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ORIGINAL PAPER

# Exploratory Space–Time Analysis of Burglary Patterns

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**Abstract** This paper introduces two new methods for the exploratory analysis of the spatial and temporal dynamics of residential burglary patterns. The first is a conditional spatial Markov chain which considers the extent to which a location's probability of experiencing a residential burglary in a future period is related to the prevalence of residential burglaries in its surrounding neighborhood in an initial period. The second measure extends this conditional perspective to examine the joint evolution of residential burglary in a location and its surrounding neighborhood. These methods are applied to a case study of residential burglary patterns in Mesa, Arizona over the period October 2005 through December 2009. Strong patterns of spatial clustering of burglary activity are present in each year, and this clustering is found to have an important influence on both the conditional and joint evolution of burglary activity across space and time.

**Keywords** Space–time · Residential burglary · hotspots · Markov chain

## Introduction

Both space and time matter in the perpetration of criminal acts. Although variation exists across crime types, certain places are more prone to criminal activity at particular times of day than others (Lersch 2007). Environmental criminology (Brantingham and Brantingham 1984) and criminological theories, such as routine activities theory and optimal foraging theory, also suggest time and not space alone is a key factor in the perpetration of criminal offenses. The occurrence of a criminal event represents the confluence of a motivated offender, a suitable target, at the right time, in the right environment (Brantingham and Brantingham 1993). Despite this recognition of the need to consider both spatial and temporal aspects of crime, until recently, the joint consideration of both components of crimes has been passed over in favor of spatial approaches to crime analysis. Two reasons

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for this emphasis on spatial methods are the complexities associated with incorporating a temporal component to spatial data within geographic information systems (GIS) (Ratcliffe and McCullagh 1999; Lodha and Verma 2000; Ratcliffe 2002; Tompson and Townsley 2010) and the well documented lack of precision in the temporal aspect of recorded crime data (Ratcliffe 2000, 2002).

Despite the challenges presented by spatio-temporal data, advances in data collection, computer technology and statistical techniques have improved crime analysts' options for analyzing data with spatial and temporal components. Several studies have demonstrated the utility of a wide variety of techniques for analyzing crime events through space and time (Townsley et al. 2000; Ratcliffe 2004; Johnson and Bowers 2004a, b; Bowers and Johnson 2005; Brunsdon et al. 2007; Grubesic and Mack 2008). These same studies have also highlighted the situations in which particular techniques are most useful for crime analysis. Consequently, the range of techniques crime analysts now have to visualize and analyze crime data through space and time have improved dramatically. Options available now include space–time statistical techniques from epidemiology (Knox 1964; Mantel 1967; Jacquez 1996) that allow analysts to test for significant spatio-temporal interaction between crime events, as well as recently developed spatio-temporal mathematical models of crime (Short et al. 2008, 2010; Jones et al. 2010; Berestycki and Nadal 2010). Combined, these techniques offer great promise for pro-active and predictive policing, and have the potential to facilitate police interventions in existing crime hotspots, as well as anticipatory interventions in forecasted locations of future crime hotspots.

While these advancements have greatly facilitated the analysis and visualization of crime events through space and time, much work remains to continuously improve our ability to analyze crime from a spatio-temporal perspective. In particular, there are three potential avenues for improving existing methods for spatio-temporal crime analysis. One, statistical analysis and visualization of the analytical results are for the most part, mutually exclusive. For example, many of the existing techniques focus on the visualization of crime to the exclusion of the statistical aspect, or, they address the statistical aspect of crime to the exclusion of visualizing the results. Two, existing techniques provide a snapshot of crime at a particular time and place, but tend not to quantify changes in crime over space and time. A common approach to visualizing both the spatial and temporal dimensions of crime is to place hotspot maps next to one another for a locale of interest. While this provides a visual picture of crime trends over time, it does not quantify changes in crime from one time period to the next. A third issue with existing techniques is that they treat spatio-temporal interaction as a phenomenon isolated to a single moment in time. In reality, however, the level of crime in a particular place at one point in time influences its future level of crime, as well as the level of crime in neighboring areas. This influence of crime levels in previous time periods on future levels of crime in an area, and the level of crime in neighboring areas are largely overlooked in current spatio-temporal approaches to crime analysis. Therefore, the current challenge for statisticians, GIScientists, and crime analysts is to develop space–time statistical and visual techniques that consider the neighborhood context of crime across multiple time periods.

This paper is an effort to address two of these outlined issues in existing spatio-temporal methods for crime analysis. Using residential burglary data from Mesa, AZ, the paper illustrates two improvements to spatio-temporal techniques for crime data. First, it presents a technique that quantifies the role neighborhood context plays in the spatial dynamics of residential burglary patterns. Second, it suggests additional analytical measures that consider the joint evolution of burglary activity within and between spatial units. This is important because it treats spatial units as connected entities through time, rather than compartmentalized units, which is a better representation of the manner in which criminals move within a study area in response to evolving crime opportunities.

## Spatio-Temporal Dimensions of Criminological Theory

Criminological theory suggests a consideration of both the spatial and temporal dimensions of crime is essential to uncovering why some places are more prone to crime than others, and how this vulnerability to crime changes over time. In this regard, four related theories help explain the decision-making process of offenders and the occurrence of crime events: routine activities theory, rational choice theory, crime pattern theory, and optimal foraging theory. Combinations of these theories are currently being used in the development of models to examine the development of crime hotspots through time and space (Short et al. 2008, 2010). These theories are also invoked in analyses of repeat and near-repeat burglaries and victimization (Johnson and Bowers 2004a, b; Bowers and Johnson 2005; Ratcliffe and Rengert 2008; Short et al. 2009).

### Routine Activities Theory

Routine activities theory suggests that crimes are the result of the convergence of three things in both space and time: a likely offender, a suitable target, and the absence of a capable guardian (Cohen and Felson 1979). It is the convergence of these three things in the same space and at the same time that produces a crime event; the absence of any of these three elements prevents a criminal act from occurring. In this regard, changes in routine activity patterns of actors within an area affect the crime rate, as does the removal of any one of the three essential elements mentioned above (Cohen and Felson 1979). This implies that police can impact the crime rates in their jurisdiction by installing more capable guardians, reducing the number of likely offenders, or removing suitable targets from places where likely offenders congregate. It also suggests that the manner in which these three elements evolve over time impacts the level of crime in a particular area.

### Rational Choice Theory

While routine activities theory explains the occurrence of criminal events, it does not explain the decision making process of criminals; this is a process addressed by rational choice theory (Clarke and Cornish 1985; Groff 2007). In this regard, routine activities theory and rational choice theory may be considered compliments to one another. Rational choice theory is rooted in economic theory and assumes that people are rational utility maximizers that make decisions in order to maximize their utility (Herrnstein 1990). Therefore, all people, irrespective of the purported logic behind the decision, choose to consume goods and participate in activities that provide them with the most utility, ceteris paribus.

