The Concentration-Dynamics Tradeoff in Crime Hot Spotting

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Abstract

Recent research leaves little doubt that crime is concentrated at micro-geographic scales. Much less is known about how spatial concentration of crime and crime pattern dynamics interact. This paper examines how the concentration of crime and the stability of crime hotspots changes as a function of the spatial and temporal scale of measurement. We find that crime is more concentrated when measured at finer spatial and temporal scales, but also more dynamic. As the scale of measurement increases, crime becomes more diffuse but the corresponding hotspots are also more stable. This fundamental tradeoff between concentration and dynamics is law-like in its behavior. The tradeoff has important implications for both theoretical understanding of crime patterns and hotspot policing.

Introduction

Current thinking in crime pattern theory relies on two somewhat contradictory observations. On the one hand, it is well-known that a small fraction of locations in any one environment account for a large fraction of the crime (Sherman et al. 1989, Weisburd 2015). On the other, there is good evidence that crime events themselves occur with a high degree of spatial-temporal variability (Bowers et al. 2004, Mohler et al. 2011, Short et al. 2009, Wang et al. 2013, Wang and Brown 2012, Wang et al. 2012).

Both observations hold important implications for understanding not only the causes of crime, but also designing crime prevention strategies. The former observation tends to encourage the view that crime patterns are predominantly static, persisting from one time period to the next in a roughly constant spatial configuration. The implication is that there is a tight coupling between crime and place that remains reasonably stable over time (Weisburd et al. 2012). If true, then it is clearly advantageous for police to repeatedly target the same places to achieve crime reduction (Sherman and Weisburd 1995).

The latter observation, by contrast, encourages the view that crime patterns are predominantly dynamic, with hotspots emerging, spreading, and dissipating only to reemerge in new locations (Johnson et al. 2008, Short et al. 2010). The implication is that crime is coupled to place quite loosely via a probabilistic decision making process (Brantingham and Brantingham 1978, 1981, Maltz et al. 1990, pg. 1). If true, then police may find advantage in anticipating how that probabilistic process is evolving in space and time and target a shifting series of locations on the landscape (Bowers et al. 2004, Mohler et al. 2011, Wang et al. 2013, Wang and Brown 2012, Wang et al. 2012). Recent work has looked at whether dynamic targeting of places by police has an impact on crime (Gorr and Lee 2015, Mohler et al. 2015, Telep et al. 2014). The present work seeks to show how both of these perspectives can simultaneously be true.

Our presentation gets straight to the point. We forego a review of the theoretical and empirical literature on crime and place, as there are several recent works that cover such information in great detail (see also Eck and Weisburd 1995, Weisburd et al. 2016, Weisburd et al. 2012). We therefore focus singularly on the analysis of crime concentration and the dynamics of crime hotspots. The paper is structured as follows. In section 1, we introduce our analytical approach, which is motivated by recent studies on the micro-geographic patterning of crime and place (Weisburd 2015, Weisburd et al. 2004, Weisburd et al. 2012, Wyant et al. 2012). As in Weisburd (2015), we are interested in the concentration of crime in a small number of geographic locations. However, we focus on how measured crime concentration changes as both the temporal and spatial windows for counting crime change (see also Brantingham et al. 1976, Chainey et al. 2008, Steenbeek and Weisburd 2016, Townsley 2008). We are also interested in measuring the stability of crime patterns in the context of changing spatial and temporal scales. We introduce a very simple measure that counts the percentage overlap in hotspot locations from one time period to the next when measured at different temporal and spatial scales (see Mohler et al. 2015). The approach is far simpler than other recent assessments of crime pattern stability (Johnson et al. 2008, Weisburd et al. 2004, Weisburd et al. 2012), but offers practical advantages in terms of ease of interpretation.

Section 2 turns to empirical assessments. We analyze crime patterns in Los Angeles during the years 2009-2015, and Chicago during 2008-2015. In both settings, we analyze assault, burglary, motor vehicle theft, and robbery, independently for each crime type. We offer theoretical motivation for choosing these crimes based on fundamental differences in the potential mobility of offenders and victims involved in each of these crime types (Tita and Griffiths 2005).

Section 3 presents our two principal findings. First, hotspots defined at smaller temporal and spatial scales capture the same amount of crime, while covering less total land area. In other words, crime appears to be much more concentrated when using smaller, short-term counting units compared with larger, long-term counting units. Second, hotspots defined at smaller temporal and spatial scales are much more dynamic than those defined at larger temporal and spatial scales. In other words, small, short-term hotspots spatially overlap much less from one time period to the next compared with larger, long-term hotspots. There is thus an apparent tradeoff with crime hotspot characterization. Smaller, short-term hotspots are better at identifying the highest crime concentrations in an environment, but those locations change substantially in placement at that short time scale. Alternatively, more stable crime patterns can be identified by adopting larger spatial and temporal scales, but at the cost of reduced crime concentration.

The final section discusses implications of the work. We discuss how the concentration-dynamics tradeoff impacts our understanding of crime causation. We then draw some general observations about the scale of analysis and policing and crime prevention. The punchline is that crime patterns do not exist only at one scale (Brantingham et al. 2009, Steenbeek and Weisburd 2016). This is not necessarily an indication of aggregation bias. Rather, it is indicative of behavioral processes operating at different scales. Policing and crime prevention efforts can benefit from calibrating to these scales.

Methods

Our methodological approach is divided into four principal parts. The first involves defining the spatial and temporal counting units for hotspot quantification. The second concerns measuring the global concentration of crime given those spatial and temporal units. The third concerns assessing the spatial stability (or lack thereof) of hotspots from one time period to the next. Our measure of spatial stability of hotspots is likely dependent upon macroscopic patterns of how smaller spatial units are organized into larger clusters (see Steenbeek and Weisburd 2016, Weisburd et al. 2012). We therefore also tabulate cluster sizes for each spatial and temporal scale.

We adopt a straightforward method for defining spatial and temporal counting units. Our spatial units are constructed as a regular square lattice or grid laid out over the entire jurisdiction. Specifically, we examine grids where each cell is 200 x 200, 400 x 400, or 800 x 800m in size. Fixed grid counting units may be contrasted with categorical spatial units such as street segments (Davies and Bishop 2013, Weisburd et al. 2012), reporting districts, census tracts, or formally recognized neighborhoods (Wooldredge 2002). Our temporal units are similarly defined in discrete terms as fixed time windows measured in days, months, or years. These discrete spatio-temporal units lead naturally to a histogram method for counting crime. We count all of the crimes of a specified type occurring in each grid cell during each defined time period. For example, we will count all of the robberies occurring in each 200 x 200m grid cell per day, or all burglaries in each 400 x 400m grid cell per month. Note that common hot spotting methods such as kernel density estimation (KDE) are closely related to the histogram counting procedure suggested here, as both are non-parametric estimators for the probability density function of a point process.

After counting the number of crimes within grid cells, the resulting counts are ranked in decreasing order by crime count. For example, the Rank 1 cell will contain the greatest number of crimes among all cells, the Rank 2 cell will contain the second greatest number of crimes, and so on. It follows that the Rank 1 cell will capture the greatest percentage of crime compared to all other individual cells for that specific time period, the Rank 2 cell will capture the next greatest percentage, and so on. Starting at the top of the ranked list, we flag each cell in order until the collection of flagged cells in total represents a predefined cumulative percentage of the total crime over that time window. For example, we might flag cells until 5%, 10%, 25% or 50% of all crime within that time period is captured by those cells.

For simplicity, we will use the term hotspot to refer to an individual grid cell flagged in this way. All of the cells not flagged in this way are not considered crime hotspots for that particular cell size and time period. Collections of flagged grid cells are referred to as clusters, when they form contiguous spatial blocks, or simply by the plural hotspots, when their spatial arrangement is not relevant. Note that our procedure is very closely related to Weisburd (2015), who counts the percentage of all street segments needed to capture a fixed percentage of crime (see also Weisburd et al. 2004, Weisburd et al. 2012). To facilitate comparison with Weisburd's results we report results for hotspots capturing 25% and 50% of crime, respectively. We caution, however, that crime counts aggregated by street segments and areal units such as grid cells may not be strictly equivalent (see Steenbeek and Weisburd 2016).

