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Huang, Z., Xu, Y., Li, Y. et al. (2 more authors) (2025) Where drinks and danger meet: Analyzing the spatial link between Bars and crime in Detroit. Applied Geography, 174. 103480. ISSN 0143-6228

https://doi.org/10.1016/j.apgeog.2024.103480

Where Drinks and Danger Meet: Analyzing the Spatial Link Between Bars and Crime in Detroit

Abstract

Alcohol consumption has long been linked to various crimes, including homicide, assault, sex-related offenses, family violence, and chronic aggressiveness in adults. While the association between alcohol use and violent crime is well-documented, few studies have examined the spatial co-occurrence of bar locations - a primary venue for alcohol sales - and crime incidents across precise geographical locations and over time. This study employs the global colocation quotient (GCLQ) and the local colocation quotient (LCLQ) to analyze the spatial correlation between five types of liquor establishments (bar, lounge, live house, nightclub, and pub) and seven types of crimes (aggravated assault, burglary, larceny-theft, murder, motor vehicle theft, rape, and robbery) in Detroit, Michigan from 2017 to 2022. Findings demonstrate stable spatial relationships between bars and crimes across different years, with downtown bars showing a lower crime association, bars in clusters showing diverse patterns, and isolated bars in higher risk. The analysis reveals discrepancies in risk among different types. The safety index of the neighborhood surrounding bars is assessed through colocation analysis, demonstrating a correlation with bar-related security. Based on these insights, the study recommends heightened supervision for bars in high-risk areas and developing tailored prevention measures.

Keywords: Colocation quotient; Alcohol establishment; Crime; Detroit; Spatial analysis

1 Introduction

As an entertainment venue that integrates social and leisure functions, an alcohol establishment can meet the social and recreational needs of the public (Martin, 2004). The bar industry has been an important part of the economy in the United States. According to research on Gitnux (*Must-Know Bar Industry Statistics [Recent Analysis]*) and Statista (*Bars and nightclubs in the U.S. - statistics & facts*), the bar industry employed over 4.4 million people in 2019. As of 2021, there were approximately 65,000 bars, taverns, and nightclubs across the country, generating about $23.1 billion in revenue. On average, around 31% of adult consumers visit alcohol establishments at least once a week.

The effects of alcohol stimulation may easily result in disputes and conflicts, which can lead to violent crimes in alcohol establishments (McGill et al., 2022; R. Britt et al., 2005; Taylor et al., 2020; Toomey et al., 2012). The classic portrayal of "bar room brawls" in popular culture underscores the commonality of crime in these environments. Alcohol has been found to affect the GABA-benzodiazepine receptor complex in the brain, influencing the physiological, cognitive, affective, or behavioral functioning of the drinker (Miczek et al., 1997; Miczek et al., 1993). The study also reported women were significantly more likely to sustain injuries in assaults by an intimate partner if the partner had been drinking (Lorenz & Ullman, 2016).

Research consistently shows that bars are hotspots for violent crime, with murder, aggravated assault, and simple assault being more likely to occur in these establishments based on criminological theories (Hobbs et al., 2020; Savard et al., 2019; Taylor et al., 2020). This risk is further exacerbated by the presence of off-premise alcohol outlets, which are associated with higher rates of violent, property, and disorder crime (Gmel et al., 2016; Haley et al., 2023; Lardier et al., 2020). These findings align with the "routine activities theory, " suggesting that crime cases increase in areas with more illicit behavior opportunities (Hollis et al., 2013). Therefore, exploring the spatial impact of alcohol establishments on criminal behavior is of great significance (Savard et al., 2019). Spatial data could enable the examination of the multiple spatial scales where bars are related to crimes (Caplan, 2011). Early investigations were plagued by flaws, including statistical weakness and datasets that focused on larger geographic units such as cities, states, or counties (Gmel et al., 2016). Though more recent studies have used census track data as the geographic unit of analysis by employing spatial analysis techniques - which suggest a positive relationship between alcohol outlet density (AOD) and violent crime (Gmel et al., 2016; Gruenewald et al., 2023; Snowden et al., 2020; Zhu et al., 2004) - few have considered evaluating the risk associated with specific alcohol establishments, typically presented as point features. Additionally, previous studies have highlighted differences between off-licensed, on-licensed, and other types of alcohol establishments (Conrow et al., 2015; Jiang et al., 2017) and attractors for different crimes (Roncek & Bell, 1981; Stoll, 2024). Therefore, dividing crime type and bar type into finer categories is necessary, given association differences.

Colocation pattern analysis has been applied in diverse fields, including urban planning (Wang et al., 2017), transportation (Hu et al., 2018), and public health (Chen et al., 2021), proving its versatility in examining spatial relationships among points features. Recent application of colocation patterns in criminology can be classified into three main areas: colocation between different crime types (Shiode et al., 2023), colocation between crime types and facilities (He et al., 2020; Wang et al., 2017), and colocation between crime incident sites and surrounding land use features (Norita et al., 2024; Yue et al., 2017). Given that crime and bar locations both constitute point data, the use of colocation analysis in this study has the potential to address the Modifiable Areal Unit Problem (MAUP) (Dark & Bram, 2007). This statistical issue emerges when aggregating data across various spatial scales, which commonly arises in previous area-level analyses of the social and environmental determinants of crime. Additionally, colocation analysis can be adjusted for different situations by changing the range of data to optimize the analysis results. By examining the temporal variation of crime patterns based on colocation analysis, we can detect the deterioration of security in the area around bars. This can provide evidence supporting the Broken Windows theory (Kelling & Wilson, 1982), which suggests that the presence of crime indicates deterioration of the local community and that these crimes (i.e., a broken window neighborhood) lead to the emergence of increased in more severe crimes in the same area (Hakyemez et al., 2023; Shiode et al., 2023).

In this study, we aim to explore crimes potentially related to bars and identify bars that might be under criminal risks. We examined the spatial associations between alcohol establishments and crimes using two colocation quotient models (GCLQ and LCLQ) to identify targeted interventions at different scales. The spatial colocation patterns of five categories of alcohol establishments (bar, hotel bar, live music bar, sports bar, and nightclub) and seven categories of crimes (aggravated assault, burglary, larceny-theft, murder, motor vehicle theft, rape, and robbery) were included. Our study's focus on various subtypes and aspects of crime associated with bars could yield targeted insights for intervention strategies. Our study also uncovers the temporal transition of spatial colocation patterns, theoretically informing the Broken Window theory on the combination of crimes that tend to concentrate in the same region. From an application perspective, our study helps to inform policing strategies and the deployment of police resources in areas close to alcohol establishments. It also makes contributions for bars to optimize their operating hour, enhance security measures, or collaborate with local law enforcement to improve community safety jointly.

2 Material and Methods

2.1 Study area and data sources

The city of Detroit, known for its high crime rate, serves as the study area for our research. According to local police department detention records, Detroit has been grappling with issues of illegal drugs and sex trafficking, with more than half of the city's murders related to the underground economy. In 2014, Detroit's murder rate was 43.4 per 100,000 people, ranking as the second highest in the nation, following St. Louis (McDonald, 2014). In 2022, Detroit had the nation's third-highest homicide rate, at 50.0 per 100,000 individuals (Center for Public Safety Initiatives, 2023). Recent trends indicate that crime rates in Downtown Detroit neighborhoods have generally fallen below national and state averages, signifying a notable reduction in crime. At the same time, the majority of the city continues to experience high crime rates, significantly affecting daily life (Regan & Myers, 2020).

Data on alcohol establishments, including bars and nightclubs, was obtained from the Michigan Liquor Control Commission (Michigan Liquor Control Commission, 2024b) and verified using Google Maps. Establishments that closed at night or permanently shut down were removed from the dataset. Some representative bars were individually listed based on elements such as price, atmosphere, service, and presentation, including hotel bars, live music bars, and sports bars. Hotel bars are available to guests staying at the hotel and open to the public with more exclusive admittance policies. They are generally permitted to have B-Hotel liquor licenses in Detroit (Michigan Liquor Control Commission, 2024). Live music bars usually have a stage or designated area for a band or DJ to perform and a dance floor for guests to enjoy while drinking. Sports bars tend to be casual and focus more on providing entertainment than serving unique drinks, with games and sporting events displayed on TV screens throughout the bar (Rocklin, 2024). Nightclubs are venues that open at night for drinking, dancing, and other entertainment, typically offering a more vibrant and high-energy atmosphere (Wikipedia Contributors, 2024). Figure 2 displays their spatial distribution after geocoding (Zandbergen, 2009). Most alcohol establishments are in the downtown districts. Discrepancies in the proportions of different types are shown in Table 1.

