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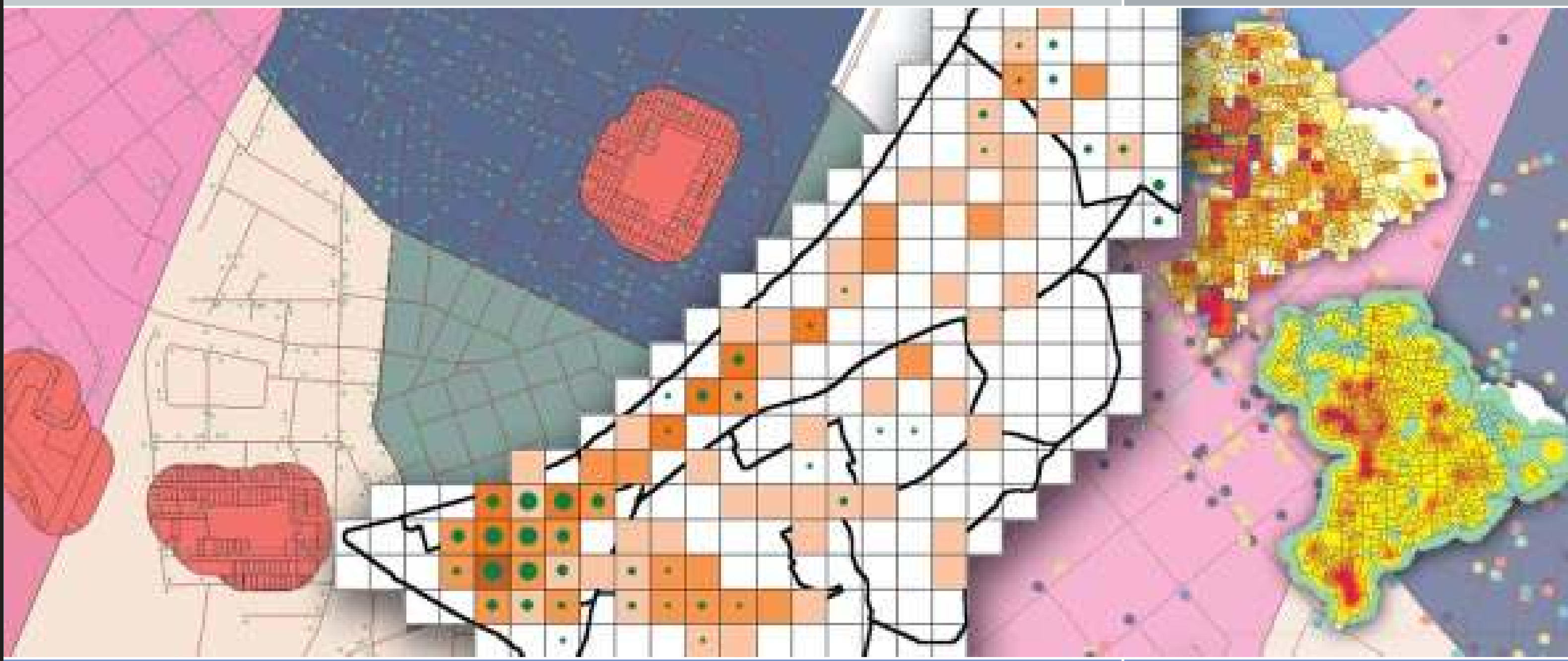

Mapping Crime: Understanding Hot Spots

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Mapping Crime: Understanding Hot Spots

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Background map by Jeff Stith and the Wilson, North Carolina, Police Department

About This Report

Much of crime mapping is devoted to detecting high-crime-density areas known as hot spots. Hot spot analysis helps police identify high-crime areas, types of crime being committed, and the best way to respond.

This report discusses hot spot analysis techniques and software and identifies when to use each one. The visual display of a crime pattern on a map should be consistent with the type of hot spot and possible police action. For example, when hot spots are at specific addresses, a dot map is more appropriate than an area map, which would be too imprecise.

In this report, chapters progress in sophistication. Chapter 1 is for novices to crime mapping. Chapter 2 is more advanced, and chapter 3 is for highly experienced analysts. The report can be used as a companion to another crime mapping report published by the National Institute of Justice in 1999, *Crime Mapping: Principle and Practice*, by Keith Harries.

What did the researchers find?

- Identifying hot spots requires multiple techniques; no single method is sufficient to analyze all types of crime.
- Current mapping technologies have significantly improved the ability of crime analysts and researchers to understand crime patterns and victimization.
- Crime hot spot maps can most effectively guide police action when production of the maps is guided by crime theories (place, victim, street, or neighborhood).

Who should read this study?

Crime analysts and researchers in police departments.

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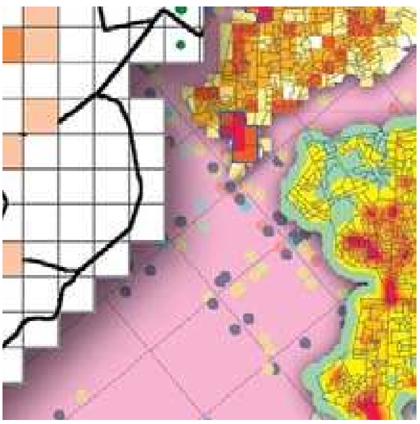
Chapter 1. Crime Hot Spots: What They Are, Why We Have Them, and How to Map Them

John E. Eck, University of Cincinnati



Crime is not spread evenly across maps. It clumps in some areas and is absent in others. People use this knowledge in their daily activities. They avoid some places and seek out others. Their choices of neighborhoods, schools, stores, streets, and recreation are governed partially by the understanding that their chances of being a victim are greater in some of these places than in others. In some places people lock their cars and secure belongings. In other places they do not. Along some streets people walk swiftly and view approaching strangers with suspicion. Along other streets they casually stroll and welcome the next interesting person they might meet, and notice others making the same choices in the same areas.

Some might argue that this behavior merely shows that people are unreasonably fearful of some areas but not of others. This may often be true, but the fact that people are not equally fearful of all places suggests that they understand that crime is not evenly distributed. People might be mistaken about the risks of some places, but they are not mistaken that their risk of being a victim of crime is not geographically constant.

Police use this understanding every day. Decisions about how to allocate scarce resources are based partially on where the demands for police are highest and where they are lowest. Officers are told to be particularly attentive to some behavior in some areas, but are given no guidance about other areas where this behavior is scarce. Community policing is particularly attentive to high-crime neighborhoods, where residents have great difficulty exerting social controls. Problem-oriented policing pushes police officials to identify concentrations of crime or criminal activity, determine what causes these concentrations, and then implement responses to reduce these concentrations. Much of what is called crime analysis is dedicated to locating concentrations of crime—hot spots—and much of crime mapping is devoted to their detection.

This chapter discusses how different interpretations of hot spots require different types of crime maps. *The principal theme is that crime hot spot maps can most effectively guide police action when production of these maps is guided by theory.* With the appropriate crime theory, crime maps can communicate vital information to police officials and community members efficiently and effectively.

Many useful crime theories provide guidance for selecting mapping symbols. Which theory is most useful depends on the type of problem being mapped. Maps that are not based on theory will provide officers with inadequate and even misleading information.

The term hot spot has a number of meanings. This chapter begins with a discussion of what the term means and how the meanings relate to the concept of levels of spatial analysis of crime. Different theories of crime explain crime at different levels, so this chapter briefly describes various levels of crime theories and explains how they can be depicted on maps. This chapter examines four types of crime theories in greater detail: place (point) theories; street (line) theories; area (polygon) theories; and repeat victim theories, which can operate on point, line, or polygon level. These theories describe the levels of hot spots and how these levels can be depicted on maps. This chapter examines why crime theory, crime mapping, and police actions need to be consistent. The end of the chapter examines how the map symbols implied by each theory communicate to users of crime maps.

What is a hot spot?

Areas of concentrated crime are often referred to as hot spots. Researchers and police use the term in many different ways. Some refer to hot spot addresses (Eck and Weisburd, 1995; Sherman, Gartin, and Buerger, 1989), others refer to hot spot blocks (Taylor, Gottfredson, and Brower, 1984; Weisburd and Green, 1994), and others examine clusters of blocks (Block and Block, 1995). Like researchers, crime analysts look for concentrations of individual events that might indicate a series of related crimes. They also look at small areas that have a great deal of crime or disorder, even though there may be no common offender. Analysts also observe neighborhoods and neighborhood clusters with high crime and disorder levels and try to link these to underlying social conditions.

Though no common definition of the term hot spot of crime[1] exists, the common understanding is that *a hot spot is an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimization*. This suggests the existence of cool spots—places or areas with less than the average amount of crime or disorder. It also suggests that some hot spots may be hotter than others; that is, they vary in how far above average they are.

Levels of hot spot analysis

If hot spots are merely areas with an above average amount of crime or disorder, why do practitioners and researchers use the term in such a variety of ways? In fact, with recent developments in crime mapping, one can find hot spots of any size—from hot spot places to hot regions. Although all of these perspectives on hot spots have something in common—concentrations of crime or disorder separated by areas with far less crime or disorder—they differ in the area covered by the hot spots. More importantly, the factors that give rise to hot spot places are different from the factors that give rise to hot spot streets, hot spot neighborhoods, or hot spot cities. Further, the actions one takes to deal with a hot spot place will be different from the actions needed to address a hot spot street, hot spot neighborhood, or hot spot city.

These approaches differ on the *level of analysis*, or the size of the geographic area of crime about which one is concerned.[2] The level at which one examines crime or disorder is dictated by the question one asks, which will determine the usefulness of the results. Consider two related, but very distinct, questions: Where are drugs being sold? What is the market for drugs?

The precise answer to the first question requires identifying specific drug-dealing locations or street segments (very small areas) where drug dealers and customers routinely meet. To answer the second question, the analyst needs to find out where the customers are coming from, just as he would if he asked the question, "What is the market for new cars?" The answer to the first question—specific locations or street segments—is not particularly useful for answering the second question. Rather, the analyst would be interested in larger areas with high concentrations of drug users. These areas might surround the locations and street segments identified when answering the first question, or they may be physically separated from the dealing sites (as would occur when suburban high school and college students drive into cities to find drugs). The types of police actions that might remove drug-dealing locations are likely to be different from the actions needed to dry up the market. So identifying the appropriate level of analysis is critical to understanding the problem and determining what action to take.

Crime theories are critical for useful crime mapping because they aid in the interpretation of data (Eck, 1998) and provide guidance as to what actions are most appropriate. Therefore, understanding how crime theories account for hot spots is critical. Several theories of crime and disorder concentration (hot spots) exist. Some theories disagree, but often the theories do not contradict each other. Rather, they explain different types of crime phenomena that occur at different geographic levels.

Each level has basic units of analysis—the things being examined. One can think of units as corresponding to the geographic areas being depicted on maps: points, lines, or polygons (Harries, 1999). Some theories help explain point concentrations of crime. Other theories help explain linear concentrations of crime or hot spot crime polygons. However, theories of crime are useful for helping to guide crime and disorder mapping only if one selects a theory appropriate for the level of analysis and action.

Crime hot spot theories

Place theories

Place theories explain why crime events occur at specific locations. They deal with crimes that occur at the lowest level of analysis—specific places. They involve looking at specific incidents and asking such questions as, "At what places are burglaries occurring and at what places are they not occurring?" Crime phenomena at this level occur as *points,* so the appropriate units of analysis are addresses, street corners, and other very small places, which are typically represented on maps as dots. Police action, such as warrants, which specify exact addresses (not blocks or neighborhoods), is very precise at this level. Similarly, nuisance abatement focuses on specific locations.

Street theories

Street theories deal with crimes that occur at a slightly higher level than specific places; that is, over small, stretched areas such as streets or blocks. A prostitution stroll is an example. At this level of analysis analysts ask such questions as, "On which streets are prostitutes found and on which streets are they not found?" The appropriate units of analysis can be street segments, paths, and sections of highways, which would be represented on maps as *straight, bent, or curved lines*. Police action is still relatively precise, although not as precise as at the place level. Concentrated patrolling occurs at this level, for example, as well as efforts to change traffic and street patterns.

Neighborhood theories

Some theories of crime attempt to explain neighborhood differences.[3] At a higher level than place or street, neighborhood theories deal with large areas. Here analysts are interested in such questions as, "What areas are claimed by gangs and what areas are not?" The appropriate units of analysis are quite varied and can include square blocks, communities, and census tracts, to name a few. Two-dimensional shapes such as *ellipses, rectangles, and other polygons* are used on maps to represent crime phenomena at this level. At this level police action is far less precise because the areas are typically too large for effective concentrated patrolling (Sherman, 1997). Nevertheless, depending on neighborhood characteristics, relevant action might include efforts to engage residents in collective action against crime and disorder. If offenders are mobile throughout an area, rather than concentrated at a few places, then efforts to deter them should occur at this level.

Other large area theories

Still other theories attempt to explain differences in crime patterns at much higher levels of aggregation. For example, theories of crime differ among cities and among regions. On the city level, suggested actions may include citywide changes in economic, transportation, education, welfare, and recreation policies, to name a few. On the multijurisdictional or multistate regional levels, suggested actions against concentrations of crime could include even broader scale policies or social change. Although these are interesting theories, they are far less useful for local police agencies. Thus, they are not examined here.

Repeat victimization theories

Finally, repeat victimization theories pertain to questions of why the same victims are targeted repeatedly. They can operate at any of the three levels discussed: *points, lines, or polygons*. However, not all repeat victimization can be shown on maps.

Exhibit 1 organizes and summarizes the discussion of hot spot analysis so far and introduces what is to come. The first column describes the geographic concentration at various levels of interest. The second column describes the basic pattern formed by hot spots at each level. The third column lists the geometric dimension to be used on a crime map to depict each type of hot spot. Place theories suggest maps with dots, street theories suggest maps that emphasize lines, and area theories suggest the use of polygons on maps. Repeat victimization theories do not directly correspond to a single dimension or level. They can be depicted on maps by dots, lines, or polygons. The last three columns highlight points discussed next. Examined are four types of hot spots—places, victims, streets, and areas.

Types of hot spots

Repeat places hot spots

The most basic form of a hot spot is a place that has many crimes. A place can be an address, street corner, store, house, or any other small location, most of which can be seen by a person standing at its center (Sherman et al., 1989). Places typically have a single owner and a specific function—residence, retail sales, recreation, school (Eck and Weisburd, 1995). Crime often is concentrated at a few places, even in high-crime areas. Although hot places often are concentrated within areas, they often are separated by other places with few or no crimes. Because such hot spots are best depicted by dots, they have a dimension of zero.

Underlying causes. Routine activity theory helps to explain why crime often is concentrated at specific places. In particular, routine activity points to how behavior is regulated at the location by place managers—owners of places or people acting on an owner's behalf. Behavior regulation falls under place management theory, a part of routine activity theory. For example, the difference between a bar that has few or no incidents or assaults and a bar with frequent assaults is likely to be that in the first instance the bar employees regulate the behavior of patrons to minimize the chances of an assault, and in the second instance, they do not. Such regulation has three effects. It directly prevents criminal activity through early intervention (e.g., controlling the number of drinks a patron can consume), it attracts place users who desire a well-regulated location over a weakly regulated place (such people are less likely to create problems), and it repels place users who desire a weakly regulated location over a well-regulated place (Brantingham and Brantingham, 1995). Repeat places tend to be stable over time (Spelman, 1995a), and this is consistent with the routine activity theory that an absence of effective place management is at the heart of the problem.

Maps for repeat places. Maps for repeat places include—

- **Graduated symbols.** When looking for hot places, dot maps are superior to other forms of mapping. The goal is to identify isolated high-crime locations, which can be done in a number of ways. One can use graduated dots, so that dot size is proportional to the number of crimes at the location. This method

Exhibit 1. Hot spot concentrations, evidence, theory, and causes

Concentration	Map pattern	Geometric dimension	Theories	Likely causes	Examples
Place—at specific addresses, corners, or other places	Point concentration; a few places with many crimes and many places with few or no crimes. Repeat crime places are often concentrated.	Zero; concentration at points	Routine activity theory; place management	Management of behavior at places	Bar fights, convenience store robberies, ATM patron robberies, drug dealing locations
Among victims	Often confused with repeat crime places (above). Only visible on maps if victims are concentrated at places, on streets, or in areas.	Zero, one, or two; concentration at points, lines, and areas	Routine activity theory; lifestyles	Victim routines and lifestyle choices	Domestic violence
Street—along a street or block face	Linear concentration along major thoroughfares; a few blocks with much crime and many blocks with little crime	One; concentration along lines	Offender search theory	Offender movement patterns and target concentrations	Outside street prostitution, street drug dealing, robberies of pedestrians
Area—neighborhood areas	Concentration covering multiblock areas	Two; concentration in areas	Disorganization theory and related ecologic theories of crime; opportunity theories	Low collective efficacy, social fragmentation, concentrations of youth, economic disinvestments; concentrations of crime targets	Residential burglary, gang violence

allows the depiction of repeat and nonrepeat places on the same map and permits comparison among repeat places about the number of crimes. Graduated dots also allow one to find concentrations of hot places (e.g., an area that contains several repeat assault bars). Because graduated dots can obscure nearby features (e.g., a large dot may overlap nearby smaller dots), this technique is best used on large-scale maps.

- **Color gradient dots.** Two other approaches are useful on small-scale maps. One is to use a color gradient—yellow through red, for example—to depict the number of crimes at each location. A yellow dot may be used to represent places with a single crime, a light orange dot may represent locations with two crimes, and a deeper orange dot might represent places with three crimes. This approach has the advantage of the use of graduated symbols but overcomes the overlap problem.

- **Repeat addresses.** Another method is to select the most serious hot spot addresses. For example, one might want to find the worst 10 percent of the addresses. This is called repeat address mapping (RAM). The addresses would be the 10 percent of repeat addresses that have the most crimes. They would be plotted on a map using dots to represent hot spots. This method has two distinct advantages. First, the map is clearer because it has less clutter. Second, such maps are useful for clearly specifying police targets. The deficiency of RAM is that it leaves out information about the other locations. This deficiency can be overcome by producing supplementary maps that show all locations or by combining RAM with the use of a color gradient so that the targeted hot spots have a distinct color (Eck, Gersh, and Taylor, 2000).

Repeat victimization hot spots

Repeat victimization refers to the multiple attacks on the same individual, regardless of location. It often is confused with repeat crime places. A repeat place might have a number of different victims. Clearly one can have both repeat victimization and repeat crime places (Eck, 2000). For example, a person could frequent a bar where he is assaulted on a number of different occasions. But if repeat victimization is distributed over many locations (as would occur if repeat victims are assaulted at different bars, but never the same bar twice), it will not show up on a map as a hot spot place (zero dimension). Repeat victimization could show up as lines (one dimension) if the victims are repeatedly attacked along the same thoroughfares, or as a polygon (two dimensions) if victims are repeatedly attacked in the same neighborhoods.

Mapping repeat victimization is more likely to reveal patterns with vulnerable populations—potential victims who engage in similar activities. Consider taxicab robberies and homicides. These crimes are unlikely to be concentrated in places. One might find attacks on this victim group occurring along specific streets where the drivers are particularly vulnerable or where offenders have a better chance of escape. More likely, however, taxicab robberies and homicides will be spread over a neighborhood or in a multineighborhood area within a city.

Underlying causes. Repeat crime places with different victims and repeat victimization with different places have different causes. Repeat crime places (with different victims) can be attributable to the behavior of place managers, but if the victimizations occur at different places, place managers have less of a role. In those cases, one should look at the occupations, commuting patterns, or lifestyles of the potential victims (Farrell and Pease, 1993; Spelman, 1995b; Stedman and Weisel, 1999). The most obvious example comes from the increasing evidence that the people most likely to become victims of assault are those people most likely to be involved in deviant and criminal activity (e.g., drug dealing, drug use, heavy alcohol consumption, prostitution) (Menard, 2000). Some occupations increase the chances of victimization, which can increase repeat victimization. Police officers, for example, have a greater rate of victimization than many other occupations (Block, Felson, and Block, 1985). However, the things that make a person a target for crime are sometimes difficult for that person to change.

Repeat streets hot spots

Repeat streets are those thoroughfares or streets with a high degree of victimization. Repeat places and some repeat victimization hot spots show up as dots on crime maps. If one increases the dimension of the hot spot from zero to one, hot spots that form lines appear. Linear hot spots are likely to be the results of the interaction of targets and offenders along thoroughfares. Brantingham and Brantingham (1981) describe the search behavior of offenders. Their offender search theory points to the importance of street patterns for how offenders look for targets.

Underlying causes. Offenders find targets while going about their normal legitimate business—going to and from work, recreation, shopping, school, and other nodes of activity. Potential targets that are not along the routes or near nodes used by offenders will unlikely be victimized, but those close to offenders' routes and nodes have elevated risks of victimization. Since major thoroughfares concentrate people (including offenders), targets situated along thoroughfares face higher crime risks than targets on side streets far from thoroughfares. Further, some types of targets concentrate along major streets. Convenience stores, fast food stores, gas stations, and other retail places are sited along major thoroughfares because that is where their customers concentrate. So for both reasons of offender movement patterns and target placement patterns, many crime hot spots are actually hot lines.

Some offenses may be concentrated at points or along lines. Street drug dealing is one example. Many street drug dealers simultaneously work along streets but anchor their activities to a specific address. In such circumstances, one might find a concentration of drug dealing along a few street segments and concentrations of drug locations at anchor sites. Weisburd and Green (1995) used street segments to identify drug hot spots in Jersey City because of offender movement patterns. Eck (1994), however, identified drug-dealing places because they seemed to be the anchor points of the drug trade in the San Diego neighborhood he was studying.

Distinguishing hot places from hot streets can be difficult. In fact, one can sometimes find both. Imagine robbers attacking pedestrians on a street leading from restaurants and bars to a parking area. The attack sites may form a line along this street. But even along this hot street, hot places where multiple attacks have occurred may exist. However, one should always be suspicious of such findings. It might be that the hot places are not actual robbery occurrence sites. Instead, they may be locations to which victims run for help, or they may be addresses that officers put in their reports when they cannot easily find the correct robbery address.

Knowledge of offender, victim, and police behavior is critical to separating the underlying crime pattern from reporting and recording patterns.

Maps for repeat streets. Commonly available mapping programs make it easy to identify hot spot places or hot spot areas, but do not make linear hot spots easy to identify. Simple dot maps can be used to identify hot street segments, and this may be the most straightforward method. Most clustering algorithms, unfortunately, will show areas of concentration even when a line is the most appropriate dimension. If high levels of precision are not required, such area maps may be adequate.

Neighborhoods and other area hot spots

More has been written about neighborhood concentrations of crime (hot spots) than about any other form of concentration of crime. In their pathbreaking book *Social Factors in Juvenile Delinquency* (1931), Shaw and McKay noted persistent concentrations of deviancy in the 1920s. They noted that some neighborhoods had high levels of juvenile delinquency, year in and year out, decade after decade, regardless of who lived in the areas (Shaw and McKay, 1969). Since that time, many explanations for differences in neighborhood crime levels have surfaced. Most of these theories focus on the ability of local residents to control deviancy (Bursik and Grasmick, 1993).

