We manually selected nine typical counties and cities from 50 counties/cities with different scales to visualize the current patterns. The daily time series (from 1 January 2020, to 15 June 2020) for the total crime in several counties/cities are shown in Figure 4. The results do not show the same trend of crime in different cities or counties during the COVID-19 pandemic. In Figure 4a–e, crime dropped between the date that the first confirmed case was reported and the date that the stay-at-home order was implemented, then slowly increased or remained stable when the stay-at-home order was implemented. Meanwhile, in (f)-(i), crime did not change during the COVID-19 pandemic. The overall trend of crime during the COVID-19 pandemic concur with those seen in other studies. However, we only provide an analysis of the total number of crimes, noting that not all crime types have the same trend under the COVID-19 pandemic.

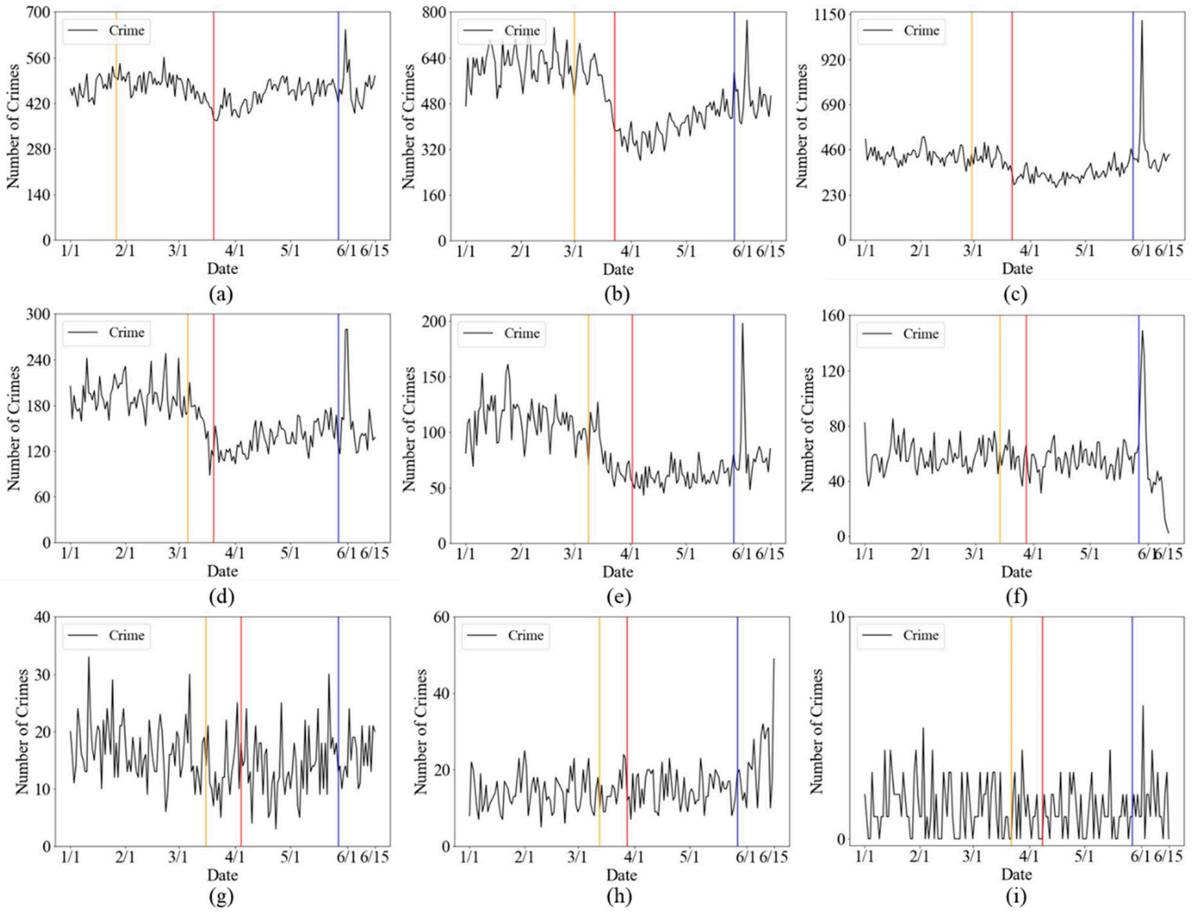


Figure 4. Time series of crimes per day (**a**) Los Angeles County, CA; (**b**) New York City, NY; (**c**) Chicago, IL; (**d**) San Francisco, CA; (**e**) Washington, DC; (**f**) Minneapolis, MN; (**g**) Shelby County, AL; (**h**) Olmsted County, MN; (**i**) Newberry County, SC. Yellow vertical line indicates the date first confirmed case reported, red vertical line indicates the date stay-at-home order implemented, and blue vertical line indicates the death date of George Floyd (26 June 2020).

As shown in Figure 4a–f, crime rose sharply in a few cities/counties during the BLM protests. The trend of crime in Figure 4g–i performs a consistent fluctuation with other periods. Additionally, there were no outliers (greater than or less than three standard deviations) in the days before and after the BLM protests for all counties/cities. This suggested that the BLM protest took place in the backdrop of relative crime stability. For the current stage, we only provide an analysis of the total number of crimes; trends in different types of crime are needed.

To summarize, Figure 4 does not show the same trend of crime in different cities or counties during the COVID-19 pandemic and BLM protests, i.e., heterogeneity exists across cities/counties. The heterogeneity between counties/cities may be related to their socioeconomic difference. We will explore the changes in different types of crime, the spatiotemporal variations of burglary, and the driving factors of burglary changes during BLM protests in the next three subsections.

3.2. Changes in Different Crime Types during Black Lives Matter Protests

From the overall time series analysis, crime changed a lot in a few counties/cities during the BLM protests, and there is heterogeneity across counties/cities in the context of the COVID-19 pandemic. However, the overall trend of crime cannot reflect all types of crime. The daily time series for the various crime types are shown in Figure 5. Lines with different colors represent seven different crime types.