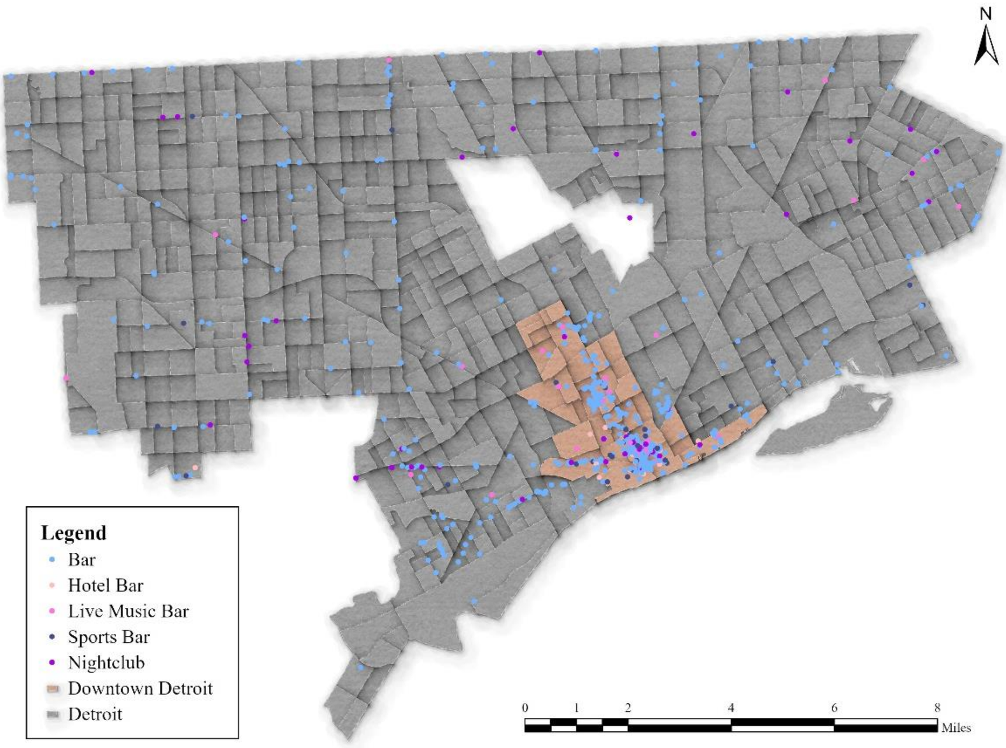


Figure 1 Alcohol establishments in Detroit City.

Table 1 Numbers and proportions of Alcohol establishments of different types

Category	Count	Proportion
Bar	693	92.03%
Hotel bar	24	3.19%
Live music bar	38	5.05%
Sports bar	37	4.91%
Night club	60	7.97%
Summary	753	100%

Crime data was sourced from the official Detroit Open Data Portal's "RMS Crime Incidents" dataset, which is compiled from the Detroit Police Department's records management system (Detroit's Open Data Portal, 2024). We categorized the cases according to the FBI's Uniform Crime Reporting Program (FBI, 2019) into violent crimes –subdivided into aggravated assault, murder, and rape – and property crimes - subdivided into burglary, larceny-theft, and motor vehicle theft. This categorization enabled the vast majority of types of crime to be covered in order to fully explore the spatial links between bars and various types of crime.

We selected the period from 2017 to 2022 as the study timeframe because it encompasses both the pre-COVID-19 and post-COVID-19 lockdown periods, allowing for the examination of temporal variation in bar safety and crime patterns during the pandemic. In our research, crime incidents were recorded during evening hours, from 18:00 to 6:00 the following day. This period is characterized by a higher frequency of crimes and a thriving nighttime economy, particularly within the bar industry (Cremeens et al., 2014; Gruenewald et al., 2023; Haleem et al., 2021). The total number of cases during this period amounted to 206,308 cases in total, as illustrated in Table 2. Temporal fluctuations in crime are demonstrated in Figure 2, showing an increase from 34,732 incidents in 2017 to 36,401 in 2019. This trend was followed by a reduction during the COVID-19 period, with figures dropping to 32,194 in 2020 and 31,611 in 2021. The economic downturn in 2022, a repercussion of the pandemic, has led to a resurgence in crime rates.

Table 2 Statistics of crime in evening hours from 2017 to 2022

Crime Category	Count
Aggravated assault	91,696
Murder	1,178
Rape	7,735
Robbery	8,015
Burglary	20,859
Larceny-theft	46,531
Motor vehicle theft	30,294

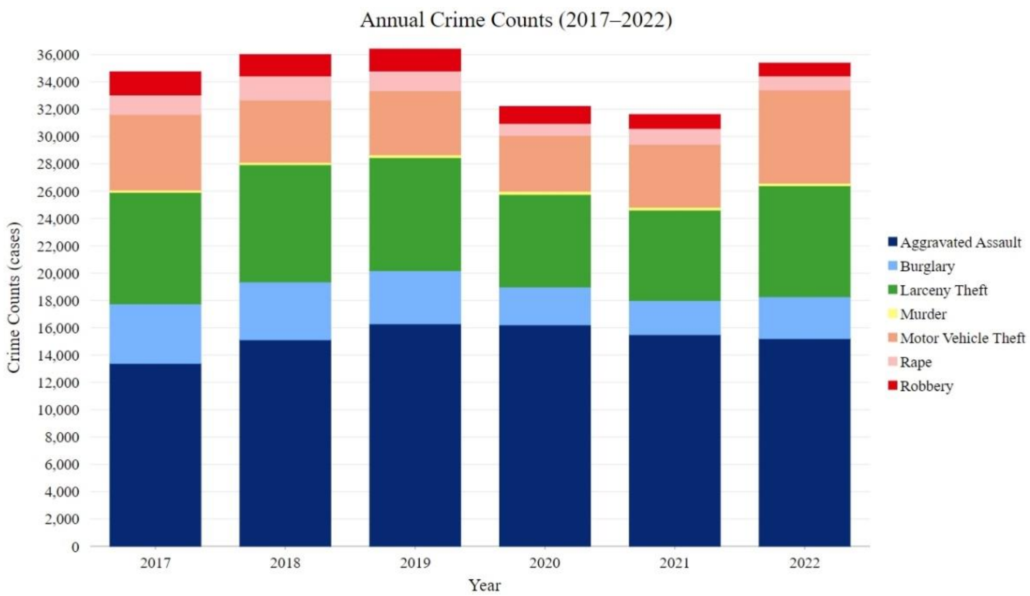


Figure 2 Annual crime counts from 2017 to 2022.

2.2 Global colocation quotient

The colocation quotient, as proposed by Leslie and Kronenfeld (Leslie & Kronenfeld, 2011), comprises the global colocation quotient (GCLQ) and colocation quotient (LCLQ) models. The GCLQ, diverging from the K function (Peterson, 2009), utilizes nearest neighbors to measure the overall colocation pattern between two types of point objects and their joint distribution and is formulated as follows:

$$CLQ_{A\rightarrow B} = \frac{\frac{N_{A\rightarrow B}}{N_A}}{\frac{N_B}{N-1}} \tag{1}$$

Where N represents the total number of point objects under investigation, N_A and N_B depict the count of A and B, respectively, and $N_{A\rightarrow B}$ is the number of type A points whose nearest neighbor belongs to type B points. The numerator calculates the observed proportions of B, which are the closest neighbors of A, where the denominator estimates the expected proportion by chance. As a point cannot be the nearest neighbor of itself, $N-1$ rather than N is used when measuring the expected proportion.

