Chapter XIV
The Simulation of the Journey to Residential Burglary

Karen L. Hayslett-McCall
The University of Texas at Dallas, USA

Fang Qiu
The University of Texas at Dallas, USA

Kevin M. Curtin
The University of Texas at Dallas, USA

Bryan Chastain
The University of Texas at Dallas, USA

Janis Schubert
The University of Texas at Dallas, USA

Virginia Carver
The University of Texas at Dallas, USA

ABSTRACT

This chapter presents an innovative approach to the study of the journey to residential burglary. We demonstrate a simulation model that is built upon the integration of cellular automaton (CA) and multi-agent system (MAS). The model utilizes both social disorganization (SD) and routine activity (RA) theories to predict locations of residential burglary targets. The model simulates an offender as an intelligent agent of MAS that interacts with the target and place automata of CA. The likelihood of a residential burglary is modeled as a function of offender's motivation, target desirability and place guardianship, which in turn are determined by the offender's individual characteristics often used by RA and the target and place's neighborhood properties frequently utilized in SD. The model was initialized and parameterized using *"real" crime data from Dallas, Texas Police Department. Results under two different weighting scenarios were obtained and compared with the actual distribution of offense locations, revealing the flexibility of model in its capability to assessing the influence of the two theories in burglary crime simulation. In closing we propose possible modifications that could be made to the model in the future.*

INTRODUCTION

In this chapter, the offender and the residential location that was targeted for burglary are discussed in the terms of modeling them as agents and automata in a cellular automaton (CA) and multi-agent system (MAS) modeling. The offender agent has the following properties: age (i.e., experience), race, and gender that are related to motivation (i.e., poor neighborhood burgling in a wealthier neighborhood). In addition to its location, the target has properties such as income level (i.e., wealth of neighborhood) and race composition that determines its desirability. The residential location also has several properties that define the lack of guardianship (e.g., commuting time of residents and tenure, etc.). Our model is developed based on the essential components of routine activity (RA) and social disorganization (SD) theories, calibrated and validated utilizing the attributes of both the offenders and residential targets from the reports database from the Dallas Police Department (Dallas, TX). Our models are also supported by publicly available neighborhood attribute information (e.g., U.S. Census and tax parcel data), and location and distance information derived through geographic information systems (GIS) techniques in the model of the journey to crimes of residential burglary.

JOURNEY TO CRIME

The study of journey to crime is an evaluation of offense patterns—exploring the distance traveled between an offender's residence and the offense location. "Distance, so far as it enters into human relationships, is thus entirely relative to the available techniques for overcoming the friction of space" (Hawley, 1950: 237). Time and space are obstacles in human movement; criminal behavior is not exempt from these constraints. Research demonstrates that offenders generally commit crimes close to home, although significant differences exist by type of crime. The average crime trip is relatively short, reported as 1.66 miles (White, 1932), 1.43 miles (Philips, 1980), 1.22 miles (Gabor & Gottheil 1984), 1.93 miles (Costello & Wiles, 2001) and 0.4 miles (Turner, 1969). Many of the studies that measure crime trips as distances report a significant percent occurring over less than one mile (Costello & Wiles 2001; Rengert, Piquero, & Jones, 1999; Turner, 1969). When compared, property offenses are consistently committed farther from the home than crimes against persons (DeFrances & Smith, 1994; Pyle, 1976; Rand, 1986; Rhodes & Conly, 1981; White, 1932). The difference is related to the motivations behind crimes and the availability of suitable targets.

Considerations of the journey to burglary must account for a target selection process. Burglars begin in a general area, from which they select a specific target (Wright & Decker, 1994). An area's attractiveness can influence the direction and timing of burglaries (Rengert, 1981). Burglary follows the typical journey-to-crime pattern: many offenses are located within a few miles of the burglar's home (Costello & Wiles, 2001; Ratcliffe, 2001; Snook, 2004) and the number of burglaries committed decreases as the distance from the offender's home increases (Rengert, Piquero, & Jones, 1999). Offenders are "likely to minimize the time and energy involved in criminal activities by selecting crimes that can be executed at relatively short distances from their homes as opposed to long distances" (Rengert, et al., 1999:429).

MODELING BURGLARY WITH SOCIAL DISORGANIZATION AND ROUTINE ACTIVITY THEORIES

The most popular theories on burglary are probably social disorganization theory and routine activity theory, using both neighborhood and residential characteristics as important tenets. For example, the commission of a crime requires a suitable target. In the case of residential burglary, that target is going to be a place of residence: a house, an apartment, a trailer, and so forth. Ratcliffe (2001) also reports on the timing of burglaries based on activity patterns. Residential and public spaces are burgled at opposite times, with residential offenses occurring mostly during the day while residential owners are at work. In addition to distinct temporal patterns of area traffic and subsequent crime, the presence of targets in a neighborhood influences offender behavior.

Social disorganization theory and routine activity theory are compatible explanations of the neighborhood-crime relationship. Both theories are control theories, in that they both assume that "people would commit crime if left to their own devices" (Vold, Bernard, & Snipes, 1998, p. 201). Social disorganization theorists believe that control mechanisms are present in neighborhoods, and that these controls have varying degrees of effectiveness in deterring or preventing predisposed offenders from committing crime. Routine activity theorists also discuss control, in that motivated offenders are assumed to be disinhibited and will commit crime against suitable targets when a capable guardian is not present. Both social disorganization and routine activity theorists agree that when controls are in place, predisposed offenders will be less likely to act even when an opportunity is present. In the case of social disorganization theory, the social controls include the three levels of social control (private, parochial, and public) (Hunter, 1985), while routine activities discusses control in terms of the presence of the capable guardian (Cohen & Felson, 1972).

In the last 20 years, social disorganization theorists have focused more closely on neighborhood-level financial resources and activity patterns, including criminal activity patterns. The systemic social disorganizationists have explored a series of new variables, beyond the variables of the original linear model, which have identified levels of social disorganization by a neighborhood's social composition patterns. These theorists have developed a body of research that studies the linear disorganization variables including neighborhood level of poverty and the amount of residential mobility. In addition, they have updated the model to include variables such as: the percentage of residents that rent vs. own, a higher number of abandoned buildings, the percentage of female-headed households, length of tenure, and high crime rates (Morenoff & Sampson, 1997; Sampson, 1985, 1987; Sampson & Groves, 1989; Sampson, Morenoff, & Earls, 1999; Sampson, & Raudenbush, 1999; Skogan, 1990; Taylor, 1997; Warner & Pierce, 1993). Where these variables are present, researchers have used this expanded list of important neighborhood factors to define "disorganization" within neighborhoods. Of these variables, we focus on the length of tenure in our study. This measure operates as a guardianship function for our 'targets.'

