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Geographic approaches to quantifying the risk environment: a focus on syringe exchange program site access and drug-related law enforcement activities

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Abstract

The concept of the “risk environment” – defined as the “space … [where] factors exogenous to the individual interact to increase the chances of HIV transmission” – draws together the disciplines of public health and geography. Researchers have increasingly turned to geographic methods to quantify dimensions of the risk environment that are both structural and spatial (e.g., local poverty rates). The scientific power of the intersection between public health and geography, however, has yet to be fully mined. In particular, research on the risk environment has rarely applied geographic methods to create neighbourhood-based measures of syringe exchange programs (SEPs) or of drug-related law enforcement activities, despite the fact that these interventions are widely conceptualized as structural and spatial in nature and are two of the most well-established dimensions of the risk environment. To strengthen research on the risk environment, this paper presents a way of using geographic methods to create neighbourhood-based measures of syringe exchange programs (SEPs) or of drug-related law enforcement activities, despite the fact that these interventions are widely conceptualized as structural and spatial in nature and are two of the most well-established dimensions of the risk environment. To strengthen research on the risk environment, this paper presents a way of using geographic methods to create neighbourhood-based measures of (1) access to SEP sites and (2) exposure to drug-related arrests, and then applies these methods to one setting (New York City). NYC-based results identified substantial cross-neighbourhood variation in SEP site access and in exposure to drug-related arrest rates (even within the subset of neighbourhoods nominally experiencing the same drug-related police strategy). These geographic measures – grounded as they are in conceptualizations of SEPs and drug-related law enforcement strategies – can help develop new arenas of inquiry regarding the impact of these two dimensions of the risk environment on injectors’ health, including exploring whether and how neighbourhood-level access to SEP sites and exposure to drug-related arrests shape a range of outcomes among local injectors.
Keywords

Risk environment; HIV; injection drug use; geographic methods; syringe exchange programs; drug-related law enforcement

The concept of the “risk environment” – defined as the “space…[where] factors exogenous to the individual interact to increase the chances of HIV transmission” (Rhodes, Singer, Bourgois, Friedman, & Strathdee, 2005, p. 1027) – draws together the disciplines of public health and geography. The scientific power of this intersection, however, has yet to be fully mined. Geography offers advanced quantitative methods that can enrich our capacity to assess dimensions of the risk environment that are simultaneously structural and spatial. We define structural and spatial dimensions of the risk environment as geographically-bounded social, economic, and political conditions, and organized responses to these conditions, that shape drug users’ vulnerability to HIV infection (Blankenship, Bray, & Merson, 2000; Des Jarlais, 2000). While geographic methods have been increasingly applied to measure these dimensions of the risk environment (Friedman et al., 2006; Latkin, Williams, Wang, & Curry, 2005; Maas et al., 2007; Rothenberg, Muth, Malone, Potterat, & Woodhouse, 2005), to date these methods have rarely been used to assess access to syringe exchange programs (SEPs) or exposure to drug-related law-enforcement activities, though these interventions are among the most well-studied dimensions of the risk environment (Bluthenthal, Lorvick, Kral, Erringer, & Kahn, 1999; Cooper, Moore, Gruskin, & Krieger, 2005; Friedman et al., 2006; Ksobiech, 2003; Maher & Dixon, 1999; Wodak & Cooney, 2005; Wood et al., 2003), and are routinely conceptualized as structural interventions operating within defined geographic areas (Bastos & Strathdee, 2000; Blankenship et al., 2000; Des Jarlais, 2000; Sumartojo, 2000; Sumartojo, Doll, Holtgrave, Gayle, & Merson, 2000).

Here, we discuss the rationale for conceptualizing SEP access and exposure to drug-related law enforcement activities as structural and spatial dimensions of the risk environment; review geographic methods that allow us to operationalize them as such; and illustrate the application of these methods to one setting (New York City [NYC], USA). We preface this review by locating the intersection of geography and public health within its disciplinary and historical context.

