International Journal of *Geo-Information*

MDPI

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Spatiotemporal Analysis of Nighttime Crimes in Vienna, Austria

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Abstract: Studying the spatiotemporal dynamics of crime is crucial for accurate crime geography research. While studies have examined crime patterns related to weekdays, seasons, and specific events, there is a noticeable gap in research on nighttime crimes. This study focuses on crimes occurring during the nighttime, investigating the temporal definition of nighttime crime and the correlation between nighttime lights and criminal activities. The study concentrates on four types of nighttime crimes, assault, theft, burglary, and robbery, conducting univariate and multivariate analyses. In the univariate analysis, correlations between nighttime crimes and nighttime light (NTL) values detected in satellite images and between streetlight density and nighttime crimes are explored. The results highlight that nighttime burglary strongly relates to NTL and streetlight density. The multivariate analysis delves into the relationships between each nighttime crime type and socioeconomic and urban infrastructure variables. Once again, nighttime burglary exhibits the highest correlation. For both univariate and multivariate regression models the geographically weighted regression (GWR) outperforms ordinary least squares (OLS) regression in explaining the relationships. This study underscores the importance of considering the location and offense time in crime geography research and emphasizes the potential of using NTL in nighttime crime analysis.

Keywords: nighttime crimes; streetlights; nighttime light (NTL); geographically weighted regression (GWR); Vienna; Austria

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Citation: Lee, J.; Leitner, M.; Paulus, G. Spatiotemporal Analysis of Nighttime Crimes in Vienna, Austria. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 247. https://doi.org/10.3390/ijgi13070247

Academic Editor: Wolfgang Kainz

Received: 25 April 2024
Revised: 1 July 2024
Accepted: 6 July 2024
Published: 10 July 2024

1. Introduction

Crimes are committed for various reasons and can happen in different places and time periods. It is important to have a deep understanding of the spatiotemporal dynamics of crime to obtain accurate and reliable results in crime geography research. Various studies have examined the crime patterns related to weekdays and weekends [1,2], seasonal/temperature changes [3,4], before and after sporting events [5–7], disasters [8,9], or day- and nighttime crime [10–19].

Nighttime crime studies find that criminals are more likely to commit crimes at night in dimly lit areas [11,12,16]. In addition, studies in the existing literature examined the impact of enhanced streetlights and crime prevention strategies based on environmental design on nighttime criminal activities [10,13–15]. However, the correlation between nighttime light systems and nighttime crime remains controversial. Previous research often relied on data that may not entirely capture the complex factors of nighttime crime, such as simply using the real streetlight intensity or estimating the streetlight intensity through modeling. However, nighttime crimes are not only influenced by streetlights but also by the ambient conditions of the neighborhood (e.g., the brightness of surrounding areas, facilities, or stores) and socioeconomic factors (e.g., income level, education level, race). NTL extracted from satellite images can secure the limitation of existing nighttime crime studies, although NTL is often used for estimating population density [20,21] and tracking urban sprawl [22,23]. Thus, the detailed objectives of this study are (1) to precisely define the temporal pattern of nighttime crime activities; (2) to investigate the relationship between streetlight and nighttime crime types, similar to previous research; (3) to extend this analysis by comparing the correlation between nighttime crimes and nighttime brightness levels that are detected in satellite images; and (4) to examine the correlation between socioeconomic indicators and nighttime crimes.

The subsequent sections of this paper are as follows. Section 2 reviews the existing literature on NTL and nighttime crimes and demonstrates its key findings. Section 3 explores the study area and provides detailed explanations of dataset selection, acquisition, and preprocessing methods. This section also introduces analysis methodologies, which are ordinary least squares (OLS) regression and the geographically weighted regression (GWR). Section 4 presents the findings from the OLS and GWR analyses, which examine the relationship between the four types of crime and two different lighting variables: streetlight density and the median of NTL values. Streetlights are turned on at specific times every night to, e.g., prevent accidents and crimes, and streetlight densities are computed for analysis. The median of NTL values corresponds to the median brightness of city lights at night, as captured by the day/night band (DNB) of the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite. Both univariate and multivariate regression models are employed in the analysis. It highlights the main findings and implications of this study. Finally, Section 5 addresses the significance, limitations, and future research that could be considered in subsequent studies.

2. Literature Review

The relationship between NTL and crime has been analyzed since the 1940s [10–19,24–28], but controversy remains over the advantages of nighttime streetlights regarding nighttime crimes. Streetlight and crime rate research are important because most people have a higher fear of crime at night, and brighter lighting systems may reduce their fears and the probability of crimes [24–26]. Some researchers argue that streetlights can reduce nighttime crime rates based on this assumption. Many studies support their opinions. Chalfin et al. (2022) argued that street lighting systems can reduce crime rates based on a randomized experiment in New York City, US. The researchers chose forty public housing areas and found that lighting systems reduced 36 percent of outdoor nighttime index crime. This is supported by the fact that 4% of index crimes, which were robbery, assault, property crimes, and murder, were reduced in the targeted communities. Thus, they strongly argued that streetlights can improve public safety.

Xu et al. (2018) draw similar conclusions that improving street lighting systems can lead to better neighborhoods with low crime rates in Detroit, Michigan. These researchers calculated spatial autocorrelation based on the location and brightness of nighttime streetlights and the location and number of crimes in each census boundary of Detroit. The results showed that low-density streetlight areas had high crime rates. The southwest parts of the city, which are the outskirts of the city center, had high crime rates associated with low streetlight density. Similarly, a commercial area in Portland, Oregon, tried to reduce crime by changing the surrounding environment, for example, by improving lighting systems, in the late 1970s. Through this project, commercial burglary decreased over time but it did not decrease the fear of crime [27,28].

Welsh and Farrington (2008) found that improving street lighting systems can decrease crime rates in public areas, but different cities revealed different results. The researchers reviewed thirteen studies in two countries, covering five cities in the United Kingdom and eight cities in the United States. Different cities yielded different results, especially cities in the United States. Four studies in the US showed that street lighting was ineffective in controlling crime rates, while those for the other four cities found it effective. Meanwhile, the studies of all five cities in the UK showed that crime reduction could be attributed to improved lighting systems. Similarly, Pease (1999) conducted case studies on the effectiveness of streetlights in preventing nighttime crime in the UK and the US. The scholar found that the effectiveness of streetlights in the UK was much stronger than in the US. In other words, there is a general relationship between well-lit areas and crime prevention, but it might not be universal. Steinbach et al. (2015) argued that there is no evidence that four lighting strategies—white light, switch off, dimming, and part-night lighting—are related to changes in the amount of crime in England and Wales. Local authorities have reduced street lighting to reduce carbon dioxide emissions and save money. Thus, Steinbach et al. (2015) analyzed the relationship between less or no lighting and crime from December 2010 to December 2013, finding a low relative risk (RR) of 1.0 or below with crime and the four lighting strategies. An RR of 1.0 represents no difference in risk between the experimental and control groups, which means there was no evidence of a link between crime and lighting systems.

The Department of Streets and Sanitation (2000) conducted a study to analyze the relationship between alley-light installation and crime rates in West Garfield Park, Chicago, Illinois. According to this project, installing alley lights increased crime rates by at least 19–40%. This is because the better visibility and lighting led to more crimes occurring. For example, graffiti and vandalism occur more often under night lighting systems. Trenz (2017) found no significant change in crime rates in Houston between 2010 and 2015. Areas with more streetlights have higher crime rates because these overlap with a higher rate of human activities, meaning more crime opportunities exist. Trenz (2017) also found no relationship between poverty and crime but that there was a relationship between racial/ethnic characteristics and streetlights. Yang et al. (2020) suggested a spatiotemporal cokriging algorithm to integrate historical crime data and urban transitional zones to predict weekly street crime and hotspots in Cincinnati, Ohio. For the primary variable, they used a time series of crime data. They used urban transitional zones identified from the VIIRS nightlight imagery for the secondary covariable. Using their algorithm, the correlation coefficient increased by 5.4% for weekdays and 12.3% for weekends.

At least two key takeaways can be drawn from the aforementioned research studies. First, nighttime crimes can be influenced by the impact of NTL and may show different results across various crime types. Second, previous researchers do not clearly define nighttime crime and when it occurs. Thus, this research is an important step in investigating the relationship between nighttime crime types and NTL and if there are future potential variables to consider for its application in nighttime crime analysis. Furthermore, this study can be a guide to how nighttime crime can be defined.

3. Study Design

3.1. Study Area

According to the Criminal Intelligence Service Austria, Vienna, the capital city of Austria (see Figure 1), accounted for approximately 36% of all crimes in Austria reported in 2019. While the crime rate in Vienna has been steadily declining, it remains higher than in other cities in Austria. Therefore, reported crime records in Vienna, Austria, from January 2014 through December 2019 were analyzed. Since the COVID-19 pandemic impacted crime rates and patterns, we have not included 2020 or later in our study period. Specifically, the Austrian Federal Government, including the night State Governments, issued lockdown policies to minimize COVID-19 cases and deaths. This impacted crime rates and their patterns, which were somewhat different from the pre-pandemic period beginning in 2020 [29–31].

Figure 1. The study area in this research: Vienna, Austria. Note: "Wien" means "Vienna" in German. All 23 district names of Vienna are written in German and added to the base map together with their respective boundaries shown with thin black lines.

3.2. Data and Preprocessing

3.2.1. Crime Data

The Austrian Federal Criminal Police Office, which has served as the central repository for reported crimes in Austria since 2004 [32,33], was contacted to obtain crime records specifically from Vienna. All address-level crime data from 2014 to 2019 were provided. This dataset contains a total of 522,880 crime incidents. Each address-level crime includes the starting occurrence date/time and the ending occurrence date/time of each crime, latitude/longitude, specific location (i.e., street, parking lot, bank, residential building, etc.), and crime type in the German language. Four preprocessing procedures were conducted on the crime dataset for analysis: (i) translating the dataset to English, (ii) identifying temporal approximation of occurrence time, (iii) determining the criteria for classifying a nighttime crime, and (iv) selecting specific nighttime crime types for analysis. Accurate determination of the offense time is a crucial aspect of criminology research, but it is frequently challenging to know with precision [34,35]. For example, residential burglaries that occur while people are commuting or traveling are hard to identify without witnesses, alarm systems, or CCTV recordings. The lack of evidence makes it difficult to know the occurrence time of crime [35,36]. This study used the average time between the start and end of times of reported crime incidents if an accurate offense time was not provided. This decision was made for two reasons: First, recent research from Vienna, Austria, shows that novel temporal approximation methods that include accurately known time stamps from historical crime data are more accurate than any naïve (e.g., average time) or aoristic methods [34,35]. The same research also indicates that in the case of burglaries, aoristic methods do not perform better than the "average time" approximation method. Secondly, these novel temporal approximation methods require about the first half of the crime data (2014–2016) to be used as the historical crime dataset, leaving "only" the second half of the crime data (2017–2019) to explore the spatiotemporal analysis of nighttime crime. For this reason, we opted to use the entire time period of the dataset for the spatiotemporal analysis in combination with an "average time" approximation method.

