Sex offender clusters

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Abstract

In the United States, sex offender management strategies continue to receive significant public attention and scrutiny. In addition to federal and state mandated community notification laws, many locales are also implementing a variety of supplemental residence restrictions to protect sensitive facilities (e.g. schools) and combat the emergence of sex offender “clusters”. Interestingly, while there are no generally accepted guidelines or municipal benchmarks for defining exactly what constitutes an offender cluster – subjective observation, and more generally, public perception appear to be the major inputs for cluster identification and related legislation. The purpose of this paper was to explore the utility of spatial statistical methods for objectively identifying sex offender clusters. Using offender registry data from the state of Illinois, a number of spatial applications are investigated which highlight the differences in clusters produced by each approach.

Introduction

Recent estimates indicate that nearly 603,000 sexual offenders are registered in local, state and federal databases in the U.S. (NCMEC, 2008). Further, approximately 60,000–70,000 arrests are made each year in the U.S. for charges of child sexual assault (Nieto & Jung, 2006). Given the recent heightened public awareness of these types of sexual offenses, it is not surprising that there is significant public support for legislation that provides information to communities regarding released offenders (e.g. community notification) (Bedarf, 1995; Hughes & Kadleck, 2008; Levenson & D’Amora, 2007; Levi, 2000) or limits the locations where sex offenders can establish a residence (e.g. residence restrictions) (Barnes et al., 2008; Chajewski et al., 2008; Grubesic et al., 2007; Zandbergen & Hart, 2006). In part, support for these types of social controls can be attributed to a public perception that sex offenders are likely to recidivate. These fears are not unfounded. Recent studies suggest that over 13% of offenders recidivate (Hanson & Bussiere, 1998). That said, Meloy (2005) notes that recidivism rates vary widely based on the type of sex offender under investigation, although serious/high-risk offenders are the most likely to re-offend (Hanson & Morton-Bourgon, 2005). In addition, there are significant methodological and theoretical gaps between clinical studies of offenders and the impacts of both formal and informal social controls on recidivism within a community.

Not surprisingly, the general public and their elected political representatives largely fail to differentiate between real or perceived dangers associated with offender recidivism. A particularly worrisome component for many communities is the emergence of sex offender clusters (Avila et al., 2007; Bain & German, 2006; Hughes, 2004). As noted by Grubesic and Murray (2008), there is no formal definition of a sex offender cluster; however, most of the anecdotal evidence presented in the popular press suggests that these areas have a noticeably higher concentration of offenders when compared to surrounding communities (Gonnerman, 2007; Maloney, 2006; Philips, 2007). Fears associated with offenders and their resulting clusters are best

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encapsulated by Patricia Eddington, a State of New York Assembly representative whose district includes a highly publicized “offender cluster” on Long Island, “It’s putting children at risk. … It’s a candy store for sex offenders” (Bain & German, 2006). Reasons cited for the existence of apparent clusters of offenders include the availability of low-cost rental units, locations outside of mandated restriction zones and landlords who are willing to rent to convicted offenders (Bain & German, 2006). As one might expect, the factors cited as fueling the emergence of offender clusters parallel many of the collateral consequences associated with community notification laws and residence restrictions (Burchfield & Mingus, 2008; Tewksbury, 2005).

While public perception and opinion is certainly an important factor in developing public policy, the inability to objectively determine if offenders are clustering within a community is problematic. Further, the implementation of residence restrictions or any supplemental spatial strategies for mitigating offender clusters can lead to highly ineffective public policy decisions that both endanger sensitive populations within a community and potentially rebuff rehabilitation efforts targeted to convicted offenders.

The purpose of this paper was to identify and explore spatial statistical methods for aiding policy makers, correction agencies and local law enforcement officials in objectively identifying sex offender clusters. Using offender registry data from the state of Illinois, a number of spatial applications are investigated which highlight the differences in clusters produced by each approach.

The remainder of this paper is structured as follows. Sex offender clusters: context and policy provides an overview of the distributional issues associated with sex offenders and their management. Methodology outlines a suite of methodological approaches that can be utilized for detecting sex offender clusters. Study area, data and results provides details on the study area, data and the results of several spatial applications. The final section provides a brief discussion of the results and discusses the limitations of the methodological framework.

Sex offender clusters: context and policy

Broadly defined, “clustering” refers to a group of people or things relatively close to each other in geographic space. Obviously, the ability to define exactly what “close” means is important. In the socio-economic, planning and environmental sciences, closeness is often defined with basic spatial statistical techniques such as nearest neighbor analysis (Ratcliffe, 2005; Wing & Tynon, 2006), or more advanced quantitative methods such as multivariate cluster analysis (Grubesic, 2006; Murray, 2000). While these types of approaches strive for objectivity, subjective interpretations are a reality and can strongly influence public policy development – rightly or wrongly. For instance, Siegrist et al. (2001) note that perception of cancer clusters by lay people often include areas with any values above average, even if the cancer incidences occur by chance.1