Underlying causes. Explanations for differing neighborhood crime levels include the following:

- **Social disorganization theory.** This theory suggests that the natural ability of people to control deviancy in their neighborhoods is impaired in some areas by constant residential turnover and net outmigration. These changes either disrupt social networks or prevent such networks from forming. Since these networks, according to disorganization theory, are responsible for most social control in neighborhoods, their absence leads to higher levels of deviancy. Other factors, such as poverty and racism, also have been identified as undermining social networks.

- **Social efficacy.** Recent evidence from Chicago points to the role of social efficacy, which is "the willingness of local residents to intervene for the common good." It depends on "mutual trust and solidarity among neighbors" (Sampson, Raudenbush, and Earls, 1997, page 919). Neighborhoods that have a great deal of social efficacy have less crime and disorder than neighborhoods that have low levels. Social efficacy—like disorganization and social networks—is not a property of individual people or places, but a characteristic of groups of people.

- **Broken windows theory.** The broken windows theory also is an area theory of crime concentration. Wilson and Kelling (1982) claim that in most well-functioning neighborhoods, small transgressions of social norms (e.g., failure to keep one's yard tidy) result in social pressures to bring the offending party into compliance. Once a place becomes untended, however, it undermines the willingness and ability of residents to enforce social order. Consequently, residents withdraw from enforcing neighborhood norms, which allows further deviancy to occur. This in turn results in additional withdrawal and fear and the neighborhood begins to spiral downward. Skogan (1990) found evidence in support of this basic thesis, although others suggest the evidence is weak (Harcourt, 1998) or show that the theory is seriously flawed (Taylor, 2000).

- **Crime opportunity theories.** Another explanation for neighborhood-level hot spots comes from routine activity theory and related theories that point to crime opportunities as the principle cause of crime. Rather than concentrations of offenders or the absence of social controls, opportunity theories suggest that analysts should look for concentrations of crime targets. For example, a dense urban neighborhood with no off-street parking will have many cars parked on the street. Such an area may become an area hot spot for thefts from vehicles. A suburban subdivision inhabited by dual-income families will have few people at home during weekdays. Since their property is unprotected, their neighborhood can become an area burglary hot spot. Note that in this type of situation, several layers of hot spots can exist simultaneously. Within area hot spots, defined by the subdivision in this example, might be streets with even greater numbers of burglaries, and some of the homes on these streets may be broken into multiple times.

Maps for area hot spots. Problems arising from processes described by neighborhood-level theories are best depicted on maps by shaded areas, rather than dots or lines. Area hot spots on maps can be shown in a variety of ways: ellipses, shaded areas (choropleth maps), or crime-frequency gradients (e.g., isoline maps that depict crime frequency or risk as graduated contours, just as feet above sea level is depicted on topographical maps).

Selecting the Appropriate Hot Spot Map

Action level, hot spot level, and mapping

The discussion so far has highlighted theories relevant to understanding different levels of hot spots. By now, it should be obvious that each form of concentration—place, victim, street, or neighborhood—requires its own form of mapping. It should also be apparent that the types of actions police should take correspond to the type of the concentration. These factors have important implications for how maps of hot spots are constructed and how the hot spots are depicted.

Dot maps. When hot spots are at specific addresses, corners, and other places, the relevant depiction of the hot spot is a dot because mappers want to distinguish between the places with problems and very nearby places without problems. Such distinctions are critical for delivering effective and efficient action. A gas station with many robberies needs to be distinguished from the gas station across the street with no robberies. In this circumstance, a map highlighting a street or area is far less useful to police than a map highlighting the gas stations that are robbery hot spots. Dot maps of crime places can identify widely spread locations that are hot spots. Such places might be overlooked if lines or polygons are used to define hot spots.

Line maps. When the hot spots are along streets, point maps and area maps are of far less utility than line maps. Point maps draw attention to the hot spot places along the street and imply that the intervening locations have low risk, when they may be future targets. Area maps include streets that have few or no crimes. Street robberies of people leaving bars and nightclubs are good examples of this. The bars and nightclubs are specific points, but the robberies do not occur there. These entertainment spots may be concentrated in one neighborhood, but even within this neighborhood, many streets do not have street robberies. The robberies may occur along streets leading from the entertainment spots to car parking locations.

Knowing which streets have the robberies and which do not is critical for addressing such a concentration. So showing this form of hot spot requires lines—straight, jointed, curved, or intersecting.

Ellipse, choropleth, and isoline maps. When hot spots cover broader areas and coincide with neighborhoods, they need to be depicted in another way. Ellipse and choropleth maps imply that the areas within the designated hot spots share the same risk level, so a specific street or location within the area is irrelevant. Isoline maps imply a continuous gradient of risk within a hot spot, so a particular place has risks similar to but not the same as an adjacent place or street. A gang-related robbery problem can be an example. If gang members commit robberies throughout specific neighborhoods (i.e., do not focus on specific streets or around specific sites), but refuse to commit robberies outside their territories, and their territorial boundaries are streets, then a choropleth map might be useful. One could create a map of the gang areas and shade the areas according to the robbery frequency within each. If the likelihood of a gang-related robbery diminishes the farther one goes from the center of gang activity, then an isoline map depicting gradients of robbery frequency does a better job of showing the problem.

Ellipses may be far less useful. They suggest a firm boundary between crime on the inside and no crime on the outside, but they frequently do not follow natural movement patterns of people. Using an ellipse to define an area hot spot is like saying, "Look in this general area," because neither its shape nor its boundary are likely to conform to the nature of the underlying problem. Consequently, ellipses provide police officers with far less information than other ways of depicting area hot spots.

Limitations of hot spot maps

Concentrations of victimization sometimes can be shown with maps, but often they cannot. If victimization risk is in part geographical, then maps are useful. A citywide dot map of gas stations with two or more robberies within the last 6 months shows concentration at two levels. The dots depict concentrations of robbery at specific places. Groupings of dots depict streets or neighborhoods with concentrations of repeat robbery gas stations. Dot maps for this type of victimization makes some sense, but they do not work for all forms of victimization concentration. If victims are mobile, street or area maps might be more useful. However, the use of maps is limited for some forms of victimization analysis. If the population of potential victims is spread throughout an area (not concentrating at places, along streets, or within neighborhoods), the analyst would be better off using an analytical technique other than maps to convey the concentration. For example, taxicab robberies may be spread quite thinly across a city. The relevant features of the robbery victims might be related to the cab companies, the drivers' ages, hours of operation, installed security within cabs, or a host of factors that cannot be shown on a map. Police officers trying to investigate or prevent such robberies would find maps less useful than bar charts showing the characteristics of victims and nonvictims.

Exhibit 2 links the major points discussed thus far. The first two columns are from exhibit 1. The third column shows where the police action needs to be focused. If the concentration level, action level, and form of hot spot depiction are not aligned, then the map will be useless at best and suggest inappropriate action at worst. A map depicting hot streets or areas does not help identify places where nuisance abatement would be useful. Alternatively, a point map is too specific for implementing street reconfigurations or neighborhood redevelopment efforts.

The consequences of using the wrong type of map are not equal. Point maps are more forgiving than street or areas maps. Dot maps allow the user to see the underlying pattern of crime and determine whether to go up a level. However, maps of hot streets or hot areas often do not show the hot places, thus place concentration can remain hidden. This suggests that crime mapping should start at the lowest level and work upward to avoid overlooking low-level concentrations where effective action can be taken.

Conclusion

Different kinds of hot spots, which develop from different causes, require different kinds of police action. For crime mappers, this means that the visual display of the crime pattern on the map should be consistent with the type of hot spot and possible police action. Plotting area maps when the hot spots are addresses is not useful to the police officers using the map because the map is imprecise. It directs their attention to large areas where little effort needs to be expended and away from the places where attention is needed. At the other extreme, focusing attention on point locations when the problem is at the area level focuses attention at too precise an area and suggests action that is too focused.

Maps convey powerful messages to their readers, most of whom are not knowledgeable about the technicalities of crime mapping. These messages are conveyed in symbols, as shown in exhibit 3. Dots (A) draw attention to specific places and suggest that places without dots can be ignored. A point conveys the message that the hot spot is located at this exact location and should be the focus of police efforts. A shaded street segment (B) suggests that the chances of crime are roughly equal along the entire segment and police efforts should focus along this line, but not along other lines. A shaded area (C), such as one used in a choropleth map, also suggests equivalent risks of crime throughout the area with a dramatic reduction in risk at the border. It suggests that police activity throughout the area is appropriate. An area covered by a gradient (D), such as that depicted in isoline maps, implies that a center of high-crime activity exists and that criminal activity tapers off gradually from that center. It directs police attention to the center and its surroundings. Each way of

Exhibit 2. Concentration, mapping, and action

Concentration	Hot spot depiction	Action level	Action examples
Place—at specific addresses, corners or other places	Points	Place, corner	Nuisance abatement, hot spot patrols
Among victims	Points, lines, and areas depending on the nature of concentration	High-risk targets and potential victims	Developing networks among potential victims, repeat victimization programs
Street—along streets or block faces	Lines	Streets, highways	Concentrated patrolling of specific streets, traffic reengineering
Area—neighborhood areas	Ellipses, shaded areas, and gradients	Large areas	Community partnerships, neighborhood redevelopment

depicting hot spots is connected with useful theories, each of which suggests different types of police action. Recognition of these links in mapping practice will lead to better use of crime maps.

Notes

1. Although one could have hot spots of anything that can be geographically distributed—a hot spot of automobile dealerships, for example—usage of this term is restricted to crime or disorder. So unless otherwise specified, hot spots means hot spots of crime or disorder.

2. Level does not indicate superiority or rank in this instance. A high-level hot spot is not better or worse than a low-level hot spot. Rather, higher level hot spots can be composed of groups of lower level hot spots. In this sense, level refers to level of aggregation.

3. Some disagreement exists over the geographic scope of neighborhood theories of crime. Most researchers refer to areas covering several square blocks, although Taylor (1997, 1984) makes a strong case for the relevant area being about the size of a single block. Clearly, the difference between a large place and a small neighborhood is blurry.

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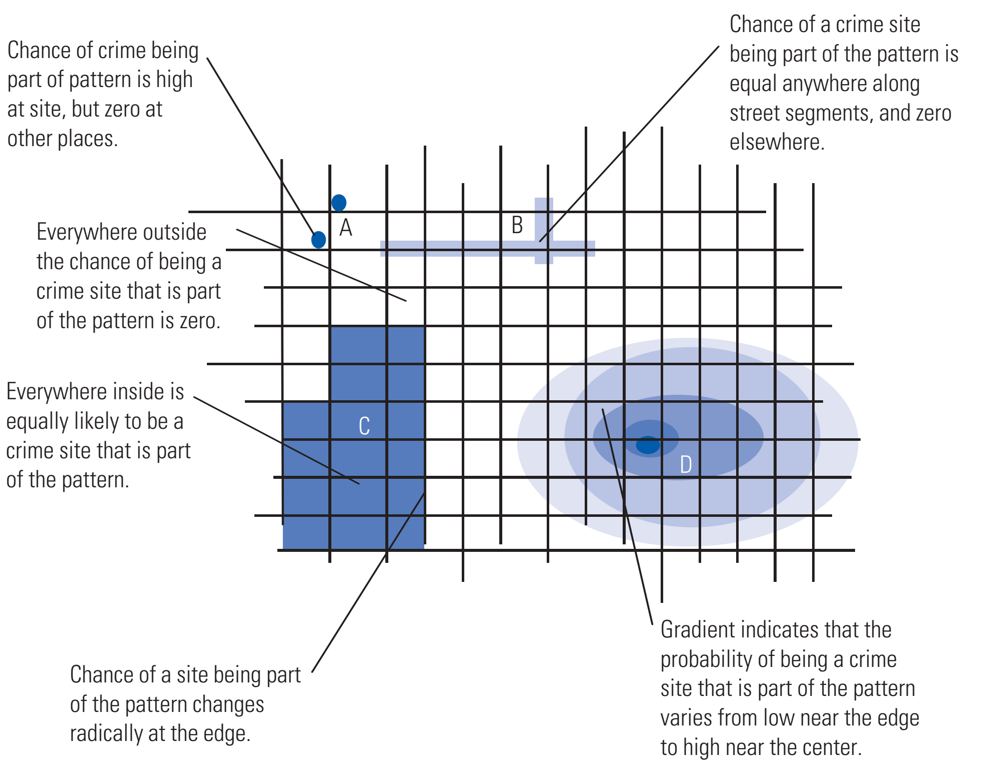
Exhibit 3. Messages in crime maps



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Chapter 2. Methods and Techniques for Understanding Crime Hot Spots

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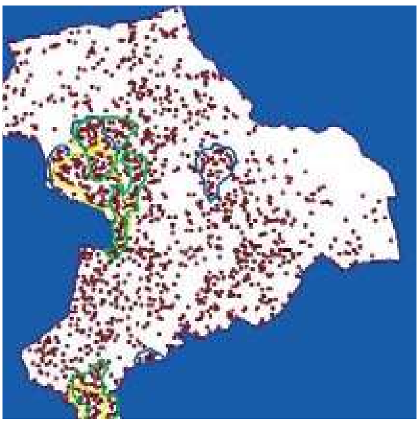


This chapter presents a number of methods and techniques to understand and describe patterns of hot spots in crime data. It explains the advantages and disadvantages of certain techniques, focusing on methods that are easy to understand and practical to apply. Four data sets are used to test the methods. The results help evaluate how the methods improve understanding of crime patterns. This chapter does not attempt to find the *optimal* method. Rather, it presents a procedure for applying a number of complementary methods that can help analysts understand hot spots in the data.

The four data sets are from the London Metropolitan Police Force's Crime Report Information System for Hackney Borough Police for the period June 1999 through August 1999. This chapter contains tests developed and conducted to help analysts understand hot spots in representative samples of crime data sets of—

- All crime (9,972 records) and three subsets.
- Street robbery (588 records).
- Residential burglary (1,068 records).
- Vehicle crime (1,747 records).

The geographic area for these data is insignificant to explain the different methods for trying to understand crime hot spots. The data should be treated merely as point events of crime within a geographical boundary area. In some cases, these points will be aggregated to small area geographies such as beats or census blocks to demonstrate the applicability of certain techniques. The methods discussed and tested on these data are perfectly applicable to analysts' own data.

Preliminary global statistical tests

A number of simple-to-use global statistical tests can be used to help analysts understand general patterns in the crime data presented here. These tests include—

- Mean center.
- Standard deviation distance.
- Standard deviation ellipse.
- Tests for clustering.

Mean center

The mean center point can be used as a relative measure to compare spatial distributions between different crime types or against the same crime type for different periods of time (i.e., for measuring spatial shifts in the same crime type). For example, exhibit 1 shows the mean center points for all crime, street robbery, residential burglary, and vehicle crime. The all-crime mean center can be used as a control to compare against crime type subsets. Residential burglary has a mean center that is more north than all crime and the two other crime subsets. The mean center for vehicle crime is the farthest south of all the crime types, and street robbery is nearly as far north as that for residential burglary but slightly farther west. These mean centers can be used to generally indicate that residential burglary and robbery offenses show a greater tendency to occur in the northern part of the borough and that vehicle crime affects the southern areas of the borough more.

Standard deviation distance

Measures of standard deviation distance help explain the level and alignment of dispersion in the crime data. These statistics are best used as relative measures, comparing crime types against each other or the same crime types for different periods of time. Exhibit 2 shows the standard deviation distances for the four crime types. The greater the standard deviation distance, the more dispersed are the crime data. These results show that vehicle crime is the most dispersed; robbery is the least.

Standard deviation ellipses

Levels of dispersion also can be presented using standard deviation ellipses. The size and shape of the ellipse help explain the degree of dispersion, and its alignment helps to explain the crime type's orientation. Exhibit 3 shows standard deviation ellipses for the four crime types. The subtle differences between the ellipses help describe the relative differences in dispersion and alignment of the four crime types' patterns. The ellipse with the smallest area (robbery) is the least dispersed of the crime types. The position of the robbery ellipse farther north of all crime and vehicle crime, but slightly farther south of the residential burglary ellipse, reflects its

Exhibit 1. Mean center points for the four crime categories

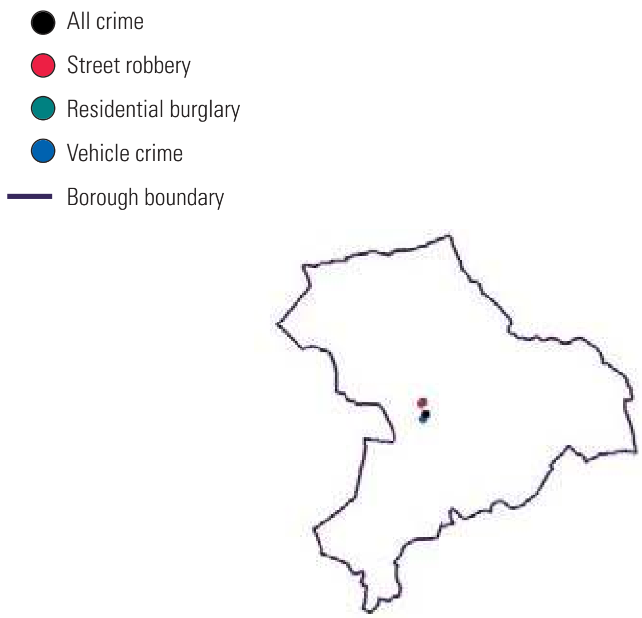


Exhibit 2. Standard deviation distance results for the four crime categories

Crime type	Standard deviation distance (meters)
All crime	1,807.94
Robbery	1,749.94
Residential burglary	1,806.28
Vehicle crime	1,820.85

mean center. Its north-west, south-east orientation also helps to describe the general direction toward which robbery crimes have a tendency to be patterned.

Tests for clustering

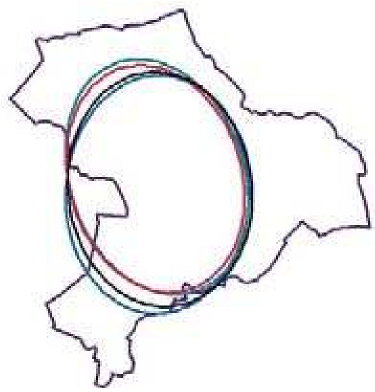
The fourth and probably most useful of the preliminary global statistics are those that test for clustering. Crime analysts often assume that crime distributions are clustered, and whether clusters exist or not, some can be identified from random crime distributions. Testing for clustering is the first step in revealing whether data has hot spots of crime.

Several approaches can be applied to test for clustering in crime distributions. Most methods incorporate the basic principles of hypothesis testing and classical statistics, in which the initial assumption is that the crime distribution is one of complete spatial randomness (CSR). By setting the CSR assumption as the null hypothesis, the crime distribution can be compared against a set significance level to accept or reject the null hypothesis. Some tests for clustering are the nearest neighbor index and the spatial auto correlation tests.

Nearest neighbor index (NNI). The NNI is a simple and quick method to test for

Exhibit 3. Standard deviation ellipses for the four crime categories

All crime
Robbery
Residential burglary
Vehicle crime



evidence of clustering. The NNI test compares the actual distribution of crime data against a data set of the same sample size, with random distribution. It can be applied when the user has access to data in which each point relates to individual crime events (irrespective of whether some of these events are mapped on top of each other at exactly the same location). The NNI method is explained in the following steps:

- For each point, calculate the distance to the nearest neighbor point.
- Sum the nearest neighbor distance for all points and divide by the number of points in the data. This value is the observed average nearest neighbor distance.
- Create a random distribution of the same number of crime points covering the same geographic area, and for each point calculate the distance to each nearest neighbor point.
- Calculate the sum of the nearest neighbor distances for all these randomly distributed points and divide by the number of points in the data. This value is the average random nearest neighbor distance.
- The NNI is then the ratio of the observed average nearest neighbor distance against the average random nearest neighbor distance.

If the result generated from the NNI test is 1, then the crime data are randomly distributed. If the NNI result is less than 1, then the crime data show evidence of clustering. An NNI result that is greater than 1 reveals evidence of a uniform pattern in crime data.

Exhibit 4 shows the NNI results for the four crime data sets. All four sets show evidence of clustering in their distribution.

The results also show the differences between the NNI results for a minimum bounding rectangle area and the actual catchment area of the crime points. When the actual catchment area is known or can easily be calculated, it should be used in the calculation of the NNI. If the area is not known, a minimum bounding rectangle around the crime distribution often is used to calculate the area representing the crime data's catchment zone.

However, minimum bounding rectangle areas used for NNI tests often can create misleading results for describing point distributions. To test and show evidence of this, analysts purposely designed a regular distribution of points and applied three different types of bounding areas: minimum bounding rectangle, bounding convex hull, and true boundary area. After applying NNI tests, the bounding convex hull method and true boundary area revealed similar results, correctly describing the point

Exhibit 4. Nearest neighbor analysis results for the four crime data sets

Crime type and bounding area*	NNI	Z-score
All crime		
Bounding rectangle area	0.32	–129.11
True boundary area	0.46	–103.14
Robbery		
Bounding rectangle area	0.59	–19.14
True boundary area	0.80	–9.20
Residential burglary		
Bounding rectangle area	0.57	–27.14
True boundary area	0.74	–16.46
Vehicle crime		
Bounding rectangle area	0.52	–38.73
True boundary area	0.72	–22.16

*Crime distribution is clustered for all areas.

data's distribution to be regular. The result from the minimum bounding area suggested the same distribution to be random. Where the true boundary area is not available, a convex hull that bounds the limits of the point distribution will return a more accurate result for evidence of clustering than a minimum bounding rectangle.

A z-score test statistic can be applied to help place confidence in the NNI result. This test for statistical significance describes how different the actual average nearest neighbor distance is from the average random nearest neighbor distance. The significance of the z-score can be found in any table of standard normal deviations. The general rule to follow is that the more negative the z-score, the more confidence can be placed in the NNI result, bearing in mind that for smaller sample sizes the z-score will be less than that for larger samples of crime points.

Test for spatial auto correlation. Spatial autocorrelation techniques test whether the distributions of point events are related to each other. Positive spatial autocorrelation is said to exist where events are clustered or where events that are close together have similar values than those that are farther apart.

Spatial autocorrelation tests, of which Moran's I is one commonly applied method, have been used previously to test for evidence of crime event clustering (Chakravorty, 1995). Spatial autocorrelation techniques require an intensity value, be it a weighting linked to the event or a count of crimes where the crime point relates to the coordinate of an area to which crime events have been aggregated (e.g., the centroid of the area). If the original crime event data exist as accurate point georeferenced data, aggregating this data to a common point will lose spatial detail. With the increased availability of accurate and precise geocoded records of crime, it would seem more important to use methods that do not require an intensity value but retain and perform tests on the original crime event point data.

