Combining System Dynamics, Social Networks, and Geographic Information Systems

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System dynamics has always held the potential to synthesize and advance theories in social science. Increasingly, social scientists and policy makers are recognizing the importance of complexity and turning to methods like geographic information systems, social network analysis, agent based modeling, chaos theory, and system dynamics. All of these approaches draw some underlying modeling mathematical framework. The approach discussed here brings system dynamics, social network analysis, and geographic information systems together in a novel way to understand a specific problem that will have scientific relevance to community psychologists, urban planners, social workers, geographers, political scientists, and public administration. Moreover, showing how the various mathematical frameworks connect within a concrete example will help realize the potential of system dynamics to advance theories and interventions of contemporary social problems.

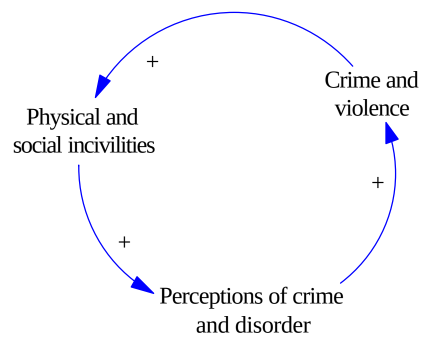
Keywords: methodology, social networks, geographic information systems, urban modeling

1. Introduction

What is the relationship between environment and perceptions of safety? Previous research has characterized unsafe and violence-prone areas as possessing social and physical incivilities (Perkins et al. 1993). *Social incivilities* are signs in the neighborhood of public drunkenness, noisy neighbors, prostitution, drug trafficking, gang-related activity, homelessness, and loitering. *Physical incivilities* refer to visual indicators of disorder and can range from vandalism, graffiti, and yard debris to unkempt, dilapidated, and abandoned houses and buildings (Perkins et al. 1993). Research has shown that incivilities invoke *perceptions* of crime and disorder among residents and potential offenders (Perkins, Meeks, and Taylor 1992; Taylor 1999; Taylor and Gottfredson 1986; Taylor, Gottfredson, and Brower 1984). In turn, residents withdraw leaving spaces *undefined*. Undefined spaces are characterized by the fact that no one feels that it is their responsibility to monitor or maintain them. As a consequence, potential offenders commit crime and violent acts that add to existing incivilities, forming the causal feedback loop depicted in Figure 1 where an increase in *Physical and social incivilities* leads to increases in *Perceptions of crime and disorder*, leading to more *Crime and violence* that feed back and increase *Physical and social incivilities*. The positive feedback loop depicted in Figure 1 has been popularized as the “broken window” theory. Although several studies discuss the importance of understanding the physical environment in relation to crime, many do not directly show how such changes lead to a stable reduction in neighborhood crime.

Establishing formal and informal social control over undefined spaces has been a critical component of reducing crime, incivilities, and increasing perceptions of safety. However, our “perceptions” of physical spaces do not necessarily correspond to maps of such spaces. Thus, we argue that perceptions of spaces are mental representations with systematic biases that change dynamically with the social network and perceptions of crime. In order to develop a better understanding of the dynamic relationship between environment and perceptions of safety, we need to employ a combination of methods like system dynamics computer modeling, social network analysis, and geographic information systems to represent and study the complex interactions of multiple nonlinear feedback loops.

Figure 1. Feedback relationship between incivilities, perception, and crime and violence



Kubrin and Weitzer (2003) have called for new studies in social disorganization theory that model spatial dynamics, including methods that develop dynamic models, attend to reciprocal or feedback effects, and address context effects on individual level outcomes. This paper addresses this call by developing and illustrating a method for modeling the spatial and social structures underlying the dynamics of crime and violence and perceptions of safety. Theoretically developing such models and then testing them empirically will up avenues of research in social geography, geographic information sciences, community and environmental psychology, environmental criminology, and system dynamics.

2. Background and theoretical considerations

In 2000, approximately 22.0% of St. Louis city residents fell below the poverty line, compared to 11.3% nationally (National Council of Churches 2002). In that same year, St. Louis ranked third in the nation for violent crimes (Federal Bureau of Investigation 2001). It is important to state that there is nothing inherently negative about residents that live in poor areas. Rather, there is something about the physical design of these areas that contribute to a perception of danger and disorder, which leads to increase criminal activity among youth. These design features include communities that have large numbers of abandoned and dilapidated buildings, debris in streets, graffiti, drug-related activity, loitering, and overall neighborhood disorganization (Astor, Meyer, and Behre 1999; Pitner, Lloyd, and Bell under review; Reiss and Roth 1993; Astor, Meyer, and Pitner 1999, 2001; Meyer and Astor 2002; Perkins et al. 1993; Sampson and Lauritsen 1994; Taylor and Gottfredson 1986).

In contrast to theories organized around the demographic explanations for crime, social disorganization theory emphasizes the effects of places (Kubrin and Weitzer 2003). Social disorganization theory posits that “weak social networks decrease neighborhood’s capacity to control the behavior of people in public, and hence increase the likelihood of crime” (Kubrin and Weitzer 2003, p. 374). Studies from environmental psychology, urban planning, social work, education, public health, and environmental criminology suggest that physical cues serve as markers for unsafe and violence prone areas (Brantingham and Brantingham 1981; Skogan 1976; Eck and Weisburd 1995; Newman and Franck 1980; Perkins et al. 1990; Perkins, Meeks, and Taylor 1992; Taylor 1994, 1997; White 1990; Taylor and Gottfredson 1986). Many of these unsafe and violence-prone areas have similar characteristics that have been defined as social and physical incivilities (Perkins et al. 1993).

2.1. Undefined public spaces

Areas that have high levels of social and physical incivilities may be thought of as undefined public spaces (Cisnernos 1995; Newman 1973, 1995; Newman and Franck 1980). The term 'undefined' refers to areas where no one feels that it is their responsibility to monitor or maintain. As a consequence to this lack of care, the level of incivilities in these areas increase, which leads to heightened perceptions of lawlessness and crime. Politicians and police departments often refer to this concept as the "broken window" theory, which posits that a sequence of events typically take place in undefined public spaces:

> Evidence of decay (accumulated trash, broken windows, deteriorating building exteriors) remains in the neighborhood for a reasonably long period of time. People who live and work in the area feel more vulnerable and begin to withdraw. They become less willing to intervene to maintain public order or to address physical signs of deterioration. Sensing this…offenders become bolder and intensify their harassment and vandalism. Residents become yet more fearful and withdraw further from community involvement and upkeep. This atmosphere then attracts offenders from outside the area, who sense that it has become a vulnerable and less risky site for crime (Wilson and Kelling 1982, p. ?).

Several studies have documented the relation between undefined spaces and residents' perceptions of danger (Day 1994; Goldstein 1994; Greenberg, Rohe, and Williams 1982; Newman and Franck 1980; Perkins, Meeks, and Taylor 1992). More recent community-based interventions focus on the dynamics of individuals participating in defining and defending their public space (Donnelly and Kimble 1997).