There has been a broad shift in public health in recent years, from locating the causes of health and disease almost solely within individuals to exploring putative causes within multiple intersecting levels of life, including genetic, biological, psychological, network, and macrosocial processes (Krieger, 1994; Macintyre & Ellaway, 2003; Susser & Susser, 1996a, 1996b). This etiologic shift is evident in recent theoretical advances which conceptualize health and disease as produced by intersections among these processes (e.g., ecosocial and eco-epidemiologic theories (Krieger, 1994; Susser & Susser, 1996a, 1996b)). It also manifests in analytic methods which seek to allocate variation in an outcome to specific levels of life (e.g., hierarchical linear modelling methods) (Raudenbush & Bryk, 2002), and in multilevel interventions.

This etiologic shift in public health has fostered a generative engagement with the discipline of geography (McClafferty, 2003). This engagement is largely rooted in mounting recognition that structural factors are potent determinants of health (Berkman & Kawachi, 2000; Navarro & Muntaner, 2004), and that a subset of these factors is geographically bounded (Diez-Roux, 2002, 2003, 2004; Macintyre & Ellaway, 2003). To illustrate, income inequality, frequently studied as a possible structural determinant of health, is produced in part by fiscal policies and labour laws that are promulgated and enacted by governments with sovereignty over particular geographic areas (Neckerman & Torche, 2007; Smeeding, 2005). Accordingly, an emerging
line of public health research has turned to geographic methods to quantify exposure to select structural factors, and to assess their impact on patterns of health and disease (e.g., Austin et al., 2005; McClafferty & Grady, 2004, 2005).

As explicitly recognized in Rhodes’ earliest writings on the subject (Rhodes, 2002), the development of the “risk environment” concept is part and parcel of this etiologic shift within public health, and one that emerged in response to the failure of biomedical models to adequately explain, and intervene in, the HIV epidemic among drug users. Paralleling trends in the broader field of public health, research on the risk environment has increasingly turned to geographic methods to quantify structural exposures and study their consequences for users’ health (Cooper, Friedman, Tempalski, & Friedman, 2007; Friedman et al., 2006; Fuller et al., 2005; Hembree et al., 2005; Latkin et al., 2005; Vernez Moudon, 2007). For example, Bluthenthal and colleagues (2007) located study participants within census tracts and concluded that injectors residing in tracts with higher proportions of Black residents were less likely to engage in receptive syringe sharing than were other injectors, net individual-level characteristics.

To date, however, the engagement between public health and geography has rarely extended to include two of the most well-established dimensions of the risk environment: SEP access and drug-related law enforcement activities. Next, we review the rationale for conceptualizing these dimensions of the risk environment as spatial and structural interventions, and present geographic methods that allow one to operationalize them as such. The geographic methods presented here are not new; researchers in multiple disciplines have frequently applied them to quantify law enforcement activities and access to health services in the past. We present them here to promote their application to research on the risk environment, and in particular to capture access to SEP sites and exposure to drug-related enforcement activities.

We have focused our discussion on ways of conceptualizing and measuring SEP access and law enforcement activities as interventions that operate within relatively small geographic areas, like neighbourhoods. We select this geographic level because (1) the prevalence of drug-related health outcomes and behaviours among injectors often vary across neighbourhoods and other small areas (Buchanan, Shaw, Teng, Hiser, & Singer, 2003; Des Jarlais et al., 2003; Thorpe, Bailey, DeZheng, Monterroso, & Ouellet, 2001), and (2) as discussed below, evidence suggests that SEPs and drug-related law enforcement activities have pronounced local effects (though their impacts are also evident at larger scales).