It is a simple matter to convert the number of crime hotspots into a measure of crime concentration. First, the number of flagged hotspots is converted into an area by multiplying by the known area of each cell (e.g., 200 x 200 m). Dividing this total hotspot area by the total land area of the jurisdiction yields the percent land area needed to capture a fixed percent of crime.

The smaller the percentage land area sufficient to capture a target crime percentage, the more concentrated crime is in space. For example, crime is two times more concentrated if 0.1% of a jurisdiction's land area captures 25% of crime, compared with 0.2% of the total land area capturing 25% of crime.

We measure hotspots stability in a similarly direct manner. For any given collection of crime hotspots, we measure the percentage overlap in hotspot locations from one time period to the next. For example, imagine a collection of one hundred hotspots each 400 x 400m in size sufficient to capture 25% of recorded crime over the course of one month. Now imagine that we perform the same analysis for the following month, again yielding one hundred hotspots of the same size. We then compare the hotspot locations from month 2 with those present in month 1 and find that 50% of the locations are the same. Thus half of the pattern is stationary at this temporal and spatial scale, and the other half is dynamic. Our approach is similar to Andresen (2011) wherein spatial units are compared across two time periods for the volume of crime present. Units are scored as stationary if the volume of crime is statistically equivalent across time periods. Our approach is considerably different from Weisburd et al. (2004) and Weisburd et al. (2012) who use group-based trajectory analysis to identify latent hotspot groups given the entire history of crime on street segments over a 16 year time period. They find that some latent groups display very stable crime patterns at an annual time scale over the study period, while others display secular variation in crime volume over time.

We also examine hotspot cluster sizes. To find the size of a hotspot cluster, we simply count the number of contiguous flagged hotspots present in a given time window. The counting procedure is as follows. Given a starting grid cell flagged as a hotspot, each immediately adjacent cell is joined to the same cluster if it is also flagged as a hotspot. These first-order neighbors are then used to look for unique adjacent cells that are also flagged as hotspots. These comprise second-order neighbors. The process is repeated until no unique hotspots can be joined to the component. We are primarily interested in how cluster size changes as a function of the spatial and temporal scale of measurement. To assess whether observed cluster sizes are different from what would be expected given random occurrence of crime, we simulate random hotspot placement for equivalent hotspot densities and then compute cluster sizes using the method above for these randomly placed hotspots.

Crime Patterns in Los Angeles and Chicago

Our analyses focus on crime patterns in Los Angeles, California, and Chicago, Illinois. Los Angeles is a city of nearly 4 million people and encompasses a land area of approximately 1,301 square km (509 square miles). Address-geocoded data on aggravated assault, burglary, motor vehicle theft, and robbery were provided by the Los Angeles Police Department for the years 2009-2015. Chicago is a city of approximately 2.7 million people and covers an area of 606 square km (234 square miles). We obtained block-geocoded open source data from the City of Chicago Open Data Portal (https://data.cityofchicago.org), which we examine for the years 2008-2015.

Our focal crime types are chosen because each encompasses different fundamental potentials for dynamic behavior given the mobility of offenders and victims or targets. At one extreme, we might expect burglary hotspots to inherently have lower dynamic potential. By definition, the offender in a burglary is mobile, but the target is stationary. Assuming that houses change in their baseline attractiveness only very slowly, then any temporal and spatial dynamics in burglary hotspots must be tied only to how burglars move and mix in the broader environment. At the other extreme, we might expect assault and robbery to inherently have higher dynamic capacity. Both crime types can involve mobile offenders and mobile victims (see Tita and Griffiths 2005). Hence, robbery and assault hotspots may be less tied to place because offenders and victims can move and mix independent of place. Between these extremes we might expect to find motor vehicle theft. In this case, the offender is mobile but targets experience short-term turnover in the composition of the car assemblage (Brantingham 2013). The nature of the opportunity for motor vehicle theft shifts through space and time as car assemblages change. At an abstract level, we might expect motor vehicle theft hotspots to have intermediate dynamic capacity.

For both Los Angeles and Chicago, we count crimes in grid cells of size 200 x 200, 400 x 400, and 800 x 800 m. While ultimately each of these is an arbitrary length scale, the finer spatial unit is consistent with the linear dimensions of street blocks in many American cities. Thus a short-hand way to think about the length scales is as one, four, and sixteen square block areas. The largest length scale we consider is at the small end (~0.064 square km) of what would be perceived as a neighborhood in inner-city contexts (Pebley and Sastry 2009).

The availability of years' worth of crime data means that we can examine multiple time windows for scoring hotspots. We use one week, one month, three month, six month, and one year time windows for both Los Angeles and Chicago. In Chicago, we also examine crime patterns at two-year intervals. In both Los Angeles and Chicago, we also look at each sample as a whole, representing seven years in Los Angeles and eight years in Chicago.

Results

We first examine patterns in Los Angeles. Figure 1 presents crime concentration as a function of the time window at which hotspots are quantified. Shown is the percentage land area necessary to capture 25% and 50% of crime, respectively, with time windows ranging from one week (7 days) to 7 years (2555 days). The length scale for hot spotting in Figure 1 is 200 x 200m. Figure 1A shows the results for robbery, while Figure 1B shows the results for burglary. Numerical results for all four crime types are presented in Table 1.

Crime is clearly more concentrated when the time window used for hotspot quantification is shorter. For example, when hotspots are computed with 7 day time windows, approximately 0.1% of the total land area must be flagged as hotspots to capture 25% of robberies (Table 1). The percentage land area needed increases to 0.3% when the time window is 1 month. In other words, robberies are 3 times more concentrated with hotspots measured on the scale of 7 days compared with one month. When the time window is further increased to 3 months, 6 months, and one year, the percentage land area needed climbs to 0.5%, 0.7% and 0.8%, respectively. At 7 years, the full temporal extent of our data, 1.1% of the total land area needs to be flagged to capture 25% of crime. In other words, robberies are 11 times more concentrated when measured at the 7 day scale compared with the 7 year scale. This pattern is replicated for each of the crime types considered here and when the target crime fraction for hotspots changes to 50% (Table 1). For example, the percentage land area necessary to explain 50% of burglaries increases from 0.4% of land area to 12.5% of land area when the time window for hot spotting increases from 7 days to 7 years, respectively. Burglaries are 31 times more concentrated at the shortest versus the longest time scale considered. The empirical pattern is well-fit by a logarithmic function of the form $y = a * LN[x] + b$.

Figure 2 examines the dynamics of crime hotspots as a function of hot spotting time window. The percentage overlap in the location of crime hotspots from one time period to the next increases as the time window increases (Table 1). This indicates that hotspots measured at shorter time-scales are much more dynamic than those measured at longer time scales. For example, only 2.9% of robbery hotspots flagged in one week are in the same locations in the following week, when those hotspots are set to capture 25% of crime (Figure 2A). The vast majority of flagged robbery hotspots are in different places from week to week. When the time window is increased to 1 month, 11.9% of robbery hotspots on average are flagged in the same location from one month to the next. This represents a greater degree of stability in crime patterns, but the majority of flagged locations still differ from month to month. For hotspots quantified on a yearly time scale, 47.2% of hotspot locations are the same location from year to year. The quantitative pattern is the same when the criterion for designating robbery hotspots shifts to capturing 50% of crime (Figure 2A). Burglary crime patterns similarly increase in stability with increasing hot spotting time window, but here the stability is more pronounced when seeking to capture 50% of crime compared with 25% of crime (Figure 2B). The relationship is well-fit by an exponential function of the form $y = a - ae^{-bx}$.

Given the data on hand, we can examine the interaction between crime concentration and hotspot dynamics. Figure 3 shows the percentage overlap in hotspot locations from one time period to the next against the percentage land area sufficient to capture 25% and 50% of crime (Table 1). Hotspots flagged using shorter time windows are more concentrated in space, but also more dynamic. Those flagged using longer time windows are less concentrated, but also more stable. The relationship between these two measures of crime patterns is non-linear. The non-linear trend is very pronounced for robbery patterns (Figure 3A). It is also visible for burglary patterns where hotspots are flagged for 25% of crimes. It is less obvious that the trend is non-linear where hotspots are flagged for 50% of burglaries. Assault and motor vehicle theft follow the burglary pattern (Table 1). Nevertheless, the relationship is well-fit by a polynomial equation of the form $y = ax^2 + bx$.