Spatial autocorrelation methods include the following:

- **Moran's I.** If analysts have access only to crime point data that are aggregate counts (representing the number of crime events within a certain geographic area, e.g., census blocks), an appropriate method to apply to test for clustering is the spatial autocorrelation technique, Moran's I. (See exhibit 5.) Moran's I statistic works by comparing the value at any one location with the value at all other locations (Levine, 2002; Bailey and Gatrell, 1995; Anselin, 1992; Ebdon, 1985). Moran's I requires an intensity value for the crime point, which is often represented as the centroid of the geographic boundary area. This point is then assigned an intensity value. For crime applications, this most often is the count of crimes within that geographic area. The Moran's I result varies between –1.0 and +1.0. Where points that are close together have similar values, the Moran's I result is high. The significance of the result can be tested against a theoretical distribution (one that is normally distributed) by dividing by its theoretical standard deviation. (For more details on this test, see Levine, 2002.)

- **Geary's C statistic.** A second spatial autocorrelation method is Geary's C statistic. (See exhibit 5.) This method is best applied to describe differences in small neighborhoods. (Moran's I gives more of a global indicator of spatial relationships; Levine, 2002). Geary's C statistic is a measure of the deviations in intensity values of each point with one another. The values of C typically vary between 0 and 2, where values less than 1 indicate evidence of positive spatial autocorrelation and values greater than 1 indicate evidence of negative spatial autocorrelation. Similar to Moran's I, the Geary coefficient can be tested for significance against a theoretical distribution (one that is normally distributed) by dividing by its theoretical standard deviation.

The differences in the sensitivities of the two spatial autocorrelation tests are noted in the results on the four crime categories. For example, evidence exists of positive spatial autocorrelation for robbery at a more global level. However, the Geary coefficient reveals that at the smaller neighborhood level, areas that have a high number of robberies are surrounded by areas with a low number of robberies.

The preliminary global statistics reveal a wealth of knowledge about the crime data even before the mapped distributions are explored in detail. The analysts have generated an understanding of the global patterns in the crime data and shown that evidence of clustering exists in all of the four crime categories. This clustering does, however, vary at different scales. The dispersion tests have revealed that although clustering exists in the data, the crime hot spots for vehicle crime are more dispersed than any of the other crime categories. These tests, therefore, begin to reveal a picture of what the hot spot maps may look like. For example, when the robbery data are mapped, analysts can expect hot spots of crime to exist and to be concentrated together more than any other crime category.

The following sections explore various techniques for mapping crime. These sections mainly use the vehicle crime data set to explore the different applications of these techniques to help in understanding hot spots of crime.

Crime mapping techniques

Point mapping

The most common approach for displaying geographic patterns of crime is point mapping (Jefferis, 1999). Point mapping is popular mainly because it is a simple digital version of a familiar and traditional method of placing pins representing crime events onto a wall map. In a digital application, if these individual geographic point objects are suitably attributed with information, such as the code describing the type, date, and time of offense, sets of points meeting particular conditions can be simply and quickly selected. These selections can then be displayed using suitable symbology representing the crime category displayed. However, trying to interpret spatial patterns and hot spots in the crime point data can be difficult, particularly if the data sets are large.

Exhibit 6 shows the 1,747 events of vehicle crime. The large volume of points shown on map A makes it difficult to feel

Exhibit 5. Spatial autocorrelation results for the four crime categories

Crime type	Moran's I	Z-score	Geary's C	Z-score
All crime	0.003116	2.161428	0.979587	–1.635861
Robbery	0.000660	1.185983	1.022821	3.585178
Residential burglary	0.002996	2.113746	0.987718	–1.929432
Vehicle crime	0.006658	3.568309	0.918423	–12.815473

completely confident in identifying the hot spots of this particular crime. The preliminary global tests revealed that clusters of vehicle crime were evident, but that these hot spots were more dispersed than any of the other crime types. To demonstrate the ambiguity in trying to identify the hot spots of crime from this particular data set, the analysts asked three crime analysts who were not familiar with the study area to draw the location of the top three hot spots of vehicle crime on map B. The three analysts identified two common areas as being hot spots of crime, but the areas drawn at these locations differed in size and shape. Two hot spots identified by analyst 1 are completely different from those identified by analysts 2 and 3.

Which analyst is correct? At this stage it is difficult to tell because each hot spot drawn is plausible. Not all of those drawn will be completely correct. This example demonstrates the difficulty in trying to consistently identify crime hot spots from point data. Also, at certain locations, what appears to be a single crime point may be more than one crime point. These points at coincident locations are impossible to identify using the point map in exhibit 6. Point maps do have their application for mapping individual events of crime, small volumes of crime, and repeat locations through the use of graduating symbol sizes (see exhibit 7), but they can become less effective for identifying hot spots of crime, particularly from large data volumes.

Spatial ellipses

The application of spatial ellipses for attempting to identify crime hot spots has a long tradition in crime mapping. The Spatial and Temporal Analysis of Crime (STAC) software distributed by the Illinois Criminal Justice Information

Exhibit 6. A: Point map of vehicle crime
B: Three sets of hot spots identified by different analysts

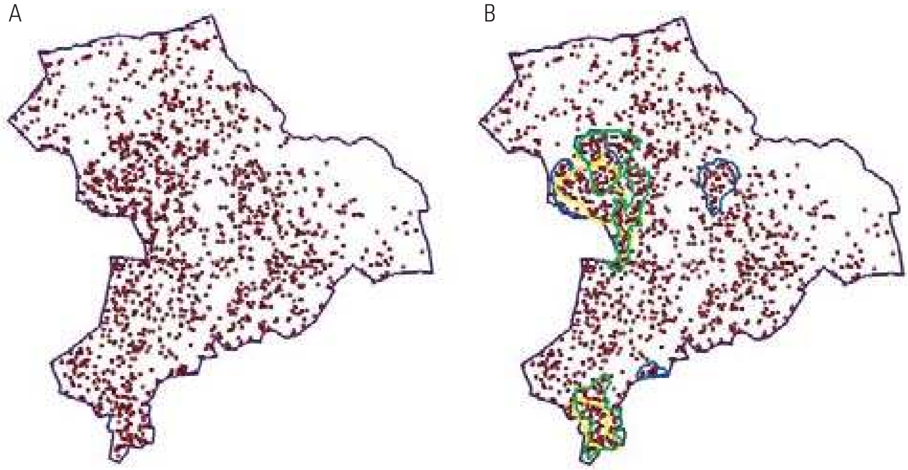
Crime analyst 1

Crime analyst 2

Crime analyst 3

Point hot spots

A B

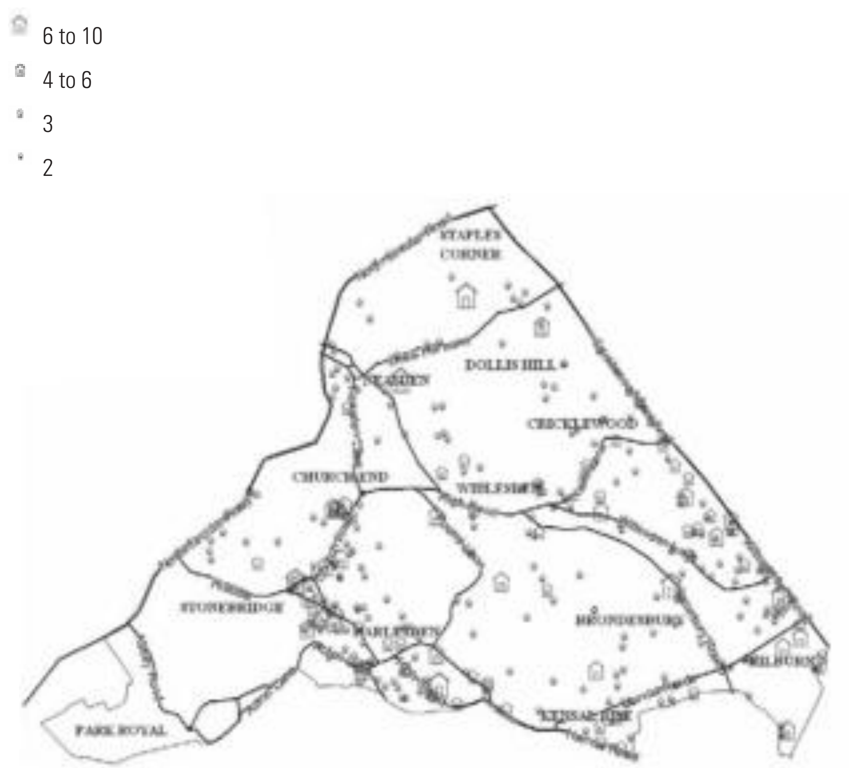


Authority is one type of available software used for spatial ellipses. The Space Analyzer component of STAC works by creating standard deviational ellipses around crime point clusters. Other spatial ellipse techniques include hierarchical clustering and the K-means clustering routine.

Hierarchical clustering. This method uses a nearest neighbor analysis technique to identify groups of a minimum number of user-defined points. The nearest neighbor analysis technique used identifies only those points that are closer than expected under spatial randomness. The first set of ellipses generated through this process is referred to as first-order clusters. Grouping the first-order clusters can then generate second-order ellipses. This process can then be repeated until all crime points fall into a single cluster or when the grouping criteria fails (Levine, 2002).

K-means clustering. The K-means technique creates a user-defined number (K) of ellipses by partitioning the crime point data into groupings. The routine finds the best positioning of the K centers and then assigns each point to the center that is nearest. Exhibit 8 shows five ellipses created using the K-means method. The method demonstrates how spatial ellipse techniques are useful for grouping crime point clusters and revealing areas for closer inspection. However, the ellipse outputs also demonstrate certain weaknesses in these types of techniques if analysts are trying to accurately identify the location of crime hot spots. Crime hot spots do not naturally form spatial ellipses. These

Exhibit 7. Properties with multiple breakins (January 1996–July 1997)



methods, therefore, do not represent the actual spatial distribution of crime and can often mislead the analyst to focus on areas of low crime importance within an ellipse. Also, all of these techniques require a thorough understanding of the routines at work because each method requires a number of parameters to be entered. Users with a vague understanding of the actual methods are given few rules to enter appropriate parameters, thus introducing ambiguity and influencing variability in the final output. For example, different crime analysts investigating crime hot spots from the same data may produce different results because of the different parameters they have chosen to enter into the routine. Grouping events into elliptical clusters also excludes from any visual result those events that do not belong to a cluster.

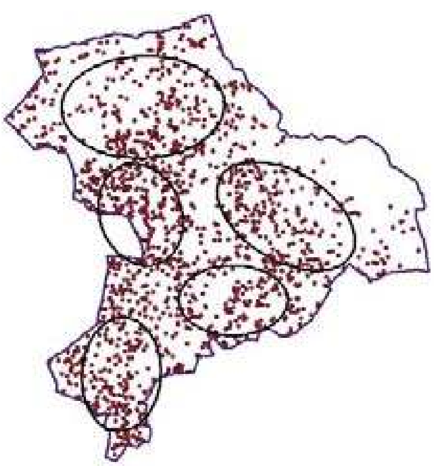
Four of the five ellipses drawn using the K-means method partially overlap the hot spot areas drawn by the three crime analysts from the point map. One ellipse differs completely from an area identified by analyst 1. At this stage it is difficult to understand which one is correct or which method returns more accurate results. Both methods are plausible and importantly present the opportunity to explore the nature of crime in these areas in more detail. However, neither method presents the immediate opportunity to prioritize the main crime hot spots to assist in prevention targeting.

Thematic mapping of geographic boundaries

A popular technique for representing any spatial distribution is geographic boundary thematic mapping. These geographic boundaries usually are defined administrative or political areas such as beats, census blocks, polling districts, wards, or borough boundaries. Crime events mapped as points can be aggregated to these geographic region areas. These counts of events by their geographic areas can then be thematically mapped to display the spatial pattern of crime across the area of interest (see exhibit 9).

When thematic maps of this type are created, the user is required to identify the type of range to represent the distribution

Exhibit 8. K-means elliptical clusters for vehicle crime



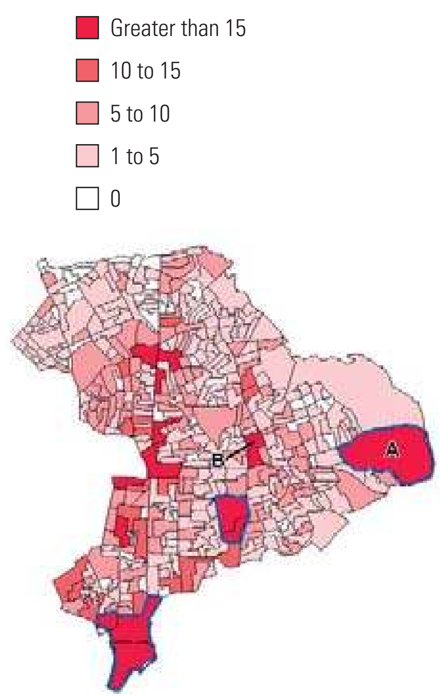
of crime (e.g., equal count, equal ranges, natural break, standard deviation, quantile, or custom range; for a good review of these different types of range settings, see Harries, 1999). This freedom to choose a range of any type creates variability in any thematic map produced for identifying crime hot spots. Different range types structure the groupings of geographic boundary crime counts into differing threshold categories. At what range threshold can the crime analyst confidently conclude that geographic boundaries in that range and above represent hot spots of crime? In other words, when is a hot spot a hot spot?

Considering the theory and application behind the map the user is trying to produce and the target audience is important at this stage. If the application is to identify the hot spots of crime, the range thresholds should be structured to focus on revealing the locations of these high-volume crime areas. The analysts also should consider structuring the thematic ranges in a manner that is easy for the audience to understand. The map should be the central message and the thematic ranges should follow in a logical sequence. If the thematic ranges require explanation or confuse the audience, the analysts have lost the opportunity to present their central message: mapping and displaying crime hot spots. Mapping is an iterative process. The first map a user produces is unlikely to be the one printed or included in a report. Decide on the message and follow through with this message by testing different settings available for the thematic thresholds.

Exhibit 9 shows the vehicle crime data thematically mapped by census blocks. The range created is a custom one that follows in a logical and easy-to-understand sequence. It identifies those census blocks that are grouped in the highest crime count categories. From this map, a crime analyst was asked to identify those areas he believed to be the three main hot spots of crime. These are the three hot spot areas drawn on the map. Notice how these interpreted hot spot areas differ from those drawn directly from the point data and those identified by spatial ellipses. Which map is correct?

Thematic maps such as the one in exhibit 9 tend to attract the audience to the largest areas shaded in the top threshold color range. Therefore, the single census block A has been selected as a hot spot as it stands out boldly. Census block B has not been selected as a hot spot, yet its area is one-eighth of that of census block A and it has a similar crime count, as it features in the top threshold range. This reveals a problem with using geographic boundary thematic maps to identify hot spots of crime. Due to the varying size and shape of the census blocks (and most

Exhibit 9. Vehicle crimes mapped by census tract



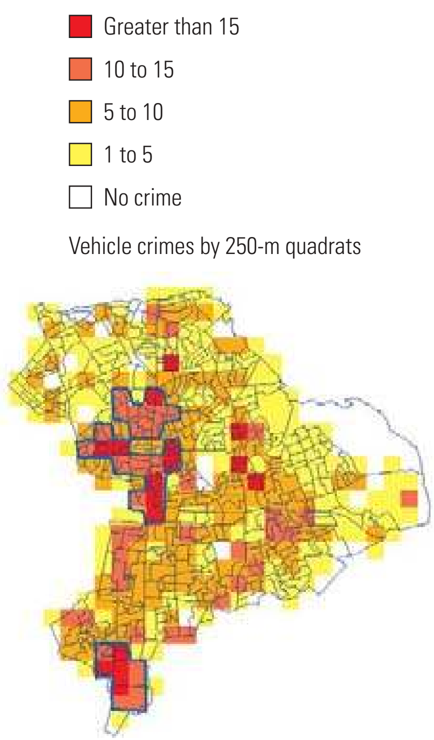
geographic boundaries), thematic shading can mislead the audience in identifying where the spatial cluster of crime may exist. Census block A may contain an area with a cluster of crime events. These crime events, however, may be evenly spread across the whole area of this large census block. Thus an actual hot spot in this area may not exist. If this was the case, the map in exhibit 9 may misinform any targeting initiative to hot spots of crime identified by this method.

An additional problem with mapping by defined boundaries is that presented by the Modifiable Area Unit Problem (MAUP) (Bailey and Gatrell, 1995; Openshaw, 1984), in which changes in the geographic boundary areas used to thematically represent the distribution of crime can affect and further mislead map interpretation. However, the geographic boundary thematic mapping method should not be completely discounted. Boundary thematic maps are important map outputs, as the areas they represent often are geographic regions used for political and administrative purposes. For example, a police inspector may have management responsibility for combating crime in a group of geographic areas. This inspector will want to be informed with general information such as the thematic map shown in exhibit 9. The inspector will also most likely be interested in receiving summarized information of patterns that exist in neighboring geographic areas (e.g., a geographic boundary thematic map, with a table of crime counts by categories for these areas of interest). These methods do, therefore, have an important application for providing summarized management information across areas of accountability, but may mislead focused crime prevention targeting because of failing to reveal patterns within and across the geographic division of boundary areas.

Quadrat thematic mapping

To get over the problem of varying sizes and shapes of geographic administrative boundary areas, uniform grids (or quadrats) can be drawn across the study area and thematically shaded. The unit to thematically map could be a count of crimes per grid cell or a density value calculated from the count and cell area. If the grids are small enough, the analysts can then expose if hot spots of crime actually exist within large geographic boundary areas, while retaining and displaying high crime volumes in the smaller geographic areas. Exhibit 10 shows a 250-meter (m) quadrat thematic map of vehicle crime. Similar to the other mapping outputs, a crime analyst has drawn areas on the map that he interprets as being the three main hot spots (shown in blue). Interestingly, the quadrat hot spots identified fit closely

Exhibit 10. 250-m quadrat thematic map



with a number of the hot spots identified from the point map. In addition, notice that the census block A identified as a hot spot in the geographic boundary thematic map (exhibit 9) is not revealed as a hot spot using this method. The crimes that contributed to the high count in this large census block are generally spread across the whole geographic region. The quadrat method, therefore, appears to offer a more accurate method for identifying hot spots of crime, particularly where applications for crime prevention targeting are required.

However, the quadrat method still restricts analysts to using a defined geographic area to represent the size and shape of crime hot spots. The restriction of using thematically shaded, defined geographic grid cells often results in loss of spatial detail within each quadrat and across quadrat boundaries. This can lead to problems of inaccurate interpretation. The map also looks blocky and does not entirely invoke interest. A common request to address this problem is to reduce the grid cell size. All this does is produce a speckled map of small, thematically shaded grid cells that fail to draw the user to any firm conclusions as to the size, shape, or location of crime hot spots for resource targeting. Also, issues with thematic range settings still exist with this method, including those that relate to the MAUP.

Interpolation and continuous surface smoothing methods

Interpolation. Interpolation is an increasingly popular method for visualizing the distribution of crime and identifying hot spots. It aggregates points within a specified search radius and creates a smooth, continuous surface that represents the density or volume of crime events distributed across the area. Common interpolation techniques, such as inverse distance weighting, triangulation with smoothing, kriging, and splining are all designed to use an intensity, population, or 'z' value taken from sample locations to estimate values for all locations between sample sites. For example, interpolation techniques are commonly used to create surfaces representing the distribution of rainfall, where the values between rain gauges are estimated from a function that considers the rainfall readings and the distribution of sample sites (i.e., rain gauges). With crime data, sample sites with an intensity value do not necessarily exist. Neither would it make sense to apply one of these techniques to estimate the number of crimes that may have occurred between the existing crime point locations. No crimes have been recorded in the areas between crime points, so the analysts should avoid methods that aim to create estimated intensity values in the gaps between the points. Instead, surfaces that the analysts wish to create that represent the distribution of crime should act as visualizations for helping them understand crime patterns. Methods that suit the analysts' application should therefore represent, as a continuous surface, the relationships or densities between crime point distributions.

Quartic kernel density estimation. The most suitable method for visualizing crime data as a continuous surface is quartic kernel density estimation (Chainey et al., 2002; McGuire and Williamson, 1999). The quartic kernel density method creates a smooth surface of the variation in the density of point events across an area. The method is explained in the following steps:

1. A fine grid is generated over the point distribution (see exhibit 11). In most cases, the user has the option to specify the grid cell size.

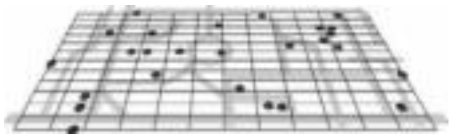
2. A moving three-dimensional function of a specified radius visits each cell and calculates weights for each point within the kernel's radius (see exhibit 12). Points

closer to the center receive a higher weight and therefore contribute more to the cell's total density value.

3. Final grid cell values are calculated by summing the values of all circle surfaces for each location (see exhibit 13).

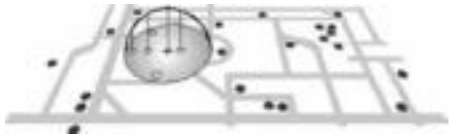
The quartic kernel estimation method requires two parameters to be set prior to running. These are the grid cell size and bandwidth (search radius). Bandwidth is the parameter that will lead to most differences in output when varied. Guidelines exist for working out suitable values for these two parameters. For crime mapping applications, a suitable method to follow for choosing bandwidth is that suggested by Williamson et al. (1999), where the bandwidth relates to the mean nearest neighbor distance for different orders of K. These nearest neighbor distances for different orders of K usually are calculated as

Exhibit 11. A fine grid is placed over the area covered by the crime points



Source: Ratcliffe, 1999a.

Exhibit 12. A search radius (or bandwidth) is then selected

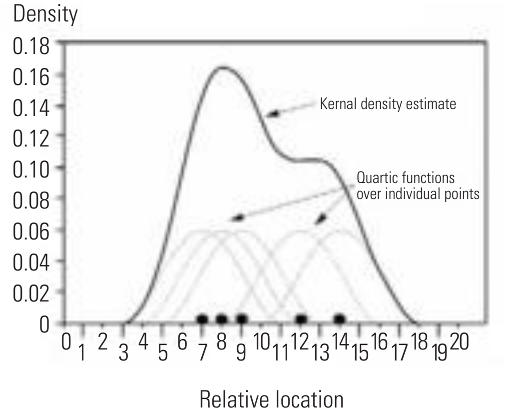


Source: Ratcliffe, 1999a.

Note: Within the bandwidth, intensity values for each point are calculated. Points are weighted, so that incidents closer to the center contribute a higher value to the cell's intensity value.

Exhibit 13. Grid cell values are calculated

Kernel Density Estimates
Summing of Quartic Kernel Function



Source: Levine, 2002.