As Diez-Roux (2007) has noted, multiple methods exist to assign exposure values to small areas; each of these methods carries particular strengths and weaknesses. Here, we capture exposures by applying Geographic Information Systems (GIS) to existing data (e.g., archived SEP schedules). Alternative measures based on human observation are also possible. For example, local SEP access could be assessed via participant self-report, aggregated to neighbourhoods (Diez-Roux, 2007). A strength of this approach is that it captures an exposure as experienced by residents. The stability of such measures, however, rests on having relatively large samples in each neighbourhood; (Diez-Roux, 2007) moreover, the resulting measures will be relatively blunt, and thus may hamper explorations of variations across time and space. Alternatively, trained raters could assess SEP access or enforcement activities (Diez-Roux, 2007). This method does not require large samples in each neighbourhood, but may be limited in its ability to capture an exposure as experienced by residents, and will produce relatively blunt measures. The GIS-based methods presented here allow us to create more precise measures that facilitate analyses of spatial and temporal trends, and are less resource-intensive than those based on human observation (particularly if multiple geographic areas are studied over time). However, they are predicated on the availability and accuracy of needed datasets, and fail to capture exposures as experienced by residents (Diez-Roux, 2007). These measures
are not mutually exclusive, and perhaps the GIS-based measures described here could be coupled with measures based on human observation.

**Conceptualizing Syringe Exchange Programs as Structural and Spatial Interventions**

Many investigators have noted that SEPs are structural interventions: they alter the conditions in which people use drugs by increasing their access to sterile syringes, health services, and social services (Bastos & Strathdee, 2000; Blankenship et al., 2000; Des Jarlais, 2000; Sumartojo, 2000; Sumartojo et al., 2000). Commonly-used measures of these interventions, however, tend to query individual-level access to syringes via these programs (Bastos & Strathdee, 2000; Des Jarlais, 2000). Research relying exclusively on these measures to assess SEP impact elides the possibility that SEPs affect health and health behaviours through multiple mechanisms, including (1) increasing the quantity of sterile syringes available through secondary and satellite syringe distribution and street-based sales, and (2) reducing background HIV prevalence, and thus diminishing the likelihood that receptive syringe sharing events will result in infection. Recent research on syringe coverage of geographically-defined populations of injectors responds to calls to conceptualize and measure SEPs as structural interventions (Aceijas, Hickman, Donoghoe, Burrows, & Stuikyte, 2007; Sharma, Burrows, & Bluthenthal, 2007; Tempalski et al., 2008).

A vital but nascent complement to research on syringe coverage and HIV lies in conceptualizing and measuring SEP sites themselves as structural and spatial interventions operating within relatively small geographic areas – that is, as interventions that shape injectors’ vulnerability to HIV by altering their local access to health and social services. Health services research routinely treats service delivery sites (e.g., health clinics) as structural interventions operating in local areas (Bamford et al., 1999; Haynes, Bentham, Lovett, & Gale, 2002; Love & Lindquist, 1995; US General Accounting Office, 1995), but this construction has rarely been extended to include SEPs. There are three core reasons to pursue related research. First, individuals who regularly attend SEPs in person engage in fewer injection-related risk behaviours than other injectors (including those who receive syringes from SEPs via secondary exchange) (Huo, Bailey, Hershow, & Ouellet, 2005; Lorvick et al., 2006). Second, many SEPs offer health and social services on-site that improve participants’ well-being, including case management services, wound care, and housing assistance (Grau, Arevalo, Catchpool, & Heimer, 2002; Pollack, Khoshnood, Blankenship, & Altice, 2002). Accessing these services requires in-person contact with program staff. Third, proximity to an SEP site is a major determinant of program utilization: Rockwell et al. (1999) found that injectors in New York City who lived within a 10-minute travel distance of an SEP were almost three times more likely to attend a program than other injectors, controlling for potential individual-level confounds. As is the case with other health services, the presence, addition, or removal of an SEP site from a local area may thus shape local injectors’ engagement in harm reduction services.

Geographic methods can be applied to create measures of SEP sites as structural and spatial interventions in local areas. Creating these measures will allow the field to explore new questions, including (1) whether variations in spatial access to an SEP across geographic areas and/or time shape variations in a range of health behaviours and outcomes among local injectors; and (2) whether the relationships between spatial access to an SEP and these outcomes vary by neighbourhood and individual characteristics. In areas where SEP site location can be planned to some extent, these measures can also help determine whether geographic areas with high rates of drug-related health problems need improved spatial access to SEPs.
Conceptualizing Drug-Related Law Enforcement Activities as Structural and Spatial Interventions

Police departments design and implement drug-related law enforcement strategies as structural and spatial interventions that often target relatively small geographic areas (Fyfe, 1992; Moore, 1990). These strategies are explicitly constructed to alter the conditions in which drugs are sold, acquired, and used; strategic emphasis on “deterrence” exemplifies this structural construction (Fyfe, 1992; Moore, 1990). Testifying to the spatial and relatively local nature of drug-related enforcement strategies, initiatives often target specific neighbourhoods or clusters of neighbourhoods (Fyfe, 1992; Moore, 1990).

