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Crime Geo-surveillance in Micro-Scale Urban Environment - *NetSurveillance*

Abstract

Events and phenomena such as crime incidents and outbreak of an epidemic tend to form concentration of high risks known as hotspots. Geosurveillance is an increasingly popular notion for detecting and monitoring the emergence of and changes in hotspots. Yet the existing range of methods are not designed to accurately detect emerging risks at the micro-scale of street-address level. This study proposes *NetSurveillance*, a method for monitoring the emergence of significant concentration of events along the intricate network of urban streets. Through a simulation test, the study demonstrates the high accuracy of NetSurveillance in detecting such clusters, and outperforms its conventional counterpart conclusively when applied at the individual street address level. Empirical analysis of drug incidents from Chicago also illustrates its capacity to identify rapid outburst of crimes as well as a more gradual build-up of such concentration, and their disappearance, either as a one-off or as part of a recurrent hotbed.

Keywords: *geo-surveillance, micro-scale, street network, crime, hot spot*

Introduction

Monitoring changes in the patterns of geographical distributions across space and time constitutes an important part of geographical inquiry. In particular, detecting signs of an emerging concentration of events at an early stage of its formation has become indispensable when identifying risks ahead. For instance, in the field of epidemiology and public health, detecting a sudden outbreak of a communicable disease is called *syndromic surveillance* and has been studied rigorously in recent years (Kulldorff 2001). Historically, syndromic surveillance was commonly linked to the detection of anomaly in disease outbreak in time than in space, typically derived by using non-spatial, time-series data (Chen *et al.* 2011). However, temporal analysis that gives out signals of warning across the entire study area is less sensitive to changes in local neighbourhood areas (Chen, Zeng and Yan 2010). The importance of involving geographical information has been increasingly recognised in recent years (Kleinman, Lazarus and Platt 2004), which has prompted the development of methods that focus on ‘geographic surveillance’ or ‘geo-surveillance’ (Rogerson 1997) that monitors geo-spatial data as opposed to ‘surveillance’ that monitors traditional time-series data.

While many geo-surveillance methods have been proposed and applied in epidemiology, their uptake in geography and more generally in the wider humanity and social science disciplines have been limited so far. This is despite that a range of events in social and human contexts would benefit from the rapid and accurate detection of their emerging concentrations. Among the few exceptions is crime geo-surveillance, which has recently become feasible through increasing opportunities to access up-to-date, digitalised data. The importance of carrying out geo-surveillance analysis for crime events is supported by mounting empirical evidence in criminological research which collectively suggest that crime incidents tend to form strong concentrations over space and time (Sherman, Gartin and Buerger 1989; Sherman and Weisburd 1995; Braga 2001; Weisburd *et al.* 2004; Braga, Papachristos and Hureau 2010). As it usually takes a certain amount of time for such a concentration to fully grow, signalling their emergence at an early stage of their formation holds a key to implementing effective crime intervention measures (Groff and LaVigne 2002).

The foremost challenge in the field of geo-surveillance research has been the performance, or more specifically, the accuracy of the system; i.e. how quickly and how precisely the location and time of an emerging risk can be identified. On the technological level, the constant improvement in the computational power has helped ensure faster data analysis and visualisation. At the methodological level, various disease surveillance techniques, including those that involve statistical, mining, or geographical solutions, have been developed with the aim to improve the level of accuracy for detecting outbreaks. Yet their performance to signal the extent of crime concentrations at an early stage of their emergence still has room for improvement.

Literature Review

In recent years, an increasing number of studies on geo-surveillance have been carried out across a range of disciplines, including geography, social science, medical science and astronomy. Many of these studies adopt scan statistics or their variants as their methodology (Kulldorff and Nagarwalla 1995; Kulldorff 1997; Duczmal and Buckeridge 2006). The family of scan-statistic-type geo-surveillance techniques can be seen as an extension of the standard spatial scan statistics and space-time scan statistics (i.e. those designed for *retrospective* analysis for detecting hotspots) to facilitate *prospective* analysis (Kulldorff 2001). Methodologically, spatial scan statistic creates a circular or some other type of search window around the centroid of each aggregated areal unit. The radius of their search window changes continuously to take any value between zero and a predetermined upper threshold. In other words, each search window defines a zone that may contain a potential cluster of increased risk. A space-time scan statistic uses a cubic (cylindrical or other column-shaped) search window that extends in both the spatial and the temporal dimensions. Methods that belong to scan-statistic-type geo-surveillance, or the prospective scan statistics, also use space-time search windows. They are designed to set off alarms every time data is added and a search window identified the number of events being

significantly above the expected value. It has been adopted widely by those studying the syndromic surveillance of communicable diseases to signal the emergence of an outbreak of an infectious disease or detection of bioterrorism attacks (Lazarus *et al.* 2002). Many of them focus on providing an accurate estimation of the amount of risk expected (i.e. the expected number of events per unit area) through mathematical modelling (e.g. Neill 2009; Kulldorff *et al.* 2005).

The Cumulative Sum (CuSum) and its variants (e.g. Prospective Support Vector Clustering (Chang, Zeng and Chen 2005) is another strand of methods used widely in geography and cognisant fields (Rogerson 1997, 2001, 2005; Lawson and Kleinman 2005). A CuSum statistic stems from the tradition of industrial process control for monitoring the quality of production characteristics. It calculates the observed counts that exceed the expected counts, which are cumulatively counted to the current time point. The CuSum statistic is updated every time when an alarm is signalled or when it observes values greater than a pre-set threshold. Although the CuSum methods have long been used in a purely temporal (time-series) context for examining the global tendency of clustering of events, it was recently extended to account for the spatial dimension as a multi-regional CuSum method to detect the locations where changes were observed by creating a CuSum chart for each region (Rogerson and Yamada 2009).

Other studies mainly take a modelling approach with a focus on forecasting increased risks and outbreaks. For instance, Kleinman, Lazarus and Platt (2004) use Generalized Linear Mixed Models (GLMM) statistics to incorporate space and time into the model. Their model predicts the expected count of cases for each time points and in each area, and hypothesis testing is carried out against the recorded count to signal any unusual level of counts observed. As it is a regression-type causal model, it has an advantage over scan statistic and CuSum in that it can incorporate covariates into the model more easily as indicator variables. On the other hand, it has less focus on geographical contiguity; i.e. unlike scan statistic and spatial CuSum approaches, GLMM is not designed to detect elevated counts over several contiguous areas (Kleinman, Lazarus and Platt 2004). Some other methods such as SMART (Bradley *et al.* 2005) is known to have largely overcome this disadvantage of GLMM's (Chen, Zeng and Yan 2010). There are many other spatial-econometric forecast models that can be used for geo-surveillance (Deadman 2003; Gorr, Olligschlaeger and Thompson 2003; Cohen, Gorr and Olligschlaeger 2007; Deadman and Pyle 1997; Kennedy, Caplan and Piza 2011). For example, leading indicator models use the past and current variables to estimate the occurrence of future crime incidents (Gorr and Olligschlaeger 2002). Some other modelling approaches for geo-surveillance use Bayesian statistics such as space-time Bayesian modelling (Bernardinelli *et al.* 1995), Bayesian Poisson mixed linear regression modelling (Martinez-Beneito, Garcia-Donato and Salmeron 2011), as well as those that involve machine learning such as Bayesian network modelling (Chen, Zeng and Yan 2010). Other recent approaches include *self-exciting point process modelling* by Mohler *et al.* (2011), which was originally developed for capturing space-time clusters of seismic activities among a series of earthquake events. They adopt this model for analysing the patterns of residential burglary incidents that exhibit a self-exciting pattern where a space-time cluster is formed after a certain event takes place and acts as a trigger.

As mentioned before, these methods have so far been developed and adopted predominantly in the field of epidemiology. A crucial difference between the epidemiological and the social-science approaches is that the former has less focus on the spatial granularity used in the analysis, whereas the latter tends to be affected more heavily by the choice of the scale of the analysis. This is partly because surveillance of pandemic outbreaks (e.g. swine flu) and other epidemiological events requires monitoring across a large area, which usually requires data aggregated by large urban and rural areal units. On the contrary, analysis of human-scale events such as crime incidents is often expected to cater for more diverse situations where disaggregate or small-scale aggregation units in a small study area are often used.

Recent criminological literature states that concentrations of crime events are closely linked to specific places and time, often at a scale smaller than local neighbourhoods and census areas (Bowers and Johnson 2005). For instance, Braga *et al.* (2010) reports that 74% of serious gun assault incidents in Boston were recorded on 5% of its street segments and intersections. Similarly, Weisburd *et al.* (2012) note that, over a period of 16 years, 50% of crime events were found within 4.7% to 6% of the street

segments in Seattle. More recent studies by Weisburd and Amram (2014) and Weisburd (2015) show a cross-city comparison of crime concentrations and conclude that roughly 50% of all crimes are concentrated in about 5% of places within any city they have studied. The importance of focusing on micro-scale problem places is further strengthened by studies that revealed the considerable variability of crime counts from one street to another (Groff *et al.* 2009, Groff *et al.* 2010, Weisburd *et al.* 2012 and Wheeler *et al.* 2015). For instance, Groff *et al.* (2010) argue that a concentration of a high volume of crimes on one street segment may follow a temporal trajectory that is unrelated to those observed among its immediate adjacent streets.

In the criminological literature, the mounting evidence on concentrations and variabilities of crime at micro places is supported by *crime opportunity theory* (Felson and Clarke 1998). It contextualises situations and processes of crime occurrences at the micro-scale by attributing the high volume of crimes in micro-scale places to specific conditions and situational factors found in those places. Specifically, it proposes that a favourable combination of *crime opportunity* is confined to specific places at which offenders meet targets and make decisions to commit a crime. Such places are highly specific and are mostly smaller than the aggregated areal units which have been typically used in conventional studies (Weisburd *et al.* 2009, Braga and Weisburd 2010).