Some aspects of this theory are criticized, such as the perfect information assumption, and the assumption that people are capable of comprehending a wide variety of factors prior to making complex decisions. Nevertheless rational choice theory is widely applied across numerous behavioral disciplines (Herrnstein 1990). In the context of criminology, rational choice theory views the actions of criminals as the outcome of a decision-making process that considers the opportunities, costs, and benefits attached to each criminal act (Cornish and Clarke 1987). The act of committing a crime therefore reflects a criminal's efforts at maximizing their utility, albeit a perhaps deviant utility. Rational choice theory is not only a tool to understand the decision making process of criminals, but a theory that may be leveraged to understand the impacts of crime prevention efforts. Cornish and Clarke (1987) demonstrate how misperception of the criminal decision-making process can result in the development of inefficient crime prevention efforts. Their study demonstrates that incorrect perceptions of criminal decision-making can actually result in the displacement of crime from one area to another rather than the elimination of crime.

### Optimal Foraging Theory

A similar concept to rational choice theory is the behavioral ecology theory of optimal foraging (Krebs and Davies 1987, 64–66). Frequently used to examine repeat and near-repeat events (Johnson and Bowers 2004b; Bowers and Johnson 2004; Johnson et al. 2007, 2009; Brantingham and Tita 2008; Short et al. 2010), the basic tenet of this theory is that actors seek to maximize reward and minimize risk when foraging for an object of interest. In an ecological context, this means that animals seek to forage for as much food as possible while minimizing the time spent foraging for food and also the risk of being attacked or eaten (Krebs and Davies 1987, 64–66). For criminals, particularly burglars, this theory translates into targeting houses that represent the greatest possible reward but also minimize their risk of arrest (Johnson and Bowers 2004b). Repeat and near-repeat victimization are believed to be expressions of foraging behavior because the households targeted correspond to the ideal target in the mind of the offender (Johnson et al. 2007). A property is first burgled because of its potential for maximum reward with minimum risk. The same property, or nearby properties are then frequently at risk for additional burglaries because of the information the offender gained from the first burglary (Johnson and Bowers 2004a; Johnson et al. 2007). Given this additional knowledge of the risks and rewards associated with the initially burgled property and nearby properties, offenders are more likely to return to that location, rather than burgle other relatively unknown properties (Johnson et al. 2008).

## Spatio-Temporal Analyses of Crime

Several visualization and modeling approaches leverage the criminological theories discussed above when analyzing crime through space and time. Over the years, these approaches range from variations on the techniques suggested by Hagerstrand (1970) in his time geography, to sophisticated mathematical models of crime hotspots (Short et al. 2008, 2010; Brantingham and Tita 2008; Berestycki and Nadal 2010). These myriad approaches to unlocking the decision making processes of criminals given the right environmental conditions, and the presence or absence of the necessary actors suggested by routine activities theory, may be grouped into four categories: space–time visualization of crime, spatio-temporal tests of interaction, mathematical models of crime, and studies that emphasize change in spatio-temporal trends in crime. This section will discuss each of these spatio-temporal approaches to crime analysis before proceeding to a discussion and demonstration of the statistical approaches developed in this paper in "Exploratory Space–Time Analysis of Burglaries".

### Spatial Studies of Crime

Spatial studies of crime have yielded several important insights about the location and intensity of criminal activity (Cohen and Tita 1999; Tita et al. 2005; Tita and Ridgeway

2007; Livingston 2008). These studies recognize that crime is unevenly distributed across space and seek to uncover areas of elevated crime so that appropriate intervention and prevention strategies may be designed. They also recognize the influence of surrounding areas on the criminal activity of a particular location. Although criminologists have a long history of interest in spatial aspects of crime data, which has origins in nineteenth century French social ecologists and the Chicago School of sociology, spatial analysis of crime events has advanced dramatically in recent decades with advances in computer based mapping applications and GIS (Anselin et al. 2000). A wide variety of methods are now available for spatial analysis of crime (Harries 1999; Anselin et al. 2000).

Spatial analytical methods for crime may be subdivided into two categories, exploratory and confirmatory analyses (Bernasco and Elffers 2010). Exploratory analyses may be used to explore data and suggest hypotheses about crime that are worthy of additional research (Messner et al. 1999). Confirmatory approaches are used to test specific relationships of interest or hypotheses about crime. Over the years, both exploratory and confirmatory approaches have provided valuable information about the distribution of crime, and the factors that encourage and prevent crimes. Exploratory approaches are commonly used (Harries 1999; Messner et al. 1999; Murray et al. 2001; Eck et al. 2005; Ye and Wu 2011) to locate elevated areas of crime and generate hypotheses about the cause of this increased incidence of crime. For example, Cohen and Tita (1999) used exploratory spatial analytical techniques to find evidence of spatial diffusion in Pittsburgh homicides.

Spatial regression is a commonly used confirmatory technique that has increased in popularity since its introduction in 1988 (Bernasco and Elffers 2010). This technique has been utilized extensively to examine the influence of particular variables on different kinds of crime activity and provide support for particular criminological theories (Anselin and Hudak 1992; Baller et al. 2001; Messner and Anselin 2004; Lawton et al. 2005; Andresen 2006; Porter and Purser 2010). For example, Baller et al. (2001) used spatial regression models to examine the explanatory factors behind county level homicide rates. This approach uncovered spatial clustering of homicides, as well as regional differences in the impact of explanatory factors on homicide rates. Despite the utility of spatial approaches, these studies are inherently cross sectional and static in nature.

## Space–Time Visualization of Crime

A range of techniques for spatio-temporal analyses of crime have extended these spatial approaches, yet these techniques vary widely in their purpose. Some seek to provide explicit visual evidence of changes in crime trends, while others are purely exploratory in nature. Other techniques use statistical tests from epidemiology or sophisticated mathematical models to predict the behavior of criminals and hotspots through space and time. Although the latter two techniques represent more technical and sophisticated approaches to spatio-temporal crime analysis, many studies still rely on visual comparisons of hotspot maps to evaluate changes in crime trends through space and time. Typically, outputs from an analysis are displayed together to highlight the change in appearance of crime trends in an area for a particular study period. For example, it is common to produce hotspot maps of crime at two points in time and display their results together to visualize changes in crime intensity over time within a study area (Eck et al. 2005; Xie and Yan 2008). Although some studies are beginning to emphasize techniques that quantify change in crime over time (Johnson et al. 2008; Berk and MacDonald 2009; Nakaya and Yano 2010; Tompson and Townsley 2010), these efforts often provide a summary measure of crime levels within a study area and do not currently address localized changes in crime trends.

This section discusses current approaches to spatio-temporal crime analysis, which may be placed into four primary categories. Category one is comprised of taxonomic approaches that seek to compare the strengths and weaknesses of the myriad exploratory techniques available to crime analysts. Category two is comprised of studies that leverage tests for spatio-temporal interaction from the epidemiology literature. Category three consists of sophisticated models developed by mathematicians and physicists that seek to model the behavior of criminals and subsequent crime hot-spots through space and time. Category four is comprised of studies that seek to quantify changes in crime trends through space and time.

### Taxonomic Approaches

A vast number of exploratory approaches with applicability to crime analysis have been developed in the statistics and geographic and information systems literature (Eck et al. 2005) as well as the computer science, geovisualization and geocomputation literature (Moellering 1976, 1980; MacEachren and DiBiase 1991; MacEachren et al. 1998; Brunsdon 2001; Harrower and Fabrikant 2008; Kalnis et al. 2005; Rey and Janikas 2006). Examples of exploratory approaches include work by Brunsdon et al. (2007) and Townsley (2008). The Townsley study used a hotspot plot to visualize space–time patterns while the Brunsdon et al. (2007) study used three visualization tools, map animation, the comap, and the isosurface to explore spatio-temporal patterns in crime data.