Reflecting the spatial and structural nature of drug-related law enforcement strategies, qualitative studies routinely generate rich descriptions of the processes through which a particular strategy re-shapes the contexts in which users live (Cooper et al., 2005; Maher & Dixon, 1999; Rhodes et al., 2003; Small, Kerr, Charette, Schechter, & Spittal, 2006). Likewise, this design and implementation are evident in the conceptualization of the exposure in quantitative studies of drug-related law enforcement and users’ health. For example, in articles quantifying the relationship between drug-related law enforcement activities and users’ health, introductory text often describes local changes in surveillance activities and police presence (Davis, Burris, Kraut-Becher, Lynch, & Metzger, 2005; Wood et al., 2004).

Quantitative measures, however, rarely capture law enforcement activities as structural and spatial interventions. With rare and recent exception, quantitative studies of research on the risk environment tend to operationalize drug-related law enforcement efforts either (1) as an individual-level exposure, querying participants’ arrest histories and fear of arrest (Bluthenthal et al., 1999; Grund, Heckathorn, & Anthony, 1995) or (2) in terms of a strategy’s presence or absence over time (Davis et al., 2005; Wood et al., 2004). Individual-level measures may underestimate the impact of policing on users’ health: the enforcement strategy may affect users’ health through multiple mechanisms which include – but are not limited to – an individual’s arrest history and fear of arrest. For example, high arrest rates in a neighbourhood may escalate turnover in injectors’ local sexual and drug use networks, and thus increase exposure to HIV. While studies comparing drug use practices before and after the onset of a police strategy recognize that the strategy can set the conditions for participants’ harm reduction efforts and health, a dichotomous measure (i.e., presence vs. absence) may be too blunt to adequately assess the strategy or its health impacts. To illustrate, the intensity of enforcement may wax and wane over the lifetime of a single strategy, and officers implementing a particular strategy may or may not disproportionately target specific subgroups within the affected geographic areas.

Several recent analyses speak to the utility of applying geographic methods to bridge the gap between conceptualizations of law enforcement activities as structural and spatial interventions and current quantitative measures of this construct. For example, Shannon et al. (2008) mapped police activity, violence, and health service sites as experienced by sex workers in Vancouver (Canada), and concluded that the geographic correspondence among these phenomena restricted women’s access to health care and sterile syringes.

Applying geographic methods to create measures of drug-related law enforcement activities as structural and spatial interventions can open up new arenas for research, including exploring (1) whether the impact of elevated drug-related arrest rates on local injectors’ risk behaviours and health varies over time; and (2) the extent to which high syringe coverage in a local area buffers the deleterious effects of an elevated drug-related arrest rate on receptive syringe sharing.
Next, we describe the application of geographic methods to create small-area measures of access to SEP sites and exposure to drug-related enforcement activities that recognize their spatial and structural nature. We accompany each description with illustrations from an ongoing study of the risk environment and injectors’ health in NYC (“Spatial Variations in IDU HIV Risk: Relationship to Structural Interventions”, DA023391). The implementation of the measures described here assumes access to ArcInfo (ESRI) or another GIS software package and to digital maps of relevant administrative boundaries (see Figure 1 for a list of geospatial resources). All analyses were run on ArcInfo 9.2 (ESRI, 2006).

Measuring Spatial Access to SEPs

We define “spatial access to SEPs” as the presence of SEP sites within a local area in a given time period. This concept is distinct from “aspatial access”, which refers to barriers and facilitators of SEP use that are not rooted in geography (e.g., stigma) (Khan, 1992; Luo & Wang, 2003). Moreover, we are seeking to capture potential access, which concerns reasonable possible use, rather than revealed access, which refers to actual service use (Phillips, 1990). We note that the measure proposed below could be adapted to assess revealed spatial access to other health service sites, including drug treatment programs.