Understanding the extent of concentrations and variability of crime within these small places requires methods of micro-scale analysis—especially those that measure such patterns along the streets. Indeed, in an urban environment where people’s behaviour is confined to the layout of the street network, the ways in which certain criminal activities form a concentration is also affected by the configuration of the street layout. This makes micro-scale surveillance (i.e. monitoring changes at each street block and individual street address) a particularly effective means to evaluate and control risks within an urban environment. Chen *et al.* (2011) point out that ‘if the region represented is too large, early outbreak cases may be hidden in the background statistical noise, and this delay may cost valuable acting time ... to control it’ (Chen *et al.* 2011, p.231). Gorr and Harries (2003) also stress the importance of focusing on micro-scale problem places within each beat for tactical policing. They suggest that an accurate short-term crime forecast at specific small places would allow a police force to take tactical actions, such as targeted patrols of the hotspots, deployment of special units (e.g. crackdowns for drug enforcement), scheduling vacations and training outside high crime months, and making crime alerts available to neighbourhood watch groups (Gorr and Harries 2003).

Nevertheless, studies of geo-surveillance are scarce in the criminological literature, especially when it comes to the analysis at micro-scale. For instance, there are approaches that focus on the temporal surveillance such as Friedman’s work (2009) on real-time surveillance of illicit drug overdoses. It uses various methods of time-series analysis to understand the concentration in their temporal frequency; namely the temporal scan statistic for retrospective analysis, as well as time-series CUSUM method, Pulse Analysis (PULSAR) (Foster and Backer 1990) and autoregressive integrated moving average (ARIMA) for prospective analysis. While the importance of identifying the frequency and timing of crimes is undisputable, geo-surveillance offers additional insights into where the problems are occurring. Another notable example is Rogerson and Sun’s study (2001) that combines the Nearest Neighbour Distance statistic (NND) and the standard time-series CuSum to carry out crime geosurveillance for detecting changes in the spatial patterns of arson data. The NND statistic is calculated every time when additional event happens, and a signal is set out when observed NND undercut the expected value. It uses detailed locational information, measuring distances from the 10 most recent events to their respective neighbours. However, it reduces the locational relationship between events into a single array of ‘distances’; which signals changes in the global tendency but does not identify where a local concentration is emerging.

Other examples of crime geo-surveillance offer a more explicit understanding of the location of concentrations. For instance, Cheng and Adepeju (2014) use the prospective scan statistic to crime data to detect emerging clusters in large areas of London. Similarly, Neill and Gorr (2007) apply a variant of the scan statistic called the *expectation-based scan statistic* (Neill and Moore 2006, Neill 2009) to detect emergence of violent crimes. It uses time series analysis to infer the expected count of incidents

for each spatial location and identifies those with significantly high values of observation. Kim and O’Kelly (2008) developed a bootstrap-based space-time surveillance model, a variant of the *permutation scan statistic* (Kulldorff *et al.* 2005) for analysing patterns of residential burglaries and robberies. Their model calculates the expected count through its own inertia and applies random sampling to generate the test statistics for detecting clusters. Gorr and Lee (2015) propose a different approach of signalling an early warning for ‘temporary’ hotspots and distinguishing them from ‘temporal’ hotspots whereby different crime prevention responses can be implemented. The early detection is based on repeating regular crime count for each areal unit, and identifying locations of temporary hotspots as they exceed a threshold value.

Most of these geo-surveillance studies take scan statistic approaches with many using medium to large size areas as the units of their analysis. For instance, Cheng and Adepeju (2014), Neill and Gorr (2007), Kim and O’Kelly (2008), and Gorr and Lee (2015) use 250m grids, 305m (1000ft) grids, fixed size of search windows with 0.5km and 1.0km radii, and three grid sizes of 152m (500ft), 229m (750ft) and 305m (1000ft), respectively. While analyses at this scale are suitable for monitoring overall changes across large geographical areas, they fall short of offering detailed information for implementing targeted tactical measures at highly localised places. In such instances, a method which is sensitive to more geographically focused changes would be more desirable. As mentioned above, the importance of offering solution at the micro-scale level of street segments or less has been emphasised by many, yet it is still under-explored (Bowers and Johnson 2005, Weisburd, Groff and Yang 2012, Weisburd and Telep 2014). More recently, Shiode and Shiode (2013) introduced the notion of space-time *network-based search window* for retrospective hotspot detection, and subsequently proposed a network-based geo-surveillance method (Shiode and Shiode 2014) similar to scan statistics. Unlike scan statistics whose search window is flexible in size, it uses space-time search windows of a fixed size, but allows the search windows to change their shape as they search along the street network.

Against this background, this study aims to propose a geo-surveillance method that is designed for monitoring emerging concentrations of activities at micro-scale so as to detect the emergence of concentration at the scale where many human and social events take place in an urban environment. It builds on the scan statistic for micro-scale geo-surveillance proposed by Shiode and Shiode (2014). This is because of its geographical focus on the use of individual, disaggregate data, thus avoiding preselection bias that usually arise from the size and the location of clusters. This flexibility makes it most suitable for micro-scale analysis where the search window needs to cover areas smaller than street blocks. The flexible shape of the search window also allows for searches along the actual street network.

As is the case with many other crime surveillance studies, at-risk population has not been used in this study. This is not because of technical limitations, as the proposed method can monitor the situation with respect to either the raw counts or the proportional risks. Rather, it is because crime surveillance generally places its emphasis on the detection of emerging counts as opposed to the increase in rates as pursued by disease surveillance.

The main limitation of Shiode and Shiode’s approach (2014) is that their search window is fixed to a predefined size and, therefore, can be changed only by taking on discrete values. This creates some room for error in pinpointing the location of emerging concentrations, especially when compared with the scan statistic approach whose search window can change more continuously. This study proposes an extended variant of their method and overcome this point.

In the following, the study first describes the methodological framework of the proposed method, starting with the underlying assumption and then explaining how the concept of the space-time *network-based search window* can be applied to geo-surveillance. It detects emerging concentrations of crime activities at the street-address level by repeatedly sweeping across a street network. The study evaluates the performance of the proposed method through a simulation study in comparison to that of the conventional scan statistics; specifically with respect to *days-to-detect* for assessing temporal accuracy and *positive predictive values (PPV)* for assessing spatial accuracy. The study then applies the proposed method to drug data from Chicago, Illinois to explore how these methods can help monitor detailed crime data, and what information can be offered to aid crime intervention and prevention tactics.

Methodology

Network-based geo-surveillance: NetSurveillance

The standard scan statistics uses a test statistic called a *likelihood ratio test statistic (a scan statistic)* for detecting spatial zones where event counts are significantly higher than expected. For each zone circumscribed by a search window, *the likelihood ratio* is derived by counting the observed and the expected numbers of incidents inside and outside that window, which gives us the likelihood of the observed number of incidents occurring in each zone under the null hypothesis. The zone with the highest likelihood ratio is defined as the most likely cluster. Through hypothesis testing using the likelihood ratio test statistic, the method can also detect all zones where the underlying event-occurrence rates are statistically significantly higher inside the region than they are outside.

This study adopts the notion of the network-based scan statistics (Shiode and Shiode 2013) to suit the surveillance of space on a street network, where a sub-circular-area search window in the standard scan statistics is replaced with a sub-network search window (hereafter called a *network-based search window*). Detailed description of a network-based search window can be found elsewhere (Shiode 2011), but it forms a flexible sub-network that takes any length between 0 and a predetermined threshold value and moves along the street network of the study area to constantly record the number of point observations found within its extent.

For the purpose of this study, the notion of network-based spatial search window is further enhanced and turned into a geo-surveillance framework. It is a variant of space-time analysis that monitors emerging space-time patterns by means of space-time search windows so as to measure their concentration across time. When the notion of a conventional, non-temporal search window is extended to search through the space-time dimension, it forms a cylindrical search window whose circular segment in the horizontal direction denotes its spatial extent while the amount of vertical extrusion represents its temporal duration (Kulldorff 2001). By applying the same principle, a network-based search window can be also extruded in the vertical direction along the temporal axis so that it can be used for searching through the space-time dimension. In order to distinguish between the different types of search windows used, this study refers to a *network-based spatial search window* as $NT_S\text{-SW}$ and a *network-based space-time search window* as $NT_{ST}\text{-SW}$, and distinguishes them from the conventional *planar spatial search window* ($PL_S\text{-SW}$) and the *planar space-time search window* ($PL_{ST}\text{-SW}$).

The search windows used in the geo-surveillance are the network-based space-time search window ($NT_{ST}\text{-SWs}$). Figure 1 illustrates how $NT_{ST}\text{-SWs}$ are used in geo-surveillance for searching across the study area and over the study period. N_{st} denotes the entire *space-time network* of a study area, where N_s and N_t represent its spatial extent and its temporal duration, respectively. Similarly, w_{st} represents an $NT_{ST}\text{-SW}$ that sweeps across N_{st} , whereas w_s is an $NT_S\text{-SW}$ that sweeps across N_s .

[Insert Figure 1 about here]

Unlike standard space-time searches, geo-surveillance repeats searches with w_{st} on a space-time network N_{st} at a constant interval to account for any new incidents that have been reported (e.g. electronic crime incident reports published on a daily basis) so that the distribution of the latest incidents can be monitored for the purpose of detecting clusters as and when they emerge.