2.2. Territoriality, defensible spaces, and social control

Proshansky, Ittelson, and Rivlin (1970) defined territoriality as "achieving and exerting control over a particular segment of space" (p. 180). The notion of social control is central to social disorganization theory, yet most studies have only looked at informal social controls, and there is a need to include examination of formal controls such as enforcement of legal and regulatory codes (Kubrin and Weitzer 2003). Formal social controls have direct effects on crime and disorder, as well as the potential to influence residents' informal practices (Kubrin and Weitzer 2003). The relationship between formal controls and their effects on neighborhoods capacity to engage in informal control is inherently nonlinear. For example, both too little and too much policing can weaken neighborhood capacity to exert informal control (Kubrin and Weitzer 2003).

Informal social control can be achieved when residents construct *real* physical barriers (e.g., fences or security bars), or when they create *symbolic* ones (e.g., flowers gardens, plants, shrubs, and yard decorations) (Perkins et al. 1993). These territorial markers carry nonverbal messages of ownership and care. Thus, they serve to deter crime by creating a sense of community among residents, which makes them more vigilant of potential criminal activity in their neighborhoods. Although research is mixed on whether defensible space actually leads to less neighborhood crime, there is a general consensus that higher levels of defensible space are associated with lower levels of fear and higher informal social control (Clarke 1995; Clarke and Homel 1997).

Numerous U.S. federal government-funded studies have examined the association between design of residential settings and criminal activity (Donnelly and Kimble 1997; Kohn, Franck, and Fox 1975; Newman and Franck 1980; Taylor, Gottfredson, and Brower 1984). These projects have, at best, yielded conflicting findings (Bursik and Grasmick 1993; Rosenbaum 1988; Taylor and Gottfredson 1986). Indeed, the role that environmental design plays in crime prevention is a complex one (see Taylor (2002) for a detail discussion of this issue). And, although several studies discuss the importance of understanding the physical environment in relation to crime, many do not directly show how such changes lead to a stable reduction in neighborhood crime.

2.3. Neighborhoods, blocks, and models of spatial environments

Many studies on the influence of spatial environments on residents' perceptions of crime have typically expected a correlation between crime and perceptions at the neighborhood level, with boundaries of administrative units (e.g., census blocks or zip codes) as proxies for neighborhood boundaries. A repeated concern about weak or conflicting neighborhood effects has been the possible low correspondence between definitions of neighborhood boundaries between researchers and residents (Coulton et al. 2001). For example, Coulton et al. found that residents' definitions of urban neighborhood boundaries differed from census block tracts and from each other, even for residents living on the same street block. One strategy has been to use residents' definitions of neighborhood boundaries in the tradition of environmental psychology and urban sociology (Lee 1970). A second strategy has been to work with smaller units of analysis such as street blocks, sacrificing a correspondence with demographic data from administrative units for more salient boundary definitions. A third approach has been to ignore neighborhood and block effects in favor of physical distances between locations of crime events and residents' locations.

The problem that each of these strategies tries to resolve is how to reconcile physical models of spatial environments with cognitive models of spatial environments. We frequently regard space as defined by physical barriers such as buildings, streets, hallways, and entrances that restrict motion along with visual and auditory stimuli (Stea 1970). Hence, there is a tendency to think of cognitive models of spatial environments as cognitive maps with spatial relationships similar to geographic maps with landmarks, travel routes, and preserved metric information (Barkowsky 2002; Tversky 1993).

However, our cognitive models of spatial environments are more like “cognitive collages” and “spatial mental models”, depending on an individual’s familiarity with his or her environment (Tversky 1993). When individuals do not know the details of their environment, they are much more likely to draw on different forms of information that are unlikely to be organized into single coherent maplike representation (Tversky 1993). Instead, individual’s internal representations are more cognitive collages, i.e., “overlays of multimedia from different points of view” (Tversky 1993, p. 15). In situations where environments are simple or well-learned, people tend to develop more accurate internal representations of spatial layouts or spatial mental models.

Both cognitive collages and cognitive spatial models of spatial environments have been found to be systematically biased by language and perspective (Majid et al. 2004; Tversky 1993). Moreover, environments perceived by residents as dangerous and associated with fear are not necessarily an accurate perception of actual crime (Matei, Ball-Rokeach, and Qiu 2001; Rasmussen, Aber, and Bhana 2004). For example, individuals that are more strongly connected to media and interpersonal communication networks are more likely to also be more fearful (Majid et al. 2004). Hence, residents’ cognitive spatial models of their neighborhood environments are likely to change with their perception of crime and coping strategies (Rasmussen, Aber, and Bhana 2004), as they engage or withdraw from their neighborhood environments, and move in and out of social networks.

2.4. Social networks

Few studies have incorporated both social networks and geographic networks in their analysis, despite the potential advantages of doing so (Faust et al. 1999). Social network analysis offers a theoretical framework of the structure of social phenomena that is linked with structural theories of action (Scott 2000). Measures of network relations provide a basis for studying system structure and processes in terms of patterns of interferences (Streeter and Gillespie 1992). It is arguably the complex interactions between fast and slow dynamics of a systems components within networks that generates many of the dynamics of real-world networks (Reggiani, Nijkamp, and Sabella 2001). Hence, the combination of systems theory and network theory offers “a valid and powerful contribution to the research into analytical approaches oriented toward modeling the complexity of space-time systems” (Reggiani, Nijkamp, and Sabella 2001, p. 387).

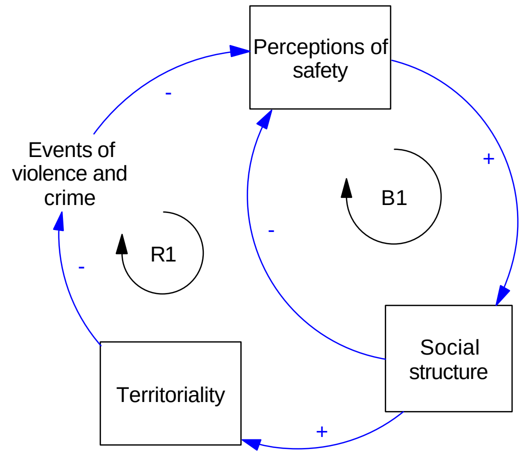
2.5. System dynamics (SD)

System dynamics (Forrester 1999, 1971; Richardson and Pugh 1986) is a method for studying the relationship between dynamic behavior and structure in terms of feedback loop mechanisms that has been applied to a variety of physical and social system problems. System dynamics has also been applied to urban problems (Alfeld 1995; Sancar and Allenstein 1989; Mass 1974; Schroeder, Sweeney, and Alfeld 1975; Levine, Hovmand, and Lounsbury 1998; Forrester 1969), with a call for more research on urban poverty and violence (Alfeld 1995).

