

Chapter 2

When Does a Drug Market Become a Drug Market? Finding the Boundaries of Illicit Event Concentrations

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Abstract The difficulties of forming valid measurements of social phenomena have been well documented in social science research (Blalock 1971; Denton and O'Malley 1999; Murphy and Arroyo 2000). As the concept under study becomes more abstract, so too does its measurement. The spatial world is no exception to this problem as we frequently rely on convenient spatial boundaries such as census areas to compartmentalize a phenomenon in a meaningful way. In this chapter we illustrate this problem through the conceptualization and operationalization of drug markets. After we have explained some of the nuances of drug market construction and 'creation' in detail, we argue that many of the current measurements used to spatially define them are subject to validity issues. We therefore propose a hierarchical clustering methodology that provides a more refined indicator of market activity. We conclude with a summary of implications for crime analysts, police resource allocation, and theory testing.

Keywords Hierarchical clustering • Validity • Drug market • Operationalization • Conceptualization

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2.1 Introduction

The illegality involved in drug markets places buyers and sellers in complicated situations (Eck 1995). Because both seller and buyer are breaking the law and neither wants to be apprehended by law enforcement, they must make a personal connection in such a way that they are reassured the other is not a police officer, and in such a way that the drug buyer is reassured the dealer is unlikely to rip them off and steal their money. Furthermore, they must converge in time and space in order for the seller to make a profit and the buyer to satisfy a narcotic dependency. While police enforcement of street drug markets can promote an indoor drug market economy (Rengert et al. 2005), conducting activity on the street still provides for some buyer security (St. Jean 2007) and sufficient dealer access to potential buyers (Eck 1994, 1995). Illegal street drug markets therefore provide opportunities for all of these needs to be addressed. Considering the variation across places as shown by environmental criminology, it comes as no surprise that certain locations are more amenable to drug markets than others. Therefore, it is important that researchers are able not only to define what a drug market is but also be able to effectively outline their locations. These are research methodology issues of conceptualization and operationalization, respectively.

The current chapter begins by discussing how drug markets are conceptualized and operationalized. After we have explained some of the nuances of drug market construction and ‘creation’ in detail, we argue that many of the current measurements used to spatially define them are subject to validity issues. Namely, much of past research has merely aggregated totals of drug sale incidents to block group areas—an approach that ignores the spatial concentration of incidents and may exaggerate the nature of the problem. Upon covering issues of validity we briefly explore additional hotspot techniques, noting the strengths and weaknesses of each as well as suitability for the current work. We finally suggest an alternative method to create distinct boundaries of drug markets by identifying areal concentrations of criminal incidents using a nearest neighbor hierarchical clustering technique. This approach is demonstrated with a case study of drug sale incidents from the Philadelphia (PA) Police Department.

2.2 Literature Review

This chapter exists because, in part, researchers have failed to agree on how to conceptualize drug markets. In the most general sense, markets are merely ways in which buyers and sellers relate to one another through the sale/purchase of desired items such as antiques, foods, or illicit drugs. Markets also imply places where exchanges occur such as antique shops, grocery stores, or street corners (Reuter 2000). Murji (2007) argues that “at the most banal level, all drug transactions are market relations in that they entail an exchange between sellers, buyers, traders, and so on” (p. 782). Reuter (2000) proposed a similar idea, defining a drug market

as "... a place to which a drug user can go with fair confidence of finding a willing seller, perhaps even one whom he does not know" (p. 7).

The conceptualization of drug markets is, however, highly dependent upon the disciplinary lens used (Ritter 2006). Economic studies define markets as exchanges for commodities based upon principles of supply and demand. Criminological research focuses on the illegality of drug exchanges, behavioral and sociological theories explaining those exchanges, and the responses of law enforcement. Ethnographic work, however, describes the experiences of those involved in and/or exposed to illicit drug exchanges within the broader social context. These related yet distinguishable definitions bring confusion to drug market research because "the absence of a unifying definition is important—one cannot presume to know what a particular discipline or researcher is referring to when the term 'drug market' is used" (Ritter 2006, p. 460).

Understanding how researchers conceptualize drug markets is important because it has distinct implications as to how drug markets are operationalized as a variable and thus how results are to be interpreted. Perhaps the primary reason that researchers have operationalized drug markets in so many different ways is because—as illustrated above—not only does the disciplinary paradigm influence one's perception of drug markets, but within disciplines the drug market concept is continually modified to address innovative research inquiries.

Within criminology, drug markets have been conceptualized in a number of ways. Eck (1995) alludes to the systemic nature of drug markets, arguing that they are adaptations to the unique situations buyers and sellers encounter while making transactions. These include: avoiding police attention, the inability of relying on the police to settle disputes, and the need to conduct transactions in secure places. He goes on to provide a classification of drug markets. What he calls 'social network markets' are those in which buyers only purchase from screened sellers or those recommended by a mutual acquaintance. This technique provides security because buyers and sellers know one another and can be confident that the other party is not a representative of law enforcement. From a policy perspective, social network markets are hard to detect because they usually serve few buyers and are less likely to be located on street corners, but rather on private premises away from the surveillance of police. Conversely Eck's 'routine activity markets' are open to a larger number of customers and generally are found in public places. They are usually found along major arterial routes and demonstrate high place attachment. Such markets usually afford less protection from enforcement interdiction due to their more open nature (Eck 1995).

May and Hough's (2004) 'open markets' are similar to Eck's (1995) routine activity markets in that they are 'open' (i.e. available) to all buyers willing to purchase a product. Sellers are able to maximize their customers' access by being in the same location on a regular basis, making them sensitive to the spatial pattern of demand. However, open markets make buyers and sellers vulnerable to policing because they are more likely to be located outdoors. Because of this, certain areas (such as the Kings Cross commercial district in London) afford buyers and sellers protection due to the high population concentration and the difficulty in determining who is in the area for legitimate or illegitimate reasons (May and Hough 2004). In this way drug markets often sprout up near transportation hubs.

'Closed markets' are similar to social network markets because both parties know one another (May and Hough 2004). Sellers only sell to people they trust or to those who are vouched for through third parties. The risk of police apprehension is less than that of open markets, and buyers like closed markets due to the stability of supply, quality of drugs purchased, and trust between themselves and sellers. Furthermore, technology has changed the face of drug markets making them more flexible and convenient. Buyers and sellers can make appointments to meet at specified places using 'Pay as you go' phones that don't retain a record of the user's home address (Beckett et al. 2006).