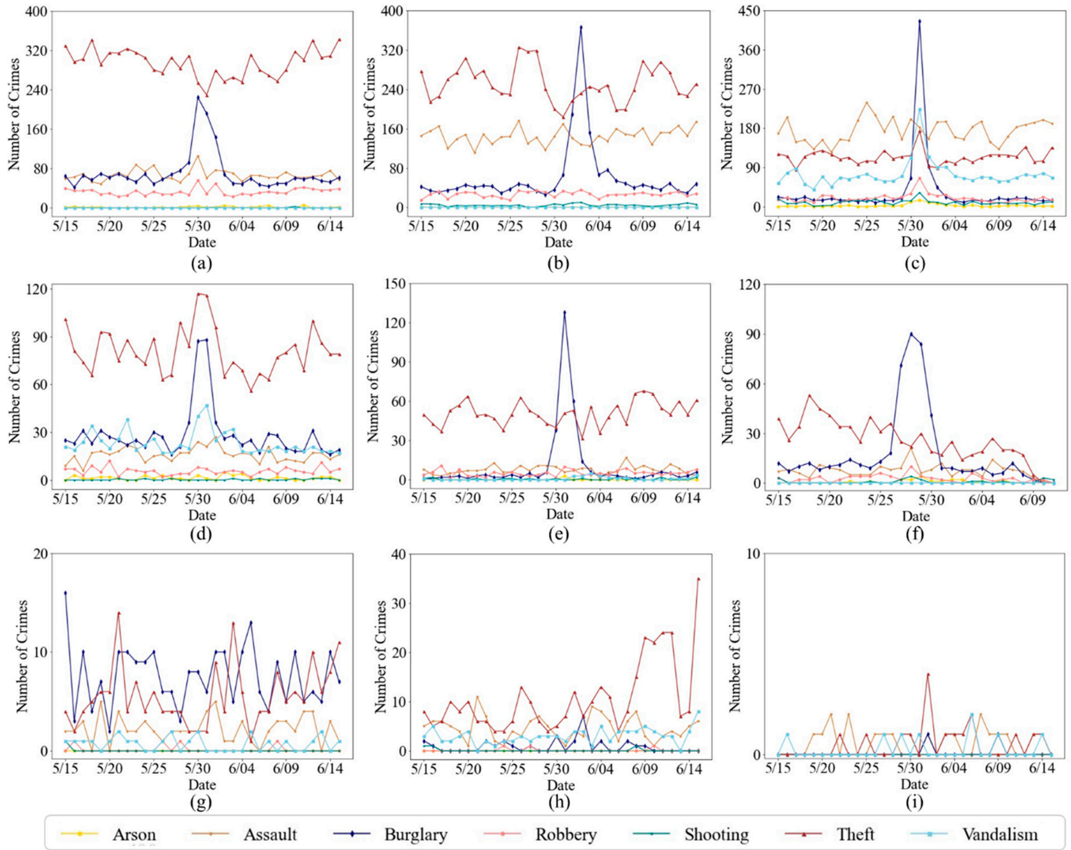


Figure 5. Number of crimes for different types (**a**) Los Angeles County, CA; (**b**) New York City, NY; (**c**) Chicago, IL; (**d**) San Francisco; (**e**) Washington DC; (**f**) Minneapolis, MN; (**g**) Shelby County, AL; (**h**) Olmsted County, MN; (**i**) Newberry County, SC.

Figure 5a–f show that there are sharp changes in burglary in both cities. Minor increases exist in vandalism and assault in several cities, such as vandalism increasing slightly in San Francisco and Chicago, along with assault in Los Angeles County and Minneapolis. The trends of other crime types changed less, and they exhibited a consistent fluctuation in relation to other periods. That means other crime types except burglary were not seriously affected by BLM protests. This is likely because the Covid-19 epidemic shifted routine activities by moving owners and customers away from business locations, leaving them highly vulnerable to burglary and trespassing [19]. In addition, protests happened in a few cities accompanied by reports of burglary, and dozens of shops and stores have been stolen from and damaged during protests periods. Although there are reports that the numbers of homicides and victims shot increased during BLM protests [37,38], the increase was less obvious compared with burglary.

Additionally, burglary peaked between 27 May 2020, and 3 Jun 3 2020, and continued three to five days since the start of the early protests. Then, the number of burglaries decreased to their regular value. Hence, the effects of the protests on burglary appear to be somewhat transitory and fade over the short-run period, as the violence and scope of the protests abate. Thus, the protests in these cities that were accompanied by crime became peaceful after three to five days.

Figure 5g–i shows that crime has no obvious changes in these counties in late May or early June 2020 when it would be expected to increase. Compared with bigger counties/cities with higher populations (i.e., Los Angeles County, New York City), Shelby County, Olmsted County, and Newberry County had smaller protests and were not seriously affected by the BLM Protests.

In summary, Figure 5 does not show the same trend in different crime types and cities/counties during the BLM protests. The change in burglary accurately reflects the change in crime during the BLM protest compared to other crime types or total crimes. The heterogeneity of burglary between counties/cities may be related to their socioeconomic difference. We will analyze the spatiotemporal patterns and driving factors of burglary changes (instead of total crime changes) during BLM protests in the next two subsections.

3.3. Spatiotemporal Variations of Burglary during Black Lives Matter Protests

We analyzed the spatial distribution changes in burglary instead of total crime. It should be noted that geocoding the locations of these crimes introduces error. We made topologic analysis and deleted points outside the boundary of cities/counties. This may slightly affect the results of the average nearest neighbor analysis. The resulting ANN shows that counties/cities with higher changes in burglary showed spatial aggregation during protests. This is probably because burglaries centered around the protests. The spatial distribution of counties/cities with lower changing rates is not obvious.

Figure 6 illustrates the average nearest neighbor values in burglary for six sample counties/cities. Bars with brown color mean that the P values are greater than or equal to 0.05, and ANN values are statistically significant. The red line represents the start day of protests in each city/county. ANN values decrease after the start of the protest, compared to before in both cities. The trend of ANN values illustrates that the activity of burglary clustered in several certain regions during the protests period. Additionally, different from Los Angeles County and San Francisco, burglaries in Chicago, Washington DC, and Minneapolis are considered more clustered than ever before.