A conceptual model of perceptions of safety is shown in Figure 2. This conceptual model includes the main relationships discussed in the previous sections, and provides the general functional form for a theory of perception of safety:

$$\frac{d\,\mathbf{P}}{dt} = f_1(\mathbf{E},\mathbf{S})$$
$$\frac{d\,\mathbf{S}}{dt} = f_2(\mathbf{P})$$
$$\frac{d\,\mathbf{T}}{dt} = f_3(\mathbf{S})$$
$$\mathbf{E} = f_4(\mathbf{T})$$

Figure 2.



Such conceptual models might be satisfactory for studying the plausibility of a general theory, and could be operationalized by modeling the relationships between the macro variables. For example, on could have a single scalar variable representing social structure and operationalize the variable using any one of the many summary statistics for social networks. Likewise, one might talk about average territoriality or average perception of safety over a group of blocks. While this would allow one to test whether or not the feedback structure in Figure 2 could account for the dynamic behavior patterns, such a strategy would not allow one to test the strong underlying assumptions behind the summary statistics. To do this, one will need to disaggregate the major stock variables, and this entails combining geographic information systems or spatial information, social networks, and system dynamics while preserving the essential features of each.

It is worthwhile to note that each of these approaches has a different but complementary way of representing some facet of complex relationships in a social environment (see Table 1). Geographic information systems (GIS) are excellent for presenting and analyzing the spatial relationships and identifying spatial patterns in attributes. Social networks analysis is an excellent way to represent social structure, and the strength of system dynamics is the explicit modeling of causal feedback relationships to explain dynamic phenomena.

Table 1. Comparison of geographic information systems, social network analysis, and system dynamics

	Spatial relationships	**Social structure**	**Dynamics/temporal dimension**
Geographic information systems (GIS)	✓	**?**	**?**
Social network analysis (SNA)	**?**	✓	**?**
System dynamics (SD)	**?**	**?**	✓

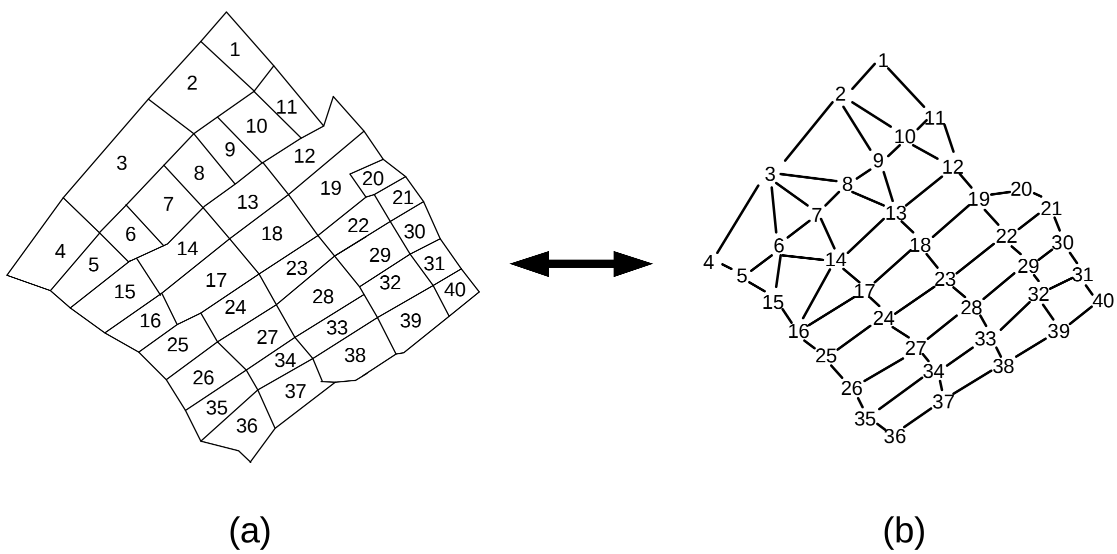
'✓' = solid application of method, '?' = difficult or questionable application of method

3. Method

Three different approaches have been considered for embedding spatial phenomena within system dynamics models: as attributes at locations in space, as nodes in graph networks, and as cells (Sancar and Allenstein 1989). The basic approach taken here is to model spatial phenomena as attributes within geographic network models (Haggatt 1967), and define social networks in terms of these graphs.

Geographic spaces are typically depicted as planar maps with attributes assigned to points. Spatial patterns are identified by analyzing the relationship between attributes and their spatial location. These relationships can be abstracted in the form of a graph where the nodes represent areas and the edges represent adjacency relationships. For example, Figure 3a shows the crossroads that define the blocks of a City of St. Louis neighborhood while Figure 3b shows the corresponding graph. Each node in the graph corresponds to a block, and each edge corresponds to a pair of adjacent blocks. So, for example, block 4 corresponds to node 4. And since blocks 3 and 5 are both adjacent to block 4, there are corresponding edges between nodes 3 and 4, as well as 4 and 5.

Figure 3. Correspondence between (a) a map of neighborhood blocks, and (b) a graph of their spatial relationships



Spatial information about each block is treated as an attribute of a node, while relationships between blocks (adjacency, distances, etc.) are described in the form of a square matrix. For example, in a model with *n* blocks, information about crime or degree or territoriality is represented as a vector of length *n* (or equivalently a 1-by-*n* matrix) where each element corresponds to a block. In a similar fashion, information about relationships can be represented as an *n*-by-*n* matrix where each element quantifies the relationship between two blocks or nodes in the graph. So one might have a 40-by-40 matrix describing the adjacency of one block to another with 1's indicating that the blocks are adjacent and 0's otherwise. In general, one can consider several types of relationships simultaneously (e.g., geographically adjacent blocks, social relationships between blocks, effects of noise such as sirens and gunshots on other blocks) by including multiple square matrices, one for each type of relationship.

By representing areas as nodes and relationships as edges, one can include both spatial and social network variables within a common graph framework. Since graphs can be represented as matrices, a system dynamics model relating spatial and social network dynamics can be written as expressions involving various matrix operations. The extent that one can then explore the form of a dynamic model involving spatial relationships and social networks is therefore only limited by the ways that one can combine the various vectors and matrices. To do this and illustrate the process, several basic formulations will be described and applied in a simple model of perception of safety.

3.1. Networks as graphs

The neighborhood graph in Figure 3b is represented as an *n-by-n* matrix **G** where each element $e_{i,j} \in \mathbf{G}$ defines an attribute of the relationship between node *i* and *j* (e.g., distance between blocks, strength of the social connections between the blocks, amount of interaction). In some cases, the nature of the relationship is symmetric so $e_{i,j} = e_{j,i}$. For other types of graphs, it will be useful to represent asymmetric relationships such as relative differences between two entities, and $e_{i,j}$ will not necessarily be the same as $e_{j,i}$. The main point to note is that there is quite a bit of flexibility in what types of relationships can be represented in the form of a graph. For a more detailed discussion on representing social relationships as graphs, see Wasserman and Faust (1994).

