ORIGINAL PAPER

Crime and Place: A Longitudinal Examination of Street Segment Patterns in Vancouver, BC

**Andrea S. N. Curman · Martin A. Andresen ·
Paul J. Brantingham**

Abstract

Objectives   To test the generalizability of previous crime and place trajectory analysis research on a different geographic location, Vancouver BC, and using alternative methods.
Methods   A longitudinal analysis of a 16-year data set using the street segment as the unit of analysis. We use both the group-based trajectory model and a non-parametric cluster analysis technique termed k-means that does not require the same degree of assumptions as the group-based trajectory model.
Results   The majority of street blocks in Vancouver evidence stable crime trends with a minority that reveal decreasing crime trends. The use of the k-means has a significant impact on the results of the analysis through a reduction in the number of classes, but the qualitative results are similar.
Conclusions   The qualitative results of previous crime and place trajectory analyses are confirmed. Though the different trajectory analysis methods generate similar results, the non-parametric k-means model does significantly change the results. As such, any data set that does not satisfy the assumptions of the group-based trajectory model should use an alternative such as k-means.

Keywords   Crime and place · Trajectory analysis · Spatial criminology

Introduction

The field of criminology has evolved from asking the question, 'why criminals behave the way they do' to 'where and when does criminal behaviour take place'. The emergence of

A. S. N. Curman
Police Services, Ministry of Justice, Province of British Columbia, Burnaby, BC, Canada

M. A. Andresen (✉) · P. J. Brantingham
School of Criminology, Institute for Canadian Urban Research Studies, Simon Fraser University,
8888 University Drive, Burnaby, BC V5A 1S6, Canada
e-mail: andresen@sfu.ca

this new focus has emerged because the reasons for criminality are as various and complex as each individual offender. Focusing on the 'where' and when' of criminal behaviour has been termed the 'criminology of place' (Sherman et al. 1989) and revealed that criminal activity, when viewed from a place perspective, is highly patterned and predictable (Brantingham and Brantingham 1991).

The understanding of these patterns is relative to the spatial scale of analysis. As shown by Brantingham et al. (1976), when the "cone of resolution" changes so may the observed patterns. The pattern changes occur, at least in part, because of the spatial heterogeneity within areal units. This is one of the reasons why there has been a trajectory of ever smaller units of analysis in spatial criminology (Weisburd et al. 2009). Generally speaking, research has shown that studies focussing on larger geographic areas mask important micro level variation in criminal activity (Groff et al. 2010) and may lead to inaccurate conclusions about crime at the individual level, the ecological fallacy (Robinson 1950).

Some of the most recent research in spatial criminology has shown the utility of the street block as the optimal unit of analysis in crime and place studies. The street block has been described as large enough to avoid the impractical focus of singular addresses but not so large to lead to erroneous conclusions about crime at the micro level (Groff et al. 2010). In 2004, Weisburd, Bushway, Lum and Yang, conducted a seminal study examining longitudinal patterns of criminal activity at the street block level in Seattle, Washington. Considering police incident reports from the Seattle Police Department from 1989 to 2002, Weisburd et al. (2004) employed a cluster analysis technique termed 'group-based trajectory model' (GBTM) to investigate whether street blocks evidence criminal developmental trajectories over time. Traditionally, in mathematics, a trajectory would be described as "the path which an object travelling through space and time follows" (Elragal and El-Gendy 2012). Applied to a social scientific context, the term trajectory has been used to describe the long-term pattern of criminal offending behaviour (see Nagin and Land 1993) and more recently to describe the longitudinal pattern of crime volumes on urban streets (see Weisburd et al. 2004, 2012).

GBTM was originally applied to the field of life-course criminology by Nagin and Land (1993) to track a panel dataset of juvenile offenders longitudinally and determine whether identifiable sub-groups of offending behaviour existed. It was not the research findings that garnered the majority of the attention, but, rather, the statistical method of GBTM. Weisburd et al. (2004) were the first study within spatial criminology to apply the GBTM technique to a place-based focus, specifically, the street block. The findings revealed that street blocks do evidence distinct developmental trajectories and that these criminal trajectories remain largely consistent over time. Specifically, the majority of street blocks in Seattle evidenced stable trajectories of crime volume over time, and a smaller proportion showed significant increasing or decreasing trajectories.