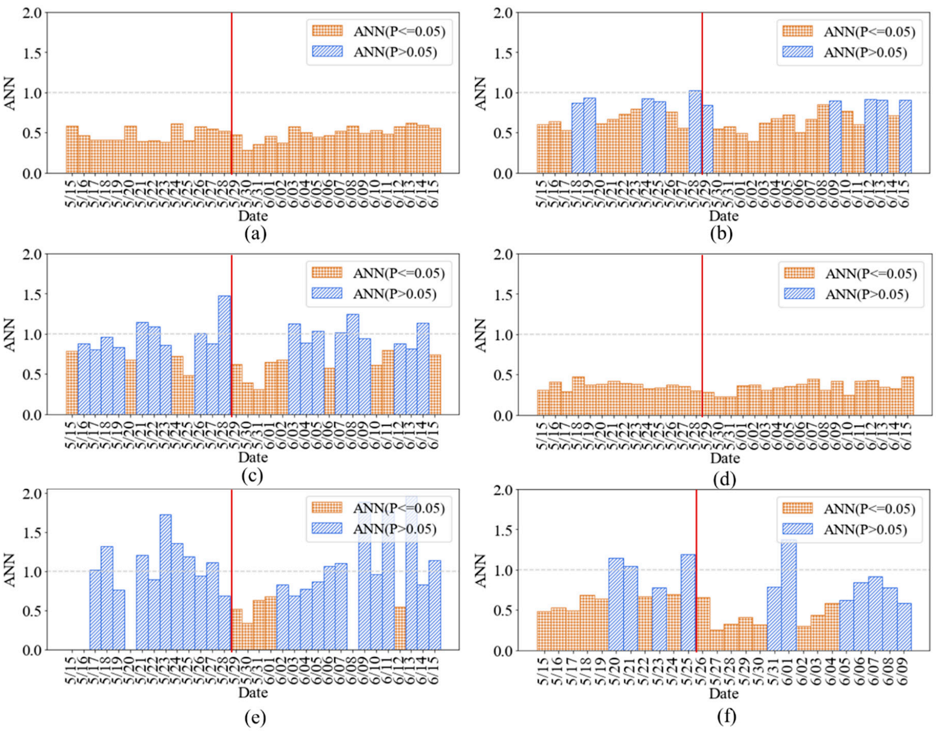


Figure 6. Average nearest neighbor value (**a**) Los Angeles County, CA; (**b**) New York City, NY; (**c**) Chicago, IL; (**d**) San Francisco; (**e**) Washington DC; (**f**) Minneapolis, MN. Red vertical line indicates the first protest date reported of each county/city.

Furthermore, the hotspot maps of burglary in six sample counties/cities are shown in Figures 7–12. We selected the day with the peak value of burglary, the 7th day before, and the 7th day after the peak day for each county/city. The second figure (i.e., (b)) in Figures 7–12 shows the hotspots maps of the peak day. Hot spots can be found in both counties/cities during BLM protests. Figures 7–12 shows that burglaries are spread throughout the city in the usual time and mainly occur in the downtown areas during BLM protests. This means burglaries gathered in space on the peak day, coinciding with the ANN analysis. Furthermore, the spatial distribution of burglary in Chicago, San Francisco, and Minneapolis exhibits a clear spatial concentration pattern along the street. This is because burglaries occurred in non-residential areas where protests gathered, where there are many commercial buildings and shops along the street. Therefore, both the volume and distribution of burglaries were altered during BLM protests. The spike in burglaries is characterized by its abruptness, size, brevity, and clustering.

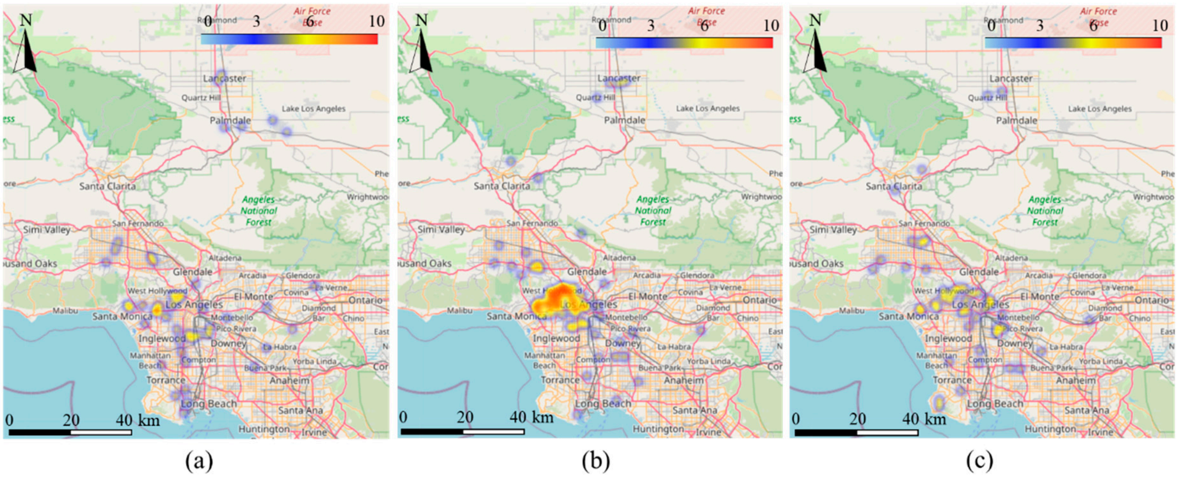


Figure 7. Hotspots of burglary in Los Angeles County, CA (**a**) 23 May 2020; (**b**) 30 May 2020; (**c**) 6 June 2020.