Along these lines, the presence of multiple convicted sex offenders within a relatively localized area represents an interesting problem for many communities in the United States and abroad. Mustaine et al. (2006) note that sex offenders routinely receive harsh punishments and are generally treated as pariahs within society even after rehabilitation. Because of several relatively high profile crimes during the past decade, including the brutal rape and strangulation of 7-year-old Megan Kanka, legislation pertaining to sex offenders has undergone several notable transformations (Logan, 2003). This includes the Adam Walsh Child Protection and Safety Act (Walsh Act) which was passed in 2006. The Walsh Act classifies offenders into three different tiers, mandating that each updates his/her whereabouts periodically. While Tier 3 offenders must do this every 3 months, Tier 1 offenders are required to update every year for 15 consecutive years. In addition to community notification laws, which mandate that federal, state and local agencies track the whereabouts of convicted offenders (Cohen & Jeglic, 2007; Tewksbury, 2002; Zevitz, 2006), many communities are now enacting laws that ban sex offenders from residing too close to schools, parks and other sensitive facilities where children congregate. These residential restriction zones, often ranging between 500 and 3000 ft, can create a unique set of collateral consequences for both the offenders and the community; ranging from potentially increased risks for recidivism due to social isolation and a lack of support (Edwards & Hensley, 2001; Freeman-Longo, 1996; Levenson & Cotter, 2005), to perceived shortages of viable housing options (Grubesic et al., 2007; Zandbergen & Hart, 2006).

Paradoxically, the restriction zones employed by many communities in the U.S. are believed to be creating clusters of convicted sex offenders because housing options are so limited (Bacon, 2007; Gonnerman, 2007; Longa, 2009; Whittle, 2008). For example, in Coram and Gordon Heights, New York, two communities located in Suffolk County, 39 convicted sex offenders are living within 0.5 square miles of each other (Maloney, 2006). Needless to say, this presents a rather difficult situation for local governments and law enforcement agencies. To date, while there is no empirical evidence confirming an increased risk to communities that have elevated numbers of registered sex offenders, neighborhood groups and many local residents remain concerned over their perception that an inequitable distribution of offenders exists in certain areas (Kilgannon, 2006; Maloney, 2006).

Coordinating policy

One of the nagging complexities associated with the development and implementation of offender management strategies in the United States is the lack of cross-jurisdictional coordination. For example, Florida state law stipulates that no convicted offenders may live within 1000 ft of a school, day care center, park or playground. However, many communities in

1 This perception of risk is particularly salient in the context of sex offender clusters.
Florida have established more aggressive residence restrictions. In fact, there are 128 different restrictions on the books, ranging from the statewide minimum of 1000 ft to a local maximum of 3000 ft (Killian, 2008). The resulting patchwork of residence restrictions and their varying geographic extent creates a somewhat haphazard landscape of residential availability throughout the state. Consider the impacts of sex offender restrictions in communities throughout Volusia and Flagler Counties. For example, while Deltona, Flagler Beach, Orange City and Palm Coast (among others) have enacted stricter ordinances of 2500 ft, neighboring Oak Hill maintains a 1500 ft restriction. To further complicate matters, Flagler Beach and Orange City have added libraries and houses of worship to their list of sensitive facilities and the community of Holly Hill stipulates that restricted areas may lie outside its city limits (Longa, 2009). Clearly, there is very little coordination between communities in the same county, let alone between counties throughout the state.

A second problem emanating from this patchwork of residence restrictions is that many of the unincorporated areas within the State of Florida which are lacking sensitive facilities inherit an unfair share of convicted offenders. Perhaps the best example is the Palace Mobile Home Park (PMHP) in Lealman (Pinellas County, Florida), where nearly 50% of the 200 residents are convicted sex offenders (Raghunathan, 2007). More importantly, because the Lealman area is unincorporated, the only sex offender ordinance that applies is the 1000 ft statewide residence restriction. The nearest sensitive facility to the PMHP is Lealman Intermediate School, which is approximately 2100 ft to the southwest. As a result, portions of Lealman (i.e. PMHP) have become a catch-all for registered offenders seeking available accommodations and affordable rents.

Pinellas County is not the only location where these types of conditions exist. For example, during a recent meeting in Hamilton County, Ohio, officials debated the possible outcomes of sex offender out-migration (i.e. spillover) (Brown, 2007). County commissioners and law enforcement representatives believe that convicted offenders will ultimately settle in the unincorporated areas of Hamilton County that have no power to enact laws to prevent it (Brown, 2007). These coordination problems, including the untidy geographic distribution of offenders and residence restrictions, both within and between states and other political jurisdictions at the local level, suggests the need for an objective suite of approaches for identifying offender clusters. This is important for two reasons. First, regional cluster identification can function as a forensic tool for identifying communities that; (a) have spatial concentrations of convicted offenders – even with statewide legislation in place (e.g. residence restrictions) and (b) identifying communities that are subjected to offender spillover emanating from more aggressive ordinances in neighboring communities. Second, if clusters are identified, policy makers would have the opportunity to develop more informed interventions to help communities cope with these populations, while simultaneously ensuring that offenders are not forced into social situations and/or neighborhoods where access to rehabilitation programs and facilities becomes difficult. This is certainly a more appealing and fair approach for a community or region, particularly when compared to the largely ineffective “one-size fits all” approach that would continue to marginalize offender populations, forcing them into unsafe living conditions (Zarrella & Oppmann, 2007).