Of interest to the current study is the work by Sampson et al. (1987; 1997), who found that social integration factors, such as mobility, affected individual likelihood of being the victim of a crime. Indeed, some research has shown that neighborhoods still capable of exercising some level of informal social control could reduce their collective likelihood of criminal victimization Sampson, Raudenbush, and Earls (1997) found that the relationships between concentrated disadvantage and violent victimization as well as between neighborhood residential instability and victimization were mediated significantly by collective efficacy. Collective efficacy was defined as the "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (Sampson et al. 1997, p. 918). Thus, neighborhoods that were willing to act for the common good were able to affect the number of victimizations that occurred within their boundaries.

Unlike previous research, Smith et al. (2000) found several interactions between "individual risk factors (as specified by routine activity theory) and type of neighborhood (as specified in social disorganization theory)" (p. 491). Overall, according to docial disorganization theory, along with a higher rate of offenders, residents are less likely to engage in active guardianship (i.e., collective efficacy). Disorganization results in high rates of instability and anonymity. Weak guardianship and motivated offenders, two of the three tenets of RA theory, are present in disorganized neighborhoods. The third tenet, presence of suitable targets, varies by the type of crime.

All of these factors from RA and SD theory can be applied in a simulation to the journey to residential burglary. They are given as characteristics to each of the following: the offender, the target agent, and the place agent.

CELLULAR AUTOMATA AND MULTI-AGENT SYSTEMS APPLIED IN THE SIMULATION OF CRIME

Cellular automata have been integrated into GIS through the fundamental operations of map algebra (Takeyama & Couclelis, 1997). They have been accepted as a structure for the modeling of space-time processes in GIS (Wu, 1999), and they have been identified as one of the prominent advances in GIS modeling (Goodchild, 2003).

Cellular automata (CA) is a discrete model consisting of an infinite number of regular grid cells, each in one of a finite number of states. However, in reality the model generally consists of a finite number of cells. The state of a cell at time t is a function of the states of a finite number of cells (or neighborhood) at time t-1. These neighbors are a selection of cells relative to the specified cell. Two standard neighborhood types are the "Moore" neighborhood and "von Neumann" neighborhood (Benenson & Torrens 2005). The former includes neighbors of single-point adjacency (similar to a queen's moves on a chessboard), while the latter does not (similar to a rook's moves on a chessboard). Every cell has the same rule for updating, based on the values in this neighborhood. In general, the state of an automaton can be defined as a function of the states of the automaton of the focal cell and its neighbors, the set of transition rules needed to adapt the automaton over time (Benenson & Torrens 2005). CA was first conceived by John von Neumann in the late 1940's and early 1950's, and then in the 1980's Stephen Wolfram made it famous for use in other fields (von Neumann, 1949; Wolfram, 1986). Soon after, the spatial aspects of CA were examined (Couclelis, 1985, 1988, 1989; Hogeweg, 1988; Green et al., 1990; Phipps, 1989; Smith, 1991; White & Engelen, 1992). One distinct feature of CA is the stationarity of the automata. The cell positions and most of time the spatial relations of their neighborhoods remain constant over time. Information can be exchanged with neighbors over time, which allows for spatial information propagation.

Multi-agent systems (MAS) have the ability to consider individual-oriented behavior. Their interpretation of automata states and transition rules allow for the design of autonomously behaving agents. These agents can be designed to make human-like decisions (to a certain degree), and are capable of moving through space. This capability is the key distinguishing feature from CA, in which automata are fixed. The variety of spatial relationships between automata can be relaxed in MAS, allowing for arbitrary neighborhood assignments between automata.

Franklin and Graesser (1996) define an agent as: "*An autonomous agent (1) is a system situated within and part of an environment; (2) that senses that environment and acts on it, over time; (3) in pursuit of its own agenda, and (4) so as to effect what it senses in the future.*" Cellular automata do not appear to meet at least two of these rules. The cells in CA do not have their own agenda nor do they sense the future. More importantly, they do not act by themselves. An agent should be able to "act", "pursue its own agenda", and "sense the future."

Beyond this, agents are heterogeneous—other modeling simply looks at the "average" individual. In MAS, agents have the ability to be anywhere on the spectrum, and can be modeled to fit a known distribution, if desired. Agents are proactive about reaching their set of goals (Terna, 1998). For example, geographic agents can be set to follow certain paths. In terms of residential burglary, agents can be set to seek targets of "best opportunity" (i.e., perceived gain of wealth). Similar to automaton in the neighborhoods of CA, agents are also perceptive of their environment and are able to sense their surroundings. We hypothesize that residential burglars are sensitive to their environments. We know from the literature that individuals preferred to offend in neighborhoods composed mainly of their own race (Reppetto, 1974). In addition, MAS agents are sensitive to the other agents and are aware that socially disorganized neighborhoods have higher success rates of offences, and residents are less likely to engage in active guardianship. Unlike CA, however, agent perception is not constrained to a neighborhood, because of their ability to travel. In closing, agents are also able to adapt to their environment. Agents are able to modify their behavior based on experience gained during the model lifespan.

Cellular automaton and related agent based models have been used to explore some crime-related issues, but the investigation of crime through CA is still in its infancy. CA has been used to study the prisoner's dilemma (Alonso, Fernandez, & Fort, 2006), in modeling the outbreak of infectious disease, and in planning for crowd control (Batty, Desyllas, & Duxbury, 2003). CA have been used in transportation applications including the modeling of pedestrian behavior (Blue & Adler, 2001) and the simulation of road traffic states (Wahle, Neubert, Esser, & Schreckenberg, 2001). In a geographic context a substantial amount of research has focused on the use of CA for simulating urban dynamics (Batty, 2005; Batty, Xie, & Sun, 1999), growth (Barredo, Kasanko, McCormick, & Lavalle, 2003; Clarke & Gaydos, 1998), and sprawl (Torrens, 2006), with very limited mention of crime.

Not explicitly following the paradigm of cellular automata though, rule based systems for the support of police operations have been implemented (Brahan, Lam, Chan, & Leung, 1998), and economic simulations of criminal offenses have been modeled (Winoto, 2002). All of these elements (CA, GIS, and criminology) have come together in a recent work that used CA to model the criminological theory of routine activities and street robbery and implemented this model in a GIS context (Liu, Wang, Eck, & Liang, 2005).

COMPONENTS OF RESIDENTIAL BURGLARY CRIME

For residential burglary crimes, we have identified three major players: offender, target, and place. In this study, we integrated both the MAS and CA approaches into our model of these three components. An offender, a mobile individual with autonomous behavior to response perceived environment, is modeled as agent. Target and place, with stationary locations in the case of residential crime, are simulated as automata as in a typical CA model. Each of these components has been assigned a set of properties and behaviors according to our hypotheses, which are based foremost on previous studies in social disorganization and routine activity theories.