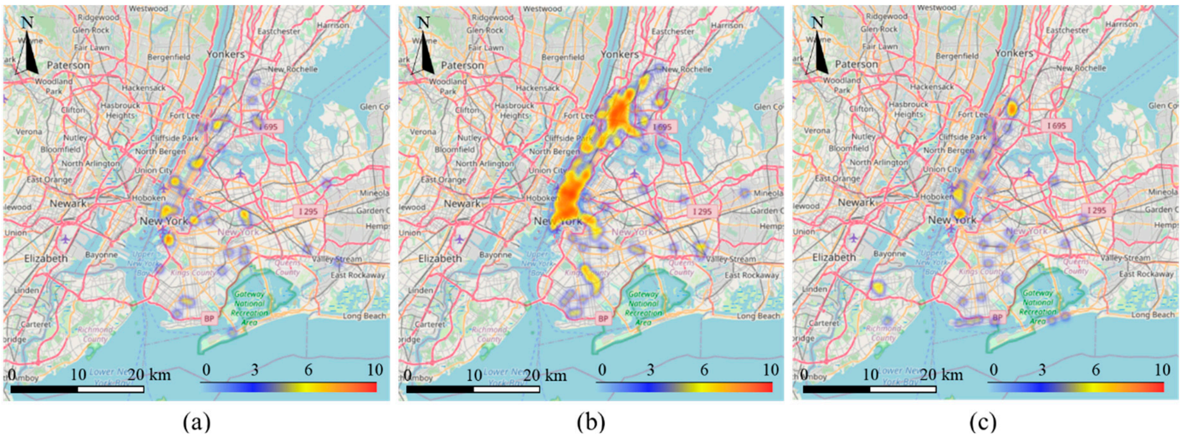
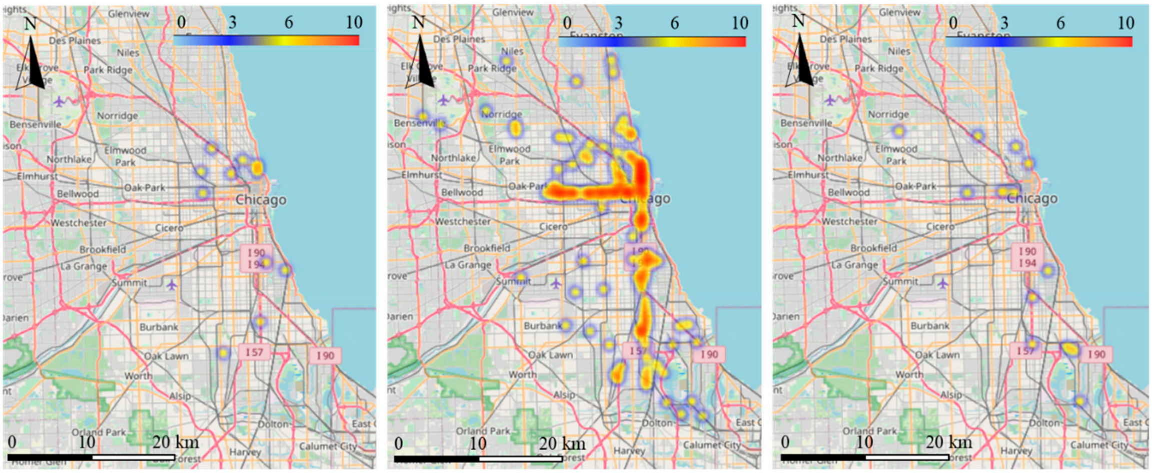
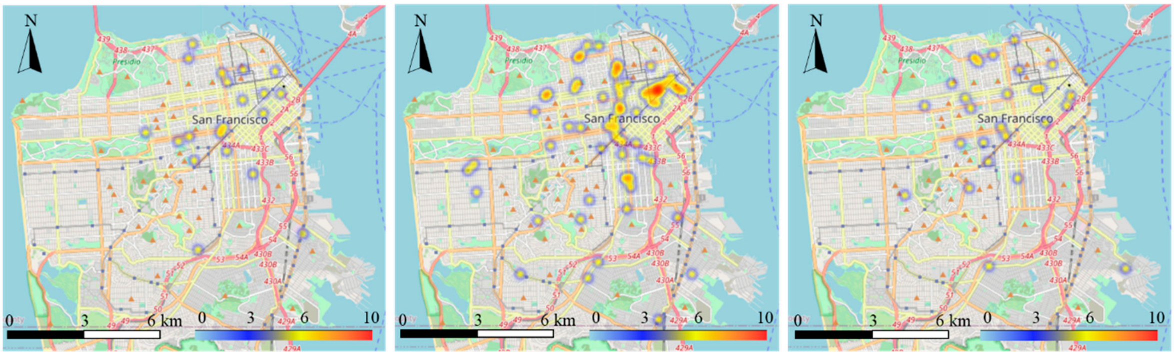


Figure 8. Hotspots of burglary in New York City, NY (**a**) 26 May 2020; (**b**) 2 June 2020; (**c**) 9 June 2020.



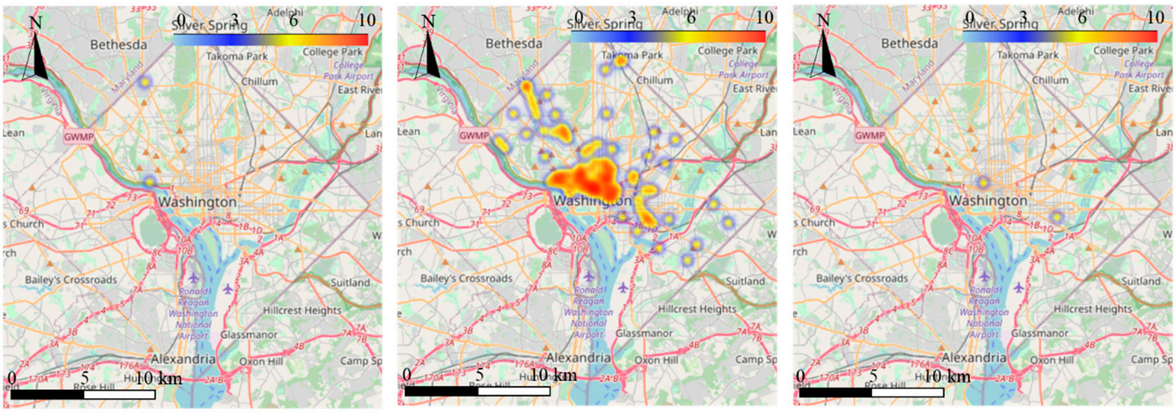
(a) (b) (c)

Figure 9. Hotspots of burglary in Chicago, IL (**a**) 24 May 2020; (**b**) 31 May 2020; (**c**) 7 June 2020.



(a) (b) (c)

Figure 10. Hotspots of burglary in San Francisco, CA (**a**) 24 May 2020; (**b**) 31 May 2020; (**c**) 7 June 2020.



(a) (b) (c)

Figure 11. Hotspots of burglary in Washington DC (**a**) 24 May 2020; (**b**) 31 May 2020; (**c**) 7 June 2020.