All of the results presented in Figures 1-3 were computed for a spatial grid with 200 x 200m cells. A larger spatial length scale produces equivalent results (Table 2). Figure 4 is a direct extension of Figure 3 across three different spatial length scales for hotspots capturing 25% of crime. Note that the 200m curves in Figure 4A and 4B match exactly the 25% curves in Figures 3A and 3B, respectively. At each spatial length scale it is clear that shorter time windows produce greater crime concentration, but also yield more dynamic hotspots. Longer time windows produce lower crime concentration, but hotspots are more stable. With the 200m curve from Figure 3 for reference, it is clear that increasing the spatial length scale shifts the relationship between concentration and dynamics up and to the right. A larger grid size requires a greater percentage land area to capture the same amount of crime, but also produces greater stability in hotspots across time periods. Table 2 illustrates the relationship for hotspots defined for one year time windows. For example, for assaults the mean percentage of land area sufficient to capture 25% of crime increases from 1.1% to 2.8% as the spatial length scale increases from 200 x 200m to 800 x 800m. The percent overlap in assault hotspots also increases from 28.1% to 63.3% over the same range of spatial scales.

To illustrate that the observed patterns are not unique to the Los Angeles setting we computed the same metrics for Chicago. Tables 3 and 4 present the primary results. Figure 5A shows the percentage overlap in hotspot locations against the percentage land area required to capture 25% of robberies and burglaries for a 200 x 200m length scale. The functional form for the relationship is equivalent to that seen in Los Angeles, though the quantitative parameters for the fitted models differ depending upon crime type. In Chicago, for example, hotspots sufficient to capture 25% of robberies over a one year time scale cover 2.3% of the total land area (Figure 5A; Table 3). The overlap in hotspot locations is 46.5% from year to year. By contrast, in Los Angeles, hotspots sufficient to capture 25% of robberies cover only 0.8% of the total land area, while 47.2% of locations overlap from year to year. The numerical comparisons for burglary are more similar (see Tables 1 and 2).

Shifting to a larger spatial length scale of 800 x 800m replicates many of the same patterns (Figure 5B; Table 3). For example, at a yearly time scale hotspots needed to capture 25% of robberies in Chicago cover 5.7% of land area, while 66.4% of those hotspots remain in the same place from year to year. In Los Angeles, the comparable figures are 2.2% of land area and 67.6% overlap. Overall, the relationship between crime concentration and the dynamics of hotspots displays considerable regularity across regions.

All of the analysis to this point has focused on discrete hotspot locations. For example, we have examined the concentration of crime within and dynamics of discrete 200 x 200m cells defined with fixed time windows. Here we consider whether these discrete locations cluster to form larger components and how cluster size is dependent upon the spatial and temporal lengths scales used. This was an issue first addressed by Brantingham et al. (1976).

Tables 5 and 6 show the observed and expected average size of the largest hotspot cluster for any given hot spotting time window. Results are presented for 200 x 200m hotspots sufficient to capture 25% of crime. The results are consistent for larger spatial length scales and for higher crime percentage targets. Table 5 presents data from Los Angeles. Table 6 presents data from Chicago.

For any given spatial and temporal length scale, individual hotspots cluster to form larger components. For example, the largest assault hotspot clusters in Los Angeles for a 7 day time window contains on average 1.3 cells each 200 x 200m in size (Table 5). At one month, the largest assault hotspot clusters are typically 2.9 cells. This rises to 6.7, 11.5, 19.6 and 34 grid cells for 3 months, 6 months, 1 year, and 7 years, respectively. Whether these clusters are larger or smaller than those expected by chance varies with the time window for hot spotting. The expected hotspot cluster size is computed by taking the observed number of hotspots for any given time window and generating 10^3 repeated random spatial placements of that same number of hotspots. We restrict random cell placement to only those locations that recorded at least one crime over the given time period. The largest observed clusters are typically smaller than that expected by chance for hot spotting time windows of one month or less. For example, the largest observed 30 day robbery cluster in Los Angeles is typically 4.9 cells in size, while that generated by random placement is typically 6.5 cells in size (Table 5). For hot spotting time windows of 3 months, however, the typical maximum cluster size is very similar to that occurring by chance. Beyond 3 month hot spotting windows, the observed maximum cluster sizes are larger than that expected by chance. For example, 6 month burglary hotspots in Los Angeles are typically 11.1 cells in size compared with 9.9 cells by chance. The size difference is much larger at one year with observed burglary hotspot clusters of 18 cells compared with 12 expected by chance. At the maximum time window, the gap becomes 74 cells observed compared with 12 expected by chance for burglary hotspot clusters. Equivalent patterns are observed in Chicago (Table 6). Importantly, crime appears to be more concentrated into spatially contiguous counting units when measured at larger temporal scales than at smaller temporal scales.

Discussion & Conclusions

There is a clear tradeoff between crime concentration and the dynamics of the corresponding crime patterns. The tradeoff is driven by the spatial and temporal scale of measurement. Crime appears to be more concentrated when measured using smaller spatial units and shorter time windows. The same percentage of crime is captured in a smaller percentage land area when the flagged hotspots are small in spatial extent and brief in temporal duration. However, crime measured at finer scales is also more dynamic. A larger fraction of hotspots shift locations from one time period to the next when those locations are small in spatial extent and brief in temporal duration.

The tradeoff between concentration and dynamics is more than just an artifact of the scale of measurement. There is good reason to link the tradeoff to fundamental causal processes occurring at different scales. Short-term crime pattern dynamics reflect local stochastic fluctuations in situational conditions and criminal opportunities. This is where we expect random effects in offender decision making and crime opportunities to dominate measured patterns. For example, a collection of street segments may differ in the total number of parking spaces from one segment to the next, which may lead to differences in the average density of motor vehicle theft (Brantingham 2013). However, that one of these street segments *today* happens to have more late 1990s model Honda Civics parked there, and therefore more thefts *today*, may be entirely random. Tomorrow it may be another of the street segments in the set that has a higher density of such cars, or perhaps none of them does. Such random fluctuations in opportunity will be very visible if hotspots are measured at short spatial and temporal scales. Such variation is averaged out when measured at larger spatial and temporal scales. It is at these larger scales that mesoscopic routine activity processes take hold. The density of parking spaces regulates not only the relative volume of offenders and targets, but also how they move and mix. We expect these routine activity patterns to be more stable precisely because the density of parking spaces across street segments does not change on short time scales. Such processes will generate a clear signal when measuring motor vehicle theft hotspots over months or years.

Close inspection of Tables 1 and 3 suggest that our assumptions about the dynamic capacities of different crime types are inconsistent with observed patterns. We relied on general principles from routine activities theory to suggest that burglary would be the least spatially and temporally dynamic of crimes, robbery and assault the most dynamic, and motor vehicle theft somewhere in between. If we compare robbery and burglary in Los Angeles, robbery hotspots overlap to a much greater degree from one time period to the next compared with burglary (Table 1). For example, with 200 x 200m cells sufficient to capture 25% of crime on a yearly basis, 47.2% of robbery hotspots remain stationary from one year to the next. Only 23% of the burglary hotspots remain in the same place from year to year. This general observation holds true for robbery and burglary across all time scales of observation. The pattern also holds true for robbery and burglary in Chicago for all time scales save the shortest time window (Table 3). It would seem that robbery hotspots are less dynamic than burglary hotspots in spite of the potential mobility of both offenders and victims in the case of robbery. The patterns are somewhat more complex for assault and motor vehicle theft (Table 1). Assault and motor vehicle theft hotspots are more dynamic than burglary hotspots in Los Angeles for longer time scales of a year or more, contrary to our initial assumptions, but more dynamic at shorter time scales, consistent with our assumptions. In Chicago, assault hotspots are less dynamic and motor vehicle thefts more dynamic compared to burglary across all time scales. These results also show that there are potential regional differences in relative hotspot dynamics among different crime types.