As always, the selection of the unit of analysis should be based on the study’s purpose. For example, if the study’s ultimate goal is to explore the impact of NIMBY (“not in my backyard”) policies and practices on spatial access to SEPs, then the unit of analysis should correspond to the geographic area at which these policies and practices are enacted. If instead the study’s ultimate goal is to explore the impact of spatial access to SEPs on injecting residents’ HIV risk, then the measure might assess SEP access within neighbourhoods. We refer to the full complement of analytic units as the “study area”. Regardless of the unit selected, the measure of spatial access to SEPs within these areas can be created in three stages, and will capture SEP density per square mile for each unit of analysis and time period of interest.

Stage 1: Locating SEP sites

The first stage of this measurement process consists of identifying (or “geocoding”) the latitude/longitude of each of the SEP sites in the universe of SEPs relevant to the analysis (Cromley & McClafferty, 2002). At a minimum, the universe of SEPs should include all sites operating in the study area during the time period of interest (e.g., year, month). For studies of the impact of spatial SEP access on injectors’ health, this universe should also include SEPs located in a buffer zone encircling the study area (or each of the units of analysis, when these units are not adjacent) (Lawson, 2001). We address the size of this buffer zone below, but the inclusion of SEPs lying within this zone reflects the possibility that injectors living within the study area may travel to SEPs lying just outside this study area, unless geopolitical obstacles impede such travel.

The term “geocoding” refers here to the process of identifying the longitude/latitude of each SEP site’s street address, and then locating this point on a digital map of the study area (and possibly in the buffer zone encircling the study area). Geoencoding SEP sites may be more complex than geocoding other healthcare sites because SEPs may operate out of vans or walkabouts, and thus have no street address. In these cases, geocoding accuracy is improved when research staff members collaborate with SEP staff members to identify the nearest intersection to the van or walkabout stop, and geocode that intersection. Sites lacking a street address that are located on a block face can be geocoded by identifying the two intersections that define that block, and then locating the longitude/latitude point that lies on the block face at the midpoint between these two intersections.
Stage 2: Calculating SEP access

Kernel density estimation (KDE) methods are commonly used in health services research to calculate spatial access to services (McClafferty & Grady, 2004, 2005), and can also be applied to create measures of spatial access to SEPs. To initiate this estimation method, a grid of small, equally-sized square cells is laid atop the digital map of SEP site point locations (Cromley & McClafferty, 2002). Using this map of cells and SEP point locations, KDE methods then calculate an SEP site access value for each cell. As described in Figure 2, site access is calculated as a function of the following three parameters: (1) the maximum distance \( r \) that an individual would reasonably travel to reach an SEP; (2) the Euclidean distance between the cell centre (or “centroid”) and each SEP site within \( r \) distance of the cell centroid; and (3) a distance-decay probability function which lets access decline with the centroid’s distance from the SEP site (Cromley & McClafferty, 2002).

One can envision this estimation process as follows. For each cell in the grid, a circle of radius \( r \) is drawn with the cell’s centroid as its centre (Cromley & McClafferty, 2002). A cell with many SEP sites within its circle will have a higher access value than a cell with few or no sites; because of the distance-decay function, a cell with one site located close to its centroid will have a higher SEP access value than one with a single SEP site located near the cell’s perimeter (Cromley & McClafferty, 2002). The quartic kernel function is conventionally used to model decaying spatial access to health service sites (Cromley & McClafferty, 2002).

The value of \( r \) – the distance an individual will reasonably travel to reach an SEP – is pivotal in this formula, and ideally should be derived using local data on injectors’ travel patterns to SEPs. In areas where injectors commonly drive or take public transportation to SEPs, \( r \) should be substantially larger than in areas where injectors walk to reach these sites.