Drug markets can also be conceptualized within an economic framework in that they involve exchanges where sellers position themselves closer to communities with more potential customers (geographic perspective) or closer to more disorganized communities (social disorganization perspective) (Robinson and Rengert 2006). It is therefore clear that how drug markets are conceptualized from a theoretical or disciplinary framework has the potential to influence the choice of data used to identify a market, and the analytical regime employed. For example, closed or social network markets are more likely to utilize qualitative data (Warner and Coomer 2003) or social network links to identify central nodes, whereas open markets may be better identified through official data, such as arrest records or relevant calls for service.

Because of the variation in conceptualization, the operationalization of drug markets within criminal justice is just as varied. By 'operationalization' we mean the manner by which social phenomena are measured for inclusion in empirical analysis (Blalock 1971). Unfortunately while features such as neighborhood socioeconomic status have relatively standard constructions (commonly measured by creating an index of educational attainment, household income, and poverty status), no such mechanism exists for drug markets. The myriad variants of official data, while adding richness and texture to the picture of criminality, do not immediately suggest a uniform approach. Oakland's Beat Health Program identified drug market locations using emergency call data and contacts from community organizations at the spatial scale of the street block level (Mazerolle et al. 1998, 2004). Evaluations of the program took place at the street block level using surveys of place managers and on-site observations of social and physical disorder (Mazerolle et al. 2004). In the Jersey City Experiment, drug markets were defined as hot spots of crime by mapping narcotic sale arrests and drug-related emergency calls for service to street intersection areas (Weisburd and Green 1995). Researchers defined the hot spot areas by seeking input from narcotics detectives and then created market boundaries based on those data.

Sophisticated continuous surface mapping techniques such as kernel density estimation (KDE) have been used to define drug markets using arrest data (Lum 2008). Mapping techniques effectively view a drug market as a hotspot of individual crime events and seek to identify these crime hotspots. Hotspots can be individual locations among groups of victims, streets, or areas (Eck et al. 2005). Chainey and colleagues argued that an approach using KDE provided the best opportunity to create statistically robust crime hotspot maps (Chainey et al. 2003, p. 29).

Using KDE, the locations of geocoded crime incidents are overlaid with a fine grid of digital cells. After that, a three-dimensional function of a specified radius is

superimposed over the center of each cell and an inverse distance weight is calculated for each point within the kernel's radius. Points closer to the outer edge of the radius have a lower scaling factor. In most cases the value for each crime event is one; therefore the weighting becomes the *de facto* value for the crime event for that particular cell calculation.¹ The final cell value comprises the summed value of all points within the radius of the superimposed function scaled against their individual inverse distance weighting (Chainey and Ratcliffe 2005; Eck et al. 2005; Ratcliffe and McCullagh 1999a). The end result is a continuous surface of fine grid cells that cover the study area, each cell containing a value indicative of the intensity of crime around the location. In this case, the term 'around' is important because the cell size is often selected to be smaller than the radius of the kernel function to ensure a continuous surface where every point is included in the study. A cell size of 0.8r (radius) was proposed over a decade ago as a reasonable scaling to ensure overlap (Ratcliffe and McCullagh 1999b) but this is largely a decision of the analyst. Cartographically, extreme clustering is usually indicated by bright eye-catching colors such as red or yellow while dispersion is indicated by less vibrant colors, such that the eye is drawn to the crime hotspots.

Drug markets pose a particular challenge to law enforcement, but they are not everywhere across our urban areas. A considerable body of research has focused on trying to explain why some areas have more drug-related incidents than others. Taniguchi et al. (2009) set out to determine whether drug markets demonstrate agglomeration effects similar to legitimate business firms. In other words, drug markets were viewed as businesses that cluster in space to appreciate benefits (intentionally or unintentionally) that would not be realized if they were more spatially dispersed. In Taniguchi and colleagues' research drug markets were operationalized as a count of drug sale arrests in each of Philadelphia's 1,816 block groups. Agglomeration was identified using a spatial lag variable to determine whether block groups with high drug sale arrests cluster near others with high drug sale arrests. They found that agglomeration was predictive of higher drug sale arrests within block groups, controlling for local demand, social disorganization, concentrated disadvantage, and land use correlates.

Other research has aggregated counts of drug sale arrests to block groups to explain changes over time (Robinson 2008; Robinson and Rengert 2006) and has examined the influence of social disorganization and criminal opportunity on the locations of drug markets by aggregating drug arrest counts to block groups (McCord and Ratcliffe 2007). It appears that single female-headed households, low educational attainment, and the percentage of minorities are positively related to drug arrest counts, while (surprisingly) the percentage of renter-occupied households and male unemployment are negatively related to drug arrest counts (McCord and Ratcliffe 2007).

¹ However while it is usual to count a crime incident as 1.0 for the purposes of scaling with the weighting factor, it is possible to create crime hotspot maps based on other characteristics of the crime, such as the value of property stolen. The inverse distance weight in this case would be scaled against the value of the good stolen to create a map showing hotspots of property value lost.

Alternative spatial units such as census tracts have also been used to outline drug markets. Rengert et al. (2000) argued that drug markets are sites where exchanges of drugs take place but their location depends on whether customers are local or regional. Retail marketing would suggest that dealers would want to locate near suspected drug-using populations. Research shows that such populations tend to be young, without a high school diploma, and unemployed. Using census data and operationalizing drug markets as the number of drug sale arrests per square mile of each census tract, they found that local drug markets tend to locate near tracts with the greatest proportions of young members, unemployed, with less than a high school education while regional markets tend to locate near highway on/off ramps.

Recent research by Ratcliffe and Taniguchi (2009) and Taniguchi et al. (2011) took an innovative spatial approach to drug market identification. In their research, a drug markets were conceptualized as street corners where known gang members were witnessed selling drugs, the street corner being an original unit of spatial analysis for this context. To investigate whether drug corners controlled by gangs are more violent than those not controlled by gangs, the researchers constructed Thiessen polygons around each corner in the city of Camden, New Jersey. The counts of drug incidents within polygons became the operationalization of drug markets.

Some have questioned how well arrest data are indicators of real drug activity. Warner and Coomer (2003) used a regression model that incorporated resident self-report surveys on the witnessing of drug activity as a predictor of official drug arrest data across 66 neighborhoods (block groups). They found that the survey measure was significant and positively associated with drug trafficking arrests, but demonstrated no real relationship with drug possession arrests. This suggests not only that respondents were able to distinguish trafficking from possession, but possibly that drug trafficking is a more visible and readily identifiable drug crime than possession. Other research at the city level has also supported the use of official drug arrest data, with construct validity tests indicating strong relationships with public health data (Rosenfeld and Decker 1999). Finally, Rengert et al. (2005) found that drug-related calls for service data co-varied with illegal drug arrests.