Note: Each grid cell value is the sum of values of all circle surfaces for each location.

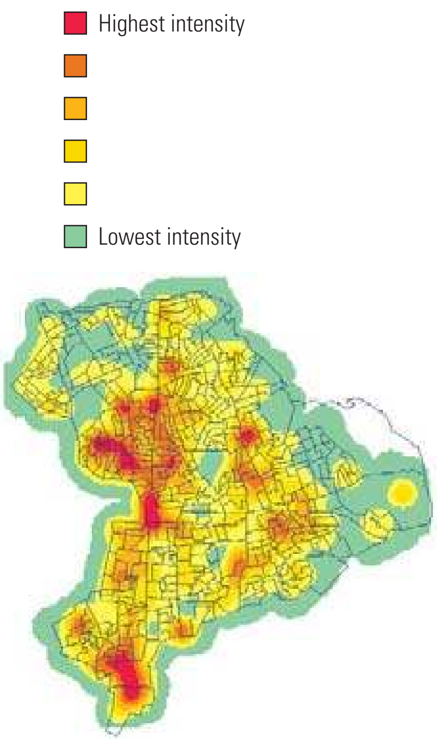
part of the nearest neighbor analysis test for clustering. If this method is adopted, the user is still required to choose which K order to apply. This can be regarded as an advantage of the technique because users are prompted to think about the data they are mapping and apply the K order's mean nearest neighbor distance as the bandwidth relevant to their crime mapping application. For example, a smaller bandwidth would be used for an application that requires output for focused police patrolling than for one that requires a more strategic view of crime hot spots.

Users also are required to specify a grid cell size. This can be regarded as a positive feature in kernel estimation because users have the flexibility to set sizes relevant to the scale at which the output will be viewed. Large cell sizes will result in more coarse or blocky-looking maps but are fine for large-scale output, while smaller cell sizes add to the visual appeal of the continuous surface produced but may create large file sizes. When unsure of the cell size, the user can follow the methodology of Ratcliffe (1999b), who divides the shorter side of the minimum bounding rectangle (or the shortest of the two extents between minimum X/maximum X or minimum Y/maximum Y) by 150. Cell size for the area that the data cover has been set to 30 m. The cell values generated from quartic kernel estimation also are in meaningful units for describing crime distributions (e.g., the number of crimes per square kilometer). Exhibit 14 shows the quartic kernel density estimation surface generated from the vehicle crime point data, where the bandwidth chosen was a K order of 16 (220 m).

The quartic kernel density estimation method creates understandable grid cell value outputs that relate to crime and requires fewer parameters to be set than those required for many other methods. The parameters entered can relate to the spatial distribution of the points being analyzed. The method also has the advantage of deriving crime density estimates based on calculations performed at all locations (Levine, 2002), and retains some practical flexibility in map design.

The increased application of this type of continuous surface smoothing method is due largely to its more common availability and visual appeal. Continuous surface hot spot maps allow for easier interpretation of crime clusters and reflect more accurately the location and spatial distribution of crime hot spots. The quartic kernel density estimation method also considers concentrations of crime at all event levels, rather than cluster grouping some and discounting others. As their appeal has increased, however, few questions are

Exhibit 14. Quartic kernel density estimation surface for vehicle crime using a bandwidth of 220 m (K16)



being asked of the outputs generated. The issue over which thematic range to choose to represent the different thematic thresholds remains a problem. Many agencies often fail to question this validity or statistical robustness of the map produced, being caught instead in the visual lure of their sophisticated looking geo-graphic. Thus, little regard is given to the legend thresholds that are set to help the analyst decide when a cluster of crimes can be defined as a hot spot. For example, the number of hot spots on a map showing the distribution of crime as a kernel density surface depends on the ranges selected by the map designer to show spatial concentrations of these point events. Careful selection of range settings is therefore required, but this opens the opportunity for crime analysts to create different kernel density estimation hot spot maps of crime from the same data.

One method that has been suggested to help standardize the thematic threshold settings of kernel density estimation hot spot maps is the application of incremental multiples of the grid cells' mean (Chainey et al., 2002). Calculations for the mean are applied only to grid cells that have a value of greater than 0 and that are within the study area boundary. From this grid cell set, the mean can easily be calculated within a geographic information system (GIS) with grid cell thematic thresholds set at—

- 0 to mean.
- Mean to 2 mean.
- 2 mean to 3 mean.
- 3 mean to 4 mean.
- 4 mean to 5 mean.
- Greater than 5 mean.

Exhibit 15 shows the application of this incremental mean threshold approach for vehicle crime. The method is visually appealing and structures the thematic thresholds to clearly identify areas of highest crime concentration. It is simple to apply because it requires only the calculation of the grid cell mean; it uses K order mean nearest neighbor distances to define bandwidths; it retains flexibility in map design by allowing the user to apply different K order bandwidths and grid cell sizes to the suited application; and it uses a consistent methodology to separate thematic thresholds.

As a statistic, the mean is an easy value for novice map readers to understand. Increments of the mean would be more obviously linked to increasing values and their relative significance. This makes the incremental mean threshold approach immediately appealing as a method to define crime hot spot legend thresholds.

Exhibit 16 shows the results of applying this hot spot threshold approach, based on quartic kernel density estimation surfaces, to the robbery and residential burglary data. The incremental mean legend threshold approach consistently defines mapped crime hot spots. In addition, the analysts can now observe the global descriptions calculated earlier and see that they match the crime hot spot mapping output. The kernel surface hot spot maps for vehicle crime, robbery, and residential burglary display areas of crime clustering, and when compared against each other show relative levels of dispersal. For example, the hot spot maps of vehicle crime show a greater degree of dispersion compared to that of robbery.

Local indicators of spatial association statistics

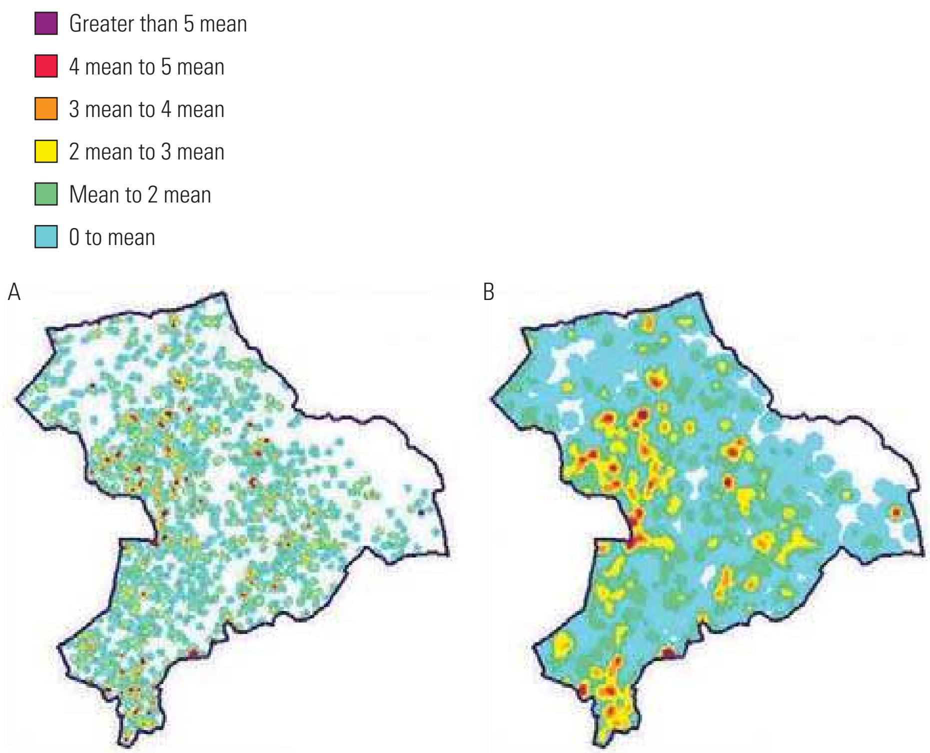
A more advanced method to help understand hot spots of crime is the application of local indicators of spatial association (LISA) statistics (Anselin, 1995; Getis and

Ord, 1996). LISA statistics assess the local association between data by comparing local averages to global averages. For this reason they are useful in adding definition to crime hot spots and placing a spatial limit on those areas of highest crime event concentration (Ratcliffe and McCullagh, 1998). One of the more applied LISA statistics on crime point events is the Gi* statistic (see Ratcliffe and McCullagh, 1998, for more details).

The Gi* statistic is applied to a grid cell output, such as a quartic kernel density estimation map, from which local associations are compared against the global average. The user typically is required to enter a search distance within which local associations are explored and a significance level is related to the confidence in the final output. The search distance usually is set to three times the grid cell size of the original kernel estimation surface (i.e., for data in this chapter, the search distance was set to 90 m). Although levels in significance can often range between 99.9 percent, 99 percent, and 95 percent, this range has far less effect over eventual hot spot areas than parameters set for grid cell size or bandwidth (Ratcliffe, 1999b). The most common significance level to apply is 99.9 percent.

Exhibit 17 shows the result of the Gi* LISA statistic (mapped as grey areas) for robbery. This LISA output has been

Exhibit 15. Crime hot spot thresholds for vehicle crime
A: Bandwidth 62 m (K2)
B: Bandwidth 138 m (K7)



mapped with the quartic kernel density estimation surface generated using a bandwidth of 117 m (K2). The map shows the matching between this LISA output and kernel value results above the 3-mean threshold. This LISA output adds definition to the quartic kernel density estimation, indicating the level at which hot spots can be more clearly distinguished from other levels of crime concentration.

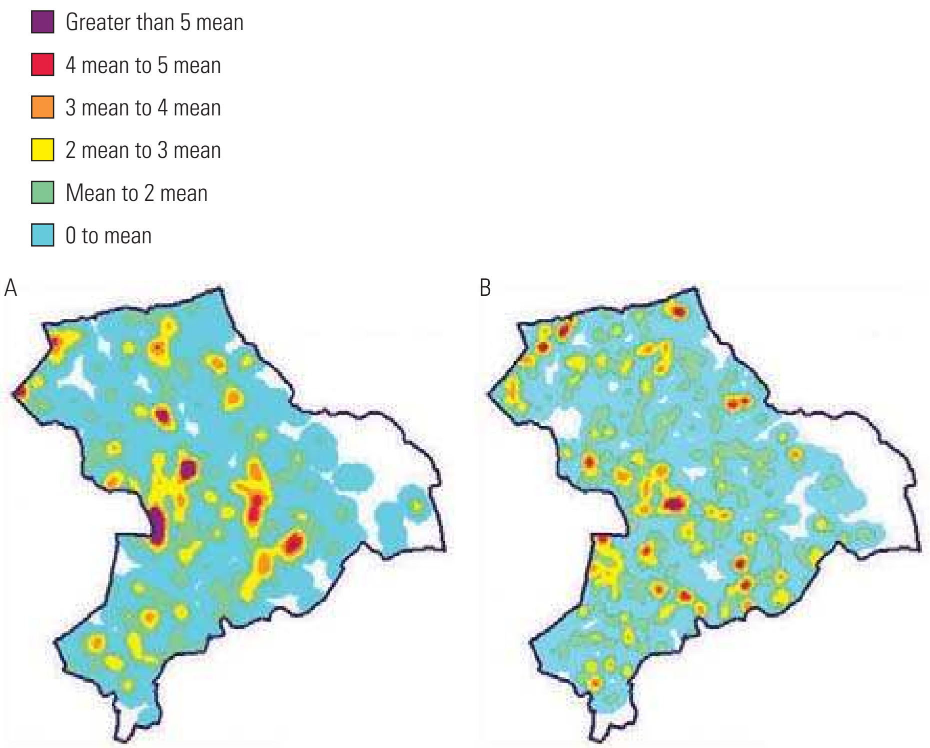
Additional elements to consider

All the methods described above consider volume crime patterns and do not consider any underlying population distribution. Therefore, in certain cases, such as hot spot maps for residential burglary, the crime hot spots may simply be displaying locations of high housing density. Rate maps can be created to take account of the underlying population distribution. For residential burglary, maps that consider the underlying housing distribution can be generated by calculating a rate of burglaries per certain number of households (e.g., burglaries per 1,000 households). The most reliable housing counts available usually are those sourced from the population census. The household counts usually are collected at the census block level, thus allowing the analysts to generate maps representing the distribution of residential burglary by their rates. However,

Exhibit 16. Quartic kernel density estimation hot spot maps for robbery and residential burglary using the incremental mean approach

A: Robbery: Bandwidth 207 m (K6)

B: Residential burglary: Bandwidth 161 m (K6)

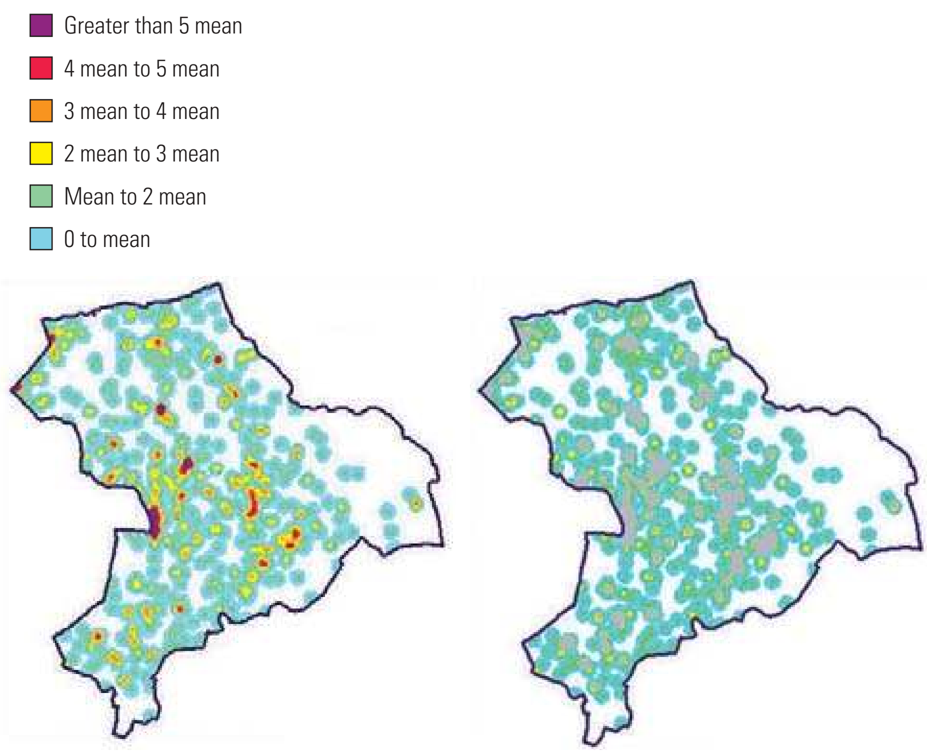


although the underlying spatial distribution of housing is considered, the hot spot maps generated still suffer from the problems described in the section on geographic boundary thematic maps.

Also, suitable denominators for calculating rates rarely are available for other crime types, such as robbery and vehicle crime. Analysts often use population counts as denominators for calculating rates for these other crime types. This approach, however, may merely create hot spot mapping output that misleads by exaggerating the crime problem in town centers that have few residents but a concentration of crimes such as robbery and vehicle crime. Ideally, it is preferable to use denominators that are directly relevant to the crime type for which the analysts wish to create a rate. In the case of residential burglary, analysts usually have this with census tract household counts.

Suitable denominators for calculating rates for other types of crime are rarely available. For robbery, a suitable denominator for calculating rates would be pedestrian counts for the area; for vehicle crime, a suitable denominator would be vehicle counts. The analysts would also wish to access these counts at a more precise source, such as point sample locations from which estimations at unsampled locations could be interpolated. This would then allow the analysts to be more flexible in the area rate calculation by not restricting them to counts aggregated to geographic boundary areas of varying sizes and shapes.

Exhibit 17. Robbery quartic kernel density estimation surface (117 m (K2) bandwidth) and Gi* LISA statistic output (grey areas) derived from this robbery surface



In the United Kingdom, several local authority and police forces have access to local property gazetteers. These are point-specific geographic records of all properties across the local authority area. Every property across the local authority area has a unique record that can be mapped exactly (within 1 meter) to the property location. These records often also describe property use (e.g., residential or nonresidential). When a local property gazetteer such as this exists, crime analysts can use accurate point-based records of the distribution of residential properties to create continuous surface crime rate hot spot maps that consider both the point-based distribution of crime and the point-based underlying residential property distribution.

Variations in time

Each hot spot map considered in this chapter accounts only for a specific snapshot period in time. New areas of research are beginning to explore space-time interaction (Ratcliffe and McCullagh, 1998) and the use of test statistics such as those devised by Knox and Mantel (see Bailey and Gatrell, 1995). These methods aim to reveal whether certain types of crime display temporal hot spots in particular areas (e.g., crime hot spots that emerge only on certain days of the week). A step that many crime analysts already have taken in this direction is the creation of crime hot spot animations to visualize space and time interaction. Each frame produced for the animation is itself a hot spot map that is then knitted to a time sequence of other hot spot maps to produce a series that can be displayed as an animation. (For an example of a hot spot map animation, visit http://www.crimereduction.co.uk/toolkits/fa020405.htm). Animated hot spot maps are very alluring, but require direct application if they are not to be merely gimmicks of the crime mapping trade.

Conclusion

The methods and techniques in this chapter have indicated how crime analysts can examine crime-related data to visualize and understand crime hot spots. Preliminary global statistics have shown how simple-to-apply tests can reveal an understanding of what is to be expected in a hot spot map, even before the map has been created. Tests for clustering are particularly important. Analysts may waste valuable resource time in their attempts to create a crime hot spot map if a test such as the NNI quickly reveals that no clusters, and thus no hot spots, exist in their data. The different mapping techniques have revealed the different applications to which they are suited and demonstrated the advantages and disadvantages in their underlying routines and the mapping outputs they generate. The kernel density estimation method in particular has been demonstrated as being more than just a method that presents an attractive map of crime, but is a more robust technique suited to understanding spatial patterns of crime hot spots.

Also important to remember is that map production is an iterative process. The first map produced is very rarely the one presented to the target audience. The intended message should also be seen as the driving force behind what the map should look like. Map creation and design requires flexibility. Methods and techniques described in this chapter retain this flexibility but suggest some simple-to-apply operations that help to understand crime hot spots.

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Chapter 3. Spatial Analysis Tools for Identifying Hot Spots

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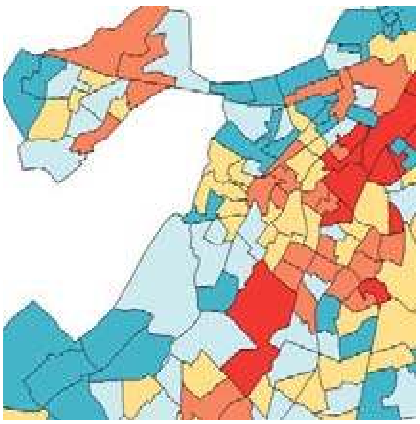


Recent developments in geographic information systems (GIS) and spatial analysis applications have significantly improved the ability of researchers and analysts to look more closely at the spatial patterns and locational contexts of crime. As a visualization tool, GIS can be used to integrate data from diverse sources into a single georeferenced database that contains observations from neighboring locations. Spatial patterns can then be represented and visualized across locations, providing insight into potential spatial clustering, heterogeneity, and spread over time. As an exploratory data analysis tool, GIS spatial analysis applications can be used to examine data more rigorously as a way of generating new hypotheses from the data or identifying unexpected spatial patterns.

A central concern of hot spot analyses of crime is assessing the degree of spatial randomness observed in the data. Most of the available tools provide different ways of determining whether the underlying pattern is uniform over space or whether significant clusters or other spatial patterns exist, which are not compatible with spatial randomness. Thus, simple mapping techniques can now be supplemented with new methods and applications to detect meaningful patterns and associations either as part of an inductive approach to visualizing and exploring data or as a deductive approach to model building and hypothesis testing.

This chapter focuses on four of the available tools that can be used to identify crime hot spots: ArcView® choropleth mapping, ArcView Spatial Analyst, CrimeStat®, and GeoDa™. Each software package has particular strengths and weaknesses as well as different types of applications. This chapter provides an overview of these applications and discusses advantages and disadvantages encountered in using these tools for different purposes.

Visualization applications

Moving beyond the manual pin-mapping approaches of the past, desktop GIS technologies have introduced crime analysts to new ways of visualizing and mapping crime. Specifically, tools for dynamic visualization and mapping in a GIS environment make it possible to inductively describe and visualize spatial distributions, identify unusual observations or spatial outliers, and discover patterns of spatial association, including clusters or hot spots.

This section deals primarily with the application of ArcView choropleth mapping and ArcView Spatial Analyst for visualizing hot spots and clusters of crime (see Harries, 1999, for a more extensive look at specific issues related to crime mapping in a GIS environment). ArcView choropleth mapping applications are used for the analysis of vector data; Spatial Analyst allows for the use and analysis of raster data. Vector data represent geographic features as point, line, or area features, which are defined and processed in terms of discrete X,Y coordinates. Raster data represent geographic features as a grid of cells on a continuous surface. Vector data usually can represent irregular object boundaries with more precision, but raster data can generally model geographic patterns across continuous space with greater efficiency.

Choropleth mapping with ArcView

The data for the examples used in this chapter consist of burglary incidents from the city of Boston for 1999. These crime incidents are represented as point locations and have been aggregated up to the census tract level to demonstrate different types of analyses.

Choropleth mapping is a common technique for representing data summarized by statistical or administrative areas and is particularly useful for obtaining a general picture of the overall spatial distribution of crime. Choropleth maps are primarily used in crime mapping applications to show the relative density or amount of crime occurring in different areas. This is done by assigning graduated colors or varying shades across the range of value categories, going from lowest to highest.

As a first step, examine the general statistical distribution of the data. This can be done by plotting a scattergram or histogram of the data and employing basic descriptive statistics such as the mean, median, range, and standard deviation to explore its distribution. Knowing the distribution of the data will help the analyst figure out the best classification scheme to use for creating class groupings with similar values. Ideally, the classification scheme used should minimize the inner class variance as much as possible and maximize the variance between classes as much as possible. In other words, the range of values within each class should be more similar to one another, while the difference in values between classes should be as far apart as possible.

In addition to user-defined ranges for class categories, ArcView provides several standard classification scheme options. The four most common classification methods are natural breaks, quantile, equal interval, and standard deviation. The default classification option in ArcView is natural breaks. In this approach, class categories are identified based on natural groupings in the data. Arcview uses a statistical procedure to identify optimal groupings so that values within each class are more similar and values between classes are farther apart. Usually, class breaks are set to correspond with relatively large jumps in the distribution of values. The quantile classification method assigns an equal number of areas to each class. Thus, if 160 census tracts and four classes exist, then each class grouping contains 40 census tracts, with the lowest 40 in the first group and the highest 40 in the last group. The equal interval approach divides the distribution of values so that the range of values within each class is identical. In other words, the difference between the highest and lowest value is the same for each class grouping. With the standard deviation approach, class breaks are defined by standard deviational distances from the mean.