Since these graphs will be dynamic and the value of the elements changing over time are functions of other variables, it is necessary to draw a distinction between weak connections and non-existent connections. For example, if the edges in the graph are taken to represent the strength of the relationship between neighboring blocks, then one will need to be able to distinguish between the weak relationships and the relationship that can't logically occur (e.g., because two blocks are not neighbors in the geographic sense). In this case, one might can adopt the convention that $e_{i,j} > 0$ indicates a neighbor relationship, however weak, while $e_{i,j} = 0$ indicates no possibility of a relationship.

3.2. Adjacency of two nodes

In order to calculate the effects between neighbors, it is frequently useful to have an indicator matrix of a graph representing the existence of a connection. For example, if one wants to represent the effects of sound transmitted to adjacent blocks, then one doesn't necessarily want to know how strong the relationship is, but just that there is a particular type of relationship between two nodes. To do this, it's useful to have an *n-by-n* indicator matrix of the graph $\mathbf{G}$, $a_{i,j} \in \mathbf{A}(\mathbf{G})$ where:

$$a_{i,j} = \begin{cases} 1 & \text{if } e_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \text{for } e_{i,j} \in \mathbf{G}\,.$$

3.3. Connectedness of two nodes

It is also useful to know whether or not two nodes are connected by a path. This can be done with an *n-by-n* indicator matrix of the graph $\mathbf{G}$, $c_{i,j} \in \mathbf{C}(\mathbf{G})$, where entries are 1 if the nodes are connected via a path, and 0 otherwise. The easiest way to calculate $\mathbf{C}(\mathbf{G})$ is to take the inner or dot product of $\mathbf{G}$, $n-1$ times. That is, for $c_{i,j} \in \mathbf{C}(\mathbf{G})$:

$$c_{i,j} = \begin{cases} 1 & \text{if } c^{*}_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \text{ where } c^{*}_{i,j} \in \underbrace{\mathbf{G} \cdot \mathbf{G} \cdot \ldots \cdot \mathbf{G}}_{n-1 \text{ times}}\,.$$

3.4. Propagation of event information over a network

An event such as a crime or incivility happens at a particular location or in a specific area represented by a node. A description of an event is therefore a vector **E** of length *n*. How event information is passed throughout the neighborhood depends on the relationships between the nodes as represented by $\mathbf{G}$, and the nature and representation of information. The actual information received about the event also has a spatial component. It is not just that one is aware that a crime occurred, but that it occurred on a particular block. So the information received about the event is another *n*-length vector **O.** To represent the propagation of event information, we must then write an expression for **O** in terms of **E.** A simple model of event information propagating over the social network $\mathbf{G}$ is a word-of-mouth mechanism where if one person knows about the event (there was a robbery on a particular block), then everyone within that social network knows about the event. Thus any two nodes that were connected would know the same information. This can be written as an expression involving the connectedness indicator matrix $\mathbf{C}(\mathbf{G})$ and transpose of $\mathbf{E}$ (denoted $\mathbf{E}'$):

$$\mathbf{O} = \mathbf{C}(\mathbf{G}) \cdot \mathbf{E}' \ .$$

3.5. Relative differences

Differences between various blocks play an important role in shaping expectations, perceptions, and as drivers of behavior. If $\mathbf{V}$ is a *n*-length vector of node attributes, then the relative differences between the nodes can be calculated as $\Delta_{\mathbf{V}} = 1' \cdot \mathbf{V} - (1' \cdot \mathbf{V})'$ where 1 is a *n*-length vector containing only 1's. However, $\Delta_{\mathbf{V}}$ represents the differences between all pairwise combinations of nodes, whereas relative differences between two groups are usually constrained by what can be observed between two nodes. An easy way to include the effects of such constraints is to take the entry-wise or Hadamard product (written as $\circ$) of the difference matrix Δ_V with either the adjacency or connectedness indicator matrix. For example, if perception of safety is represented as a *n*-length vector, then the relative differences in perceptions of safety between neighboring blocks can be expressed as:

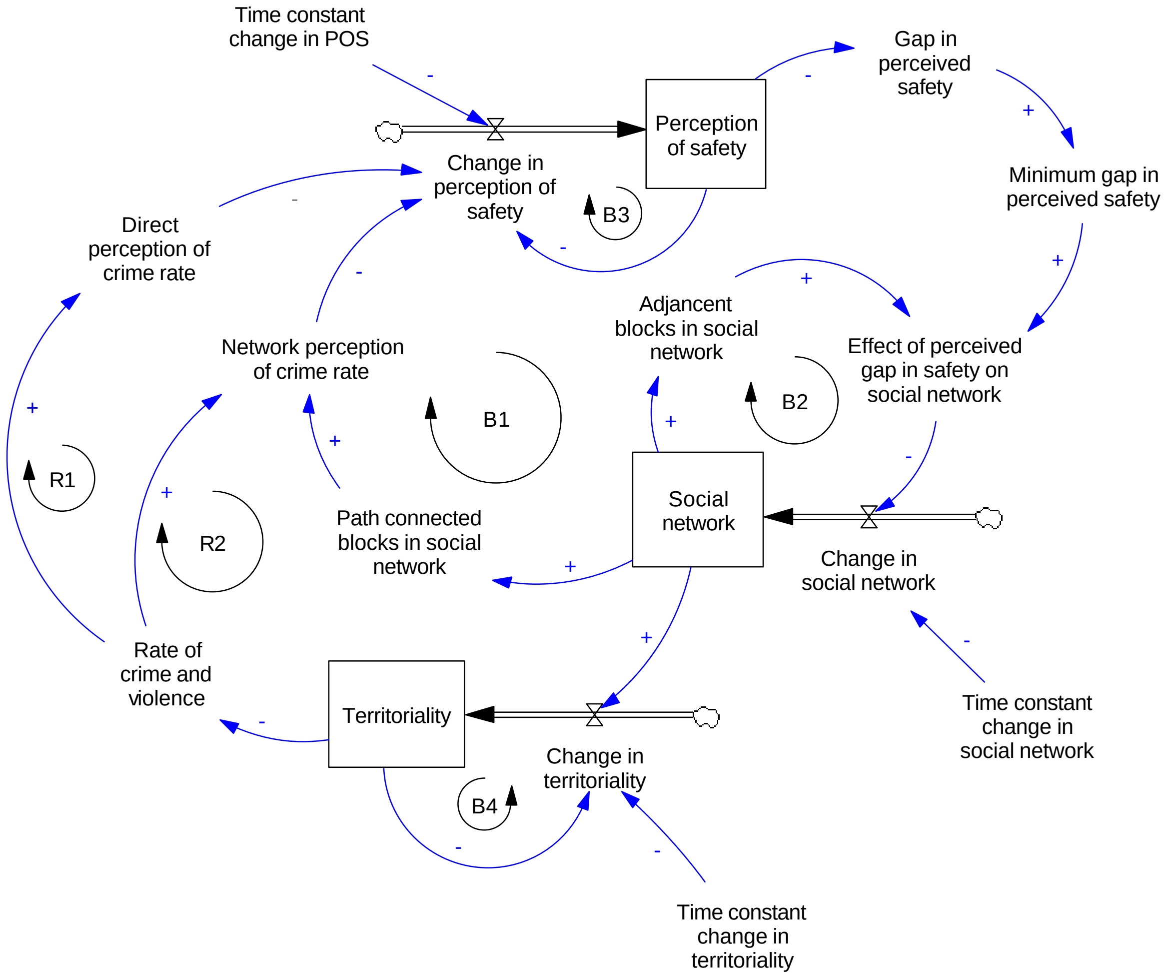
$$\left(1' \cdot \mathbf{POS} - (1' \cdot \mathbf{POS})'\right) \circ \mathbf{A}(\mathbf{G}) \ .$$

It is generally easy to develop expressions that capture the explicit relationships between spatial variables and social networks using graphs as the common topological representation. The next section shows how these components can be combined in a system dynamics simulation model of perception of safety.