THE OFFENDER AGENT

Offender agents have several properties relative to committing residential burglary, such as location, age, race and gender of the offender.

First is the home location of the offenders, which is often recorded in crime report. For the purposes of this chapter, we have to assume that this is the location from which the offender agents begin their journey to crime. These are known offenders that have burgled in the Dallas area. We have data from the Dallas Police Department regarding both the place of residence and the place of offense. This data will be used to both initialize our model and to validate our findings. We are limited in that we have no other information other than where the offender lives and where the offender offended—thus, we must assume that they are starting from their home locations. However, this is a reasonable assumption, as crime researchers have found that the journey to crime is generally inversely related to the distance from an offender's residence (Brantingham & Brantingham, 1991).

In addition to the offender's location is the offender's motivation. With residential burglary, the motivation of an offender is often influenced by his individual characteristics, such age, race, and gender. Often assumed to be positively correlated with distance traveled, age has received limited attention in prior research. The inconsistent ranges used to evaluate age compound the problem. When evaluated in journey to crime research, age is classified arbitrarily, eliminating the ability to detect a pattern among research. The varied age categories prevent cross-comparisons of findings, so that although age is assumed to increase mobility, empirical evidence is lacking. Increased mobility afforded by access to transportation and a wider knowledge of surrounding areas is presumed to increase an offender's range. While youth is commonly stated as a factor limiting distance to offense, few studies have effectively evaluated its impact and results have been conflicting. Some find age positively correlated with mobility (Gottheil & Gabor, 1984; Turner, 1969; Phillips, 1980; Warren et al., 1998), while others report no effects (Canter & Gregory, 1994; Costello & Wiles, 2001; Tita & Griffiths, 2005).

The impact of race is also relevant to motivation. However, in previous research, the impact of race on offender mobility is unclear. Some studies report no effect on offender distance due to race (Messner & Tardiff, 1986; Rand, 1986). One found black offenders stayed closer to familiar locations, branching out less than white offenders (Carter & Hill 1979). Both white and black subjects preferred to offend in neighborhoods composed mainly of their own race (Reppetto, 1974). With one study suggesting that black offenders stayed closer to familiar locations than their white counterparts (Carter & Hill 1979). Based on the general demographic patterns of racial residential patterns in Dallas, Texas, we expect that black offenders would be less motivated to travel long distances. Previous researches have seldom studied Hispanic journey to crime. We speculate that their travel distance is probably the shortest among the three races, because they are geographically dispersed throughout the city more than are African Americans and Whites.

Little work has examined the difference between the male and female journey to crime. In our research sample of 148 residential burglaries, the females were likely to travel further to commit a residential burglary. This may be due to selection of targets that are suitable for their physical abilities. For example, Dallas has large numbers of tall privacy fences (e.g., six and eight feet) that may be more difficult for a female to climb than a male.

THE TARGET AUTOMATON

A target automaton in the residential burglary crime is a house or an apartment unit, instead of a human victim. Previous research suggests that both potential costs and rewards factor into the selection of a target. A target is attractive when an offender perceives a large gain, the crime requires little investment, and there is a minimal perceived chance of apprehension (Rhodes & Conly, 1981). We identified three important properties for target: location, income and race composition of the residential area. The location of offenses is also reported in the data. For a residential burglar, the location is usually the home address of the target. The distance between the offender's location and offenses location basically provides the length of the journey to crime.

Except for the items that were stolen, we may not have much information about the target itself in the crime report. As a residential location has no true "routine activities" of its own, it assumes those of the people that reside within it and around it. That is, we are constrained to assign the target the average socioeconomic status (SES) of the members of the blockgroup within which the residence falls.[1] In this study, we used medium household income of the census blockgroup and assigned to all cells in it to represent the desirability of the potential targets. We use income level as a surrogate for desirability because the distance an offender is willing to travel will not be great, unless the reward is great. Further, no offenders was found to prefer to offend in neighborhoods composed mainly of the opposite race (Reppetto, 1974), thus we expect that motivation would be less to offend in a neighborhood where the racial make-up was markedly different from the offender's race.

THE PLACE AUTOMATON

Place automaton is the target residence's neighboring area in this case. Place has several properties, such as mean commute time, and mean length of residential tenure, which is often related to the guardianship of the target. For a house to be burgled, the house's own resident must be absent or unaware of the entry. Thus, the only place managers that are left to guard the house are the residence's neighbors. We suggest that the strength of place managers (i.e., the effectiveness) is determined by the average tenure and the average commute time of neighborhood residents.

Even as early as 1938, Wirth noted the growing sense of anonymity even in residential neighborhoods. He felt that residential neighborhoods had long been the harbor for interpersonal knowledge of those persons who lived nearby. Simply put, historically neighborhoods were viewed as a location where people living on the same block would know each other. Wirth believed that anonymity was evidenced by the loss of primary contacts, and the effects of formal control replacing traditional informal neighborhood controls. Further works, which later became known as social disorganization theory (Shaw & McKay, 1942), introduced the notions that residential mobility led to the disruption of a community's social organization and community solidarity, which led to crime. Residential tenure (i.e., staying in the same neighborhood for longer periods of time) and commute time are key factors for the place automaton, and are crucial according to social disorganization theory (Bursik & Grasmick, 1993; Hunter, 1985, Sampson, 1987; Sampson & Groves, 1989). Longer periods of residential tenure will strengthen the effectiveness of the guardianship. The longer the average commute that neighborhood residents have outside of their neighborhood, the fewer available guardians and the weaker the guardianship capacity of the place.

THE JOURNEY TO RESIDENTIAL BURGLARY SIMULATION MODEL

Based on the previously discussed theories and criminological research, the journey to residential burglary is related to an interaction between the offender, the targeted residential unit and the complex neighborhood structure within which the target resides. The likelihood of a residential burglary is primarily based on the motivation of the offender, the desirability of the target, and the lack of guardianship of the place. While RA assumes that all persons are potential offenders, some may be more motivated than others. Following SD theory we would possibly suspect that, offenders might be more motivated to travel further if they are older or a female. Offenders of different races may choose to commit the burglary either closer or further from their homes. The desirability of the target is positively correlated with the income value of its contents. This desirability may be curtailed by their desire to offend in neighborhoods where they may be more likely to racially "blend" with residents. Place guardianship is enhanced by longer tenures and is weakened by longer commute times.