To date, the application of the GBTM to examine micro crime places over time has not been applied to any city outside of Seattle. In a more recent publication, Weisburd et al. (2012) questioned whether their results are generalizable beyond Seattle. They encouraged other researchers to replicate their study in other jurisdictions to "build a science of the criminology of place" (p. 219). This paper answers their call for a replication and marks the first study examining the issue of micro crime places over time, outside of Seattle. The methodology originally employed by Weisburd et al. (2004) is replicated in Vancouver, British Columbia based on a 16-year dataset of calls-for-service from the Vancouver Police Department (VPD). The GBTM technique is applied to investigate whether street blocks in Vancouver evidence distinct developmental trajectories of crime volume from 1991 to 2006. Additionally, a separate non-parametric cluster analysis technique termed k-means is

conducted to augment the GBTM method. This statistic provides an efficient alternative for researchers whose datasets hold a sizeable number of cases greater than 50, a much more significant issue in Vancouver than Seattle.

The purpose of this paper is twofold. First, a replication of the Weisburd et al. (2004) study is carried out for the city of Vancouver to test the generalizability of the findings for Seattle. And second, to further research in the field of crime and place, this paper emphasizes the utility of examining crime at the street block level and the advantage of establishing longitudinal patterns of place-based criminal activity.

Trajectory-Based Research in Spatial Criminology

The street block has recently been recognized as an optimal compromise within crime and place research (Weisburd et al. 2004, 2012; Groff et al. 2010; Braga et al. 2011; Bernasco and Block 2011). Weisburd et al. (2012) stressed the accuracy of the street block in assessing crime volumes as well as the benefit that the street block is a "social unit that has been recognized as important in the rhythms of everyday living in cities" (p. 27). The street block is also large enough to avoid coding errors inherent in geocoding processes, but not so large to lead to ecological fallacy conclusions. Research observing criminal activity at the block level is consistent within the theories of environmental criminology[1] in that crime clusters are stable over time, and holds particular use for crime prevention initiatives and police enforcement strategy.

Weisburd et al. (2004) examined patterns of criminal activity on the street blocks of Seattle from 1989 to 2002. The focus of the study was to assess whether street blocks evidenced developmental trajectories such that groups of micro crime places could be systematically identified similar to that of individual criminal behavioural patterns. This study marked the first attempt to apply the statistical methodology of trajectory analysis to geographic places and was particularly insightful in that the geographic concentration of crime had been well documented, but the stability of those concentrations had not.

Their study propelled the field of *crime and place* in two main ways. First, the research examined longitudinal crime pattern trends over a 14-year period, that representing the longest study period examined in the crime and place literature at the time. Secondly, the research implemented a relatively new semi-parametric statistic, GBTM, to uncover crime trends on street blocks over the 14-year study period. Looking at over 1.4 million incident reports from the Seattle Police Department from 1989 to 2002, Weisburd et al. (2004) assigned each case to a street segment and used GBTM to identify clusters of criminal activity at the block face level, defined as "two block faces on both sides of a street between two intersections" (p. 290).

Overall, Weisburd et al. (2004) found that street segments in Seattle saw a 24 % decline in the number of incident reports recorded from 1989 to 2002. More interestingly, the results showed a strong indication for the concentration of crime and the existence of 'hot spots'. Specifically, and similar to Sherman et al. (1989), between 4 and 5 % of street segments accounted for 50 % of incidents. Weisburd et al. (2004) also reiterated that the overall distribution of criminal activity evidenced stability from year to year. All criminal activity was found between 48 and 53 % of street segments. The street segments with no reported crime only varied between 47 and 52 % and the street segments with more than 50 crimes per year occurred on only 1 % of street segments for each of the 14 years observed.