Exhibit 1 illustrates the distribution of burglary rates (per 100,000 population) for Boston census tracts in 1999. In this example, burglary rates are plotted along the horizontal axis and the number of census tracts having burglary rates within each category of values is shown on the vertical axis. With this data, analysts can experiment with different classification schemes and see what happens with a distribution that is positively skewed (as most crime data are).

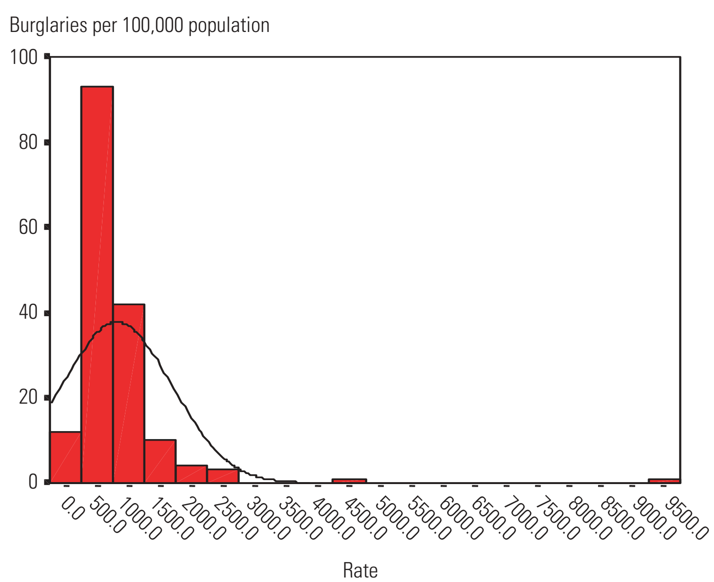
Exhibit 2 is a map of burglary rates for Boston based on natural break classifications. This method places extreme outliers in a category of their own and emphasizes the differences between census tracts with the highest burglary rates and those with the lowest rates. With this data, using natural breaks appears to be a good method for highlighting hot spot clusters and outliers in the data.

Using natural breaks to classify data tends to be useful when mapping data values that are not evenly distributed, since it places value clusters in the same class. The disadvantage of using this approach is that it is often difficult to make comparisons between maps since the classification scheme used is unique to each data set.

Exhibit 3 is a map of burglary rates for Boston based on quantile classifications. This method arranges all observations from low to high and assigns equal numbers of observations to each classification category. This approach is useful when the data values are fairly evenly distributed or when a need exists to highlight a proportion of the observations. For example, if the objective is to show which census tracts are in the top 20 percent for burglary rates, then the analyst would apply the quantile method of classification and select five classes. The disadvantage in using this approach, especially with positively skewed data, is that differences between classes may be exaggerated since a few widely ranging adjacent values may be grouped together in one class while an equal number of relatively homogeneous values may be grouped together in another class.

Exhibit 4 is a map of burglary rates for Boston based on equal interval classifications. Using this method, the range of values is the same for each class. This approach is useful when data are normally distributed and the analyst is interested in emphasizing observations around the mean. The disadvantage in using this method with positively skewed data is that most observations will be assigned to the lower value categories and only a few observations will be assigned to the higher

Exhibit 1. Burglary rates for Boston census tracts, 1999



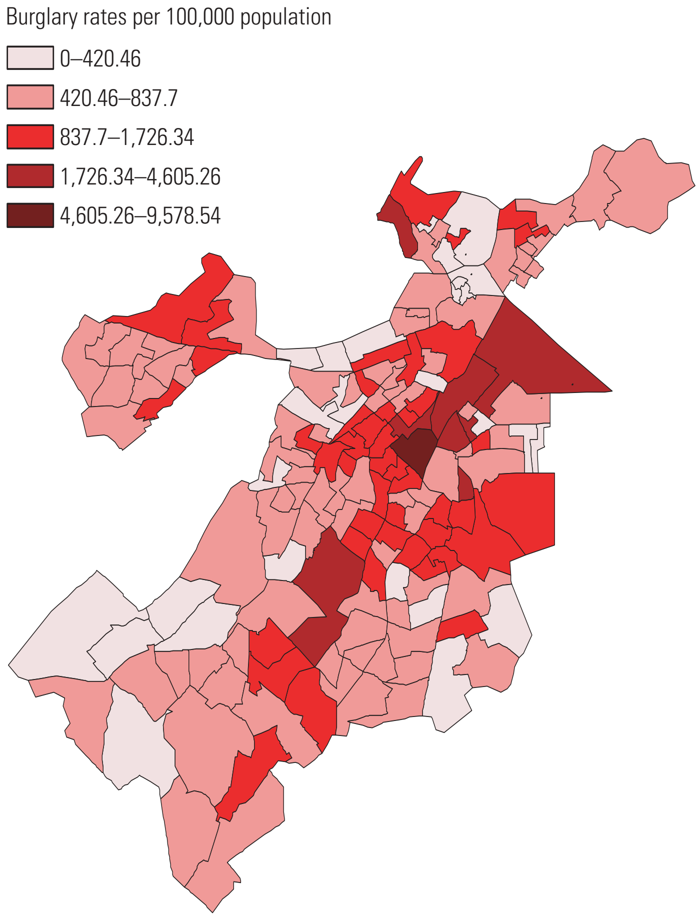
Note: Standard deviation = 875.10; Mean = 812.7; *N* = 166.

value categories. However, when the objective is to emphasize outliers with high crime rates or hot spot clusters, this could be a useful approach to classifying and mapping the data.

Exhibit 5 is a map of burglary rates for Boston based on standard deviation classifications. With this method, each class is defined by its standard deviational distance from the mean. Again, with positively skewed distributions, outliers and hot spot clusters can easily be isolated and identified. The disadvantage in using this approach is that the map does not show the actual values in each class, only how far each class category is from the mean.

To know which classification scheme to use, an analyst needs to know how the data are distributed and the mapping objective. If the data are unevenly distributed, with large jumps in values or extreme outliers, and the analyst wants to emphasize clusters of observations that house similar values, use the natural breaks classification approach. If the data are evenly distributed and the analyst

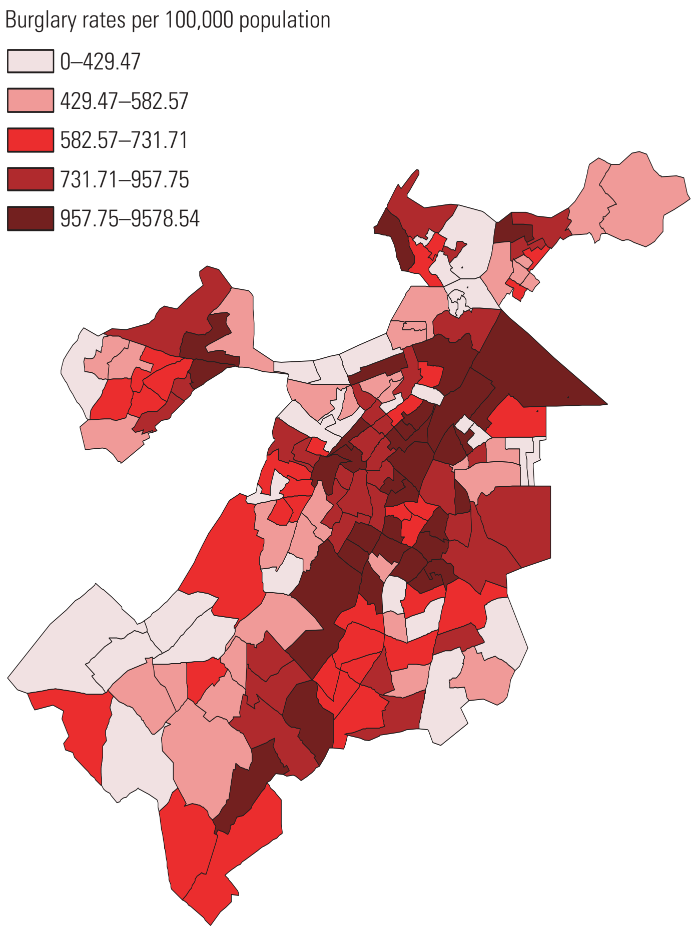
Exhibit 2. Classification using natural breaks



wants to emphasize the percentage of observations in a given classification category or group of categories, use the quantile classification approach. If the data are normally distributed and the analyst wants to represent the density of observations around the mean, use the equal interval approach. If the data are skewed and the analyst wants to identify extreme outliers or clusters of very high or low values, use the standard deviation classification approach.

In the final analysis, although choropleth maps are very useful for visualizing spatial distributions, using them for hot spot analyses of crime has certain disadvantages. First, attention is often focused on the relative size of an area, so large areas tend to dominate the map. Second, choropleth maps involve the aggregation of data within statistical or administrative areas that may not correspond to the actual underlying spatial distribution of the data. In other words, incidents of crime are usually not evenly distributed throughout a

Exhibit 3. Classification using quantiles

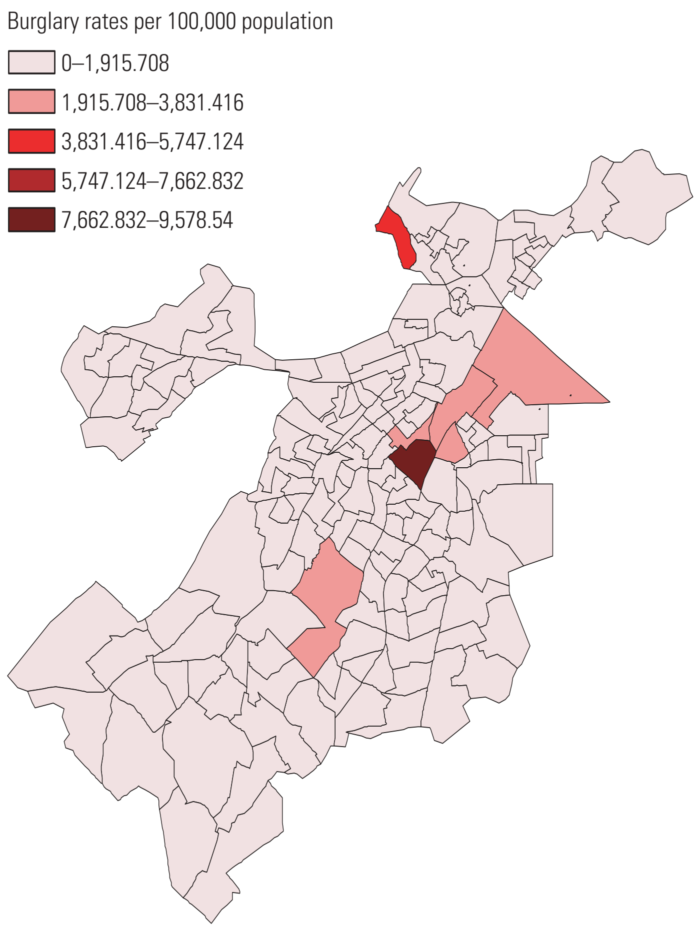


given administrative area. Consequently, the actual distribution of crime incidents may be difficult to identify when mapping aggregated data.

ArcView Spatial Analyst

Although choropleth mapping is a useful tool for representing the spatial distribution of aggregated crime data, ArcView Spatial Analyst is useful for mapping the density of individual crime incidents on a continuous surface. Using a raster data structure, Spatial Analyst represents geographic space as a continuous surface that is divided into a grid of equally sized square cells. Continuous surfaces are created from existing data observations through a process called interpolation. In the case of crime mapping, this means that known crime locations are used to estimate the density of crime across a continuous surface. Mapping crime density on a continuous surface thus allows the analyst to identify where the highest concentrations of crime are taking place.

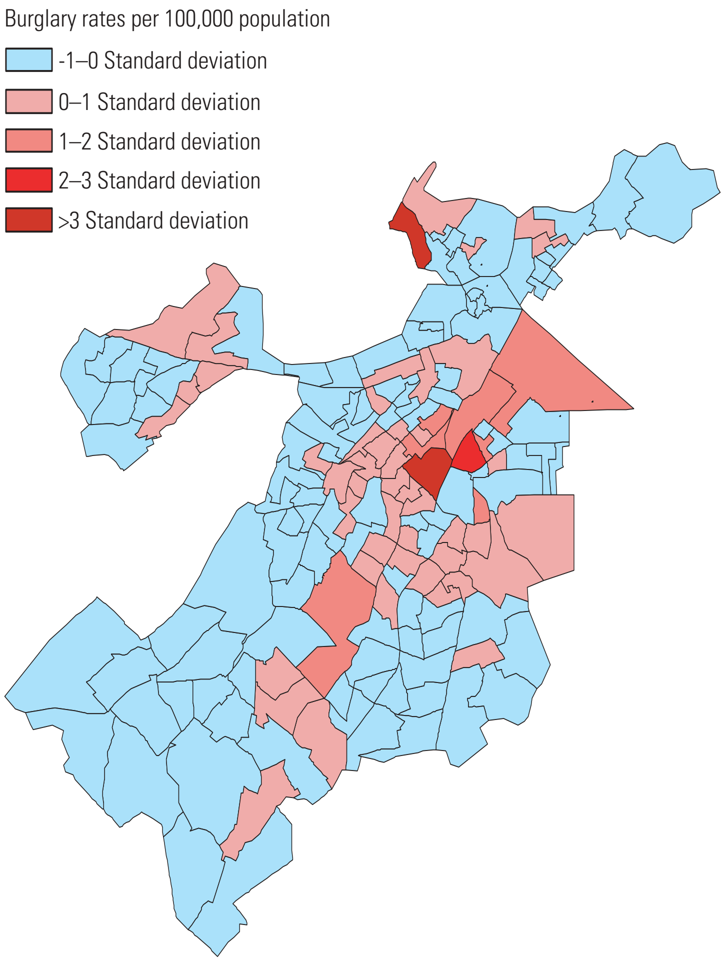
Exhibit 4. Classification using equal intervals



Concentrations of crime can sometimes be seen simply by mapping the location of individual crime incidents. In areas with a large amount of criminal activity, however, identifying which locations have higher concentrations than others may be difficult. To alleviate this problem, Spatial Analyst can create density maps, which measure the number of crimes occurring within a uniform areal unit, such as the number of crimes per square mile. This makes it easier to see the overall distribution of crime across space so that the analyst can more clearly identify hot spots and high-crime clusters.

To create a density map with Spatial Analyst, first calculate a density grid from the ArcView point theme containing locations of individual crime incidents. Each cell in the grid is assigned a specific size and has a circular search area applied to it, both of which are defined by the user. Cell size determines how coarse or smooth the patterns will appear. The smaller the cell size, the smoother the density surface

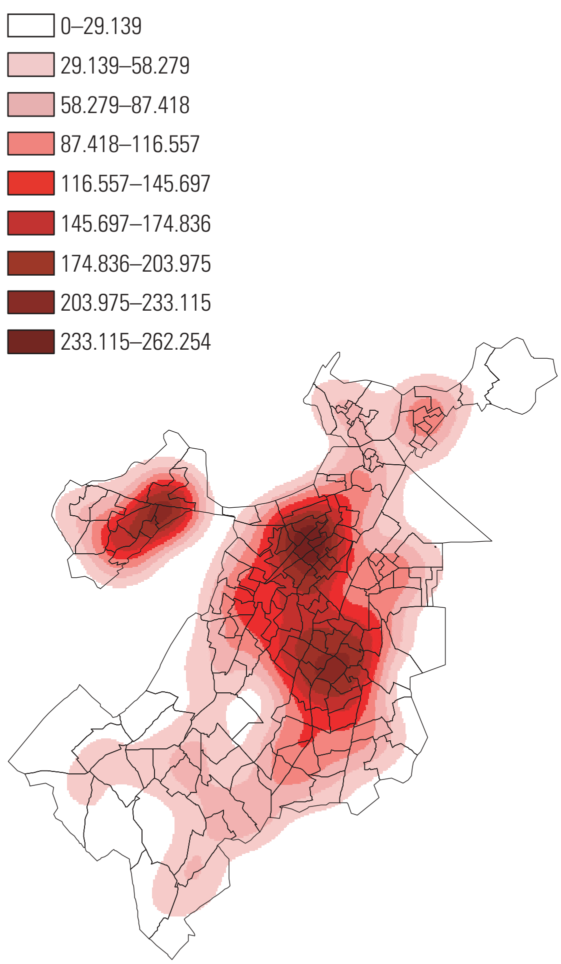
Exhibit 5. Classification using standard deviations



will be. However, very small cells also require considerably more processing time and computer storage space. The size of the search radius will determine how generalized the density patterns will appear. A smaller search radius will show more local variation, while a larger search radius will show broader patterns in the data. Specifying either simple or kernel density calculations also is possible. Simple density calculations total the number of crime incidents that fall within the search area parameter for each cell and then divide this number by the search area size to get each grid cell's density value. Kernel density calculations, however, give more weight to points near the center of the search area than to those near the perimeter. This results in a smoother distribution of density values across cells.

Thus, the first step is to create a density surface map as a raster layer using the Spatial Analyst menu interface in ArcView. In this way, each grid cell in the raster layer will have a density value assigned to it based on the number of crime incidents within the specified search radius of the cell. The map in exhibit 6 represents the

Exhibit 6. Density map of burglary locations per square mile



density surface of burglary locations in Boston for 1999 and shows burglary incidents per square mile based on kernel density calculations.

The density surface map in exhibit 6 shows three burglary hot spot locations, signified by the darker patterns on the map. The analyst might notice a few discrepancies between the hot spot clusters identified by the density surface map and the hot spot locations identified by the choropleth map applications. As noted earlier, choropleth maps involve the aggregation of data within statistical or administrative areas that may not correspond to the actual underlying spatial distribution of the data. This means that any variations in the distribution of crime within the aggregated areas are lost during the aggregation process. In contrast to the aggregated area patterns represented on choropleth maps, the patterns in a density surface map are based on the distribution of individual crime events. A density surface is therefore able to show with greater spatial detail how crime varies across a region. Keep in mind, however, that the values in the areas between points are estimated interpolations. Thus, the more data points and the more dispersed they are, the more valid the resulting density patterns will be.

Exploratory spatial data analysis applications

Visualization and mapping applications are perhaps currently the most familiar use of GIS for many crime analysts. Recently, however, several tools have been introduced to facilitate more rigorous analyses of spatial patterns through the use of exploratory spatial data analysis (ESDA) procedures. A central feature of ESDA is the use of formal statistical tests to determine whether crime locations show evidence of clustering or are randomly distributed. These include nearest neighbor analysis tests for point pattern data and spatial autocorrelation tests for aggregated data or event data that have intensity values applied to them.

This section examines two of the available software applications for exploratory spatial data analysis: CrimeStat (Levine, 1999) and GeoDa. The primary difference between the two applications is that CrimeStat is used to analyze crime incident location data (point patterns) and GeoDa is used to analyze aggregated crime data (area patterns). In addition, GeoDa has a spatial regression package included, but CrimeStat does not have a regression module available for modeling correlates or determinants of crime.

CrimeStat

As a Windows® based program, CrimeStat uses a graphical interface for database management operations as well as for the implementation of a number of statistical procedures that can be linked to a GIS. The procedures vary from descriptive centrographic applications to more sophisticated nearest neighbor and spatial autocorrelation statistics.

The spatial statistics package provided with CrimeStat is divided into four categories:

1. Spatial distribution or centrographic statistics: mean center, center of minimum distance, standard deviational ellipse, and Moran's I spatial autocorrelation index.

2. Distance statistics: nearest neighbor analysis and Ripley's K statistic.

3. Hot spot analysis routines: hierarchical nearest neighbor clustering, K-means clustering, and local Moran statistics.

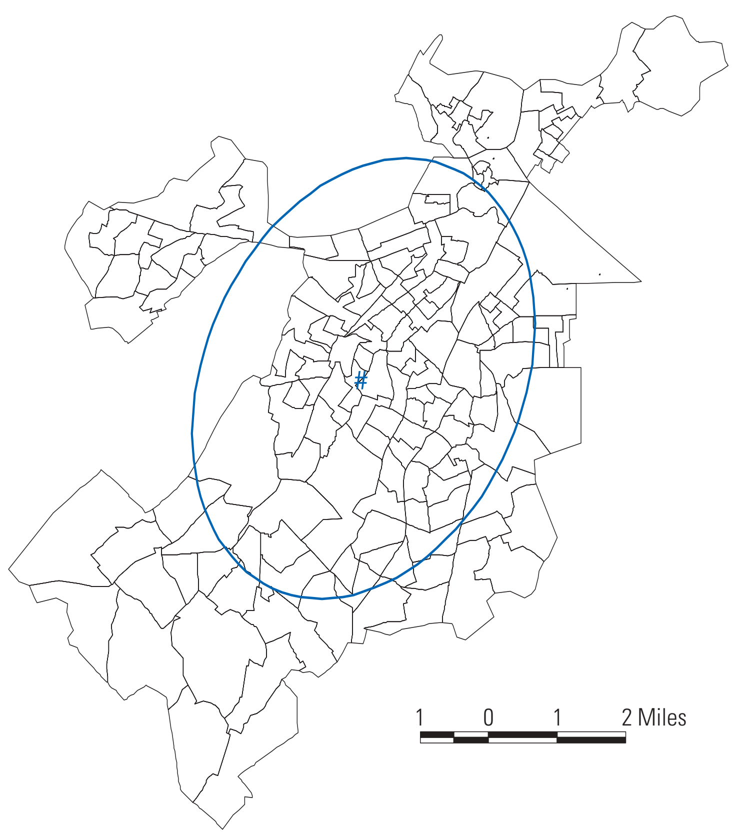
4. Interpolation statistics: kernel density estimation routines (see Spatial Analyst application discussion earlier in this chapter).

Data files used with CrimeStat are point files with X,Y coordinates. These can be ASCII, dBase *.dbf*, or ArcView *.shp* files. Also, intensity values can be associated with each point location for spatial autocorrelation tests.

Centrographic statistics. The first group of statistical routines available with CrimeStat are centrographic statistics for finding the central tendency and overall spatial distribution of crime incidents. The ones examined here are the mean center and the standard deviational ellipse for measures of central tendency and dispersion. The mean center identifies central location as the arithmetic mean of all incident locations. The standard deviational ellipse identifies dispersion as the standard deviation of the distance of each incident location from the mean center as well as the direction or orientation of that dispersion. The output produced by CrimeStat includes tabular summaries containing a number of descriptive statistics and graphical objects, which can be saved and imported as ArcView shape files (or as MapInfo® *.mif* or AtlasGIS *.bna* files).