Sex offender clusters

It is somewhat ironic, given the concerns associated with emergent sex offender clusters (Boyd, 2008; Eakins, 2008; Lujan, 2003; Mazza, 2008; Sahagun, 2008) that so little empirical work exists for aiding policy makers, correction agencies and local law enforcement officials in objectively identifying them. Unfortunately, the few studies that do exist are poorly executed or lack the appropriate statistical context. For example, in addition to relying on ArcGIS generated geocodes for locating offender residences, Clontz and Mericle (2004) determined a sex offender cluster exists in Grundy County, Illinois because four offenders were found living within 500 ft of each other. They conclude, “results bolster the child sexual offender hot spot hypothesis that asserts residency restrictions on offenders may artificially saturate an area” (Clontz & Mericle, 2004, 5). Considering that there is no statistical basis for this statement, it remains uncertain if Grundy County is, in fact, the location of an offender cluster. Along the same lines, Maghelal et al. (2008) use density mapping to identify “risk zones” in Brazos County, Texas. While this type of approach certainly helps display offender densities, there is no way to attribute statistical significance to the results as presented. Clearly, a more rigorous framework that identifies appropriate and valid quantitative methods for detecting and evaluating clusters is needed.

Methodology

Several different methodological approaches can be used for identifying sex offender clusters, including both exploratory spatial data analysis (ESDA) and confirmatory statistics. In many instances, simple cartographic analysis can be helpful. For

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2 In essence, this is a spatial spillover of convicted offenders and occurs when the bulk of available and affordable housing becomes off limits due to residence restrictions implemented by neighboring municipalities.

3 PMHP charges $400 in rent and offers access to a licensed mental health counselor who works with residents in group sessions (Raghunathan, 2007).

4 The misapplication of spatial tools, including geocoding is fairly widespread in the literature on sex offenders. For example, there are multiple instances where researchers rely on calculations of physical distances between offender residences and sensitive facilities using the Google Earth “ruler tool” (e.g., Duwe et al., 2008; MDOC, 2007). Not only is the approach prone to user error, the accuracy of calculations is questionable because of issues associated with Google Earth’s default map projections (Zandbergen, 2008). In other instances, as noted by Zandbergen and Hart (2008), researchers fail to leverage available parcel information when assigning geographic coordinates to offenders, instead opting for spatial estimates of offender locations derived by geocoding routines (e.g., Barnes et al., 2008; Duwe et al., 2008), which are known to generate major positional errors (Cayo & Talbot, 2003).
example, if regional count data associated with sex offender residence information (e.g. the count of sex offenders in an enumeration district) is available; outlier maps can provide one avenue for highlighting extreme values in the distribution and their associated location. For example, Anselin (1998) suggests using a box map, which is a specialized form of a quartile map, for exploring outliers. Of the six categories generated from the data distribution, four correspond to the four quartiles, while the fifth and sixth categories represent bins for high and low outliers. In the context of sex offenders, this type of approach would provide a good first-cut at determining where higher counts of offenders may exist.

A more relevant approach for evaluating the degree of risk associated with offender distributions in a community is a proportional measure. Consider, for example, the total count of offenders in a region, \( O_i \), and the total population within the same region, \( P_i \). The raw rate can then be represented by a simple proportion:

\[
 r_i = \frac{O_i}{P_i} \tag{1}
\]

It is also possible to capture a measure of relative risk by comparing the rate at each location to the overall mean which is the ratio of all convicted offenders in the study region over the total population within the study region:

\[
 \hat{\theta} = \frac{\sum_{i=1}^{N} O_i}{\sum_{i=1}^{N} P_i} \tag{2}
\]

where \( N \) is the number of enumeration districts in the study region. In the case of Illinois (the region to be used as a case study for this analysis), the overall mean is 0.0010. Based on this measure of average risk, the expected number of events can be derived from an underlying population:

\[
 \hat{O}_i = \hat{\theta} \times P_i \tag{3}
\]

Based on Eq. (3), if the observed number of sex offenders either exceeds or falls short of the expected number for a location, a measure of excess risk is captured.

In addition to this type of basic cartographic analysis and data manipulation, nonparametric smoothing also has the potential to help monitor sex offender distributions. Spatial rate smoothers are largely based on the principle of locally weighted estimation (Waller & Gotway, 2004). For example, if a binary proximity measure is used to capture spatial adjacency between enumeration districts, then:

\[
 w_{ij} = \begin{cases} 
 1 & \text{if districts } i \text{ and } j \text{ share a boundary} \\
 0 & \text{otherwise}
 \end{cases}
\]

Given this measure of contiguity, the smoothed rate for a given location \( i \) becomes:

\[
 \hat{r}_i = \frac{\sum_{j=1}^{N} w_{ij} O_j}{\sum_{j=1}^{N} w_{ij} P_j} \tag{4}
\]

Similarly, the smoothed relative risk is specified as:

\[
 \hat{\theta}_i = \frac{\sum_{j=1}^{N} w_{ij} O_j}{\sum_{j=1}^{N} w_{ij} P_j} \tag{5}
\]