Due to the voluminous literature and exploratory techniques now available for crime analysis, studies have sought to add clarity to the literature by developing taxonomies of the myriad statistical and visual techniques developed in past years. Taxonomic approaches to spatio-temporal visualization include work by Ratcliffe (2004) and Chung et al. (2005). Ratcliffe proposed a conceptual framework for use in policing to differentiate between spatial patterns (dispersed, clustered, hotpoint) and temporal patterns (diffused, focused, acute) crime patterns. A study by Chung et al. (2005) takes the taxonomic approach one step further and constructs a taxonomy of visualization tools and techniques to evaluate an existing coordinated event visualization tool developed by Buetow et al. (2003), the COPLINK Spatio-Temporal Visualizer (STV). The Chung et al. (2005) taxonomy considers multiple attributes of existing techniques including the dimensions of the events analyzed (spatial, temporal, content, people), the applications of the event visualization, and the objects used to represent the events.

### Tests for Spatio-Temporal Interaction

Studies evaluating the spatio-temporal dynamics of crime via tests for space–time interaction (Johnson and Bowers 2004a, b; Bowers and Johnson 2005; Johnson et al. 2007, 2009; Grubesic and Mack 2008) improve upon the purely visual and/or exploratory techniques mentioned above. Tests for spatio-temporal interaction of crime are borrowed from epidemiology (Jacquez 1996) and test whether events cluster in both space and time after adjusting for purely spatial and purely temporal clustering (Kulldorff and Hjalmars 1999). The most commonly used tests are the Knox test (Townsley et al. 2003; Johnson and Bowers 2004a, b; Johnson et al. 2007, 2009; Grubesic and Mack 2008) and the Mantel test (Johnson and Bowers 2004a, b; Bowers and Johnson 2005). The advantage of these tests is that they can quantify the spatial and temporal scales at which interaction in space and time are occurring. For example, the Knox test can state whether events separated by a distance of 1 mile and 2 days are close together in space and time. This kind of information is important because it can provide valuable clues about criminals committing particular offenses; whether it is one person or multiple individuals (Grubesic and Mack 2008). Different kinds of crime have also been illustrated to have different spatio-temporal signatures (Grubesic and Mack 2008), and this kind of information may prove valuable for predictive policing in the future.

These tests are also valuable because the results of some tests may be stored and visualized. For example, visual output from the Mantel and Knox tests is possible, which enables analysts to visualize where events are interacting within the study area. A drawback of these tests however, is that it is difficult to quantify change over time because the output from these tests provides for a snapshot depiction of the results. Thus, while these tests are an improvement over their visual and exploratory counterparts, they are unable to pinpoint the locales within a study area that have experienced statistically significant changes in spatio-temporal interaction over time.

### Mathematical Models of Spatio-Temporal Interaction

More recent developments in spatio-temporal analyses of crime are also prone to some of the same issues as tests for spatio-temporal interaction. Although these highly sophisticated simulations are capable of predicting when and where hotspots of crime are likely to occur, they do not quantify changes in hotspots across a study area of interest. This is because the output of these mathematical models rely on visual comparisons of hotspot maps over time and do not statistically pinpoint areas that have experienced significant changes in their crime levels. For example, Brantingham and Tita (2008) use Levy mobility models to mimic the foraging behavior of burglars. These models are capable of incorporating the movement directions of offenders, the distance of their movements, and the time offenders return to an origin, such as a residence, before and after the commission of a crime. Although the patterns produced by varying different Levy model inputs yield useful insights into the movements of offenders, comparisons of the output produced by the models is visual and not statistical. Therefore differences in the intensity of the movements are not quantifiable, and must rely on visual comparisons to evaluate changes in the intensity of movements over time.

Other studies have implemented reaction-diffusion models to examine the formation of burglary hotspots from a routine activities theory perspective (Short et al. 2008, 2010; Berestycki and Nadal 2010). Short et al. (2010) find this approach to space–time modeling uncovers two kinds of hotspots, supercritical and subcritical, each of which suggests a different police intervention. Subcritical hotspots are large local upticks in crime that overwhelm the steady crime rate of an area and may be eliminated with policing efforts (Short et al. 2010). Supercritical hotspots are small spikes in crime resulting from general crime instability in a study area (Short et al. 2010). Policing efforts directed at supercritical hotspots merely result in the displacement of the hotspot to a different location whereas focused police efforts on subcritical hotspots is capable of eliminating crime in a particular location (Short et al. 2010).

The reaction-diffusion model developed by Berestycki and Nadal (2010) finds two kinds of hotspots similar to those found by (Short et al. 2010). These hotspots are classified as “warm spots” or “tepid milieu” where criminal activity persists without exploding and “true hots spots” where high levels of crime may be observed. While the results of both these studies are informative for policing efforts, the output produced by the Berestycki and Nadal (2010) model is aspatial and graphical in nature. The relative disappearance or displacement of the hotspots uncovered by Short et al. (2010) is also determined via a visual comparison of the simulated model results. Thus, the need for a method that quantifies change in hotspots through space and time persists.

### Quantifying Change in Spatio-Temporal Crime Trends

Some studies have attempted to move beyond visualization of statistical and modeling results and seek to quantify spatio-temporal trends in crime (Johnson et al. 2008; Berk and MacDonald 2009; Nakaya and Yano 2010; Tompson and Townsley 2010). Many of these studies however do not quantify the change in hotspots of crime over time within the study area, but instead employ one statistic to summarize crime trends for the whole study at a particular point in time. For example, the Johnson et al. (2008) study is a comparative spatio-temporal kernel density analysis that quantifies the level of crime in each output raster cell by its coefficient of variation. The results are then displayed sequentially as snapshots of crime over time. Although one might be able to visually understand general trends in crime across the study area, this approach does not quantify changes in crime within the raster cells over time.

Berk and MacDonald (2009) employ an aspatial approach to analyze how crime regimes constructed from principal components analysis change over time. First, the authors organize crime into a Temporal Spatial Crime Count Data Matrix (TSCCDM) where the rows represent time and the columns represent a location. Next, the cells of this matrix are populated with the number of crimes that occur at a particular time and place. Third, principal components are used to convert the data matrix into lines which can be plotted on a graph to examine temporal variations in crime across all spatial units. While this is an innovative way to analyze temporal trends in crime, the spatial component in the matrix is lost, and an examination of local variations in crime is not possible.

The present study seeks to fill some of these gaps in our ability to quantify changes in crime through space and time. Specifically, the study makes two contributions to the analysis of spatio-temporal crime data. First, it offers a technique to assess the extent to which the dynamics of burglary activity in a given location are conditioned on crime in the surrounding area in previous periods. Second, it also suggests methods to consider the joint evolution of burglary activity in and across neighborhoods. This is important because it treats spatial units as connected entities rather than compartmentalized units that are unaffected by nearby units.