The next step was to determine what time would qualify as a nighttime crime since crimes can occur at any time during the day and at night [15,17,28]. However, the existing literature lacks a clear definition of nighttime crime [37]. Nina (1946) discussed a case where the burglary occurred between 6 p.m. and 7 p.m., and the court had to determine if this time qualified as nighttime. This specific case highlights the ambiguity in defining nighttime crime. Moreover, Vienna enjoys extended daylight throughout the summer. At the same time, taking into account that Vienna is a popular tourist destination with plenty of nocturnal events, using a narrow timeframe does not entirely reflect the current crime status in Vienna.

To address this, nighttime crimes in Vienna were considered as those occurring from civil dusk until civil dawn the following morning. Civil dusk refers to the evening when the center of the sun is six degrees below the horizon, and civil dawn refers to the morning when the center of the sun is six degrees below the horizon (see Figure 2). Essentially, this definition encompasses the timeframe from shortly after sunset to shortly before sunrise. Due to the fluctuating time of civil nightfall and civil dawn throughout the year, different durations were assigned to nighttime offenses for each day (see Table 1). This methodology guarantees a thorough and contextually appropriate characterization of nighttime crime for this study.

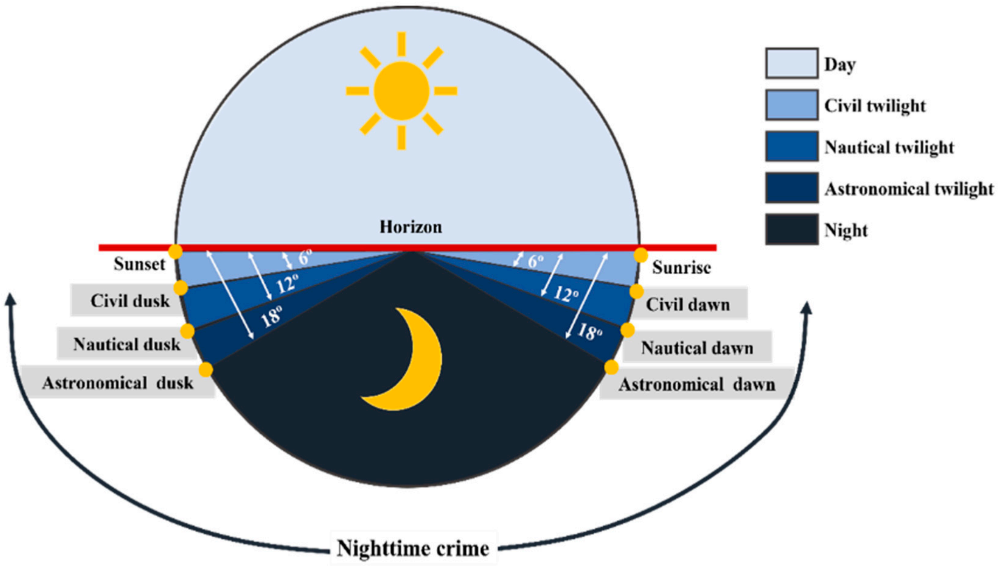

Figure 2. Definitions for different degrees of twilight. In this study, nighttime crimes were defined as including all crimes from civil dusk until civil dawn the next morning (adapted from National Weather Service: https://www.weather.gov/lmk/twilight-types (accessed on 13 May 2021)).

Subsequently, the study proceeded to distinguish between daytime and nighttime crime, examining the distinct characteristics of each type of crime. Vienna exhibited a higher percentage of daytime crimes (see Table 2) in the eleven crime types gathered from the Austrian Federal Police. While some crime types (e.g., murder, homicide, arson, and rape) could potentially be affected by nighttime brightness, their overall occurrences during the night were too low to facilitate a comprehensive spatial, temporal, and statistical analysis across the entire study area and timeframe (see Table 2).

This analysis focused on four specific nighttime crime types: nighttime assault, nighttime theft, nighttime burglary, and nighttime robbery. The selection was based on the expectation that the brightness levels at night would influence these four types of nighttime crimes [10]. Consequently, a subset of 128,322 crime incidents, encompassing the four selected nighttime crime categories, was extracted from the original dataset for in-depth analysis. This subset combines both indoor and outdoor crimes, but this specific distinction was not provided with the original dataset. If it had been provided, crimes committed indoors (e.g., theft in a mall, robbery in an enclosed parking lot, etc.) would have been removed, since such crimes are not influenced by the degree of lightness outside. We recognize that analyzing both indoor and outdoor crimes together may have introduced some bias into the results analyzing the impact of the median of NTL values and the degree of streetlighting on crime.

Table 1. Vienna nighttime crime periods: daily start and end times.

Start Date of Nighttime Crime	Start Time of Nighttime Crime	End Date of Nighttime Crime	End Time of Nighttime Crime	Time Duration of Nighttime Crime
1 January 2014	16:47	2 January 2014	07:08	14 h 21 min
2 January 2014	16:48	3 January 2014	07:08	14 h 20 min
3 January 2014	16:49	4 January 2014	07:08	14 h 19 min
⋮	⋮	⋮	⋮	⋮
1 August 2017	21:07	2 August 2017	04:53	7 h 46 min
2 August 2017	21:05	3 August 2017	04:54	7 h 49 min
3 August 2017	21:03	4 August 2017	04:56	7 h 53 min
⋮	⋮	⋮	⋮	⋮
29 December 2019	16:44	30 December 2019	07:08	14 h 24 min
30 December 2019	16:45	31 December 2019	07:08	14 h 23 min
31 December 2019	16:46	1 January 2020	07:08	14 h 22 min

Table 2. Daytime and nighttime crime incidents by crime type in Vienna, Austria, from January 2014 through December 2019.

	Murder	Homicide	Assault	Serious Assault	Theft	Serious Theft	Burglary	Robbery	Serious Robbery	Arson	Rape	Total
Day	209 (52%)	2 (100%)	43,357 (54%)	3480 (47%)	233,451 (78%)	3178 (74%)	98,072 (82%)	3033 (45%)	1096 (42%)	172 (41%)	734 (47%)	386,784 (74%)
Night	191 (48%)	0 (0%)	36,828 (46%)	3885 (53%)	65,611 (22%)	1131 (26%)	22,242 (18%)	3641 (55%)	1486 (58%)	251 (59%)	830 (53%)	136,096 (26%)
Total	400 (100%)	2 (100%)	80,185 (100%)	7365 (100%)	299,062 (100%)	4309 (100%)	120,314 (100%)	6674 (100%)	2582 (100%)	423 (100%)	1564 (100%)	522,880 (100%)

Among nighttime crime, theft is the most dominant. Theft includes cell phone theft, handbag theft, bicycle theft, and pickpocketing. Vienna is one of the most popular tourist destinations. Tourists outnumber Vienna's residents threefold [38]. Based on this urban characteristic, theft targeting tourists appears more frequently than other types of crime.

3.2.2. Nighttime Light Imagery from Satellites

The VIIRS was launched in 2011 to produce high-quality global data, producing a new generation of NTL datasets through DNB. The VIIRS provides global coverage, with a high spatial resolution of one arc second (~500 m). The overpass time of VIIRS is 1:30 a.m. local time. The northern hemisphere has less nighttime coverage during the summertime because of the longer days. The DNB of the VIIRS consists of a collection of streetlights and electricity usage of houses, shops, and factories during the night, but it does not include moonlight values. In addition, the VIIRS has onboard calibration systems, making it more reliable than the DMSP/OLS. The VIIRS has a resolution of 13 bits for medium- and low-gain settings, and 14 bits for high-gain settings, so it can contain more detailed values than the DMSP/OLS (6 bits). Smaller values indicate darker areas and larger values mean brighter areas. Overall, the VIIRS is better than the DMSP/OLS by several accounts [39,40]. Taking everything into consideration, the monthly products of the VIIRS from 2014 to 2019, a six-year dataset, are used in this study. The analysis utilized 500-by-500 m regular grid polygons, leading to 3106 grid polygons covering the 23 districts in Vienna. The cell sizes align with VIIRS imagery cell dimensions, ensuring spatial consistency (see Figure 3). Any values below zero were eliminated using the ERDAS IMAGINE software, 2022.

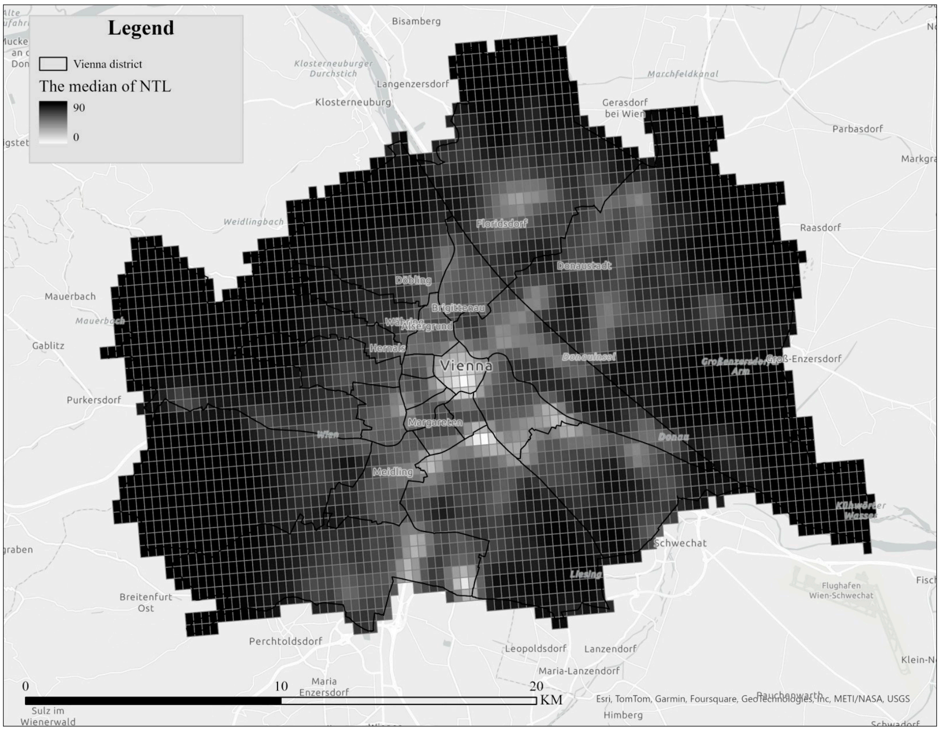

Figure 3. NTL of VIIRS for Vienna in January 2014. Interval values for each cell from 0 to 90. A value of 90 indicates the brightest areas, whereas 0 means the darkest areas. Note: All 23 district names are written in the original German language.

