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ORIGINAL PAPER

# Spatio-Temporal Interaction of Urban Crime

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**Abstract** Over the past decade, a renewed interest in the analysis of crime hot-spots has emerged in the social and behavioral sciences. Spurred by improvements in computing power, data visualization and geographic information systems, numerous innovative approaches have materialized for identifying areas of elevated crime in urban environments. Unfortunately, many hot-spot analysis techniques treat the spatial and temporal aspects of crime as distinct entities, thus ignoring the necessary interaction of space and time to produce criminal opportunities. The purpose of this paper is to explore the utility of statistical measures for identifying and comparing the spatio-temporal footprints of robbery, burglary and assault. Functional and visual comparisons for spatio-temporal clusters are analyzed across a range of space–time values using a comprehensive database of crime events for Cincinnati, Ohio. Empirical results suggest that robbery, burglary and assault have dramatically different spatio-temporal signatures.

**Keywords** Crime hot spots · Space–time · GIS · Cluster analysis

## Introduction

Areas of elevated crime are not random occurrences but are symptomatic of environmental, economic, political and sociological factors in that area. In many cases, crime hot-spots are indicative of an increased likelihood of illicit activities in an environment where there is a greater motivation to commit crimes due to socio-economic strife or an environmental setting which is conducive to criminal behavior (Felson 1994; Brantingham and Brantingham 1981). Previous research linking crime hot spots to theories of social disorganization, social control and collective efficacy (Taylor et al. 1984; Smith et al. 2000; Morenoff et al. 2001; Jobes et al. 2004) recognizes the enabling role of environments where criminal activity is concentrated. Hot-spot analysis is a relatively popular approach

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for exposing these problematic areas in urban and suburban environments (Jefferis 1999; Ratcliffe and McCullagh 1999; Eck et al. 2005; Grubesic 2006) and has emerged as a principal tool for researchers in the behavioral and social sciences. That said, the majority of previous hot-spot analyses treat space and time as separate components of crimes, largely ignoring the interaction of space and time in the production of criminal opportunities. As a result, spatio-temporal interaction receives somewhat less attention in the hot-spotting literature.

Spatio-temporal interaction arises when events located relatively close in geographic space occur at about the same time (Jacquez 1996; Kulldorff and Hjalmars 1999). Recent work suggests that spatio-temporal interaction may be an important tool for crime analysis. Studies examining repeat victimization suggest that there is an elevated risk of burglary following an initial incident (Johnson et al. 1997), and there are regularities in the timing and spacing of these repeats (Bowers and Johnson 2005; Sagovsky and Johnson 2007). However, questions remain, particularly concerning the degree to which these regularities exist across space and time in alternative environments. More specific to this study, are questions pertaining to how these regularities compare between crime types (e.g. burglary, assault, robbery, etc.) within a single environment.

Previous work that focused on criminal mobility (Capone and Nichols 1976; Deutsch et al. 1984), as well as variations in crime patterns by crime type is suggestive of two things. First, the spatial typologies of crime often vary according to crime type (Groff and McEwen 2007). Second, the corresponding spatio-temporal signatures might also be distinct. For example, investigations of the characteristics of robberies (Duffala 1976; van Koppen and Jensen 1998) reveal a certain degree of professionalism associated with the act of robbery. As a result, the level of planning associated with the crime can impact the distance traveled by the offender (van Koppen and Jensen 1998). In a similar vein, commercial burglars are likely to vary the time of day of their activities depending upon the location of their selected target (Hakim and Shachmurove 1996). These studies suggest that not only do spatio-temporal approaches have the potential to add additional information about the nature of the offense, but perhaps provide clues about the perpetrator. At the very least, recognizing the differences in the spatio-temporal signatures of crimes, and how they vary, can deepen our understanding of criminogenic processes.

Given the potential utility of spatio-temporal techniques for hot-spot analysis, the purpose of this paper is four-fold. "Theoretical Foundations for Variations in Crime Patterns", provides an abbreviated literature review that touches on the potential motivations for criminal behavior and the resultant variations in crime patterns. Special attention is paid to the theoretical underpinnings of how different crime types may yield different space–time "footprints". "Space–Time Interaction for Crime" discusses two spatio-temporal approaches for examining space–time interaction between crime events, which is followed by an application and case study for Cincinnati, Ohio that compares the spatio-temporal signatures of burglary, assault and robbery. Finally, a brief discussion on the problems and prospects of spatio-temporal analysis of crime will conclude the study.

## Theoretical Foundations for Variations in Crime Patterns

While the links between crime, the environment and human activity patterns are relatively well-understood, quantifying these relationships still proves challenging. In this regard, there is a gap between theories that are relatively generalized and broad-ranging in scope, and more specific quantitative methods and techniques which represent highly specialized approaches for addressing a specific question of a more general theory (Mingers and Brocklesby 1997). For example, crime analysts might be able to answer why a suitable guardian (e.g. police officer) was not present in a location where a crime occurred through the use of use patrol records and vehicle routing information. However, determining why both the criminal and victim converged at a particular location requires a completely different set of quantitative (or even qualitative) methods.

While a complete evaluation of criminal motives and activity is beyond the scope of this paper, a variety of theoretical constructs are important for providing the appropriate context when linking geographic space, time, law, offenders and victims to the emergence of crime patterns. In fact, each of these theoretical constructs provides important insights into the development of crime patterns and their typological variations. For example, environmental criminology (Brantingham and Brantingham 1984; Block and Block 1995; Sideris 1999) recognizes the role that characteristics of places play in engendering criminal activity, and supports the idea that areas of elevated criminal activity are not entirely random. In addition, routine activity theory (Cohen and Felson 1979; Sherman et al. 1989; Sherman 1995) explicitly addresses both the spatial and temporal components of crime. The convergence of a motivated offender with a suitable target and no capable guardian, at a particular place and time, combine to form the necessary stimuli for a crime event to transpire (Cohen and Felson 1979). The fundamental premise of routine activity theory is this *convergence* of actors in space and time representing a unique interaction. In this context, space and time must be treated as *interdependent* entities in an effort to make sense of spatio-temporal patterns and structures related to a crime.

Time geography (Haagerstrand 1970; Pred 1977; Pred 1981; Miller 1991) can also recognize the inherent spatial and temporal aspects of crime. The basic tenet of this theoretical construct is that the planning of everyday events is performed relative to spatial and temporal constraints geography (Hagerstrand 1970; Pred 1981). For example, in its simplest manifestation, the time geography of crime events, such as robberies and assaults, represent the “convergence in time and space of the paths being traced out by two or more people” (Pred 1981, p. 10). Clearly, the ability to track the dynamics of this convergence/interaction is important. Unfortunately, many analyses dealing with crime hot-spots neglect these important space–time linkages and treat spatial and temporal aspects of crime as discrete entities. In part, this can be attributed to the limitations associated with the availability of spatial and temporal data (Groff 2007).

Given the inherent difficulty of quantifying the relationships between human activity patterns, the environment and crime, many of the most persuasive empirical studies are often exploratory in nature (Murray and Estivill-Castro 1998; Messner et al. 1999; Craglia et al. 2000; Murray et al. 2001; Grubesic 2006) and lend an air of simplicity to their depictions of these complex relationships. For example, the innate appeal of a crime hot-spot map is the perception that the visualized patterns encapsulate an accurate representation of underlying crime vectors, events and intensity. Kernel density maps (McLafferty et al. 2000) and maps produced with local indicators of spatial association (Mencken and Barnett 1999; Messner et al. 1999) are good examples of pattern visualization techniques that are both visually pleasing, relatively simple to generate, yet provide a valuable perspective on spatial patterns of crime. In the spirit of exploratory data analysis, this paper will utilize a suite of spatio-temporal methods for evaluating the space–time footprints of burglaries, assaults and robberies in an urban environment. The focus of this study is to examine spatio-temporal patterns of crime and if these patterns exhibit variation by crime type. In other words, do space–time footprints differ across crime type?