Suppose that $[N_0, N_t]$ represents the whole period for which the most recent data exist, and t_s and t_e denote the start date and the end date of an $NT_{ST}\text{-SW}$, respectively (i.e. $N_0 \leq t_s \leq t_e = N_t$, where $t_s - t_e = w_t$). N_t is updated every time new data set becomes available. Similarly, the most recent date t_e of an $NT_{ST}\text{-SW}$ also moves forward as new data become available.

Figure 1 illustrates an example of w_t with a fixed size and duration, but an NT_{ST} -SW flexibly changes its size and shape during the actual analysis. In other words, value of w_t changes continuously and, for monitoring purposes, only NT_{ST} -SWs that reach N_t are considered. This proposed method is hereafter referred to as *network-based geo-surveillance* (NetSurveillance), and the conventional scan-statistic type geo-surveillance as *planar geo-surveillance* (PLSurveillance).

Likelihood ratio and detection of emerging clusters

The process of deriving the likelihood ratio for the continuous homogeneous Poisson model on a street network is similar to that for the original scan statistics. Under the null hypothesis H_0 of no clusters (H_0 : “the underlying intensity of crime occurrence is spatially-temporally uniform”) and the alternative hypothesis $H_1(w_{st})$ that expects the presence of a cluster in search window w_{st} ($H_1(w_{st})$: “The underlying intensity of crime occurrence is higher inside regions w_{st} than outside region w_{st} ”), NetSurveillance detects an increased count if the ratio of the observed counts to the expected counts is higher inside a window w_{st} than it is outside.

The likelihood ratio $T(w_{st})$ for a given region w_{st} is the likelihood of the data under the alternative hypothesis $L(w_{st})$ divided by the likelihood of the data under the null hypothesis L_0 . It shows how likely the observed data for w_{st} are given the difference in incident rates between inside and outside of w_{st} . The likelihood ratio test statistic $T(w_{st})$ for a fixed w_{st} can be thus written as

$$T(w_{st}) = \frac{L(w_{st})}{L_0} = \left(\frac{n_{w_{st}}}{\lambda(w_{st})} \right)^{n_{w_{st}}} \left(\frac{n_{N_{ST}} - n_{w_{st}}}{\lambda(N_{ST}) - \lambda(w_{st})} \right)^{n_{N_{ST}} - n_{w_{st}}}, \quad \text{if } n(w_{st}) > \lambda(w_{st}),$$

$$\text{and } \frac{L(w_{st})}{L_0} = 1, \quad \text{otherwise.}$$
(1)

where $n_{w_{st}}$ denotes the observed number of points in w_{st} , $n_{N_{ST}}$ is the total number of observed points in study network N_{ST} , $\lambda(w_{st})$ is the number of points expected inside w_{st} under the null hypothesis, and $\lambda(N_{ST})$ is the total number of points expected to be found in study network N_{ST} .

By comparing the likelihood ratio across all window locations and sizes, a single w_{st} that constitutes the most likely cluster can be identified. The likelihood ratio calculated for this window would have the maximum likelihood ratio test statistic, thus making it the cluster that is most unlikely to be formed under the null hypothesis. The maximum likelihood ratio T over all possible w_{st} can be derived as

$$T = \max_{w_{st} \in W} T(w_{st}) = \max_{w_{st} \in W} \left\{ \frac{L(w_{st})}{L_0} \right\}.$$
(2)

This allows the selection of \hat{w}_{st} such that $L(\hat{w}_{st}) \geq L(w_{st})$ for all $w_{st} \in W$, and window $\hat{w}_{st} \in W$ is selected as the most likely cluster. Other, secondary clusters with a likelihood ratio that is statistically significant can be also identified by calculating the statistical significance (p -value) for all potential clusters through Monte Carlo simulations, and reporting all other clusters with p -value less than a significance level α as secondary clusters.

Recurrence intervals

Unlike the retrospective space-time method that makes a single sweep across an N_{st} , NetSurveillance runs multiple cycles of searches, which introduces further multiplicity issues. Adjusting for multiplicity is a highly debated subject for syndromic surveillance in epidemiology. However, results from this study will not be adjusted. Instead, for each cycle of geo-surveillance, the rarity of a signal that represents the emergence of a crime concentration is presented in the form of *recurrence intervals* calculated for the respective time point $t_e, e = 1, \dots, N_t$ (Takahashi *et al.* 2008). It gives an indication of how often such a cluster will be observed by chance. Specifically, this study defines a recurrence

interval as *the expected number of days required for witnessing a signal of at least the observed magnitude through geo-surveillance*; i.e. it is once in R/p days, where R is the number of days in each time interval and p is the p -value (Nordin *et al.* 2005). As it is inversely proportional to the p -value, the larger it is, the more unusual the detected cluster would be. The observed p -value is also used as the cut-off for a signal in this study at the 5% significance level.

Performance Test through Simulation Analysis

Execution of NetSurveillance and PLSurveillance

In order to compare their relative performance for detecting emerging clusters, both NetSurveillance and its conventional counterpart PLSurveillance were applied to a simulated data set. The simulated data set was created by creating 14 space-time clusters randomly across N_{st} , and placing 200 random points across these 14 clusters. Additional 100 points were also placed randomly across N_{st} . Figure 2 shows all 300 points in a space-time cube, where the extent of the study area is shown on the xy -plane while the duration of the study period is reflected onto the vertical axis. The NetSurveillance was coded as a proprietary computer program to carry out the simulation study as well as the empirical case study described in the next section. In order to test the performance of the PLSurveillance, a piece of software called *Prospective Space-Time SaTScan* was used (Kulldorff 2001).

[Insert Figure 2 about here]

Geo-surveillance often uses the number of events that happened during a certain period in the past as the baseline count for deriving the expected count. However, in the case of the simulation data, its distribution, by definition, follows uniform Poisson process across space and time. Therefore, the simulation study uses the same expected counts of the total number, derived from the existing data, as the baseline counts across all time periods.

[Insert Figure 3 about here]

Figure 3 shows the outcome of PLSurveillance analysis using a space-time search window with a maximum time period of 15 days with 999 simulation runs. Each of the grey circles represents the time, location and size of a statistically significant search window that triggered an alarm at the significance level of 0.05. A total of 353 signals were set off against the simulated data. The vertical distance of each circle from the xy -plane reflects the date the respective alarm was sounded. The red circles collectively show the projection of all the alarms onto the study area so as to illustrate their spatial distribution. While the alarms collectively offer a broad coverage of the 14 injected cluster areas, they are not an exact match. In particular, some of the search windows are considerably larger than the actual size of the respective cluster they cover, as they tend to include other nearby clusters in the extent of their search, thus merging several clusters into one.

[Insert Figure 4 about here]

NetSurveillance was also carried out against the same data with 500ft as the maximum total length along the streets, and 15 days as the maximum time period for the search window size. It set off 249 alarms in total. Figure 4 shows the space-time locations of the emerging clusters signalled by

NetSurveillance. Each block of bars that resemble a wall in fact consists of a series of alarms sounded in the same location on consecutive days (as shown in the inset of Figure 4).

The red line segments collectively show the projection of all the NT_{ST} -SWs that triggered an alarm onto the street network N_s to illustrate their spatial distribution across the year. Compared with the outcomes of PLSurveillance in Figure 3, the locations of the injected clusters are identified more accurately by the alarms raised by NetSurveillance.

[Insert Figure 5 around here]

Figures 5(a)~(d) show the recurrence intervals and the temporal durations of search windows for each individual signal produced by PLSurveillance and NetSurveillance, respectively.

Some clusters initially have a low recurrence interval in their emerging stage (green circles) and take a higher value as they form denser clusters (progressing to yellow and on to red circles), which shows the gradual build-up of a concentration. In contrast, some clusters start with a high recurrence-interval value, because the points are concentrated at the beginning of the cluster, thus suggesting a rapid outburst of events on the outset.

Figures 5(b) and 5(d) illustrate the durations of search windows for PLSurveillance and NetSurveillance, respectively. Some clusters are shown to have short-term alarms (1-3 days), which suggest an abrupt increase in the number of events found at those locations. In such a case, points are concentrated in the first few days of a cluster by chance, despite that the points in this simulated dataset should be, in theory, distributed uniformly random over space and time. This is consistent with the nature of the distribution of the clusters injected, where some clusters emerge suddenly and show a rapid increase in their point density.

One notable difference between the results from PLSurveillance and those from NetSurveillance is that the recurrence intervals for the large circular areas in PLSurveillance are estimated as relatively low, because such large areas include places with no incidents. Technically speaking, this result would not be incorrect, as it is quite likely to witness another recurrence of events that would show a medium-level intensity of similar magnitude across a large circular area. However, it would not serve the purpose of understanding exactly where and when we will likely witness heightened risks.

Performance assessment through days-to-detect

In this section, performance of PLSurveillance and NetSurveillance is measured in terms of their response time, or how soon they can set off the alarms after observing increase in crime activities (Nordin *et al.* 2005). In the context of crime surveillance, the response time for sounding an alarm constitutes one of the primary concerns, as failure to detect emerging clusters rapidly means no practical, timely intervention can be made. The timeliness of such signals can be measured in the form of *days-to-detect*, which examines the number of days it took from the time the earliest incident within a single simulated cluster occurred, and the day that cluster was detected and set off an alarm (Woodall *et al.* 2008; Neill 2009).