As expected, due to the concentration of numerous buildings and tourist attractions, the city center of Vienna is brighter, while the outskirts of the city are darker. The range of monthly median of NTL in Vienna is from 7 to 18 (see Figure 4). Winter has higher median NTL than summer. Vienna is famous for its Christmas markets, with light decorations installed at and throughout the city. This can result in elevated NTL results over the winter. Changing atmospheric conditions may be another factor for monthly variations in the median values for NTL in addition to season and large-scale events and festivities that are happening at nighttime.

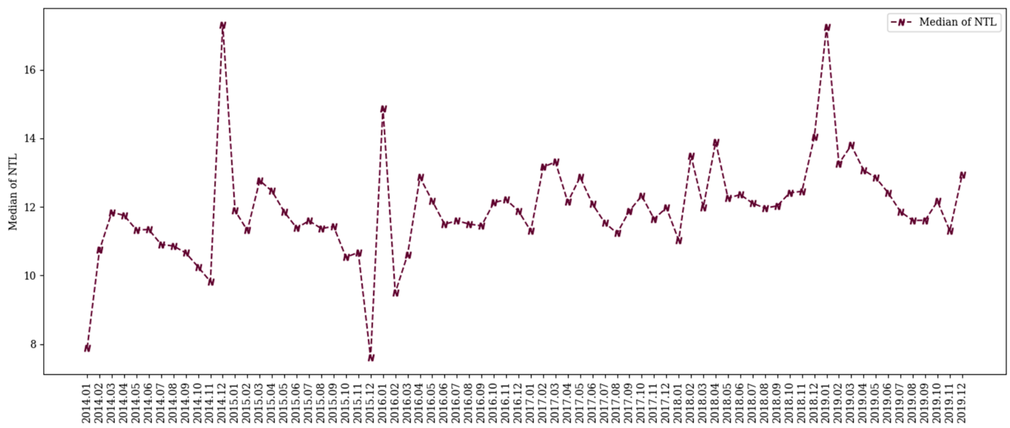

Figure 4. Monthly median values for NTL in Vienna from January 2014 through December 2019. The highest median value is in December 2014; the lowest median value is in December 2015.

3.2.3. Streetlight

The streetlight dataset was downloaded from the Open Data Austria website https://www.data.gv.at/katalog/dataset/f40f7946-06ab-41bf-b595-560f27e91643 (accessed on 1 June 2021). This dataset shows the status of exchanging LED streetlights as of June 2021 (see Figure 5). The dataset employs five colors: A gray-colored point means no exchange is planned; a yellow-colored point means the luminaire will be exchanged. A blue-colored point indicates that the LED streetlight will be exchanged within the next two weeks, and a green point represents that the pendant luminaire has been modified. A pink-colored point shows that a side-mounted luminaire has been modified. In this study, 20 m buffer areas around each streetlight location were applied based on the Licht 2016—Der Masterplan report, thereby defining the influence of the brightness of each streetlight. The number of buffer areas of the streetlights falling into each grid polygon of NTL. Streetlights are turned on at different times each month and on every day of each month. For example, during a field trip to Vienna from 25 June through 28 June 2021, streetlights were turned on at 8:52 p.m. Streetlamps are turned on relatively late in June because daylight during summer in the northern mid-latitudes, where Vienna is located, lasts quite late. However, streetlights are expected to be turned on early in winter with a short period of daylight. In our discussions with city officials responsible for street lighting, it was never mentioned that streetlighting was turned off or temporarily shortened for austerity purposes at any time during our study period (2014–2019).

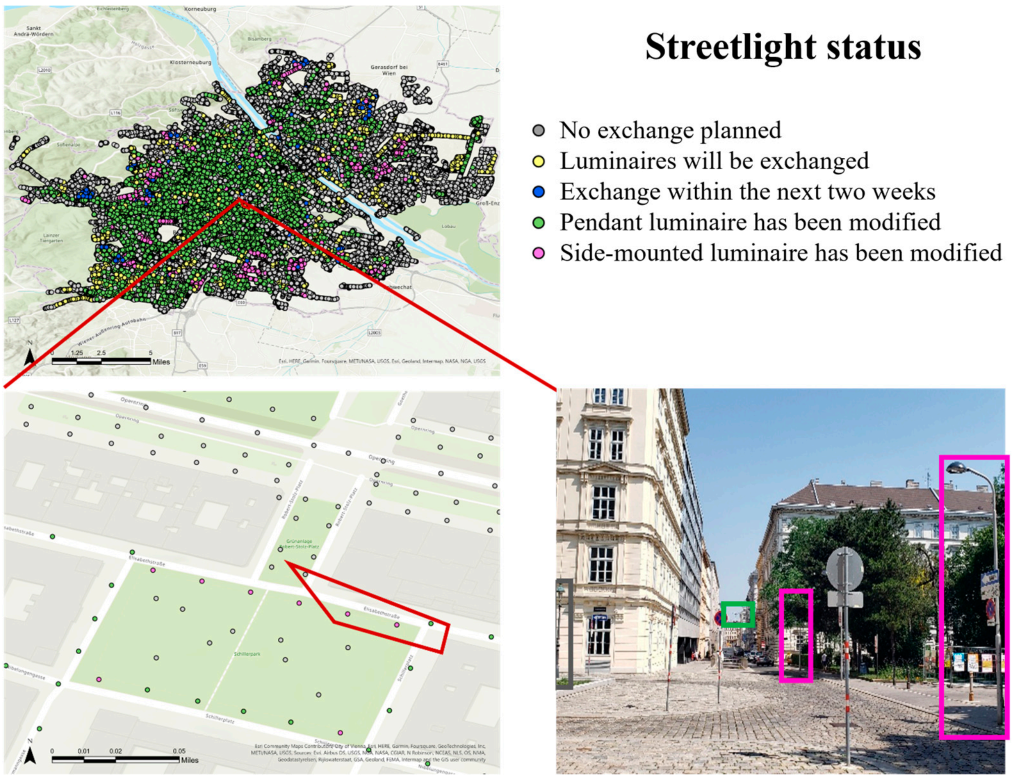

Figure 5. Top: Streetlight locations with their status shown in different colors in Vienna. Bottom left: zoomed streetlight status map with the address Schillerplatz, located in the first district of Vienna. Bottom right: examples of different street light status, taken during a field trip on 25 June 2021; gray rectangle (left border of the image) means that no exchange is planned (status 1); green rectangle (image middle) means that pendant luminaire has been modified (status 4); pink rectangles mean that side-mounted luminaire has been modified (status 5).

3.2.4. Other Variables

For the multivariate regression analysis, other variables such as population (Austrians and immigrants), race, education level, commuters, schools, parking lots, playgrounds, police stations, public transport stations, and sightseeing places were considered. The data for these variables were downloaded from https://www.data.gv.at/en/ (accessed on 30 June 2021). The rates for race, education, and commuters were also calculated. For other variables, densities were calculated.

3.3. Model and Method

Figure 6 illustrates the overall structure of the analysis in this research. After preprocessing the VIIRS image dataset, the raster images were converted to a grid polygon to conduct a spatial join with crime incidents. Specifically, raster image files were converted to a vector dataset with 3106 grid polygons. The size of each grid polygon is the same as the pixel size of a raster image, and it contains brightness values. Using grids as the spatial unit, NTL of VIIRS was compared, thus avoiding the modifiable areal unit problem (MAUP) [41]. MAUP occurs when researchers perform a spatial analysis based on administrative boundaries, such as census blocks, block groups, or census tracks. The designation of administrative boundaries is likely to have a notable impact on spatial statistical results, so this problem cannot be ignored. To mitigate irregularly shaped boundaries, regularly shaped grids have been used in many studies [42–44].

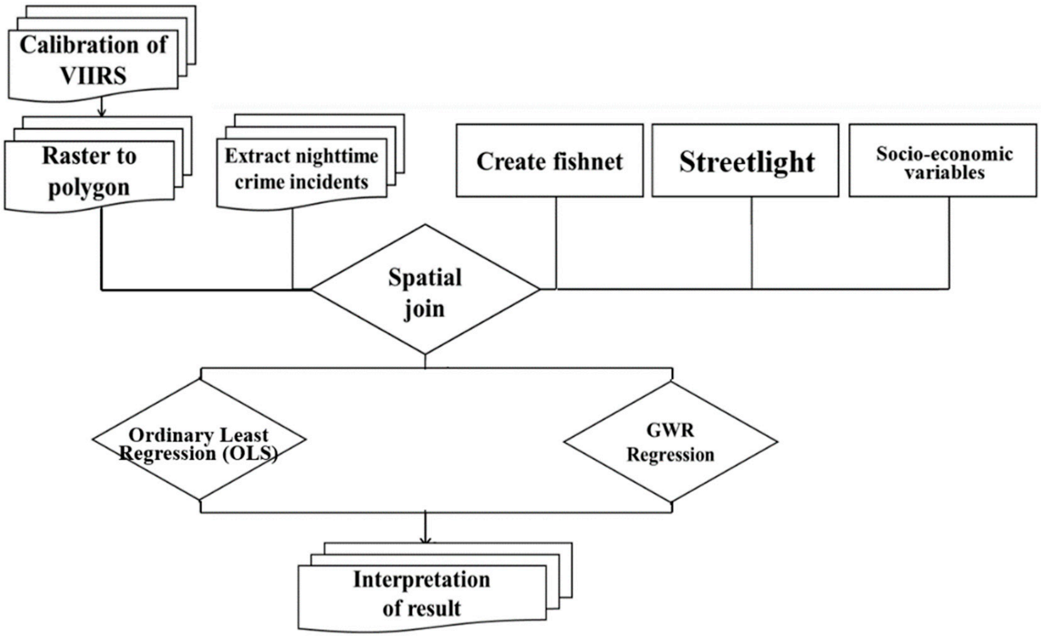

Figure 6. The flow chart for the spatiotemporal crime analysis.

Then, each monthly crime type, and the socioeconomic and urban infrastructure variables were assigned into monthly NTL grid polygons via spatial join. In other words, after completing the preprocessing of all datasets, the spatial join was performed again to create one single dataset. Based on this one dataset, we ran ordinary least squares regression (OLS) and geographically weighted regression (GWR). Using these statistical methods, the relationships among NTL values, nighttime crimes, socioeconomic, and urban infrastructure variables were analyzed (see Figure 6).

To begin with, based on Equation (1), OLS was computed to examine the global relations between one dependent variable and one or more independent variables [8]. For example, OLS is useful in explaining crime characteristics by analyzing the impact of different socioeconomic variables [45–47]. In this study, it provides insight into each independent variable on the dependent variable. A general formula of the OLS model is

$$Y = a_0 + a_i x_i + \cdots + a_n x_n \tag{1}$$

where Y indicates the dependent variable, x_0 the Y-intercept, a_i represents the regression coefficient, and x_i the independent variable.