## Spatio-Temporal Approaches

While the criminological literature recognizes the importance of the joint treatment of spatial and temporal aspects of crime (Hakim and Shachmurove 1996; Ratcliffe 2002; Ratcliffe 2004; Ratcliffe 2005; Ratcliffe 2006), this does not necessarily equate to recognition of spatio-temporal interaction. Therefore, it is important to establish a working distinction between explicitly spatial and temporal approaches to hot-spot analysis and spatio-temporal interaction. As noted previously, spatio-temporal approaches for identifying crime hot-spots are actually tests of space–time interaction. These methods evaluate whether there is space–time clustering after adjusting for both purely spatial and purely temporal effects (Kuldorff and Hjalmars 1999). Tests for space–time interaction were developed for use in epidemiology to examine patterns in infectious and non-infectious disease cases (Jacquez 1996). In this context, the interaction of space and time for clustering is relatively well-understood. In most instances, the spatial clustering of a disease over a short period of time is related to (1) the degree of infectiousness, or (2) a transient environmental hazard (Marshall 1991).

Although the implementation of space–time tests for crime analysis holds much promise, its interpretation is more complex. Perhaps the most intuitive way to conceptualize spatio-temporal interaction as it pertains to crime is to separate each crime event into its respective spatial and temporal components. For example, if space is held constant, there are several unique temporal elements or categories of crime worth mentioning; this includes crime series, crime sprees, and crime trends. A *series* is a group of similar crimes committed by the same individual(s) against single or multiple victims (Velasco and Boba 2000), such as a house that is repeatedly burgled by an offender. A crime *spree* typically involves the same offender(s) committing a high number of crimes over a relatively short period of time (hours or days). This might include burgling 10–15 houses in a neighborhood over the span of 2 days. Finally, a crime *trend* is represented by an increase or decrease of a certain crime or groups of crimes in an area over time. This often corresponds, for example, to monitoring the burglary rate for a given neighborhood over a 5 year time-span. Exceptions to these temporal classifications of crime do exist. For instance, there may be a noticeable increase in the number of robberies around a bar or tavern immediately after closing time (Roncek and Maier 1991). While these crimes occur about the same time, they are not necessarily indicative of a serial, spree or trend pattern. Ratcliffe (2004) labels such an area as an *acute hotpoint*.

If time is held constant, there are also several spatial elements to consider. First, the spatial distribution of offenders and targets can vary dramatically between places. This spatial variation is a primary consideration within the theoretical constructs of environmental criminology and routine activity theory. Differences in the socioeconomic structure of places (Sampson and Groves 1989), demographic composition (Morenoff et al. 2001) and many other factors contribute to these spatial variations. Hot-targets and hot-products, are two examples of a more specific spatial representation of crime events. A hot-target is an individual, single residence, business or other location that has suffered repeated crime events (Velasco and Boba 2000). A hot-product refers to a specific type of property that is the target of crime (e.g. bicycles).

A final concern is the propensity for space and time relationships to compress when travel (i.e. journey to crime) is involved with a criminal offense (Rengert 1989; Warren et al. 1998; Levine 2007). Because both offender motivation and the space–time activity patterns associated with crime events change dramatically when travel is involved, the fundamental relationships between space and time can be altered. For example, when considering crime travel demand modeling, Levine (2007) notes that incidents occurring closer to an offender's home suggest chance encounters while incidents further away suggest a planned event.

This decomposition of spatio-temporal interaction is important, particularly in the context of understanding and interpreting the results of space–time tests, the subtle differences of which are addressed in later sections. Moreover, there is a need for developing a stronger linkage between spatio-temporal statistical approaches, criminological theory and practice. Not surprisingly, the most fundamental problem that analysts must deal with in this domain is selecting and implementing the appropriate statistical and visualization techniques for uncovering spatio-temporal relationships. When performed correctly, the end product can provide insight into newly emerging crime trends and their positionality in space and time. When performed incorrectly, the generated analysis produces information that is misleading to analysts and may introduce inefficiencies into the law enforcement system. In an effort to explore these issues and develop additional clarity regarding spatio-temporal approaches and their utility, the next section explores the statistical foundations of two space–time techniques, the Knox test and the Jacquez *k*-nearest neighbor test. Functional comparisons are provided in an empirical analysis of crimes in Cincinnati, Ohio in "Case Study: Cincinnati, Ohio".

## Space–Time Interaction for Crime

### Data Requirements

One of the most important considerations in determining the appropriate spatio-temporal method for exploratory crime analysis is the nature/form of the data available for testing. Typically, inputs for spatio-temporal analysis are either individually geocoded event data (micro-level), or data in aggregate (group) form, such as a Census block groups, or patrol zones (macro-level). Polygonal units are usually represented as centroid points for analysis and the temporal components correspond to a pre-defined time interval. Popular group-level tests used to identify excess crime events in space and time are Kuldorff's Scan (Kuldorff and Nagarwalla 1995; Kuldorff et al. 1997) and Grimson's method (Grimson 1989; Grimson and Rose 1991). Individual level data are somewhat different than group level data because they correspond to discrete crime events that are assigned latitude and longitude coordinates and a time-stamp of when the event occurred or was reported. If individual-level data are available for analysis, spatio-temporal test options include the Mantel test, the Knox test and the Jacquez *k*-nearest neighbor test.[1]

The selection of the appropriate test for the detection of space–time interaction depends not only upon the available data, but the appropriate geographic and temporal scales for the

[1] The Mantel test is widely used in epidemiology and has been applied to space–time analyses of burglary (Johnson and Bowers 2004b), but will not be used in this analysis. Although the Mantel test does not require the specification of a critical space and time distance, it does require the subjective selection of a constant to use in the Mantel recommended transformation (Jacquez 1996). An argument in favor of the Mantel test could be made because of its insensitivity to edge effects (Johnson and Bowers 2004b) however, a Monte Carlo approach to the Knox test (which is used in this study) has been shown to minimize edge effects (Johnson et al. 2007).

analysis. Group level data for example, allow for more robust measures for estimating populations at risk and tying socioeconomic and demographic data to criminal activity. However, these data are not able to detect events or trends "internal" to the defined scale of analysis. Therefore, a more detailed analysis of crime activity in a particular area would make use of individual level data to achieve the desired level of detail. In the subsections that follow, the details of two individual data tests, the Knox test (1964) and the Jacquez *k* nearest neighbor test (Jacquez 1996), will be discussed. The discussion of these tests will be followed by an analysis of crime event point data for Cincinnati neighborhoods in 2003.