The simulated data used in the previous section cannot be used directly for measuring the days-to-detect performance of PLSurveillance and NetSurveillance, because the intensity of events measured in a planar space is different from that measured in a network space. In the case of network-based analysis, the expected point intensity over the extent of 100ft of a street network can be derived directly from the point density along a 100ft-long stretch of a street network whereas, in the case of the planar-based analysis, it measures the point density within a circle with a diameter of 100ft. The expected counts in network space E_{NT} and that in planar space E_{PL} can be derived respectively, using the number of events in the study area and the extent of the study area, under the assumption of uniform randomness across the study area. In the case of the simulated data,

$$E_{NT} = 300\text{points} \times 100\text{ft}/41,530\text{ft} \text{ (i.e. } 0.72 \text{ points per } 100\text{ft of street network), and}$$

$$E_{PL} = 300\text{points} \times (50^2\pi)\text{ft}^2/7,224,672\text{ft}^2 \text{ (i.e. 0.33 points within a 100ft-diameter area).}$$

These figures suggest that the expected count in the network space is more than twice as high as that in the planar space. This makes the detection of an emerging cluster takes longer in the network space, because a higher expected count requires a higher number of points to be detected as a significant cluster. In order to eliminate such a bias in the measurement of timing of signalling between the two methods, a double weight was given to the observed point distribution for NetSurveillance.

[Insert Figure 6 around here]

Figure 6 shows the 423 locations and the timing of the alarms signalled by NetSurveillance after the adjustment. The days-to-detect performances were calculated for both methods with the adjusted simulation data (Table 1).

[Insert Table 1 around here]

The amount of time lag for each alarm varies, and the NetSurveillance and the PLSurveillance returned comparable performances. However, for 13 out of 14 locations of injected clusters, NetSurveillance took either the same number of days to detect, or slightly less than that by PLSurveillance. Consequently, the overall performance from NetSurveillance was slightly better than that by PLSurveillance, where PLSurveillance averaging at 3.71 days, and NetSurveillance at 3.29 days). While the outcome of Mann-Whitney’s U test is not significant ($U=89.5$, $p\text{-value}=0.71$), these differences suggest that NetSurveillance is slightly more sensitive to changes in the point density, if not by a significant margin.

Performance assessment through Positive Predictive Values (PPV)

In addition to the promptness of their response time, the level of accuracy in covering the correct areas is also an important measure to assess the performance of a geo-surveillance method. The *Positive Predictive Value (PPV)* is useful in this regard, as it measures “the proportion of the true regions within the detected clusters” (Takahashi *et al.* 2008). In syndromic surveillance, they are calculated with respect to *the number of regions* detected, as they usually study aggregate units. Given the focus of this study on individual locations represented by points, we will replace them with *the number of reference points*, and define the PPV as the ratio of correctly detected locations (i.e. the number of detected reference points within the respective true cluster regions) to all detected locations (i.e. the number of reference points in the respective detected regions). In other words, the PPV is inversely proportional to the degree of *overshooting*; i.e. if the level of overshooting is low, the PPV score is high and converges to 1, whereas if there is excessive amount of overshooting, then the PPV score becomes low.

[Insert Table 2 around here]

Table 2 is a list the average PPV scores of all signals set off against each of the 14 injected clusters by PLSurveillance and NetSurveillance, respectively. The overall average PPV score across all clusters (i.e. an overall average of the 423 signals) was 81% for PLSurveillance, whereas NetSurveillance returned a perfect rate of 100%. Mann-Whitney’s U test also confirmed with the values of $U = 14.0$, $p\text{-value} = 0.00$ that NetSurveillance returned better PPV scores than PLSurveillance did.

Results from the simulation analysis

The simulation analysis measured the performance of the two geo-surveillance methods (NetSurveillance and PLSurveillance) in the forms of the days-to-detect and PPV values. Of the two

methods, NetSurveillance was slightly faster in detecting the emergence of clusters, although the margin of difference was not statistically significant. In terms of their spatial coverage, the alarms raised by NetSurveillance provided a 100% match for the extent of the actual clusters and was statistically confirmed to be more accurate than PLSurveillance was. The spatial and the temporal performance of PLSurveillance was affected primarily by the over-representation of clusters with its exceedingly large circular search windows. Since the performance of a geo-surveillance system should be measured as a combination of spatial and temporal accuracies, the results from the two performance assessments confirms that NetSurveillance offers better performance than the PLSurveillance can in identifying locations of emerging clusters and setting off alarms against them.

In the process of measuring the days-to-detect performance, the simulation data was adjusted for NetSurveillance so that both methods would be tested under similar point density. This leaves a question as to whether PLSurveillance can set off alarms faster than NetSurveillance can when analysing real data with no adjustment. In reality, it would largely depend on the density of the street network in the study area. In the case of this simulation, the point density in the study area was unusually high, but this is usually not the case with real crime data. Indeed, in the case of an empirical dataset (drug data from West Englewood, Chicago) used in the next section, the point density in the network dimension is lower than that in the planer dimension ($E_{NT} = 4.22$ points per 1000ft of street network, and $E_{PL} = 13.48$ points within a 100ft-diameter area), which would make NetSurveillance more sensitive and thus setting off alarms faster than PLSurveillance would.

Empirical Analysis

Application of NetSurveillance on drug data in Chicago

The simulation study confirmed that NetSurveillance has methodological advantages over its conventional counterpart. Following this result, this section applies it to real crime data to explore how it can help provide deeper insights into the understanding of real crime patterns. The data used in this empirical study consists of drug-related incidents recorded by the Chicago Police Department in 1999 (1,500 cases) and 2000 (1,563 cases), respectively. The street network in the study area runs for a total of 370,000ft.

[Insert Figure 7 about here]

Figure 7 shows the location of the drug-related incidents recorded in 2000. In the subsequent analysis, data from the year 1999 is used for deriving the expected incident counts for each cycle of geo-surveillance against the data in 2000. The period calculated for the baseline count is set to one year; i.e. the expected count for geo-surveillance at t_1 (1st January 2000) is calculated from the incident counts between 1st January 1999 and 31st December 1999; the expected count at t_2 (2nd January 2000) is calculated from the incident counts between 2nd January 1999 and 1st January 2000, and so on. Using these baseline counts, geo-surveillance is conducted for each day of the year for 2000 (i.e., t_1, \dots, t_{366}), with the assumption that no data is available beyond the time point t_i for which the respective cycle of geo-surveillance is being executed. In other words, each cycle of geo-surveillance is carried out as if it is based on the latest set of records. For each point in time, geo-surveillance is run with 800ft as the maximum spatial extent of the search window and up to 60 most recent days as its maximum duration; i.e. in total 366 cycles of geo-surveillance search is carried out, each of which consisting of searches of various spatial lengths and temporal durations to investigate the exact shape and period of significant clusters; and these cycles are repeated for all 1,480 reference points placed at a 200ft interval on the street network.

[Insert Figure 8 about here]

Results from the empirical analysis

Figure 8 shows the distribution of the emerging active clusters detected through 869 alarms across 17 different areas in the study area. Unlike the simulation data where the injected clusters maintained a consistent intensity across its duration, the intensity of the concentration of activities may change even within a single space-time cluster; and this is reflected in the change in the size of the alarms (as seen in the inset of Figure 8). The alarms show a clear pattern of persistence in several but distinct locations, highlighting the location of hotbeds and the recurrent nature of the intense activities. The duration of the alarms varies considerably, ranging from short outburst of a single day, to a persistent hotbed lasting for 61 days of continued alarms. Figure 9 shows the level of recurrence intervals for each alarm—the warmer the colour, the higher the recurrence interval; i.e. more unlikely they are to happen. Of the most prominent are the four hottest locations whose recurrence intervals are particularly high. One of them is part of a recurrent hotbed, and the pattern of the alarms show that activities at this location are both intense as well as persistent in nature.

[Insert Figure 9 about here]

[Insert Figure 10 about here]

It should be noted that each of the bars shown in Figures 8~9 only reflects the last day of the detected space-time search window, and the duration of the detected search window itself for the respective time point is not presented. In other words, each alarm shows the day an emerging cluster was detected at that location, but it does not reflect the temporal size of the search window that detected a cluster as of that time point, which would have otherwise trailed below each bar. Similarly, Figure 10 shows only the actual days an alarm was sounded, but they are colour coded by the duration of the respective search window that set off each alarm.

As noted earlier, the duration of these search windows ranged from one day to 61 days. Alarms sounded by a relatively long search window are shown in a green shade in Figure 10. These clusters are considered to have been formed through a gradual concentration of criminal activities. In contrast, clusters detected by a short search window (shown with red alarm bars in Figure 10) indicate places that had experienced a sudden rise of crime counts in a short period of time. Interestingly, no clear relationship is identified between the temporal length of a search window that sounded the first alarm (Figure 10) and the rarity of the cluster that is presented in the form of recurrence intervals (Figure 9).

Of the clusters detected through these alarms, two cases are identified by short search windows at the beginning both of which showed high recurrence intervals from the outset. They reflect an abrupt increase of risks with a high rarity, thus indicating places where a strong and sudden outburst was observed. The urgency of such outburst is likely to require swift and decisive policing action. In contrast, many other alarms are set off by search windows with a longer temporal duration with a modest recurrence interval. They reflect a gradual accumulation of moderate risks that is expected more regularly. These places may benefit from a long-term, strategic solution such as crime prevention through design.

Discussion and Conclusion

This study proposed NetSurveillance — a variant of scan statistics that is network-based and executes geo-surveillance. Building on the same methodological principles drawn from disease surveillance, NetSurveillance can raise early warning alarms against emerging elevations of risks at highly localised and specific places on the street network. The crime surveillance carried out in this study demonstrated how the information on the time and location of the emerging clusters can be obtained in the form of signals. They can be utilised for raising an early warning to facilitate a rapid and timely intervention, at

the very fine scale of the street-address level, especially in areas highlighted as a place of highly active crime concentration.