4. Example

Figure 4 shows a system dynamics model of three state variables: perception of safety to the social network structure of a neighborhood with *n* blocks, and territoriality. Perception of safety is an *n*-length vector **POS (***Perception of safety* in Figure 4), the social network structure of the neighborhood is the *n-by-n* matrix **S** (*Social network* in Figure 4), and territoriality is an *n*-length vector **T** (*Territoriality* in Figure 4). These variables are explicitly related through set of differential equations that define 6 major feedback loops. They also specify a family of dynamic hypotheses about the relationship between the causal feedback structure in Figure 4 and the dynamic behavior patterns of perception of safety.

Figure 4. Stock-and-flow representation of Perception of Safety (POS) Model



4.1. Equations

Perceptions of safety do not change when perceptions match observations. So change in perception of safety is considered a function of the difference between (a) current perceptions of safety, and (b) observed events of crime and safety. Events can be observed directly ($\mathbf{O}_{direct}$) or indirectly through social networks ($\mathbf{O}_{network}$), and the total effect on perception of safety is the sum of the two. The time that it takes to adjust perceptions of safety is represented by the time constant TC_p. The rate of change for perceptions of safety can then be is expressed as:

$$\frac{d\,\mathbf{POS}}{dt} = \frac{-(\mathbf{O}_{direct} + \mathbf{O}_{network}) - \mathbf{POS}}{TC_P}.$$

The social network changes as a function of the relative differences in perceptions of safety between neighboring blocks. In this model, it is assumed that between two neighboring blocks, the lowest relative perception of safety will determine the relationship. This can be calculated by taking the minimum of the relative difference and its transpose. The time that it takes to change the strength of ties in a social network is represented by the time constant TC_S. So the change in the neighborhood's social network is:

$$\frac{d\,\mathbf{S}}{dt} = \frac{Min(\Delta, \Delta') \circ \mathbf{A}(\mathbf{S})}{TC_S} \text{ where } \Delta = 1' \cdot \mathbf{POS} - (1' \cdot \mathbf{POS})'.$$

Change in territoriality is taken as a function of the difference between the total weakness of the social ties with neighboring blocks and the current territoriality. The total weakness of the social ties for a given block is essentially the reciprocal of the total strength of its social ties with neighboring blocks, which can be expressed as $(\mathbf{S} \cdot 1')^{-1}$. The time that it takes for changes in territoriality to respond to changes in the social network is represented by the time constant TC_T. Thus, changes in territoriality can be written as:

$$\frac{d\,\mathbf{T}}{dt} = \frac{1 - (\mathbf{S} \cdot 1')^{-1} - \mathbf{T}}{TC_T}.$$

The rate of crime and violence on a block is an *n*-length vector $\mathbf{E}$, which is taken to be inversely related to the territoriality of that block. This can be expressed as $\mathbf{E} = 1 - \mathbf{T}$. The directly observed events of crime and violence that happen on the block is simply $\mathbf{O}_{direct} = \mathbf{E}$, while the indirectly observed events of crime and violence is a function of the connection matrix and $\mathbf{E}$, $\mathbf{O}_{network} = \mathbf{C}(\mathbf{S}) \cdot \mathbf{E}$.

4.2. Simulation results

In this example, the model starts with all the blocks having the same perception of safety but differing in the strengths of their network relationships. The results show how the neighborhood social structure evolves over time in response to these initial conditions (see Figure 5).

At the start of the simulation, all the blocks start out at the same level of perceived safety (see Figure 6), but differences in the strength of neighborhood ties (Figure 7) lead to changes in territoriality (Figure 8), which causes a corresponding increase in the rate of crime and violence (Figure 9). Initially these differences are small, but they feed back into the perceptions of safety, leading to more changes in the social network. The pattern continues until the ties have decayed enough to isolate block 6 from the crime and violence of block 15, and stops when blocks 5 and 15 have little or no territoriality, high levels of crime and violence, low perceptions of safety, and no social ties with other blocks in the neighborhood. Substantively, these results show us how differences in social networks might lead to a pattern of declining territoriality, increasing crime and violence, and decline in social structure.

5. Conclusion

More generally, the results also illustrate how explanations inspired by looking at the correlation between spatial elements over time (Figure 5) can be verified or refuted by examining the intervening variables (Figures 6 through 8). Moreover, one is able via the simulation to conduct additional experiments to test explanations about the relationship between specific aspects of behavior and the underlying feedback loops. This facilitates the development of more rigorous and empirically verifiable hypotheses, better social theories of crime, violence, and perceptions of safety, and thus ultimately improves our chances of developing better and more empirically based community interventions for crime and violence.

Figure 5. Changes in neighborhood social network, and crime and violence over time, where dark edges represent stronger connections, and larger circles represent higher rates of crime and violence. Dashed lines indicate weak relationships that could exist.