## Study Area and Data

Mesa, Arizona is the study area for this particular analysis. Mesa is a city of about 455,000 people (US Census Bureau 2011) in the Phoenix metropolitan area. Mesa is an interesting city to study crime because it is a mid-sized city that is taking ground-breaking steps to work towards inter-jurisdictional policing. This focus on inter-jurisdictional policing is particularly important because of the increasing violence in the state associated with Mexican drug cartels (Ross et al. 2009). The activities of the drug cartels made Phoenix the US city with the most kidnapping incidents in the world behind Mexico City (Ross et al. 2009). The activities of the cartels are also linked to increased gang activity in several parts of the state (Housley 2011), which requires cross-jurisdictional approaches to combat their activities. In response to the need for more flexible, and more informed police efforts in the Arizona East Valley, in 2007, the Mesa Police Department (MPD) opened the East Valley Gang and Criminal Information Fusion Center to facilitate the analysis and sharing of information between local police departments (Richardson 2011). The Fusion Center consists of seven partner police departments, including the Mesa PD,[1] and three associate agencies, Alcohol, Tobacco and Firearms (ATF), the Department of Corrections/Parole, and Maricopa County Probation (City of Mesa 2011). The goal of this center is to move beyond the traditional, myopic, view of policing within a single jurisdiction and to move towards an integrated, regional view of policing that is more adept at dealing with highly mobile criminals, particularly those involved in organized crime (Richardson 2011).

The residential burglary data used in this study were provided by the Mesa Police Department (PD). These data are based on the Uniform Crime Report (UCR) classification of residential burglaries (including forced and non-forced burglaries). UCR classifications represent each crime as only one record in the management system based on crime severity. For instance, if a residential burglary is associated with a homicide, this crime is classified as a homicide instead of a burglary. Hence our study is based on all instances where, if multiple crimes were involved, residential burglary represented the most severe of these crimes. We geocoded the burglary data for the months October 2005 through December 2009, a total of 51 months (October 2005 was chosen as a starting date since Mesa PD's Records Management System went into effect then). The data are organized into 685 police reporting grids shown in Fig. 1a. These grids are based on the city's quarter mile sections and are used by Mesa PD for operational purposes. Given our focus on residential burglaries we analyze only cells that contain residential units, which represent 474 of the 685 police grid cells shown in Fig. 1b.[2] We used 2006 parcel data from the Maricopa County Assessor's Office to obtain a count of residential units per grid cell.[3]

During this period, there were 9,062 number of residential burglaries throughout the residential cells. Were burglaries randomly distributed in space and time this would mean the probability of a given cell experiencing a burglary in one month would be 0.375. Empirically, the median frequency of burglaries is 0.275 per month per cell, with a maximum of 2.7 and a minimum of 0. Figure 1c provides an indication of the general frequency of these events by measuring the number of months (out of 51) that each cell experiences at least one burglary. Figure 1d isolates one particular month (October 2007) to show the spatial distribution of burglary activity.

Visual inspection of Fig. 1c and d suggests that the location of burglary activity does not appear spatially random as there is a higher prevalence of cells experiencing burglaries more frequently towards the west side of the area (Fig. 1c). Moreover, the snapshot view (Fig. 1d) also suggests a similar pattern. Below we outline a new approach to more formally examine the underlying spatial dynamics of these patterns and to disentangle the conditioning effects of the spatial distribution of residences on these patterns.

[1] The seven police departments involved in the Fusion Center are: the Apache Junction Police Department, the Chandler Police Department, the Mesa Police Department, the Salt River Police Department, the Scottsdale Police Department, and the Tempe Police Department.

[2] To focus on the extent of spill over we eliminate from the sample any residential cells that are not contiguous with other residential cells.

[3] The 2006 parcel data contains more complete information on unit counts and residential land use than the 2007–2009 parcel data. We used 2003 parcel data to supplement missing unit information in the 2006 records.

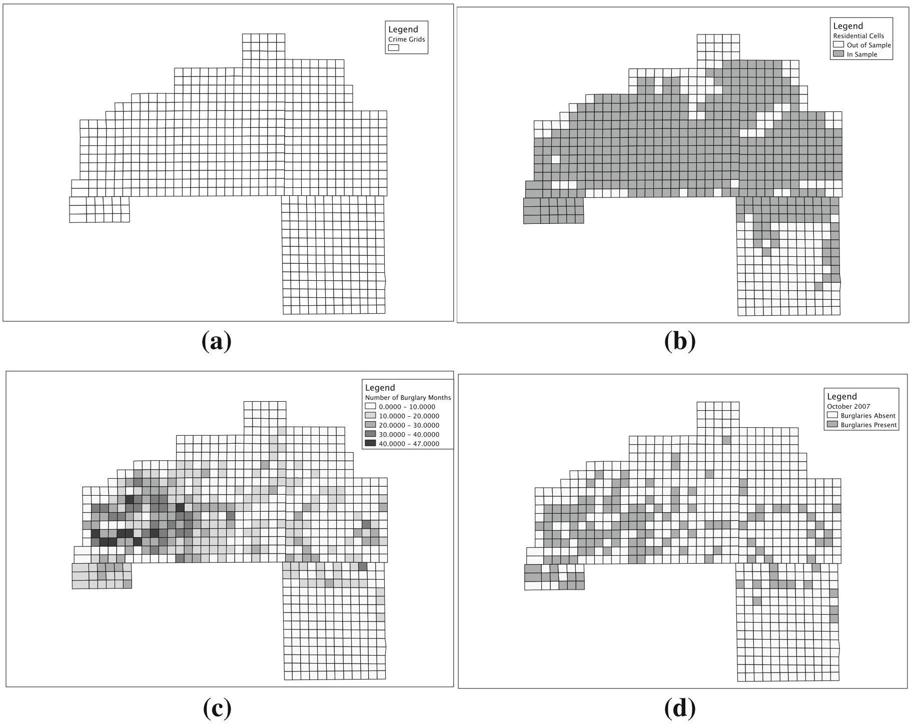


**Fig. 1** Police grid cells and residential burglary activity distributions in Mesa, AZ (october 2005–december 2009). **a** Police 1/4-mile grids, **b** residential cells, **c** number of months with burglaries, **d** burglary distribution october 2007

## Exploratory Space–Time Analysis of Burglaries

This study introduces new analytical measures that explore the spatial pattern of residential burglaries and their evolution over time. The first measure considers the role that spatial context has on the probability of a location experiencing a residential burglary in a future period. The second extends this conditional approach to examine the joint evolution of burglary incidence within and between locations. These two measures represent important techniques for evaluations of crime through space and time. Not only do the techniques consider the impact of crime levels from previous time periods, but they also consider the impact of crime at one location on crimes at neighboring locations. Therefore, these techniques enable analysts to consider crime along a temporal continuum in a neighborhood context, instead of treating crime hotspots as isolated locations at one point in time.