In line with past research, we also use drug sale incident data to identify drug market areas. Arrests for drug selling are more likely than those for drug possession to take place within or near a drug market, given that ethnographic evidence suggests that outdoor drug sellers are territorial in nature (St. Jean 2007). A drug possession incident could simply indicate that an arrestee possessed—but not necessarily purchased—drugs. It is possible that an officer didn't witness the arrestee buy drugs, but that after a search due to some other suspicious activity the officer found drugs on the arrestee's person. Such an arrest *could* happen at or near a drug market area, but it could also happen anywhere else, making it more theoretically difficult to spatially link a drug possession arrest with that of a drug market. A review of the literature indicates that research has relied heavily on aggregation of official police data to census features to operationalize drug markets. The following sections illustrate the problems with this approach and provide an alternative measure that deals with some of the threat to construct validity evidenced by past research.

2.2.1 *What Methodologies are Available?*

In this work, we seek to identify drug market areas and non-drug market areas, attempting to draw a boundary around the former in order to distinguish the market area. For the purpose of this illustration drug markets are required to be clearly delineated from other areas by evidence of statistically significant spatial concentrations of drug sale incidents. Furthermore we are interested in areas, rather than necessarily single drug sale locations. Therefore this research considers drug *markets*, areas where a drug user could expect to find more than one drug sale operation and could hope to encounter a drug seller within a general area. We also seek a definitive spatial ordering (drug market area or not), rather than a fuzzy classification. This conceptualization of drug markets therefore requires a binary spatial classification technique.

Often, kernel density estimation would be considered under these circumstances. While the technique is aesthetically appealing and commonly used among the crime analysis community, it does have some limitations. The use of a smoothing algorithm generates a smoothed display that may not indicate sudden changes in crime distribution. Furthermore, the technique often counts a single crime event into the calculation for multiple grid cells, limiting the range of statistical tests that can be applied due to the problem of independence. Finally, the technique does not suggest a definitive cut-off point whereby an analyst can determine whether a location is inside or outside a drug market. Instead, the surface map indicates an intensity value on a continuous range, and any cut-off point would be an arbitrary selection of the crime analyst.² This arbitrary limit can be highly subjective given that, due to the smoothing algorithm, cells just outside the drug market area would have KDE values close to their neighboring cells just inside the area. The approach therefore has limited applicability when trying to determine the fixed boundaries of drug markets in a robust and replicable manner. KDE does, however, have the advantage of indicating gradual declines in value as distance from a hotspot increases, reflecting a fuzzier boundary that is likely to mimic the more mutable nature of many urban drug environments.

Point location techniques such as the mode and fuzzy mode of the CrimeStat software package also fail to meet the needs of this research because they merely total the number of events taking place at or within a certain distance of user-determined features such as transit nodes or other point locations (Levine 2004). These techniques would be appropriate for assessing the count of robberies in and around a specified set of alcohol-serving establishments but not for determining statistically significant concentrations of drug selling incidents. The inability to cover the whole study area is a considerable limitation.

Partitioning cluster tools typically assign all events to a user-defined number of clusters, with each point belonging to one cluster exclusively (Levine 2004).

² Some analysts determine the dimensions of a crime hotspot simply on the basis of a change in color in the choropleth map classification system. Given the ease with which these can be manipulated with modern software, this approach is most definitely not recommended if a more robust statistical analysis is desired.

However, such techniques are likely to identify multiple clusters that are not necessarily hot spots simply because of the constraint to assign *every* point to a cluster. Also problematic is the requirement for a user-defined *a priori* estimate of the number of likely clusters. These conditions make the results arbitrary and overly subject to user specifications. Additionally, partition cluster approaches have the ability to mask variation within hot spots potentially leading to significant data reduction (Grubestic 2006). This is inadequate for the current research which seeks to discriminate significant clusters of drug arrests from those that are dispersed across space.

Similar to partitioning cluster tools is the aggregation of crime incidents to census features. Like partition clustering, every crime incident is allocated to a particular enumeration feature (e.g. block, block group, or tract). The strength of this technique is that it allows the researcher or analyst to easily blend census data with crime counts, and to measure the extent of spatial autocorrelation (Taniguchi et al. 2009). On the other hand, aggregation draws concerns of the modifiable areal unit problem (MAUP), in that the results of aggregation techniques will vary according to the number of areal units and the nesting of smaller areal units into larger ones (Openshaw and Taylor 1979). While the use of census features is convenient, they are designed for census collection and not drug market delineation. When block groups and tracts are used as units of analysis, individual areas in their entirety have the potential to take on the drug market characterization. This is unlikely to be an accurate representation of drug markets. Environmental criminology has revealed that hot spots of crime are not hot all the time, and that cold spots may be temporally intertwined within hot spots (Eck et al. 2005). High drug crime block groups or tracts may not have uniformly high drug activity within their units of analysis.

Grubestic (2006) notes that partition clustering essentially ignores the potential presence of spatial outliers; however, this is a problem that applies to aggregation techniques as well. The inclusion of *every* point (including outliers) compromises the validity of partition clustering and renders the use of areal aggregation as nothing more than a total count of crime incidents within areal features. According to Grubestic and Murray (2001) "Broadly defined, cluster analysis is a method of classification that places objects in groups based on the characteristics they possess" (p. 5).

In the section that follows, we adopt a spatial variant of a hierarchical clustering approach. Hierarchical clustering techniques have existed for many decades (Johnson 1967; Sneath 1957; Ward 1963) in both parametric and non-parametric forms (D'Andrade 1978). Hierarchical clustering routines begin by calculating some measure of dissimilarity (commonly distance) between each point and all other points in a population (Bailey and Gatrell 1995). An average of the nearest distance among all points is typically computed and used as a threshold for grouping points across space (random nearest neighbor distance). Two or more points that have a distance less than the nearest neighbor distance are then grouped into a series of first-order clusters.³ Second-order clusters are created by repeating the same

³Other measurements can be used to define the threshold such as the minimum distance and maximum distance. See D'Andrade (1978).