We have developed a model that applies both cellular automata (CA) and multi-agent systems (Gottheil & Gabor, 1984) to simulate the distribution of residential burglary in space and time using 2000 Dallas Police data. In 2000, there were 148 burglaries that were "cleared," or solved. Thus, we have the locations of 148 offenders' residences and target locations. These were all addressed utilizing geocoding capability in GIS. The average age of our offenders was 26.64, but the vast majority was under the age of 25. We had 137 males and 11 females in our sample, suggesting that males either commit more residential burglaries, or at least that they get caught more often in Dallas. We only had three races represented in our sample: White (26), Black (82), and Hispanic (40). In addition to the offender data, we gathered information from the 2000 U.S. Census. This information was selected on the basis of supporting either RA or SD theory. We included such variables as: racial composition of neighborhoods (i.e., block groups), commute time, length of tenure, and income.

The model was developed with ArcGIS software development kit (ArcObjects SDK) using Visual Basic. Similar to other CA models, we utilize cellular space, which consists of interconnected rectangular cells. These also become our places, within which the targets reside. The grid of these rectangular cells is overlain on the census blockgroup layer in order to transfer those area properties to the cells. These properties become our state variables. The offenders are modeled as intelligent agents in the simulation through vector points, because they are able to move around based on the choices they make. Unlike most of the simulation models that generate random offenders, we use the actual offenders from the Dallas Police records as our agents. The offenders are sorted based on the time and date of offenses so that we can simulate the residential burglaries across the full calendar year and compare the outputs from the model to that of the actual offenses that occurred in 2000.

The neighborhood template is often modeled in the literature as one of the two standard neighborhood types, the "Moore" neighborhood and "von Neumann" neighborhood (Benenson & Torrens, 2005). The template that we choose for our model can be extended as large as the whole blockgroup, because our offenders now can move at any distance and in any direction due to the flexibility provided by vector based MAS.

The primary variable to be simulated is the distance that a burglar is willing to travel, determined by the likelihood of such crime in a location, which is a function of motivation, target desirability and place guardianship. Currently, the distance the offender is willing to travel to commit the residential burglary is modeled as the Euclidean distance to the offender's home address. In our future studies, we will improve this model by adopting street network distance.

Motivation

Burglary is more often committed within a certain distance from the criminal's home because the offender does not want to be recognized in the offender's own neighborhood (Brantingham & Brantingham, 1993, Costello & Wiles, 2001; Ratcliffe, 2001; Snook, 2004; Rengert et al., 1999). Previous studies have assigned a threshold distance within which no burglary crime will happen. This treatment runs into a risk that would completely exclude offenses inside the offender's own community, which happens, although not so frequently. The motivation is usually increased with the distance within a certain range, after that willingness to travel further becomes diminished with the distance. Therefore, we chose use a Gaussian function to model the offender's motivation as a function of distance from his home address. For each offender, this Gaussian function can be parameterized based on the burglar's personal characteristics, which include race, age and gender of the offender. To obtain these parameters, we performed descriptive statistics on the Dallas Police data to derive the mean and standard deviation for each age, race and gender group (Table 1).

According to the statistics in Table 1, whites travel the longest of the three races. Blacks travel shorter distances than whites, as may be anticipated by social disorganization theory. Social disorganizationists, and others, have found that African Americans have historically found themselves to be the most segregated of the races (Sampson & Wilson, 1995). Research suggests that races will stay within their own comfort zone or in mixed race neighborhoods. Thus, the distance to travel for African Americans will be altered by the neighborhood patterns of racial differences in Dallas, TEXAS. On the other hand, Hispanics have typically integrated into wider parts of the Dallas area, which may be reflected in their travel distance. Hispanics travel the shortest distances to residential burglaries compared to their counterparts in the other two race categories.

Offenders between the ages of 35-40 (N= 18) travel the furthest with the second furthest traveling offenders being between the ages of 25-30 (N= 16). This first group of individuals is more likely to belong to the professional burglar status. The most active age group was the most youthful age group (N=48), however, they traveled the second fewest miles to commit their offenses. Thus, our statistics in Table 1 finds some support that suggests that age is positively correlated with mobility (Canter & Gregory, 1994; Costello & Wiles, 2001; Gabor & Gottheil, 1984; Phillips, 1980; Turner, 1969; Tita & Griffiths, 2005; Warren et al., 1998). We see two separate peaks in our data.

Within the Dallas database, females traveled further than their male counterparts (Table 1). Females traveled an average distance of 5.49 miles. Males traveled the average distance of 2.49 miles. As noted above, this may be due to the physical differences in the genders to cope with barrier (i.e., tall privacy fences in Dallas).

Desirability

In this study, desirability of the target is determined by the income and race composition data of the community it resides, due to the lack of individual level information for the target. Offenders often select targets that have a higher income level than their own and they usually avoid impoverished areas which would not have much to steal. However, this is not always the case, because occasionally offenders may select targets within their own income bracket or even lower (albeit rare). Additionally, in some locations, high income residences may be unavailable to offender because they may be within gated communities, have security guards and/or alarm systems. While the higher the income of the targets, the more desirable in general, a simple linear function is not appropriate for our model.

We used Gaussian function again to model the relationship between desirability and the income level based on the statistics obtained from Dallas census blockgroup data (Table 1). In this way, both very low and very high median household incomes would have a low desirability while medium and medium high household incomes would have a high desirability.

Generally speaking, we know that black neighborhoods are disproportionately segregated and concentrated in various zones in cities. This follows along the lines of SD theory and the notions of the "American Apartheid" (Wilson, 1987; Sampson & Wilson, 1987). In the case of Dallas, Texas, large African American communities are segregated in the South quadrant of the city. Thus, the very distribution of the neighborhoods within the city impact the offender, as we know that offenders prefer to offend within their comfort zone (within race or within a mixed race neighborhood). For example, white offenders prefer white dominant area first, and then mixed or Hispanic zone, with the least preference in a black dominant neighborhood. In order to determine a neighborhood's desirability based on race, the census statistics for the percentage of population that is white, black, and Hispanic are combined and weighted in such a fashion as to reflect an offender's general tendency to stay in a neighborhood of similar racial diversity as his own (Table 1). For whites, the desirability for target is,

$$P_w = 0.6 \times \%white + 0.3 \times \%Hispanic + 0.1 \times \%black$$

Similar formulas are used for both African Americans and Hispanics as seen in Table 1.

Guardianship

Offenders often select communities that lack of guardianship to commit burglary crimes. The lack of guardianship in this study is defined by mean commute time and mean residential tenure (% of less than 5 years' tenure). In general, the longer the commute time of neighborhood residents and the higher the percentage of new comers to the community, the higher degree the lack of guardianship. After several experiments, both variables that are used to measure lack of guardianship are transformed from raw blockgroup census data into normally-distributed values using a power transformation (Table 1). The output are then rescaled to the range from 0 (meaning very low degree of lack of guardianship), to 1 (indicating extremely high degree lack of guardianship).