## Knox Test

Although originally developed to detect space–time interaction for disease events, the Knox test (Knox 1964) is also applicable to crime event data. For a set of geocoded crime events with a corresponding time-stamp, a test for spatio-temporal interaction can be conducted. Given a number of crime events in the study area, $n$, all possible $n(n-1)/2$ pairs of events are tested for spatial and temporal distances that fall within the critical time and space distances specified by the analyst (Williams 1984).[2] If the resulting test statistic is large enough, the null hypothesis of a random distribution of crime events may be rejected in favor of spatio-temporal interaction. For instances when events are close in space only, time only, or neither, the null hypothesis is confirmed. These relationships are often summarized and displayed in a 2 × 2 contingency table (Fig. 1). The Knox test is formulated as follows:

$$X = \sum_{i=1}^{n} \sum_{j=1}^{i-1} a_{ij}^{s} a_{ij}^{t} \tag{1}$$

where $n$ = number of cases; $\delta$ = critical space distance; $\tau$ = critical time distance

$$a_{ij}^{s} = \begin{cases} 1 & \text{if the distance between cases } i \text{ and } j < \delta \\ 0 & \text{otherwise} \end{cases}$$

$$a_{ij}^{t} = \begin{cases} 1 & \text{if the distance between cases } i \text{ and } j < \tau \\ 0 & \text{otherwise} \end{cases}$$

One of the less appealing aspects of the Knox test is the subjectivity of specifying the critical space and time distances.[3] However, there are occasions where $\delta$ might reflect a known distribution or distance relationship for a particular type of crime. Johnson and Bowers (2004a), for example, suggest that repeat burglaries tend to cluster within one to 2 months and within 300–400 m of a prior burglary. In this instance, $\delta$ can be adjusted to reflect an established distance range in an effort to confirm or reject the null hypothesis of no clustering. The critical time distance, $\tau$, works in a similar fashion and can be adjusted to reflect events occurring within hours, days or months of each other.

[2] Critical distances represent a subjective threshold value that dictates the spatial and temporal distances where events are defined as "close" in space and time.

[3] The subjectivity issue is not specific to the Knox test, but is also a problem for other methods used in crime analysis. A good example is the selection of the appropriate number of groups in hierarchical or non-hierarchical cluster analysis.

| | | SPACE | |
|---|---|---|---|
| | | Close | Not Close |
| TIME | Close | Space and Time | Time Only |
| | Not Close | Space Only | Not Close |

**Fig. 1** Knox Test 2 × 2 contingency table

Jacquez *k*-Nearest Neighbor Test

The second test of spatio-temporal interaction is the Jacquez *k*-nearest neighbor test (*k*-NN) (Jacquez 1996). As the name suggests, this method is based on nearest neighbor distances, a relatively popular approach for examining crime point patterns (Cromwell et al. 1999; Ratcliffe 2005). The nearest neighbor metric is a simple proximity measure that can be conceptualized as follows. Given a set of points on a plane, we define $k$ to be the number of nearest neighbors being considered, and $n_{ij}$ to be 1 if point $j$ is a $k$ nearest neighbor of point $i$, 0 otherwise. The matrix of nearest neighbors, $\boldsymbol{N}$, has elements $n_{ij}$ that equal 0 or 1, with row sums equal to $k$. A similar process is used to define temporal nearest neighbors, see Jacquez (1996) for more details. Spatio-temporal neighbors are those elements of the resulting matrix that contain a "1" when the space and time matrices are multiplied together. The Jacquez test statistic is as follows (Jacquez 1996):

$$J_k = \sum_{i=1}^{n} \sum_{j=1}^{n} n_{ijk}^{s} n_{ijk}^{t} \tag{2}$$

where: $n$ = number of events; NN = nearest neighbor; $k$ = the set of events as near or nearer to an event than the $k$th NN

$$n_{ijk}^{s} = \begin{cases} 1 & \text{if event } j \text{ is a } k \text{ NN of event } i \text{ in space} \\ 0 & \text{otherwise} \end{cases}$$

$$n_{ijk}^{t} = \begin{cases} 1 & \text{if event } j \text{ is a } k \text{ NN of event } i \text{ in time} \\ 0 & \text{otherwise} \end{cases}$$

As outlined above, the statistic $J_k$ is a cumulative measure that counts the number of crime events that are $k$ nearest neighbors in both space and time. Interestingly, $J_k$ are not independent because all pairs of events included in smaller neighborhood definitions, $k$, are also included in subsequent, larger values of $k$. For example, as $k$ increases from three to four, all event pairs that were included in $k = 3$ are also included in $k = 4$. Thus, larger values of $k$ suggest increased levels of spatio-temporal interaction, which is not surprising given the increased likelihood of becoming a space–time neighbor as the number of events increase in the space and time matrices. To account for this statistical issue Jacquez (1996) provides a test statistic for measuring time–space interaction beyond that found for the $k-1$ nearest neighbors:

$$\Delta J_k = J_k - J_{k-1} \tag{3}$$

The $\Delta J_k$ tracks any increases in the number of space–time nearest neighbors as $k$ is increased and unlike the $J_k$, the $\Delta J_k$ are statistically independent. In other words, if one was to change the neighborhood definition by increasing the number of neighbors under consideration (e.g. three to four), Eq. 3 monitors these changes for significance.

An interesting aspect of the $k$-NN test is its ability to track a sequence of identical events through time. In an epidemiological context, this is often referred to as a "chain" of cases (Jacquez 1996). The chain begins with an index case and is spread through a contagious process to other cases. One can easily generalize this concept of relating chains of disease cases to crime sprees and/or series. In this instance, a single individual or small group of criminals commit a string of related crimes that display a strong spatio-temporal link, which is often the case with repeat burglary (Townsley et al. 2003). The next section explores the utility of the Jacquez and Knox tests for detecting space–time interaction between crime events. This includes both a functional and graphical evaluation of the Knox and Jacquez $k$-NN tests.

## Case Study: Cincinnati, Ohio

Comparative results for the two spatio-temporal tests will be presented across a range of critical space and time distances. Application data include three different sets of crime events from seventeen neighborhoods (CAGIS 2006) in Cincinnati, Ohio for the year 2003.[4] These data include information about the date of the crime,[5] the UCR code corresponding to the crime, and the address of the crime. These data were acquired from the Cincinnati Police Department (CPD 2003) and geocoded using Centrus Desktop 4.0 (Centrus 2006). Both ArcGIS 9.1 and ArcView 3.3 were implemented to manage, manipulate and analyze the crime observations. ClusterSeer 2.2 (ClusterSeer 2006) was utilized for statistical calculations, including the tests of spatio-temporal interaction. Figure 2 illustrates the study area for the analysis. Boundary polygons correspond to Census 2000 block groups (U.S. Census Bureau 2000).[6]

### Jacquez $k$-Nearest Neighbor Test: Results

Results for the $k$-nearest neighbor tests are highlighted in Fig. 3. Figure 3a displays the number of space–time crime event pairs for $k = 1$ through $k = 13$. In this instance, the total number of space–time nearest neighbor pairs is a function of the spatial and temporal distribution of each crime type (burglary, robbery and assault) in the study area. Differences between these distributions are clearly reflected by displayed event-pair curves. Figure 3a suggests that burglary has more space–time crime event pairs than assault or robbery through $k = 13$, indicating a more clustered spatio-temporal pattern.[7] However,

[4] 2,810 assaults includes UCR codes 400, 401, 432, and 810. 1,268 robberies includes UCR codes 301, 303, and 304. 1,489 burglaries includes UCR code 551.

[5] Crime events are assigned a date only. Time of day for these crimes was not available.

[6] All geographic data are projected to the Ohio State Plane coordinate system using North American Datum 1983 and are measured in meters.

[7] It is possible for there to be more nearest neighbors than the total number of crime events. Theoretically, each crime event can have $n-1$ nearest neighbors in space and $n-1$ nearest neighbors in time. If all of the potential events are nearest neighbors in both space and time, $n-1 = 1{,}267$ in the case of robbery, there are a theoretical $(n-1)(n-1)$ or 1,605,289 space–time $k$-nearest neighbors.