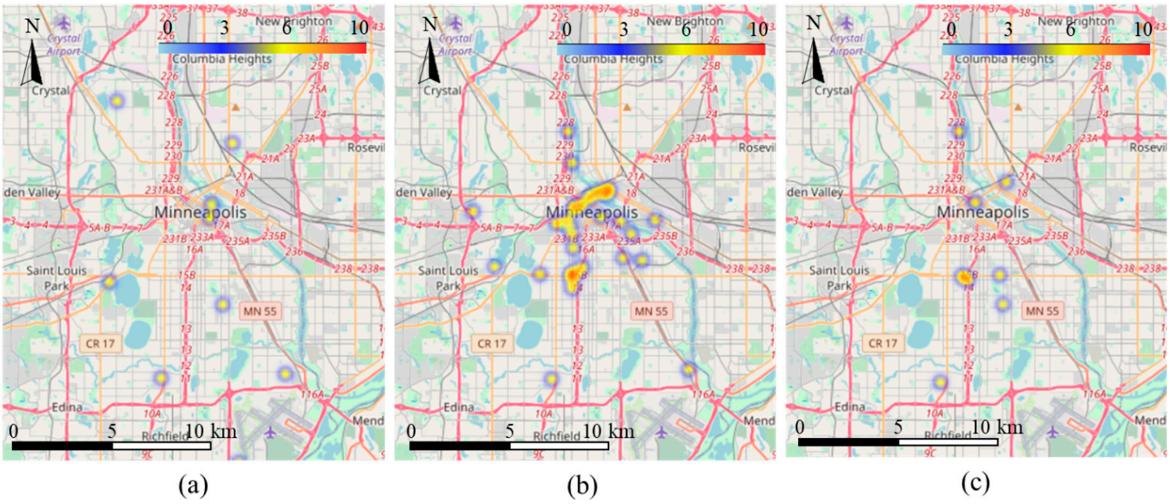


Figure 12. Hotspots of burglary in Minneapolis, MN (**a**) 21 May 2020; (**b**) 28 May 2020; (**c**) 4 June 2020

3.4. Impact of Driving Factors on Burglary during Black Lives Matter Protests

3.4.1. Changing Rate of Burglary

The results of Sections 3.1 and 3.2 lead us to explore which counties/cities have changed obviously with burglary during the BLM protest. To explain the degree of effect of protests on burglary, we calculated the changing rate using Equation (2). In addition, the parameter n is 5, because burglary usually peaked and continued three to five days from the start of the early protests. It is worth noting that when the number of burglaries is less than two per day, the rate will have a large fluctuation when adding or subtracting a small number. Therefore, we removed the cities/counties with fewer than two burglaries per day.

The changing rates of burglary in the remaining 36 cities/counties are provided in Table 3. The higher the growth rates, the higher the burglary than the average. The changing rate reflects the severity of burglaries and the effect of protests on crime. Table 3 shows that the changing rates of cities/counties differ greatly. All the cities listed in Table 3 were accompanied by mainstream media reports of burglaries on protests. Specifically, Minneapolis, Fairfax County, Boston, St. Paul, Chicago, and Washington DC had more burglaries than ever before. The result of the classification is shown in the fifth and tenth columns in Table 3.

Table 3. Changing rates of burglary.

County/City Name	avg_{before}	avg_{after}	r	Class	County/City Name	avg_{before}	avg_{after}	r	Class
Collier County, FL	7.60	4.60	−39.47	0	Pinellas County, FL	12.60	16.00	26.98	0
Baltimore County, MD	10.20	6.60	−35.29	0	Shelby County, AL	6.20	8.20	32.26	0
Honolulu, HI	8.20	5.80	−29.27	0	Sarasota County, FL	3.40	5.00	47.06	0
Miami-Dade County, FL	9.00	7.80	−13.33	0	Denver, CO	13.40	21.60	61.19	1
Montgomery County, TX	6.00	5.80	−3.33	0	Baltimore, MD	43.80	70.80	61.64	1
Orange County, CA	23.20	23.20	0.00	0	Hillsborough County, FL	8.60	18.60	116.28	1
Pierce County, WA	2.80	2.80	0.00	0	Los Angeles County, CA	64.00	144.40	125.63	1
Riverside County, CA	15.40	15.60	1.30	0	San Francisco, CA	23.00	54.60	137.39	1
Thurston County, WA	5.80	6.00	3.45	0	New York, NY	38.20	136.60	257.59	1
Bexar County, TX	4.40	4.60	4.55	0	Minneapolis, MN	13.00	59.00	353.85	1
Suffolk County, NY	3.80	4.20	10.53	0	Fairfax County, VA	1.40	7.60	442.86	1
Escambia County, FL	6.80	7.60	11.76	0	Boston, MA	2.60	19.80	661.54	1
Hamilton County, TN	6.20	7.00	12.90	0	Chicago, IL	13.00	129.40	895.38	1
Knox County, IL	4.60	5.40	17.39	0	St. Paul, MN	6.40	64.40	906.25	1
Weld County, CO	2.40	3.00	25.00	0	Washington, DC	3.00	49.20	1540.00	1

Additionally, Figure 13 shows the distribution of research regions with and without a 50% increase in burglary. The changing rates in 12 areas exceed 50%, and there are 10 areas (except Minneapolis and

St. Paul) with a population of more than 50,000 people. This means big changes in burglary exist in large counties/cities. However, not all major counties/cities have experienced a sudden increase in burglaries during BLM protests, such as Orange County, CA, and Miami-Dade County, FL.

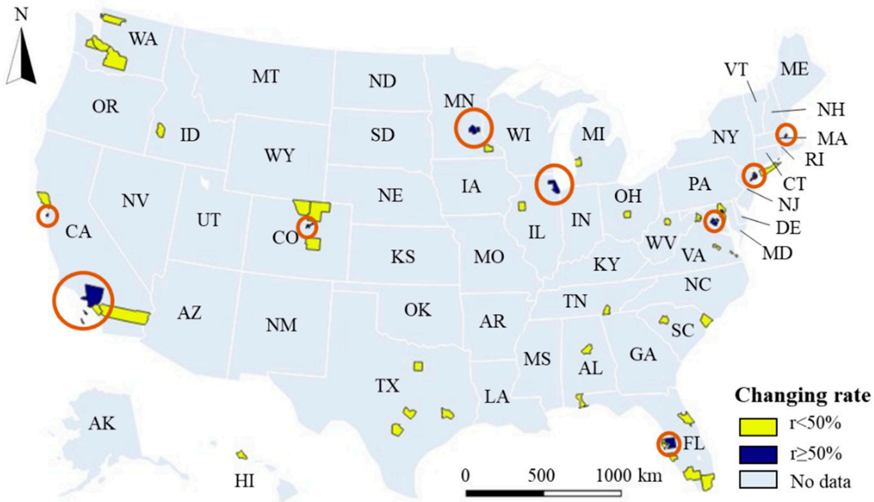


Figure 13. Distribution of burglary changing rate. Red circles denote the research regions where the burglary has increased by more than 50%.