Likelihood

Our study extends previous work by Eck (1995) and Liu, Wang, Eck, and Liang (2005), We have theoretically focused on the property crime of residential burglary by imitating the relationship between the offender's motivation, the target's desirability, and the place's guardianship. The interaction of these three elements determines the likelihood of a residential burglary, which is defined by a two levels of weighted linear combinations, with the weights customizable and summing up to 1. First, the likelihood of a burglary crime is a weighted linear combination of the offender's motivation, the target's desirability and the place's degree of lack of guardianship.

$$L_{tij} = w_m \cdot M_{tj} + w_d \cdot D_{ti} + w_{\lg} \cdot LG_{ti}$$

L is the likelihood for residential burglary committed at time t, at place (and target) i, by offender j. M stands for the offender's motivation, D is the target's desirability and LG denotes the degree of lack of guardianship for the place. w_m, w_d and w_{lg} are the weights for motivation, desirability and lack of guardianship, respectively. At the second level, motivation is a weighted linear combination of those defined by age (M_{tja}), race (M_{tjr}) and gender (M_{tjg}), with w_a, w_r and w_g are the corresponding weights for age, race and gender, respectively,

$$M_{tij} = w_a \cdot M_{tja} + w_r \cdot M_{tjr} + w_g \cdot M_{tjg}$$

Desirability is a weighted linear combination of those defined by income (D_{tic}) and race composition (D_{tie}) of the target community with their corresponding weights being w_c and w_e respectively.

$$D_{ti} = w_c \cdot D_{tic} + w_e \cdot D_{tie}$$

Lack of guardianship is a weighted combination of those defined by commute time (LG_{tiu}) and % of less than 5 years' tenure (LG_{tin}) with their corresponding weights being w_u and w_n respectively.

$$LG_{ti} = w_u \cdot LG_{tiu} + w_n \cdot LG_{tin}$$

Target Selection

Based on the two levels of weighted linear combinations, a likelihood surface is generated, covering the whole study area for each individual offender. A random surface is then produced programmatically for the offender and compared with the offender's likelihood surface. If the likelihood is greater than the random value at that location, the location will be selected as a potential target. In our one year database, there is only one offense committed by a unique offender. Therefore, the model chooses the location with the highest

Table 1. Model parameters derived from the statistics of Dallas, TX Crime Data

Components	Properties	Representation	Weights	2nd Scenario
Offender: Motivation	Race	Average distance (and standard deviation) in miles: • Whites: 3.23 (3.0065) • Blacks: 2.96 (4.4130) • Hispanic: 1.87 (3.6456)	33.3%	40%
	Age	Average distance (and standard deviation) in miles: • 16-20: 2.13 (3.47) • 20-25: 3.51 (5.09) • 25-30: 3.32 (4.70) • 30-35: 1.07 (1.44) • 35-40: 3.83 (4.39) • 40+: 2.19 (2.12)	33.3%	
	Gender	Average distance (and standard deviation) in miles: • Males: 2.49 (3.74) • Females: 5.49 (6.03)	33.3%	
Target: Desirability	Income	Average income (and standard deviation) in dollars: • Income : 46,413 (32049)	33.3%	30%
	Race composition	• For white $P_w = 0.6 \times \%white + 0.3 \times \%Hispanic + 0.1 \times \%black$ • For black $P_b = 0.1 \times \%white + 0.3 \times \%Hispanic + 0.6 \times \%black$ • For a Hispanic $P_h = 0.2 \times \%white + 0.6 \times \%Hispanic + 0.2 \times \%black$	66.7%	
Place: Lack of Guardianship	Length of tenure	$(Y^{0.5} - 1)/0.5$ This result is then rescaled to fall between 0-1	50%	30%
	Commute Time	$(Y^{0.4} - 1)/0.4$ This result is then rescaled to fall between 0-1	50%	

likelihood among the selected ones as the final target for the burglar. Then the model moves to the burglar that was caught next in time sequence from the temporally sorted database.

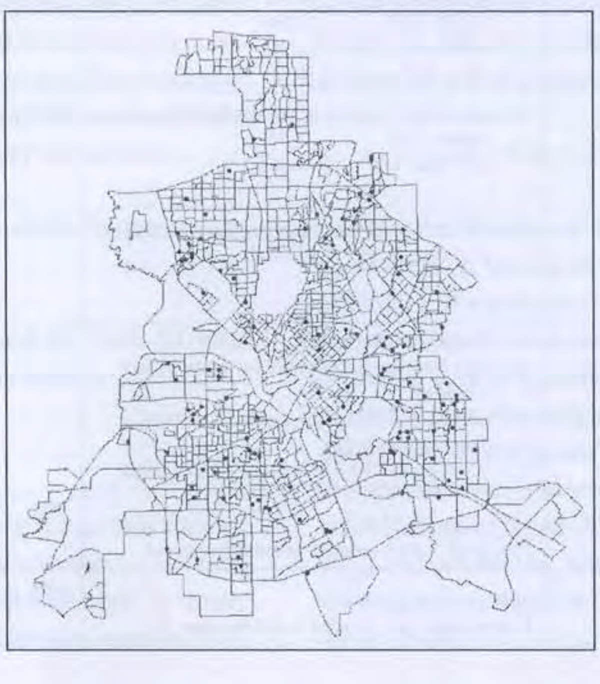
For the simulation of each subsequent burglar, if there are offenses within a neighborhood in the past 60 days, a multiplier will be derived to decrease the combined degree of the lack of guardianship (or increase of guardianship). However, unlike Liu's work, we do increase the motivation of the offenders because our one year dataset does not contain uncaught (or unsolved) offenders. There are also no updates on the target desirability, due to fact that the major variables determining desirability (income and race composition) do not change often in a short period of time.

RESULTS AND DISCUSSION

The model that we developed to simulate burglary crimes embraced both social disorganization and routine activity theories. The information related to the motivation of the offenses (i.e. age, race and gender) is available at the individual level, which is usually what the routine activity theory attempting to examine. The variables used to derive target desirability and lack of guardianship of place (i.e. income, race composition, commute time, and % of less than 5 years tenure) are only available at the neighborhood level, which is primarily what we are limited to using in order to gather information on the impact of various measures of social disorganization.