The simulation analysis confirmed that NetSurveillance can detect the timing and location of emerging concentrations of crime activities more effectively and accurately than the existing methods can. While the simulation analysis did not confirm the days-to-detect performance of NetSurveillance to be significantly faster, the fact that it was slightly faster than PLSurveillance and was capable of warning with perfect spatial accuracy confirms the importance of selecting the right geographical unit for surveillance analysis. For practical policing purposes, increased spatial accuracy is expected to greatly enhance the ways in which policing measures are implemented and, thereby, improve the efficiency of policing action. Indeed, accurate identification of the locations of emerging clusters can prove vitally important for crime cluster patrolling, as they can focus their resource to a more focused location without having to cover places that are in fact not under imminent threat. In particular, identification of emerging micro-scale clusters can help plan efficient patrolling routes in near-real-time without having to patrol less relevant areas or streets. Further exploration in this direction requires incorporation of suitable logistics and transportation modelling, but it marks a promising avenue in the practical policing scene to apply the methods developed in this study.

In the empirical analysis, NetSurveillance raised alarms against emerging risks of different size, duration and intensity. They ranged from an abrupt outburst of intense crime concentrations as indicated by a high recurrence interval, to a gradual increase in criminal activities as indicated by a long duration of the search window, including those observed at recurrent hotbed locations. The accuracy and the timeliness of the alarms sounded by NetSurveillance mean that it can cater for short-term tactical interventions, including traditional policing tactics such as drug crackdowns and arrests, for which the timing of the first alarm is critical. Some locations identified in the empirical study clearly form stable clusters where long and recurrent alarms are observed across the study period. Naturally, these locations would benefit from both an immediate, short-term policing effort, as well as a long-term intervention.

One of the long-term interventions that recently proved effective is problem-oriented policing (Weisburd and Green 1995; Braga and Bond 2008; Taylor *et al.* 2011). It focuses on resolving the underlying conditions at specific problem places, so as to have a longer-lasting impact. Problem-oriented policing is often implemented as part of *hotspot policing* activities (Braga 2001; Braga *et al.* 2014). It is suitable for treating micro-scale problem places like hotspots detected in this study, because it is designed to alleviate the fundamental crime-inducing conditions at specific targeted places to reduce crime opportunities at those places. On the other hand, some signals were set off against a one-time-only occurrence of a high risk of crime concentration. On the strategic level, investing in the long-term improvement of places identified by a one-off alarm would be less effective in reducing the volume of crimes than it would be when focusing on a hotbed location. While it is not any less important to respond to such a threat on a short-term basis, an operational-level response (e.g. increased patrol and crackdowns) should sufficiently reduce the heightened risks at such locations.

There are several directions for further research from here. Firstly, the contribution of the proposed methods is not limited to the analysis of the types of crime explored in this study. In fact, they can be extended to any other topics within or outside the domain of the geography of crime, as the principle of detecting micro-scale concentrations are fundamentally applicable in any discipline. The key to its successful applications is to identify the appropriate scale and resolution of analysis as discussed above. If it turns out that the context and the subject data required geo-surveillance at the micro-scale of the street-address level, then the accuracy of the outcome would be improved considerably by using the proposed method. Possible applications include monitoring various human activities and footfalls in a local neighbourhood that happen at the street address level. It may be also applicable to disease surveillance for monitoring outbreaks in a small urban area. The outcome may be subject to the proportion of risk against the base population (i.e. population-at-risk). For instance, Shiode *et al.* (2015) applied a network-based search-window-type approach to account for at-risk population in the context of spatial epidemiology, although their approach is retrospective and not geo-surveillance or prospective analysis. In principle, the same can be incorporated into NetSurveillance, if data on

population-at-risk were available at a very detailed scale, and were considered to have direct relevance with the type of crime being studied (e.g. street robbery). In the context of drug crimes, however, the notion of population-at-risk is implicit.

It should be noted that drug crime may exhibit a clearer tendency to form concentrations, partly because of the local policing activities to control and focus them in a limited number of places. This, however, should not affect the scope of this study where the advantage of the proposed method is demonstrated using any simulated and empirical data across board; i.e. the “relative” advantage of the proposed method will remain consistent regardless of the data used. Still, the application of the proposed method to other crime data and further confirmation of the outcome from this study constitutes one of the future research directions. It would be also interesting to see the different patterns the method reveals in emerging concentrations for other crimes where the police are usually less effective in proactively make arrests (e.g., burglary or robbery).

On an operational level, developing this method as an automated surveillance system would help make it a practical tool for ‘predictive policing’ to inform policing tactics on when and where crime is most likely to occur. As stated above, NetSurveillance offers a means to raise alarms swiftly and accurately against emerging risks and is particularly effective for monitoring events that unfold at the micro-scale of urban street-address level, which will lead to more efficient patrolling in a practical policing scene. The proprietary programme developed for executing the proposed method can be used as a basis to build a surveillance system. The main challenge lies in the logistics of designing something that is practical and feasible for use in the day-to-day policing operation and feed in to the wider policing tactics. These issues may be resolved in part by learning from the literature on predictive policing (e.g. Mohler *et al.* 2011; Gorr and Lee 2015) and existing tools such as PredPol (2017) and HunchLab (2017). Whether the increased accuracy NetSurveillance has demonstrated over existing geo-surveillance methods can be also maintained for predictive modelling should be examined through systematic performance testing.

Finally, NetSurveillance can be used for highlighting micro-scale street locations where crime displacement has taken place. For instance, if a problem place saw decrease in crime activities, possibly as a result of a recent application of crime prevention or interruption measures in the area, and a nearby location suffered from elevated crime activities instead, NetSurveillance should be able to detect it, because it is sensitive to both increase and decrease in crime activities. Interestingly, literature on crime displacement suggests that the notion of crime displacement may not be as prominent as it was once suggested; instead, spatial displacement may occur in a more subtle and disparate manner (Clarke and Weisburd 1994, Weisburd and Green 1995). The patterns of these subtle displacements are yet to be explored fully, primarily because we did not have an effective means to measure such changes at the micro-scale until now. This can all change, as the fine spatial granularity of NetSurveillance could help reveal micro-scale displacements, which was previously suggested but remained unconfirmed.

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Table 1: The days-to-detect performance by PLSurveillance and NetSurveillance for the 14 injected clusters measured with the revised simulated data.

Hotspot ID	Start Date	End Date	Number of Events	Date of First Event	First Signal Date PL	First Signal Data NT	Days to Detect PL	Days to Detect NT
1	221	251	15	223	234	234	11	11
2	135	165	8	136	137	137	1	1
3	130	160	16	132	137	138	5	6
4	59	89	5	59	61	61	2	2
5	167	197	14	168	168	168	0	0
6	12	42	21	13	19	19	6	6
7	288	318	8	294	294	294	0	0
8	84	114	30	86	88	88	2	2
9	109	139	10	114	118	115	4	1
10	227	257	15	227	229	229	2	2
11	242	272	19	244	245	244	1	0
12	34	64	14	34	35	35	1	1
13	7	37	14	7	15	15	8	8
14	327	357	11	327	336	333	9	6

Table 2: The PPV scores for each of the 14 injected clusters with PLSurveillance and NetSurveillance.

Hotspot ID	PPV PLSurveillance	PPV NetSurveillance
1	0.79	1.00
2	0.65	1.00
3	0.68	1.00
4	0.82	1.00
5	1.00	1.00
6	0.77	1.00
7	1.00	1.00
8	0.53	1.00
9	0.77	1.00
10	0.97	1.00
11	0.90	1.00
12	0.83	1.00
13	0.76	1.00
14	0.97	1.00
Average	0.81	1.00

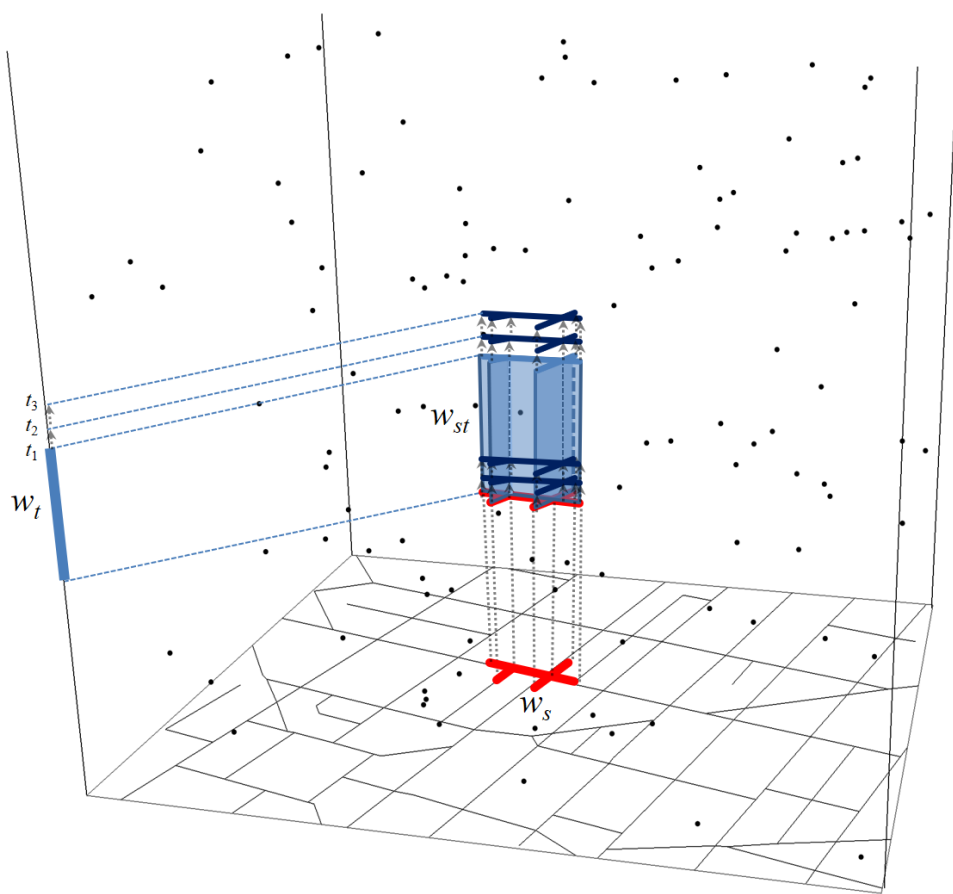


Figure 1: An illustration of an NT_{ST} -SW that captures emerging micro-crime hotspots at $t_e = t_1, t_2, t_3$.