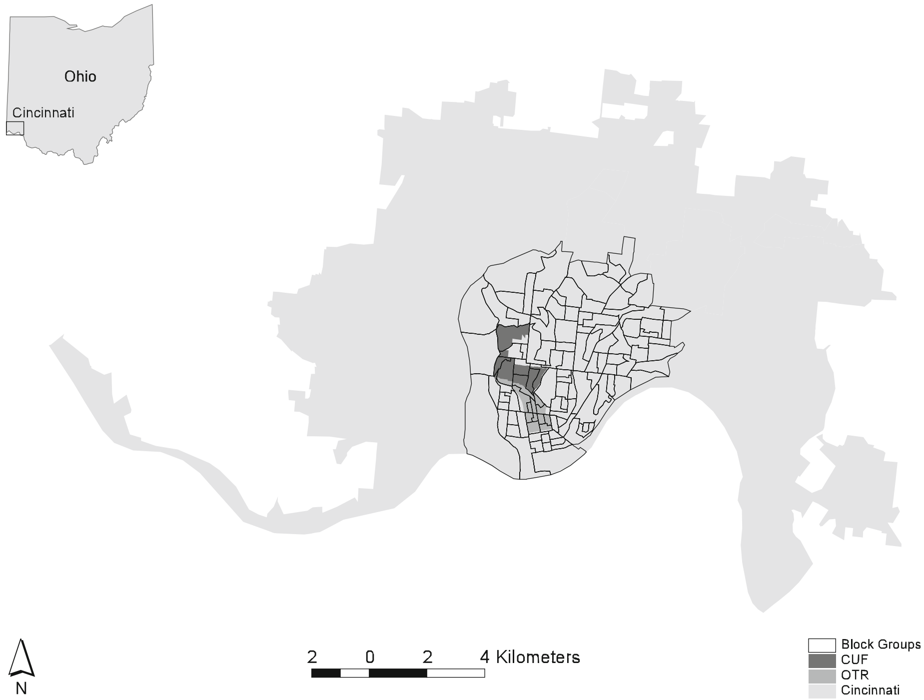


**Fig. 2** Study area: 14 neighborhoods in Cincinnati, Ohio

the results of Fig. 3a must be considered in context with those displayed in Fig. 3b, which illustrate values for each $\Delta J_k$. While burglary maintains significance throughout the testing procedure, assault does not become significant until $k = 2$, and robbery does not become significant at the 95% level until $k = 3$.[8] Jacquez (1996) suggests that this is one way to diagnose the scale of the spatio-temporal clustering process. Simply put, this result suggests that robbery begins to cluster at a different spatio-temporal scale ($k = 3$) than burglary ($k = 1$) or assault ($k = 2$).

Theoretically, there is some justification for this. The presented empirical evidence broadly supports the near-repeat victimization hypothesis (Johnson et al. 1997; Townsley et al. 2003; Johnson and Bowers 2004a; Bowers and Johnson 2005), which suggests that some degree of space–time regularity exists for burgled residences (300–400 m for 1–2 months). While the $\Delta J_k$ test will not allow for this type of spatial or temporal specificity in the reported results, the fact that burglary events in Cincinnati have significant spatio-temporal interaction with their first-order nearest neighbors suggests that closeness in space and time exists between events. As noted by Johnson and Bowers (2004a), one strategy employed by burglars is to maximize reward while minimizing time spent within any single residence. This can often lead to an initial burglary at one property, followed by

[8] Results for burglary and assault are not shown due to space limitations.

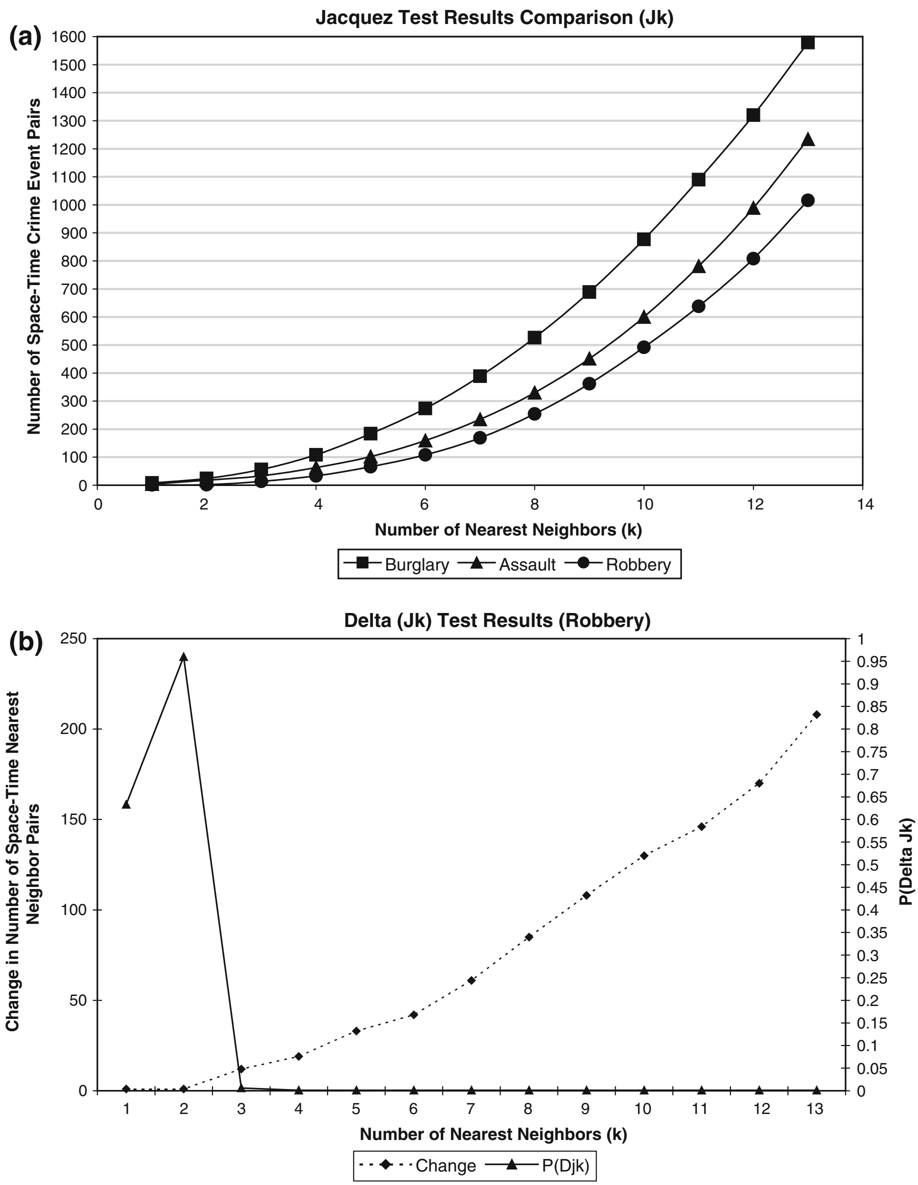


**Fig. 3** Results of the Jacquez *k*-nearest neighbor tests

subsequent burglaries at neighboring properties. This particular strategy often leads to short-run outbreaks of burglaries, close in both space and time.