Nevertheless, the concentration-dynamics tradeoff observed in both Los Angeles and Chicago is very regular, or law-like in its behavior . A candidate law-like statement is $\text{PAI} * O = K$. Here PAI is the predictive accuracy index and *O* is the percent overlap in hotspot locations for crime patterns measured at a given spatial and temporal scale. Recall that PAI is the percent predicted crime *C* divided by the percent area covered by predictions *A*. Here we equate the area covered by predictions with the area covered by flagged hotspots, making PAI retrospective rather than prospective. PAI is thus an index of crime concentration. For the above equation to be law-like in its behavior we want *K* to be a constant for all temporal and spatial scales. For the target levels of crime considered above, the equation becomes $C * O/A = K$, with C = 25% or 50%. This form of the equation clearly shows that the percentage overlap in hotspots between two adjacent time windows *O* must increase proportionally with *A* for *K* to be a constant. The constant of proportionality linking hotspot overlap to area flagged as hotspots is *K*/*C*.

Figure 6 shows values of *K* plotted against the time window for crime hot spotting for all four crime types considered here. For *K* to be a constant for a given crime type, we would expect that the slope of the curve relating *K* to the time window for crime hot spotting in Figure 6 to be zero. In both Los Angeles and Chicago, computed slopes for these curves are not significantly different from zero for burglary (Los Angeles: $p = 0.158$; Chicago: $p = 0.158$) and motor vehicle theft (Los Angeles: $p = 0.576$; Chicago: $p = 0.809$). In other words, *K* is a constant estimated by the intercept of the regression equation (Figure 6). In Los Angeles, the computed slope is also not significantly different from zero for assault ($p = 0.186$), but is marginally different from zero for robberies ($p = 0.053$). This indicates law-like behavior for assaults in Los Angeles, but not necessarily for robberies. In Chicago, the computed slope is significantly different from zero for both assaults (p = 0.005) and robberies (p = 0.002). Thus, for five out of eight examined crime types, the tradeoff between concentration and dynamics appears to be constant over a range of temporal scales. Whether this is truly law-like behavior will require more theoretical and empirical investigation, focusing not only on more geographic settings, but also on the full combinatorial range of spatial and temporal scales.

The concentration-dynamics tradeoff presents some practical challenges beyond the theoretical ones mentioned above. The tradeoff is an inherent challenge for policing and crime prevention at a given focal scale. It seems reasonable to suggest that the more concentrated crime is in an environment the greater the potential impact of directed police patrol on crime given limited policing resources (Sherman and Weisburd 1995, Weisburd 2015). Since crime is demonstrably more concentrated when measured at finer spatial and temporal scales, then a clear recommendation is that place-based policing should be focused at such micro-geographic *and* micro-temporal scales. For example, 25% of assaults in Los Angeles are successfully captured by flagging just 0.1% of the total land area on a weekly basis with 200 x 200m grid cells (Table 1). Policing such a small fraction of the city may have an outsized impact on the problem. However, focusing at such small scales also necessitates that place-based policing be dynamic. To consistently capture 25% of assaults each week, 99.2% of those locations must also change each week. If, however, we determine hotspot cells every month rather than every 7 days, then we must double the number of cells to 0.2% of the city to capture the same 25% of crime. In other words, failing to adjust micro-geographic hotspots in sufficiently dynamic fashion would either necessitate a doubling of police resources to cover the increased number of hotspots, or reduce the amount of crime targeted by place-based policing as crime concentration is necessarily lower if we hold constant a fixed number of flagged hotspots. Assuming that the same policing tactic has equal effects across different places, the simple difference in exposure arising from insufficiently dynamic hot spotting would be expected to produce less crime prevention.

The assumption of equal effects of policing and crime prevention efforts across space is of course dangerous (Cousineau 1973, Groff et al. 2015). Efforts to build community trust, for example, may find great success in some places and fail in others (Tyler 2005). Moreover, there is still considerable uncertainty about the comparative effects of different tactics in and of themselves (see Groff et al. 2015). It seems plausible that different policing and crime prevention tactics also have effects that operate at different spatial and temporal scales. We expect policing and crime prevention strategies targeting places and times proximal to the criminal event will mainly have local, short-term effects. Strategies targeting places and times distal to the criminal event may primarily drive broader, long-term changes.

Consider, for example, a city in which bars and nightclubs are widely dispersed across the urban landscape. Knowing that a range of criminal and nuisance behavior often follow last call, police might choose to have a physical presence at some of those bars at closing time, especially on Friday nights. The presence of police exactly at closing time may go a long way towards disrupting the opportunity for robberies, assaults, drug deals, vandalism and public disorder (Berkley and Thayer 2000). Offenders and victims are already in contact with one another in a setting ripe for problems. Police simply prevent some types of interactions from occurring in spite of the existing conditions. However, the impact of such proximate interventions is limited to the bars targeted and likely dissipates soon after the police leave (Cohen et al. 2003, Koper 1995). By contrast, better training of place managers such as bartenders for all of the city's bars may also reduce crime and disorder rates (Sampson et al. 2010). Here small nudges to the routine activities of bar patrons by well-trained bar tenders tweak the probabilities that victims and offenders mix as well as the conditions under which that mixing occurs. In the same way that you can only identify a subtly biased coin after a large number of coin flips, small probabilistic shifts in routine activities will only amount to real crime reduction over larger areas and over longer time horizons. Strategies that aim to change the physical environment or core features of culture and social organization may operate at even longer temporal horizons. Changing tax incentives to encourage the development of balanced-use entertainment districts may take years to effect change (Berkley and Thayer 2000), with a correspondingly long time horizon for effects on crime and disorder. Programs designed to alter risk preferences among youth, for example smoking or alcohol consumption, may only yield results over decades and then only at the spatial scale of whole populations (Ng et al. 2014).

A reasonable implication is that policing and crime prevention activities may benefit from adopting an analytical scale and dynamic capability appropriate to the behavioral processes targeted by deterrence or prevention programs (Greenberg et al. 1981). In general, policing and crime prevention tactics with known or expected hyper-local and short-term effects are best supported by analytics focused on very small-scale geographic targets. This is what is advocated by Weisburd (2015) and others (e.g., Groff et al. 2015, Wyant et al. 2012). But the evidence here suggests that such a small-scale focus should also be dynamic to approach optimal effectiveness. Indeed, fighting crime on short time scales may require dynamic prediction (Mohler et al. 2015, Mohler et al. 2011). By contrast, those policing strategies known or expected to have effects that operate over larger geographic areas and longer time horizons may benefit most from analytics that encompass larger geographic spaces and are static over time. In other words, fighting crime on long time scales requires stationary pattern characterization. Aggregating in larger units averages over spatial and temporal heterogeneity in the system (Cousineau 1973). Policing and crime prevention tactics paired with analytics that are suboptimal with respect to the scale and dynamics of the underlying behavior may therefore also perform suboptimally. Though recent research seems to argue that micro-geographic units are superior to other scales, the present work suggests that this is only true for policing tactics and crime processes operating at such a micro-geographic scale. Further research is required to assess how scale matching might be put to best effect in not only understanding the dynamics of crime, but also how best to attack such problems.

References Cited

Andresen, Martin A., and Nicolas Malleson. 2011. "Testing the Stability of Crime Patterns: Implications for Theory and Policy." *Journal of Research in Crime and Delinquency* 48 (1):58-82.

Berkley, Blair J., and John R. Thayer. 2000. "Policing entertainment districts." *Policing: An International Journal of Police Strategies & Management* 23 (4):466-491.

Bowers, Kate J., Shane D. Johnson, and Ken Pease. 2004. "Prospective Hot-Spotting The Future of Crime Mapping?" *British Journal Of Criminology* 44 (5):641-658.

Brantingham, P. Jeffrey. 2013. "Prey selection among Los Angeles car thieves." *Crime Science* 2 (1):1-11.

Brantingham, Patricia L., Paul J. Brantingham, Mona Vajihollahi, and Kathryn Wuschke. 2009. "Crime Analysis at Multiple Scales of Aggregation: A Topological Approach." Pp. 87-107 in David Weisburd, Wim Bernasco and Gerben J. N. Bruinsma (eds.), Putting Crime in its Place: Units of Analysis in Geographic Criminology. New York, NY: Springer New York.

Brantingham, Paul J., and Patricia L. Brantingham. 1978. "A Theoretical Model of Crime Site Selection." Pp. 105-118 in M. Krohn and R.L. Akers (eds.), Theoretical Perspectives on Crime and Criminal Justice. Beverly Hills: Sage.