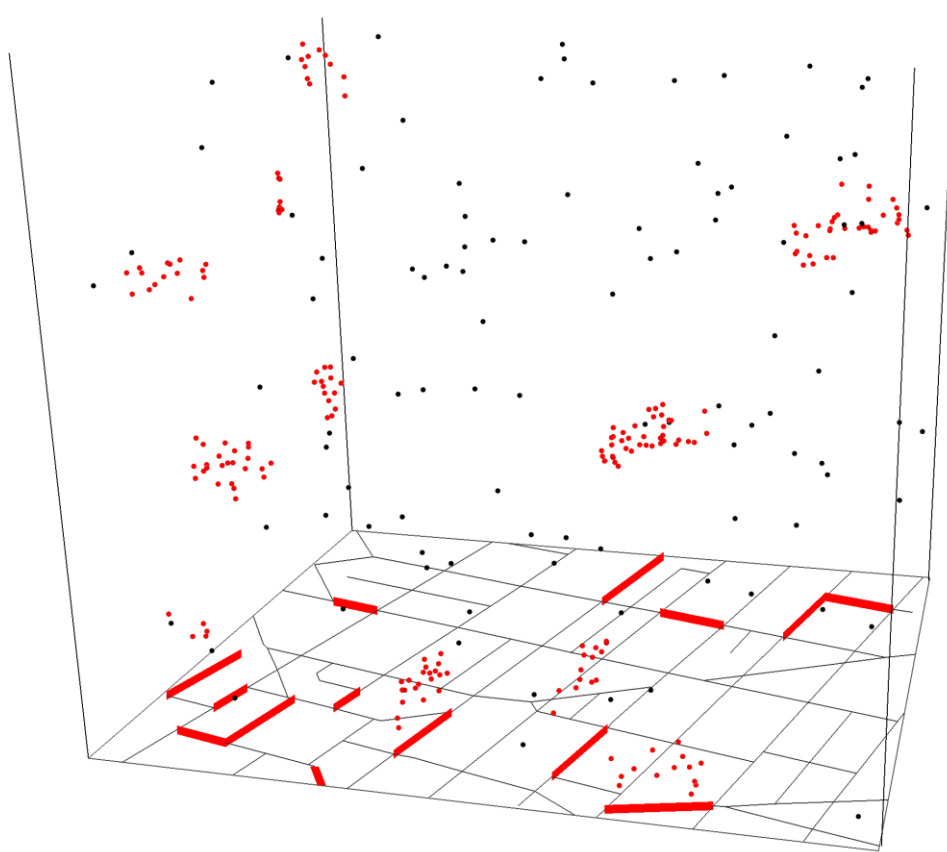


Figure 2: Simulated space-time Poisson cluster points presented in a space-time cube. The 200 points injected at the hypothetical hotspots of 14 space-time locations are coloured in red.

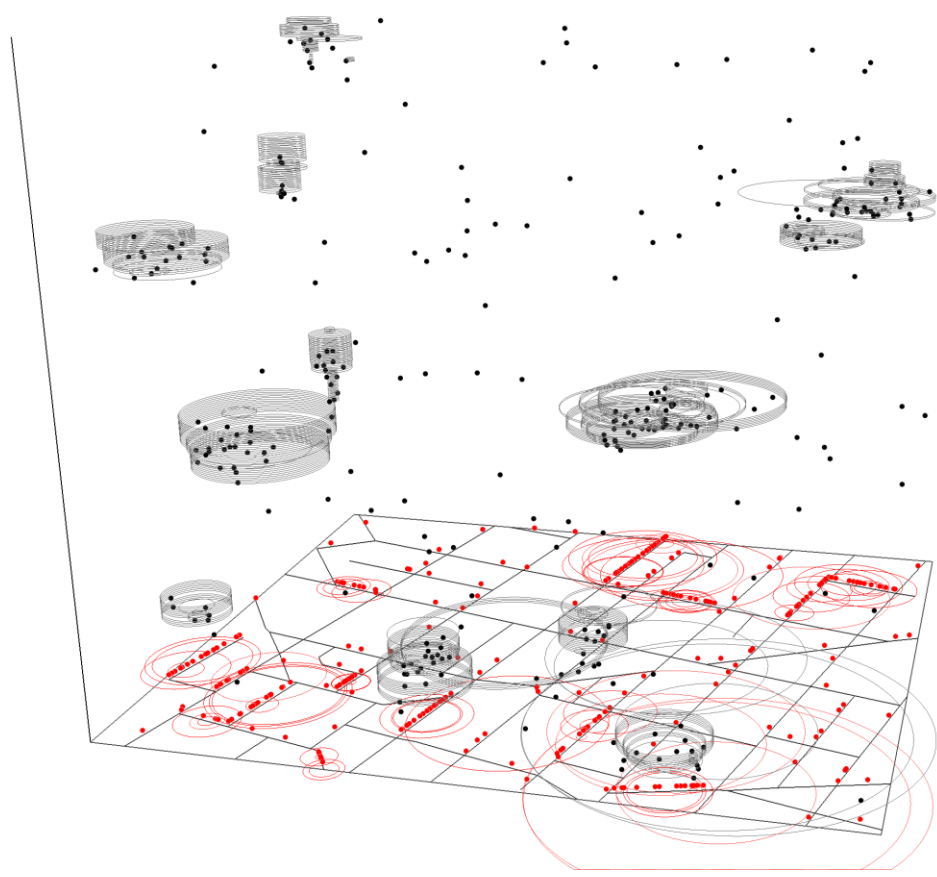


Figure 3: A three-dimensional view of the locations, size and timing of the circular alarms set off by PLSurveillance (grey circles), with their coverage being projected onto the xy -plane (red circles).