### Conditional Spatial Markov Chains

The first approach to the spatial dynamics of burglaries is based on Markov chain theory. In particular we adopt a discrete Markov chain framework to analyze the evolution of burglaries over space and time. A discrete first-order Markov chain is a stochastic process $X(t)|t \in T$ such that for any $t_0 < t_1 < \ldots < t_T$ the conditional cumulative distribution function of $X(t_l)$ depends only on $X(t_{l-1})$:

**Table 1** Markov transition probabilities for grid cell residential burglary states

| $t_0$ | $\sum_j f_{i,j}$ | $t_1$ | |
|---|---|---|---|
| | | No burglary | Burglary |
| No burglary | 17,683 | 0.810 | 0.190 |
| Burglary | 6,017 | 0.564 | 0.436 |
| Ergodic | | 0.748 | 0.252 |

Burglary indicates the state of experiencing one or more burglaries in a grid cell during a month

$$P[X(t_l) \leq x_l | X(t_{l-1}) = x_{l-1}, X(t_{l-2}) = x_{l-2}, \ldots, X(t_0) = x_0] \\ = P[X(t_l) \leq x_l | X(t_{l-1}) = x_{l-1}]. \tag{1}$$

If $X(t)$ is a discrete random variable that can take one of $k$ different values, then it is a discrete Markov time homogeneous chain[4] if:

$$P[X(t_l) = j | X(t_{l-1}) = i, X(t_{l-2}) = j, \ldots, X(t_0) = i] \\ = P[X(t_l) = j | X(t_{l-1}) = i] = p_{i,j} \forall i, j \tag{2}$$

and the $p_{i,j}$ satisfy the following conditions:

1. $0 \leq p_{i,j} \leq 1.0$
2. $\sum_j p_{i,j} = 1.0 \ \forall \ i$

where $p_{i,j}$ is the probability that a cell which was in state $i$ in period 1 moves to state $j$ in period 2. For burglary dynamics we define $k = 2$ states: the first is that a given grid cell $c$ did not have any residential burglaries (i.e., $X_{c,t} = 0$), while the second is that it had one or more burglaries in a given period ($X_{c,t} = 1$).

In our implementation we use the maximum likelihood estimator of these transition probabilities:

$$\hat{p}_{i,j} = \frac{f_{i,j}}{\sum_j f_{i,j}} \tag{3}$$

where $f_{i,j}$ is the number of transitions from state $i$ in the initial period to state $j$ in the following period, obtained as $f_{i,j} = \sum_c \sum_{t=0}^{T-1} \phi(i,j)_{c,t}$ with

$$\phi(i,j)_{c,t} = \begin{cases} 1 & \text{if } X_{c,t} = i \text{ and } X_{c,t+1} = j \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Table 1 contains the estimated Markov transition probabilities for the Mesa grid cells.[5] The initial marginal distribution of the cell-state distribution has approximately 0.746 of the cells starting a transition period free of burglary, while the remaining 0.252 cells were subject to burglaries in the initial period. The conditional distribution of the cell-state distribution is strikingly different for these two initial states as those cells that were the location of burglaries in the initial period have an estimated probability of 0.436 of experiencing additional burglaries in the following month while this probability drops to 0.190 for cells that were free of burglaries in the initial month. A test of the independence

[4] Time homogeneity implies that the transition probabilities are time invariant.

[5] All computations were carried out using (Rey and Anselin 2010). PySAL is an open source library with code and documentation available at http://pysal.org.

of the starting state of a cell and the ending state of a cell yielded a value of $\chi^2_{(1)}$=1264.7 which is significant at $p = 0.0001$. Clearly the future burglary status of a grid cell is not independent of its state in the preceding period.

The estimated transition probability matrix can be used to examine the long run properties of residential burglary distribution in Mesa. More specifically, the ergodic distribution for the chain is reported in the bottom of Table 1. The estimated ergodic distribution has 0.748 of the grid cells free of burglaries at any time, while 0.486 are subject to one or more burglaries. Because this distribution is close to the marginal distribution observed during the estimation period, it suggests that the chain has reached an equilibrium.

One assumption underlying the interpretation of the steady state distribution is that the Markov chain is time homogeneous. That is, the transition probabilities hold over every month. To test this assumption we split the sample period in half and estimate separate transition probability matrices for each sub period. A formal test of temporal heterogeneity indicates that the chain is homogeneous over time ($\chi^2_{(1)} = 1.480$, $p = 0.224$).

Thus far the application of the Markov framework to the burglary dynamics has assumed spatial homogeneity. That is all cells in the sample, irrespective of their absolute or relative locations, are subject to the same transition probabilities. To the extent this assumption holds, the experience of each grid cell can be treated as an independent observation. However, this assumption is at odds with the consensus view that many crime types are not randomly distributed across space and time (Cohen and Felson 1979; Brantingham and Brantingham 1981, 1984; Anselin et al. 2000; Eck et al. 2005; Lersch 2007).

Relaxing this assumption allows for the exploration of how the transition probabilities of each cell may be affected by neighborhood context. To address this question we adapt the notion of a spatial Markov chain (Rey 2001) to the case of residential burglary dynamics. We define a cell's neighborhood using first order queen contiguity.[6] The transitions are then stratified depending on the state of the neighboring cells. Two strata are used: cells whose neighborhood was free of crime in the initial period, and cells whose neighborhood had some crime in the previous period. Let $P$(NB) represent the transition probability matrix for cells with neighborhoods that were free of crime in the initial period and $P$(B) the transition probability matrix for cells whose neighborhood was not free of crime in the previous period. The null hypothesis of interest here is that $P$(B) = $P$(NB).

In the context of Markov theory, we can ask if these two chains come from the same Markov transition probability matrix. A formal test of the homogeneity of the dynamics across the different neighborhood contexts is:

$$\chi^2_{(k(S-1)(k-1))} = 2\sum_{s=1}^{S}\sum_{i=1}^{k}\sum_{j=1}^{k} f_{s,i,j} \ln\left(\frac{\frac{f_{s,i,j}}{f_{s,i,.}f_{.,i,j}}}{f_{.,i,.}}\right) \quad (5)$$

where $S$ is the number of strata (in our case 2), $f_{s,i,.} = \sum_j f_{s,i,j}, f_{.,i,j} = \sum_s f_{s,i,j}$, and $f_{.,i,.} = \sum_s \sum_j f_{s,i,j}$, and $f_{s,i,j}$ is the number of transitions for cells that were in strata $s$ and state $i$ in the first period and state $j$ in the second period.

The estimated Markov transition probability matrices for the homogeneous case along with the two strata are reported in Table 2. Inspection of the table reveals a number of key spatial dimensions underlying burglary dynamics. First, cells are more frequently

[6] This means that only those grid cells which share a border or a vertex are considered neighbors of one another.

**Table 2** Conditional spatial Markov chains for residential burglaries in Mesa, AZ police grid cells

| Neighborhood | $t_0$ | $n$ | $t_1$ | |
|---|---|---|---|---|
| | | | NB | B |
| | NB | 17,683 | 0.810 | 0.190 |
| | B | 6,017 | 0.564 | 0.436 |
| NB | NB | 5,171 | 0.902 | 0.098 |
| | B | 692 | 0.723 | 0.277 |
| B | NB | 12,512 | 0.771 | 0.229 |
| | B | 5,325 | 0.544 | 0.456 |

*NB* indicates absence of burglary, *B* indicates presence of burglary. Neighborhood signifies the presence (B) or absence (NB) of burglary in geographically contiguous cells during period $t_0$

surrounded by cells with burglaries than they are cells free from burglary in a given month. Second, this pattern is more pronounced for cells that experience burglaries, as the neighboring burglary strata claims 0.88 of these cells versus 0.70 of the cells free from burglary.