Brantingham, Paul J., and Patricia L. Brantingham. 1981. *Environmental Criminology*. Beverly Hills: Sage.

Brantingham, Paul J., Delmar A. Dyreson, and Patricia L. Brantingham. 1976. "Crime Seen Through a Cone of Resolution." *American Behavioral Scientist* 20 (2):261-273.

Chainey, S., L. Thompson, and S. Uhlig. 2008. "The utility of hotspot mapping for predicting spatial patterns of crime." *Security Journal* 21 (1-2):4-28.

Cohen, Jacqueline, Wilpen Gorr, and Piyusha Singh. 2003. "Estimating intervention effects in varying risk settings: Do police raids reduce illegal drug dealing at nuisance bars." *Criminology* 41:257.

Cousineau, Douglas F. 1973. "A Critique of the Ecological Approach to the Study of Deterrence." *Social Science Quarterly* 54 (1):152-158.

Davies, Toby P., and Steven R. Bishop. 2013. "Modelling patterns of burglary on street networks." *Crime Science* 2 (1):1-14.

Eck, John E, and David L. Weisburd. 1995. "Crime places in crime theory." Pp. 1-34 in John E Eck and David L Weisburd (eds.), Crime and place.

Gorr, Wilpen L., and YongJei Lee. 2015. "Early Warning System for Temporary Crime Hot Spots." *Journal of Quantitative Criminology* 31 (1):25-47.

Greenberg, David F., Ronald C. Kessler, and Charles H. Logan. 1981. "Aggregation Bias in Deterrence Research: an Empirical Analysis." *Journal of Research in Crime and Delinquency* 18 (1):128-137.

Groff, Elizabeth R., Jerry H. Ratcliffe, Cory P. Haberman, Evan T. Sorg, Nola M. Joyce, and Ralph B. Taylor. 2015. "Does What Police Do at Hot Spots Matter? The Philadelphia Policing Tactics Experiment." *Criminology* 53 (1):23-53.

Johnson, Shane D., Steven P. Lab, and Kate J. Bowers. 2008. "Stable and Fluid Hotspots of Crime: Differentiation and Identification." *Built Environment (1978-)* 34 (1):32-45.

Koper, Christopher S. 1995. "Just enough police presence: Reducing crime and disorderly behavior by optimizing patrol time in crime hot spots." *Justice Quarterly* 12 (4):649-672.

Maltz, Michael, Andrew C Gordon, and Warren Friedman. 1990. *Mapping crime in its community setting: Event geography analysis*: Michael Maltz.

Mohler, G.O., M.B. Short, P.J. Brantingham, F.P. Schoenberg, and G.E. Tita. 2011. "Self-exciting point process modeling of crime." *J. Am. Stat. Assoc.* 106.

Mohler, George, Martin B. Short, Sean Malinowski, Mark Johnson, George E. Tita, Andrea L. Bertozzi, and P. Jeffrey Brantingham. 2015. "Randomized Controlled Field Trials of Predictive Policing." *Journal of the American Statistical Association* 110 (512):1399-1411.

Ng, Marie, Michael K. Freeman, Thomas D. Fleming, M Robinson, Laura Dwyer-Lindgren, Blake Thomson, Alexander Wollum, Ella Sanman, Sarah Wulf, Alan D. Lopez, Christopher J.L. Murray, and Gakidou Emmanuela. 2014. "Smoking prevalence and cigarette consumption in 187 countries, 1980-2012." *JAMA* 311 (2):183-192.

Pebley, Anne R, and Narayan Sastry. 2009. "Our place: perceived neighborhood size and names in Los Angeles." *Los Angeles: California Center for Population Research, University of California*.

Sampson, Rana, John E Eck, and Jessica Dunham. 2010. "Super controllers and crime prevention: A routine activity explanation of crime prevention success and failure." *Security Journal* 23 (1):37-51.

Sherman, L.W., and D. Weisburd. 1995. "General deterrent effects of police patrol in crime “hot spots”: A randomized, controlled trial." *Justice Quarterly* 12 (4):625-648.

Sherman, Lawrence W., Patrick R. Gartin, and Michael E. Buerger. 1989. "Hot spots of predatory crime: Routine activities and the criminology of place." *Criminology* 27.

Short, Martin B., P. Jeffrey Brantingham, Andrea L. Bertozzi, and George E. Tita. 2010. "Dissipation and displacement of hotspots in reaction-diffusion models of crime." *Proceedings of the National Academy of Sciences* 107 (9):3961.

Short, Martin B., Maria R. D'Orsogna, P. Jeffrey Brantingham, and George E. Tita. 2009. "Measuring and modeling repeat and near-repeat burglary effects." *J. Quant. Criminol.* 25:325-339.

Steenbeek, Wouter, and David Weisburd. 2016. "Where the Action is in Crime? An Examination of Variability of Crime Across Different Spatial Units in The Hague, 2001–2009." *Journal of Quantitative Criminology* 32 (3):449-469.

Telep, Cody W., Renée J. Mitchell, and David Weisburd. 2014. "How Much Time Should the Police Spend at Crime Hot Spots? Answers from a Police Agency Directed Randomized Field Trial in Sacramento, California." *Justice Quarterly* 31:905-933.

Tita, George, and Elizabeth Griffiths. 2005. "Traveling to Violence: The Case for a Mobility-Based Spatial Typology of Homicide." *Journal of Research in Crime and Delinquency* 42 (3):275-308.

Townsley, Michael. 2008. "Visualising space time patterns in crime: the hotspot plot." *Crime patterns and analysis* 1.

Tyler, Tom R. 2005. "Policing in black and white: Ethnic group differences in trust and confidence in the police." *Police quarterly* 8 (3):322-342.

Wang, Tong, Cynthia Rudin, Daniel Wagner, and Rich Sevieri. 2013. "Learning to detect patterns of crime." Pp. 515-530), Machine Learning and Knowledge Discovery in Databases: Springer.

Wang, Xiaofeng, and DonaldE Brown. 2012. "The spatio-temporal modeling for criminal incidents." *Security Informatics* 1 (1):1-17.

Wang, Xiaofeng, Matthew S Gerber, and Donald E Brown. 2012. "Automatic crime prediction using events extracted from twitter posts." Pp. 231-238), Social Computing, Behavioral-Cultural Modeling and Prediction: Springer.

Weisburd, David. 2015. "The Law of Crime Concentration and the Criminology of Place." *Criminology* 53 (2):133-157.

Weisburd, David, Shawn Bushway, Cynthia Lum, and Sue-Ming Yang. 2004. "Trajectories of Crime At Places: A Longitudinal Study of Street Segments in the City of Seattle." *Criminology* 42 (2):283-322.

Weisburd, David L., Elizabeth R Groff, and Sue-Ming Yang. 2012. *The criminology of place: Street segments and our understanding of the crime problem*: Oxford University Press.

Weisburd, David, Cody W Telep, Breanne Cave, Kate Bowers, John E Eck, Gerben Bruinsma, Charlotte Gill, Elizabeth Groff, Julie Hibdon, and Joshua C Hinkle. 2016. *Place Matters*: Cambridge University Press.

Wooldredge, John. 2002. "Examining the (Ir)relevance of Aggregation Bias for Multilevel Studies of Neighborhoods and Crime with an Exanple Comparing Census Tracts to Official Neighborhoods in Cincinnati." *Criminology* 40 (3):681-710.

Wyant, Brian R., Ralph B. Taylor, Jerry H. Ratcliffe, and Jennifer Wood. 2012. "Deterrence, Firearm Arrests, and Subsequent Shootings: A Micro-Level Spatio-Temporal Analysis." *Justice Quarterly* 29 (4):524-545.

1. Tables

Table 1. Los Angeles 2009-2015 average area fraction of 200m x 200m hotspots required to capture 25% and 50% of total crime along with the average fraction of hotspots that overlap from period to period.