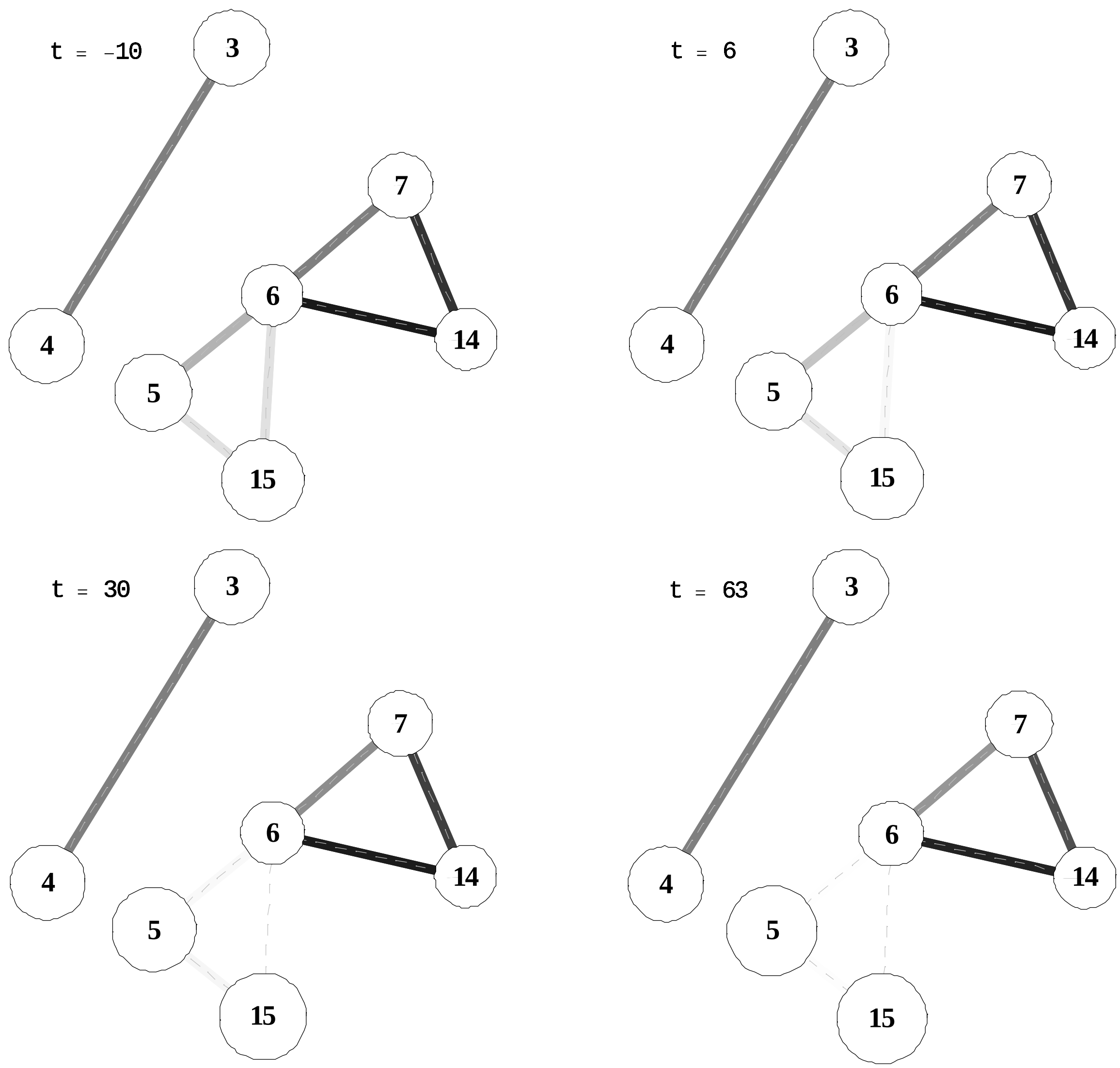


Figure 6. Perception of safety for blocks 5, 6, and 15.

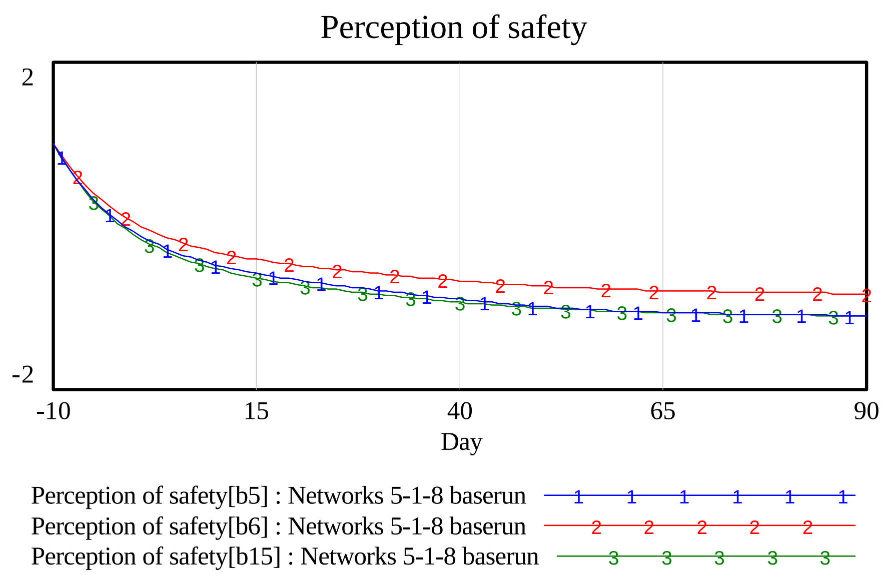


Figure 7. Strength of neighborhood ties in social network between blocks 5, 6, and 15.

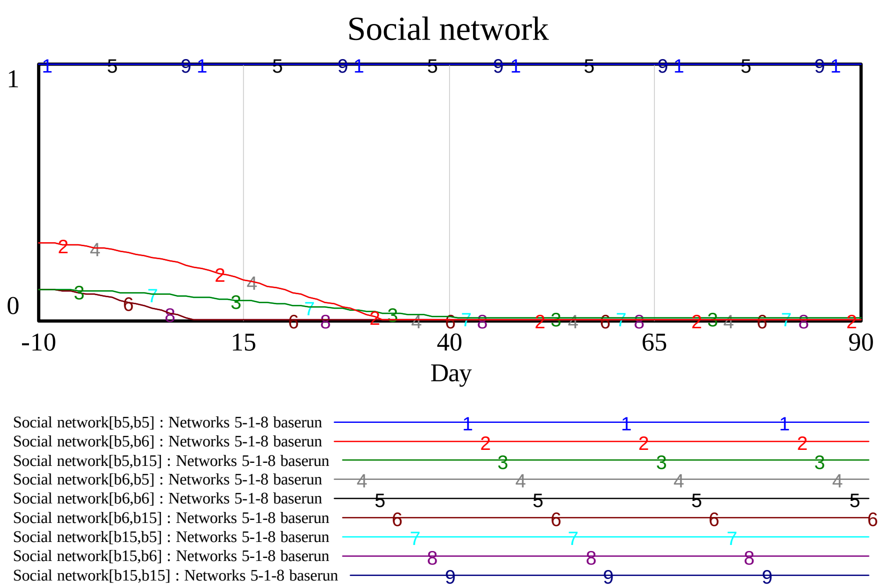


Figure 8. Territoriality of blocks 5, 6, and 15.