A point might have multiple neighbors, while GCLQ allocates equivalent weight to calculate $N_{A\rightarrow B}$. As formulated in Eq. (2), i denotes each A point, nn_i represents the number of nearest neighbors of i, j depicts each of the nn_i nearest neighbors, and f_{ij} is a binary variable indicating whether the point i's nearest neighbor j is of B type under investigation or not (1 indicates yes and 0 otherwise).

$$N_{A \to B} = \sum_{i=1}^{N_A} \sum_{j=1}^{nn_i} \frac{f_{ij}}{nn_i} \tag{2}$$

GCLQ can differentiate the spatial interactions between A and B in both directions. $\text{GCLQ}_{A \to B}$ informs the extent to which type A points are attracted to type B objects, while $\text{GCLQ}_{B \to A}$ expresses the extent to which type B points are drawn to type A points. $\text{GCLQ}_{A \to B}$ has an expected value of one when all points are allocated randomly given a fixed distribution pattern of points (Leslie & Kronenfeld, 2011). A $\text{GCLQ}_{A \to B}$ value larger than one indicates a possible colocation pattern, and the larger the value is, the stronger the colocation pattern would be. On the contrary, a $\text{GCLQ}_{A \to B}$ value less than one impresses a possible isolation pattern.

In our study, GCLQbars→crime and GCLQcrime→bars are the two indicators that evaluate the general links between bars and crimes in Detroit City. GCLQbars→crime indicates the potential for criminal activity to occur near bars. A GCLQbars→crime value of less than one means that the overall likelihood of crime occurring near bars is relatively low compared with other areas, indicating that bars in Detroit are generally safe. Conversely, a GCLQbars→crime value larger than one means that the crime occurring around bars is of high probability, which may indicate a high risk associated with bars in Detroit. A GCLQcrime→bars less than one means that crimes are spatially dispersed from bars in general, which may result in a lower likelihood of bars being the cause. A larger GCLQcrime→bars than one shows an overarching colocation pattern of crime to bars, revealing that crimes may be more likely induced by bars and alcohol than not.

2.3 Local colocation quotient

The GCLQ model is valuable for identifying the overarching colocation patterns across a large area. However, it may not be suitable for every individual part of a region, particularly urban areas with a diverse mix of objects and complex spatial distributions. The spatial layout of urban facilities often results in significant disparities in colocation patterns at the micro-scale. In contrast, the LCLQ model, developed by Cromley et al. (Cromley et al., 2014), is capable of revealing spatial variability in point dataset associations and measuring localized colocation patterns.

The LCLQ is formulated as

$$LCLQ_{A_i \to B} = \frac{N_{A_i \to B}}{\frac{N_b}{N-1}} \tag{3}$$

$$N_{A_i \to B} = \sum_{j=1(j \neq i)}^{N} \left(\frac{w_{ij} f_{ij} t_{ij}}{\sum_{j=1(j \neq i)}^{N} w_{ij}} \right) \tag{4}$$

$$w_{ij} = \exp\left(-0.5 * \frac{d_{ij}^2}{d_{ib}^2} \right) \tag{5}$$

where A_i represents the ith A point, f_{ij} depicts a binary variable showing whether or not point j is a marked B point (1 for yes and 0 otherwise), t_{ij} is also a binary variable judging whether or not point j is temporal related to point i (1 for yes and 0 otherwise), w_{ij} indicates the weight of point j, denoting the significance of point j to the ith A point, d_{ij} shows the distance between point A_i and point j, and d_{ib} is the bandwidth distance around point A_i. The other notations express the same as themselves in Eq. (3) and the denominator in Eq. (3) still calculates the proportion of observed type B objects that are the nearest neighbors of each type A object. Eq. (4) demonstrates how to calculate $N_{Ai \to B}$, the weighted average counts of type B points that are the nearest neighbors of point A_i. The Gaussian kernel density weighting function is illustrated in Eq. (5), stating that the closer a neighbor is to object A_i, it will be assigned a greater weight.

Specifically, we set a series of space-time windows to calculate t_{ij} in Eq. (3), estimating which features are included in the analyzed neighborhood. The features that are near each other in space and time are analyzed together, allowing for the assessment of all feature relationships relative to the location and time stamp of the target feature (Esri, 2020). In our study, space-time windows are applied to calculate $LCLQ_{crime \rightarrow bars}$, given that the time of criminal incidents should be taken into consideration. Crimes committed too temporally far apart should not be counted as each other's spatial neighbors when assessing one's correlation to its nearing bars by $LCLQ_{crime \rightarrow bars}$. However, when evaluating an individual bar's correlation to surrounding crimes by $LCLQ_{bars \rightarrow crime}$, there is no need to use space-time windows because there can be no spatial irrelevance between bars. Therefore, when calculating a bar's $LCLQ_{bars \rightarrow crime}$ value, all the neighbors are appointed the same t_{ij} of one.

$LCLQ_{bars \rightarrow crime}$ indicates the potential for crime to occur in proximity to a specific bar. If a bar has an $LCLQ_{bars \rightarrow crime}$ value of less than one, there are few crimes in its vicinity, indicating that the bar is relatively safe. If the $LCLQ_{bars \rightarrow crime}$ value is larger than one, multiple crimes are included in its nearest neighbors, suggesting a higher risk. If the $LCLQ_{bars \rightarrow crime}$ value is approximately one, the local bar and crime numbers are nearly equal, showing a potential local balance between the two.

$LCLQ_{crime \rightarrow bars}$ indicates the possibility of a crime related to nearing bars. An $LCLQ_{crime \rightarrow bars}$ value of less than one means that there are few bars near the specific crime, indicating a dispersion pattern to bars and a low likelihood of being bar-related. An $LCLQ_{crime \rightarrow bars}$ greater than one for an individual incident shows its great number of bars within the nearest neighbors and the high possibility of being induced by bars and alcohol. An $LCLQ_{crime \rightarrow bars}$ approximately one also reveals a potential local balance.

We used Monte Carlo simulation (Hammersley, 2013) to examine whether the LCLQ value is statistically significant, with a simulation trial randomly relabeling the category for each A_i point, following the frequency distribution of each category. Take $LCLQ_{bars \rightarrow crime}$ as an example. Each simulation randomly reassigns the labels of all objects except bar objects. The number of objects in each category will not change after the simulation procedure. By conducting numerous simulations, such as 499 iterations, a sample distribution for each object using the LCLQ is obtained and subsequently compared with the observed distribution to ascertain the significance level. All results are statistically significant at the 0.05 level.

The selection of parameters and metrics can affect the results when constructing an LCLQ model. The smaller the bandwidth, the more clusters with smaller areas and more pronounced variations of LCLQ values are expected. We used the K nearest neighbor method in ArcGIS Pro to determine bandwidth because it is more applicable for classification in colocation analysis compared to the distance band. This method yields more accurate results in measuring spatial impedance, as urban activities are mostly confined to the existing street network.

For our sample data, we used alcohol establishments, robbery, and murder in 2017 to search for the most appropriate bandwidth, as shown in Figure 3. We set the K nearest neighbors' numbers as 1, 8, 25, and 8 (Figure 3). A 499-time Montes Carlo simulation ran during the whole process. We displayed LCLQ results divided into five categories for subsequent experiments: Significant Colocation (LCLQ > 2.0), Colocation (1.01 < LCLQ < 2.0), Dispersion (0.5 < LCLQ < 1.0), Significant Dispersion (0 < LCLQ < 0.5) and Not Significant (LCLQ < 0). We considered points deemed Not Significant as failures.

Figure 3A shows 91 points of Not Significant, revealing that an insufficient number of neighbors substantially increases the likelihood of analysis failure. As the number of neighbors increases, the number of alcohol establishments with LCLQ values approaching one also rises, indicating that the results become smoother. A smaller bandwidth of one nearest neighbor resulted in more spiky spots, while a larger bandwidth of twenty-five nearest neighbors detects a diffused association of less extent. Investigating bars' spatial connection to areas with low crime counts, such as murder, led to larger clusters of Significant Colocation or Significant Dispersion patterns, suggesting that smaller datasets fit smaller bandwidths.

Our study showed a wide variation in the annual number of cases by type. For example, murder hovered around 150, while aggravated assaults exceeded 10,000. To reduce the effect of bandwidth differences on LCLQ analysis and ensure that the number of failure objects remained low across different experiments, we settled on setting the bandwidth to 8 nearest neighbors in the follow-up section.