Stage 3: Calculating area-based spatial access to SEPs

Once cell-specific access values have been calculated, a digital map of the boundaries of the geographic units of analysis (e.g., neighbourhoods) should be overlaid on the map containing cells and SEP point locations. To calculate SEP access for each unit of analysis, one averages cell-specific SEP access values across all cells within each unit. The resulting measure will capture the density of SEPs per square mile within each unit of analysis during the time period of interest (Cromley & McClafferty, 2002).

Reflections on the SEP access measure

The above stages can be adapted so that the resulting measure also captures temporal access to SEPs, or access to specific types of SEPs. SEP site operating hours can vary substantially within a study area and these variations will profoundly affect access. It is possible to create a spatiotemporal measure of SEP access by weighting the spatial measure by \( t \), defined as the number of hours a site is open each week divided by the highest number of operating hours reported by any SEP site during the study period, or by some ideal number of operating hours. Additionally, separate access measures can be created for different SEP modalities.

KDE-based measures may produce lower spatial access values than other spatial access measures (e.g., the “Two-Step Floating Catchment Area” [2SFCA] method) (Yang, Goerge, & Mullner, 2006). Unlike other methods, however, KDE-based measures do not require data on the number of people needing services, an important characteristic for research with injectors. Selecting shorter radii can reduce this underestimation (Yang et al., 2006), though of course these radii should still capture “reasonable access” to SEP sites.
Illustration

We illustrate Stages 1-3 using data from NYC in 2005. We selected “United Hospital Fund (UHF) districts” as the spatial unit of analysis because they approximate neighbourhoods, and key variables were available for these units. The universe of SEPs includes all sites operating within NYC’s boundaries in 2005, and also all sites located within a 1-mile buffer zone of these boundaries. There were 33 legal SEP sites in this universe as described by published schedules; each site was located on a digital map of NYC and its environs via its longitude and latitude (Stage 1). A grid of evenly-sized cells was then overlaid on this digital map, and the KDE formula applied to calculate SEP access for each cell (Stage 2; Figure 3). We set $r$ to 1 mile. We selected this value of $r$ based on Rockwell et al.’s (1999) finding that injectors living within a 10-minute travel distance of an SEP were almost three times as likely to attend an SEP; in NYC, it takes about 10 minutes to walk ½ mile. We doubled this value because, in the KDE formula, access declines to 0 at the outer limits of $r$. We then overlaid a digital map of NYC’s 42 UHF districts on the existing map, and calculated spatial access to SEP sites for each district by averaging KDE values across all cells within each district (Figure 4).

The resulting measure suggests that there was substantial variation in spatial access to SEPs across NYC’s 42 UHF districts in 2005 (Table 1). Residents of twenty-five percent of NYC’s 42 UHF districts had no SEP site within a mile of their homes. In total, 50% of the 42 UHF districts had a mean SEP access value of ≤0.09 (range: 0.00 to 4.69), indicating very low SEP density per square mile (a value of 1 indicates one SEP site per square mile). 24% of UHF districts, however, had an average spatial access value of ≥1.00, or more than 1 SEP site per square mile.

These values underestimate SEP site access because they ignore public transportation routes to each site. Future analyses may include (1) identifying bus and subway stops within a certain travel distance of each site; and (2) using the KDE formula to calculate SEP site access for cells within a particular radius of each of these stops. In this model, SEP access for each cell would be the sum of its transportation-based access value and its original, non-transportation-based access value. Additionally, the actual locations of mobile sites may occasionally have deviated from published locations because of police activity and other factors. Our measure could not accommodate these deviations. If deviations were minor or infrequent, however, their impact on the UHF-level spatial site access should be slight.

Drug-Related Criminal Justice Activity

We define “spatial exposure to drug-related law enforcement activities” as the local density of drug-related arrests within a geographic area during a particular time period, and operationalize it as the drug-related arrest rate within a given geographic area and time. We note, however, that the methods described here could also be applied to create measures of other drug-related enforcement activities reported in the aggregate for small geographic areas, including local incarceration rates and per capita police presence.

The geographic unit of analysis should be rooted in the research’s purpose. Studies of the effects of a particular police strategy on users’ health might select police precincts as their unit of analysis; studies with a broader purpose (e.g., studying the effects of multiple structural and spatial dimensions of the risk environment) might select neighbourhoods as the unit of analysis.