Exhibits 7 and 8 show the mean center and standard deviational ellipse for burglary and homicide locations in Boston for

Exhibit 7. Mean center and standard deviational ellipse for burglaries

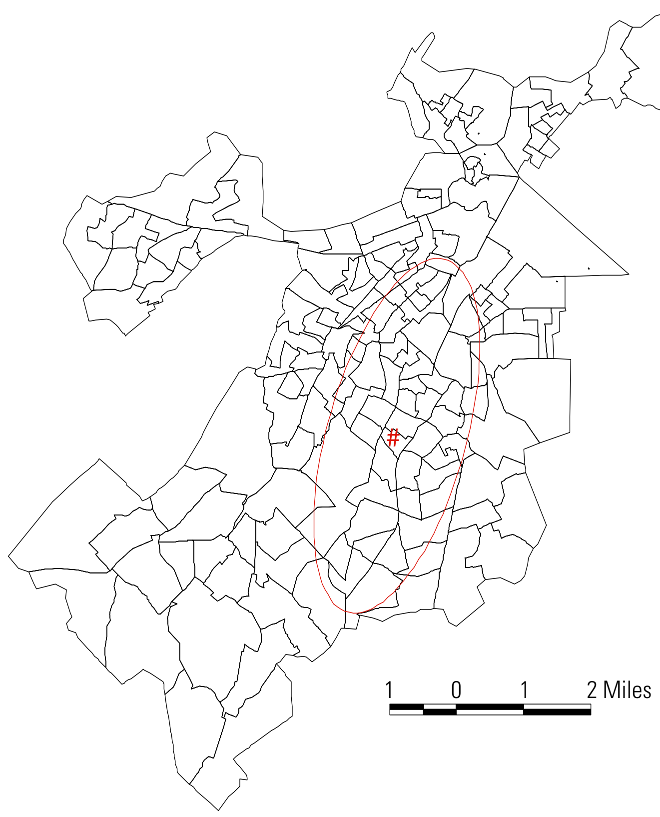


1999. The mean center for burglary incidents is slightly northwest of the mean center for homicides. This indicates that homicides are slightly more likely to occur in the southeastern part of Boston, while burglaries are somewhat more likely to occur in the northwest part of the city. While the standard deviational ellipses for both burglaries and homicides fall essentially along a north-south axis, burglaries show a much wider dispersion along the east-west axis than homicides. This indicates that homicides tend to occur in a relatively circumscribed area compared with burglaries.

Centrographic statistics can be very useful tools for examining general spatial patterns of central tendency, spread, and direction of dispersion. They represent a first step in exploratory spatial data analysis, providing a more rigorous feel for the overall distribution of crime. In addition to comparing different types of crime, these tools are useful for comparing different groups. For example, they may be used to compare the spatial distribution of gang and non-gang-related homicides. Centrographic statistics also are useful for comparing spatial shifts, which may occur for the same crime across different time periods, such as month-to-month comparisons.

Centrographic statistics, which are used to describe global spatial properties and patterns in the data, are known as first-order statistics. Second-order statistics describe local or neighborhood patterns within the

Exhibit 8. Mean center and standard deviational ellipse for homicides



overall distribution. In CrimeStat, second-order statistical tools for identifying characteristics of the distances between crime incidents include the nearest neighbor index for point patterns and Ripley's K statistic.

Distance statistics. The nearest neighbor index compares the observed distance between each point and its nearest neighbor with the expected distance if the distribution of points were completely random. More formally, it is the ratio of the observed nearest neighbor distance to the mean random distance. In other words, the index compares the average distance between nearest neighboring points with the average distance that would be expected on the basis of chance alone. If the average distance between nearest neighbors is the same as the mean random distance, then the ratio is equal to 1.0. If the average distance between nearest neighbors is smaller than the mean random distance, then the index is less than 1.0. Nearest neighbor index values less than 1.0 would thus provide statistical evidence of clustering.

Exhibit 9 contains the nearest neighbor statistics for all burglary locations in Boston during 1999. The sample size (*N*=3,851) indicates that 3,851 burglary incidents were reported in 1999. The nearest neighbor index is 0.36, thus suggesting a shorter distance between nearest neighbors than that expected under randomness, and hence spatial clustering.

Exhibit 9. Nearest neighbor statistics for burglaries in Boston, 1999 (*N*=3,851)

Mean nearest neighbor distance	0.02862 miles
Mean random distance	0.07968 miles
Nearest neighbor index	0.35913
Standard error	0.00067 miles
Test statistic (Z)	–76.0831

This deviation from randomness also is significant, as indicated by a Z-value of –76.08.

Ripley's K function is a higher order nearest neighbor statistic that compares the number of points within any given distance to the expected number for a spatially random distribution. It thus provides a test of randomness for every distance, from the smallest up to the size of the study area. CrimeStat calculates 100 distance intervals (called bins) around each point location, counts the number of crime incidents within each interval, and compares this to the expected number for a spatially random distribution. If the average number of point locations found within a given distance band is greater than that expected under randomness, this points to clustering. This empirical count is then transformed into a square root function called L and is calculated for each of the 100 distance intervals (bins). Values of L that are greater than the upper limit of a simulated random distribution confidence interval indicate clustering.

Hot spot analysis routines. In addition to nearest neighbor applications, CrimeStat provides several statistical tools for identifying clusters or hot spots of crime. These include hierarchical spatial clustering, K-means clustering, and local Moran statistics. Each of these techniques represents a slightly different approach to grouping crime incident locations into relatively coherent spatial clusters.

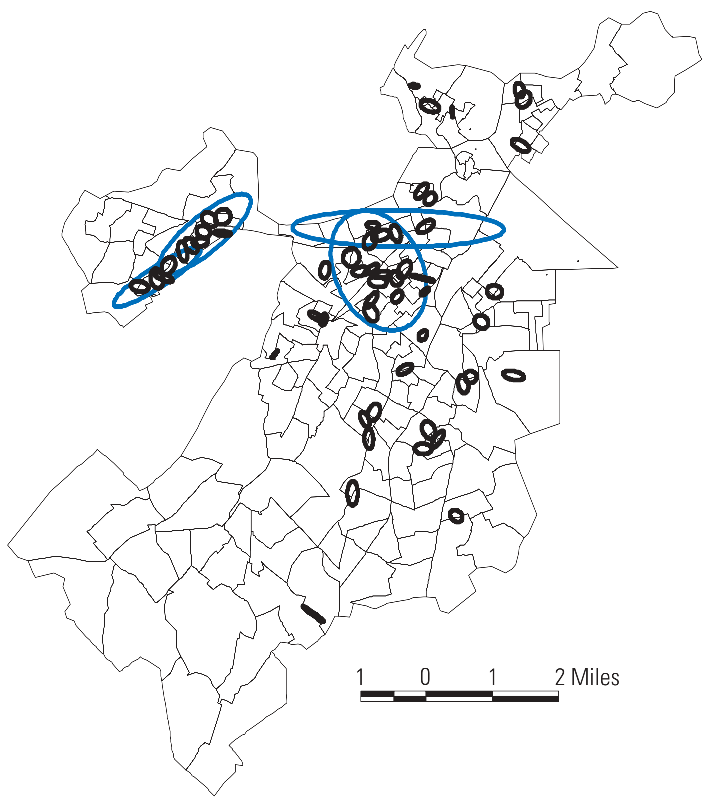
Hierarchical clustering is based on a nearest neighbor analysis technique, in which crime incident locations are first grouped into nearest neighbor clusters containing a minimum number of point locations specified by the user. These first-order clusters are further grouped into larger, second-order clusters, and this process continues until no more clustering is possible. As with nearest neighbor approaches in general, only clusters that are closer than expected under randomness are included at each step. Thus, the criterion used for clustering points together is the user-specified lower confidence interval for a random distribution.

Exhibit 10 shows a map of burglary hot spots for Boston in 1999 (*n*=3,851) identified by the hierarchical clustering routine in CrimeStat. A one-tailed probability level of .05 was selected and each cluster was required to contain a minimum of 10 burglary incident locations. CrimeStat returned 56 first-order clusters and 4 second-order clusters. The locations of the second-order clusters coincide with two of the three hot spot locations identified on the density surface map in exhibit 6. While the first-order clusters tend to be more scattered, the second-order clusters show a clear pattern in the north and western parts of the city.

K-means clustering is a partitioning technique for grouping crime incidents into a specific number (K) of clusters specified by the user. The default number of clusters assigned by CrimeStat is five. The routine tries to find the best center (seed location) for each K number of clusters specified and then assigns each crime incident to the client seed location.

Exhibit 11 shows a map of burglary hot spots for Boston in 1999 identified by the K-means clustering routine. The map shows three relatively concentrated clusters and two that are more dispersed. The more concentrated clusters, especially the one located in the western arm of the city,

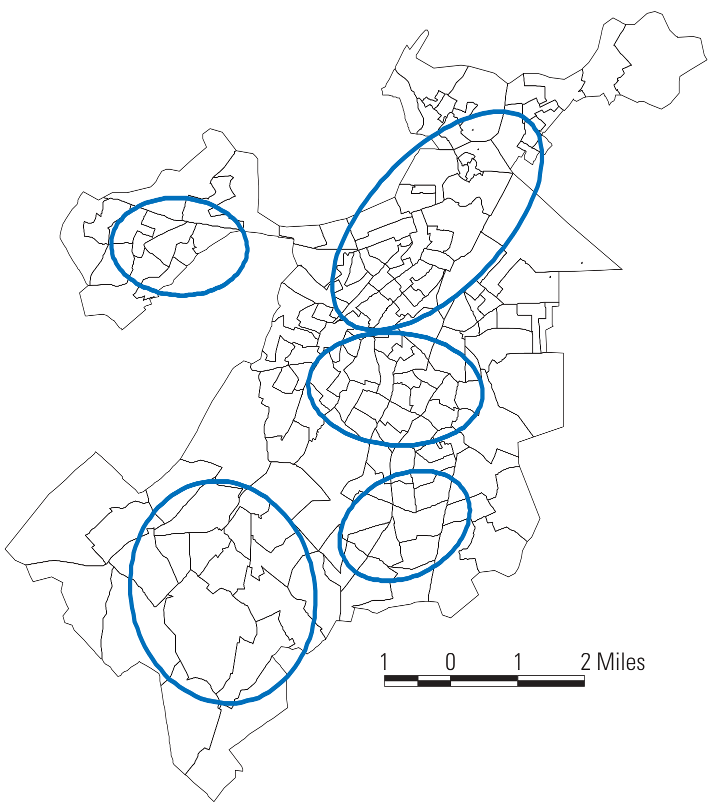
Exhibit 10. Burglary hot spots using hierarchical clustering



are closer to the hot spot locations identified by other methods. This example highlights one of the disadvantages to using the K-means clustering procedure. Whether the clusters make any sense will depend on how carefully the user has selected the criteria to be used in grouping crime locations. Choosing too many clusters may result in the identification of patterns that do not really exist; choosing too few may diminish significant differences that actually do exist between neighborhoods. Thus, while the K-means procedure provides a great deal of user control, this same flexibility can make the technique prone to misuse and the results difficult to interpret.

A *local Moran procedure* approach is based on the concept of local indicators of spatial association (LISA), in which each observation is assigned a score based on the extent to which significant clustering of similar values around that observation exists. In this case, the score assigned to each observation is the Moran's I statistic for spatial autocorrelation. Locations with high Moran's I scores have intensity values higher than the average value intensity for all other observations, while locations with low Moran's I scores have intensity values

Exhibit 11. Burglary hot spots using K-means clustering

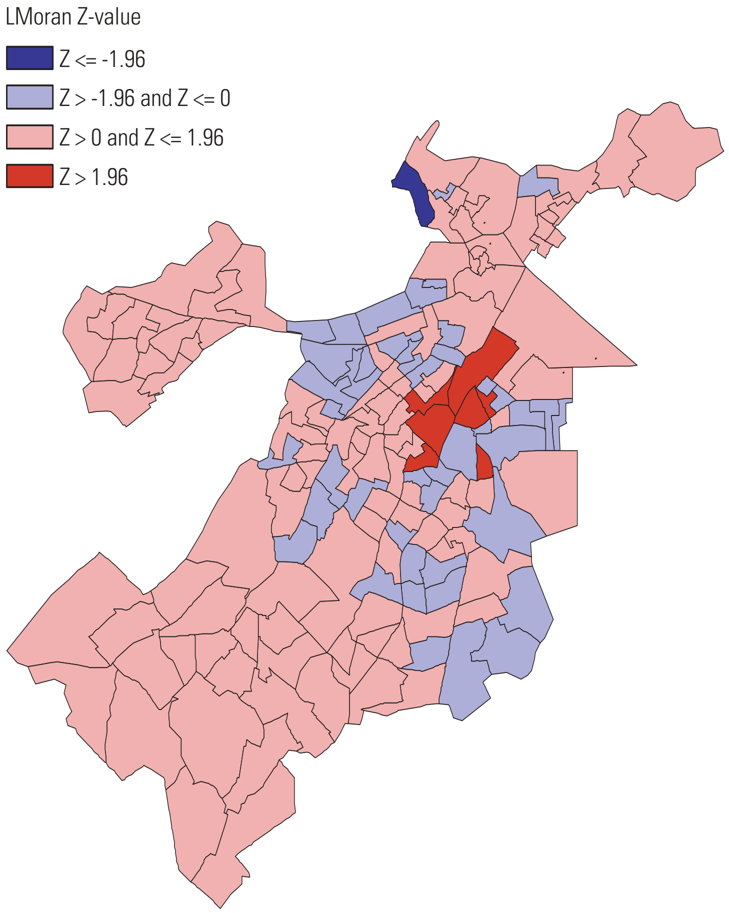


lower than the average value intensity for all other observations. The local Moran procedure thus provides information about the degree of value similarity between near neighbors.

Two conditions must be met in order to calculate Moran's I. First, each observation must have a value attached to it. This means that an intensity variable must be specified in CrimeStat's primary file menu. In this case, the point location is the centroid of each census tract in Boston, and the intensity variable is the burglary rate (number of burglaries per 100,000 people). Second, the neighborhood must be defined either as adjacent locations or according to distance-based weights. Adjacency specifications, in which adjacent locations are given a weight of 1 and nonadjacent locations are given a weight of 0, are useful for defining near neighborhoods. Distance specifications, in which weights are assigned that decrease with distance between locations, are useful for defining spatial interaction across larger areas. The default in CrimeStat is an adjacency specification.

Exhibit 12 maps the distribution of standardized local Moran Z-values for the spatial autocorrelation of burglary rates across

Exhibit 12. Spatial autocorrelation of burglary rates: local Moran Z-value of census tracts



Boston census tracts in 1999. The pattern shows a concentration of high values toward the center of the city (shaded in darker red). Also, the northwestern part of the city contains an outlier (shaded in darker blue). This census tract has a much higher burglary rate than its neighbors and therefore has a large negative I score, indicating dissimilarity (i.e., negative spatial autocorrelation). This example highlights the usefulness of the local Moran statistic for identifying locations, which are dissimilar from their neighbors. In fact, it is the only statistic available in CrimeStat that can be used to identify spatial dissimilarity.

The three clustering techniques available in CrimeStat have both advantages and disadvantages. The advantages to using the hierarchical clustering technique include the ability to identify small geographic areas that may have higher concentrations of crime activity. This technique also is useful for identifying the linkages between several small clusters into second-order and higher clusters. The limitations of hierarchical clustering include a certain arbitrariness based on what constitutes a meaningful cluster size. Also, the size of the grouping area is dependent on the sample size. This means that crime distributions with many incident locations (e.g., burglaries) will have smaller grouping areas, while crime distributions with few incident locations (e.g., homicides) will have larger grouping areas.

The advantages of using the K-means clustering routine include the ability of the user to specify the number of spatial clusters in the data. This feature provides a great deal of control and flexibility for the user and can be used as an exploratory tool to identify different sizes and numbers of crime clusters. Yet, this same flexibility also can result in a certain arbitrariness, which may make the results difficult to interpret meaningfully.

In addition to identifying clusters with high concentrations of crime, the local Moran procedure is the only clustering tool in CrimeStat that also can identify outliers (locations that are dissimilar to neighboring locations) and clusters with low concentrations of crime. The disadvantage of using the local Moran procedure and mapping the results is that it requires the data to be summarized into zones in order to produce the necessary intensity values and then linked with comparable zonal boundaries in a GIS for mapping.

GeoDa

Similar to CrimeStat, GeoDa is a Windows-based application that is practically a reinvention of the original SpaceStat™ package and its ArcView extension, DynESDA. GeoDa is a freestanding software that does not require a specific GIS and runs under any Microsoft Windows operating system. The current version can "only" input (output) Environmental Systems Research Institute (ESRI) shape files. It can analyze objects characterized by their location in space as either points (point coordinates) or polygons (polygon boundary coordinates).

The program can be downloaded free from the University of Illinois at Urbana-Champagne, Spatial Analysis Laboratory Web site (http://sal.uiuc.edu/default.php). This Web site also includes tutorials and other useful information related to the software (Anselin et al., forthcoming; Anselin, 2004a; Anselin, 2004b).

GeoDa functions are executed through menu items or directly by clicking toolbar buttons and can be classified into six categories:

- *Spatial data manipulation and utilities:* data input, output, and conversion.
- *Data transformation:* variable transformation and creation of new variables.

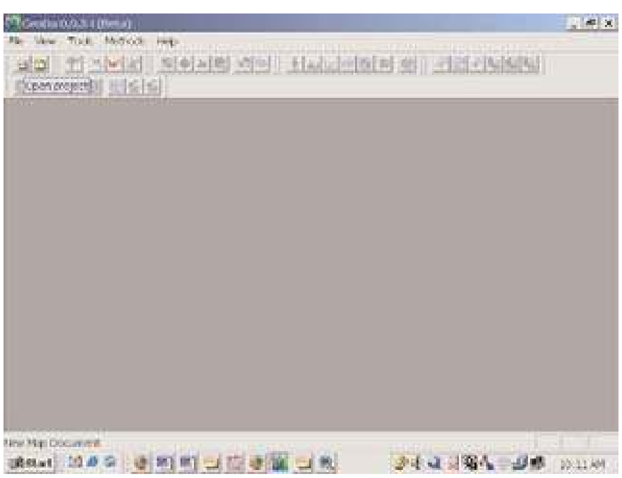
- *Mapping:* choropleth maps, cartogram, and map animation.
- *Exploratory Data Analysis (EDA):* statistical graphics.
- *Spatial autocorrelation:* global and local spatial autocorrelation with inference and visualization.
- *Spatial regression:* diagnostics and maximum likelihood estimation of linear spatial regression models.

GeoDa was developed around the central concept of dynamically linked windows (graphics), with different views of the data represented as graphs, maps, or tables. The map and associated graphs are dynamically linked in the sense that when observations are highlighted in one view, the corresponding observations in the other views are highlighted as well. This can be combined with GeoDa's data brushing capabilities, together referred to as brushing and linking. For example, the same observations that are selected in a scatter plot by means of a rectangle (brush) also are highlighted in a map or box plot that are dynamically linked to the scatter plot. Similarly, the brush can also be initiated in the map with corresponding observations being highlighted in the scatter plot or box plot. This flexibility makes both brushing and linking powerful tools for interactive exploratory spatial data analysis.

GeoDa provides several statistical applications for doing both exploratory and confirmatory spatial data analysis. Exploratory spatial analysis tools include box plot maps and percentile maps for outlier analysis, global and local indicators of spatial association, LISA local Moran maps, and Moran significance maps. Confirmatory spatial analysis tools include OLS regression with diagnostics for spatial effects, spatial regression residual mapping, and a variety of spatial regression applications. This section will examine only the exploratory spatial analysis applications provided with GeoDa.

After the program is launched, the initial (simplified) menu appears on the screen in addition to a toolbar with only two items being active. The first active item opens a project (opens an ESRI shape file); the second active item closes a project (see exhibit 13).

Exhibit 13. GeoDa simplified menu and toolbar

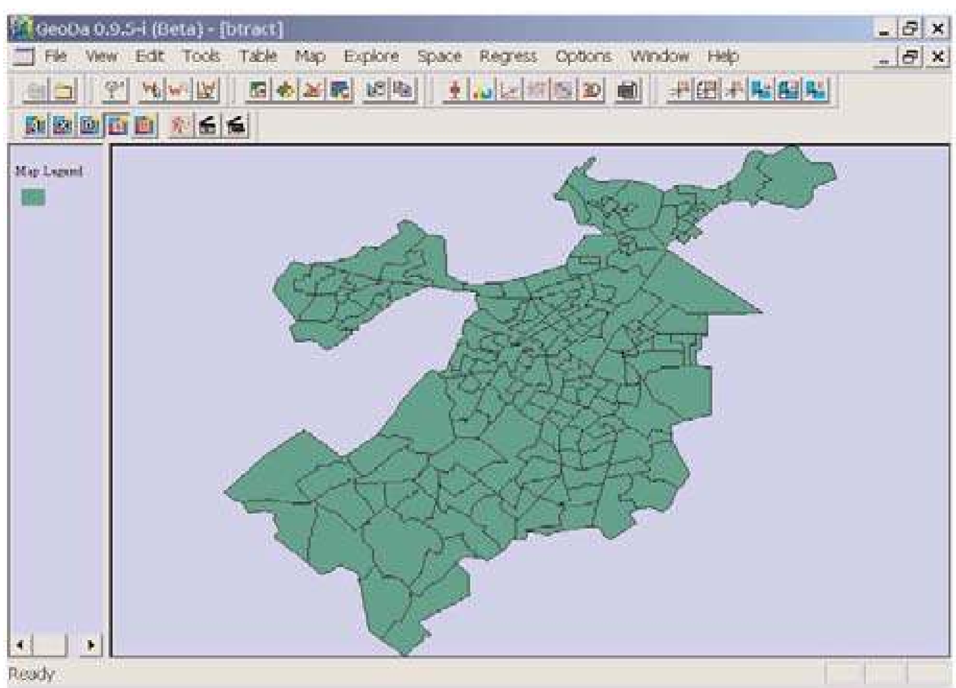


After opening the project, a Windows dialog requests the file name of a shape file and the Key variable. The Key variable uniquely identifies each observation. It is typically an integer value such as a Federal Information Processing Standards (FIPS) code, a census tract number, or a unique ID number. Next, a map window is opened, showing the base map for the analyses. Now the complete menu and all toolbars are active, as shown in exhibit 14.

The full menu bar contains 12 items. Four are standard Windows menus: *File* (open and close files), *View* (select which toolbars to show), *Window* (select or rearrange windows) and *Help* (not yet implemented). Specific to GeoDa are *Edit* (manipulate map windows and layers), *Tools* (spatial data manipulation), *Table* (data table manipulation), *Map* (choropleth mapping and map smoothing), *Explore* (statistical graphics), *Space* (spatial autocorrelation analysis), *Regress* (spatial regression), and *Options* (application-specific options). The toolbar consists of six groups of icons, from left to right: project open and close; spatial weights construction; edit functions; exploratory data analysis; spatial autocorrelation; and rate smoothing and mapping. Some functions can be executed by either clicking on one of the toolbar buttons or by selecting the matching item in the menu.