The picture is somewhat different for assaults and robberies. While spatio-temporal clustering exists, it occurs at slightly different scales. This difference is an important one and is indicative of a dissimilar spatio-temporal signature for these types of crimes. Where assaults and robberies are concerned, Sherman et al. (1989) demonstrate that concentrations of predatory crime often occur near bars, taverns, bus stops and homeless shelters. These types of facilities have a different spatial distribution than residences, and thus, the crimes committed in these locations have unique temporal characteristics. This impact of the spatial distribution of locations where robbery and assaults are commonplace is perhaps the reason the spatio-temporal signatures detected by the Jacquez *k*-NN test for robbery and assault are different than burglary. Ratcliffe (2004) provides a relatively broad conceptual framework for evaluating the space–time characteristics of crime for policing purposes, differentiating between spatial patterns (dispersed, clustered, hotpoint) and temporal patterns (diffused, focused, acute). Under these auspices, residential burglary clusters in Cincinnati *might* be categorized as "clustered/acute", although assaults and robberies are less easy to label. Clearly, spatial scale and distributions of criminal activity play an important role in the interpretation of space–time test results. A simple classification of the spatio-temporal interaction of crime events as "clustered/acute" based on the $\Delta J_k$ test might be too presumptive. A more exacting measure of the distances and times associated with significant space–time interaction, as indicated by the Jacquez test, need to be devised. In this regard, the Knox test is less ambiguous.

### Knox Test: Results

A comparative assessment for spatio-temporal interaction is displayed for robbery, assault and burglary in Fig. 4. As noted in Knox Test, the critical time and distance parameters of the Knox test can be adjusted for exploratory purposes or to account for a known spatial/temporal distribution of crime. In this instance, Fig. 4a highlights the spatio-temporal clustering for each of the three crime types when time is held constant at one day ($\tau = 1$) and the critical distance, $\delta$, is varied.[9] The statistical significance of each test, which were obtained from a Monte Carlo simulation ($n = 1{,}000$), is displayed on the *y*-axis and the critical spatial distance (meters) for each test is displayed on the *x*-axis. There are three notable results apparent in Fig. 4a. First, burglary is statistically significant at the 95% level at nearly every critical distance until the simulations reach 3 km. Second, while assault is significant at relatively shorter distances, $\delta = 161$, 201, 268 and 402 m, it loses its significance beyond 800 m. Finally, unlike assault and burglary, the statistical significance of robbery appears to be more variable at smaller distances, but more stable at larger distances. Interestingly, this corroborates the results of the $\Delta J_k$ test for spatio-temporal interaction.

For comparative purposes, a critical distance where each crime type exhibited significant space–time interaction (201 m) is illustrated in Fig. 4b. The graph shows the varied behavior of burglary, assault and robbery when distance is held constant (201 m) and the critical time value varied. Once again, while burglary is significant throughout, the results for assault and robbery are quite different. Although the spatio-temporal clustering of robbery is significant at $\tau = 1$ ($P = 95\%$), it is not significant again until $\tau = 8$. Similarly, assault is only significant during days one and two. Although these tests represent a single critical distance measure, the differences between these three crime types are noteworthy.

To put this in more of a spatial context, Fig. 5 displays the spatio-temporal hot-spots of burglary for the study area at 201 m using a critical time measure of one day. All burglary

[9] The critical distances used in this study are in meters for comparative purposes with other studies (i.e. Johnson and Bowers 2004b). Theses critical distances correspond to various subdivisions of a mile (161 m = 1/10 mile, 201 m = 1/8 mile, 268 m = 1/6 mile, 402 m = 1/4 mile, 804 m = 1/2 mile, 1,207 m = 3/4 mile, 1,609 m = 1 mile).

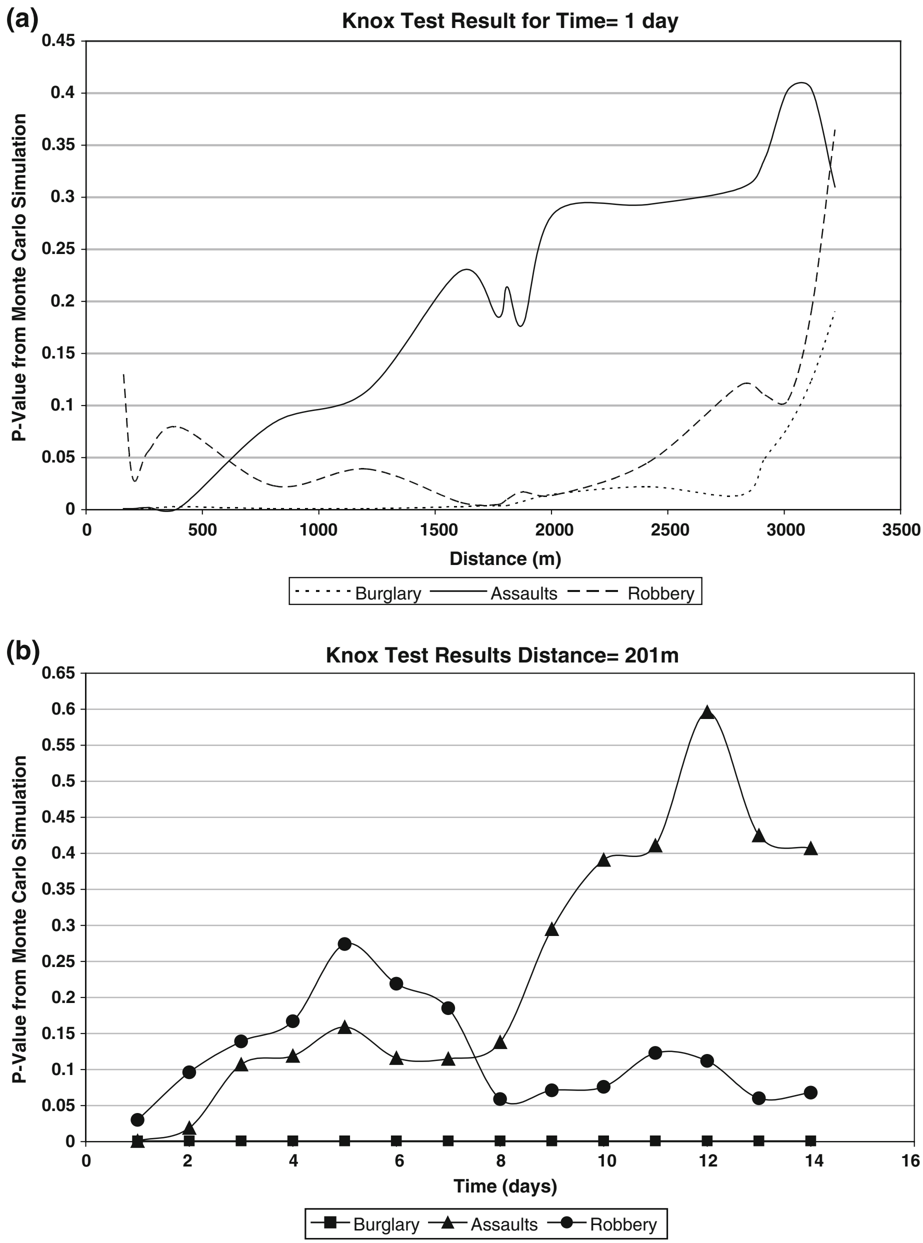


**Fig. 4** Knox test results for 1 day (distance varied) and 201 m (time varied)

events are displayed for the region, with events exhibiting spatio-temporal interaction linked by a line segment. From a cartographic perspective, there are two relatively well defined spatio-temporal hot-spots for burglary in the study area, Clifton Heights, University Heights and Fairview, commonly referred to as CUF, and Over-the-Rhine (OTR).