Variations on this general theme are also possible. For example, the spatial moving average can also be computed by using a moving window that generates a local average (Kafadar, 1996). As noted by Anselin et al. (2006), the smoothed rate becomes:

\[
 r_i = \frac{O_i + \sum_{j=1}^{N} O_j}{P_i + \sum_{j=1}^{N} P_j} \tag{6}
\]

Where \( j \in S_i \) are the neighbors for \( i \). This modification to the spatial smoother helps emphasize broad trends, but is not good for delineating outliers because it truly represents a regional average, which is specific to individual locations. However, by incorporating Bayesian principles to adjust raw rate estimates, it is possible to generate Empirical Bayes smoothers that help pull raw rate estimates with large variance (i.e. based on a small underlying population) toward the overall mean. The reverse is true for raw rate estimates with a small variance, where they typically remain unchanged (Anselin et al., 2004).

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5 It is also possible to use distance metrics for defining neighbor relationships. If the distance between spatial units exceeds a specified level, the units are not considered neighbors. If the distance is less than the specified level, the spatial units are considered neighbors.

6 For Eq. (6), both the numerator and the denominator are (weighted) sums of the values for a spatial unit together with a set of “reference” neighbors, \( S_i \).
In sum, these smoothing techniques help analysts assess the degree of stability in the results. While no single approach is “best”, Anselin et al. (2004) note that consistencies in the identification of outliers provides a more solid footing for empirical conclusions than situations where each technique yields drastically different results. It is also important to note that none of previously mentioned cartographic or smoothing techniques indicate whether the observed patterns are statistically significant.

If outliers are visually identified in a study region, the next logical step would be to determine if there are any statistically significant patterns within the study area. Specifically, if some type of systematic patterning (i.e. clustering) exists, its identification within a more rigorous statistical context is critical.

In studies where the exact form or location of a cluster is not specified a priori (which is often the case), nonparametric approaches are particularly useful. As defined by Knox (1989), nonparametric cluster detection routines uncover “a geographically bounded group of occurrences of sufficient size and concentration to be unlikely to have occurred by chance.” Many of these nonparametric approaches can be classified as ESDA techniques. Again, ESDA approaches give analysts the ability to explore patterns and uncover anomalies without an explicit hypothesis test. One of the more popular ESDA approaches, which has good potential for use in the identification of sex offender clusters, are global indicators of spatial autocorrelation (Assuncao & Reis, 1999; Moran, 1951). If we assume that a study region is divided into subregions and $O_i$ and $P_i$ represent our observed number of sex offenders and the population at risk in area $i$, respectively, with $i = 1, \ldots, m$, the observed rate in subregion $i$ is $r_i$. Moran’s $I$ is given by:

$$I = \frac{m}{\sum_{ij} w_{ij}} \sum_{ij} w_{ij}(r_i - \bar{r})(r_j - \bar{r}) / \sum_i (r_i - \bar{r})^2$$

(7)

Values of the Moran’s $I$ typically range between $-1$ and $1$, with large positive values indicating a similarity of rates in spatial proximity to each other and values of zero indicating the absence of spatial autocorrelation. While this is an extremely useful statistical test, there are many instances where the underlying assumptions of the Moran’s $I$ null distribution are violated. This is particularly true in study regions where the individual subregions display heterogeneous populations. In an effort to account for population variation across subunits, Oden (1995) proposes the $I_{pop}$ statistic, which is defined as:

$$I_{pop} = \frac{\omega^2 \sum_{ij} M_{ij}(e_i - d_j) - \omega(1 - 2\bar{B}) \sum_i M_{ii} e_i - \omega \bar{B} \sum_{ij} M_{ij} d_i}{\bar{B}(1 - \bar{B})(\omega^2 \sum_i d_i M_{ii} - \bar{v} \sum_i d_i M_{ii})}$$

(8)

where $\omega = \sum O_i$, $\bar{v} = \sum P_i / \omega$, $\bar{B} = \bar{v} / \omega$, $e_i = O_i / \omega$, $d_i = P_i / \omega$ and $M_{ij} = M_{ij} / \sqrt{d_i d_j}$. The value of $M_{ij}$ is interpreted as a spatial weight assigned to a pair of individual cases located in areas $i$ and $j$. Similar to the Moran’s $I$, values of the $I_{pop}$ statistic trending toward 1 suggest spatial autocorrelation.

Alternatively, there are instances where hypothesis tests for detecting clusters of regional count data are appealing. Spatial scan statistics (Kulldorff, 1997; Kulldorff & Nagarwalla, 1995), which can take fully parametric or semi-parametric form (Lawson, 2006), represent one group of techniques that can accommodate this type of explicit statistical testing. Specifically, spatial scan statistics are designed to uncover a geographical subset of events that are more likely than any other subset to be a hot spot or cluster. Spatial scan statistics also test these areas to determine whether or not the cluster could have occurred by chance. Simply put, the geographical subset (e.g. subunits) that maximizes the generated likelihood ratio defines the most likely cluster (Kulldorff, 1997).