For initial exploratory analyses, box plots (exhibit 15), box plot maps (exhibit 16), and percentile maps (exhibit 17) can be used to describe the overall distribution of crime and to identify outliers. With the base map shown on the screen in exhibit 14, a box plot can be drawn by using *Explore* → *Box Plot* and selecting the variable to be mapped (burglary rates) from the Windows dialog. This will display a box plot with the census tract burglary rates in

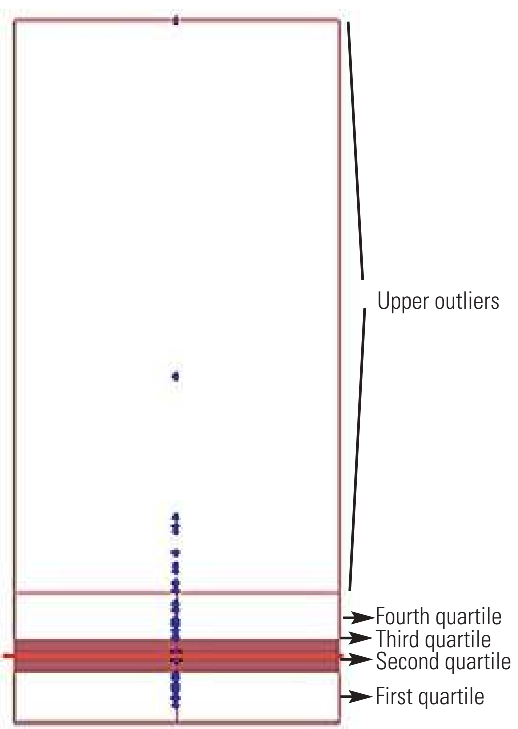
Exhibit 14. GeoDa complete menu and toolbar



Boston for 1999 (shown as blue dots) sorted from the lowest (bottom of the plot) to the highest (top of the plot) value (exhibit 15). The lowest 25 percent of all burglary rates make up the first quartile, followed by the next 25 percent of all rates that make up the second quartile, and so on. The second and the third quartiles are separated by the median (the red bar in the middle), which is the middle value of the sorted burglary rates.

In this box plot, an observation is classified as an outlier when it lies more than a given multiple of the interquartile range (IQR) (the difference in value between the 75 percent and 25 percent observation) above or below respectively for the 75th percentile and 25th percentile. The standard multiples used are 1.5 (mild outlier) and 3 (extreme outlier) times the IQR. In the box plot, the IQR is shown with the dark red band around the median. Using a standard multiple of 1.5, the box plot identifies 12 census tracts with very high values of burglary rates (mild, upper outliers). There are no mild, lower outliers (very low values of burglary rates).

Exhibit 15. Box plot of burglary rates



The corresponding box plot map can be drawn by using *Map* → *Box Map* → *Hinge=1.5* and selecting the variable to be mapped (burglary rates) from the Windows dialog. In the box plot map, the 12 census tracts with very high values of burglary rates are shown in dark red with a pattern that shows a concentration toward the center of the city, along with an additional outlier in the northwestern part of the city.

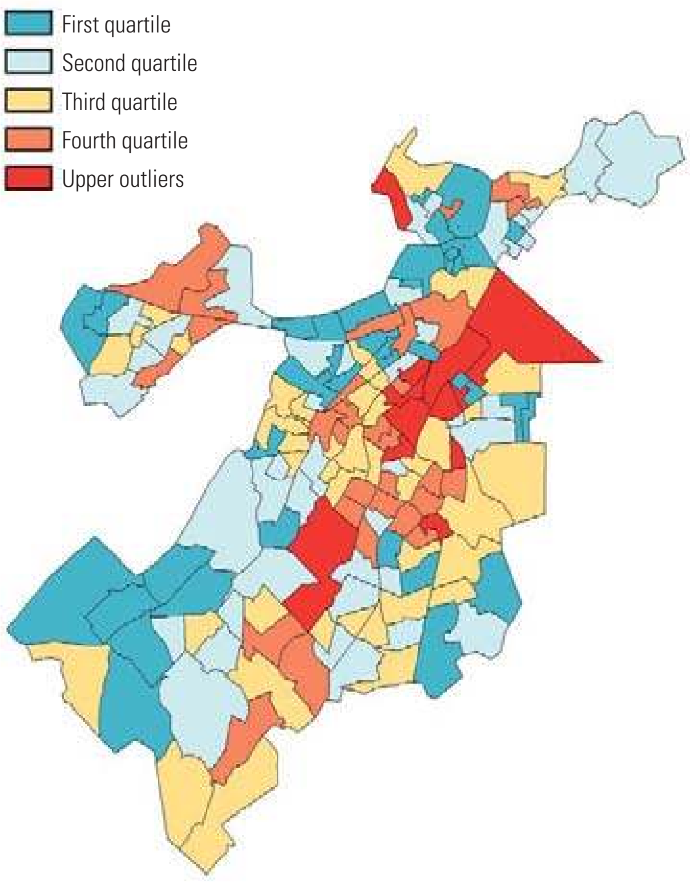
Exhibit 17 contains a percentile map of 1999 burglary rates at the census tract level in Boston. This is accomplished by using *Map* → *Percentile* and selecting the variable to be mapped (burglary rates) from the Windows dialog. Two census tracts qualify as outliers using the upper 99th percentile criterion. Compare the location of these outliers with those identified by the standard deviational choropleth map in exhibit 5. The additional census tract in the standard deviational map is due to a 95-percent cut-off point for two standard deviations as opposed to the 99-percent cut-off point used for the percentile map.

For more rigorous analyses of hot spot and clustering patterns, GeoDa provides tools for constructing spatial weights and tests for the presence of global and local spatial autocorrelation. In using a global measure of spatial autocorrelation, the overall pattern of spatial dependence or clustering in the data is summarized with a single indicator such as Moran's I. As a global measure of spatial autocorrelation, Moran's I is positive when values for locations in spatial proximity tend to be more similar than what is normally expected based on randomness, negative when they tend to be more dissimilar than what is normally expected, and approximately zero when the attribute values are randomly spread over space.

To calculate the Moran's I indicator of spatial autocorrelation, the analyst must first construct a spatial weights matrix. Spatial weights can be defined either by contiguity (where neighbors are identified according to boundary relationships, in which 1 = adjacent and 0 = nonadjacent) or by distance (where neighbors are identified according to a distance-based metric around centroid locations which decreases with distance between locations). In the examples presented here, spatial weights are calculated based on rook contiguity, in which neighbors are defined as sharing a common border. In contrast, queen contiguity defines neighbors that share common borders and/or common corners.

Creating a rook-based contiguity matrix is accomplished by either selecting *Tools* → *Create* → *Weights* from the menu or by clicking on the matching toolbar button. This opens a Windows dialog, in which the name of the input file (a polygon shape file), the name for the weights file, an ID variable for the weights file (a Key variable from the input file that uniquely identifies each observation), and the type of spatial weights matrix (rook contiguity) need to

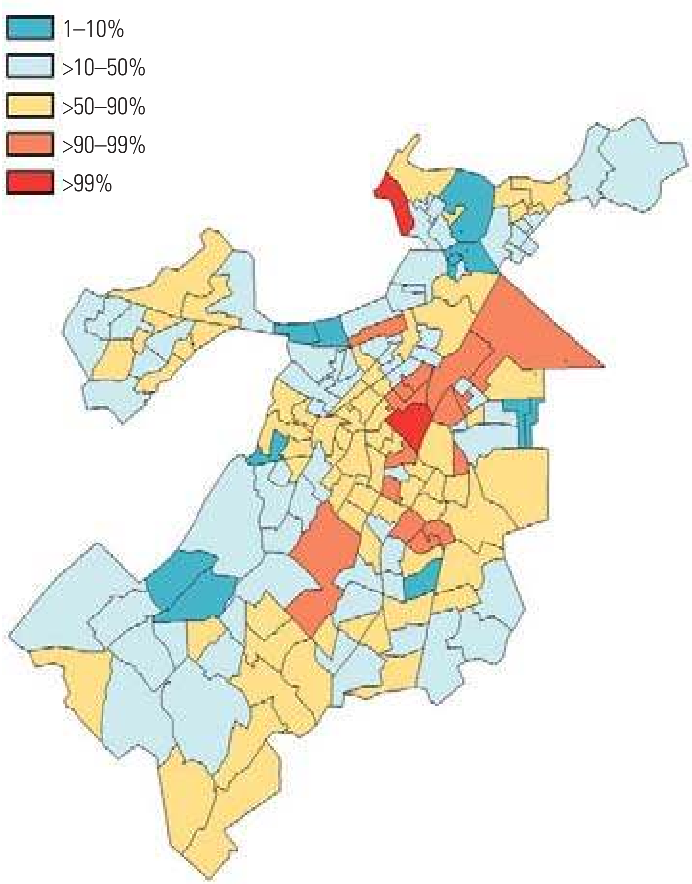
Exhibit 16. Box plot map of burglary rates



be specified (see exhibit 18). The resulting spatial weights file is stored with the file extension GAL. It is a simple text file that can be edited with any text editor or word processor.

Once the spatial weights matrix has been created, a spatially lagged variable can be computed. A spatially lagged variable (or spatial lag) is derived as the spatially weighted average of its neighboring values. A spatial lag is an essential part of the computation of spatial autocorrelation tests and the specification of spatial regression models. The spatial lag computation is part of the Table functionality in GeoDa. In the example presented here, a spatially lagged variable for 1999 burglary rates in Boston will be created. This requires first loading a base map and opening a corresponding spatial weights file by selecting *Tools* → *Weights* → *Open* from the menu or by clicking on the matching toolbar button. Next, clicking on the Table toolbar button and right clicking to select Field Calculation from the menu will open a Windows dialog. In this Windows dialog, select the Lag Operations tab and enter the information as shown in exhibit 19. The name for the new spatially lagged variable (W_BURGRT) is entered into the left most text box. The spatial weights file (same as

Exhibit 17. Percentile map of burglary rates

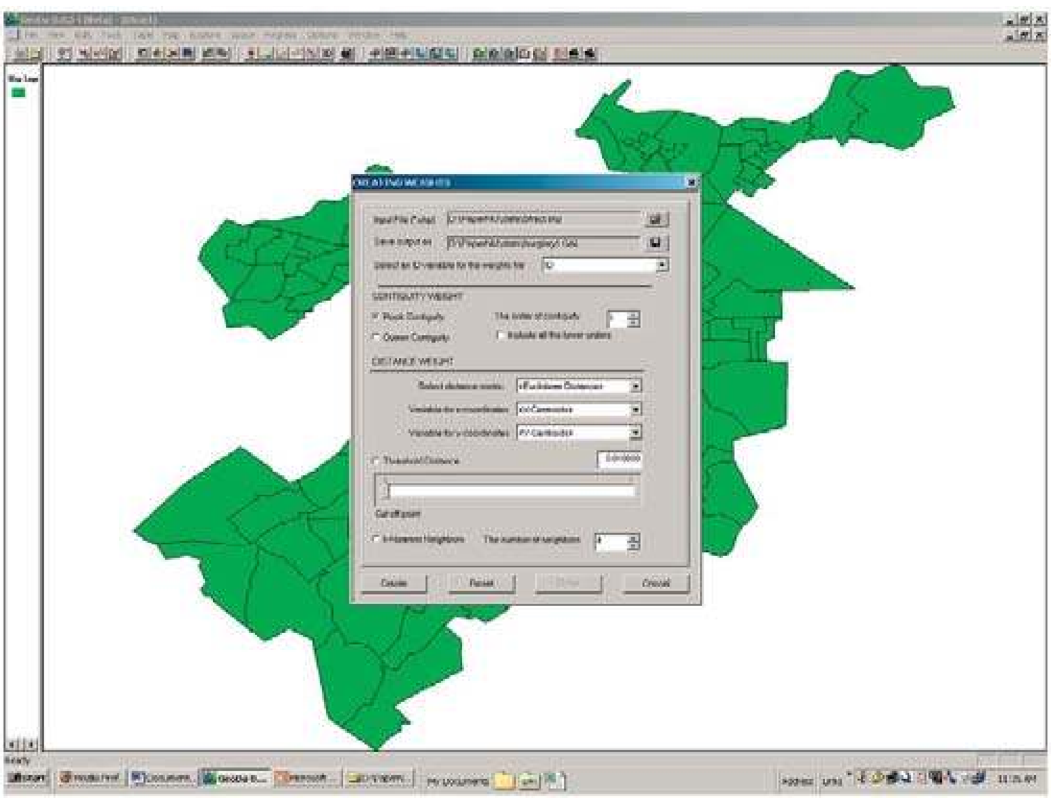


above) is selected for the text box in the middle and the variable to be lagged (1999 burglary rates in Boston) is selected for the right most text box (exhibit 19). This will add the new spatially lagged variable (W_BURGRT) as a new column to the end of the Table in GeoDa.

To briefly illustrate how GeoDa calculates the spatially lagged variable for the 1999 burglary rates in Boston, consider the census tract in the center of the city previously identified as one of two outliers using the upper 99th percentile criterion (exhibit 17). This census tract has a burglary rate of 9578.54, which is the highest rate among all census tracts in Boston in 1999. Eight rook neighbors with the following burglary rates surround this census tract: (1) 738.92, (2) 886.77, (3) 937.77, (4) 971.46, (5) 1622.72, (6) 1952.04, (7) 2434.78, and (8) 2636.20. The spatially lagged variable is simply the average of these eight burglary rates, namely 1522.58.

Positive spatial autocorrelation would indicate cases where the original and the spatially lagged variable have similar values. This would point to clustering of high values (hot spots), low values (cold spots), and medium values. On the other hand, contrasting values between the original and its spatial lag indicate negative spatial autocorrelation, or the presence of spatial outliers. Locations of negative spatial association may indicate areas of high crime surrounded by low-crime neighbors (similar to the example above), or low crime surrounded by high-crime neighbors.

Exhibit 18. Windows dialog to create a spatial weights matrix



Global indicators of spatial autocorrelation are used to assess the presence and range of spatial association. A global measure of spatial autocorrelation can be calculated in GeoDa by selecting *Explore → Scatterplot* from the menu or by clicking on the matching toolbar button. In the Windows dialog, choose the spatial lag variable (W_BURGRT) as the first variable (Y) and the original variable (BURGRT) as the second variable (X). The slope of the regression line in the scatter plot is the global Moran's I (see exhibit 20). In the present example, the global Moran's I for burglary rates is 0.184, indicating positive spatial autocorrelation across census tracts.

As a measure of global spatial autocorrelation, the global Moran's I, can be divided into four categories, corresponding with four quadrants in a Moran scatter plot (see exhibit 21). A Moran scatter plot can be computed by selecting *Space → Univariate Moran* from the menu or by clicking on the matching toolbar button. In the first Windows dialog, choose the original variable (BURGRT) as the first variable (Y). In the second dialog, select a spatial weights matrix.

The four quadrants in a Moran scatter plot identify four types of spatial association between a location and its neighbors. Two of these categories imply positive spatial association: (Quadrant I) where a location with an above-average value is surrounded by neighbors whose values are also above average (high-high), or (Quadrant III) where a location with a below-average value is

Exhibit 19. Creating a spatially lagged variable of burglary rates

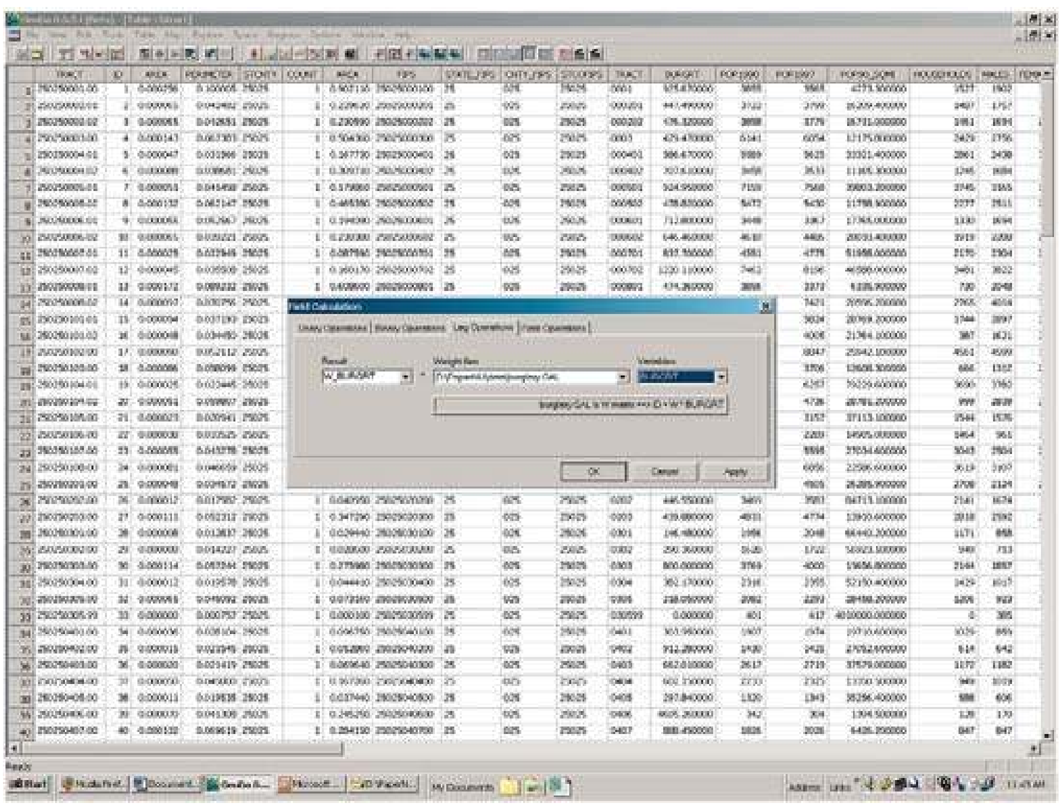


Exhibit 20. Scatter plot and global Moran's I of burglary rates

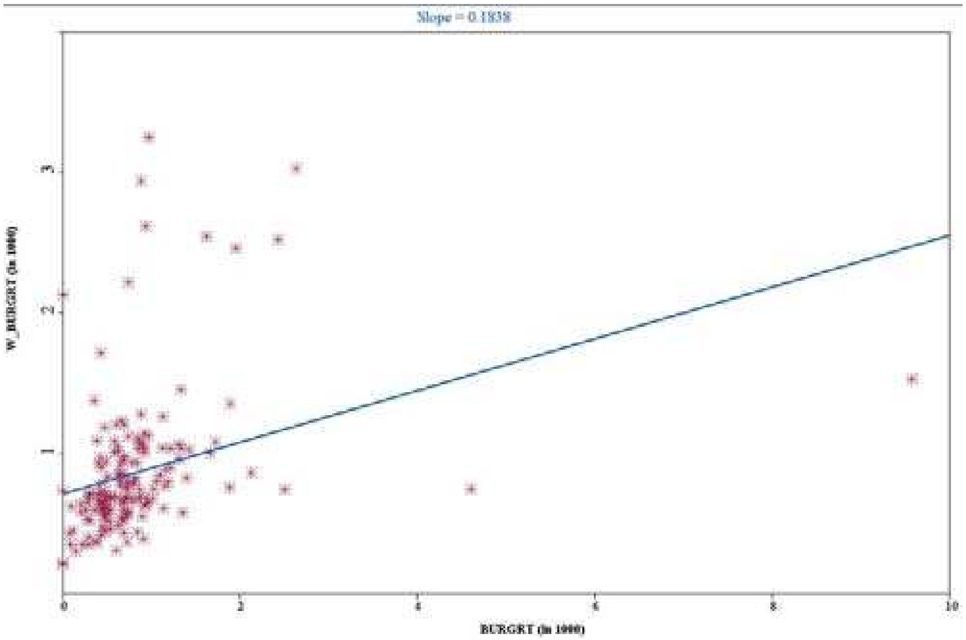
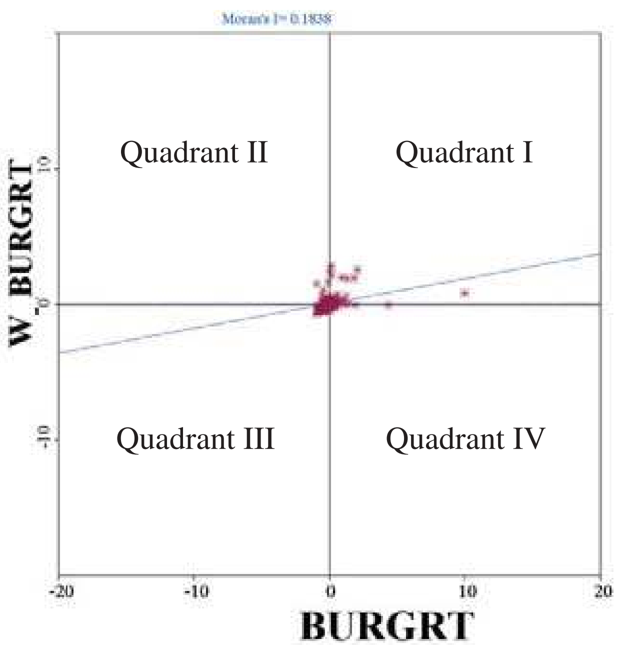


Exhibit 21. Moran scatter plot of burglary rates



surrounded by neighbors whose values are also below average (low-low). The other two categories imply negative spatial association: (Quadrant IV) where a location with an above-average value is surrounded by neighbors with below-average values (high-low), or (Quadrant II) where a location with a below-average value is surrounded by neighbors with above-average values (low-high) (see exhibit 21). The observations from each quadrant could easily be selected and visualized using a GIS. The resulting Moran scatter plot map would provide a visual representation of spatial clustering (hot spots and cold spots) and the location of spatial outliers. Unfortunately, Moran scatter plot maps cannot be directly compiled within GeoDa.

With larger data sets, the assessment of global spatial autocorrelation needs to be supplemented by local measures of spatial dependence as well. According to Anselin (1995), local indicators of spatial association (LISAs) achieve two objectives: (1) they can be used to identify significant patterns of spatial association around individual locations, such as hot spots or spatial outliers; and (2) they can be used to assess the extent to which the global pattern of spatial association is spread uniformly throughout the data or whether there are significant types of locations affecting the computation of Moran's I.

Measures of local spatial autocorrelation can be visualized by LISA local Moran maps and Moran significance maps. Local Moran LISA statistics can be computed by selecting *Space* → *Univariate LISA* from the menu or by clicking on the matching toolbar button. In the first Windows dialog, choose the original variable (BURGRT) as the first variable (Y). In the second dialog, select a spatial weights matrix, and in the third dialog, check the boxes next to "The Significance Map" and "The Cluster Map."