Brunsdon et al. (1996) introduced GWR, one of a suite of spatial regression techniques, to model nonstationary variables (i.e., variables, whose attribute values vary across space) and locally weighted relationships. The assumption of GWR is similar to Tobler's first law of geography, which states that closer locations of observations are more related than more distant observations [44,48,49]. A general formula of the GWR model is [43]

$$y_i = \beta_{i0} + \sum_{k=1}^{n} \beta_{ik} x_{ik} + \varepsilon_i \tag{2}$$

where y_l is the dependent variable at location i; β_{i0} is the intercept at location i; β_{ik} is the kth independent variable of the coefficient for the local regression at location i; n is the number of independent variables; x_{lk} is the kth independent variable at location i; and ε_i is the random error at location i.

GWR can calculate a continuously varying local coefficient for any location [43,50]. The formula for this estimation is

$$\hat{\beta}_i = \left(X^T W_i X\right)^{-1} X^T W_i y \tag{3}$$

where $\hat{\beta}_i = (\beta_{io}, \ldots, \beta_{im})^T$ is the m + 1 local regression coefficients of the vector; X^T is the independent variable matrix with a 1st column of the intercept; W_i is the diagonal matrix representing the geographical weighting for regression location i, which is computed with the kernel function as the weighting scheme; and y is the dependent variable vector. In addition, the cross-validation (CV) score and Akaike information criterion (AIC) are also considered when computing the GWR [51].

For both methods, two types of analysis were implemented, namely, univariate analysis and multivariate analysis (see Table 3). Regarding univariate analysis, two independent variables—NTL from the VIIRS and density of streetlights—were also considered separately to compare which of the two independent variables were more related to nighttime crimes (dependent variables). To avoid an error due to insufficient variation in the independent variables, areas where both nighttime crime and each of the two nighttime light variables were recorded as zeros were excluded. For the multivariate analysis, the following independent variables were considered: the median value of NTL, streetlight density, commuter rate, immigrant rate, higher education rate, parking lot density, playground density, police office density, public transport station density, and school zone density. Each crime type was related to a different set of independent variables due to the multicollinearity issue.

Table 3. Variable list for univariate analysis and multivariate analysis.

	Univariate Analysis	**Multivariate Analysis**
Dependent variable	Total number of crime incidents in each polygon	
Independent variable(s)	The median value of NTL or Streetlight density	The median value of NTL Streetlight density Commuter rate Immigrant rate Higher education rate Parking lot density Playground density Police office density Public transport station density School zone density

4. Results

4.1. Results for Descriptive Analysis

Table 4 and Figure 7 demonstrate a multi-year perspective on the relationship between nighttime crime and median NTL values from 2014 to 2019. There is a gradual decrease in nighttime crime incidents, while the median NTL values increase each year (see Table 4). In 2017, outdated hanging lights were replaced with efficient LED lights as part of the Municipal Department 33 policy, Vienna Public Lights Up. This resulted in the most significant reduction in nighttime crimes across all types. In the span between 2016 and 2017, Vienna experienced a notable downturn in nocturnal criminal activities. The most significant reduction is observed in nighttime theft, which plummeted by 3620 incidents, which is an approximately 26.59% decrease. Aligned with this trend, nighttime assaults fell by 9.39%, burglary by 18.90%, and robbery by a considerable 26.97%. This change suggests that the increased brightness in the city, as captured by the brighter LED lights in VIIRS, may be correlated with the decrease in crime incidents.

Table 4. Annual breakdown of nighttime criminal activities (assault, theft, burglary, and robbery) and median value of NTL for VIIRS (2014–2019).

Year	Nighttime Assault	Nighttime Theft	Nighttime Burglary	Nighttime Robbery	All Nighttime Crime	Median NTL Value
2014	6341	12,485	5051	804	24,681	10.88
2015	6512	12,860	4512	761	24,645	11.41
2016	6624	13,612	4053	634	24,923	11.74
2017	6002	9992	3287	463	19,744	12.03
2018	5610	8730	2594	472	17,406	12.31
2019	5739	7932	2745	507	16,923	12.63
Total	36,828	65,611	22,242	3641	128,322	

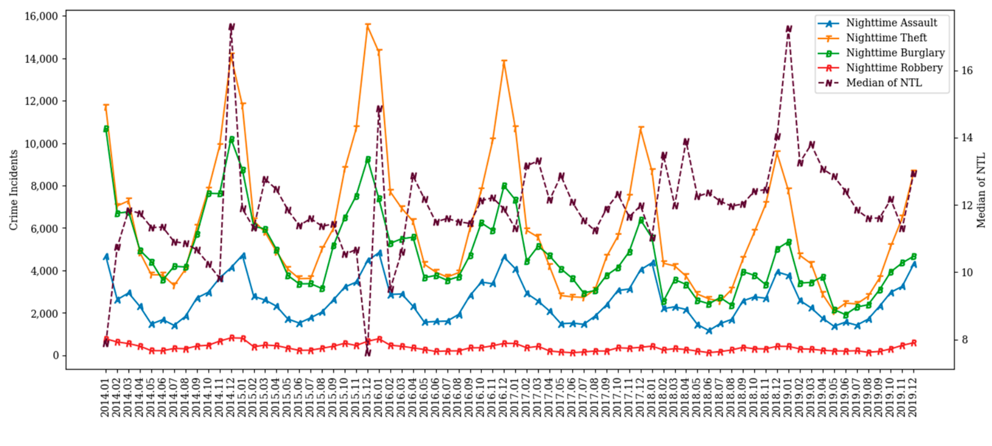

Figure 7. Nighttime crime types and median of NTL by month.

Figure 7 illustrates a more detailed monthly analysis, showing seasonal variations. Importantly, the number of nighttime crime incidents in Figure 7 has been recalculated to account for the monthly time duration of nighttime crime (see Table 1). This adjustment provides a weighted measure that reflects the varying lengths of night across different seasons, offering a better understanding of crime patterns in relation to urban lighting changes. The median of NTL increases during the winter season, whereas it decreases during the summer. A seasonal pattern is apparent for each type of crime. For instance, nighttime theft (in orange) tends to peak during winter with lows during the summer. The high peaks of nighttime theft, particularly around the end of the year, may be related to the holiday season, end-of-year events, and Christmas markets. Despite the intense brightness of artificial lights during winter seasons, more crime incidents are observed, suggesting that increased lighting may not be a simple deterrent to crime. Conversely, during summer, lower values of NTL are observed, reflecting routine lighting brightness from restaurants, signs, and streetlights, rather than the enhanced illumination for year-end events. It is also noted that summer evenings are inherently brighter than those in winter at the same time. Crime incidents also tend to decline overall, yet a consistent level of crime persists through the summer. This seasonal variation indicates a complex relationship between lighting and crime.

4.2. Results for Univariate Analysis

As is mentioned in Section 3.3, the univariate analysis was conducted with two different models, OLS and GWR, to discover the correlation between the four nighttime crime types and two independent variables: the streetlight density and the median of the NTL value. Specifically, sixteen models in total were computed, consisting of eight OLS models and eight GWR models. Each of the four nighttime crime types was used for the model's dependent variable, and either streetlight or the median of NTL value was used for the independent variable of the model (see Table 3).

The adjusted R-squared value is a statistical indicator of the explanatory power of a regression model, and sixteen models have an explanatory power between 0.17 and 0.65 (see Table 5). Among the four OLS models with streetlight density as the independent variable, the adjusted R-squared value for nighttime burglary is the highest value of all at 0.45. This indicates that the regression model can explain 45% of the variation in nighttime burglary. Nighttime assault, robbery, and theft follow, with moderate explanatory power, having adjusted R-squared values of 0.28, 0.28, and 0.23, respectively. Similarly, OLS models with the median of the NTL value and nighttime burglary had the highest explanatory power of all four models, namely, 0.30. This indicates that the regression model can explain 30% of the variation in nighttime burglary. The other crime types follow in descending order with nighttime assault (0.17), nighttime robbery (0.16), and nighttime theft (0.14).

Table 5. Adjusted R-squared values for OLS and GWR models.

Model	Crime Type (Dependent Variable)	Independent Variable	Adjusted R-Squared
OLS	Nighttime assault	Streetlight density	0.28
	Nighttime burglary	Streetlight density	0.45
	Nighttime robbery	Streetlight density	0.28
	Nighttime theft	Streetlight density	0.23
	Nighttime assault	The median of NTL	0.17
	Nighttime burglary	The median of NTL	0.30
	Nighttime robbery	The median of NTL	0.16
	Nighttime theft	The median of NTL	0.14
GWR	Nighttime assault	Streetlight density	0.39
	Nighttime burglary	Streetlight density	0.65
	Nighttime robbery	Streetlight density	0.44
	Nighttime theft	Streetlight density	0.41
	Nighttime assault	The median of NTL	0.48
	Nighttime burglary	The median of NTL	0.64
	Nighttime robbery	The median of NTL	0.38
	Nighttime theft	The median of NTL	0.42

The GWR model with nighttime burglary as the dependent and streetlight density as the independent variable possesses the highest explanatory power of 0.65 across all four models (see Table 5). The other three nighttime crime models follow, with adjusted R-squared values of 0.44 (nighttime robbery), 0.41 (theft), and 0.39 (assault). Similarly, GWR models regressing nighttime burglary on median NTL have the highest explanatory power with 0.64. This is the second-highest performing model among all sixteen models.

Nighttime assault, theft, and robbery also perform well with adjusted R-squared values of 0.48, 0.38, and 0.42, respectively.

Overall, and as expected, GWR models perform better than OLS models. Nighttime burglary and theft with the GWR method have an R-squared value approximately twice as high as the OLS method. For the eight OLS models, streetlight density performs better than when using the median NTL value, while for GWR models the opposite is true. Detailed interpretations of the results of the univariate OLS and GWR models follow in the next two subsections (Sections 4.2.1 and 4.2.2, respectively).

4.2.1. Univariate OLS

As is mentioned in Section 4.2, eight univariate OLS models were computed, in total. Detailed results, including y-intercepts, regression coefficients, and adjusted R-squared values, are shown in Table 6. The regression coefficients and y-intercepts estimate unknown population parameters and explain the relationship between a predictor variable and the response variable. All regression coefficients for each independent variable possess a positive correlation to streetlight density and the median of the NTL value. This means that brighter areas have a higher likelihood of nighttime crime incidents occurring. In general, the streetlight densities show higher correlations with nighttime crimes than the median of NTL values. Nighttime theft, especially, is impacted the most by the median of the NTL values. All *p*-values for y-intercepts and regression coefficients are less than 0.05, except for the y-intercept for the nighttime burglary and streetlight density model.