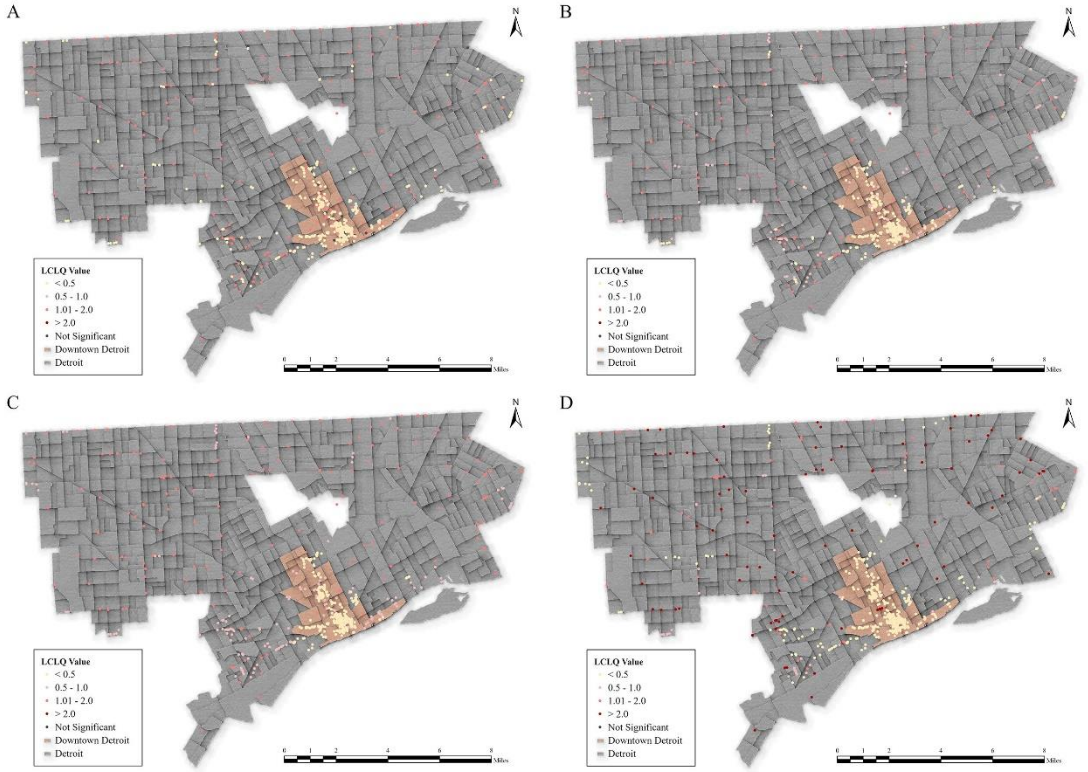


Figure 3 LCLQ results between bars and Robbery in 2017 with a bandwidth of (A) one, (B) eight, and (C) twenty-five nearest neighbors. (D) LCLQ between bars and Murder in 2017 with a bandwidth of eight nearest neighbors.

3 Results

3.1 Global colocation quotient analysis

We explored the global colocation patterns between alcohol establishments and different crimes by two different GCLQ models, $GCLQ_{bars \rightarrow crime}$ and $GCLQ_{crime \rightarrow bars}$. The former assessed the vulnerability of bars in Detroit to nearby, while the latter indicated whether crimes in the city collocate with neighboring alcohol establishments.

Both models showed spatial dispersion patterns in general, as presented in Tables 3 and 4, with all GCLQ values being less than 1, indicating that Detroit's alcohol establishments are not correlated with criminal incidents overall. GCLQ values fluctuated slightly between different years, peaking during the COVID-19 period, indicating that crimes were the least dispersed relative to bars during such a period. The economic downturn caused by the pandemic may account for this trend.

$GCLQ_{bars \rightarrow crime}$ values of burglary, rape, and robbery were the lowest, suggesting that bars were the places where these crimes are less likely to happen. According to $GCLQ_{crime \rightarrow bars}$ results, burglary and rape were the most spatially isolated types, while larceny-theft and murder were the least dispersed. This also inferred a degree of symmetrical dispersed association between bars and crimes. The result of burglary aligned with its definition (Mawby, 2013). Bars and their surrounding areas tended to have higher population densities and are usually noisier, making it more challenging to carry out a burglary. Although several studies have demonstrated an increased incidence of sexual offenses and robberies in bar environments (Baltieri & de Andrade, 2008; Feng et al., 2019), our results were contrary to this trend and may indicate the presence of more effective preventive measures against such crimes in Detroit.

GCLQ results demonstrated the overall association between bars and crimes but remained spatially and temporally stationary, hiding the local association relationship. LCLQ is more applicable to better account for the spatiotemporal heterogeneity of different criminal cases and to fit the complex urban environment.

Table 3 $GCLQ_{bars \rightarrow crime}$ from 2017 to 2022

Neighboring Categories	Year					
	2017	2018	2019	2020	2021	2022
Aggravated Assault	0.683	0.685	0.697	0.652	0.696	0.701
Burglary	0.483	0.481	0.468	0.489	0.489	0.499
Larceny Theft	0.822	0.840	0.832	0.743	0.771	0.833
Murder	0.722	0.618	0.646	0.583	0.633	0.646
Motor Vehicle Theft	0.614	0.606	0.584	0.566	0.625	0.693
Rape	0.481	0.478	0.504	0.520	0.501	0.518

Robbery	0.565	0.585	0.559	0.527	0.570	0.539

Table 4 $GCLQ_{crime \rightarrow bars}$ from 2017 to 2022

Category of Interest	Year					
	2017	2018	2019	2020	2021	2022
Aggravated Assault	0.587	0.568	0.574	0.559	0.597	0.577
Burglary	0.474	0.475	0.466	0.504	0.485	0.504
Larceny Theft	0.681	0.663	0.711	0.704	0.708	0.684
Murder	0.698	0.662	0.646	0.624	0.686	0.653
Motor Vehicle Theft	0.595	0.599	0.580	0.558	0.600	0.669
Rape	0.450	0.445	0.483	0.511	0.431	0.474
Robbery	0.569	0.587	0.579	0.536	0.578	0.568

3.2 Local colocation quotient analysis

Firstly, we used the LCLQ model to calculate $LCLQ_{bars \rightarrow crimes}$ for each type of crime in 2017-2022, which indicated the extent to which alcohol establishments attract crime incidents. This also reflected alcohol establishments' security level—the lower the value, the safer the establishment is considered to be. Figure 4 shows $LCLQ_{bars \rightarrow crimes}$ for different crimes in 2022.