3.4.2. Independent Variables Selection

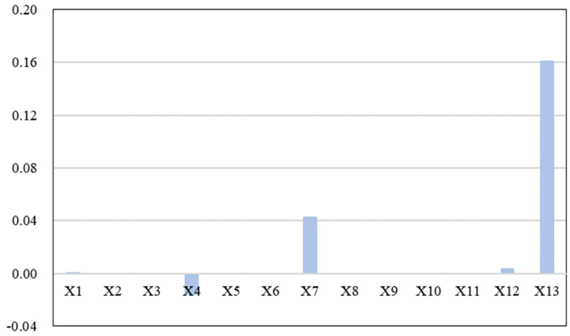
The Person Correlation Coefficient (PCC) [39,40] for these variables are provided in Table 4. The correlations shown in Table 4 exhibit a surprising relationship, with the highest of these correlations involving the 60 years and overpopulation and age dependency ratio (r = 0.86, p-value < 0.01). Owning a Bachelor's degree has a strong positive relationship with the median household income (r = 0.79, p-value < 0.01). Strong positive relationships are present between the less than 9th grade and diversity index (r = 0.69, p-value < 0.01), and population under 18 years with males per 100 females (r = 0.66, p-value < 0.01). With regard to the statistical modeling below, some correlations do cause some concerns for collinearity.

Table 4. Correlations for driving factors.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
X1	1.00												
X2	0.05	1.00											
X3	0.13	0.04	1.00										
X4	0.02	0.46 **	0.86 **	1.00									
X5	–0.01	0.66 **	0.32 *	0.49 **	1.00								
X6	0.44 **	0.34 *	0.11	0.22	0.17	1.00							
X7	0.39 **	0.17	0.08	0.01	0.34 **	0.09	1.00						
X8	0.30 *	0.38 **	0.18	0.22	0.46 **	0.21	0.79 **	1.00					
X9	0.12	0.49 **	0.31 *	0.40 **	0.55 **	0.40 **	–0.16	–0.11	1.00				
X10	–0.19	0.43 **	0.46 **	0.59 **	0.44 **	0.16	0.03	0.24	0.32 *	1.00			
X11	0.48 **	0.08	0.10	0.01	0.00	0.13	0.24	0.08	0.18	–0.40 **	1.00		
X12	0.42 **	0.44 **	–0.06	0.07	0.39 **	0.69 **	0.37 **	0.42 **	0.27 *	0.15	0.22	1.00	
X13	0.50 **	0.05	0.27 *	0.13	0.05	0.21	0.23	0.17	0.22	–0.02	0.48 **	0.09	1.00

Notes: * $p < 0.05$; ** $p < 0.01$. X1: population density; X2: population under 18 years; X3: population over 60 years; X4: age dependency ratio; X5: males per 100 females; X6: less than 9th grade; X7: Bachelor's degree; X8: median household income; X9: below the poverty level; X10: White population; X11: Black or African American population; X12: diversity index; X13: 2019 crime per 10,000 people.

The effect of collinearity makes the regression coefficients unreliable. Therefore, feature selection is needed in choosing a subset of important features to be specific factors for model development. LASSO was used in our experiments. Figure 14 demonstrates the variable importance with their probabilities. During the feature selection process, the variables that still have a non-zero coefficient are selected to be part of the model. For the value of λ_{lse} (λ_{lse} gives a model such that error is within one standard error of the minimum), the following five variables were selected: Bachelor's degree, diversity index, age dependency ratio, population density, and 2019 crime rate per 10,000 people. This means education, race, demographic, and crime rate in 2019 are related to burglary changes during BLM protests. Specifically, the crime rate in 2019 has a significant relationship with burglary changes compared with other variables.



X	X1	X4	X7	X12	X13
value	9.73E-05	-1.57E-02	4.23E-02	3.36E-03	1.61E-01

Figure 14. Variable importance with Least Absolute Shrinkage, and Selection Operator (LASSO).

3.4.3. Driving Factors Analysis

The result of Binary Logistic Regression is shown in Table 5. The Pseudo R square is 0.6479, and the p-value of this model is less than 0.01. Somewhat surprisingly, except for a Bachelor's degree, the P values of other independent variables are all greater than 0.1. There is no significant statistical evidence that x_1, x_4, x_{12}, x_{13} are related to the changing rate of burglary in this logistic regression model. To check the reliability of the results, we also performed experiments with a linear regression model, and the results were consistent.

Table 5. Regression results for change rate of burglary.

Variable	Coefficient	Standard Error	z	P > |z|	Odds Ratios
Const	–12.666	10.136	–1.250	0.211	0.000
Population density	0.000	0.000	0.753	0.451	1.000
Age dependency ratio	–0.070	0.098	–0.716	0.474	0.933
Bachelor's degree	0.159	0.082	1.938	0.053	1.172
Diversity index	0.113	0.072	1.570	0.117	1.119
2019 crime rate per 10,000 people	1.501	1.068	1.405	0.160	4.485

We observed that a Bachelor's degree had a strong and significant positive effect on the changing rate of burglary. Current research suggests that education is shown to reduce crime [41,42]. Different from the effect of education on crime, counties/cities with higher educated rates have a positive effect on the burglary changing rate. During the protests, burglaries are more likely to occur in counties/cities with a higher percentage of Bachelor's degrees.

Additionally, the odds ratios of crime rate per 10,000 people in 2019 are greater than the other four variables. For every one-unit increase in crime rate per 10,000 people in 2019, there is an increase of 4.485 for burglary changing rate during protests. That means the crime rate per 10,000 people in 2019 has a positive effect on the changing rate of burglary. This is consistent with the result of LASSO.

It is worth noting that the percent of white or black people are not selected as determinant factors in LASSO, although BLM is a movement in protest against incidents of all racially motivated violence against Black people. This is probably because the majority of Americans, across all racial and ethnic groups, have expressed support for the Black Lives Matter movement [43].

4. Discussion

Although society and social media have widely reported the protests and responded to the George Floyd incident, the incident was not a sentinel incident in changing the direction of the overall decline in crime. Our analysis was well-positioned to identify the variables of crime and driving factors during BLM protests among the 50 samples of U.S. cities examined to date. We observed sharp increases in burglaries for a particular time period in some locations, but no widespread changes were detected in overall crime trends among the counties/cities in our study. We also found that the burglary case number went back to a normal level that did not change substantially 5 days later. Therefore, our analysis confirms the long-standing understanding that the cause of crime reflects a slow process and is not affected by emergencies [22,44]. The change of crime number, no matter increase or decrease, in a short time would go back to a normal stage soon after the end of the emergency event. Additionally, there are several limitations to the present study.