Table 6. OLS findings: Nighttime crime analysis with streetlight density and the median of the NTL value (** means *p*-value < 0.05).

Crime Type (Dependent Variable)	Independent Variable	Y-Intercept	Regression Coefficient	Adjusted R-Squared
Nighttime assault	Streetlight	−4.87 **	4.6×10^{-6} **	0.28
Nighttime burglary	Streetlight	−0.12	2.00×10^{-6} **	0.45
Nighttime robbery	Streetlight	−0.64 **	4.97×10^{-7} **	0.28
Nighttime theft	Streetlight	−20.96 **	1.16×10^{-5} **	0.23
Nighttime assault	The median of NTL	−6.73 **	1.19 **	0.17
Nighttime burglary	The median of NTL	−1.18 **	0.53 **	0.30
Nighttime robbery	The median of NTL	−0.72 **	0.12 **	0.16
Nighttime theft	The median of NTL	24.88 **	2.93 **	0.14

4.2.2. Univariate GWR

As mentioned in Section 4.2, eight univariate GWR models were conducted. Their results, including AIC, and local R-squared and regression coefficient values, are discussed here. The AIC for the GWR model is a critical metric for model comparison, particularly in smaller sample sizes, as it balances the complexity of the model against its goodness of fit. A lower AIC value is generally preferred, suggesting a relatively well-fitting model. In general, the AIC values for the eight univariate GWR models range from a low of approximately 5000 to a high of roughly 18,000, with models including median NTL values usually scoring higher AIC values.

The spatial distribution of local R-squared values from all eight GWR models are shown in the maps in Figure 8. In general, local R-squared values range from a low of 0.008 to a high of 0.866. The top four maps include local R-squared values regressing nighttime crimes on streetlight density. The Results show that nighttime assault possesses high local R-squared values in the Floridsdorf and Donaustadt districts (see Figure 1 for district names). Nighttime burglary also shows high local R-squared values in the same two districts, but also in Meidling, Favoriten, and Simmering. For nighttime robbery, the Floridsdorf, Donaustadt, Währing, and Ottakring districts have high local R-squared values. Nighttime theft has higher local R-squared values in the Floridsdorf and Favoriten districts.

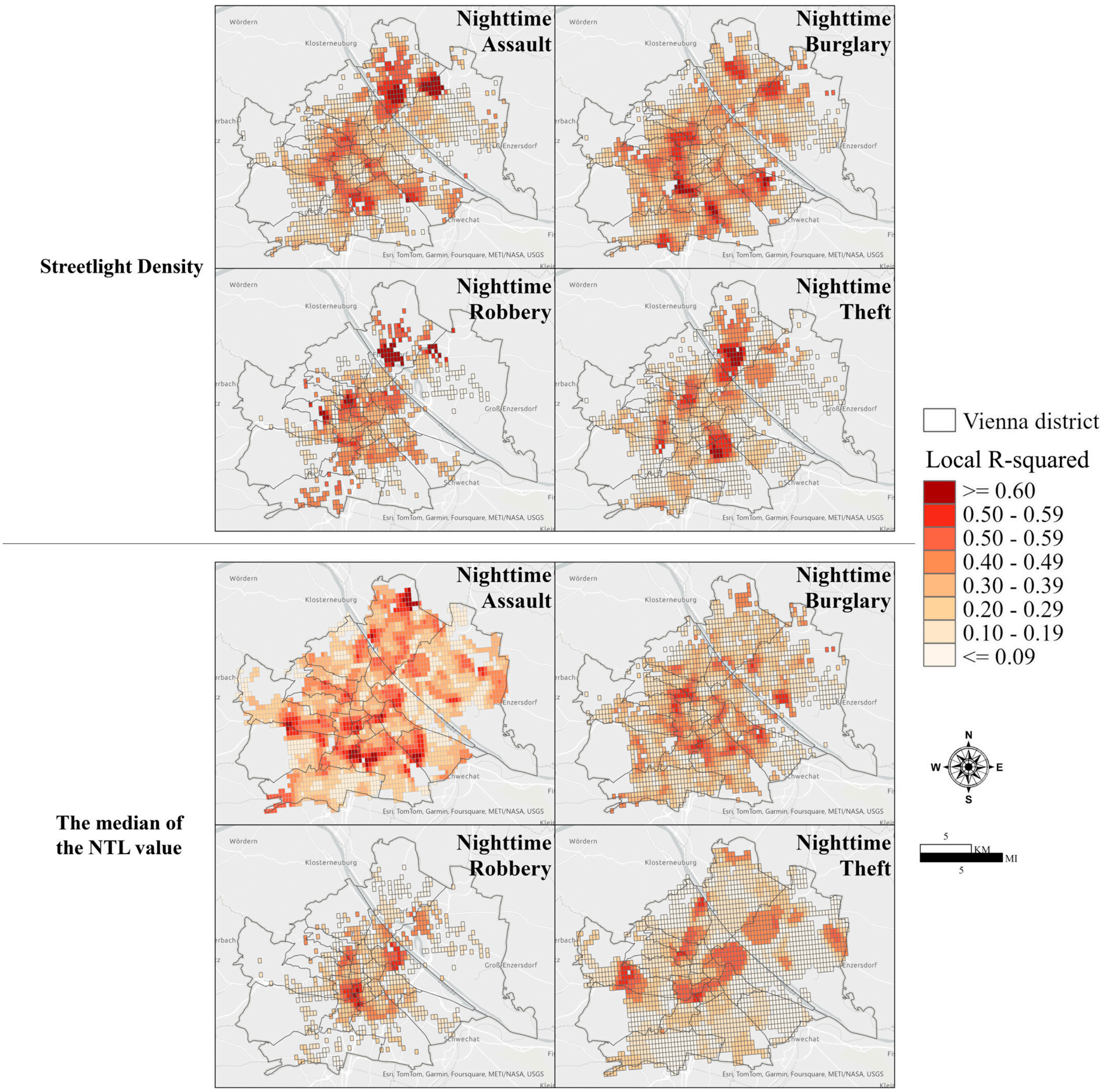

Figure 8. Local R-squared maps for univariate GWR.

The bottom four maps in Figure 8 include local R-squared values for regressing nighttime crime on the median of the NTL values. In general, this second set of four GWR models has lower local R-squared values than the streetlight density values, except for the nighttime assault model. Nighttime assault shows higher R-squared values in Floridsdorf, Landstraße, Simmering, Favoriten, Neubau, Rudolfsheim-Fünfhaus, Penzing, and Hietzing districts. Nighttime burglary has higher local R-squared values surrounding the Innere Stadt district. For nighttime robbery, the Donaustadt, Neubau, and Wieden districts show high local R-squared values. Lastly, nighttime theft has higher local R-squared values in the Donaustadt, Döbling, Rudolfsheim-Fünfhaus, Wieden, Margareten, Landstraße, and Leopoldstadt districts.

The spatial distributions of the local regression coefficients for the eight univariate GWR models are depicted in maps in Figure 9. When streetlight density is the independent variable, then local regression coefficients for the four nighttime crime categories are typically lower compared to when the median of the NTL value is the independent variable. In general, higher coefficients across all eight univariate GWR models can be found in Donaustadt district, especially close to the Siebeckstraße and Praterstern tram stations, and in Ottakring district, at the Yppengasse tram station.

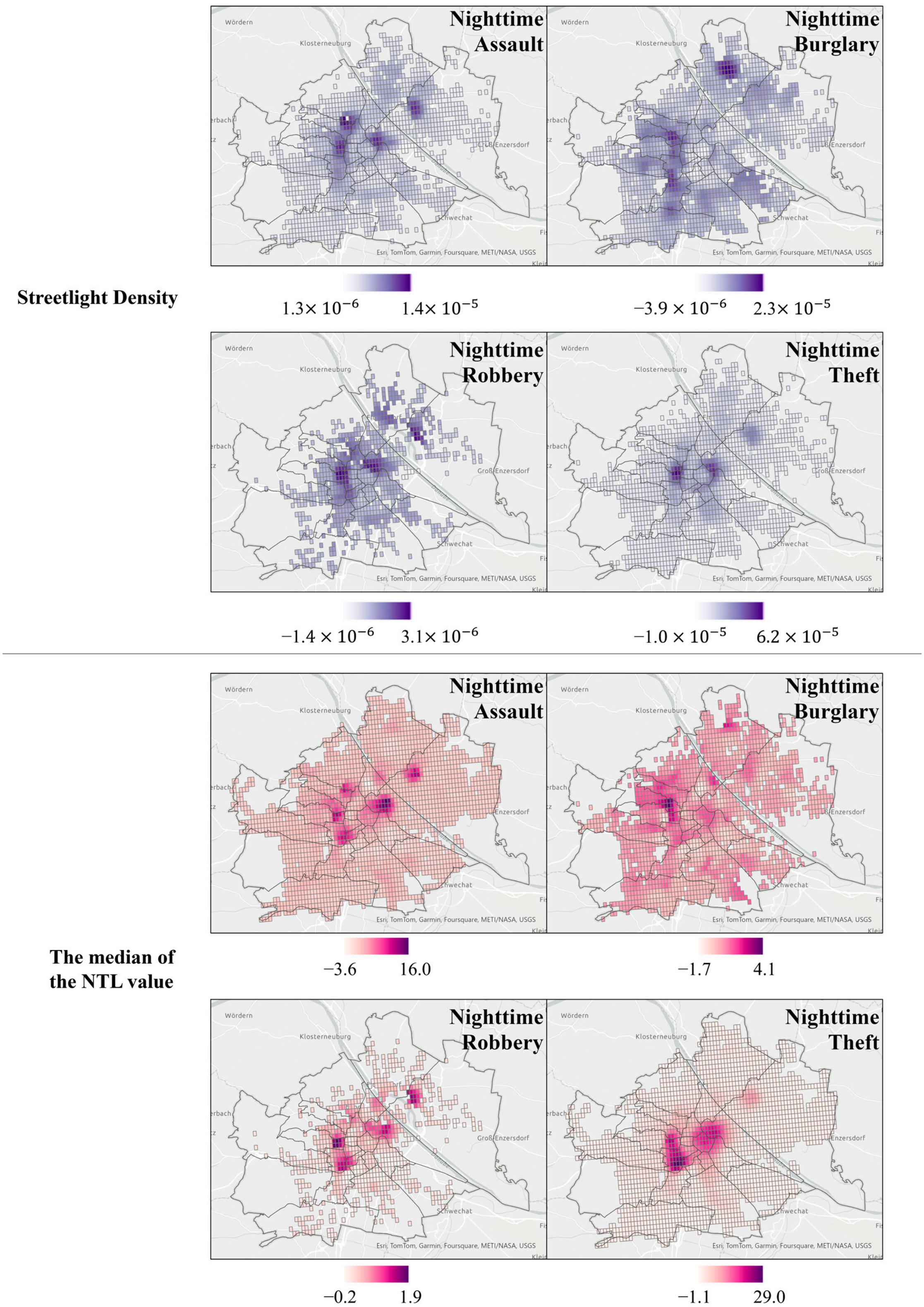

Figure 9. Local regression coefficient maps for univariate GWR.