Regardless of the unit of analysis selected, researchers often encounter difficulty calculating drug-related arrest rates: data on the rate’s numerator (i.e., total number of drug-related arrests) is often released at a different geographic scale than data on the denominator (i.e., size of the at-risk population) (e.g., Bluthenthal et al., 2007; Davis et al., 2005). Calculating drug-related arrest rates thus requires allocating data from one unit of analysis to another (e.g., allocating...
census-tract-level data on population size to police precincts, or precinct-level arrest data to tracts). Geographic methods can help resolve this boundary problem, albeit imperfectly. In the example below, the study’s unit of analysis approximates local neighbourhoods, and the goal is to allocate precinct-level arrest data to these units.

**Stage 1: Locating precincts within neighbourhoods**

One starts by intersecting the digital map of neighbourhood boundaries with the digital map of precinct boundaries in the study area. Some precincts may fall entirely within the boundaries of a single neighbourhood. Other precincts will be sliced into pieces, or slivers, that fall within the boundaries of two or more neighbourhoods.

**Stage 2: Allocating arrests to neighbourhoods**

Each sliver represents a certain percentage of its parent precinct’s surface area. The total number of drug-related arrests recorded in a parent precinct can be allocated to neighbourhoods according to the percentage of that precinct’s surface area that is located in each neighbourhood (e.g., if 50% of a precinct’s surface area is contained in a neighbourhood, then half of its arrests should be allocated to that neighbourhood).

**Stage 3: Calculating neighbourhood-specific arrest rates**

The total number of arrests made in each neighbourhood can then be calculated by summing the number of arrests that were allocated to it in Stage 2. Dividing that total by the “at risk” population then creates estimates of neighbourhood-specific arrest rates. Ideally, this denominator would capture all (and only) people engaging in illicit drug-related activity. Those data are rarely available; moreover, officers can mistakenly arrest non-users on drug-related charges. Denominators can thus (and perhaps must, due to data constraints) consist of the total neighbourhood population, minus age groups who are rarely arrested (mistakenly or not) on drug-related charges (e.g., people under 15 and over 64).

**Reflections on the measure**

This method assumes that drug-related arrests are evenly distributed across each precinct’s surface area. This assumption may be routinely violated, particularly when police target places within precincts. One can capture the magnitude of possible error introduced by violating this assumption by calculating the percent of arrests made in each neighbourhood that were originally allocated by slivers (rather than by whole precincts).

Some subgroups of users may be disproportionately likely to be arrested (Human Rights Watch, 2008). If injecting residents perceive this selective targeting, the strategy may have a greater effect on the targeted population than on other injectors (Cooper et al., 2005; Davis et al., 2005; Maher & Dixon, 1999). When possible, it might be useful to calculate subgroup-specific arrest rates for each neighbourhood to create more refined exposure measures.

**Illustration**

To illustrate this method, we return to the study of the risk environment and injectors’ health in NYC. The geographic unit of analysis is again the UHF district, and we seek to describe cross-district variation in exposure to drug-related arrests in 2000, both across all 42 UHF districts and between “crackdown” districts and “non-crackdown” districts. Crackdowns are sustained enforcement strategies designed to reduce street-level drug activity through heightened surveillance and arrests of drug users and low-level dealers (Greene, 1996). In the year 2000, there were active crackdowns in 27 of NYC’s 76 police precincts (Cooper et al., 2005).
Using the three-stage method described above, we allocated the 335,543 drug-related arrests occurring in NYC’s 76 precincts in 2000 to NYC’s 42 health districts, and then calculated drug-related arrest rates per 10,000 residents for each UHF district (see Figure 5); rate numerators and denominators were limited to individuals aged 15 to 64. Districts were classified as “crackdown districts” if at least 75% of their surface area was covered by a crackdown precinct. The median drug-related arrest rate in the eight crackdown districts was 67 arrests per 10,000 residents (range: 14 per 10,000 to 95 per 10,000); the median arrest rate in the 34 non-crackdown districts was 18 arrests per 10,000 residents (range: 2 per 10,000 to 77 per 10,000; Table 1). Notably, (1) there was considerable variation in drug-related arrest rates across crackdown districts, though all were nominally targeted by the same strategy, and (2) some non-crackdown districts had higher arrest rates than crackdown districts (neither pattern is attributable to variations in the percentage of a district’s surface area that is covered by a crackdown).