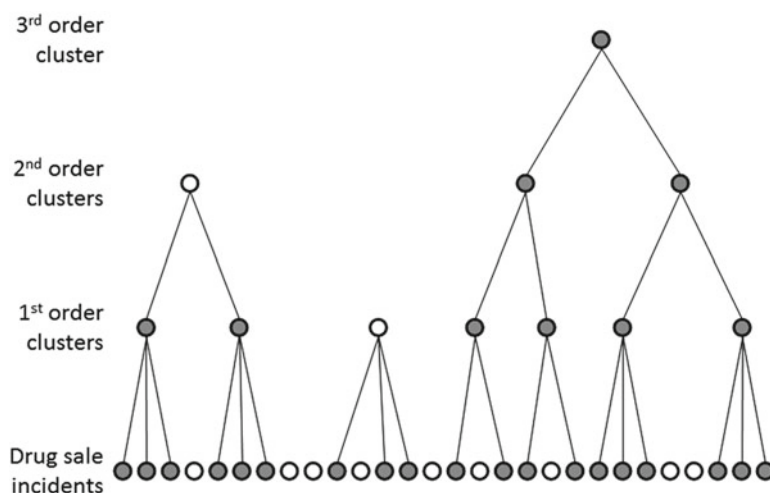


Fig. 2.1 Hierarchical clustering technique (Adapted from Levine 2004)

process on the primary clusters that were generated. According to Levine (2004) second-order clusters are grouped into larger ones, and this process is repeated until no additional clusters can be identified. Visually, hierarchical clustering resembles an inverted tree diagram (Fig. 2.1), yet it is important to note that not all points are grouped into a cluster (Levine 2004). In the diagram, drug incidents that are not part of a higher cluster are shown as white, while incidents shown in grey are part of a higher order cluster. This useful feature of hierarchical clustering will be relevant later, preventing crime events outside of drug markets to be artificially drawn into a drug market area by virtue of the analytical technique.

2.3 A Two-Stage Clustering Approach

Prior research has therefore shown that not only are there varied definitions of drug markets but that operational definitions can suffer from validity concerns. A review of the literature indicates that research has relied heavily on aggregation of official police data to census features to operationalize drug markets. The purpose of the current section is to suggest an alternative measure that deals with some of the threats to construct validity evidenced by past research. We demonstrate this with an example case study using 5 years of drug sale incident data from the Philadelphia (PA) Police Department.

Recent research has suggested that using more refined, spatially sensitive measures of drug markets may better our understanding of the extent to which they coexist in violent areas (Lum 2011); therefore, we identify drug market areas and non-drug market areas, attempting to draw a boundary around the former in order to distinguish

the market area using a two-stage nearest neighbor hierarchical clustering approach. The aim of this is to clearly delineate drug markets from other areas by evidence of statistically significant spatial concentrations of drug sale incidents.

Nearest neighbor hierarchical clustering (Nnh)⁴ is a technique available within the CrimeStat spatial statistics software package used to outline the clustering of point data (Levine 2004). Similar to the general description of hierarchical clustering above, CrimeStat's Nnh technique uses a threshold distance to group points into a cluster. Two main criteria guide the clustering process. The first criterion is the selection of a threshold distance. Nnh allows users to select their own fixed distance threshold, or to use the random nearest neighbor distance for first-order clusters. The random nearest neighbor distance is defined as:

$$d(ran) = 0.5 \sqrt{\left(\frac{A}{N}\right)}$$

where A is the size of the study area (defined by the user) and N the number of spatial events (Levine 2004).

The threshold distance is determined by selecting the appropriate one tailed confidence interval around the random nearest neighbor distance. Therefore, the confidence interval for the random nearest neighbor distance equals the random nearest neighbor distance plus or minus the standard error of the mean random nearest neighbor distance:

$$0.5 \sqrt{\left(\frac{A}{N}\right)} \pm t \left(\frac{0.26136}{\sqrt{\frac{N^2}{A}}} \right)$$

where A is the size of the study area, N is the number of spatial events, t is the Student t -value for a given probability level, and 0.26136 is a constant. Here, the confidence interval is used to determine the probability that the distance between any pair of events would be less than the random nearest neighbor distance (assuming the data are randomly distributed across space). In other words, if the data are *randomly distributed* and a user-selected significance is at $p < .05$ then about 5% of the pairs of events could be expected to be closer than the random nearest neighbor distance (for more details, see Levine 2004).

The second criterion is the selection of a minimum number of points necessary to create a cluster. This criterion is necessary to reduce the number of very small clusters that would otherwise be created by chance. A large dataset can result in

⁴ We use the abbreviation Nnh throughout the chapter for continuity with the CrimeStat manual.

many clusters if the only requirement is to have points within a specified distance of one another. As a result of this criterion, points will only be clustered if the distance between them is less than the set threshold *and* if the number of points in the cluster is greater than or equal to the minimum set by the user (Levine 2004). At present, the choice of a threshold is an arbitrary researcher-driven decision.

For the purposes of this study Nnh was used to identify significant clusters of drug activity using the CrimeStat 3.0 software package. A Nnh analysis was run on the drug sale incident data using the following parameters. The land area value used to calculate the random nearest neighbor distance was 135 square miles. A 95% confidence interval was used to determine the probability that the distance between any pair of events would be less than the random nearest neighbor distance (assuming the data are randomly distributed across space). Ten (10) was chosen as the minimum number of points necessary to create a cluster (the default option).

Before running the Nnh analysis the user can choose to map the resultant spatial clusters as convex hulls or ellipses. The problems with standard deviational ellipses that rarely mimic the geography of the underlying crime events have been known for some time (Ratcliffe and McCullagh 1999b); therefore, our results are mapped as convex hull polygons. Grubestic (2006) makes three observations with regard to convex hull polygons; convex hulls are constructs of the smallest polygons necessary to bound a set of clustered points, the use of convex hulls minimizes the area necessary to group a set of clustered points, and convex hull polygons lend themselves to crime density calculations. As a result, the conservative construction of clusters using convex hulls more accurately represents real crime clusters and demonstrates better construct validity when compared to hot spots constructed using areal features. A technique to blend multiple spatial hierarchies of convex hull polygons is a further advantage, as will be demonstrated below.

2.4 Data and Results

Drug sale incident data were sourced from the Philadelphia Police Department's Incident Transmittal System in March of 2011, covering 5 years (2006–2010). These incident data detail the date of the incident, UCR code, X/Y coordinates of the incident location, and a unique incident number. UCR codes (a code that indicates whether the crime involved buying or selling drugs, and the type of drug involved) were used to extract incidents for the sale of any of the following: opium, marijuana, synthetic/manufactured narcotics, dangerous non-narcotic drugs, powder cocaine, and crack cocaine. A total of 18,299 drug sale incidents occurred from 2006 to 2010 in the city of Philadelphia.