These two characteristics result in rather distinct marginal distributions for the two neighborhood strata. This reflects the underlying spatial autocorrelation in the burglary distribution for Mesa. The strength of that spatial dependence is displayed in Fig. 2 where BB indicates the number of spatial joins of a cell that contained one or more burglaries with a neighboring cell in the same state. For each month these counts are plotted against their expected values plus and minus 1.96 standard deviations under the null hypothesis that the B cells are randomly distributed across the residential grid cells. For example, in October, 2007 (10/07) the observed number of B cells was 136 (see Fig. 1d) and this resulted in a BB join count of 203. Were these B cells randomly distributed in space the expected value for the BB join count would have been 130.98 with a 95% CI of (89.53, 172.42). Because the observed count falls outside of this interval the spatial distribution of B cells in 10/07 is spatially autocorrelated. This is the case for 45 of the 51 months indicating that residential burglary patterns in Mesa over this period are far from spatially random.

If transition dynamics are influenced by local spatial context, then the lack of spatial randomness in the initial spatial distribution of burglary states casts doubt on the spatial homogeneity assumption underlying the classic Markov chain analysis. To assess this assumption we use data from Table 2 together with (5) yielding a value of $\chi^2_{(2)} = 500.21$ which is significant at $p = 0.001$. The dynamics are not homogeneous across the different neighborhood contexts.

One possibility is that the clustering effect in the burglary dynamics is due to the spatial distribution of the underlying population at risk. To examine this we randomly allocated the observed number of burglaries in each month according to the share of residential units, as a proxy for population density, in each grid cell. Given this distribution of crimes conditioned on the population at risk, we repeated the estimation of the spatial Markov chain probability transition matrices. For each of these conditionally random spatial distributions we obtained the spatial homogeneity test statistic from (5). We then compare the value of the same test statistic from the original data against the distribution of the values obtained in the conditionally random spatial distributions and found that the original value

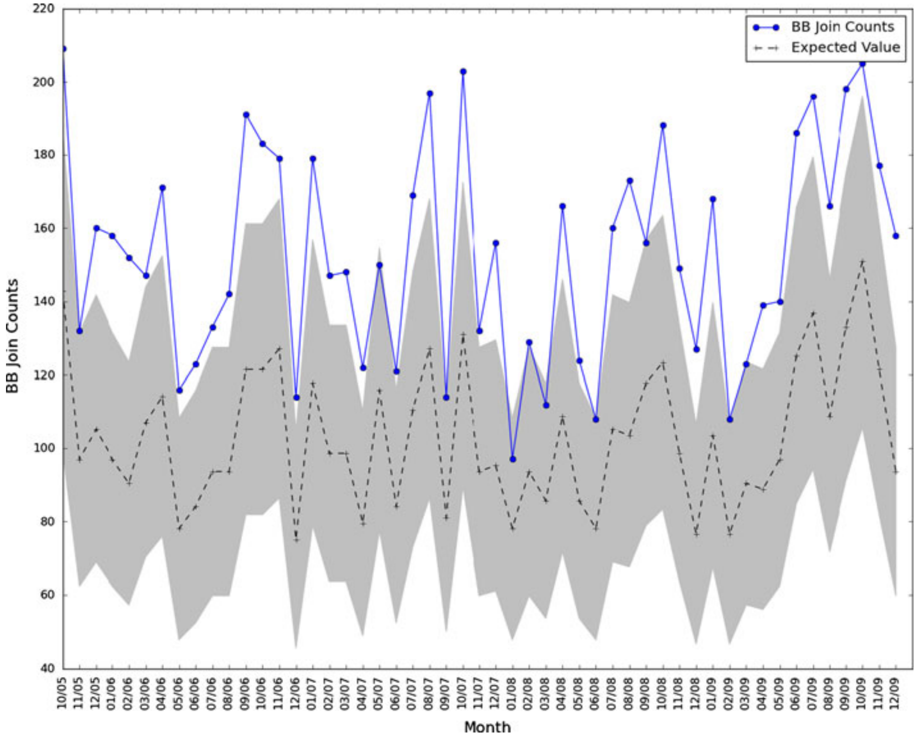


**Fig. 2** Monthly join count tests for residential burglaries in Mesa, AZ

has a pseudo $p$ value of $p = 0.005$ based on the conditional randomizations.[7] In other words, the amount of spatial heterogeneity that we observed in the actual transition probabilities is significantly above that suggested by the spatial distribution of the population at risk.

The implications of rejecting the spatial homogeneity assumption can be seen by considering different types of events and their relative odds of occurrence across these different contexts. There are four events of interest corresponding to each type of transition across our two states. For example, the odds of the event that a cell was free of burglaries in period 1 and experienced burglary in period 2 is $\Pi_{1,2} = p_{1,2}/p_{1,1}$. Similarly, the odds that a cell which was subject to burglaries in the first period is found to be free of burglaries in the second period is $\Pi_{2,1} = p_{2,1}/p_{2,2}$. Finally, there are two events where a cell occupies the same state in both periods. These have the odds $\Pi_{1,1} = p_{1,1}/p_{1,2}$ and $\Pi_{2,2} = p_{2,2}/p_{2,1}$.

To assess the impact of local spatial context on the odds of these events we calculate the odds ratio for cells with neighborhoods experiencing burglaries in the previous period relative to those cells with neighborhoods free of burglaries in the previous period. For example, focusing on the event that a cell that was free of burglaries in period 1 experiences one or more burglaries in period 2, the odds ratio is given as: $\theta_{1,2} = \frac{\Pi(\mathrm{B})_{1,2}}{\Pi(\mathrm{NB})_{1,2}}$, where

[7] The pseudo $p$ value is obtained as $p = \frac{NS+1}{NR+1}$ where $NS$ is the number of test statistics from the spatially random conditional distributions that were as extreme as the original observed value and $NR = 999$ is the number of randomizations carried out. For more details on randomization based inference in spatial criminology see Ratcliffe (2010).

**Table 3** First mean passage times for spatial Markov chains

Average number of months required to move between burglary and non-burglary states

| Stratum | $t_0$ | $t_1$ | |
|---|---|---|---|
| | | NB | B |
| NB | NB | 1.14 | 10.24 |
| | B | 1.38 | 8.40 |
| B | NB | 1.42 | 4.37 |
| | B | 1.84 | 3.38 |

$\Pi(\mathrm{B})_{1,2}$ is the odds of this event for cells bordered by cells experiencing crime in the initial period, and $\Pi(\mathrm{NB})_{1,2}$ the odds for cells whose neighbors were free of burglaries in the initial period. Based on the conditional Markov probabilities from Table 2, the odds ratio for this event is

$$\theta_{1,2} = \frac{\Pi(\mathrm{B})_{1,2}}{\Pi(\mathrm{NB})_{1,2}} = \frac{P(\mathrm{B})_{1,2}}{P(\mathrm{B})_{1,1}} \left(\frac{P(\mathrm{NB})_{1,2}}{P(\mathrm{NB})_{1,1}}\right)^{-1} = \frac{0.229}{0.771}\left(\frac{0.098}{0.902}\right)^{-1} \approx 2.742. \tag{6}$$

In other words the odds of a cell that was free of burglaries experiencing a burglary in the next period are 2.742 times greater if that cell's neighborhood was subject to burglaries in the first period.[8]

For the three other events, the odds ratios (B relative to NB) are as follows:

- burglary to burglary free: $\Theta_{2,1} = 0.458$
- remain in burglary state: $\Theta_{2,2} = 2.186$
- remain free of burglaries: $\Theta_{1,1} = 0.365$

In all four cases the odds ratios are all significantly different from 1.[9] These odds ratios all point to negative consequences for cells neighbored by burglaries.