Crime Type	**Time Window**	**Days**	**Area Fraction (25%)**	**Overlap (25%)**	**Area Fraction (50%)**	**Overlap (50%)**
Assault	7 year	2555	0.017	NA	0.052	NA
Assault	year	365	0.011 ± 0.001	0.281 ± 0.038	0.032 ± 0.003	0.344 ± 0.031
Assault	6 month	182.5	0.008 ± 0.001	0.176 ± 0.032	0.023 ± 0.003	0.250 ± 0.024
Assault	3 month	91.3	0.005 ± 0.001	0.094 ± 0.029	0.015 ± 0.002	0.146 ± 0.032
Assault	month	30.4	0.002 ± 0.000	0.044 ± 0.028	0.007 ± 0.002	0.071 ± 0.022
Assault	week	7.0	0.001 ± 0.000	0.008 ± 0.021	0.002 ± 0.001	0.023 ± 0.021
Burglary	7 year	2555	0.043	NA	0.125	NA
Burglary	year	365	0.025 ± 0.001	0.230 ± 0.015	0.076 ± 0.003	0.317 ± 0.008
Burglary	6 month	182.5	0.018 ± 0.001	0.149 ± 0.018	0.052 ± 0.003	0.217 ± 0.014
Burglary	3 month	91.3	0.012 ± 0.001	0.116 ± 0.016	0.038 ± 0.003	0.182 ± 0.018
Burglary	month	30.4	0.006 ± 0.001	0.072 ± 0.020	0.017 ± 0.002	0.105 ± 0.016
Burglary	week	7.0	0.002 ± 0.000	0.025 ± 0.020	0.004 ± 0.001	0.032 ± 0.016
MVT	7 year	2555	0.035	NA	0.097	NA
MVT	year	365	0.023 ± 0.001	0.258 ± 0.027	0.066 ± 0.002	0.352 ± 0.017
MVT	6 month	182.5	0.017 ± 0.001	0.176 ± 0.022	0.047 ± 0.003	0.257 ± 0.026
MVT	3 month	91.3	0.012 ± 0.001	0.117 ± 0.02	0.036 ± 0.003	0.192 ± 0.016
MVT	month	30.4	0.006 ± 0.001	0.068 ± 0.017	0.016 ± 0.002	0.099 ± 0.016
MVT	week	7.0	0.002 ± 0.000	0.027 ± 0.021	0.004 ± 0.001	0.031 ± 0.016
Robbery	7 year	2555	0.011	NA	0.037	NA
Robbery	year	365	0.008 ± 0.001	0.472 ± 0.031	0.028 ± 0.004	0.490 ± 0.019
Robbery	6 month	182.5	0.007 ± 0.001	0.357 ± 0.027	0.022 ± 0.003	0.385 ± 0.022
Robbery	3 month	91.3	0.005 ± 0.001	0.250 ± 0.030	0.017 ± 0.002	0.250 ± 0.028
Robbery	month	30.4	0.003 ± 0.000	0.119 ± 0.033	0.009 ± 0.002	0.137 ± 0.022
Robbery	week	7.0	0.001 ± 0.000	0.029 ± 0.029	0.003 ± 0.001	0.047 ± 0.023

Table 2. Yearly hotspots of variable sizes in Los Angeles 2009-2015. Average fraction of hotspots each year required to capture 25% and 50% of total crime along with the average fraction of hotspots that overlap year over year.

Crime Type	Area Fraction (25%)	Overlap (25%)	Area Fraction (50%)	Overlap (50%)	Cell Size (km)
Assault	0.011 ± 0.001	0.281 ± 0.038	0.032 ± 0.003	0.344 ± 0.031	0.2
Assault	0.019 ± 0.001	0.438 ± 0.066	0.058 ± 0.003	0.547 ± 0.026	0.4
Assault	0.028 ± 0.001	0.633 ± 0.061	0.081 ± 0.003	0.750 ± 0.036	0.8
Burglary	0.025 ± 0.001	0.230 ± 0.015	0.076 ± 0.003	0.317 ± 0.008	0.2
Burglary	0.046 ± 0.001	0.345 ± 0.043	0.129 ± 0.003	0.480 ± 0.019	0.4
Burglary	0.064 ± 0.002	0.560 ± 0.070	0.174 ± 0.004	0.665 ± 0.027	0.8
MVT	0.023 ± 0.001	0.258 ± 0.027	0.066 ± 0.002	0.352 ± 0.017	0.2
MVT	0.039 ± 0.002	0.411 ± 0.025	0.105 ± 0.004	0.558 ± 0.014	0.4
MVT	0.053 ± 0.002	0.631 ± 0.032	0.139 ± 0.004	0.715 ± 0.026	0.8
Robbery	0.008 ± 0.001	0.472 ± 0.031	0.028 ± 0.004	0.490 ± 0.019	0.2
Robbery	0.015 ± 0.002	0.586 ± 0.035	0.048 ± 0.005	0.629 ± 0.026	0.4
Robbery	0.022 ± 0.003	0.676 ± 0.041	0.067 ± 0.006	0.804 ± 0.029	0.8

Table 3. Chicago 2008-2015 average area fraction of 200 x 200m hotspots required to capture 25% and 50% of total crime along with the average fraction of hotspots that overlap from period to period.

Crime Type	**Time Window**	**Days**	**Area Fraction (25%)**	**Overlap (25%)**	**Area Fraction (50%)**	**Overlap (50%)**
Assault	8 year	2920	0.037	NA	0.11	NA
Assault	2 year	730	0.033 ± 0.001	0.559 ± 0.022	0.098 ± 0.003	0.63 ± 0.02
Assault	year	365	0.030 ± 0.001	0.478 ± 0.02	0.089 ± 0.003	0.55 ± 0.017
Assault	6 month	182.5	0.025 ± 0.001	0.349 ± 0.024	0.074 ± 0.004	0.436 ± 0.021
Assault	3 month	91.3	0.020 ± 0.002	0.259 ± 0.048	0.057 ± 0.007	0.325 ± 0.038
Assault	month	30.4	0.012 ± 0.002	0.137 ± 0.038	0.035 ± 0.005	0.206 ± 0.03
Assault	week	7.0	0.005 ± 0.001	0.057 ± 0.031	0.011 ± 0.002	0.077 ± 0.026
Burglary	8 year	2920	0.054	NA	0.152	NA
Burglary	2 year	730	0.045 ± 0.003	0.421 ± 0.027	0.128 ± 0.007	0.519 ± 0.051
Burglary	year	365	0.038 ± 0.004	0.338 ± 0.040	0.110 ± 0.009	0.437 ± 0.048
Burglary	6 month	182.5	0.031 ± 0.004	0.260 ± 0.039	0.088 ± 0.010	0.340 ± 0.037
Burglary	3 month	91.3	0.023 ± 0.003	0.184 ± 0.035	0.065 ± 0.010	0.262 ± 0.048
Burglary	month	30.4	0.012 ± 0.003	0.098 ± 0.033	0.037 ± 0.008	0.184 ± 0.037
Burglary	week	7.0	0.005 ± 0.001	0.056 ± 0.032	0.012 ± 0.003	0.072 ± 0.029
MVT	8 year	2920	0.064	NA	0.165	NA
MVT	2 year	730	0.051 ± 0.003	0.337 ± 0.055	0.136 ± 0.007	0.473 ± 0.050
MVT	year	365	0.042 ± 0.003	0.246 ± 0.035	0.114 ± 0.008	0.370 ± 0.043
MVT	6 month	182.5	0.033 ± 0.003	0.179 ± 0.035	0.088 ± 0.012	0.275 ± 0.048
MVT	3 month	91.3	0.023 ± 0.004	0.122 ± 0.036	0.063 ± 0.007	0.220 ± 0.021
MVT	month	30.4	0.012 ± 0.002	0.075 ± 0.022	0.033 ± 0.007	0.130 ± 0.032
MVT	week	7.0	0.004 ± 0.001	0.034 ± 0.026	0.009 ± 0.002	0.040 ± 0.022
Robbery	8 year	2920	0.03	NA	0.098	NA
Robbery	2 year	730	0.026 ± 0.000	0.577 ± 0.018	0.085 ± 0.002	0.601 ± 0.033
Robbery	year	365	0.023 ± 0.001	0.465 ± 0.046	0.074 ± 0.003	0.488 ± 0.032
Robbery	6 month	182.5	0.002 ± 0.001	0.355 ± 0.050	0.060 ± 0.005	0.380 ± 0.037
Robbery	3 month	91.3	0.015 ± 0.001	0.240 ± 0.048	0.044 ± 0.004	0.279 ± 0.037
Robbery	month	30.4	0.008 ± 0.001	0.117 ± 0.042	0.025 ± 0.004	0.171 ± 0.039
Robbery	week	7.0	0.003 ± 0.001	0.043 ± 0.032	0.007 ± 0.002	0.063 ± 0.028

Table 4. Yearly hotspots of variable sizes in Chicago 2008-2015. Average fraction of hotspots each year required to capture 25% and 50% of total crime along with the average fraction of hotspots that overlap year over year.