The top four maps in Figure 9 include the four GWR models with streetlight density as the independent variable. In case of nighttime assault, relatively high positive local relationships to streetlight density can be found in the Donaustadt, Florisdorf, Döbling, Währing, Hernals, and Ottakring districts, indicating that more streetlights are associated with more crimes and vice versa in these areas. There are relatively high positive local relationships between streetlight density and burglary in the Florisdorf, Hernals, Rudolfsheim-Fünfhaus, and Meidling districts, while there is a relatively low negative local relationship in Innere Stadt. In contrast, the Donaustadt, Hernals, and Ottakring districts show a significant positive local correlation between streetlight density and nighttime robberies. Similarly, nighttime theft and streetlight density show a relatively high relationship in the same three districts as the nighttime robbery GWR model.

The bottom four maps in Figure 9 show the spatial distribution of the local regression coefficients for the four GWR models that include the median of the NTL values as the independent variable. The local relationship between the median of the NTL values and nighttime assaults shows a relatively high positive correlation in the Donaustadt, Ottakring, and Rudolfsheim-Fünfhaus districts, indicating that the higher the median of the NTL values, the more nighttime assaults are being committed and vice versa in these areas. The highest positive correlation between the median of the NTL values and nighttime burglary is found in the Hernals district. In contrast, the Donaustadt, Ottakring, and Rudolfsheim-Fünfhaus districts show a high positive correlation for nighttime robberies with the median of the NTL values. Similarly, nighttime theft and the median of the NTL values show a relatively high local relationship in the Innere Stadt, Ottakring, and Rudolfsheim-Fünfhaus districts.

4.3. Results for Multivariate Analysis

The multivariate analysis was conducted with two different models, namely, OLS and GWR, to discover the correlation between the four nighttime crime types and a series of independent variables, similar to the univariate analysis. Twelve models in total were computed, consisting of four OLS and eight GWR models, with adjusted R-squared values ranging from 0.34 to 0.64. The independent variables of all twelve models considered the median of NTL, streetlight density, commute rate, immigrant rate, higher education rate, parking lot density, playground density, police station density, public transport station density, and school zone density, but the number of independent variables varied depending on the model (see Table 7). Particularly in the GWR models between streetlight density and the median of the NTL value, each type of crime required a distinct set of independent variables to address the issue of multicollinearity. Therefore, eight GWR analyses were implemented separately. Of those, four GWR models examined the relationship between nighttime crimes and independent variables such as streetlight density, while the other four models explored the relationship between nighttime crimes and independent variables such as the median of the NTL value.

Among the four OLS models, the explanatory power of nighttime burglary shows the highest value of 0.60, which indicates that the regression model can explain 60% of the variation in nighttime burglary. Nighttime assault, robbery, and theft show a moderate explanatory power with streetlight density, having adjusted R-squared values of 0.34, 0.35, and 0.30, respectively.

The two multivariate GWR models with nighttime burglary as the dependent variable possess the highest explanatory power of 0.64 each. The R-squared values of the other three GWR models that include streetlight as one of the independent variables are 0.53 for nighttime robbery and 0.40 for both theft and assault. The remaining three GWR models with median NTL values as one of the independent variables have similar R-squared values for nighttime assault (0.45), theft (0.46), and robbery (0.46).

Overall, the multivariate GWR models better explain the variation in the nighttime crime variables compared to the multivariate OLS models. Detailed interpretations of the results of the multivariate OLS and GWR models follow in the next two subsections, Sections 4.3.1 and 4.3.2, respectively.

Table 7. Adjusted R-squared values for OLS and GWR models.

Model	Crime Type (Dependent Variable)	Independent Variables	Adjusted R-Squared
OLS	Nighttime assault	Streetlight density, the median of the NTL value, commuter rate, immigrant rate, parking lot density, police office density, public transport station density, higher education rate, and unemployment rate	0.34
	Nighttime burglary	Streetlight density, the median of the NTL value, immigrant rate, parking lot density, public transport station density, school zone density, higher education rate, and unemployment rate	0.60
	Nighttime robbery	Streetlight density, commuter rate, immigrant rate, parking lot density, public transport station density, higher education rate, and unemployment rate	0.35
	Nighttime theft	Streetlight density, the median of the NTL value, immigrant rate, parking lot density, playground density, police office density, school zone density, higher education rate, and unemployment rate	0.30
GWR (streetlight)	Nighttime assault	Streetlight density, public transport station density, and parking lot density	0.40
	Nighttime burglary	Streetlight density, public transport station density, and parking lot density	0.64
	Nighttime robbery	Streetlight density, public transport station density, playground density, and parking lot density	0.53
	Nighttime theft	Streetlight density, public transport station density, and parking lot density	0.40
GWR (the median of the NTL value)	Nighttime assault	The median NTL values, school zone density, public transport station density, playground density, parking lot density	0.45
	Nighttime burglary	The median of the NTL value, school zone density, playground density, and parking lot density	0.64
	Nighttime robbery	The median NTL values, school zone density, public transport station density, police office density, playground density, parking lot density	0.46
	Nighttime theft	The median NTL values, police office density, playground density, parking lot density	0.46

4.3.1. Multivariate OLS

Detailed multivariate OLS findings, including regression coefficients, p-values for all regression coefficients, the variance inflation factor (VIF) value, and adjusted R-squared values, are shown in Table 8. Parking lot density usually shows the strongest positive correlation with nighttime crimes, while the unemployment rate usually represents the strongest negative relationship with nighttime crimes, except for nighttime theft, with playground density showing the highest negative relationship.

Table 8. OLS findings: Nighttime crime analysis with streetlight density and the median of the NTL value (** means p-value < 0.05).

Crime Type (Dependent Variable)	Independent Variables and Y-Intercept	Regression Coefficient	VIF	Adjusted R-Squared
Nighttime assault	Y-intercept	2.84 **	169.29	0.34
	Streetlight density	2.33×10^{-6} **	2.60	
	The median of the NTL value	0.01	2.10	
	Commuter rate	−0.11 **	1.62	
	Immigrant rate	0.17 **	6.69	
	Parking lot density	1.67 **	3.27	
	Playground density	−0.38	2.55	
	Police office density	0.42	1.06	
	Public transport station density	0.45 **	3.01	
	School zone density	0.18	1.59	
	Higher education rate	−0.05 **	4.77	
	Unemployment rate	−0.57 **	11.87	
Nighttime burglary	Y-intercept	4.84 **	169.29	0.60
	Streetlight density	7.12×10^{-7} **	2.60	
	The median of the NTL value	0.08 **	2.10	
	Commuter rate	−0.07	1.62	
	Immigrant rate	0.69 **	6.69	
	Parking lot density	6.22 **	3.27	
	Playground density	1.41	2.55	
	Police office density	1.42	1.06	
	Public transport station density	1.35 **	3.01	
	School zone density	4.14 **	1.59	
	Higher education rate	−0.18 **	4.77	
	Unemployment rate	−1.99 **	11.87	
Nighttime robbery	Y-intercept	2.84 **	169.29	0.35
	Streetlight density	2.53×10^{-7} **	2.60	
	The median of the NTL value	0.01	2.10	
	Commuter rate	−0.11 **	1.62	
	Immigrant rate	0.17 **	6.69	
	Parking lot density	1.67 **	3.27	
	Playground density	−0.38	2.55	
	Police office density	0.42	1.06	
	Public transport station density	0.45 **	3.01	
	School zone density	0.18	1.59	
	Higher education rate	−0.05 **	4.77	
	Unemployment rate	−0.58 **	11.87	
Nighttime theft	Y-intercept	106.01 **	169.29	0.30
	Streetlight density	9.35×10^{-6} **	2.60	
	The median of the NTL value	0.90 **	2.10	
	Commuter rate	−1.53	1.62	
	Immigrant rate	5.5 **	6.69	
	Parking lot density	27.42 **	3.27	
	Playground density	−53.48 **	2.55	
	Police office density	20.36 **	1.06	
	Public transport station density	3.09	3.01	
	School zone density	−17.73 **	1.59	
	Higher education rate	−1.55 **	4.77	
	Unemployment rate	−21.72 **	11.87	

The adjusted R-squared value for nighttime assault is 0.34, meaning that thirty-four percent of the variation in this crime type can be explained by the model. All but four independent variables possess a statistically significant regression coefficient at a p-value < 0.05. The median of the NTL values and the densities of playgrounds, police offices, and school zones are insignificant. Nighttime assault shows positive correlations with streetlight density, immigrant rate, parking lot density, and public transport station density, while it has negative correlations with higher education and unemployment rates (see the nighttime assault in Table 8). In other words, nighttime assault is more likely to occur in areas with higher street light density, proportion of immigrants, parking lot density, and public transport station density. Conversely, areas with enhanced education levels and higher unemployment rates are less prone to nighttime assault activities.

The adjusted R-squared value for nighttime burglary is 0.60, which is the highest adjusted R-squared value among all four multivariate OLS models. All but three independent variables possess a statistically significant regression coefficient at a p-value < 0.05. The commuter rate, the playground density, and the police station density are insignificant. Nighttime burglary has positive correlations with streetlight density, the median of the NTL value, immigrant rate, parking lot, public transport station, and school zone densities, while it has negative correlations with higher education and unemployment rates (see the nighttime burglary in Table 8).

The adjusted R-squared value for nighttime robbery is 0.35, which is the second highest of the adjusted R-squared values among the four OLS models. All but four independent variables possess a statistically significant regression coefficient at a p-value < 0.05. The same as for nighttime assault, the median of the NTL values and the densities of playgrounds, police offices, and school zones are insignificant. Positive correlations exist between nighttime robbery and streetlight density, immigrant rate, parking lot density, and public transport station density, while negative correlations are shown with higher education and unemployment rates (see the nighttime robbery in Table 8).

The adjusted R-squared value for nighttime theft is 0.30, which is the lowest value among the four nighttime crime models. All but two independent variables possess a statistically significant regression coefficient at a p-value < 0.05. The commuter rate and public transport station density are insignificant. There are positive correlations with streetlight density, the median of the NTL value, immigrant rate, and parking lot density, while negative correlations are shown between nighttime theft, playgrounds, and school zone densities, as well as higher education and unemployment rates (see the nighttime theft in Table 8).

4.3.2. Multivariate GWR

The multivariate relationship between nighttime crimes and a set of independent variables is also explored using the GWR method to include spatial variations in these relationships. As mentioned in Section 4.2, eight multivariate GWR models are formulated with a unique set of independent variables included in each model (see Table 5). Only the parking lot density is included in all GWR models among all independent variables. The multivariate GWR results shown below include both local R-squared value and local regression coefficient maps.