This study is not the final word on the crime variations. We did not consider the persistent changes of burglary after15 June 2020 due to a lack of data, which is a missing of seasonal analysis during the BLM period. Similarly, since we only calculated the change rate for 2020 (instead of a difference in difference, e.g., comparing the change rate with 2019 data), we essentially could not account for potential trending in the data.

Secondly, the spatiotemporal variations reflect the locations of protests. While the six cities in Figures 7–12 account for both a large-scale hotspot in the peak day of burglaries, it omits more precise area analysis such as residential and nonresidential areas. There may be apparent differences based on the land use type that our analysis does not capture. In addition, the distribution of burglaries may also have a connection with the distributions of commercial districts such as shops and stores. Police and business owners could take steps to prevent these events from happening again in the future.

This is a typical data mining method used to test the effect of driving factors on crime by identifying the importance of the features. Different from the statistical models, the significance could not be easily interpreted.

Additionally, tragic events such as the death of Trayvon Martin, Michael Brown, George Floyd, have sparked widespread attention and discussion over such as police accountability and police legitimacy. Such discussion, however, should be informed by solid data and detailed analysis. Policy decisions that are not based on evidence can have a negative impact on public safety and reduce government credibility. We sought to bring empirical evidence to the effect of protests on crime. We hope that our results will help provide evidence-based discussions about the crime variations and its reasons during BLM protests, especially a broader discussion of changes in crime trends.

5. Conclusions

This research offers one of the first empirical analyses of the spatiotemporal patterns and influencing factors on crime rates during the 2020 BLM protests, which has been a point of concern among public safety and health officials and the media. Specifically, we use multiple spatial (ANN and KDE) and statistical analysis (LASSO and Logistic Regression) methods to model the spatiotemporal trend and driving factors of burglary during BLM protests in 50 counties and cities, U.S. The results reflect the overall crime changes during BLM protests in the United States to a certain extent.

From the results of the experiments and statistics, we show that (1) crime in the U.S. appears to be going down overall during the COVID-19 pandemic, but the BLM protest took place in the backdrop of relative crime stability; (2) different temporal patterns of crime rates emerge during the 2020 BLM protests in the U.S.; (3) only certain types of crime, i.e., burglary, have a sharp change in numbers and spatial distribution; and (4) education, race, demographic, and crime rate in 2019 are related with burglary changes during BLM protests. Specifically, counties/cities with higher education rates have a positive effect on the burglary changing rate. The results offer suggestions and a basis for the police and governmental agencies to take steps in preventing the diffusion of violent protests and the increase in crimes.

Finally, as a future augmentation of our work, detailed spatiotemporal analysis [42,45] at a block-level or community-level will better reflect crime changes in the county/city. Additionally, violent assault and gun violence are important areas of research in criminology, and more attention will be paid to these two crime types in metropolitan cities. The spatial distribution character inspired us to conduct further study on the impact of point-of-interests on crime using various methods such as the Poisson regression model and ARIMA [14]. More detailed data, e.g., the crime incident attributes, including the suspect anonymized background, would help explain the changes. For example, does the influx of people with lower education flooding to an area with a well-educated population drive up the crime rates?

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References

1. Roth, R.E.; Ross, K.S.; Finch, B.G.; Luo, W.; Maceachren, A.M. Spatiotemporal crime analysis in U.S. law enforcement agencies: Current practices and unmet needs. *Gov. Inf. Q.* **2013**, *30*, 226–240. [CrossRef]
2. Duan, L.; Hu, T.; Cheng, E.; Zhu, J.; Gao, C. Deep Convolutional Neural Networks for Spatiotemporal Crime Prediction. In Proceedings of the International Conference on Information and Knowledge Engineering (IKE), Las Vegas, NV, USA, 17–20 July 2017.
3. Smith, W.R.; Frazee, S.G.; Davison, E.L. Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology* **2000**, *38*, 489–524. [CrossRef]
4. Sampson, R.J.; Groves, W.B. Community structure and crime: Testing social-disorganization theory. *Am. J. Sociol.* **1989**, *94*, 774–802. [CrossRef]
5. Cohen, L.E.; Felson, M. Social change and crime rate trends: A routine activity approach. *Am. Sociol. Rev.* **1979**, *44*, 588–608. [CrossRef]
6. Felson, M. *Environmental Criminology and Crime Analysis*, 2nd ed.; Routledge: New York, NY, USA, 2008; pp. 87–97.
7. Andresen, M.A. A spatial analysis of crime in Vancouver, British Columbia: A synthesis of social disorganization and routine activity theory. *Can. Geogr. Le Géographe Can.* **2006**, *50*, 487–502. [CrossRef]
8. Andresen, M.A. Crime measures and the spatial analysis of criminal activity. *Br. J. Criminol.* **2006**, *46*, 258–285. [CrossRef]
9. Eck, J.E.; Guerette, R.T. *The Oxford of Handbook of Crime Prevention*; Oxford University Press: New York, NY, USA, 2012; pp. 354–383.
10. Friedersdorf, C. How to Distinguish Between Antifa, White Supremacists, and Black Lives Matter. The Atlantic. Available online: https://www.theatlantic.com/politics/archive/2017/08/drawing-distinctions-antifathe-alt-right-and-black-lives-matter/538320 (accessed on 2 September 2020).
11. Taylor, D.B. George Floyd Protests: A Timeline. *New York Times*, 10 July 2020.
12. Dave, D.M.; Friedson, A.I.; Matsuzawa, K.; Sabia, J.J.; Safford, S. *Black Lives Matter Protests, Social Distancing, and COVID-19*; 0898–2937; National Bureau of Economic Research: Cambridge, MA, USA, 2020.