In addition to the impact of neighboring burglaries on the odds of cell experiencing future burglaries, we can also examine how neighborhood context affects the time required for a transition by individual grid cells across the different burglary-nonburglarly states. The first mean passage time is the average number of periods required for the chain which is in state $i$ to first enter state $j$. Table 3 reports the first mean passage times for the different neighborhood contexts. For example, cells whose neighborhood is currently free of burglaries and who themselves are free of burglaries require an average of 10.24 months before experiencing a burglary. By contrast, cells currently free of burglaries but who are neighbored by cells in the burglary state require only an average of 4.37 months before experiencing their next burglary.

The negative impact of surrounding burglary activity is also seen in the time required to move out of the burglary state, as grid cells that are in the burglary state but whose neighborhood is in the non-burglary state take 1.38 months to become burglary free, while

[8] The values for the odd ratios reported here are based on the unrounded probabilities.

[9] The asymptotic standard error of the log of the odds ratio is:

$$ASE(\log(\hat{\theta}_{1,2})) = \sqrt{1/f(\mathrm{B})_{1,1} + 1/f(\mathrm{B})_{1,2} + 1/f(\mathrm{NB})_{1,1} + 1/f(\mathrm{NB})_{1,2}} \tag{7}$$

where $f(\mathrm{NB})_{1,2}$ is the number of transitions involving a cell that moved from state 1 (burglary free) to state 2 (burglary) but were surrounded by cells free from burglaries in the initial period. The asymptotic approximation has been found to be poor when $n / (K{*}I{*}J) < 5$ where $n$ is the number of transitions, $K$ is the number of strata, and $I$ and $J$ are the number of states. In our case we have $n = 23{,}700$ and $K = I = J = 2$.

for cells in the burglary state whose neighbors are also in that state 1.84 months are required on average to become burlary free. Interestingly the return time to the burglary state is much shorter for cells surrounded by burglary than it is for cells with neighborhoods free from burglary activity (3.38 months vs. 8.40 months).

### Joint Spatial Markov Chains

The conditional spatial Markov analysis reveals that the transition probabilities for a grid cell moving in and out of burglary states are different depending on the local context, or the burglary state of its neighbors at the beginning of a transition period. Also of interest is the question of the joint spatial dynamics—that is whether the moves across states for a cell are independent of the moves across states made by its neighboring cells during the same time interval.

To address this question we extend the previous Markov chain framework in a number of ways. First we posit two different chains, one based on the individual cells—which we refer to as the own-chain. A second chain is based on the neighboring cells expressed as a binary variable, taking on a value of 1 if any of the neighboring cells had one or more burglaries, and 0 otherwise. We refer to this second chain as the neighbor-chain.

Let $P(O)$ represent the transition probability matrix for the own-chain and $P(N)$ that for the neighbor-chain. Each of these chains has two states, as above. A joint Markov chain can be defined on these chains to consider the simultaneous transitions of the own-cells and neighboring cells. This chain will have four states: $\Omega = [(0,0),(0,1),(1,0),(1,1)]$, with the first position in each state indicating the state of the own-chain, the second the state of the neighbor-chain. Under a hypothesis that the transitions of a cell are independent of those of its neighbors, the two marginal chains are independent. Thus, under independence, the expected transition probability matrix for the joint chain is:

$$P(ON) = P(0) \otimes P(N) \tag{8}$$

where $\otimes$ is the Kronecker product operator.

A formal test of the equality of the two transition probability matrices in Table 4 yields $\chi^2_{(9)}$ = 1937.25 which is significant at $p = 0.001$. The two marginal chains cannot be considered to be separable, since the transitions of a location into and out of the burglary state are not independent of the transitions experienced by its neighbors.

Additional insights as to the influence of the non-separability of the two chains can be gained from a comparison of the two long run distributions of the joint chain. Under the independence assumption (bottom portion of Table 5) a larger mass of the distribution falls in the second and third states—reflecting spatial heterogeneity, in the crime pattern. By contrast, for the estimated joint spatial Markov chain transition probabilities the long run

**Table 4** Marginal spatial Markov chains transition probabilities

| Chain | $t_0$ | | $t_1$ | |
|---|---|---|---|---|
| | | | NB | B |
| Own | NB | 17,683 | 0.810 | 0.190 |
| | B | 6,017 | 0.564 | 0.436 |
| Neighbor | NB | 5,863 | 0.518 | 0.482 |
| | B | 17,837 | 0.161 | 0.839 |

**Table 5** Joint spatial Markov chains transition probabilities

| $t_0$ | $n$ | $t_1$ | | | |
|---|---|---|---|---|---|
| | | (NB, NB) | (NB, B) | (B, NB) | (B, B) |
| Observed: $P(ON)$ | | | | | |
| (NB, NB) | 5,171 | 0.511 | 0.391 | 0.032 | 0.066 |
| (NB, B) | 12,512 | 0.165 | 0.606 | 0.027 | 0.202 |
| (B, NB) | 692 | 0.254 | 0.468 | 0.079 | 0.198 |
| (B, B) | 5,325 | 0.060 | 0.484 | 0.027 | 0.429 |
| | Ergodic | 0.221 | 0.527 | 0.029 | 0.223 |
| $H_0$: $P(ON) = P(O) \otimes P(N)$ | | | | | |
| (NB, NB) | 5,171 | 0.419 | 0.390 | 0.099 | 0.092 |
| (NB, B) | 12,512 | 0.130 | 0.680 | 0.031 | 0.160 |
| (B, NB) | 692 | 0.292 | 0.272 | 0.226 | 0.210 |
| (B, B) | 5,325 | 0.091 | 0.474 | 0.070 | 0.366 |
| | Ergodic | 0.186 | 0.561 | 0.063 | 0.189 |

distribution is more concentrated in the first and fourth states—implying greater spatial dependence.

## Discussion and Conclusion

The Markov based techniques demonstrated in this paper are an effort to build upon the foundational work of prior studies and resolve a few of the drawbacks in existing methods for spatio-temporal crime analysis. The results of this study, which are based on actual and not simulated data, suggest that current methods, which treat crime hotspots as isolated entities in discrete moments in time, do not necessarily capture the dynamic nature of crime through both space and time. The techniques developed in this paper demonstrate one technique that treats spatial units as connected entities through time and space. Although substantively our results are in line with prior findings, the ability to quantify the probability of burglaries across time and space opens new possibilities for extending models related to policing efforts, including predictive policing.