To test how much these two theories contribute to the explanation of journey to burglary crime in Dallas, we configured the model with two different weights. For the first scenario, we assume equal importance of all variable and assign equal weights to factors at both levels. This means, at the first level, motivation, desirability and lack of guardianship are equally weighted with a 33.3% influence for each. At the second level, each element of the first level factor is also

Figure 1. The distribution of actual burglary offenses (targets) in Dallas, TX (2000)



treated the same. For example, for motivation, age, race and gender of the offender are associated with a 33.3% weight each, while for desirability, income and race composition each receive a 50% weight. Figure 1 displays the actual distribution of all the burglary targets and Figure 2 shows the results of the model simulation with equal weights at both levels. This modeled result appears to be noticeably clustered, while the actual distribution of targets is more spread out. This is likely due to the fact that with equal weighted scenario, the factors related to social disorganization theory are more emphasized. Two of the first level factors and four of the second level factors are neighborhood level variables, which causes an over-clustering of predicted targets at certain census block groups.

In the second scenario, we modified the weights so that some of the factors are of unequal importance at different levels (Table 1). At the first level, we assign a weight of 0.4 for offender motivation to increase the influence of routine activity theory, while giving both target desirability and lack of guardianship a lower weight of 30%. At the second level, for target desirability, we downplay the influence of income factor (33.3%) compared to race composition (66.7%). Figure 3 shows the results of this second scenario. As a consequence of the modified weights, it is observed that the amount of clustering seen in the equal-weights model is greatly reduced. The modeled distribution of offenses appear to be more spread out, much closer to that of actual data, which suggests that the routine activity theory may better explain the distribution of burglary crimes than social disorganization theory, although both are regarded necessary and considered in this model. For future study, we will develop an automatic model calibration approach to derive an optimal weight configuration to achieve a prediction that is closest to the actual data.

Figure 2. The distribution of burglary offenses (targets) by an equally weighted simulation model

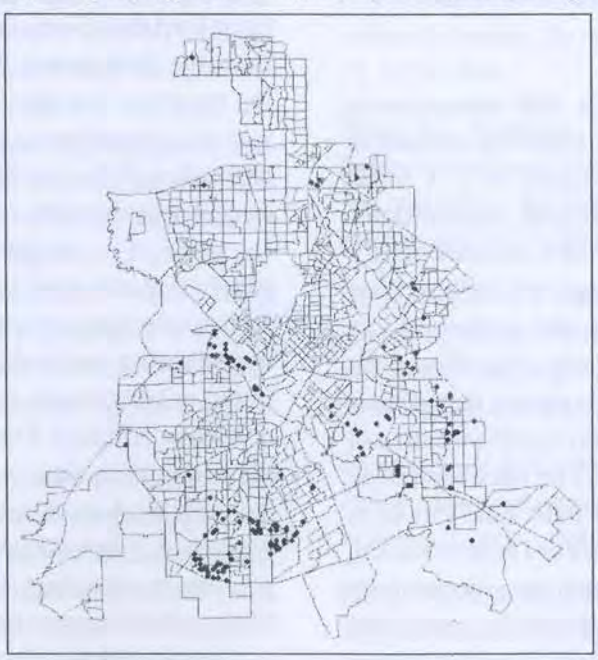
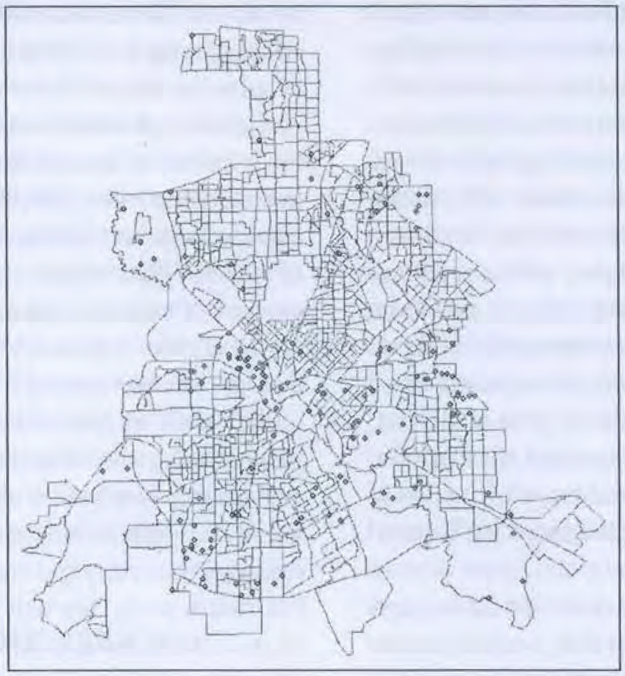


Figure 3. The distribution of burglary offenses (targets) by an unequally weighted simulation model



CONCLUSION AND FUTURE RESEARCH

The complex social fabric that encompasses neighborhood phenomena, including residential burglary, is difficult to explain with a linear formula and linear theoretical explanations. Different from previous works, we have used a multifaceted theoretical approach pulling from both social disorganization and routine activity theory. Routine activity theory offers the contributions of understanding the person that offends (i.e., the motivated offenders), and the location of the offense (i.e., the target). The likelihood of an offense is a function of the individual's motivation and individual preference of a target location, both of which are key concepts in routine activity theory. Social disorganization helps to explain the guardianship for residential burglary better for residential burglary. The very definition of burglary denotes the lack of human inhabitants in the dwelling during the course of the crime (or at least their being unaware of another person invading their home). However, when examining the place manager of a residential burglary, social disorganization theory would explain the protection of the dwelling regarding the expansion of guardianship into the larger geographical space of a "neighborhood." This pocket of people that surround the house can offer an effective management strategy by being long-term residents that are familiar with those that belong in the neighborhood and those that do not (i.e., collective efficacy). Further, according to social disorganization theory, the effectiveness of this neighborhood structure, the place manager, is weakened, when the neighborhood has a higher percentage of renters and individuals are more likely to be strangers to one another.

Our chapter provides a unique insight into the application of simulation modeling into property crimes, such as residential burglary, by integrating the traditional CA model with an innovative MAS. As such, our line of research extends previous work by Eck (1995) and Liu, Wang, and Eck (2005) through the discussion of a very different formulation of a state variable—the journey to crime. We have applied a dynamic system similar to that described by Liu, Wang, and Eck (2005), however we have theoretically focused on the property crime of residential burglary. We model our offenders, targets, and places as artificial agents and automata, which imitate what we propose above to be the relationship between these three elements.

Our model provided several advancements. First, we utilized "real" data to configure our model parameters and the initial states of the automata with statistics obtained from the Dallas, TEXAS Police Department. This data driven nature of our model freed us from the restriction of random placement and general validation modeling. Second, in addition to model configuration, our model simulates true offenders as intelligent agents, so that year-round crime activities in Dallas, Texas can be modeled. Again, we were able to avoid general randomization in most simulation studies, which made our model results more comparable to the actual offense data. Third, we were able to assign unequal importance to the various factors that were utilized to simulate burglary likelihood (e.g., offender motivation, guardianship, etc.). This allowed us to test the model to determine which factors were acting more 'strongly' in the activity pattern of the offender agent. As a result, we were able to evaluate the different contributions made by SD and RA theory components.