For implementing a typical spatial scan statistic, one partitions a study region into $i$ subregions, containing $O$ sex offenders and a total population of $P$. Similar to the autocorrelation statistics, subregions are considered neighboring when there is a transitive relationship between any two units within the zone (Duczmal, 2006). This also allows one to describe the resulting zone as a singular geometric object. Each unique zone, $z$, is formed when the centroids of $i$ spatial units are located within a geometric scanning window (e.g. circle or ellipse) (Kulldorff & Nagarwalla, 1995). In standard implementations of spatial scan statistics, the radii of circular scanning windows are allowed to vary continuously from zero upwards. The standard null hypothesis for a spatial scan statistic is that no clustering exists and the count of sex offenders for each $i$ exhibits a Poisson distribution (Kulldorff, 1997). The spatial scan approach also assumes that expected values for the number of offenders in each $i$ is proportional to its population size. To establish a framework for statistical testing the following notation is used:

$L(z)$ = likelihood under the alternative hypothesis that there is a cluster in zone $z$;

$L_0$ = likelihood under the null hypothesis;

$\psi_z$ = expected number of convicted offenders inside zone $z$ under the null hypothesis;

$a_z$ = the actual number of convicted offenders inside zone $z$.

The likelihood ratio can then be expressed as follows:

$$LR(z) = \frac{L(z)}{L_0} = \left( \frac{\alpha_z}{\psi_z} \right)^{a_z} \left( \frac{O - a_z}{O - \psi_z} \right)^{O - a_z}$$

(9)

when $a_z > \psi_z$, and one otherwise (Kulldorff et al., 1997). Given this statistical framework, one attempts to maximize the likelihood ratio (1) where the maximization is done over the collection of zones identified in the scanning procedure.
To obtain the statistical significance for identified hot-spots, Monte Carlo simulation is used (Besag & Diggle, 1977; Dwass, 1957).

One of the problems with using the spatial scan approach is that as scanning window size increases, the entire study area is eventually overtaken. This effectively mutes the statistical power of the technique in that it generates “negative clusters” outside the scanning window ( Kulldorff & Nagarwalla, 1995). As a result, they suggest using a population constraint or “upper bound” for limiting scan size, such as 50% of the total population. As mentioned previously, there are also concerns in using spatial scan statistics related to the use of geometric scanning windows. For example, by using a circle, the approach is likely to identify circular clusters, even if the associated spatial units have irregular polygonal boundaries.7 Identified hot-spots may also have heterogeneous composition (e.g. high crime mixed with low crime), although their resulting spatial representation simply indicates elevated levels of crime.

While these limitations are certainly important to consider, spatial scan statistics have proven to be effective in highlighting clusters of disease (Burkom & Elbert, 2003; Hjalmars et al., 1998), alcohol mortalities (Hanson & Wieczorek, 2002) and crime (Cecatto & Haining, 2004). In the next section, the outlined methods are applied in an effort to determine if sex offender clusters exist in the State of Illinois.

**Study area, data and results**

**Study area**

The spatial applications for detecting sex offender clusters are conducted in the state of Illinois for 2008. There are several reasons that Illinois was selected for analysis. First, statewide residence restrictions were implemented in 2000 (for schools), giving Illinois and its communities 8 years to sort out the logistics associated with the 500 ft restriction zones. Supplemental restrictions for playgrounds, child-care facilities and victim residences were added in 2006.8 That said, while there is no certainty in Illinois having achieved an equilibrium or “steady-state” for offender distributions, it is certainly a larger temporal window for making adjustments when compared to states that more recently implemented their first strategy (e.g. Idaho, 2006, Indiana, 2006, and Arizona, 2007). Further, Illinois’ 500 ft rule is one of the least restrictive state laws in the country (Meloy et al., 2008), although there are still a handful of states where residence restrictions are not active (e.g. Kansas).9 This would seem to suggest a relatively broad palette of residence choices for convicted offenders, in turn, making clusters unlikely. Finally, the population settlement morphology of Illinois, which intermixes heavily urbanized cores with more suburban, exurban and rural areas, provides the geographic diversity needed for obtaining robust results that may be generalizable to other regions.

**Data**

Sex offender data were acquired from Illinois State Police Sex Offender Information web site (http://www.isp.state.il.us/sor/sor.cfm) on September 16, 2008. Of the 23,121 entries in the database, nearly 60% had to be removed from the analysis. There are several reasons for this. First, many of the offenders in the database did not commit crimes against children. Second, many others were listed as “out of state”. In other words, they no longer lived in Illinois. Finally, 7000 were under the control of the Illinois Department of Corrections. After eliminating these records, all remaining offender address records were standardized using the Centrus geocoding engine from Pitney Bowes (Group 1 Software). Again, numerous errors were encountered, including missing ZIP code digits, offenders listed “in state” but assigned an out of state ZIP code, etc. After these records were removed, a total of 10,700 records remained for analysis.