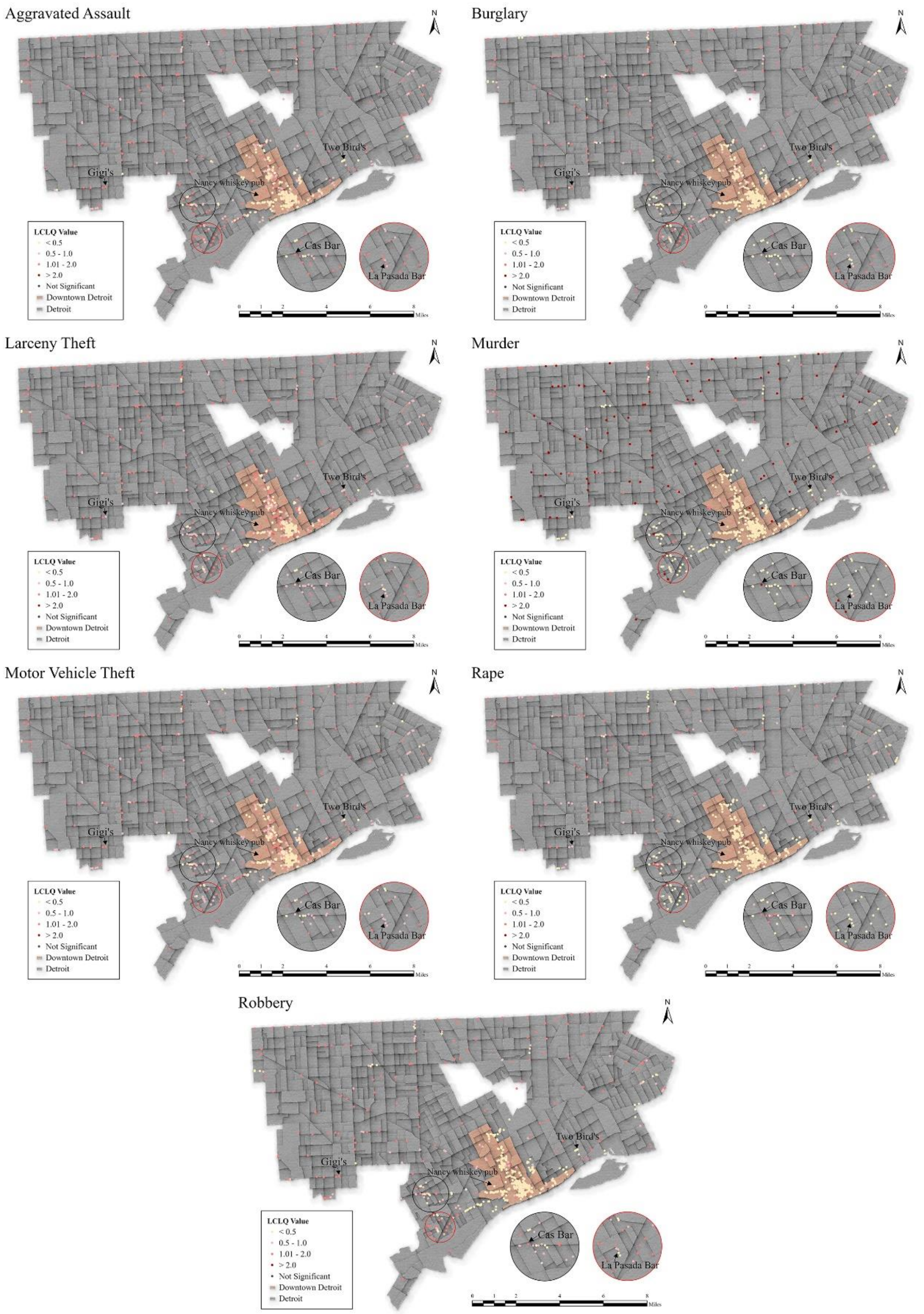


Figure 4 LCLQ$_{bars \rightarrow crimes}$ results with crimes of various types in 2022.

Colocation patterns between alcohol establishments and various crimes were overall homogenous, with most being spatially isolated in 2022. The highest number of bars with an LCLQ value lower than 1 was 625 in relation to rape. At the same time, the lowest number is 495 for larceny theft, which was still higher than 65 % of all bars. However, this did not imply that most bars were adequately safe, as regional differences within Detroit were pronounced.

Alcohol establishments in Downtown Detroit were generally dispersed to crimes, with a few notable hotspots of colocation. This pattern may be closely related to the high density of bars in the area - clusters of bars tend to draw crowds during opening hours, and there was a substantial police presence and surveillance around these bars (Doucet & Smit, 2016). Unlike other U.S. cities, Downtown Detroit boasts a middle-class population and tourist attractions, contributing to its relatively safety compared to other neighborhoods (Doucet & Smit, 2016; Mah, 2020). Alcohol establishments in colocation patterns in this region warranted special attention. They were usually found at the edge of the Downtown bar cluster, such as Nancy whiskey pub, which was collocated with aggravated assault, burglary, larceny-theft, motor vehicle theft, and rape in 2022. Crime incidences were more likely to occur in and around bars farther from the center cluster, suggesting a need for enhanced security measures in these locations.

Bar clusters located in another part of the city showed different patterns from those in Downtown Detroit. Relationships between bars along Michigan Ave in Claytown (highlighted within the black circle in Figure 4) and crimes were diverse. Half of the bars there showed colocation with aggravated assault and rape, while the majority of bars there exhibit dispersion or significant dispersion to other types of crimes. It is noteworthy that Cas Bar was collocated with most types of crimes and significantly collocated with murder. Colocation patterns between bars in and around Springwell (highlighted within the red circle in Figure 4) and crime were relatively consistent. A number of bars significantly dispersed from murder and rape but collocated to other crimes, with some exceptions like La Pasada Bar, which was dispersed to all crimes. In general, colocation patterns between alcohol establishments in a smaller cluster and crimes were not so accordant. A safer bar might be adjoint to a dangerous one.

Alcohol establishments situated away from Downtown Detroit, predominantly at the junctions of blocks, were mostly collocated with all types of crimes. These bars, intended to serve the local community, had security levels that were closely tied to community policing efforts, and the disorder within a neighborhood may influence the crime rates of these venues. Notable exceptions, like Gigi's and Two Birds, were located to the south and not too far from Downtown Detroit. Bars in the suburbs, particularly in the northern area, were more dangerous. The further one went towards the outskirts, the sparser the bars became, often with a few bars within a two-mile radius. More than half of these spots were in significant colocation with murder, and most were in a colocation pattern with other crimes. However, bars along Livernois Ave or Harper Ave were mostly in dispersion. Factors like gangs, black markets, drugs, and other risk factors in Detroit suburbs contribute to this issue.

3.3 Temporal variation of colocation pattern

There was little overall variation in colocation pattern in the time dimension from 2017 to 2022, but changes in certain individual bars in localized areas were more pronounced. $LCLQ_{bars \to crimes}$ results for rape, shown in Figure 5, were representative even though differences in details did exist compared to other crime types.

Alcohol establishments in Downtown Detroit were much safer than other areas as time went by. The farther one went away from Downtown Detroit, the larger its LCLQ value would be, more likely collocated to rape locations. Although the number of incidents decreased in 2020 and 2021, general patterns transformed slightly. Distinctive transformation can be observed in neighborhoods.

The vast majority of bars in Downtown Detroit were spread out from areas associated with rape, and those that were collocated had shown a downward trend from 2017 to 2019. Prevention measures against rape in these areas had been perfected during that period. Patterns in Downtown Detroit remained stable during and after the COVID-19 period, with less than ten bars exhibiting a colocation pattern in the last three years. It can be inferred that quarantine policy scarcely influenced the security level of Downtown Detroit. However, a portion of the bars, such as Nancy whiskey pub and Tony V's Tavern, located on the outskirts of Downtown Detroit, had consistently collocated to rape cases, with their LCLQ values showing an increase during the pandemic.

In contrast, the local colocation pattern of bars around Michigan Ave changed substantially during the six years with diverse results. Alcohol establishments located at the edge of the area, such as Blackhorse Cantina II and The Caribbean Club, were the ones whose LCLQ values were always smaller than one. Those located in the central area with high density exhibited a variability of colocation patterns, with LCLQ values generally exceeding one before 2021. Specifically, more than half of the bars on the street displayed colocation patterns in 2020 or 2021. In 2022, most of these bars became dispersed from rape incidents. The variation of bars in and around Springwells was different. Bars located in the center stayed in a dispersion pattern, while more and more bars located on the edge changed into a colocation pattern in 2020 and 2021. In 2022, almost all bars in the region became significantly dispersed to rape. It can be inferred that these bars were particularly prone to rape cases, and the situation may have worsened during the quarantine time. However, targeted interventions may have been made after the period.

Bars located away from Downtown Detroit always served the neighborhood and were mostly collocated to rape during the entire period. Only a small number of notable exceptions situated in the suburb showed dispersion to rape, such as Good Time on The Ave, Ford Patio Bar & Grill and Cornerstone Village Bar & Grill. COVID-19 had little impact on the overall spatial patterns, with few changes in patterns from colocation to dispersion or converse. The number of colocation spots was highest in 2020 and gradually decreased over the subsequent two years.