We are limited, in that we cannot address an offender's "awareness space" (Brantingham & Brantingham, 1991). Our only alternative would be to place our offenders randomly on the grid, and we do not feel that this would provide a quality model. We simply do not have that level of data available at this time. We also imagine that our findings would only be generalized to American, and perhaps Canadian, cities due to the theoretical approaches that we have chosen to present. Future research may want to test these models in other parts of the country and world. Future researchers may also enhance our modeling by adding information on the amount of goods stolen from each actual residential burglary.

REFERENCES

Alonso, J., Fernandez, A., & Fort, H. (2006). Prisoner's dilemma cellular automata revisited: Evolution of cooperation under environmental pressure. *Journal of Statistical Mechanics: Theory and Experiment, P06013*, 1-15.

Barredo, J. I., Kasanko, M., McCormick, N., & Lavalle, C. (2003). Modelling dynamic spatial processes: Simulation of urban future scenarios through cellular automata. *Landscape and Urban Planning, 64*, 145-160.

Batty, M. (2005). Agents, cells, and cities: New representational models for simulating multiscale urban dynamics. *Environment and Planning A, 37*, 1373-1394.

Batty, M., Desyllas, J., & Duxbury, E. (2003). Safety in numbers? Modelling crowds and designing control for the Notting Hill carnival. *Urban Studies, 40*, 1573-1590.

Batty, M., Xie, Y., & Sun, Z. (1999). Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems, 23*, 205-233.

Benenson, I. & Torrens, P.M. (2005). *Geosimulation: Automata-based modeling of urban phenomena.* London: John Wiley & Sons.

Blue, V. J., & Adler, J. L. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways. *Transportation Research Part B, 35*, 293-312.

Boggs, S. L. (1965). Urban crime patterns. *American Sociological Review, 30*, 899-908.

Brahan, J. W., Lam, K. P., Chan, H., & Leung, W. (1998). AICAMS: artificial intelligence crime analysis and management system. *Knowledge-Based Systems, 11*, 355-361.

Brantingham, P.J. & Brantingham P. L. (1991). *Environmental Criminology.* (2nd Ed.) Prospect Heights, IL: Waveland Press.

Bursik, R. J., & Grasmick, H. G. (1993). *Neighborhoods and crime*. San Francisco: Lexington Books.

Byrne, J. M., & Sampson, R. J. (1986). *The social ecology of crime*. New York: Srpinger-Verlag.

Canter, & Gregory. (1994). Identifying the residential location of rapists. *Journal of Forensic Science, 34*, 169-175.

Canter, & Larkin. (1993). The environmental range of serial rapists. *Journal of Environmental Psychology, 13*, 64-70.

Carter, R. L. (1979). *The criminal's image of the city.* New York: Pergamon Press.

Clarke, K. C., & Gaydos, L. (1998). Loose-coupling a cellular automaton model and GIS: Long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science, 12*, 699-714.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*, 588-608.

Costello, A. & Wiles, P. (2001). GIS and the journey to crime: An analysis of patterns in South Yorkshire. In A. Hirschfield & K. Bowers (Eds.), *Mapping and analysing crime data: Lessons from research and practice* (pp. 27-60). London: Taylor and Francis.

Couclelis, H. (1985). Cellular worlds: A framework for modeling micro-macro dynamics. *Environment and Planning A, 17*, 585-596.

Couclelis, H. (1988). Of mice and men: What rodent populations can teach us about complex spatial dynamics. *Environment and Planning A, 20*, 99-109.

Couclelis, H. (1989). Macrostructure and microbehavior in a metropolitan area. *Environment and Planning B, 16*, 141-154.

DeFrances, C. J., & Smith, S. K. (1994). *Crime and neighborhoods.*

Eck, J. E. (1994). Examining routine activites theory: A review of two books. *Justice Quarterly, 12*, 783-797.

Franklin, S., & Graesser, A. (1996) Is it an agent, or just a program?: A taxonomy of autonomous agents. Intelligent Agents III: In *Proceedings of the Third International Workshop on Agent Theories, Architectures, and Languages*, (ATAL'96), Lecture Notes in AI, Third International Workshop on Agent Theories, Architectures, and Languages, (ATAL'96), Springer-Verlag.

Goodchild, M. F. (2003) Geographic information science and systems for environmental management. *Annual Review of Environmental Resources, 28*, 493-519.

Gottheil, E., & Gabor, T. (1984). Offender characteristics and spatial mobility. *Canadian Journal of Criminology, 26*, 267-281.

Green, D., Tridgell, A., & Malcom, G. A. (1990) Interactive simulation of bushfires in heterogeneous fuels. *Mathematical Computation and Modelling, 13*, 57-66.

Hawley, A. (1950). *Human ecology.* New York: Ronald Press Co.

Hesseling, R. B. P. (1992). Using data on offender mobility in ecological research. *Journal of Quantitative Criminology, 8*, 95-112.

Hogeweg, P., (1988) Cellular automata as a paradigm for ecological modeling. *Applied Mathematics and Computation, 27*, 81-100.

Hunter, A. J. (1985). Private, parochial, and public social orders: The problem of crime and incivility in urban communities. In G. D. Suttles & M. N. Zald (Eds.), *The challenge of social control: Citizenship and institution building in modern society* (pp. 230-242). Norwood, NJ: Ablex Publishing.

Liu, L., Wang, X., Eck, J., & Liang, J. (2005). Simulating crime events and crime patterns in a RA/CA model. In F. Wang (Ed.), *Geographic information systems and crime analysis* (pp. 197-213). Hershey, PA: Idea Group Publishing.

Messner, S. F., & Tardiff, K. (1986). *The social ecology of urban homicide: An application of the 'Routine activities approach. Criminology, 22*, 241-67.

Morenoff, J. D., & Sampson, R. J. (1997). Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970-1990. *Social Forces, 76*, 31-64.

Phipps, M. (1989). Dynamical behavior of cellular automata under constraints of neighborhood coherence. *Geographical Analysis, 21*, 197-215.

Phillips, P. D. (1980). Characteristics and typology of the journey to crime. In D. E. Georges-Abeyie & K. D. Harries (Eds.), *Crime: A spatial perspective* (pp. 167-180). New York: Columbia University Press.

Pyle, G. F. (1976). Spatial and temporal aspects of crime in Cleveland, Ohio. *American Behavioral Scientist, 20*, 175-198.