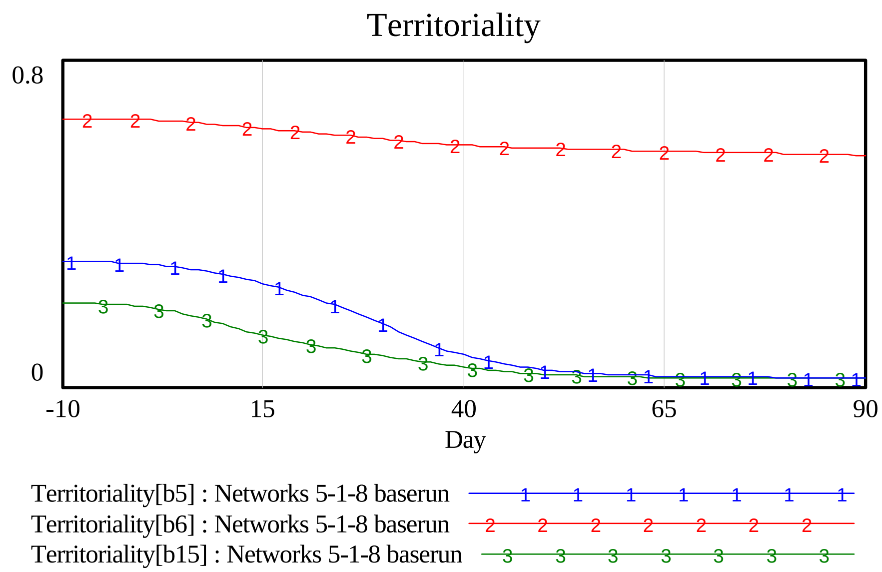
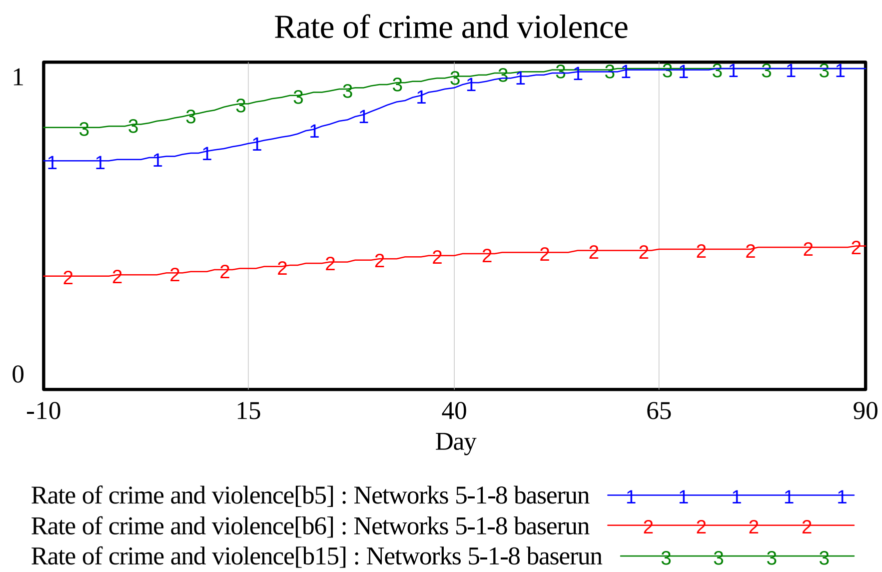


Figure 9. Rate of crime and violence for blocks 5, 6, and 15.



References

Alfeld, Louis Edward. 1995. Urban dynamics-The first fifty years. *System Dynamics Review* 11 (3):199-217.

Astor, R., H. Meyer, and W. Behre. 1999. Unowned places and times: Maps and interviews about violence in high schools. *American Educational Research Journal* 36 (1):3-42.

Astor, R., H. Meyer, and R. Pitner. 1999. Mapping school violence with students, teachers, and administrators: An intervention. In *Working with African-American males: A guide to practice*, edited by L. Davis. Thousand Oaks, CA: SAGE Publications.

———. 2001. Elementary and middle school students' perceptions of violence-prone school sub-contexts. *The Elementary School Journal* (5):511-528.

Barkowsky, Thomas. 2002. *Mental representation and processing of geographic knowledge: A computational approach*. New York: Springer-Verlag.

Brantingham, P.L., and P.J. Brantingham. 1981. Notes on the geometry of crime. In *Environmental criminology*, edited by P. L. Brantingham and P. J. Brantingham. Beverly Hills, CA: Sage.

Bursik, R., and H. Grasmick. 1993. *Neighborhoods and crime: The dimensions of effective community control*. New York: Lexington Books.

Cisnernos, H.G. 1995. Defensible space: Deterring crime and building community. Washington, D.C.: Department of Housing and Urban Development.

Clarke, R. 1995. Situational crime prevention. In *Building a safer society: Strategic approaches to crime prevention*, edited by M. Tonry and D. Farrington. Chicago: University of Chicago Press.

Clarke, R., and R. Homel. 1997. A revised classification of situational crime prevention techniques. In *Crime prevention at a crossroads*, edited by S. Lab. Cincinnati, OH: Anderson.

Coulton, Claudia J., Kill Korbin, Tsui Chan, and Marilyn Su. 2001. Mapping residents' perceptions of neighborhood boundaries: A methodological note. *American Journal of Community Psychology* 29 (2):371-383.

Day, K. 1994. Conceptualizing women's fear of sexual assault on campus: A review of causes and recommendations for change. *Environment and Behavior* 26:742-765.

Donnelly, P., and C. Kimble. 1997. Community organizing, environmental change, and neighborhood crime. *Crime & Delinquency* 43:493-511.

Eck, J., and D. Weisburd. 1995. Crime places in crime theory. In *Crime Prevention Studies: Vol. 4. Crime and place*, edited by J. Eck and D. Weisburd. Monsey, NY: Criminal Justice Press.

Faust, Katherine, Barbara Entwisle, Ronald R. Rindfuss, Stephen J. Walsh, and Yothin Sawangdee. 1999. Spatial arrangement of social and economic networks among villages in Nang Rong District, Thailand. *Social Networks* 21:311-377.

Federal Bureau of Investigation. 2004. *Uniform crime reports* 2001 [cited January 16 2004]. Available from http://www.fbi.gov/ucr/ucr.htm.

Forrester, J. W. 1971. *Principles of systems*. Waltham: Pegasus Communications, Inc.

———. 1999. *Industrial dynamics*. Waltham: Pegasus Communications, Inc. Original edition, 1961.

Forrester, Jay W. 1969. *Urban dynamics*. Cambridge, MA: MIT Press.

Goldstein, A. 1994. *The ecology of aggression*. New York: Plenum Press.

Greenberg, A., W. Rohe, and J. Williams. 1982. Safety in urban neighborhoods: A comparison of physical characteristics and informal territorial control in high and low crime neighborhoods. *Population and Environment* 5:141-165.

Haggatt, Peter. 1967. Network models in geography. In *Models in geography*, edited by R. J. Chorley and P. Haggett. London: Methuen & Co, Ltd.

Kohn, I., K. Franck, and A. Fox. 1975. Defensible space modifications in row-house communities: A final report submitted to the National Science Foundation. New York: The Institute for Community Design Analysis.

Kubrin, Charis E., and Ronald Weitzer. 2003. New directions in social disorganization theory. *Journal of Research in Crime and Delinquency* 40 (4):374-402.