The spatial distributions of local R-squared values from all eight GWR models are shown in the maps in Figure 10. In general, local R-squared values range from a low of 0.008 to a high of 0.866. The top four maps include local R-squared values regressing nighttime crimes on a set of independent variables that also include streetlight density, but not the median of the NTL values, due to multicollinearity issues. The nighttime assault have high local R-squared values, appearing as a dark red curve bent to the left side, extending from Floridsdorf to Simmering. Nighttime burglary also has high local R-squared values, defined by a dark red curve bent to the left side, extending from Währing to Simmering. For nighttime robbery, three districts of high local R-squared values are included in Döbling, Penzing, and Favoriten. Nighttime theft also displays three districts of high local R-squared values, namely, Floridsdorf, Döbling, and Favoriten.

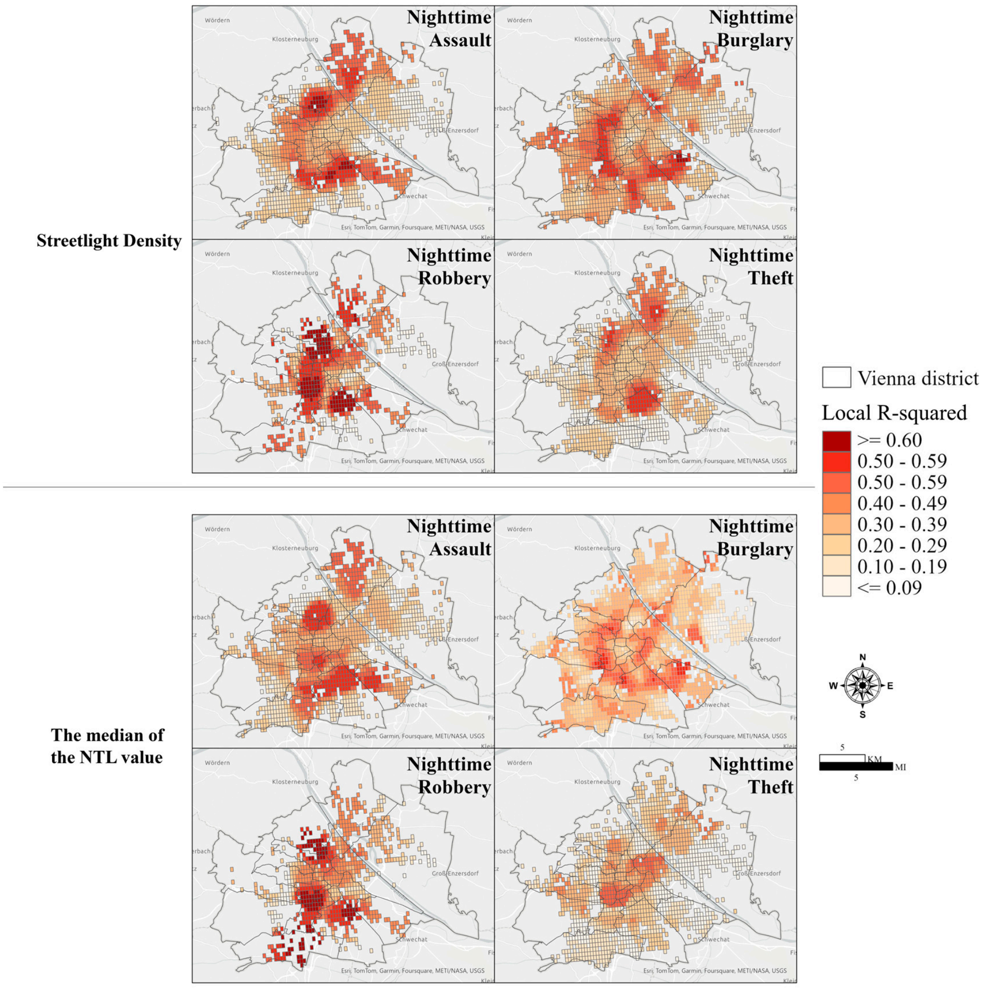

Figure 10. Local R-squared value maps for eight multivariate GWR models. The top four maps include streetlight density among the set of independent variables. The bottom four maps include the median of NTL values among the set of independent variables.

The bottom four images in Figure 10 display the local R-squared values for the four nighttime crime GWR models that include the median of the NTL values, but not the streetlight density, among the set of independent variables. In general, this second set of four GWR models has lower local R-squared values than the first set, except for the nighttime assault model. Nighttime assault shows high R-squared values in the districts of Döbling, Währing, Brigittenau, Alsergrund, Favoriten, and Simmering. Nighttime burglary has high local R-squared values in the districts of Rudolfsheim-Fünfhaus, Favoriten, and Simmering. For nighttime robbery, the districts of Döbling, Rudolfsheim-Fünfhaus, Favoriten, and Liesing show high local R-squared. Lastly, nighttime theft has high local R-squared values in the districts of Floridsdorf, Donaustadt, Rudolfsheim-Fünfhaus, and Wieden.

The spatial distribution of the local regression coefficients for the four multivariate GWR models that include streetlight density as one of the independent variables is depicted in maps in Figure 11. Three of these four models include the density of streetlights, parking lots, and public transport stations, while the fourth model, with nighttime robbery as the dependent variable, also includes playground density as an additional fourth independent variable (see Table 7). Other independent variables are not considered due to the multicollinearity issue. The relationships between these three/four independent variables and the nighttime crime variables can be interpreted as follows: Positive correlations exist between all four nighttime crimes and streetlight density in the districts of Hernals, Ottakring, and Donaustadt. Regarding parking lot density, a significant positive association is mostly observed in Innere Stadt for nighttime assault and robbery, whereas a higher negative relationship is evident in Innere Stadt for nighttime burglary and theft. Public transport station density exhibits a positive correlation in the districts of Neubau, Leopoldstadt, and Donaustadt. When regressing playground density on nighttime robbery, a strong positive relationship dominates in Leopoldstadt.

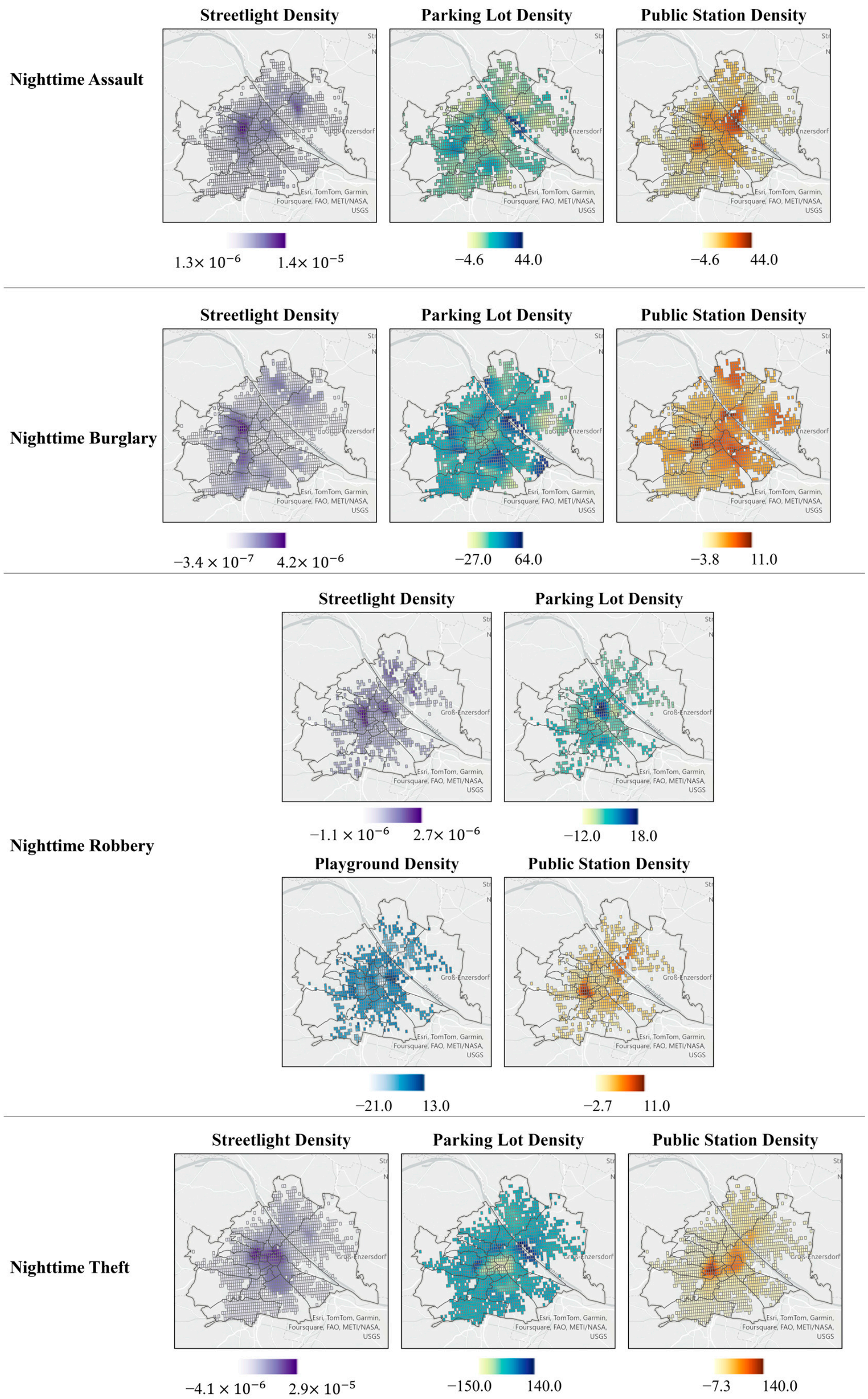

Figure 11. Local regression coefficient maps for the four multivariate GWR models that include the streetlight density among the set of independent variables.

Local regression coefficient maps for nighttime crimes that include the median of the NTL values among the set of independent variables are shown in Figure 12. The median of the NTL values, parking lot, and playground densities are typically included as independent variables in the GWR models for the four nighttime offenses, together with other independent variables that are unique to a specific crime type model. Some of the independent variables are not considered because of the multicollinearity issues (see Table 7). In the GWR model for nighttime assault, a total of five independent variables are included; the nighttime burglary model includes a total of four independent variables; the nighttime robbery model has a total of six independent variables; and finally, the nighttime theft model includes a total of four independent variables (see Figure 12).