Rand, A. (1986). Mobility triangles. In R. M. Figlio, S. Hakim, & G. F. Rengert (Eds.), *Metropolitan crime patterns*. Monsey, NY: Criminal Justice Press.

Ratcliffe, J. H. (2001). Policing urban burglary. *Trends and issues in crime and criminal justice (No. 213).* Canberra: Australian Institute of Criminology.

Rengert, G. F. (1981). Burglary in Philadelphia: A critique of opportunity structure model. In P. Brantingham & P. Brantingham (Eds.), *Environmental criminology* (pp.167-188). Beverly Hills, CA: Sage Publications.

Rengert, G., Piquero, A. R., & Jones, P. R. (1999). Distance decay reexamined. *Criminology, 37*, 427-445.

Reppetto, T. A. (1974). *Residential crime*. Cambridge: Ballinger.

Rhodes, W. M., & Conley, C. (1981). Crime and mobility: An empirical study. In P. J. Brantingham & P. L. Brantingham (Eds.), *Environmental criminology*. Beverley Hills, CA: Sage Publications.

Sampson, R. J. (1985). Neighborhood and crime: The structural determinants of personal victimization. *Journal of Research in Crime and Delinquency, 22*, 7-40.

Sampson, R. J. (1987). Does an intact family reduce burglary risk for its neighbors? *Sociology and Social Research, 71*, 204-207.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology, 94*, 774-802.

Sampson, R. J., & Wilson, W. J. (1995). Race, crime and urban inequality. In J. Hagan & R.D. Peterson (Eds.), *Crime and inequlity* (pp. 37-54), Stanford University Press.

Shaw, C. R., & McKay, H. D. (1942). Juvenile Delinquency and Urban Areas. Chicago, IL: University of Chicago Press.

Skogan, W. (1990). *Disorder and Decline: Crime and the Spiral of Decay in American Neighborhoods*. New York: The Free Press.

Smith, R., 1991, The application of cellular automata to the erosion of landscapes. *Earth Surface Processes and Landforms, 16*, 273-281.

Smith, S. K., & DeFrances, C. J. (1994). *Crime and Neighborhoods.*

Snook, B. (2004). Individual differences in distance traveled by serial burglars. *Journal of Investigative Psychology and Offender Profiling, 1*, 53-66.

Takeyama, M., & Couclelis, H. (1997). Map dynamics: Integrating cellular automata and GIS through Geo-Algebra. *International Journal of Geographical Information Science, 11*, 73-91.

Taylor, R. B. (1997). Social order and disorder of street blocks and neighborhoods: Ecology, microecology, and the systemic model of social disorganization. *Journal of Research in Crime and Delinquency, 34*(1), 113-155.

Terna, P. (1998) Simulation tools for social scientists: Building agent based models with SWARM. *Journal of Artificial Societies and Social Simulation.*

Tita & Griffiths. (2005). Traveling to violence: The case for a mobility-based spatial typology of homicide. *Journal of Research in Crime and Delinquency, 42*, 275-308.

Torrens, P. (2006). Simulating sprawl. *Annals of the Association of American Geographers, 96*, 248-275.

Turner, S. (1969). Delinquency and distance. In J. T. Sellin & M. E. Wolfgang (Eds.), *Delinquency: selected studies*. New York: Wiley.

Vold, G. B., Bernard, T. J., & Snipes, J. B. (1998). *Theoretical criminology* (4th ed.). New York: Oxford University Press.

von Neumann, J. (1949) Theory and organization of complicated automata. In A. W. Burks (Ed.), *Theory of self-reproducing automata (Part One)* (pp. 29-87). Urbana: University of Illinois Press.

Wahle, J., Neubert, L., Esser, J., & Schreckenberg, M. (2001) A cellular automaton traffic flow model for online simulation of traffic. *Parallel Computing, 27*, 719-735.

Warner, B. D., & Pierce, G. L. (1993). Reexamining social disorganization theory using calls to the police as a measure of crime. *Criminology, 31*(4), 493-517.

Warren, J., Reboussin, R., Hazelwood, R. R., Cummings, A., Gibbs, N., & Trumbetta, S. (1998). Crime scene and distance correlates of serial rape. *Journal of Quantitative Criminology, 14*, 35-59.

White, C. R. (1932). The relation of felonies to environmental factors in Indianapolis. *Social Forces, 10*, 498-509.

White, R., & Engelen, G. (1992). *Cellular dynamics and GIS: Modelling spatial complexity.* Working Paper 9264, Research Institute for Knowledge Systems, Maastricht, The Netherlands.

Wilson, W. J. (1987). *The truly disadvantaged: The inner city, the underclass, and public policy.* Chicago: University of Chicago Press.

Winoto, P. (2002). A simulation of the market for offenses in multiagent systems: Is zero crime rates attainable? In *Proceedings of the Multi-Agent-Based Simulation, Third International Workshop*, Bologna, Italy.

Wolfram, S. (1986). *Theory and applications of cellular automata.* Singapore: World Scientific.

Wright, R., & Decker, S. H. (1994). Choosing the target. *Burglars on the job: Streetlife and residential break-ins.* Boston: Northeastern University Press.

Wu, F. (1999). GIS-based simulation as an exploratory analysis for space-time processes. *Journal of Geographical Systems, 1*, 199-218.

ADDITIONAL READINGS

Brantingham, P. J., & Brantingham, P.L. (1981). Environmental criminology. Beverly Hills, CA: Sage Publications,.

Liang, J. (2001). *Simulating crimes and crime patterns using cellular automata and GIS*. Department of Geography. University of Cincinnati.

Rengert, G. (1989). Spatial justice and criminal victimization. *Justice Quarterly, 6*, 543-564.

Rengert, G. F. (1992). The journey to crime. In N. R. Fyfe, D. J. Evans, & D. T. Herbert (Eds.), *Crime, policing and place: Essays in environmental criminology*. London: Routledge.

Rengert, G. F., & Wasilchick, J. (2000). *Suburban burglary: A tale of two suburbs* (2nd ed.). Springfield, IL: Charles C. Thomas.

Takeyama, M. & Coucelis, H. (1997). Map dynamics: Integrating cellular automata and GIS through Geo-Algebra. *International Journal of Information Science, 11*(1), 73-91.

Wu, F. (1998). GIS-based simulation as an exploratory analysis for space-time processes. *Journal of Geographic Systems, 1*, 199-218.

ENDNOTE

[1] By assigning the individual residence the average SES of the blockgroup, we are breeching into a form of ecological fallacy. However, due to data constraints, this is the best measure that we have of the residence's inner contents which the burglar would be interested in stealing.