A unique feature of this analysis is that it attaches probabilities to grid cells that indicate their likelihood of experiencing a residential burglary in subsequent time periods. This probability is linked to both the presence of burglary in that cell in previous time periods and the incidence of burglary in surrounding grid cells. The approach outlined in this paper is a departure from current and historical studies of spatio-temporal trends in crime. While some of the more recent mathematical approaches to spatio-temporal analysis involve probabilities, their use varies from study to study. For example, the Levy mobility models developed by Brantingham and Tita (2008) assume the probability of crime increases the further an offender moves from a particular origin. This relationship is more general however and is used to produce visual hotspot outputs from the Levy models. The Short et al. (2008, 2010) studies incorporate probabilities into their hotspot simulations as well, but these probabilities remain hidden in the simulation and are not an output of the modeling process. Again probabilities in this instance are used primarily to obtain the hotspots and are not considered a key output of the modeling process. These approaches and the approach presented in this paper highlight different angles that are valuable to understanding varying dimensions of the geography of hotspots.

The application of the two new measures of spatial dynamics in this study reveals a number of insights as to the role of spatial context on the prevalence of residential burglary activity in a location. First, cells that had already experienced burglaries were far more likely to experience subsequent burglaries (at a probability of 0.44) than cells that had not experienced burglaries (at a probability of 0.19). Further, we find strong evidence of conditional spatial dynamics—that is the future experience of a location with regard to whether or not it experiences subsequent burglaries is related to the prevalence of burglary activity in neighboring locations in the current time period. Specifically, if a location is free of burglaries but near locations with burglaries in an initial time period, it is 5 times more likely to experience a burglary in the next time period. In all cases, being located near cells with burglaries has statistically significant negative consequences.

These space–time patterns could be driven by a number of spatial processes. For instance, consistent with optimal foraging theory, the dependence of burglaries across space and time could be related to burglars targeting homes in areas they have identified as optimal. Once offenders identify locations with suitable targets and low risk of punishment and gain experience and familiarity in navigating these areas, repeat burglaries in these locations become more attractive to the offender and nearby areas become additional optimal targets(Wright and Decker 1994, 1997; Piquero and Rengert 1999). Our findings could further be consistent with routine activities theory in the sense that the establishment of routines in one location might be likely to persist in that location and spill over to nearby locations as those become more familiar. Optimal foraging and routine activities dynamics could also be more dominant, respectively, in different parts of the city—for instance, in areas with more local burglary patterns (where burglars and burgled houses are nearby), routine activities theory might be the best fit for explaining the space–time dependence we observed. On the other hand, for housing complexes near the highway that might be targeted by more mobile organized crime units, optimal foraging theory could be the best explanation for the resulting space–time clustering.

The spatio-temporal dynamics of residential burglary in Mesa agree with prior studies of offender decision-making (Wright and Decker 1994, 1997; Piquero and Rengert 1999). The results of the analysis in this study demonstrate burglaries take place in and around select grid cells in the Mesa area, which strongly suggests repeat burglaries within grid cells and near-repeat burglaries in neighboring grid cells. These findings are in concert with the near repeat burglary hypothesis and previous studies of repeat and near-repeat burglaries, which found that nearby homes have an elevated risk of burglary once a neighbor is burgled (Polvi et al. 1991; Johnson and Bowers 2004a; Bowers and Johnson 2005; Johnson et al. 2007).

This spatial and temporal clustering of burglaries also concurs with the findings of research about the decision making process of burglars. For example, Wright and Decker (1994) found that burglars prefer to operate within their own neighborhood because of their familiarity with the people and opportunities in that area. Several studies also show that offenders do not travel far from home to commit their crimes (White 1932; Erlanson 1946; Boggs 1965; Snook 2004). Not only do burglars prefer to operate close to home, but the Wright and Decker (1994) study also found that burglars returned to a particular residence multiple times because of their familiarity with the routine of people in that particular home and neighborhood, which facilitated their chances for success and minimized the risk of being caught. Wright and Decker (1994) uncovered for example, that burglars like to revisit certain targets because they know when the place will be unoccupied, they are familiar with the goods in the place, and they have prior knowledge of the difficulties that will be encountered (i.e. locks) when they burgle the place. The impact of burglaries in previous time periods on future burglary rates in the same grid cell and neighboring grid cells is indicative of this offender decision-making process at work in the Mesa area.

From a crime prevention strategy, studies of offender decision-making also provide valuable information about useful interventions for local area police. These studies suggest interventions should focus on modifying the criminal's perception of the risk/reward balance of potential crime opportunities to prevent repeat and near-repeat victimization. In their interviews of burglars Wright and Decker (1994) found strategies that altered the perceived occupancy of places, such as dogs and burglar alarms, decreased the likelihood of a repeat burglary because criminals try to avoid burglarizing occupied residences. This same study also suggested homes that have been burglarized previously install security measures such as security bars and storm windows. These installations increase the difficulty of entering a place quickly and thus also increase the risk associated with burglarizing a particular property. Given the spatio-temporal dynamics of Mesa residential burglaries, the installation of these security devices also makes sense in nearby residences, since the results suggest spillover effects of burglary to residences in nearby grid cells. These spillover effects suggest serial burglary activity by one or multiple offenders. The key to preventing this type of activity however is to modify the relative attractiveness of burglary targets (Wright and Decker 1997), which involves modifying the risk/reward perception of potential targets.

On a wider scale, community education programs about burglary prevention could be implemented to make residents aware of modifications they can make to their properties to make them less attractive to criminals. In addition to the security measures described above, modifications to properties that make them more visible from the street and neighboring buildings will likely reduce their attractiveness to would be burglars (Wright and Decker 1994). In places where burglary prevention measures are too costly for residents, subsidies for security measures could also be provided to help residents afford preventative measures. The localized spillovers of burglary highlighted in this study suggest that crime prevention initiatives within one neighborhood are likely to have diffusion benefits for nearby neighborhoods (Clarke and Weisburd 1994). This means that prevention tactics taken in one neighborhood may cause nearby neighborhoods to also be perceived by criminals as too risky to burgle, thereby reducing burglary in a larger area than initially intended.

The discovery of joint spatial dynamics in the transition of grid cells into and out of burglary states, and the impact of neighboring locations on these impacts also suggest that intervention strategies for a particular location should take a wider geographical context into account. When integrated with intelligence-led policing strategies (Ratcliffe 2008), this information can help target intervention efforts at nearby locations of existing burglary hotspots to prevent spillovers into areas not yet affected by burglaries. For instance, strategies such as Crime Prevention Through Environmental Design (CPTED) can specifically target these border areas in efforts to prevent likely future burglaries here. The first mean passage times offered by the spatial Markov chain framework offer some estimates of the time required for geographical locations to change their burglary status, either becoming burglary free or experiencing future burglary. Because these times are found to depend on the geographical context of a cell it may be possible to utilize these estimated times in planning spatially explicit allocation of monitoring and intervention resources.

The presence of spatial effects in the dynamics of burglary patterns represents both challenges and opportunities to criminologists. On the one hand, spatial dependence complicates the statistical analysis of both cross-sectional crime data as well as panel and space–time data. On the other hand, the strong spatial clustering of criminal activity opens up the possibility of geographically targeted interventions in terms of crime reduction and prevention activities. The measures presented here provide new approaches towards the measurement of spatial spillover effects in the evolution of criminal activity, and are designed to help address this first challenge. However, these methods are global in nature in the sense that they provide overall summary measures of the extent of spatial dependence in burglary pattern dynamics. Geographical targeting in a dynamic context will require the development of local measures that can identify space–time hotspots. Extending these space–time statistics from global to local measures represents an important opportunity for future research.

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