Because ZIP codes represent the minimum “known” location for the remaining records in the sex offender database, ZIP code area polygons for the state of Illinois (n = 1253) (Caliper, 2007) will be the spatial units utilized for analysis. While the use of ZIP codes for spatial statistical analysis can be problematic in certain circumstances (Grubesic, 2008; Grubesic & Matisziw, 2006), efforts were made to insure that their topological representations were as accurate as possible. Also, while geocoded data are amenable to aggregation to more refined spatial units (e.g. block groups or tracts), this process would have excluded too many observations in the analysis. Furthermore, given the somewhat spotty record associated with the accuracies of geocoded addresses (Zandbergen & Hart, 2008), there are no guarantees that the statistical results would be any more robust at the tract or block group level when compared to the ZIP code area.

Finally, the control data used for the analysis is total population by ZIP code for 2005 (Caliper, 2007). Although Illinois’ residence restrictions are decidedly focused on offenders that target children, using the total population versus children under 18 for the control provides a more conservative estimate of risk.

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7 Recall that many spatial scan statistics simply use the centroids of spatial units for generating zones. This predisposes the approach for identifying centroid-derived zones with a circular structure.

8 Residence restrictions in Illinois target registered child sex offenders from living within 500 ft of sensitive facilities.

9 For a detailed discussion of state-level sex offender residence restrictions, see Meloy et al. (2008).
Cartographic analysis

Fig. 1 displays the results of mapping the total count of sex offenders in each ZIP code area for the state of Illinois. Not surprisingly, there are relatively high numbers of convicted offenders living in Chicago, E. St. Louis and many of the larger cities throughout Illinois. In part, this reflects the population distribution of the state. When one controls for population and calculates raw risk, a much different landscape of sex offender distribution emerges (Fig. 2). For example, while many of the suburban ZIP code areas west of Chicago simply disappear from the map, many of the more rural areas in central Illinois
appear to increase in prominence. The two most notable areas on the map, exhibiting raw rates \( > 0.1250 \), are both located in Chicago. A slightly different approach for capturing the spatial distribution of risk is displayed in Fig. 3. In this instance, offender counts are benchmarked against expected counts derived from the underlying population (i.e. excess risk). There are multiple areas with values greater than 4.0, which suggests an elevated risk of exposure to sex offenders in these ZIP code areas. While Figs. 1–3 certainly capture different aspects of offender distributions, there are dangers associated with these types of approaches for identifying sex offender clusters. Specifically, tabulation areas with extremely low populations can be flagged as areas with high risk or mistakenly classified as a cluster. For example, a ZIP code area with two residents, one of which is a sex offender, would receive a raw rate of 0.50. Is this indicative of a cluster? Probably not, but it is indicative of elevated risk (in its purest sense), which is exactly what these metrics capture.

As an alternative to mapping raw and/or excess risk, Fig. 4a, b display the smoothed spatial rate and the smoothed spatial empirical Bayes measure of sex offender distributions in Illinois. As mentioned previously, the smoothed spatial rate represents a spatial moving average – where the raw rate for spatial units is computed together with raw rates from a set of spatially adjacent units (i.e. neighbors). As illustrated by Fig. 4a, when these calculations are mapped, it appears that areas

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10 Again, 2005 population estimates (Caliper, 2007) derived from Census block group data and aggregated to ZIP code areas were utilized for this analysis.

11 A first-order, distance-based adjacency matrix was calculated for defining spatial neighbors.
with elevated levels of sex offenders emerge throughout the state. While the problems associated with capturing risk in ZIP code areas with small populations are reduced when using spatial smoothing, Anselin et al. (2006) note that the smoothed spatial rates are not good for identifying outliers or clusters because the values portrayed are actual regional averages and not specific to a single location. Similarly, the spatial empirical Bayes map (Fig. 4b) displays a smoothed risk map, but instead of using an averaged rate from a set of spatially adjacent units, it uses a separately computed reference estimate. As noted before, this estimate shrinks raw rates with a large variance toward the overall mean, while leaving those with a small variance as observed. In this case, several ZIP codes in Chicago and the area south of Decatur (central Illinois) appear to be areas of interest.

In sum, the results of the cartographic analysis, both in terms of counts, rates and smoothed rates are relatively consistent. There appears to be an area of increased risk of exposure to sex offenders in portions of Chicago and portions of rural
south-central Illinois near the communities of Ramsey and Effingham. However, it is equally important to note that these techniques used for visualizing the spatial distribution of offenders are not indicative of statistically significant “excesses” (i.e. clusters) in these areas. Instead, this information should be used and interpreted in an exploratory context. Given the consistency in these findings, however, further statistical analysis aimed at detecting spatial clusters is merited.

**Statistical analysis**

In an effort to determine if there is any indication of global clustering for convicted sex offenders, Oden’s $I_{pop}$ statistic was calculated for Illinois’ convicted sex offenders using counts aggregated to ZIP code areas. With an I* value of 0.47 and a p-value < 0.001 under both the z-score and randomization tests for significance, the results of the $I_{pop}$ suggest there is an overall pattern of spatial aggregation of sex offenders in Illinois.\(^{12}\) As noted previously, however, there is no indication as to where these clusters may exist.