The local Moran map in exhibit 22 shows that a significant "local" cluster of high burglary rates (census tracts in red) is present in the central part of the city. The significance of this cluster is 0.01 (census tracts in dark green) or 0.05 (census tracts in light green) as shown in the Moran significance map in exhibit 23. The census tracts in this "local" cluster would fall into the first quadrant of the Moran scatter plot (exhibit 21) where locations with an above-average value are surrounded by neighbors whose values are also above average (high-high). The local Moran map also identifies one larger significant pocket of low burglary rates in the southwestern and two smaller significant pockets in the western and northern parts of Boston. These census tracts with a below-average value have neighbors whose values are also below average (third quadrant in exhibit 21). Finally, two individual census tracts that can be identified as spatial outliers are located adjacent in the east and southeast of the "local" cluster of high burglary rates. Both census tracts have below-average values and neighbors whose values are above average (second quadrant in exhibit 21).

As a Windows-based application, GeoDa is much more user friendly than the original SpaceStat package and its ArcView Extension, DynESDA. It provides some useful tools for doing exploratory spatial data analysis, including dynamically linked windows and data brushing. As a standalone program it has a variety of options for data manipulation and transformation, mapping, exploratory spatial data analysis, spatial weights construction, descriptive statistics, spatial autocorrelation statistics, OLS regression with spatial diagnostics, and spatial regression modeling. To learn more about GeoDa, consider attending one of Luc Anselin's ICPSR training courses or GeoDa workshops. For more information visit Luc Anselin's homepage (http://agec144.agecon.uiuc.edu/users/anselin/).

Summary

As seen throughout this demonstration chapter, each of these packages has its own particular strengths and weaknesses as well as unique and overlapping analytical applications. Exhibits 24 through 27 summarize the strengths, weaknesses, and applications for each of the four hot spot software packages examined.

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Exhibit 22. **LISA local Moran map for burglary rates**

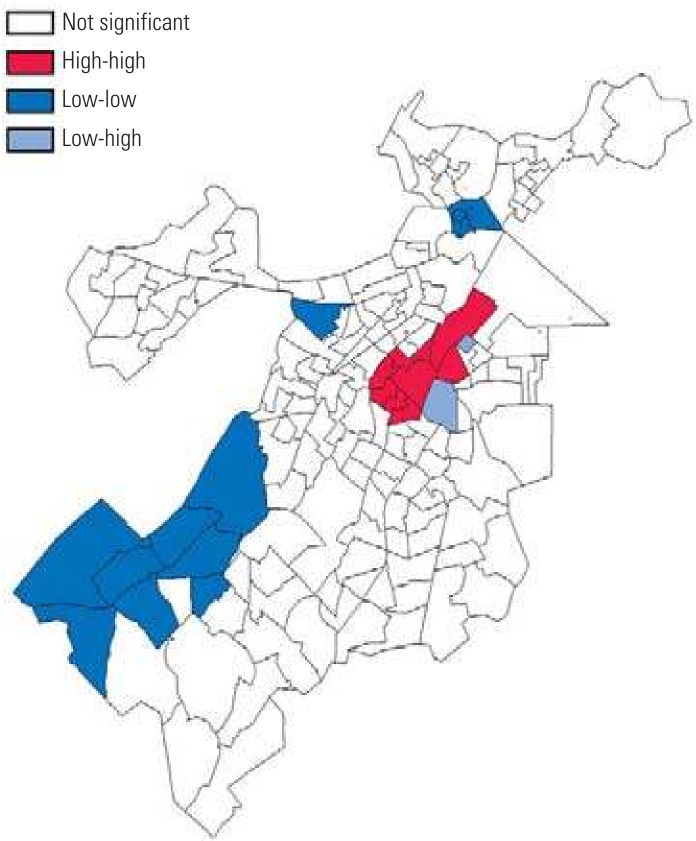

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Exhibit 23. LISA local Moran significance map for burglary rates

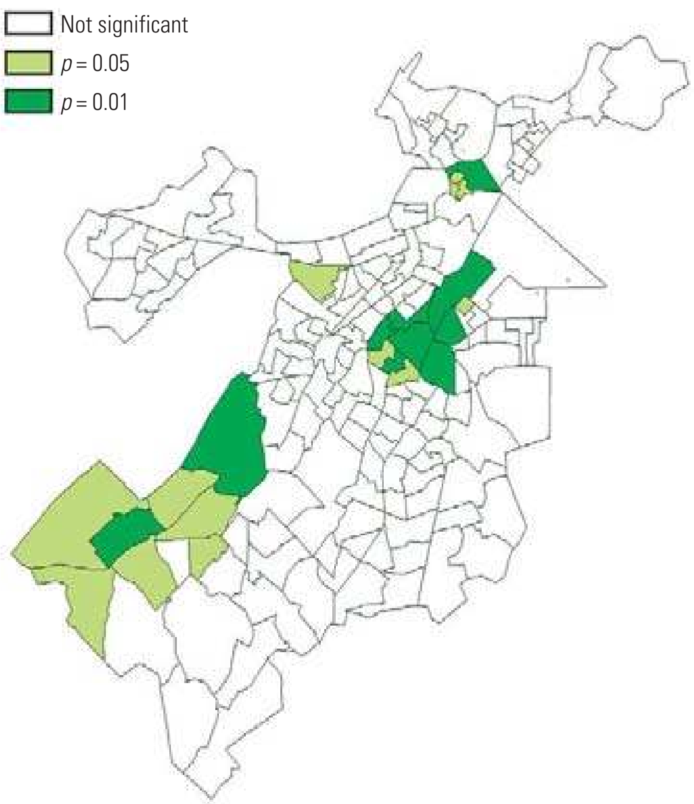

Exhibit 24. ArcView Choropleth Mapping

Strengths	• Useful for visualizing aggregated crime patterns in and across defined boundary areas. • Useful for obtaining a general picture of the overall spatial distribution of crime across areas.
Weaknesses	• Attention often is focused on the relative size of an area so that large areas tend to dominate the map. • The actual distribution of crime incidents may be difficult to identify since incidents of crime usually are not evenly distributed throughout a given boundary area.
Applications	• Used with vector data that represents geographic features according to predefined political or administrative boundaries. • Often used with crime rates to standardize for population.

Exhibit 25. ArcView Spatial Analyst

Strengths	• Useful for visualizing geographic patterns of crime across a continuous surface. • Density surface maps are based on the distribution of individual crime incidents and are therefore able to show with greater detail how crime is spatially distributed.
Weaknesses	• Because the values in the areas between crime incident locations are estimated interpolations, the validity of the resulting density patterns is highly dependent on the quantity and relative distribution of the available data points. • The interpolation process used to create a density surface generalizes and smooths the data so that extreme high and low values may disappear.
Applications	• Used with raster data that represents geographic features as a grid of cells on a continuous surface. • Individual crime incidents are used to interpolate the relative density of crime across a continuous surface.

Exhibit 26. CrimeStat

Strengths	• Useful for doing exploratory spatial data analyses with crime incident locations (point pattern data). • Provides a number of statistical routines that vary from descriptive centrographic applications to more sophisticated nearest neighbor and spatial autocorrelation functions.
Weaknesses	• While a number of useful exploratory features are provided, no applications are available for modeling correlates or determinants of crime.
Applications	• Used with point data that represents crime incidents as point locations. • Statistical routines include: spatial distribution or centrographic statistics, distance statistics for nearest neighbor analyses, hot spot and clustering routines, and kernal density interpolation functions.

Exhibit 27. GeoDa

Strengths	• Useful for doing exploratory and confirmatory spatial data analyses with either points (point coordinates) or aggregated crime data (area patterns). • Provides statistical routines with dynamically linked graphing, data brushing, and mapping applications for doing interactive exploratory data analyses as a stand-alone program. • Provides confirmatory spatial analyses tools for modeling correlates of crime using a variety of spatial regression applications.
Weaknesses	• Only uses ESRI shapefiles as input and output coverages. • Most statistical applications are for the analysis of area patterns; the application of point patterns is limited.
Applications	• Mostly used with areal data in which crime incidents are aggregated according to defined boundary areas (usually standardized as rates). • Analytical applications provided with GeoDa include (1) applications for the input, manipulation, and transformation of data; (2) applications for the construction of spatial weights; (3) applications for exploratory spatial data analysis (ESDA) using descriptive statistics, global and local measures of spatial autocorrelation, and dynamically linked graphing, data brushing, and mapping capabilities; and (4) applications for confirmatory spatial data analysis (CSDA) using OLS regression modeling with spatial diagnostics, spatial regression residual mapping, and a variety of spatial regression modeling options.

Chapter 4. Conclusion

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Approaching hot spot analysis

As seen throughout the previous chapters, conducting hot spot analysis depends on several factors, varying from theory selection, to type of crime being analyzed, to the display of output results. Carrying out analysis must have a logical and systematic approach. Analysis cannot proceed arbitrarily, depending solely on human intuition and visual inspection for identifying hot spots. Nor can analysts depend solely on the software algorithms to provide meaningful output. Such activities may result in a subjectively perceived hot spot that may or may not actually be a cluster of criminal activity.

Visually identifying a hot spot can inappropriately affect input parameters, such as the size of the search radius, because, for example, an analyst might be looking at too many observations at one time. As a result, the presence of clusters could be exaggerated or could remain undetected if too few observations are used. Conversely, a statistical approach can only examine the observations that are selected without considering environmental factors, and thus requires human interpretation to make sense of the results of analysis. Analysts should use statistical tools in conjunction with human understanding of an area to give the analysis a solid foundation for stating where hot spots actually are occurring. They must scientifically determine that a hot spot is indeed an actual cluster of events that are not occurring at random.

Gesler and Albert (2000) point out that with availability of geographic information systems (GIS) and other spatial data analysis software an analyst might, and often does, side-step an important element of analysis. That element in hot spot analysis is the understanding of the underlying spatial and social processes contributing to the presence or absence of criminal activity in an environment. Places have unique characteristics that affect the distribution of criminal activity over space (i.e., spatial processes) and temporal distributions. Social and spatial processes are nonstationary—criminal activity is affected by the variation of demographics, the built environment, economics, and other social aspects that change across space (Haining, 2003). This leads to a premise that has long been championed in geography—place matters.

Place matters because every location has a different environment, such as levels of socioeconomic status, laws governing space management, influence of informal social controls, condition of surroundings, and arrangements of the buildings. A number of confounders may also contribute to the clustering of criminal activity. As a result, the spatial arrangement of crime incidents will be different from place to place and will not lend itself to a uniform approach to hot spot analysis. Haining (2003) and Gesler and Albert (2000) note that observations change from place to place, which is an indication that the underlying spatial and social processes are different, and thus the method used for carrying out analysis will need to be adjusted to detect those processes (i.e., hot spots). Further, the fact that people and their environment are not evenly distributed across space also requires adjustment in the analysis approach.

Elements to consider

Analysis focus

Gesler and Albert (2000) point out that two different goals apply when it comes to cluster, or hot spot, analysis. These approaches are *general* and *focused* analysis. With *general* analysis, an examination is done to discover whether phenomenon is clustered within the study area (i.e., an analyst is looking for the presence of hot spots). For example, in a National Institute of Justice (NIJ) study of homicides in Philadelphia, Pennsylvania (Zahn et al., 2003), a hot spot analysis was performed over the entire city to identify places with a clustering of homicides. Subsequently, those hot spots were examined in conjunction with the presence of religious institutions and what influence they might have on homicide. In this case, the authors were trying to identify places with concentrations of homicide and then ask, "What is it about this place that might be causing so many homicides?"

With *focused* analysis, the purpose is to identify phenomena that are clustered around a particular place of interest within a study area. For example, in another study (Wilson and Everett, 2004), a *focused* analysis was done because the primary hypothesis was, "Is there more violent crime activity clustering in, and around, public housing communities?" The authors selected specific locations (public housing communities) within a study area to determine if there were clusters of violent crime at specific places, not the entire city. In this case, the authors already knew that there was "something about those places" and were trying to prove or disprove the hypothesis that violent crime was clustered in and around those communities.

Spatial dependence

Criminal activity is not the same in every place, as chapter 1 points out in the first sentence. Therefore, to detect the presence of a hot spot, the strength of spatial relationships between incidents must be established. This strength is known as spatial dependence and is based on Waldo Tobler's "First Law of Geography," whereby everything is related to everything else, but closer things are more related. Spatial dependence must be measured to establish a distance relationship limit between crime incidents where an incident is related to a set of nearby incidents. This dependency will likely change over the study area as the environmental factors change (Haining, 2003). This is known as a spatial process, and when it changes across space it will be nonstationary. An analyst will have to determine the threshold distance of influence between incidents to guide the selection of bandwidth type and size when analyzing for clusters. This cannot be measured just by visually determining what that threshold distance might be because it is too subjective and thus must be done with a scientific approach.

Currently, most hot spot analysis software only analyzes points in space without factoring in environmental variables. CrimeStat® and SaTScan™ are two of the available exceptions whereby a minimal set of environmental factors can be included in the analysis (Levine, 2002 and Kulldorff, 2004). Consulting the literature for theory or empirical evidence for the spatial dependence of criminal activity can provide a scientific base for selecting input parameters. Previous research will likely have considered the spatial relationships of criminal activity in combination with demographic, socioeconomic, and environmental variables and their distribution over space.

For example, it has been demonstrated with empirical findings (Roncek, Bell, and Francik, 1996 and Holtzman, 2004) that one-eighth of a mile is a reasonable distance to measure the diffusion of crime in places that have strong neighborhood structures that are self-contained, such as Philadelphia, Pennsylvania, or Chicago, Illinois. Residents can often meet their needs without leaving these neighborhoods. However, places like Las Vegas, Nevada, or Fort Lauderdale, Florida, have completely different spatial structures because the neighborhoods are spread out and require residents to drive everywhere to get anything. One-eighth of a mile for measuring the clustering of crime might not make sense in these neighborhoods because this distance would likely be too small for measuring clustering and would likely not yield significant results. Even if the same crime type is examined in these places, the structure of the spatial relationships of the observations will be different because the environments are different.

Absent of theory or empirical evidence, statistical techniques can be used to find spatial dependence based on the distribution of points, such as variograms or nearest neighbor indexes. These formulas measure the spatial distribution of points against a set of randomly distributed points to determine if clustering is by chance or not. Using formulas such as these, however, are only statistical exercises that assume that an area has no physical or social barriers, the shape of the study area has no relevancy, spatial and social processes are stationary (they do not change over space), and environmental factors are not considered to have influence. If these tools are not available, formulas exist for determining spatial dependency based on the presumed density of a study area, which is the number of observations divided by area. This, however, further dilutes the significance of the measure because not only are environmental or demographic factors not considered; the distribution of incidents themselves are not considered. These formulas simply state that given a number of incidents, clustering would occur based on the amount of area in which they are present. Should a bulk of the observations be located in a small portion of the study area (i.e., they are concentrated and are not evenly distributed), then the formula might give a value that is too large and detect all of those observations as a cluster. The area with the bulk of the observations could be used for analysis, but this returns the subjective selecting of parameters for analysis because some delimiting boundary must be specified.

Crime type

Consideration of crime type plays an important role as the spatial distribution of incidents varies in and between violent and property crime types. Different types of crime have different spatial relationships, dependencies, structures, and distributions, which are the result of different social and spatial processes over an area. These processes are affected by, and affect, other social and spatial processes occurring at nearby places. If all criminal activity was evenly distributed and was the result of the same social and spatial processes, then hot spot analysis would not be needed. If crime is analyzed in this fashion, a blanket statement is being made about criminal activity that assumes each type is caused by the same set of factors.

For example, in an NIJ study of public housing and violent crime (Wilson and Everett, 2004) an analysis was first conducted with all crime types classified as violent crime. The result was the impression that violent crime was clustered mostly in public housing communities. However, when broken down into individual crime types, the authors found that murder, assault, rape, robbery, and weapons violations were not clustered in public housing communities but assault on females and domestic violence were. The identification of which crime type was actually clustered in the communities might allow police to address problems focused on violence against women rather than trying to provide solutions and resources for all other violent crime types.

Exploration of crime type distributions is fundamentally important to determine which type of hot spot method should be used. Analyzing crime in general, such as violent, drug, or property crime could yield misleading or incorrect results. Breaking down crime types from general categories can allow for focused analysis or meaningful results.

Time intervals

Time further complicates the process of hot spot analysis because varying intervals can affect cluster detection of criminal activity. Certain crimes occur at particular times of day, months (seasons), or over special events. For example, assaults may occur more frequently at night in areas with nightclubs. Since these clubs are not open in the day, crimes occurring during daylight hours might lack a spatial relationship that is present during nighttime hours of operation. This is especially true if the analysis is trying to link an increase in crime to the presence of the establishment.

Depending on how many incidents are within a given period of time, the accumulation of crime incidents over too long of a time interval can indicate the presence of a hot spot when one really does not exist. Conversely, too short of a time interval can obscure a cluster of criminal activity because not enough observations were captured in relation to the actual time interval of the spatial process. During this cross-section of time, a major event might have occurred or a crime-prone establishment might have been introduced or removed that had a sudden or lagged impact on the cumulative amount of crime. Consequently, the temporal relationship does not correspond with the spatial relationship.

To counter this, select time periods that synchronize the temporal dependency with the spatial dependencies under analysis, such as separation of times of day, seasons, events, policy implementations, or the introduction or removal of establishments. A series of hot spot maps may need to be generated instead of just one. An incorrect temporal measurement, even if at a location that has a true clustering of crime, may lead to false negatives or positives.

Barriers

Physical and social barriers between places must be factored into analysis, since they will have an effect on the directional significance of spatial relationships. These barriers have a separation effect that can drastically change whether a hot spot exists and the shape and size of that hot spot. Many algorithms for determining hot spots currently do not have the capability to detect a barrier such as a river or a shopping area that separates two places.

Natural and manmade physical barriers can impede spatial relationships and create the illusion of hot spots where it is unlikely that crime incidents are related. For example, rivers, regardless of size, provide a severe break in spatial relationships, as access to each side is limited. Kernel density smoothing routines, for example, should be used on each side of these barriers independently, which allows observations to be measured on each side independently. Conversely, measuring incidents in relation to each other could cause a hot spot to be detected that crosses a barrier when actually no relationship is present. This same principal holds true for manmade barriers such as major limited access highways or large parks.

Social barriers consist of environments that make it difficult for an offender to travel through undetected. Upscale neighborhoods with high-end shopping, restaurants, or clubs provide an environment in which would-be criminals might stand out and draw attention. For example, private security is often present in affluent neighborhoods and increased surveillance, such as neighborhood watches, might provide a record of identification. Social barriers will likely be less of a consideration than physical barriers, as spatial relationships will be accounted for during analysis. A disruption will occur between observations on each side of a neighborhood, for example, that will likely cause a diminishing amount of observations from one side of the barrier to the other.

Output display

As demonstrated in chapter 2, the results of hot spot analysis can be displayed in several ways. Primarily this is done as a continuous surface or as delineated boundaries depending on the output of the analysis software. Some software programs output a grid of continuous surface values while others output a set of values within the original unit of analysis, such as a census block group. Either method requires categorizing data with an associated color.

When displaying output as a continuous surface, the underlying values will often have statistical significance. Therefore, it is important to understand the ranges of those levels of significance, such as z-scores, in order to show the significant breaks of criminal activity. Chapter 2 points out that distribution and density must be understood because categorization can make a difference on how hot spots look or even if one is present. Arbitrarily selecting categorical ranges may misrepresent the size and shape of the hot spot.

Software

Software for hot spot analysis is becoming more available in both GIS software and custom software programs. Much has been written about using software for hot spot analysis, but little about the development of hot spot analysis tools. In particular, these issues revolve around design of tools for conducting spatial data analysis that includes environmental and demographic factors. In this respect, any analysis software requires a variety of tools that allows for full and indepth investigations.

There are not enough robust statistical tools within, or that interact with, GIS software. Software programs for spatial analysis, to date, do not contain all of the tools needed to do a full analysis of data. For example, many custom software packages do not have the ability to visually display hot spot analysis results. If any further analysis needs to be done, the analyst must manipulate the data in a GIS for display and then import that work back into the statistical analysis software. As a result, analysts may use several software programs to carry out their research and analysis. For example, a hot spot analysis of public housing and violent crime (Wilson and Everett, 2004) required the use of ARC/INFO®, SPSS, Microsoft® Excel, and CrimeStat to conduct the analysis. While progress has been made in bringing spatial data analysis and GIS software together, such as GeoDa™ (Anselin, 2004), it is still not to the level that allows the flexibility and interactivity that the crime analysis community needs.

Theory and practice

Establishing a stronger link between theory and practice will help avoid the arbitrary approaches to hot spot analysis and give an analyst a scientific foundation from which to work. The literature often encourages experimentation with analysis results until the outcomes make sense, but that can be time consuming and confusing because nothing exists to substantiate that the analysis approach was appropriate. There should be solid and grounded reasons for identifying clusters, parameter selection, analysis techniques, and output display categories.

What this means for researchers

To improve hot spot analysis, researchers must do two important tasks. The first is to further develop theories to provide scientific reasons for depicting spatial relationships and the strength of the dependencies between criminal incidents, environmental and socio-demographic variables, and the interpretation of results. The second is to conduct more empirical studies that test theories of spatial relationships and crime to guide parameter selection, appropriate time intervals, crime types, and barriers. Researchers, therefore, must work to build models that are flexible and incorporate both compositional (demographic) and contextual (ecological) variables. These models must perform spatial data analysis as well as statistical analysis.

Researchers must also do more to get their theories or empirical results into the hands of practitioners through more outreach to crime analysts or policymakers. Publishing in peer-reviewed journals, such as *Criminology* or *The Professional Geographer*, will not reach an audience that wants to use theory and empirical evidence but has little recourse in doing so. These journals are expensive to obtain and are often filled with other articles that may not be relevant to the analyst.

What this means for practitioners

Practitioners must first and foremost develop strategies for conducting hot spot analyses that have a scientific foundation. Analysts must think about and organize the many elements and options that go into analysis. That is, practitioners must use a scientific approach to carrying out analysis that is logical, systematic, and critically examined. This will give strong credibility to the statistical output and interpretation of the results. Further, analysts must provide feedback to researchers on analysis that tested a particular theory or whether the use of empirical evidence worked in their jurisdiction.

Practitioners must understand that their approach to hot spot analysis will be different every time they conduct analysis. Their approach will change based on place, purpose of analysis, spatial dependence between crime and environment, crime type, time, barriers, and the visual display of results. This will subsequently determine which software programs they use and how they will use them.

Full circle

Researchers and practitioners must work more closely together. Researchers often will make contact with law enforcement agencies to get data needed to conduct research with little or no further contact. Although exceptions exist and the problem is decreasing as crime analysis progresses, minimum contact is still largely the norm. One way to bring these two groups together is to develop software tools that can provide an opportunity for instant feedback between the groups. Such timely feedback could lead to the development of software that more closely models ground truth. More so, researchers and practitioners should continue to attend events such as NIJ's Crime Mapping Research Conference or the Jill Dando Institute of Crime Science Crime Mapping Conference to maintain the discourse about what works and what does not.

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