Crime Type	Area Fraction (25%)	Overlap (25%)	Area Fraction (50%)	Overlap (50%)	Location Scale (km)
Assault	0.030 ± 0.001	0.478 ± 0.020	0.089 ± 0.003	0.55 0± 0.017	0.2
Assault	0.048 ± 0.001	0.578 ± 0.024	0.132 ± 0.001	0.709 ± 0.016	0.4
Assault	0.065 ± 0.001	0.768 ± 0.035	0.171 ± 0.002	0.838 ± 0.017	0.8
Burglary	0.038 ± 0.004	0.338 ± 0.040	0.110 ± 0.009	0.437 ± 0.048	0.2
Burglary	0.056 ± 0.003	0.510 ± 0.032	0.157 ± 0.005	0.598 ± 0.046	0.4
Burglary	0.071 ± 0.002	0.648 ± 0.030	0.193 ± 0.002	0.738 ± 0.034	0.8
MVT	0.042 ± 0.003	0.246 ± 0.035	0.114 ± 0.008	0.370 ± 0.043	0.2
MVT	0.066 ± 0.002	0.407 ± 0.040	0.170 ± 0.004	0.576 ± 0.047	0.4
MVT	0.085 ± 0.002	0.549 ± 0.053	0.212 ± 0.003	0.722 ± 0.037	0.8
Robbery	0.023 ± 0.001	0.465 ± 0.046	0.074 ± 0.003	0.488 ± 0.032	0.2
Robbery	0.039 ± 0.001	0.572 ± 0.041	0.113 ± 0.002	0.667 ± 0.027	0.4
Robbery	0.057 ± 0.001	0.664 ± 0.054	0.150 ± 0.002	0.783 ± 0.021	0.8

Table 5. Observed and expected average size of the largest cluster for 200 x 200m hotspots given different time windows in Los Angeles.

Days	Assault		Burglary		MVT		Robbery	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
7	1.3	2.9	2.3	3.4	2.4	3.6	2.0	3.9
30.4	2.9	5.0	4.8	6.1	5.3	6.5	4.9	6.5
91.25	6.7	7.1	8.3	8.2	8.0	8.9	10.6	8.4
182.5	11.5	8.5	11.1	9.9	11.9	10.9	15.7	7.7
365	19.6	8.4	18.0	12.0	24.4	12.7	21.1	8.1
2555	34	13	74	12	53	12	32	7

Table 6. Observed and expected average size of the largest cluster for 200 x 200m hotspots given different time windows in Chicago.

Days	Assault		Burglary		MVT		Robbery	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
7	3.3	4.4	3.7	4.7	2.9	3.9	2.9	4.1
30.4	5.1	7.1	6.9	7.6	6.6	6.8	4.7	6.3
91.25	9.0	9.1	15.7	10.2	10.6	9.7	8.9	9.1
182.5	11.3	9.6	29.2	11.1	16.5	11.6	11.4	9.6
365	16.8	10.4	41.3	11.9	22.3	13.3	14.5	10.1
2920	28	10	121	11	76	17	19	9

2. Figures

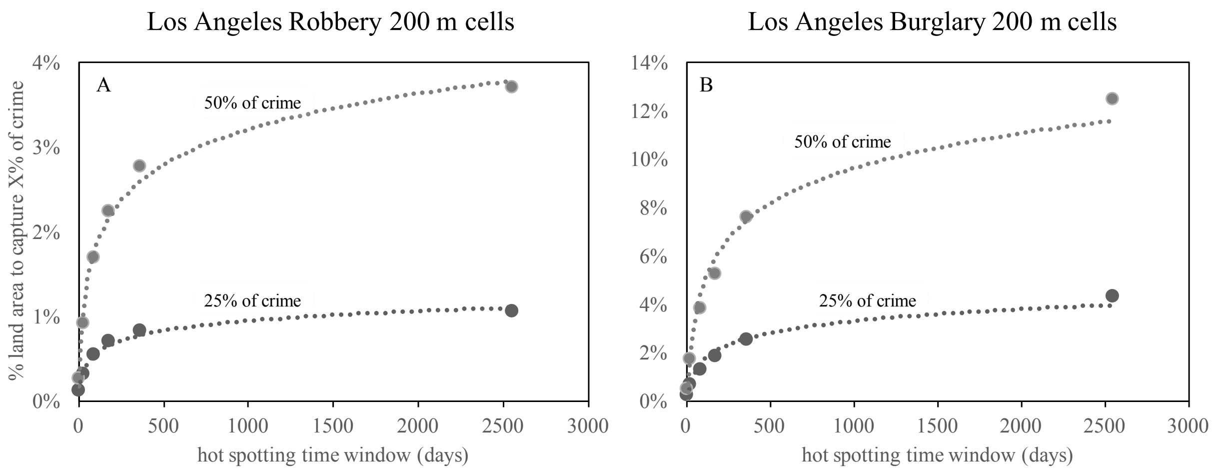

Figure 1. Percent land area needed to capture a fixed percentage of crime increases as the time window for hot spotting increases. A. Robberies. B. Burglaries. Results are shown for micro-geographic hotspots 200 x 200 m in size.

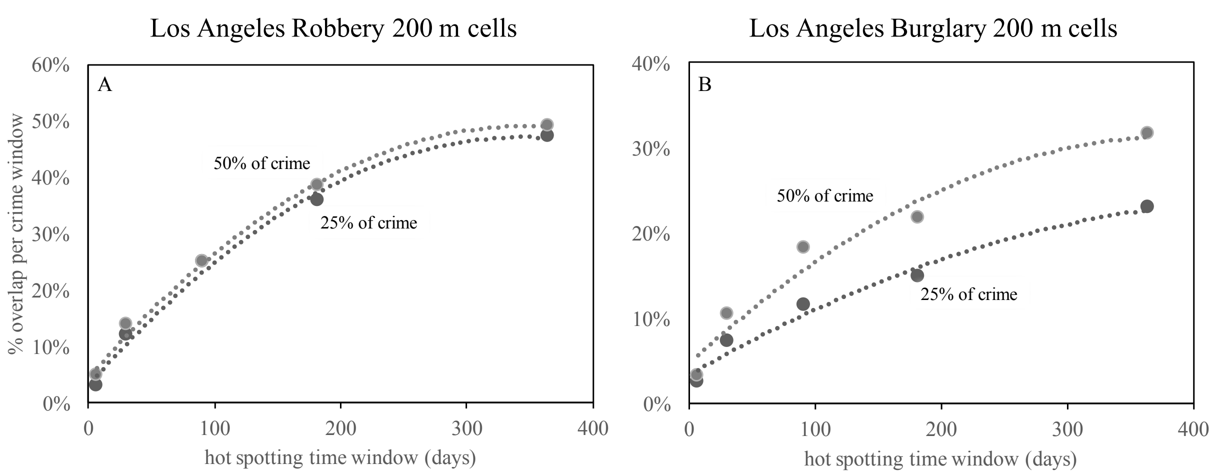

Figure 2. The percent overlap in hot spot locations from one time period to the next increases as the hot spotting time window increases. A. Robbery. B. Burglary. Results are shown for micro-geographic hotspots 200 x 200 m in size.