Conclusions

Geographic methods supported the creation of neighbourhood-based measures of SEP site access and of exposure to drug-related arrests that capture their spatial and structural natures, and that are thus congruent with conceptualizations of these interventions. As applied to NYC, these measures suggest that injectors living in about half of the city’s UHF districts have extremely poor or no access to an SEP site, while those living in 24% of the districts have >1 SEP site per square mile. Additionally, measures revealed considerable variation in drug-related arrest rates across districts that were nominally undergoing the same drug-related enforcement strategy, and also identified districts that were not targeted by this strategy yet still experienced elevated drug-related arrest rates. Geographic methods allowed us to capture the complexity of a drug-related law enforcement strategy as it was enacted.

These measures can help further develop research on the aetiology of HIV among injectors, and can support SEP-related planning efforts. Multilevel models can explore the impact of neighbourhood-level SEP access and drug-related arrest rates on individual injectors’ HIV risk. One particular topic merits inquiry. Neighbourhoods with high SEP site access may also have high drug-related arrest rates. Past research on policing, SEP utilization, and HIV risk suggest that the relationship between neighbourhood-level SEP access and injectors’ HIV risk may vary by local drug-related arrest rates. Multilevel models can quantify this interaction, identify sub-groups of injectors who are particularly affected, and explore causal pathways. Moreover, when complemented with local data on the distribution of injectors across neighbourhoods, these measures can also support SEP planning efforts. Overall, the measures discussed here can help better align the conceptualizations of SEPs and drug-related law enforcement activities with their operationalization, and further explorations of the risk environment.

Acknowledgments

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Moore, M. An analytic view of drug control policies. Cambridge, MA: Harvard University; 1990.


1. Maps and georeferenced data
   - Geography Network: [http://www.geographynetwork.com](http://www.geographynetwork.com)
   - Univ. of Edinburgh School of GeoSciences: [http://www.geo.ed.ac.uk/](http://www.geo.ed.ac.uk/)
   - University of Oregon Map Library: [http://libweb.uoregon.edu/map/map_section/map_internationaldatasets.html](http://libweb.uoregon.edu/map/map_section/map_internationaldatasets.html)
   - GIS @ the Univ.of Chicago: [http://gis.uchicago.edu/data.htm](http://gis.uchicago.edu/data.htm)
   - US Census Bureau (US only): [www.census.gov](http://www.census.gov)
   - Federal Geographic Data Committee: [http://www.fgdc.gov/nsdi/nsdi.html](http://www.fgdc.gov/nsdi/nsdi.html)

2. GIS software:

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*Figure 1.*

Geospatial Resources
Figure 2.
Measuring Spatial Access to SEP Sites
Figure 3.
Figure 4.
Mean Density of Syringe Exchange Programmes (SEPs) per Square Mile in New York City’s 42 United Hospital Fund (UHF) districts, 2005.
Figure 5.
Drug-related arrest rates per 10,000 adult (age 15-64 years) residents in New York City’s 42 United Hospital Fund (UHF) districts, 2000. UHFs with drug crackdowns are depicted with hatching.
Table 1

Descriptive statistics for measures of spatial access to syringe exchange program (SEP) sites (2005) and of exposure to drug-related arrests (2000) in New York City’s 42 United Hospital Fund districts

<table>
<thead>
<tr>
<th>Descriptive Statistics</th>
<th>Average district-level SEP site density per square mile (2005)</th>
<th>District level drug-related arrest rates per 10,000 residents aged 15 to 64 years (2000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median (Range)</td>
<td>Crackdown districts (n=8)</td>
</tr>
<tr>
<td></td>
<td>0.09 (0.00, 4.69)</td>
<td>67 (14, 95)</td>
</tr>
</tbody>
</table>