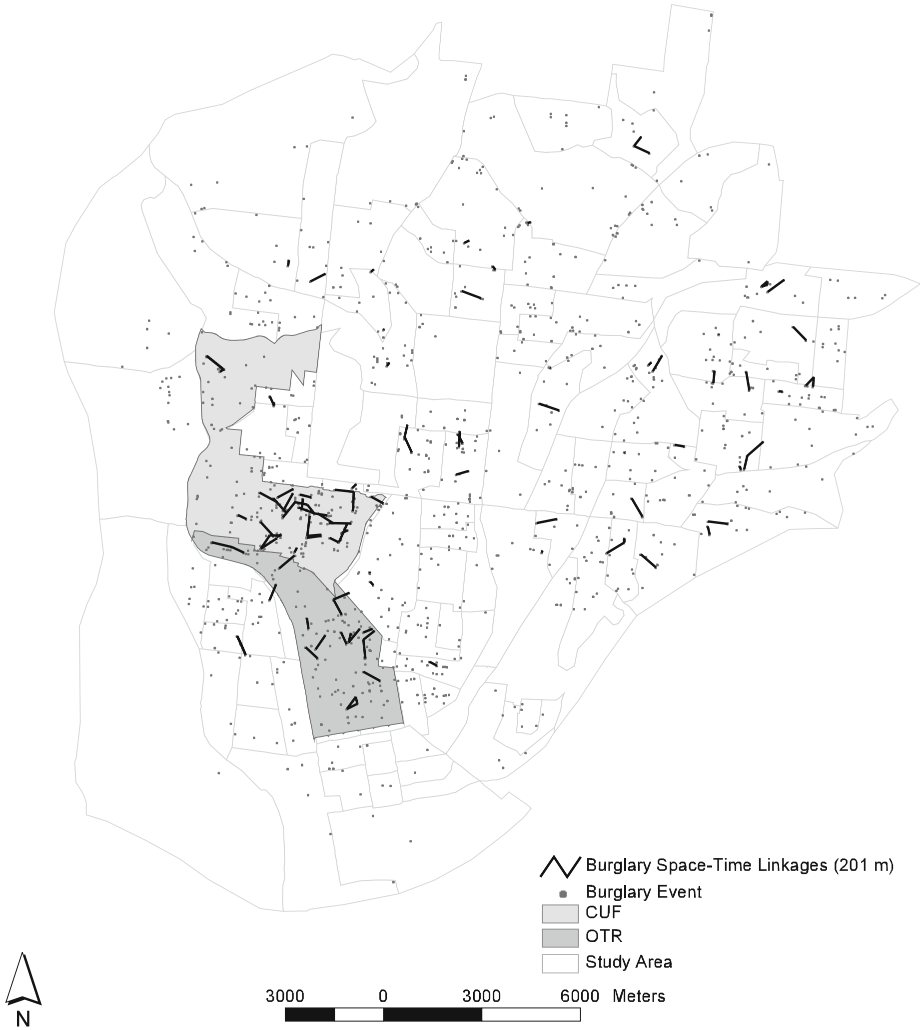


**Fig. 5** Knox test for spatio-temporal interaction of Burglary ($\tau = 1$ and $\delta = 201$ m)

Over-the-Rhine is the most problematic neighborhood for crime in the city of Cincinnati; in 2006, 23,000 calls for police service were made for this area (3CDC 2006).[10]

Considering this apparent need for service and the associated crime levels, the high degree of spatio-temporal interaction of burglaries is not particularly surprising for this area. Furthermore, given CUF's proximity to this high crime area, the high level of burglary in this neighborhood is also not surprising. The residential population of this area

[10] As a neighborhood unit, Over-the Rhine is extremely impoverished, with 95% of its residents living below the federal poverty guidelines. Recent estimates suggest the presence of 500 vacant buildings, 700 vacant lots and 1,667 vacant housing units (5,261 total) in the neighborhood (3CDC 2006). Although the data utilized for this analysis are from 2003, as recently as 2006, neighborhood residents requested that Cincinnati City Council declare a state of emergency in OTR in an effort to qualify for additional state and federal funds to fight crime (Osborne 2006).

is dominated by students attending the University of Cincinnati (enrollment ~38,000). Fisher and Wilkes (2003) note that, in general, the university student population closely parallels those who are at a high risk of being victimized. This factor, combined with CUF's proximal location to relatively high-crime neighborhoods[11] suggests that the spatial and temporal union between vulnerable targets and potential offenders increases the likelihood of victimization, (Cohen and Felson 1979) and the empirical results appear to provide some proof of this. By comparison, the spatio-temporal clustering of assaults is quite different (Fig. 6). Cartographic analysis suggests that the vast majority of these spatio-temporal hot-spots are located in Over-the-Rhine, but several secondary and relatively isolated pockets of spatio-temporal clusters also exist.

Finally, the spatio-temporal hot-spots of robbery are displayed in Fig. 7. In addition to a relatively large cluster in Over-the-Rhine and the northern reaches of downtown Cincinnati, there are smaller clusters in the Short Vine area and a fourth zone, known as Peebles Corner. In the 1950s and 60s, the Peebles Corner intersection was one of the primary public transportation hubs in the city and a relatively vibrant economic center. More recently, urban decline and economic disinvestment in this area largely mimics that of Over-the-Rhine. As a result, many of the same problems associated with crime in OTR also exist at Peebles Corner.

### Composite Knox-based Spatio-Temporal Interactions

A final battery of tests for spatio-temporal hot-spot detection is illustrated in Figs. 8–10, which show Knox-based spatio-temporal interaction tests for burglary, assault and robbery, in Cincinnati during 2003 for a select set of critical time and distance parameters. The figure displays differences between nine different critical space distances through a period of 14 days.[12] Critical space distances are organized into three bins reflecting small (161–268 m), medium (402–1,207 m) and large (1,609–1,810 m) distances. As with nearly every test conducted in this study, burglary is significant, regardless of space or time for Cincinnati (Fig. 8).

However, this is not the case for assault (Fig. 9) which has more spatio-temporal interaction at smaller distances within shorter spans of time. For example, Fig. 9 indicates that assaults cluster at 161, 201, 268 and 402 m during 1 or 2 day periods, with 161 m having the longest run of significant results (up to 9 days). Broadly interpreted, this suggests that spatio-temporal hot-spots of assaults are spatially localized in Cincinnati (161 m), occurring within approximately 9 days of each other.

Perhaps the most intriguing results are displayed in Fig. 10, which summarizes statistical simulations for reported robberies in Cincinnati. Clearly, there is significant variation between both critical distances and times for robbery, which is suggested by three notable trends. First, for small values of time ($\tau$), robberies exhibit spatio-temporal interaction for nearly all distances ($\delta$). Figure 10 suggests that distances of 201, 804, 1,207, 1,609, 1,770 and 1,810 are significant for either 1 or 2 days. Second, all critical distance simulations for robberies lose significance past a 4 day window, with 161 and 201 m returning to significance at day eight. Third, 804 m, a somewhat larger critical distance, returns to significance at day thirteen.

[11] See Fig. 2

[12] Readers should carefully note the values on each *y*-axis.