Nnh analysis revealed 329 first-order, 34 second-order, and 2 third-order clusters, shown in Fig. 2.2. For purposes of clarity, the map on the left side of the figure shows the first- and third-order clusters. First-order clusters appear as small specks or dots on the map (Fig. 2.2a). Third-order clusters appear to resemble large drug market regions (Fig. 2.2a). They are located close to one another in North

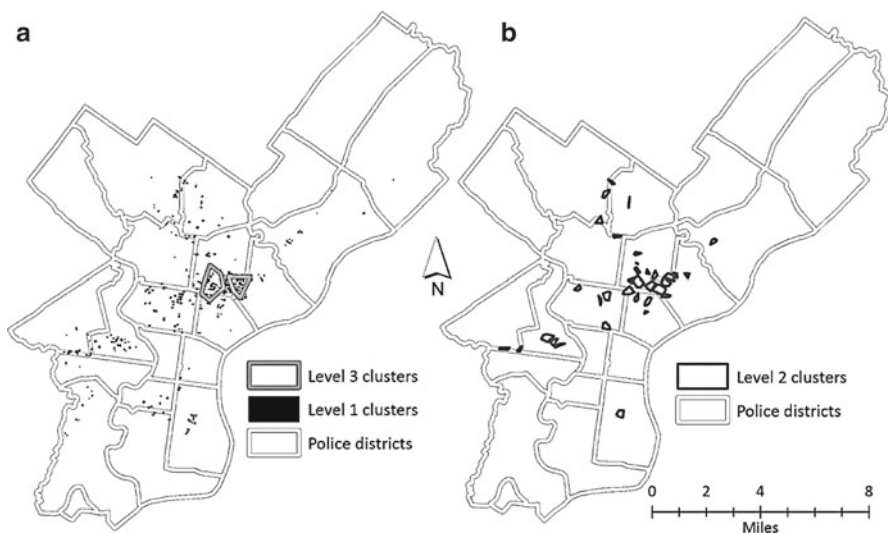


Fig. 2.2 1st and 3rd order clusters of drug sales incidents (*left*), 2nd order clusters (*right*)

Philadelphia, in an area historically known as ‘The Badlands’. The map at (b) on Fig. 2.2 displays the locations of the 34 second-order clusters (revealed by the Nnh analysis) which are concentrated throughout North and West Philadelphia.

There were a number of operational issues with both first- and second-order spatial clusters. First-order clusters, when examined for a city such as Philadelphia, identify a large number of very small areas often concentrated around individual street intersections. Even though they were within the random nearest neighbor distance, and constituted sufficient offenses to overcome the minimum number of points threshold, these first-order areas were more representative of drug selling corners (which can also be hot spots of drug activity). Table 2.1 provides descriptive statistics for each of the cluster-orders produced from the hierarchical clustering process. First-order clusters possess a median area of about 5,000 square feet, indicating that these clusters are generally very small and cover an area resembling the size of a street intersection. The minimum area value of zero is the result of some first-order clusters resembling “problem” addresses that have had multiple calls for service for drug activity. For example, over the 5-year study period, 61 separate incidents for the sale of illegal drugs occurred near the corner of N 61st Street and W Thompson Street in West Philadelphia.

A total of 34 second-order clusters were produced by the Nnh analysis, and were substantially larger than those within the first-order. Second-order clusters had a median area of slightly over 730,000 square feet, or about 5–6 city blocks. Second-order clusters collated various first-order clusters into more cohesive units, but did so based on the centroid of the first-order clusters. Depending on the orientation of the first- and second-order spatial units, a considerable number of crime events

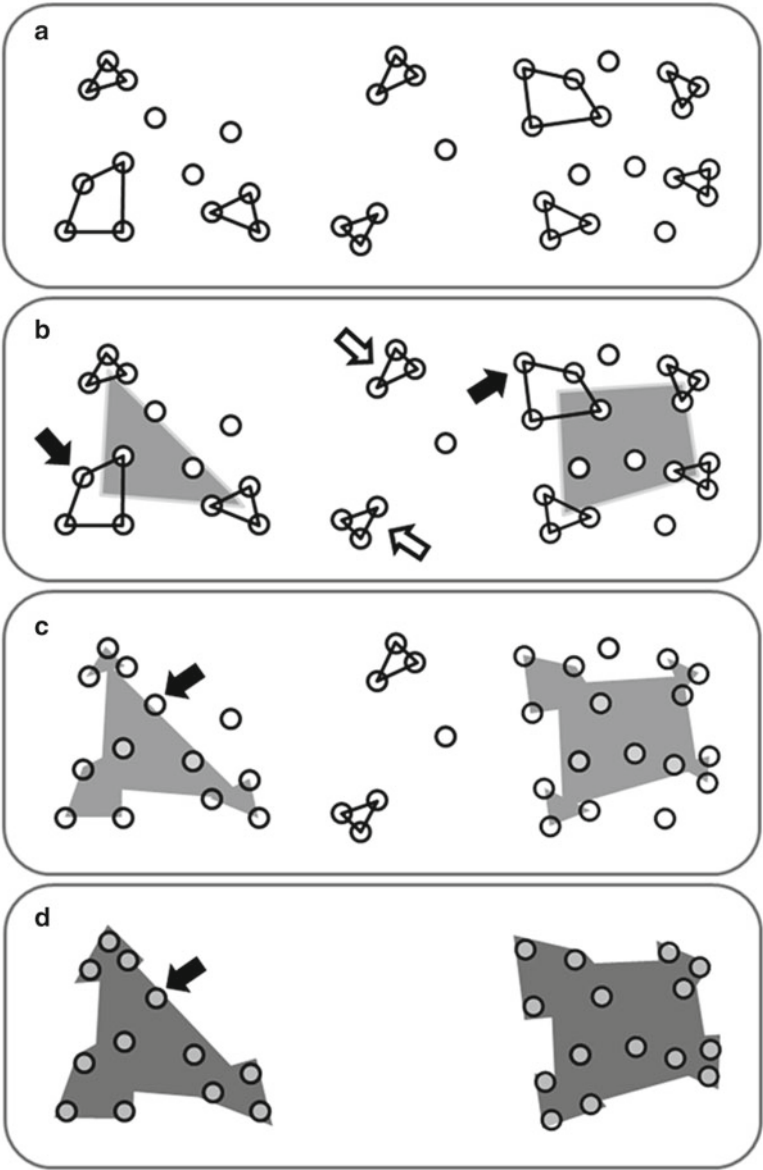


Fig. 2.3 Modification of nearest neighbor hierarchical clustering process

within first-order clusters were excluded from second-order clusters, *even* when they were members of a first-order cluster that was part of the second ordering. This problem is demonstrated in Fig. 2.3, where (a) shows a pattern of crime events as circles, among which are a number of first-order cluster areas, indicated by black angular shapes linking certain points. The grey area in (b) shows the second-order

Table 2.1 Descriptive statistics of hierarchical clusters

Clusters	n	Mdn. area	Min.	Max.	Mean area	St. Dev. area
1st order	329	4,775	0	63,612	10,239	12,614
2nd order	34	730,452	33,289	3,400,609	1,015,249	801,344
Merged	34	757,923	39,673	3,447,044	1,045,814	807,534
Buffer	34	1,896,528	450,016	4,486,090	2,153,066	972,246
3rd order	2	13,491,178	9,514,580	17,467,776	13,491,178	5,623,759
Phila. BG	1,816	1,022,856	149,391	95,735,799	2,191,157	5,313,473

Note: Values are in square feet

hierarchical spatial relationship between a number of the first-order clusters, based on the centroid of the first-order areas. Two hollow arrows indicate a couple of areas that were first-order spatial clusters but were too remote from other areas to be included in a second-order cluster. These isolated first-order clusters were not considered further.