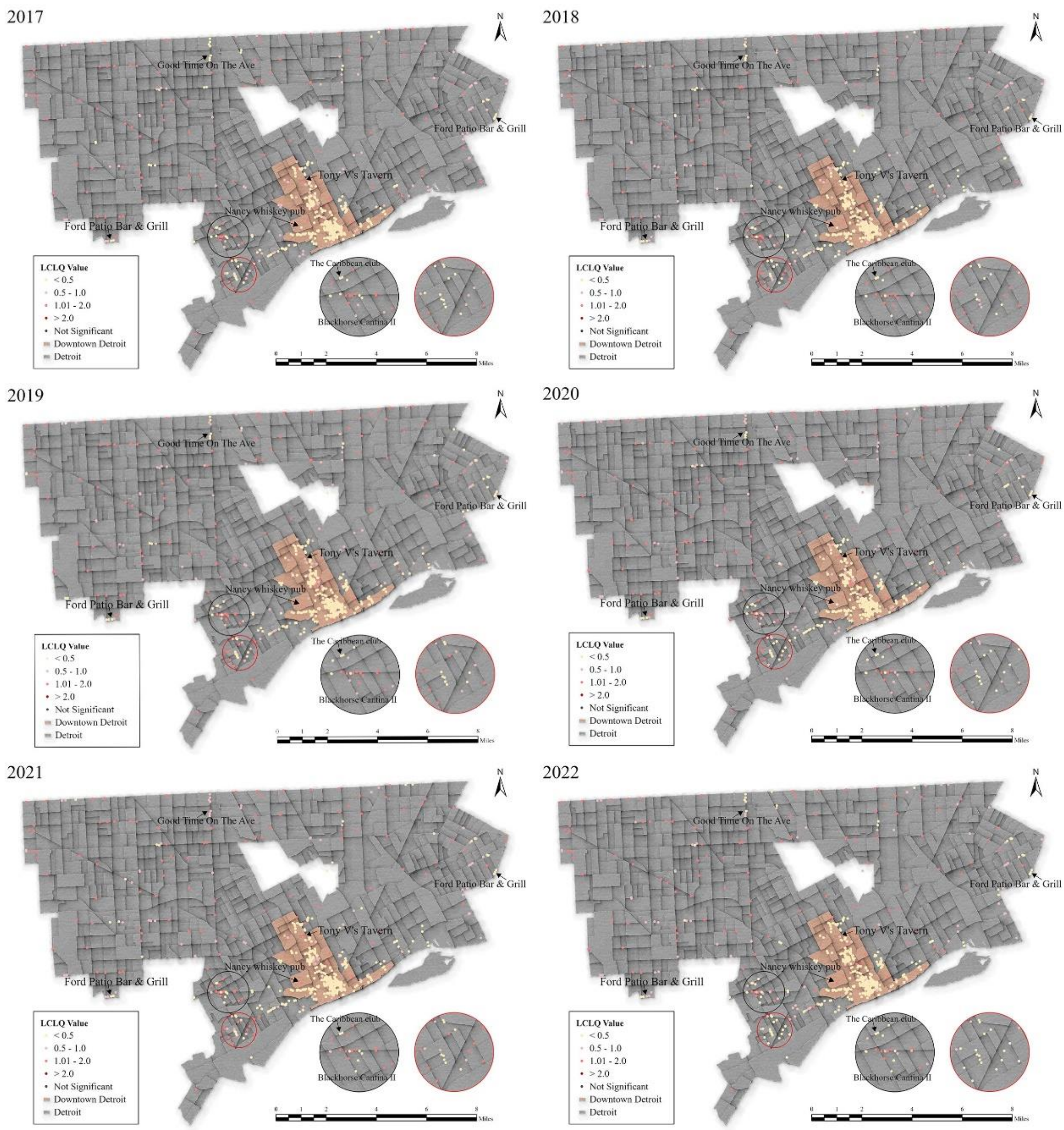


Figure 5 LCLQ$_{bars \rightarrow crimes}$ results of Rape from 2017 to 2022.

3.4 Discrepancies in colocation patterns across different types of bars

The spatial interplay between alcohol establishments and crimes had wide differences for different bar types. We chose aggravated assault in 2022 as sample data to reveal the scenarios in Figure 6. The number of category “Bar” was the largest, with the most widely distribution. It should be noted that the following establishments, except the nightclub, were classified under the “Bar” category. In Downtown Detroit, the southeastern part was much safer than others, where all bars were dispersed from incidents, with most showing significant dispersion. There were several establishments located in the middle part, surrounded by bars isolated from crime spots. Given the fact that "Bar" was the main category of alcohol establishments in the two bar clusters in southern Detroit, these spots could mainly represent the characteristics of the two areas. The number of bars collocated with aggravated assault and those dispersed to it was close near Michigan Ave. Bars located in Spingwell were mainly collocated to the crime. Bars located in the neighborhood distant from the downtown area were majorly collocated to aggravated assault incidences. Only bars in the eastern suburbs showed an overall dispersion.

The majority of hotel bars, live music bars and sports bars are all located in Downtown Detroit. Hotel bars had the highest portion of colocation pattern while all sports bars were dispersed to aggravated assault there. In blocks away from Downtown Detroit, most sports bars were in colocation pattern, but about half of live music bars were in dispersion. The number of nightclubs in and out of Downtown Detroit was close. Those located in the downtown area or along Michigan Ave were all dispersed from crime spots. In contrast, those located distantly from others in the hood were mostly collocated to aggravated assault. Gracies was the only suburb nightclub showing significant dispersion.

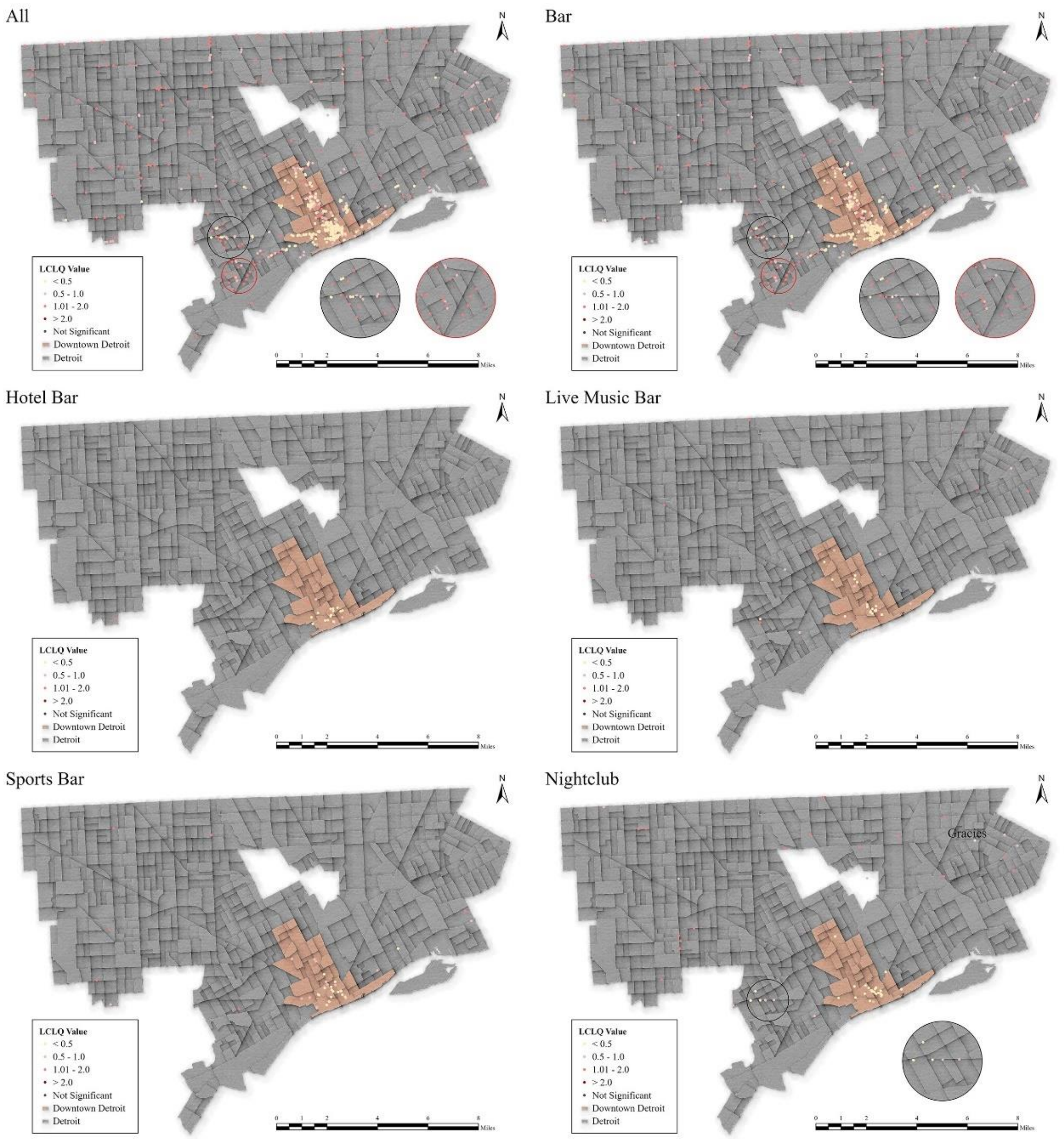


Figure 6 LCLQ$_{bars \rightarrow crimes}$ result of Aggravated Assault in 2022, classified by alcohol establishment types.