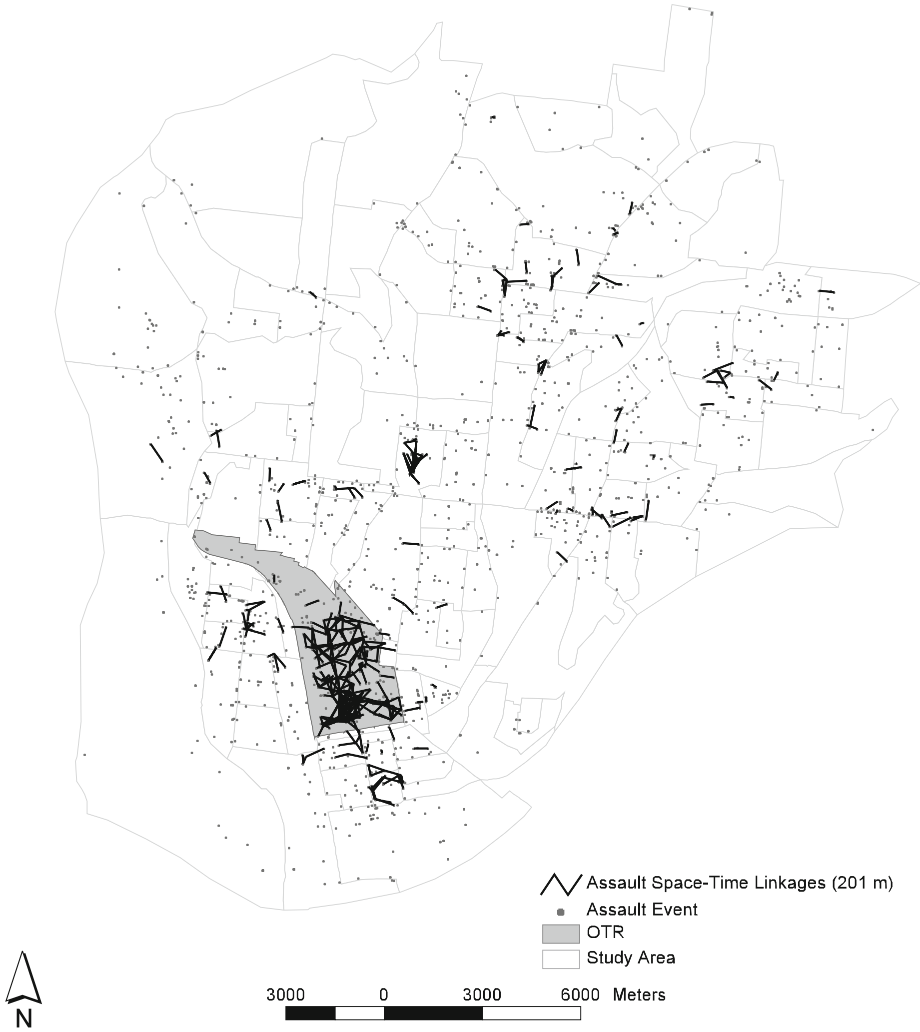


**Fig. 6** Knox test for spatio-temporal interaction of assault ($\tau = 1$ and $\delta = 201$ m)

Although the exploratory nature of this analysis is not able to completely explain these patterns, the results do conform to several well-known behaviors of robbers, particularly that of effort minimization and opportunity maximization (van Koppen and Jansen 1998; Harries 1980). Unless there is a major incentive to leave known territory, robbers typically stay close to home and engage easy, yet profitable targets. For the city of Cincinnati, this type of behavior must be set in the context of the larger literature on criminology. The likelihood of illicit activities often increases in neighborhoods ridden with socio-economic strife and in urban environments conducive to criminal behavior (Felson 1994; Brantingham and Brantingham 1981). In Cincinnati, there is nearly a complete correspondence between spatio-temporal hot-spots of robbery and these types of environments (e.g. Over-the-Rhine, Peebles Corner and portions of the CBD immediately adjacent to OTR). This


**Fig. 7** Knox test for spatio-temporal interaction of robbery ($\tau = 1$ and $\delta = 201$ m)

supports the well-known distance decay function for crime, particularly for robberies. However, by incorporating a temporal element into this exploratory analysis, specifically, measures of spatio-temporal interaction, a much richer picture emerges. Aside from the initial flurry of spatio-temporal interaction between 1 and 3 days, there is a relatively large gap in interaction between days four and eight, regardless of distance. Interestingly, these empirical results suggest possible ties to rational choice models of offending (Becker 1968). Criminals often weigh the expected utility of a crime, its potential returns and the probability of not getting caught, against the utility of returns, minus the punishment if caught (Matsueda et al. 2006). It is quite possible that potential perpetrators living within the neighborhood are aware of the establishments most recently robbed and avoid these locations and their proximal areas for a time because victimized businesses and the police

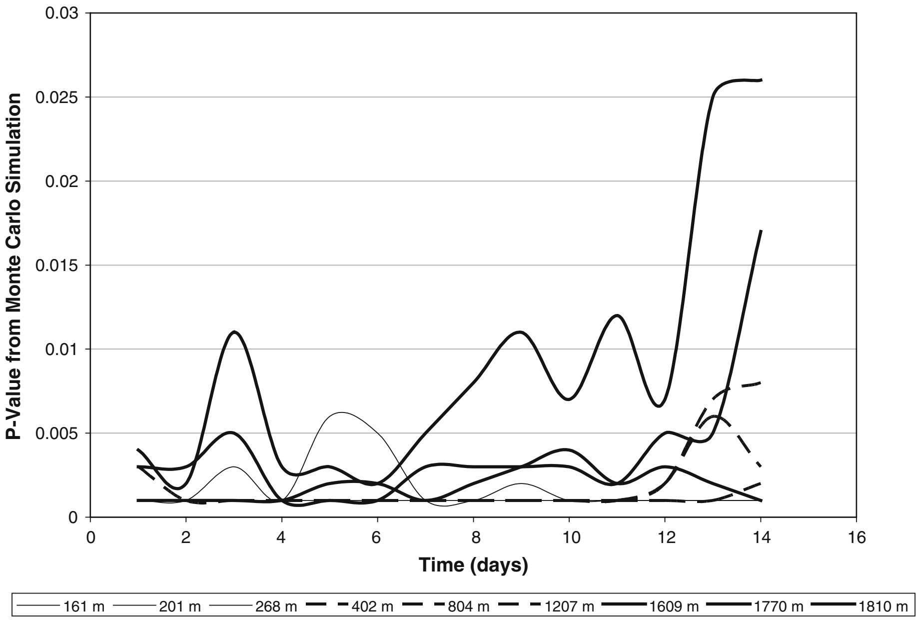


**Fig. 8** Spatio-temporal signature of burglary

are on high alert.[13] When the area is perceived to be "safe" again for committing robberies, another localized wave of events begins.

## Spatio-temporal Problems and Prospects

Given the evidence presented in "Case Study: Cincinnati, Ohio", it is important to discuss the problems and prospects in applying spatio-temporal tests to crime analysis. Where the *k*-NN test is concerned, there are several notable limitations. Although critical time and space distances need not be specified for the *k*-NN, elements of this test remain subjective given there is relatively little guidance provided for selecting the value of *k* to use in the analysis. Although the selection of *k* does not directly impact the performance of the statistic, like the critical time and space distances for the Knox test, the need to conduct a sensitivity analysis to examine changes in the statistical output generated by toggling values of *k* can be time-consuming and computationally burdensome. Further, there is no corresponding distance or time metric for *k* so it is difficult to evaluate the specific distances and times at which significant spatio-temporal interaction occurs. One can only say spatio-temporal interaction occurs over larger values of *k*, which are assumed to correspond to greater distance and time intervals. Clearly, this might not always be the case and is largely contingent on the existing spatial and temporal distribution of events in a study area. A solution to this issue has yet to be devised. Clearly, this lack of specificity is not desirable for crime applications given the importance of precision for detecting space–time

[13] This can also apply to patrons of a business, particularly if there have been robberies occurring during the closing time of a bar or tavern.