The black arrows in (b) indicate two problematic areas, from the perspective of drug market identification. These are crime event clusters that were included in the first-order clusters. Centroids of first-order clusters are used by the Nnh analysis to construct the shape of the second-order clusters. Because of this problem, some events can be inadvertently excluded. For example, if it was determined to select all of the points within a second order cluster, the crime events identified with the black arrows would not be included in the identified areas, even though they were part of a first order cluster that contributed to the second order spatial pattern.

The solution we employed was to spatially merge the first- and second-order convex hull areas so that points that were contained within an entire first order cluster were not lost when the second-order hierarchy was applied. In other words, a convex hull was created for each level 1 cluster, and then these were spatially joined to the relevant level 2 cluster convex hull. This is demonstrated in part (c) of Fig. 2.3.

One issue to consider at this stage is shown by the arrow in Fig. 2.3c. The arrow indicates a crime event that is very close to the drug market area but which is just outside the formal spatial polygon. Therefore for both purposes of visual clarity, and to avoid any potential ambiguities, the final combined first- and second-order polygon areas have had a small buffer applied. This process allows the drug market area to retain all of the original first-order events that clustered to create the crime hotspot area in the first place, as well as any points right on the edge of the drug market area. This final stage is shown in Fig. 2.3d, where the arrow now shows the drug incident included in the drug market area.

Descriptive statistics of merged first- and second-order clusters (Table 2.1) indicate that the median size of the merged clusters is not substantially different from the second-order clusters. This is because the first-order clusters generally covered very small areas and contributed very little additional area to the second-order clusters, once they were merged. Conversely, the two third-order clusters appear to denote large drug regions of the city. The smallest of such clusters has an area of over 9.5 million square feet or .34 mi², and the largest is .63 mi².

2.4.1 *Analytical Considerations*

2.4.1.1 **Rigidity of Convex Hulls**

According to Levine (2004) the advantage of using convex hulls is that they reflect an outline of clustered points, but the disadvantage is that they may exclude areas that should be included in the hot spot. Furthermore, there could be incidents related to the drug market but outside of its rigid boundaries. Arguably, this is not a concern from a strictly spatial statistics perspective; however, a little latitude in the boundary can alleviate concerns of geocoding accuracy as well as other anxieties of accuracy in relation to micro-geography. We addressed this problem by creating a small buffer around each cluster to ensure that we captured drug incidents associated with the drug market, as well as provided for the chance to include points very close to the drug market cluster but originally excluded by the convex hull. If the analyst chooses to take this route, the selection of an appropriate buffer size requires the user to balance the need to include points within a theoretically relevant distance of the clusters while not making buffer areas so large that they overlap one another or become so large as to be unrealistic indications of the drug market extent. This factor was noticeable in the North Philadelphia – Badlands area where some of the clusters are within one city block of another (Fig. 2.2).

Similar to the approach taken in Fig. 2.3d, a 200 ft buffer⁵ was applied to the merged Philadelphia clusters⁶ to provide a chance to capture additional incidents that may be just outside the boundaries of the drug market, but nonetheless most likely related. Figure 2.4 shows a map of Philadelphia level 2 cluster drug markets including a 200 ft buffer. The dashed rectangle indicates the inset region displayed on the right of Fig. 2.4. The shaded polygons indicate areas where two markets overlap one another. Statistically speaking, overlapping areas violate the assumption of independent observations. This may not be a problem for crime analysts, but it does cause problems for researchers looking to take an analysis to the next level. A solution to this issue, in line with the research by Haberman et al. (in press), involves measuring the distance from the centroid of each overlapping area to that of its respective drug markets. Each overlapping area is then merged with its closest drug market. This is done in Fig. 2.4.

⁵ The median length of a street segment in Philadelphia is 277 ft. Using a buffer a little under this size would theoretically mean that any incident within 200 ft of a drug market's boundary is attributable to the dynamics of that drug market's immediate block.

⁶ Buffers were applied to the merged clusters for visual clarity. The decision to apply a buffer as well as considerations of which order clusters they should be applied should be guided by practicality and the theoretical interests of the research at hand.

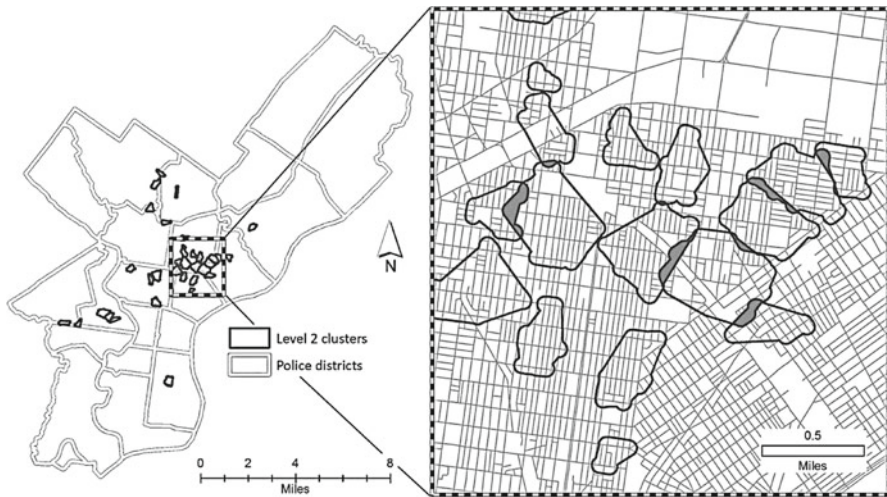


Fig. 2.4 Drug markets with 200 ft buffer

2.4.1.2 Statistical Significance

The second consideration with the Nnh analysis concerns how to determine statistical significance of the clusters. The test to determine whether two points are clustered by chance is traditionally the confidence interval around the random nearest neighbor distance. If the probability level is set to .05 then one could expect that 5% of all point pairs are grouped by chance. However, Nnh groups more than just two points within a cluster, depending on the minimum number of points set by the user. A Monte Carlo simulation can address this problem by constructing confidence intervals based on the first-order clusters. It is essentially a test of the null hypothesis that the data are *not* spatially clustered. This occurs by randomly assigning the same number of cases to a rectangle containing the same area as the study region. For each simulation (the total number of simulations is determined by the user) the number of expected clusters created is calculated and reviewed against the observed number.