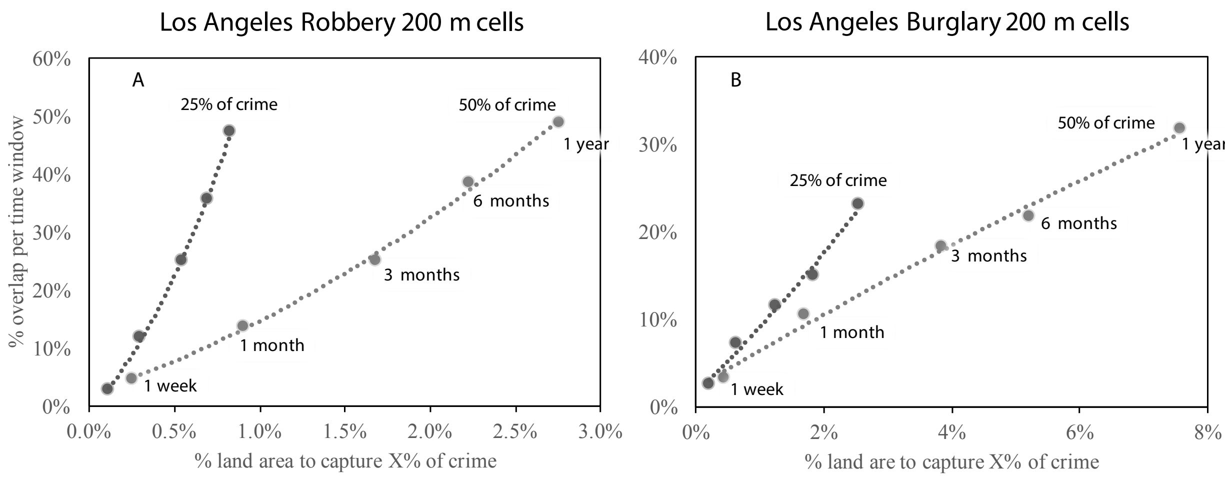

Figure 3. The percent overlap in hot spot locations from one time period to the next increases in tandem with the percent land area needed to capture a fixed percentage of crime. A. Robbery. B. Burglary. Results are shown for micro-geographic hotspots 200 x 200 m in size.

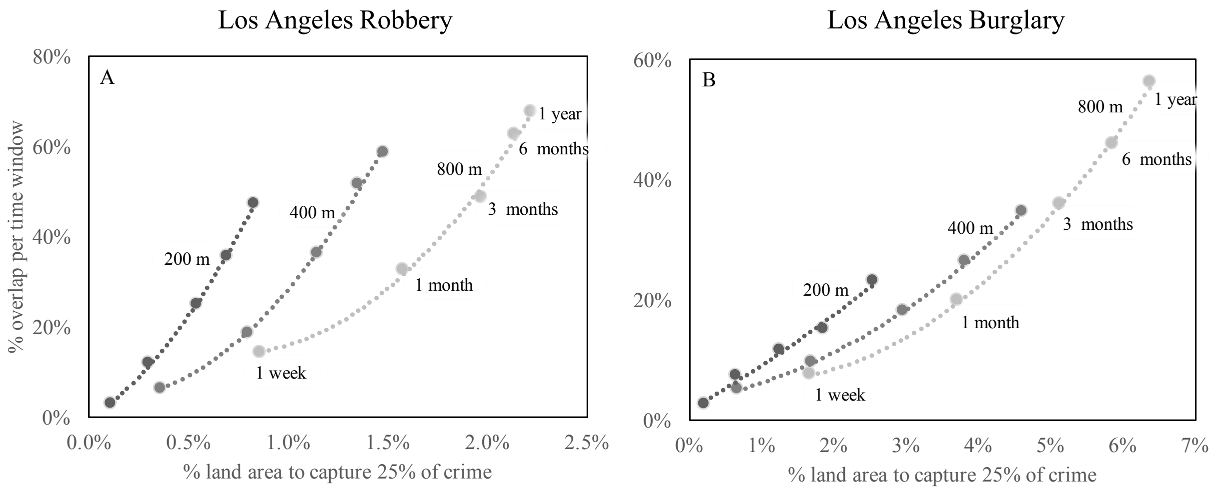

Figure 4. Larger hot spotting spatial scales require greater total land area to capture the same amount of crime, but also produce greater overlap in hot spot locations from one time period to the next. A. Robbery. B. Burglary. Results are shown for 200m, 400m and 800m cells at 1 week, 1 month, 3 months, 6 months, and 1 time windows.

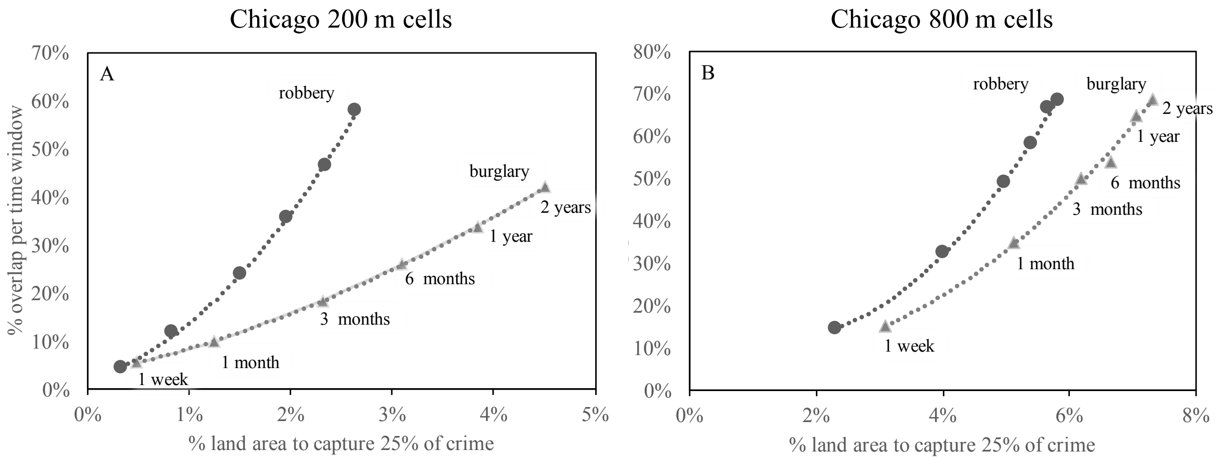

Figure 5. The percent overlap in hot spot locations from one time period to the next increases in tandem with the percent land area needed to capture 25% of crime. A. Robbery and burglary hotspots at a 200 x 200 m spatial scale. B. Robbery and burglary at an 800 x 800 m spatial scale. Results are shown for 1 week, 1 month, 3 months, 6 months, 1 year and 2-year time windows.

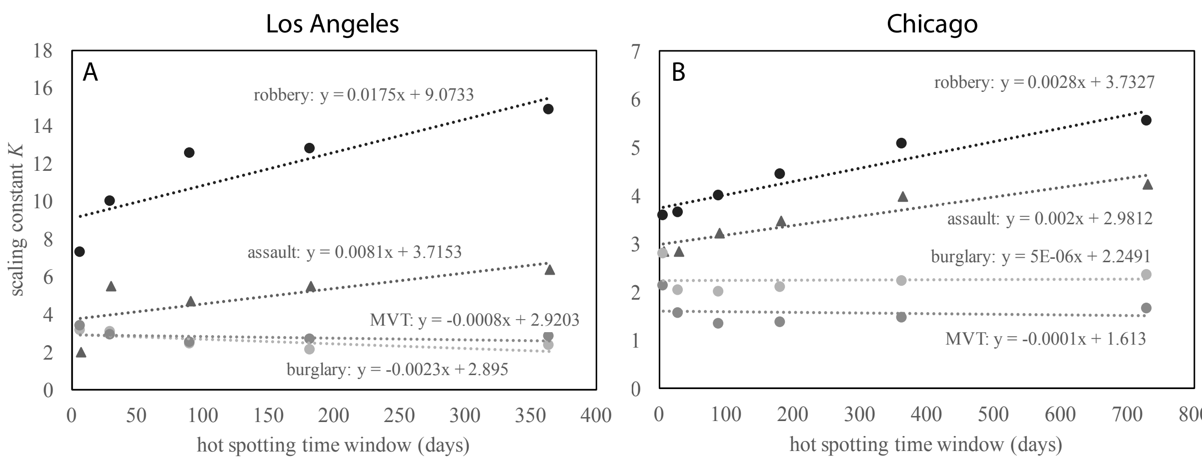

Figure 6. Law-like behavior in the concentration-dynamics tradeoff. Shown is the value of the scaling constant *K* against the hot spotting time window. A. Los Angeles crime types. B. Chicago crime types.