Lee, Terence. 1970. Urban neighbourhood as socio-spatial schema. In *Environmental psychology: Man and his physical setting*, edited by H. M. Proshansky, W. H. Ittleson and L. G. Rivlin. New York: Holt, Rinehart and Winston, Inc.

Levine, R., Peter S. Hovmand, and D. Lounsbury. 1998. Urban modeling revisited: Psychological and social dynamics of a city which has to adjust to a large number of plant closings. Paper read at 16th International Conference of the System Dynamics Society, July, at Québec City, Canada.

Majid, Asifa, Melissa Bowerman, Sotaro Kita, Daniel B. M. Haun, and Stephen C. Levinson. 2004. Can language restructure cognition? The case for space. *TRENDS in Cognitive Sciences* 8 (3):108-114.

Mass, Nathaniel J., ed. 1974. *Readings in urban dynamics*. 2 vols. Vol. 1. Cambridge, MA: Wright-Allen Press, Inc.

Matei, Sorin, Sandra J. Ball-Rokeach, and Jack Linchaun Qiu. 2001. Fear and misperception of Los Angeles urban space: A spatial-statistical study of communication-shaped mental maps. *Communications Research* 28 (4):429-463.

Meyer, H., and R. Astor. 2002. Child and parent perspectives on routes to and from school in high crime neighborhoods. *Journal of School Violence* 1 (101-128).

National Council of Churches. 2004. *Poverty by the numbers* 2002 [cited January 16 2004]. Available from http://www.ncccusa.org/poverty/by-the-numbers.html.

Newman, O. 1973. *Architectural design for crime prevention*. Washington, D.C.: U.S.

———. 1995. Defensible space: A new physical planning tool for urban revitalization. *Journal of the American Planning Association* 61:149-155.

Newman, O., and K. Franck. 1980. Factors influencing crime and instability in urban housing developments. Washington, D.C.: US Government Printing Office.

Perkins, D., P. Florin, R. Rich, A. Wandersman, and D. Chavis. 1990. Participation and the social and physical environment of residential blocks: Crime and community context. *American Journal of Community Psychology* 18:83-115.

Perkins, D., J. Meeks, and R. Taylor. 1992. The physical environment of street blocks and resident perceptions of crime and disorder: Implications for theory and measurement. *Journal of Environmental Psychology* 12:21-343.

Perkins, D., A. Wandersman, R. Rich, and R. Taylor. 1993. The physical environment of street crime: Defensible space, territoriality, and incivilities. *Journal of Environmental Psychology* 13:29-49.

Pitner, R., J. Lloyd, and V. Bell. under review. Creating the perception of safety among vulnerable groups: An evaluation of Operation SafeStreet.

Proshansky, H., W. Ittelson, and L. Rivlin. 1970. *Environmental psychology: Man and his physical setting*. New York: Holt, Rinehart, & Winston.

Rasmussen, Andrew, Mark S. Aber, and Arvinkumar Bhana. 2004. Adolescent coping and neighborhood violence: Perceptions, exposure, and urban youths' efforts to deal with danger. *American Journal of Community Psychology* 33 (1/2):61-75.

Reggiani, Aura, Peter Nijkamp, and Enrico Sabella. 2001. New advances in spatial network modelling: Towards evolutionary algorithms. *European Journal of Operational Research* 128:385-401.

Reiss, A., and J. Roth. 1993. Understanding and preventing violence. Vol. 1. Washington, D.C.: Commission on Behavioral & Social Sciences & Education.

Richardson, G. P., and A. L. Pugh. 1986. *Introduction to system dynamics modeling with DYNAMO*.

Rosenbaum, D. 1988. Community crime prevention: A review and synthesis of the literature. *Justice Quarterly* 5:323-395.

Sampson, R., and J. Lauritsen. 1994. Violent victimization and offending: Individual-, situational-, and community-level risk factors. In *Understanding and preventing violence, Vol. 3: Social influences*, edited by R. Albert and J. Roth. Washington, D.C.: National Academy Press.

Sancar, F. H., and S. Allenstein. 1989. System dynamics simulation of spatial character. In *Computer-based management of complex systems: Proceedings of the 1989 International Conference of the System Dynamics Society, Stuttgart, July 10-14, 1989*, edited by P. M. Milling and E. O. K. Zahn. New York, NY: Springer-Verlag.

Schroeder, Walter W., Robert E. Sweeney, and Louis Edwar Alfeld, eds. 1975. *Readings in Urban Dynamics*. 2 vols. Vol. 2. Cambridge, MA: Wright-Allen Press, Inc.

Scott, John. 2000. *Social network analysis: A handbook*. Second ed. Thousand Oaks, CA: SAGE Publications.

Skogan, W. 1976. Citizen reporting of crime: Some national panel data. *Criminology* 13:535-549.

Stea, David. 1970. Space, territory and human movments. In *Environmental psychology: Man and his physical setting*, edited by H. M. Proshansky, W. H. Ittleson and L. G. Rivlin. New York: Holt, Rinehart and Winston, Inc.

Streeter, Calvin L., and David F. Gillespie. 1992. Social network analysis. In *Quantitative methods in social work: State of the art*, edited by D. F. Gillespie and C. Glisson. Binghamton, NY: The Haworth Press, Inc.

Taylor, R. 1994. *Research methods in criminal justice*. New York: McGraw-Hill.

———. 1997. Social order and disorder of streetblocks and neighborhoods: Ecology, microecology and the sytemic model of social disorganization. *Journal of Research in Crime and Delinquency* 33:113-155.

———. 1999. The incivilities thesis: Theory, measurement, and policy. In *Measuring what matters*, edited by R. Langworthy. Washington, D.C.: National Institute of Justice, Office of Community Oriented Policing Services.

———. 2002. Crime prevention through environmental design (CPTED): Yes, no, maybe, unknowable, and all of the above. In *Handbook of environmental psychology*, edited by R. Bechtel and A. Churchman. New York: John Wiley & Sons, Inc.

Taylor, R., and S. Gottfredson. 1986. Environmental design, crime, and prevention: An examination of community dynamics. In *Communities and crime*, edited by A. J. Reiss Jr. and M. Tonry. Chicago: University of Chicago Press.

Taylor, R., S. Gottfredson, and S. Brower. 1984. Understanding block crime and fear. *Journal of Research in Crime and Delinquency* 21:303-331.

Tversky, Barbara, ed. 1993. *Cognitive maps, cognitive collages, and spatial mental models.* Edited by A. U. Frank and I. Campari, *Spatial information theory: A theoretical basis for GIS*. New York: Springer-Verlag.

Wasserman, Stanley, and Katherine Faust. 1994. *Social network analysis: Methods and applications*. New York, NY: Cambridge University Press.

White, G. 1990. Neighborhood permeability and burglary rates. *Justice Quarterly* 7:57-68.

Wilson, J., and G. Kelling. 2004. *Broken windows: The police and neighborhood safety* 1982 [cited January 16 2004]. Available from http://www.theatlantic.com/politics/crime/windows.htm.