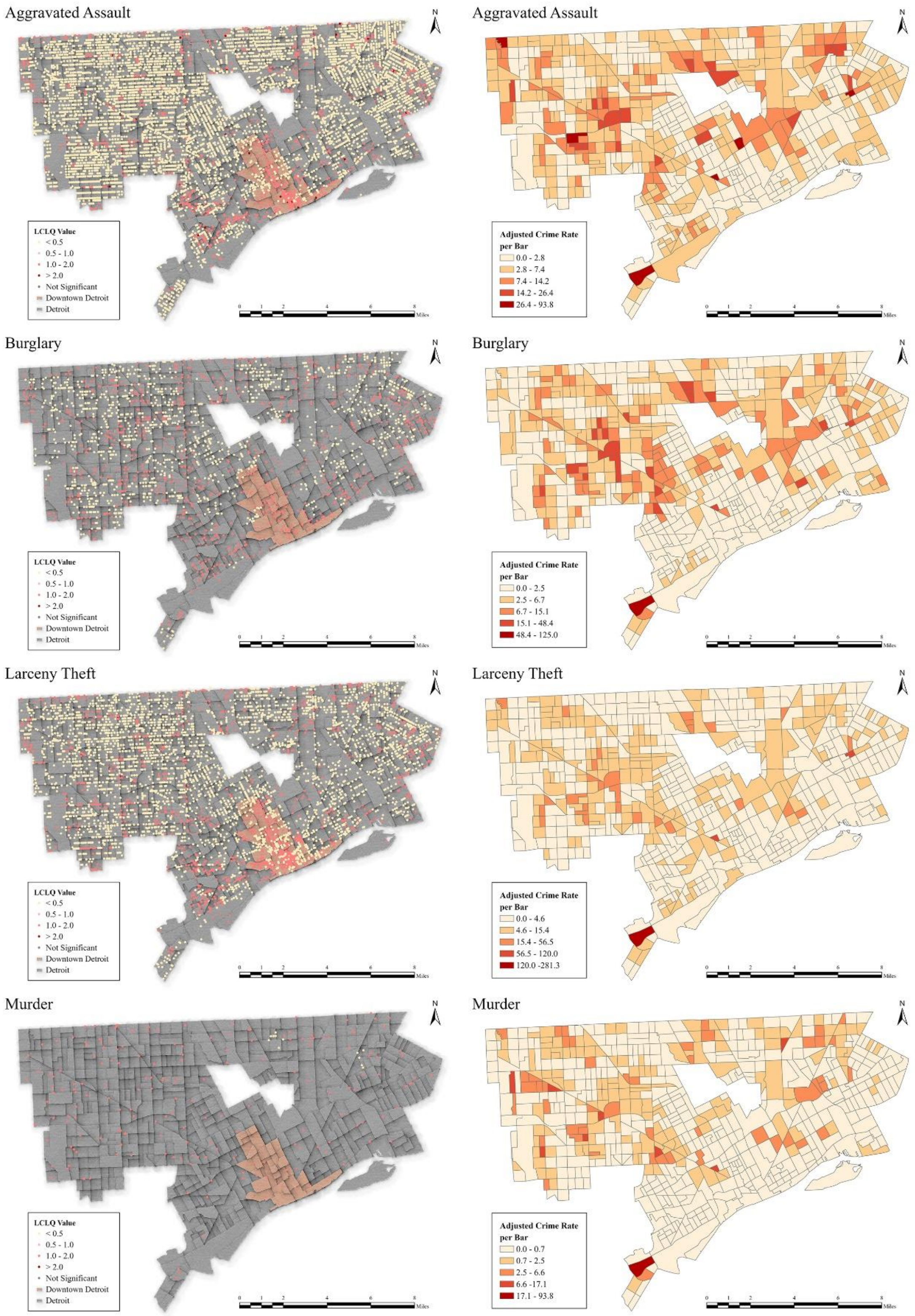
3.5 Impact of bar-related crimes on neighborhoods through colocation analysis

LCLQ$_{crimes \rightarrow bars}$ represents how crime spots are attracted to bar locations, partially judging whether the occurrence of a specific case is related to an alcohol establishment. In calculating the LCLQ value for individual crime incidents, a seven-day temporal window was established after parameter selection to filter out unrelated cases and minimize the influence of incidents occurring far removed in time (Li et al., 2022).

Results for different types of crimes in 2022 were demonstrated on the left side of Figure 7. Basically, the closer a crime location was to a bar, the more likely it was collocated to the establishment. Additionally, as bar density increased, both the proportion and number of nearby incidents in the colocation pattern rose. For example, Downtown Detroit had the largest number of colocation spots. LCLQ values of crime spots significantly dispersed to bars were all zero, and the majority of them were located in the middle block groups and suburbs. Proportions of murder, rape and robbery of colocation pattern were the highest, while aggravated assault and three types of property crime were lower.

Given that $LCLQ_{crimes \rightarrow bars}$ results could not directly reflect the impact of bar-related crimes on neighborhoods, we calculated the crime rate per bar for each block group on the right side of Figure 7 to assess the safety index of neighborhoods near bars. The number of bars within each block group and a 500-meter radius was counted, drawing from routine activity theory (Miró, 2014). To ensure comparability across block groups, this bar-related crime rate was adjusted for every 1,000 residents based on population data obtained from the American Community Survey (ACS, 2018–2022). The lower the bar-related crime rate of a block, the higher the implied safety for neighborhoods near those bars concerning that specific crime type. Notably, this indicator serves as a warning of bar-related security risks rather than a direct count of crimes. For instance, areas with a high number of bars, such as downtown, may report higher overall crime counts but show lower bar-related crime rates per bar, indicating relatively safer conditions for specific crime types.

Block groups in southern Detroit had lower bar-related crime rates than others, except for Oakwood Heights, which had one of the most dangerous bars collocated to almost all types of crime. Some block groups located in the middle part and along Grand River Ave had high bar-related crime rates, such as Littlefield Community. Suburban regions, particularly in the west, had consistently lower rates. A relatively larger number of block groups had a risk of encountering bar-related aggravated assault, which aligns with inferences based on $LCLQ_{bars \rightarrow crime}$.