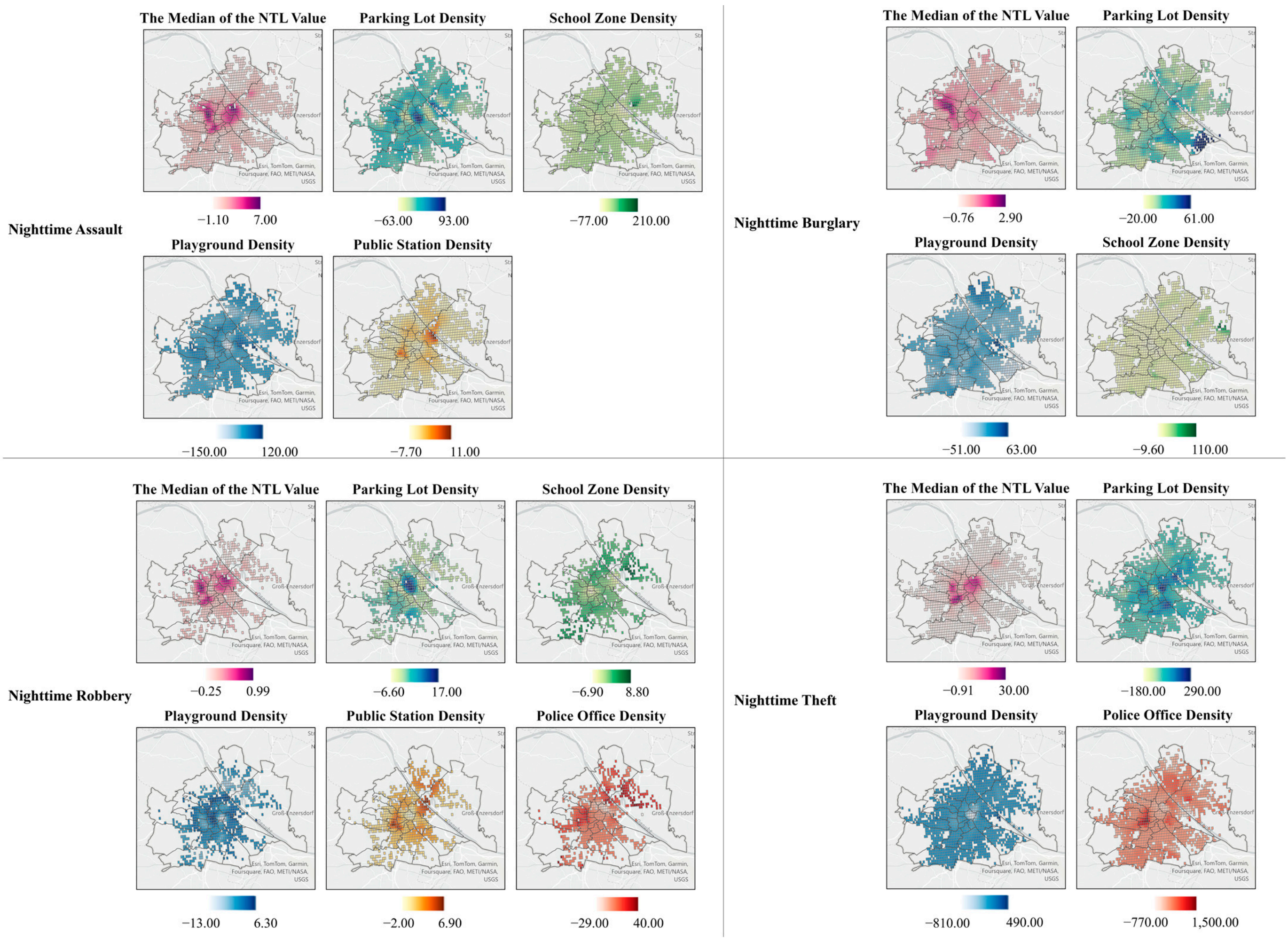

Figure 12. Local regression coefficient maps for the four multivariate GWR models that include the median of the NTL value among the set of independent variables.

In general, positive correlations exist between the four nighttime crimes and the median of the NTL values in the Ottakring district. Specifically, regarding parking lot density, a significant positive association is mostly observed in Innere Stadt, whereas for burglary, a higher positive correspondence is evident in the Simmering district. A negative association is shown in Innere Stadt regarding playground density, suggesting that fewer playgrounds are associated with an increase in nighttime crimes. A significant positive association is identified for the school zone density in the Donaustadt district. Public transport station density exhibits a positive correlation in the districts of Donaustadt and Rudolfsheim-Fünfhaus, but a negative correlation in Innere Stadt. Positive relationships are shown for police station density in Hernals, Ottakring, and Rudolfsheim-Fünfhaus.

5. Discussion

Based on descriptive statistics, there is a declining trend in monthly nighttime crimes in Vienna, subsequent to the enhancement of the public lighting system in 2017 (see Figure 5). This finding is similar to previous studies that suggested that enhancing public lighting systems would deter nighttime crimes [10,15]. However, regression analysis conducted using data from 2013 to 2019 reveals positive relationships between nighttime light resources and crimes, which is contrary to what is shown in Figure 5. This suggests that well-lit places may contribute to criminal activities by enhancing the visibility of potential targets [2,37]. These seemingly contradictory outcomes indicate that the influence of light on nighttime criminal activities is very complex. Thus, nighttime crime studies should vary considerably based on specific circumstances [14,52], and this study enhances the nighttime crime domain by conducting a comprehensive examination of the spatial and temporal patterns of nighttime criminal activities in Vienna.

This study has certain limitations that need to be addressed in future research. One limitation is that it did not consider the influence of weather conditions on nighttime crime. Weather can affect both the likelihood of criminal activities and the performance of nighttime light resources. Additionally, the study did not incorporate detailed land use data, which could provide further insights into how different types of land use (e.g., commercial or residential) interact with lighting and crime. Future research should include these factors to offer a more comprehensive analysis of the environmental and contextual influences on nighttime crimes. The median NTL values should be collected over many years as well, in order to find a more detailed relationship between nighttime crimes and lights. Additionally, future research should be considered customizing independent variables for each crime type, based on the effective variables identified in this study. This approach will provide deeper insights and help develop more effective crime prevention strategies and policies. Another unexplored research direction is the intersection of lighting with capable guardianship, especially when visibility is concerned. In other words, there appears to be an interesting balance between better lighting to identify opportunities to commit a crime and better lighting to increase the risk of detection/apprehension. This seemingly contradictory effect that increasing lighting has on crime is yet another valuable avenue for future research.

6. Conclusions

The exploration of nighttime crime in the city of Vienna, Austria, presents the dynamics of urban lighting, demographic factors, and the temporal–spatial characteristics of criminal activities. This study defines nighttime crime as any unlawful activity occurring between civil dusk and civil dawn. This definition not only aligns with the operational hours of streetlights but also overlaps with the operational timeline of the VIIRS satellites that monitor illumination levels, as well as the business hours of local restaurants and bars. This innovative approach to defining nighttime crime accurately captures the essence of nighttime criminal activities, offering a novel timeframe through which to examine the intersection of urban lighting and nighttime crime. Based on the definition, this study utilizes a substantial dataset consisting of 128,322 crime occurrences spanning a period of six years. This enables the use of statistical analysis and ensures the production of reliable results.

The findings from the descriptive analysis show a pivotal shift in the pattern of nighttime crimes, including nighttime theft, assault, burglary, and robbery, following the replacement of Vienna’s public lighting system in 2017. The shift to an efficient lighting system may have contributed to a substantial decrease in nighttime criminal activities. This correlation emphasizes the importance of strategic lighting systems in urban planning in fostering safer environments. The seasonal difference in Vienna is also one of the valuable findings. A pronounced peak in nighttime light during the winter season suggests the influence of external factors, such as seasonal social patterns and festivals, on nighttime crime rates. This observation points to the relationship among nighttime crimes, environmental, social, and temporal factors.

On the other hand, inferential statistical analysis, including OLS and GWR, shows a mostly positive relationship between streetlight density or NTL values with nighttime crimes. This means that brighter areas lead to a statistically significant increase in nighttime crimes, which seems to contradict, at least to some degree, our interpretation of the descriptive analysis results that the installation of an efficient lighting system may have contributed to a substantial decrease in nighttime criminal activities. Our regression analysis results may imply that brighter areas can potentially amplify the visibility of the targets for crime activities, inadvertently facilitating the execution of criminal intents. Additionally, brighter areas have higher chances to observe and report crime incidents. This emphasizes the complexity of urban crime dynamics, suggesting a more detailed exploration is needed that incorporates time series analysis to reveal the temporal relationship between nighttime lights and crimes.

Overall, the robustness of the results is demonstrated despite the relatively small adjusted R-squared values. The GWR models result in higher adjusted R-squared values than the OLS models. For example, nighttime burglary has the highest adjusted R-squared values of all regression models. The GWR models reveal that areas with higher streetlight density or the median of NTL values also show higher rates of nighttime burglary, particularly within central districts such as Innere Stadt, Neubau, Ottakring, Rudolfsheim-Fünfhaus, and Favoriten. Most of these areas are mixed land used areas like residential buildings, commercial, and sightseeing places. This highlights the importance of considering local context and geography when assessing the impact of lighting on crime. The multivariate regression analysis helps further to refine the understanding of nighttime crimes. This comprehensive analysis highlights the relationship between nighttime crimes and various factors, ranging from urban infrastructure to socio-demographic dynamics. Based on these results, multidimensional crime prevention strategies are necessary. Parking lots, public transport stations, and playgrounds are among the urban infrastructure that leads to an increase in crime. Police officers should prioritize these areas during their patrol routes to improve urban safety and contribute to crime prevention.

In conclusion, the study presents urban lighting, demographic characteristics, and spatial–temporal dynamics to offer an increased understanding of nighttime crime in Vienna. This study can help implement better strategies for urban safety and advise police where to patrol. This multifaceted approach may be necessary for effective crime prevention strategies.

Author Contributions: Conceptualization, Jiyoung Lee, Michael Leitner, and Gernot Paulus; methodology, Jiyoung Lee, Michael Leitner, and Gernot Paulus; software, Jiyoung Lee; validation, Jiyoung Lee and Michael Leitner; formal analysis, Jiyoung Lee; resources, Jiyoung Lee and Michael Leitner; data curation, Jiyoung Lee; writing—original draft preparation, Jiyoung Lee; writing—review and editing, Michael Leitner; visualization, Jiyoung Lee; supervision, Michael Leitner; project administration, Jiyoung Lee; funding acquisition, Jiyoung Lee. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by a research assignment agreement, 1065 1314 12 25 2020, from the Austrian Marshall Plan Foundation at the Carinthia University of Applied Sciences (CUAS) in Villach, Austria, from 10 May through 13 August 2021.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors thank the Austrian Federal Criminal Police Office for providing the reported crime data from Vienna to be analyzed in this research.

Conflicts of Interest: The authors declare no conflicts of interest.

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