The process is demonstrated here for Philadelphia. A Monte Carlo simulation was run on the data, using 1,000 iterations. An equivalent number (to the 18,299 drug sale incidents) of randomly assigned points were thrown on a plane with an area matching the square footage of Philadelphia. The same nearest-neighbor distance and cluster minimum frequency (10) was applied to the simulation data and tested for the presence of clusters. This random allocation and test process was repeated 1,000 times. Across all iterations of spatial randomization, zero clusters were produced, suggesting that it is extremely unlikely that any of the first- and second-order clusters actually observed were produced by chance ($p < 0.001$).

Table 2.2 Sensitivity analysis

Min. # of points	1st-order clusters	% change	Clusters obtained by chance (95th percentile)
8	420	–	1
9	375	–10.71	1
10	329	–12.27	0
11	307	–6.69	0
12	266	–13.36	0

2.4.1.3 Arbitrariness of Parameter Selections

The third consideration is that the selection of a minimum number of points for cluster determination does render Nnh slightly arbitrary (Grubestic and Murray 2001) and research has yet to empirically guide the selection of a suitable minimum number. The purpose of a choice such as 10 (the default CrimeStat option) is to minimize the number of extremely small clusters (Levine 2004). In other words, the aim is for the cluster detection to identify small neighborhood clusters rather than collections of a couple of points at a street corner; however, it is recognized that the requirement to pre-determine a minimum cluster density is a limitation of the process.

To determine the sensitivity of this option, the analysis was re-run using 8, 9, 11, and 12 points as the minimum. There appears to be an inverse relationship between the minimum number of points selection and the number of first-order clusters produced (see Table 2.2), which substantiates (personal) communication with Levine (2010). Increasing the minimum number of points necessary to form a cluster from 9 to 10, decreases the number of first-order clusters produced by 12%. Using 11 points instead of 10 points decreases the number of clusters by a further 7%. Monte Carlo simulations were run for each additional analysis using 1,000 iterations to determine the number of clusters that would be obtained by chance, assuming a random spatial distribution. Results indicate that when setting the threshold to eight or nine points, using 18,299 incidents it is possible that one cluster (or in this case drug market) is a statistical artifact. Selecting any number of points greater than nine reduces the chance of statistically artificial clusters to essentially zero. This suggests that clusters revealed by setting the minimum number of points to ten are robust clusters of drug sales activity. Therefore, the appropriate minimum number of points (for the Philadelphia data at least) is any option of at least ten points, noting that there is an inverse relationship between the minimum number of points and the number of first-order clusters that will be identified.

Returning to the issue of validity, we investigated whether census features or clusters from the Nnh analysis produce a more valid measure of drug markets. Specifically for the purpose of this illustration we compared the drug sale crime densities of block groups to the buffered clusters. Considering that the Nnh clusters delineate the hottest clusters of drug sale incidents they were only compared to

Table 2.3 Density measures of cluster analyses

	Median	Min.	Max.	Mean	St. Dev.
Merged	2,416.88	1,379.56	8,796.87	3,113.07	1,987.26
Phila. BG	831.77	0	12,455.47	1,394.13	1,833.06

Note: Values reflect incidents per square mile

census block groups they encompass or intersect ($n=221$). Drug sale crime density was calculated by dividing the total count of incidents within each spatial unit feature by the respective feature area. Higher density values indicate a larger number of incidents per square mile than lower values.

Table 2.3 displays descriptive statistics of drug sale density calculations for block groups and the merged 1st and 2nd order clusters (including the 200 ft buffer). The median density value for the merged Nnh drug market cluster is 2,417 drug sale incidents per square mile, while the median for comparable block groups is 832 drug incidents per square mile. The density of drug incidents within Nnh clusters is about three times greater than that of comparable block groups indicating that they are indicators of more highly concentrated areas of drug crime than areal aggregation to census boundaries. Only three block groups had density values greater than the maximum Nnh density value of 8,797 per square mile. A visual inspection of those block groups indicated that two are entirely encompassed by Nnh clusters, and about 95% of the third block group coincided with a Nnh cluster

2.5 Discussion

We have proposed a new method to spatially operationalize drug markets. Much of the past research on drug markets has accomplished this by aggregating counts of drug sale data to census features. Although this allows researchers to conveniently append census data, such an operationalization has the potential to be over-inclusive and runs the risk of labeling large tracts as drug markets when the reality is quite different. This becomes apparent when we consider research indicating that neighborhood drug problems can stem from places as geographically small as one address (Mazerolle et al. 2004). Using official drug crime data from the Philadelphia Police Department, we have shown that the nearest neighbor hierarchical clustering technique addresses this limitation by identifying significant clusters of drug incidents at multiple geographic levels ranging from street intersections to areas of over half of a square mile.

Although our example of the two-stage nearest neighbor hierarchical clustering technique used drug sale incident data, the process can be applied to other crime categories, such as violence. Perhaps the most detrimental aspect of urban drug markets is the violence by which they are often characterized. Concentrated disadvantage appears to be strongly related to drug market activity, with drug market

activity in turn having a strong causal connection with robbery rates (Berg and Rengifo 2009). Such communities tend to be socially disorganized and unable to regulate drug crime and the related violence that it engenders (Berg and Rengifo 2009). However, even controlling for sociodemographic factors such as instability, heterogeneity, and deprivation, drug activity still has a significant positive effect on assault and robbery rates (Martínez et al. 2008). Ousey and Lee (2002) found that increases in drug arrest rates were positively related to homicide rates; however, that relationship is contingent on the preexisting level of resource deprivation.

While studies such as these contribute to our understanding of violence, they are subject to how drug markets are operationalized and conceptualized. A positive relationship between neighborhood drug arrest rates and violence within census tracts is operationally different from empirically derived statistically significant clusters of drug sale arrests and the violence that occurs within. The former examines community correlation between drug arrest rates and violence while the latter focuses on the significance of the most problematic drug crime areas (hot spots) and how they engender violence.

The use of two-stage nearest neighbor hierarchical clustering presents a new way for studying drug markets, while addressing issues of the MAUP, over-inclusion, and construct validity. The crime density comparison of Nnh clusters and the aggregation technique indicated that Nnh was about three times better at aggregating incidents and identifying hot spots (Table 2.3). Nnh may be preferable for researchers and analysts when the desire is to visually outline areas of highest drug sales activity.