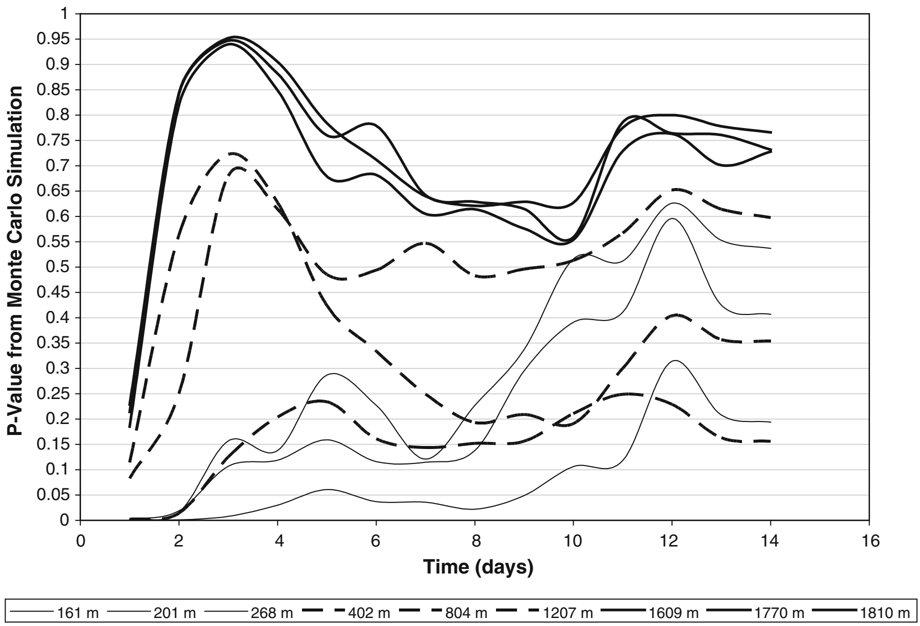


**Fig. 9** Spatio-temporal signature of assault

interaction. This is particularly salient given the vast differences uncovered in crime types and their associated spatial and temporal signatures illustrated in this paper.

The Knox test also has some relatively well-known limitations. As noted previously, the specification of critical time and space parameters can be subjective unless there is a well established time or space distance criterion for a particular crime event. Fortunately, in many instances, these parameters do exist. For example, a study of West Nile virus selected critical space and time parameters based upon the distance infected birds could travel and how long they survived (Theophilides et al. 2003). Also, the Knox test does not handle variations in population density particularly well because the critical space distance is invariant during the testing procedure. Therefore, the performance of this test can be questionable in areas where population densities vary dramatically. Finally, because the Knox test is fundamentally a Chi-square test, analysts run the risk of overestimating its significance when using probability values generated in the traditional manner. Levine (2004) notes that interaction between space and time is compounded when calculating a Chi-square statistic; it gets larger as the sample size increases. For instances where observations are independent, this does not typically occur. Given the spatial and temporal dependence of crime data however, analysts must address this statistical dependence through the use of Monte Carlo simulation to construct the distribution of the Knox statistic so that an accurate spatio-temporal test may be conducted (Levine 2004; Theophilides et al. 2003).

Clearly, issues of varying population distributions in a study area can pose problems for both the Knox and Jacquez *k*-NN tests. That said, when studies occur over a relatively short period of time in a small geographic area, the assumption of a constant population at risk may be valid (Aldstadt 2007). However, where large population shifts occur, these spatio-temporal tests can be biased (Kulldorff and Hjalmars 1999). An additional complicating

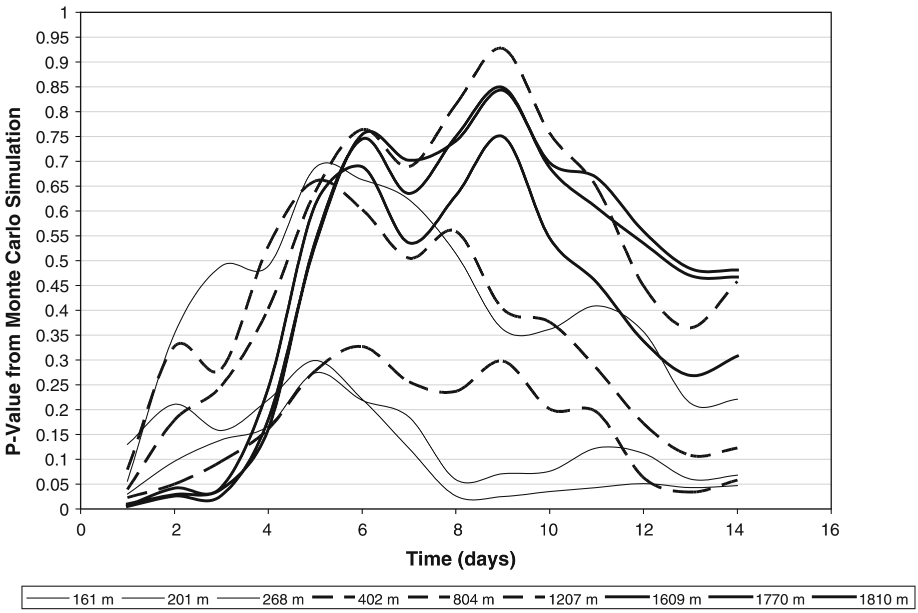


**Fig. 10** Spatio-temporal signature of robbery

factor is the potential "seasonality" influence on crime (Sutherland 1947). Where our study area is concerned, the population at risk in the CUF neighborhood, including areas adjacent to the University of Cincinnati, can vary based on the school calendar. While late September (the start of the Autumn quarter) represents an increased availability of targets, mid-July might represent a decreased availability of targets due to summer break. The same can be said for street robberies during the summer versus winter months.[14] Regardless, a comprehensive knowledge of the study area, including its population dynamics and environmental characteristics, is important for developing a robust and reliable testing methodology and for interpreting its output.

## Conclusion

As illustrated by this paper, burglary, robbery and assault were found to have relatively unique spatio-temporal signatures in Cincinnati. Despite some of the limitations associated with the outlined techniques for analyzing the spatio-temporal interaction of crime, the results of this exploratory spatial data analysis suggest that these approaches represent relatively informative alternatives to the more traditional hot-spot analysis methods. While they certainly cannot replace the more conventional, purely spatial or temporal methods of hot-spot analysis, the Knox and Jacquez *k*-NN tests are certainly complimentary, providing a valuable, alternative view of crime clustering. That said, more work is needed to determine how varying parameters (e.g. spatial and temporal scales) impact the statistical results derived by these approaches. Specifically, further research is needed to evaluate the robustness of the spatio-temporal interactions for burglary, robbery, assault and other

[14] For a more thorough review of crime seasonality, see Landau and Fridman (1993).

crimes across different spatial and temporal scales, through multiple years and alternative locations. Variations on the space and time inputs to the *k*-NN test may also be investigated as a way to overcome the ambiguity associated with its results.

Finally, given the results of this analysis, the process of isolating and exploring the different space–time footprints of burglaries, robberies and assaults, is a productive step in establishing stronger connections between criminological theories, methods and practice.

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