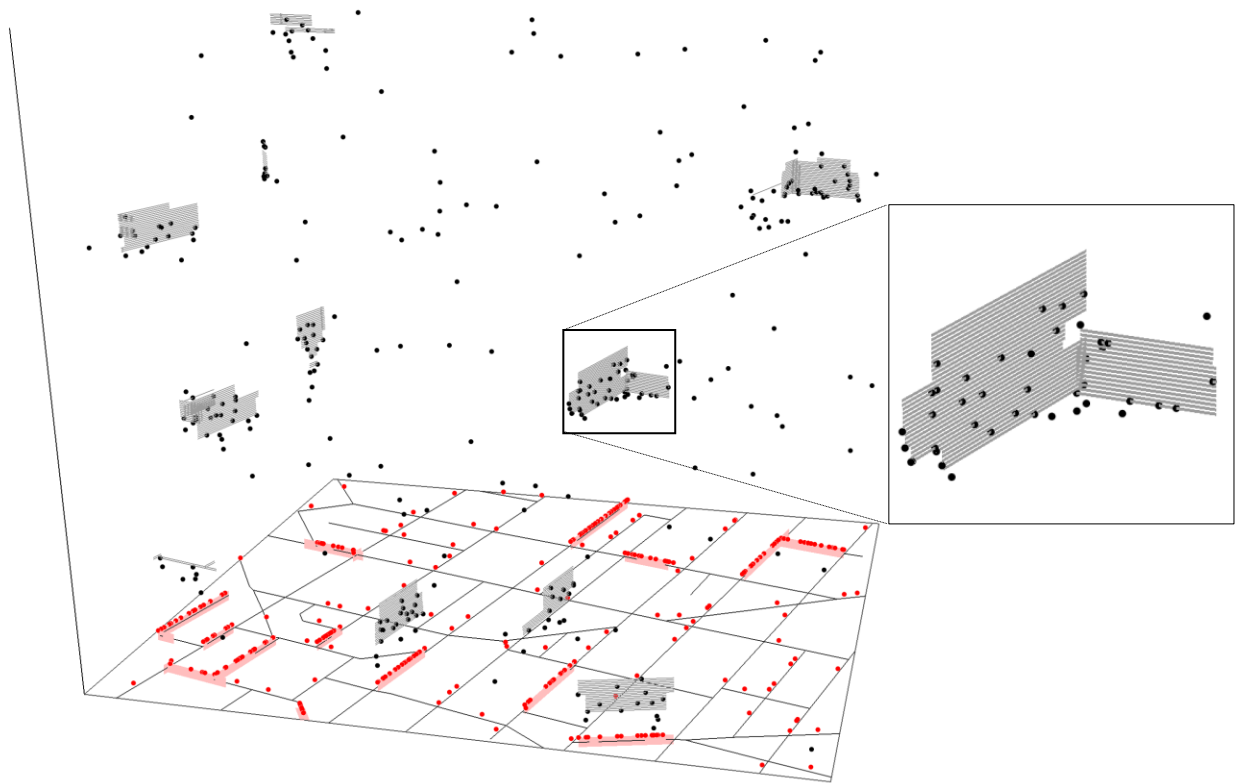
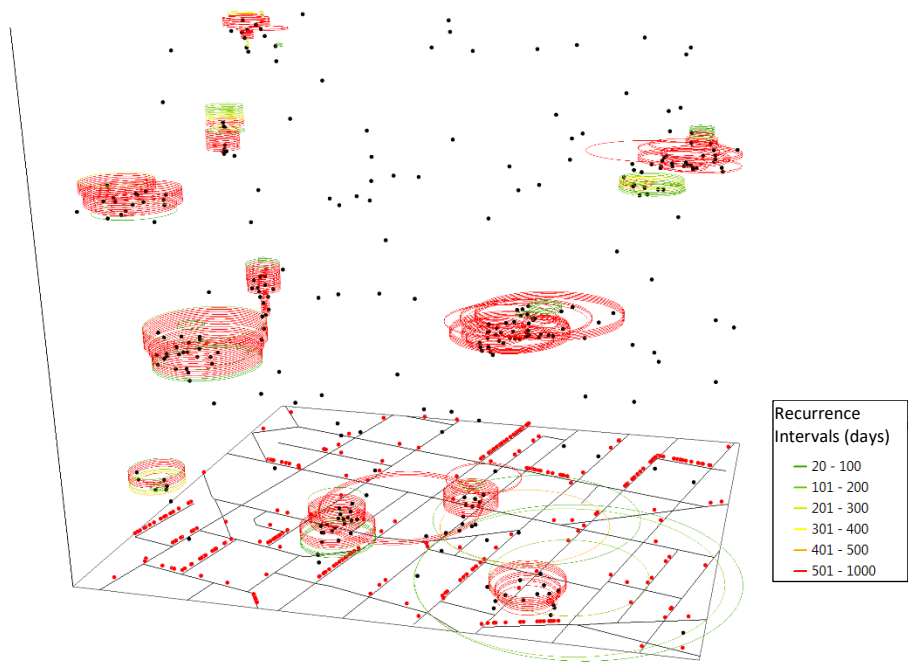
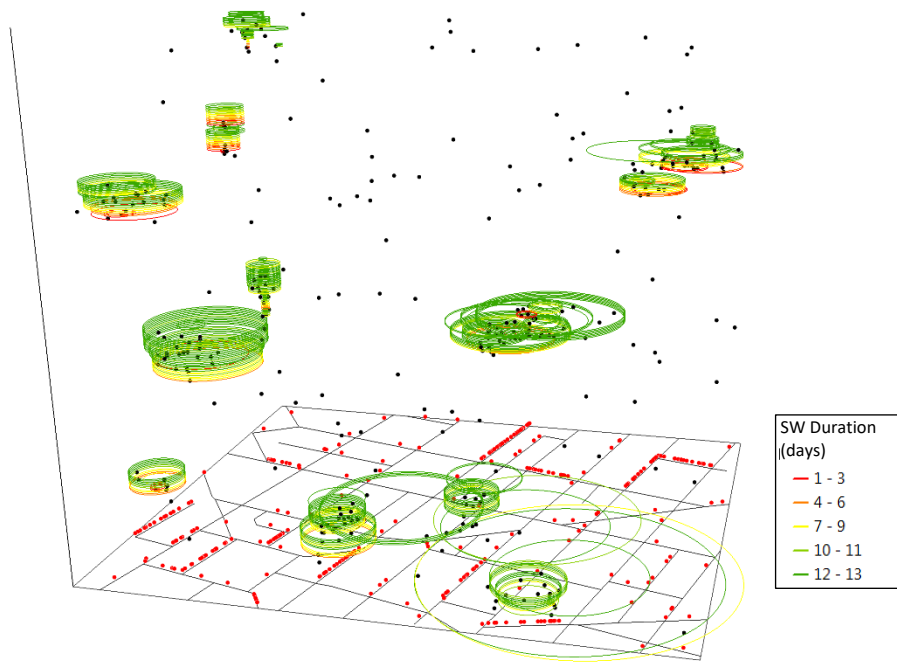


Figure 4: A three-dimensional view of the linear alarms set off by NetSurveillance, with their projection on the xy -plane (shown with pink line segments).

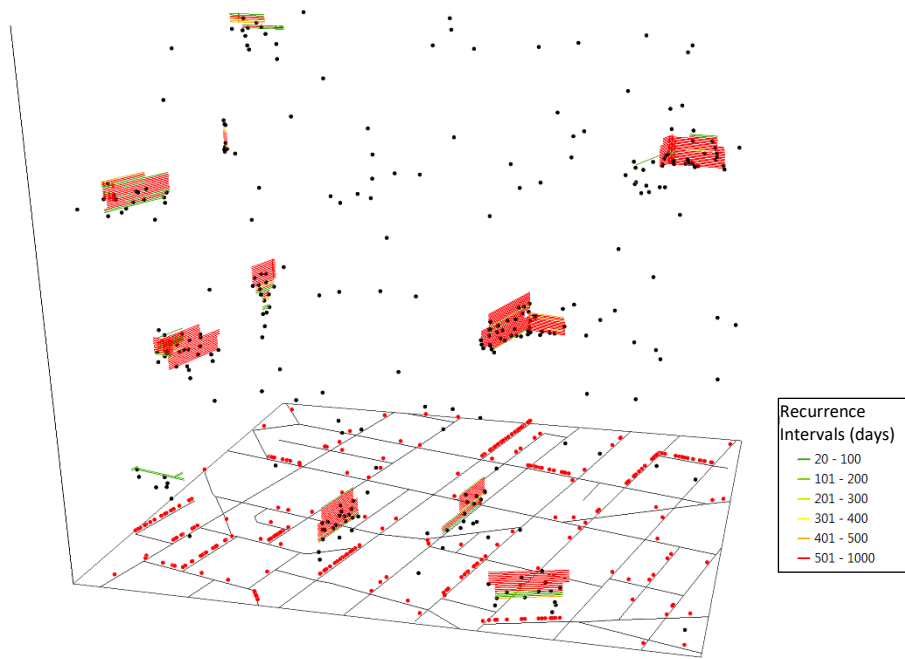


(a)

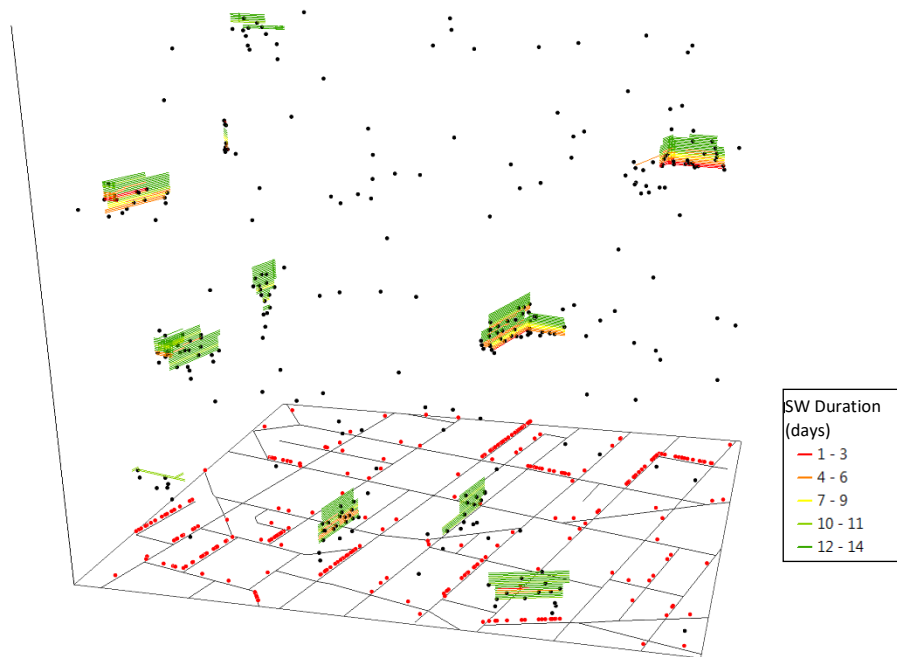


(b)

(b)



(c)



(d)

Figure 5: Signalled search windows coloured by (a) recurrence intervals from PLSurveillance, (b) temporal durations of the search windows from PLSurveillance, (c) recurrence intervals from NetSurveillance, and (d) temporal durations of the search windows from NetSurveillance.

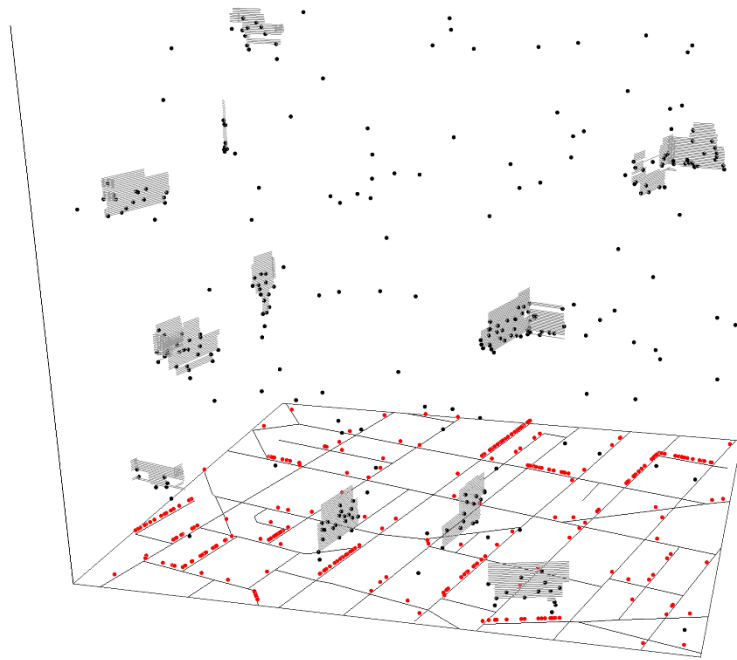


Figure 6: Locations and timings of alarms calculated for the revised simulated data.