In an effort to delineate clusters and uncover their geographic location, Kuldorff’s (1997) spatial scan statistic is implemented with SaTScan v. 8.0 (SaTScan, 2009). The implementation is a fairly simple affair. In delineating high-risk clusters, the scanning circle (or ellipse) with the maximum likelihood ratio (9) is flagged as the most likely (i.e. primary) cluster and the logarithm of the likelihood ratio (LLR) is reported.\(^{13}\) Similarly, it is also possible to scan for low rates. As done previously, sex offender count data aggregated to ZIP code areas are utilized as the cases and 2005 population estimates are used for the controls. One of the interesting caveats in using SaTScan for this type of analysis is the difficulty associated with determining an optimal setting for SaTScan scaling parameters (Chen et al., 2008). While SaTScan’s default scanning parameter includes

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\(^{12}\) Significance levels were obtained through 999 Monte Carlo randomizations.

\(^{13}\) Both circular and elliptical scanning windows produced identical results in this study.
50% of the population at risk, Haining (2003) notes that the resulting primary cluster often occupies a large proportion of the study area – generating less than meaningful results. Second, many times the primary cluster’s composition is heterogenous, intermixing both high-risk and low-risk areas. To combat these problems, Chen et al. (2008) recommend a geovisual analytics approach to enhance the interpretation of spatial scan statistics. In essence, this involves implementing multiple spatial scans with systematically varied parameters. For the purposes of this paper, circular scans are conducted, systematically varying the “population at risk” parameter from 5% to 50% using intervals of 5%.

Due to space constraints, not all of the generated spatial scan results can be highlighted, but Table 1 and Figs. 5 and 6 highlight a compelling case for sex offender clusters in Illinois. As the population parameters were varied in SaTScan, the primary cluster proved to be relatively dynamic – morphing from nearly the entire state (at 50%), to a large swatch of ZIP code

Table 1
Sex offender clusters in Illinois

<table>
<thead>
<tr>
<th>Scan parameters</th>
<th>Approximate locations (^a)</th>
<th>Population</th>
<th>Number of offenders</th>
<th>Expected offenders</th>
<th>Relative risk</th>
<th>LLR</th>
<th>p-Value</th>
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<tr>
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<td>2.02</td>
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<tr>
<td>Chicago 2</td>
<td>104 13</td>
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<td>126.64</td>
<td>50.03</td>
<td>0.001</td>
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<tr>
<td>Chicago 3</td>
<td>694,961 1211</td>
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<td>1.84</td>
<td>174.34</td>
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<tr>
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<td>13.45</td>
<td>0.003</td>
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<tr>
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<td>Chicago 3(^a)</td>
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</table>

\(^a\) Regional names and corresponding ZIP code areas.
areas that include Moline, Davenport, Peoria and Macomb at 5% (Fig. 5). This clearly corroborates the concerns regarding the spatial scan statistic outlined by Haining (2003) and others. In an effort to maximize the LLR, extremely large geographic areas are often identified as primary clusters, particularly when the default values of SaTScan are utilized. While these primary clusters can be relatively meaningless, as is the case in this analysis, there is remarkable consistency in the lower-order clusters for Illinois. Specifically, many of the areas within the city of Chicago and its northern suburbs are delineated as sex offender clusters, regardless of the population parameters used (Fig. 6). Table 1 displays several values for the detected offender clusters in northeast Illinois. In addition to the population and observed/expected offenders, the relative risk, log-likelihood ration and \( p \)-values for the detected clusters are also displayed. Excluding Joliet, the Northwest and Lakes communities, which were not statistically significant, there are six unique clusters of offenders that are identified consistently by the spatial scan statistic. As displayed in Table 1, LLR values for significant clusters range from 13.45 (Chicago Heights) to 174.34 (Chicago 3). The cluster with the most statistical strength is Chicago 3, which includes 25 of the 77 community areas in the city.\(^{14}\) The cluster with the second highest level of statistical strength is Chicago 1, with a LLR of 82.82.\(^{15}\)

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\(^{14}\) Community areas in the Chicago 3 cluster are: Oakland, Grand Boulevard, Fuller Park, New City, Kenwood, Hyde Park, Washington Park, Englewood, West Englewood, Woodlawn, Grater Grand Crossing, South Shore, Auburn Gresham, Avalon Park, South Chicago, Chatham, Calumet Heights, Roseland, Burnside, East Side, South Deering, Pullman, Hegewisch, Riverdale and West Pullman.

\(^{15}\) Community areas in the Chicago 1 cluster are: Austin, East Garfield, West Garfield and Humboldt Park.
Discussion and conclusion

Given the results presented in Study area, data and results, there are several issues worth further discussion. First, the primary objective of this paper was to develop a rigorous and repeatable methodological framework for identifying sex offender clusters. With a combination of ESDA and confirmatory statistical analysis, a range of methods were implemented. One of the more notable outcomes of this analysis was the general correspondence between the areas of interest identified via basic cartography and ESDA and the clusters identified by the spatial scan statistic. In particular, the smoothed empirical Bayes analysis did a relatively good job of highlighting problematic areas in portions of Chicagoland, although the area of interest highlighted in Central Illinois had no clear, corresponding cluster.16

As noted in Sex offender clusters: context and policy, cluster detection can serve multiple purposes, including attempts to determine the existence of spatial concentrations of convicted offenders in communities which may not be benefiting from existing statewide legislation (e.g. residence restrictions) and identifying communities that are subjected to offender spillover emanating from more aggressive ordinances in neighboring communities. While an analysis of spatial spillover for Illinois was outside the scope of this study, it is important to note that the overall framework for detecting sex offender clusters presented in this paper has great potential for highlighting disparities in other communities or regions where residence restrictions vary.