13. Mohler, G.; Bertozzi, A.L.; Carter, J.; Short, M.B.; Sledge, D.; Tita, G.E.; Uchida, C.D.; Brantingham, P.J. Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis. *J. Crim. Justice* **2020**, *68*, 101692. [CrossRef]
14. Yang, C.; Sha, D.; Liu, Q.; Li, Y.; Lan, H.; Guan, W.W.; Hu, T.; Li, Z.; Zhang, Z.; Thompson, J.H. Taking the pulse of COVID-19: A spatiotemporal perspective. *Int. J. Digit. Earth* **2020**, *10*, 1186–1211. [CrossRef]
15. Hu, T.; Guan, W.; Zhu, X.; Shao, Y.; Liu, L.; Du, J.; Liu, H.; Zhou, H.; Wang, J.; She, B.; et al. Building an Open Resources Repository for COVID-19 Research. *Data Inf. Manag.* **2020**, *4*, 130–147.
16. Sha, D.; Miao, X.; Lan, H.; Stewart, K.; Ruan, S.; Tian, Y.; Yang, C. Spatiotemporal analysis of medical resource deficiencies in the U.S. under COVID-19 pandemic. *PLoS ONE* **2020**, *15*, 1–23. [CrossRef]
17. Payne, J.; Morgan, A. COVID-19 and Violent Crime: A Comparison of Recorded Offence Rates and Dynamic Forecasts (ARIMA) for March 2020 in Queensland, Australia. SocArXiv de9nc, Center for Open Science. 2020. Available online: https://ideas.repec.org/p/osf/socarx/g4kh7.html (accessed on 2 September 2020).
18. Piquero, A.R.; Riddell, J.R.; Bishopp, S.A.; Narvey, C.; Reid, J.A.; Piquero, N.L. Staying Home, Staying Safe? A Short-Term Analysis of COVID-19 on Dallas Domestic Violence. *Am. J. Crim. Justice* **2020**, *3*, 1–35. [CrossRef] [PubMed]
19. Felson, M.; Jiang, S.; Xu, Y. Routine activity effects of the Covid-19 pandemic on burglary in Detroit, March, 2020. *Crime Sci.* **2020**, *9*, 10. [CrossRef] [PubMed]
20. 250 Fined for Breaking 1.5 Metre Rule, but 'Traditional' Crime Drops Sharply. Available online: https://www.dutchnews.nl/news/2020/04/250-fined-for-breaking-1-5-metre-rule-but-traditional-crime-drops-sharply/ (accessed on 2 September 2020).
21. Rosenfeld, R.; Lopez, E. *Pandemic, Social Unrest, and Crime in U.S. Cities: August 2020 Update*; Council on Criminal Justice: Washington, WA, USA, 2020.
22. Pyrooz, D.C.; Decker, S.H.; Wolfe, S.E.; Shjarback, J.A. Was there a Ferguson Effect on crime rates in large U.S. cities? *J. Crim. Justice* **2016**, *46*, 1–8. [CrossRef]
23. Updegrove, A.H.; Cooper, M.N.; Orrick, E.A.; Piquero, A.R. Red states and Black lives: Applying the racial threat hypothesis to the Black Lives Matter movement. *Justice Q.* **2020**, *37*, 85–108. [CrossRef]
24. How Average Nearest Neighbor Works. Available online: https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-average-nearest-neighbor-distance-spatial-st.htm (accessed on 2 September 2020).
25. Silverman, B.W. *Density Estimation for Statistics and Data Analysis*; CRC Press: Boca Raton, FL, USA, 1986; Volume 26.
26. SpotCrime. Available online: https://spotcrime.com/ (accessed on 2 September 2020).
27. Corso, A.J. Toward predictive crime analysis via social media, big data, and gis spatial correlation. In *iConference 2015*; iSchools: Newport Beach, CA, USA, 2015.
28. UCR Offense Definitions. Available online: https://www.ucrdatatool.gov/offenses.cfm (accessed on 2 September 2020).
29. Esri. 2020 Esri US Diversity Index Methodology Statement. Available online: https://downloads.esri.com/esri_content_doc/dbl/us/J10170_US_Diversity_Index_2020.pdf (accessed on 2 September 2020).
30. Esri. Diversity in the United States. Available online: https://www.arcgis.com/home/item.html?id=def0151deab74cdb881eb92ea6d860d4 (accessed on 2 September 2020).
31. Chainey, S.; Tompson, L.; Uhlig, S. The utility of hotspot mapping for predicting spatial patterns of crime. *Secur. J.* **2008**, *21*, 4–28. [CrossRef]
32. Nitta, G.R.; Rao, B.Y.; Sravani, T.; Ramakrishiah, N.; BalaAnand, M. LASSO-based feature selection and naïve Bayes classifier for crime prediction and its type. *Serv. Oriented Comput. Appl.* **2019**, *13*, 187–197. [CrossRef]
33. Santosa, F.; Symes, W.W. Linear inversion of band-limited reflection seismograms. *SIAM J. Sci. Stat. Comput.* **1986**, *7*, 1307–1330. [CrossRef]
34. Tibshirani, R. Regression shrinkage and selection via the lasso. *J. R. Stat. Soc. Ser. B* **1996**, *58*, 267–288. [CrossRef]
35. Fonti, V.; Belitser, E. Feature selection using lasso. *VU Amst. Res. Pap. Bus. Anal.* **2017**, *30*, 1–25.
36. Hosmer, D.W., Jr.; Lemeshow, S.; Sturdivant, R.X. *Applied Logistic Regression*; John Wiley & Sons: Hoboken, NJ, USA, 2013; Volume 398.
37. Hoonhout, T. Homicides in Los Angeles Increase 250 Percent from Previous Week. Available online: https://news.yahoo.com/homicides-los-angeles-increase-250-125611007.html (accessed on 2 September 2020).

38. McEvoy, J. 14 Days of Protests, 19 Dead. Available online: https://www.forbes.com/sites/jemimamcevoy/2020/06/08/14-days-of-protests-19-dead/#4d7181ca4de4 (accessed on 2 September 2020).
39. Rodgers, J.L.; Nicewander, W.A. Thirteen Ways to Look at the Correlation Coefficient. *Am. Stat.* **1988**, *42*, 59–66. [CrossRef]
40. Stigler, S.M. Francis Galton's account of the invention of correlation. *Stat. Sci.* **1989**, *4*, 73–79. [CrossRef]
41. Lochner, L. *Non-Production Benefits of Education: Crime, Health, and Good Citizenship*; CIBC Working Paper, No. 2010-7; The University of Western Ontario, CIBC Centre for Human Capital and Productivity: London, ON, Canada, 2010.
42. Machin, S.; Marie, O.; Vujić, S. The crime reducing effect of education. *Econ. J.* **2011**, *121*, 463–484. [CrossRef]
43. Parker, K.H.; Juliana, M.; Anderson, M. Amid Protests, Majorities Across Racial and Ethnic Groups Express Support for the Black Lives Matter Movement. Available online: https://tinyurl.com/ycslfon5. (accessed on 2 September 2020).
44. Goldberger, S.; Rosenfeld, R. *Understanding Crime Trends: Workshop Report*; The National Academies Press: Washington, WA, USA, 2008.
45. Yang, C.; Clarke, K.; Shekhar, S.; Tao, C.V. Big Spatiotemporal Data Analytics: A research and innovation frontier. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1075–1088. [CrossRef]