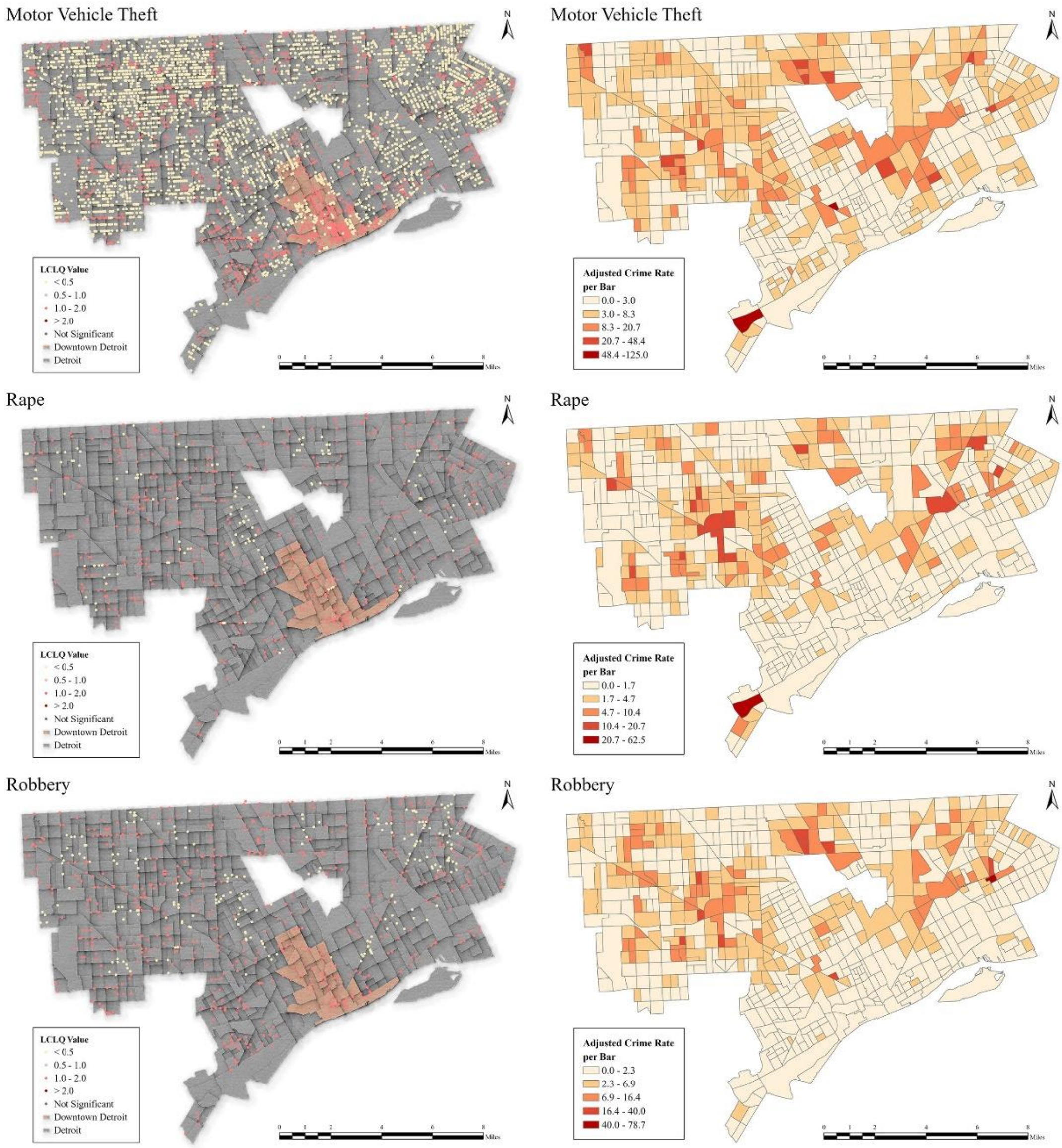


Figure 7 $LCLQ_{crimes \rightarrow bars}$ results with crimes of various types in 2022.

4 Discussion

Although multiple studies have examined the relationship between alcohol establishments and crimes, their results were either unable to provide policy-makers with detailed information about individual bars or were limited by the MAUP effect, particularly those studies that utilized GIS algorithms. Moreover, few have delineated the relationships between bars and all crime types individually. Our research proposed a novel method, with two indicators, the GCLQ and the LCLQ, to reveal the spatial interplay between different types of alcohol establishments and various types of crime in Detroit City. Specifically, the GCLQ assesses citywide patterns, while the LCLQ extracts localized patterns at specific sites. We also evaluated different bandwidths of the LCLQ model, utilizing the one of universal applicability across all datasets. Based on the GCLQ results, alcohol establishments and crime spots were dispersed from each other, regardless of category, and were scarcely influenced by the COVID-19 pandemic. In comparison, the LCLQ results revealed the spatial discrepancies of bars' collocation patterns in relation to crimes and assessed bar-related security of neighboring regions. Bars in Downtown Detroit were the most dispersed, those in other smaller clusters showed the greatest variety, bars isolated away from downtown were the most collocated, and some of the bars located in the suburbs were in great dispersion. Given that the factors influencing criminal cases are multifaceted, CLQ analysis is not sufficient to fully deduce the specific causative factors of crime cases. However, the application of CLQ analysis helps us to understand the possible links between pubs and crime and assess the risk level of the areas near alcohol establishments. The discoveries also provide a reference for policymakers and owners on criminality prediction in the subsequent years.

Therefore, arrangements should be tailored across different regions, as factors such as location and community culture may influence the impact of bars on crime (Conrow et al., 2015). Although downtown has a high bar density, a stronger dispersion between bars and crime, and a higher neighborhood safety index, the positive relationship between bar density and crime cannot be overlooked. Specifically, bars still collocated with crime in this area should be given special attention. The use of security personnel to protect patrons and staff should be enhanced, and bar managers are expected to circulate regularly throughout the establishments to ensure safety (Savard et al., 2019). Security staff should be adequately trained to intervene promptly before conflicts escalate into violent crimes (Davis et al., 2024). The employee-to-customer ratio can be increased, referred to as the standard of The New York Nightlife Association (Association, 2011). In bar clusters within more collocated establishments, surveillance, lighting, and police patrols might be more efficient in reducing the risk of crime. Bars located in economically and socially disadvantaged communities, which are often collocated with crime, can have a negative impact on residents (Horsefield et al., 2023). To prevent such bars from contributing to the broken window effect on the neighborhood, there should be a restriction on their operating hours, as well as an increase in police presence and supervision. Regular inspections should be carried out, and liquor licenses should be revoked if necessary, depending on the safety situation.

Based on the characteristics and motivations of different types of crimes, targeted measures should be implemented in conjunction with spatial distribution patterns for the specific crime. Violent crimes are usually generated by risk factors in alcohol establishments, such as organizational practices and physical characteristics (Franquez et al., 2013). Maintaining law and order in and around pubs should be a priority. For bars collocated to rape, such as La Pasada Bar, managers should consider whether the physical environment and practices facilitate sexual aggression (Davis et al., 2024). Training sober staff who are motivated to intervene as part of their employment duties is also effective (Davis et al., 2024; Leone et al., 2018). In terms of property crimes, which few studies have explored in relation to bars, we also found collocation pattern clusters between alcohol establishments, larceny theft and motor vehicle theft, particularly in the safer block groups in Downtown Detroit. Reduced vigilance while drinking may account for the former, while the lack of parking security could explain the latter. Patrols around parking areas may be the best method for dealing with it.

Previous studies have proposed a theory that individual patrons select the contexts in which they drink based on their preferences (Morrison et al., 2016). We emphasized the necessity of evaluating an alcohol establishment's security level in relation to its theme and type in Detroit. Alcohol establishments with overcrowded and noisy environments, such as sports bars and nightclubs, were more frequently collocated with crime. For example, a "hip-hop" or "gangster rap" style live music bar may be more prone to attract crimes than one featuring a "folk singer" (Graham et al., 2006). In sports bars, “highly-identified dysfunctional sports fans” may be loud, obnoxious and aggressive (Wann, 2001). With alcohol stimulation, verbal altercations between them might escalate to violence like aggravated assault. Stylistic differences in alcohol establishments were more pronounced in blocks farther from the city center, resulting in a greater variation in the level of crime risk across bar types. In Downtown Detroit, all types of alcohol establishments mainly showed consistent dispersion. Therefore, location is a more significant factor influencing the level of danger in bars and surrounding neighborhoods, while bar type can be used as a supporting element in governance decisions. Targeted regulations, such as designating a dress code, limiting alcohol availability in nightclubs, and increasing the number of security guards in sports bars during tournaments, can make a difference.

Though the crime rate decreased during the COVID-19 period (Halford et al., 2020; Meyer et al., 2022), serious crimes, which were generally not committed with co-offenders, may have been more related to alcohol establishments locally. Several bars in clusters became more collocated with rape, and more isolated bars located in the neighborhoods became collocated with murder. While lockdowns and quarantine clearly impacted group-based offending, they were unlikely to have any bearing on criminal acts that generally occur in situations when peer groups are not present (Boman & Gallupe, 2020). Given the fact that some bars had to suspend business during the period, location and environment account for the occurrence of bar-related criminal cases. Even though we still couldn’t conclude whether COVID-19 lockdowns were positive for improving bar security, the CLQ results can be a reference for policymakers when similar situations arise in the future.

5 Conclusion

This study explores the spatial dynamics between five types of liquor establishments and seven types of crime patterns in Detroit, revealing consistent relationships over time with significant variations based on bar types and locations.

Downtown bars were less associated with crime, clustered bars displayed diverse patterns, and isolated bars faced higher risks. A clear link between bar safety and surrounding crime levels highlights the need for targeted prevention strategies in high-risk areas. These findings contribute to urban safety research and offer practical insights for crime prevention and urban planning.

Future research should address several limitations to enhance the current study. Expanding the scope to encompass a broader range of entertainment establishments and urban infrastructure would provide a more holistic understanding of the contextual and motivational factors influencing crime patterns. Furthermore, incorporating detailed crime data and comprehensive references could uncover deeper connections between incidents, thereby improving the analytical rigor and reliability of the findings. These advancements would contribute to the formulation of targeted policies designed to promote safer and more sustainable urban environments.

Appendix

Definitions of all types of crime involved in our study

Crime Type	Definition
Aggravated Assault	An unlawful attack for the purpose of inflicting severe or aggravated bodily injury is frequently witnessed in bars.
Murder	The willful killing of one human being by another.
Rape	Penetration of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim. Bar-related rape has received widespread attention.
Robbery	The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear, which is more common in bars located in chaotic neighborhoods.
Burglary	The unlawful entry of a structure to commit a felony or theft.
Larceny Theft	The unlawful taking of property from the possession or constructive possession of another.
Motor Vehicle Theft	The theft or attempted theft of a motor vehicle.

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