A second point worth briefly acknowledging pertains to the underlying factors that may play an important role in fueling the emergence of these spatial clusters. The composition of Chicago 1 is of interest because it includes several of the most socially disorganized and violent communities in the region (Humboldt Park, Austin and West Garfield) (Morenoff & Sampson, 1997). With a history of gang violence and sexual assault in these communities (Block & Block, 1993; Lloyd, 1997), the underlying compositional features of the Chicago 1 cluster seems to correspond to research that suggests disadvantaged neighborhoods have a disproportionate share of sex offenders (Mustaine et al., 2006). Ironically, Hughes and Burchfield (2008) note that the disadvantaged neighborhoods in Chicago, including areas like Humboldt Park and Austin, have

16 The areas south of Decatur were included in many of the primary clusters.
a disproportionate share of sensitive facilities such as parks, schools, and daycares. Why are offenders *not* spurning these disadvantaged neighborhoods and opting to establish residence in communities with fewer sensitive facilities, restricted areas and less social disorganization? There are many potential reasons for this. First, Illinois’ 500 ft restriction zone is one of the least restrictive in the United States. Simply put, this residence restriction leaves plenty of options for convicted offenders in all neighborhoods, including those dense with sensitive facilities in Chicago. A second factor may relate to the location of reentry points for sex offenders into the community. In many locations, formal rehabilitative facilities are located in socially disorganized areas. As Grubesic et al. (2008) note, this is certainly the case for sex offenders in Ohio and, in fact, may be the case in Chicago. The Illinois Department of Corrections operates its largest sex offender counseling service in the state for

![Fig. 7. Geographic scale and sex offender cluster detection.](image-url)
offenders being released to Cook County at 3508 West Grand Ave, which is located in the Chicago 1 cluster, specifically, the Humboldt Park neighborhood. A third factor may be related to affordability – with lower rental costs in disadvantaged areas. Finally, there is a fledgling notion, with relatively little empirical proof, that many sex offenders actually gravitate to socially disorganized areas because they are less likely to be “noticed” by community members and will not be forced to tolerate any type of post-release hazing or harassment by concerned residents (Kilgannon, 2006). This was found to be the case, at least for the spatial distribution of offenders, in Hamilton County, Ohio (Grubesic et al., 2008).

Another facet of this study worth further discussion pertains to the heterogeneity of clusters, particularly the composition of Chicago 3. As noted previously, a weakness of the spatial scan statistic is its propensity to include heterogeneous levels of zonal risk in identified clusters. In this context, this translates to incorporating ZIP code areas into clusters that may not exhibit particularly high levels of relative risk. This is certainly the case for Chicago 3, where relative risks range from 0.79 to 2.76. From a geometric perspective, one could argue that such instances arise when the spatial scan window encounters a “doughnut” configuration of spatial risk – with the edges of the scan window containing high-risk areas that are surrounding relatively low-risk areas. Because the window is circular, all of the areas are eventually included in the cluster. Obviously, there are other geometric configurations that could generate this error too. Regardless, care is needed when interpreting the identified clusters.

In addition to the problems with heterogeneity in clusters, it is also essential to note that issues of geographic scale are important to consider in sex offender cluster detection. The analysis and results presented in this paper take a decidedly “regional” approach to cluster detection. While the clusters identified for Illinois certainly represent high-risk locations, this is statistically relevant at the statewide scale only. If the geographic scale of analysis was shifted to Census block groups, tracts or communities in Chicago, a much different picture of risk may emerge. For example, while portions of Chicago 1 and Chicago 3 may be included as clusters when using different subregions for analysis, it is unlikely that the overall morphology of risk would be identical. As illustrated by Fig. 7, when the ZIP code defined clusters from this analysis are overlaid on Census community areas, not only is there a spatial mismatch in terms of both geographic scale and boundary delineation, when these areal units are visualized with geocoded offender locations, the nuances of spatial cluster detection become more evident. Specifically, in both detected clusters, there are clearly portions of the ZIP code areas with more offender presence than others. This would also hold true if the scale of analysis was changed to community regions.

In closing, this paper provides a rigorous and repeatable methodological framework for identifying sex offender clusters. Results indicate that several areas in the Chicagoland region exhibit spatial clusters of convicted sex offenders, although the level of risk varied significantly between these areas. In addition, although the analysis was conducted at the regional scale, a similar mixture of ESDA and confirmatory statistical analyses would perform well at more local levels of analysis. Finally, the methodological framework outlined in this paper has significant potential for aiding policy makers, correction agencies and local law enforcement officials in objectively identifying sex offender clusters, which is an important first step in developing a more fair and balanced approach to sex offender policy in the United States.

References