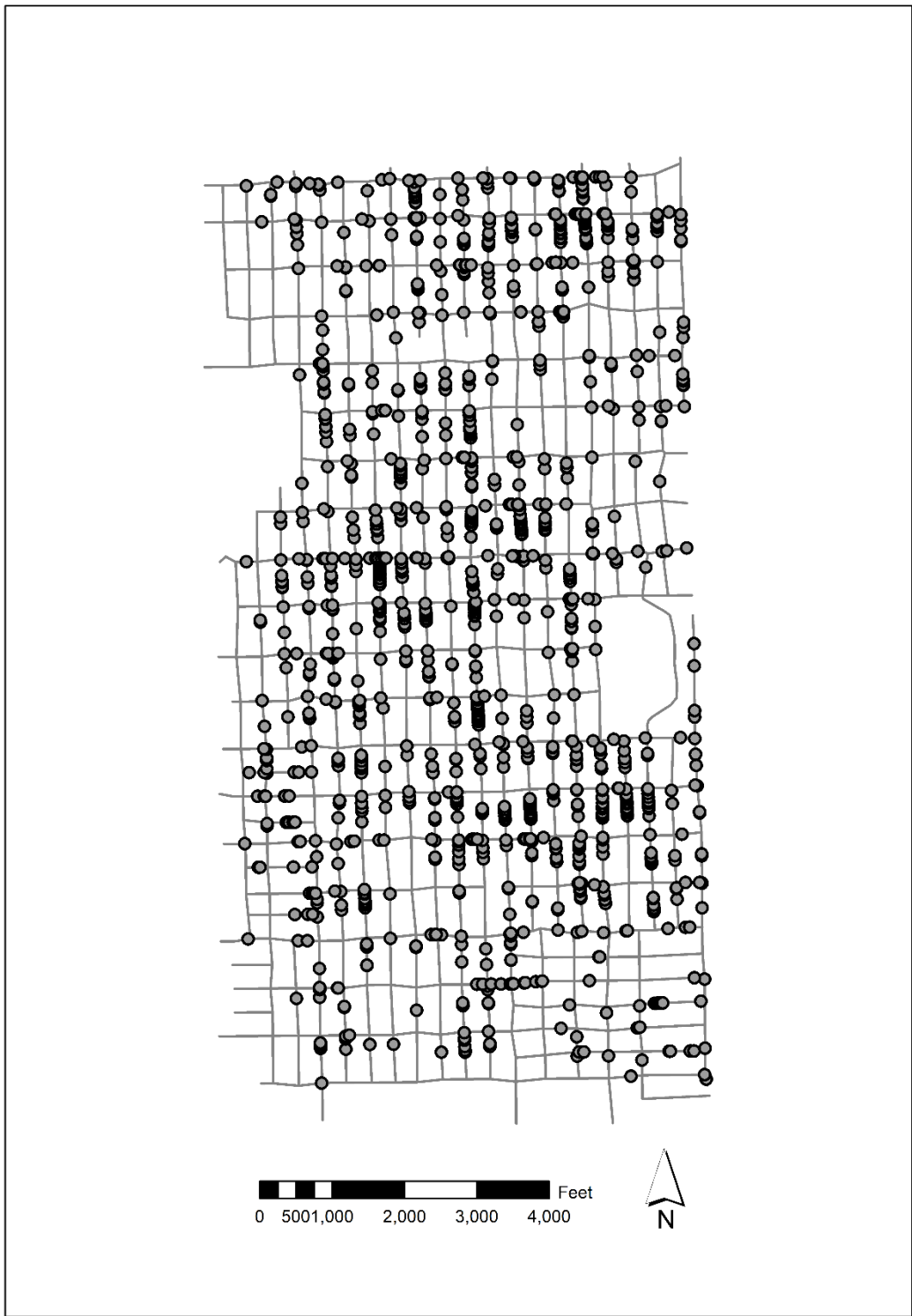


Figure 7: The study area, the street network, and the locations of drug incidents recorded in 2000.

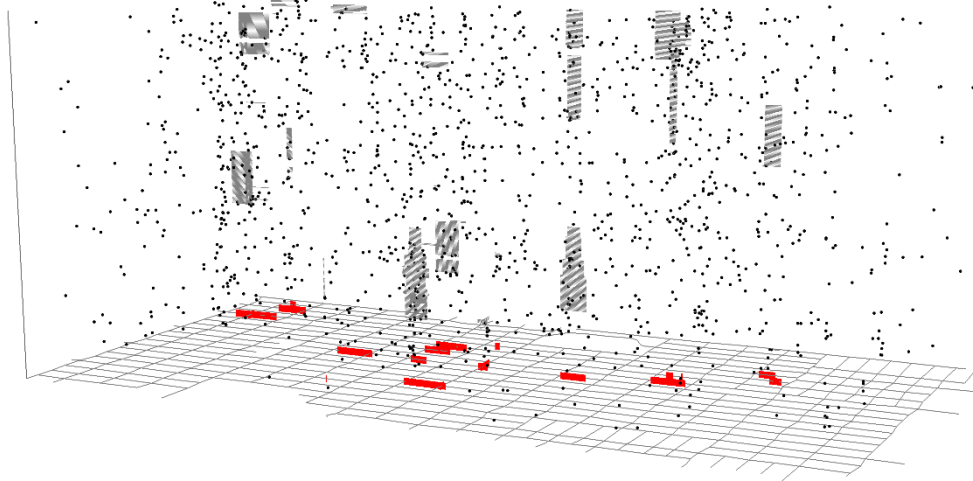


Figure 8: The alarms set off for drug incident data

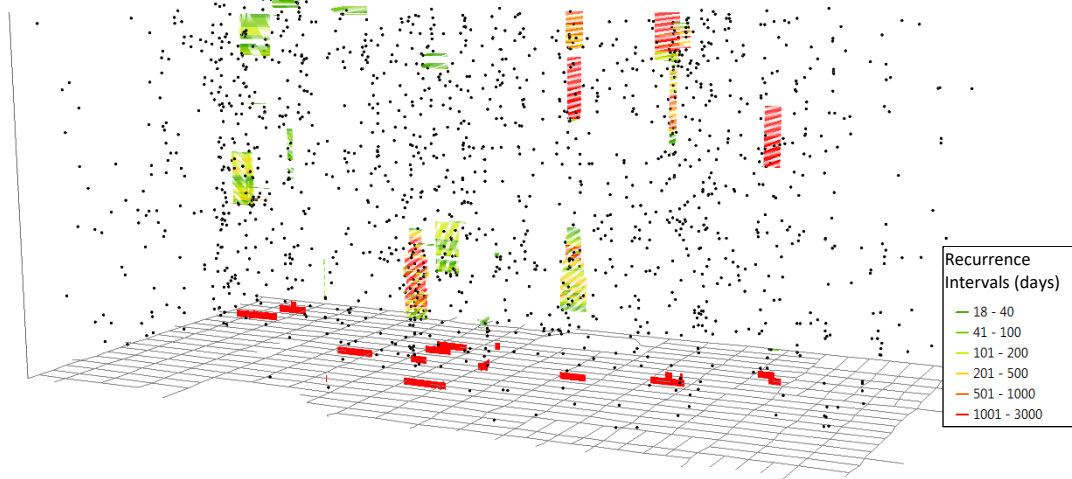


Figure 9: Recurrence intervals for each signalled cluster of drug-related incidents in West Englewood, Chicago IL.

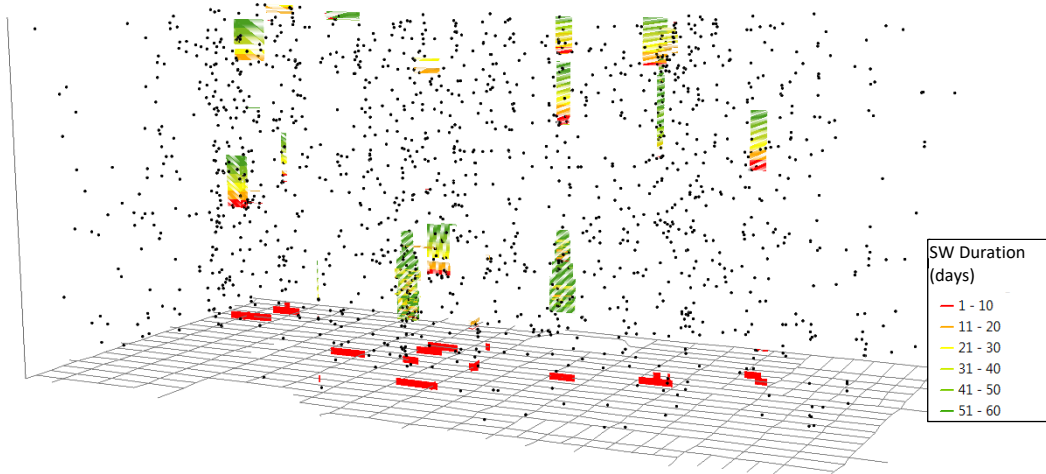


Figure 10: The temporal duration of the alarmed search windows of drug-related incidents in West Englewood, Chicago IL.