Although clustering techniques such as the one described here are fundamentally descriptive in nature and often the starting point for an analysis rather than an end point, hierarchical clustering could provide crime analysts with a more accurate method to inform the targeting of police resources across multiple levels of police organization. For example, Fig. 2.1 suggests that 1st order clusters which tend to outline street intersections or problem addresses may be of interest to beat officers who routinely patrol assigned areas and need to be aware of potential threats. District commanders may see more value in larger, 2nd order clusters that outline larger areas of drug activity for the direction of additional officers, or for planning neighborhood level community oriented policing or situational crime prevention efforts. Such information could aid in the planning of police crackdowns and the targeting of specific drug sellers or selling organizations that may be the cause of violence in the community. These areas are also more conducive to community organization.

Finally, 3rd order clusters may be of interest to police executives and federal agencies that plan for the assignment of personnel at scales larger than local police districts. Although targeted police efforts to hotspots may cause some displacement, interdiction of the most spatially advantageous sites may displace sellers to less advantageous locations in turn making the market less profitable (Robinson and Rengifo 2006).

The technique shown here therefore has the capacity to indicate at least three levels of drug market organization that roughly conform to commonly used drug market terminology;

- Level one Nnh spatial clusters equate to *drug places* (such as around an intersection)
- Level two Nnh spatial clusters equate to *drug markets* (groups of blocks with drug problems)
- Level three Nnh spatial clusters equate to *drug regions* (such as the Philadelphia Badlands)

These spatial units have operational benefits to crime science and crime prevention, given that the first two spatial clusters operate at scales that are amenable to local policing and problem-solving approaches, while the third scale indicates a region or area than may need a broader investment to combat the drug problem.

It is recognized that while we have endeavored to bring an objective approach to the spatial identification of urban illicit drug markets, there still remains the issue of the arbitrary minimum number of points required to form a level one cluster. We hope that additional research will identify some guidelines that can inform future decisions. In the meantime, we recommend that analysts using this approach clearly publish the selected number in any maps and publications.

A final theoretical note deserves comment. It is possible that the drug markets constructed from the nearest neighbor hierarchical clustering technique are not real, but abstractions of reality. Recent work by Taylor (2010) argues that there are several inconsistencies that hot spot policing researchers must address before hot spot policing can advance to a national policy. Although it is not in the theoretical interest of this work to address the nuances of hot spot policing at the national level, Taylor's point does bring into question the construct validity of hot spots techniques. Analytically and methodologically this work has taken steps to address some of these concerns, and communication the Philadelphia Police Department during the summer of 2009 has confirmed that many of the drug markets outlined in this work are areas of high drug activity. The reader is referred to Taylor's (2010) interesting polemic for more detail.

2.6 Limitations

First, it is worth noting that the use of a 200 ft buffer around second-order polygons is arbitrary. The mere selection of a specified buffer has implications for the size and intensity of the cluster. As we argued earlier, for strictly spatial statistical applications, it may not be necessary, though this would assume that (1) the drug market does not extend beyond the combined convex hull polygons, and (2) the points that are the basis for the convex hull polygons have been accurately geocoded. These are constraints that suggest caution with all but the most carefully generated data sets. With regard to buffers around crime points (and not drug markets *per se*), Guerette (2009) argues that large buffers may encompass too much data and exaggerate statistical relationships, while small buffers may fail to capture incidents theoretically

associated with the location in question. These observations are equally applicable to our modest buffer at the edge of the drug markets.

A further concern with an arbitrary buffer refers to the fact that the current approach ignores the physical geography of the areas surrounding the hot spots. Admittedly buffers that consider the physical geography are ideal; however, this would involve researchers venturing to each drug market to identify physical and perceived barriers. Even physical barriers are hard to estimate from remotely accessed data. For example, while a railway line can often be a barrier, in some parts of Philadelphia residents routinely cross the lines, rendering this physical barrier inconsequential. Perceived barriers are even harder to estimate. The fieldwork to more accurately use the urban mosaic to reflect 'real' boundaries was beyond the scope of the project, and we have had to settle for an arbitrary distance.

A second limitation is that our analytical approach assumes that the drug markets are stable over time. In other words it is believed that the drug markets are not contracting or expanding spatially. The validity of such an assumption is subject to empirical investigation. This concern was mitigated by using 5 years of data to identify ongoing drug problem areas rather than using 1 or 2 years of data that may be as reflective of temporary policing initiatives as long-term chronic drug markets. The advantage of the technique used here is that it allows for the identification of historically stable drug market areas. Nonetheless, drug markets—like other social phenomena—may change over time. Therefore aggregate use of multiple years of data may amount to data reduction and thus mask the extent to which markets contract or expand over time.

One method by which to address the spatial rigidity of drug markets would be to systematically perturb the incident locations (Murray 2003). Perturbing works by selecting a random distance (limited up to a predetermined threshold) *and* direction to move each point within a dataset. Iterations of perturbed locations are produced in separate spatial datasets that can be compared to the locations included in the original dataset by way of the nearest neighbor index. Values less than 1 suggest significant clustering, while values greater than 1 suggest dispersion (Levine 2004). In turn, nearest neighbor hierarchical clustering routines can be run on perturbed datasets to remove the rigidity of market boundaries and account for greater flexibility.

A final limitation with regard to the hierarchical clustering routine is the grouping of incidents with other incidents in order to form a first cluster level. As noted by Grubestic (2006) the weakness of this form of clustering is that this process happens on a pair-by-pair basis. In other words, although two grouped points may be within the threshold distance of one another, each respective point may not satisfy the threshold distance requirement when being compared to other points within the group. This not only draws concerns for the validity of second and third order clusters, but also suggests that hierarchical clustering routines may be more accurate at indicating local versus global clustering. This limitation is acknowledged, though it should be noted that our research is inherently interested in more local scales within a larger study area. Our research here is a first step to a more methodologically robust method, however further research in this area is warranted.

2.7 Conclusion

Perhaps one of the most significant advancements in recent criminology (and crime science specifically) is its geographical focus on unique places through the science of GIS. Although an accomplishment in its own right, spatial criminology is also subject to the problems of construct validity that have been well documented in other social sciences. As the 'cone of resolution' (Brantingham et al. 1976) continues to shrink, aggregations of crime to broad geographic areas simply for analytical convenience will increasingly be drawn into question. Clustering tools that influence the targeting of scarce police resources must be as geographically specific as possible. The use of hierarchical clustering may represent a methodological step in the right direction.

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