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[1] Routine activity theory, geometric theory of crime, rational choice theory, and crime pattern theory.

When Weisburd et al. ([2004](#)) conducted the GBTM, they found that 8 of the 18 trajectories were classified as 'stable' in nature, with slopes very close to 0. These street blocks represented 84 % of all street segments in Seattle and evidenced low levels of overall criminal activity. Only three of the 18 groups were identified as increasing and they accounted for about 2 % of all street segments in Seattle—one trajectory evidenced an increase in its average crime rate of more than fourfold during the study period. The remaining seven trajectories were identified as having a decreasing crime volume pattern and accounted for about 14 % of all street segments. The decreasing street segments appeared to account for the overall crime drop in Seattle during the 14-year period.

Overall, Weisburd et al. ([2004](#)) confirmed prior research showing that criminal activity is clustered. Further, it demonstrated that micro places evidenced a high degree of stability over time and that this stability was shown for both street segments with low rates of crime and street segments with high rates of crime. All three cluster groups of stable, increasing and decreasing street segments were found across the city's landscape, emphasizing the importance of studying criminal activity at a more micro level. Lastly, it was shown that the crime drop in Seattle over the study period from 1989 to 2002 was confined to a specific group of street segments with decreasing trajectories. As such, the crime drop in Seattle should not be seen as a phenomenon occurring uniformly across the city's landscape, but driven by changes in crime volume specific to a small region of Seattle.

Weisburd et al. ([2009](#)) examined whether juvenile arrest incidents evidence spatial concentrations at the street block level and whether developmental trajectories of juvenile crime could be identified throughout Seattle's streets. Juvenile arrest incidents from 1989 to 2002 were analyzed amongst Seattle's street blocks and the findings revealed a 41 % decline. Approximately 3–5 % of street segments were responsible for all juvenile arrests and less than 1 % of the total streets were responsible for 50 % of the crime. In their GBTM they identified eight groups of distinct subpopulations of street segments with respect to juvenile offending. The majority of those evidenced minimal juvenile criminal activity, with one group constituting 85 % of all street segments but only 12 of all arrest incidents for the study period. Three trajectories accounted for approximately one-third of all juvenile arrest incidents, yet included only 86 (or 0.29 %) of all streets in Seattle.

Groff et al. ([2010](#)) examined the spatial–temporal patterns of crime incidents throughout Seattle, 1989–2002. In particular, their research sought to answer whether crime trajectories of the same kind exhibited a non-uniform spatial distribution and whether street segments of different trajectories are more likely to be found spatially near or far from each other than one would expect by chance. Are 'known' crime hotspots uniformly 'hot' and conversely, are 'good' areas uniformly low in crime? Or, do these neighborhoods exhibit pockets of problematic high crime areas in what would otherwise be termed a 'safe' neighborhood?

Groff et al. ([2010](#)) found that chronically high crime street segments exhibited the greatest degree of local clustering. In addition, the street segments categorized as being low in crime yet slightly increasing over the study period were also more likely to be proximally close to one another followed by the low decreasing street segments. Interestingly, the streets categorized as either being crime free or low stable in nature were the least likely to be clustered, suggesting their more uniform distribution across Seattle. Further statistical analysis showed that crime free street segments, low stable and low decreasing trajectories, were statistically independent of one another.

Lastly, Groff et al. ([2010](#)) found that the street segments with higher crime or changing temporal trajectories (i.e. increasing in crime volume) tended associated with other streets that exhibited the same developmental trend. This research highlights the spatial variability

of micro crime places. Within any given neighborhood, one may find crime free zones, next to streets with consistently high crime, next to streets with consistently low crime, and so on. Thus, the importance of understanding crime occurrence at the micro level is underscored here, emphasizing the limitations of labelling larger areal units of a city as either 'good' or 'bad' in nature—see Sherman et al. (1989: 29) for a discussion of this issue.

The most recent research by Weisburd et al. (2012) marks the most comprehensive examination of crime and place. In addition to a trajectory analysis for the years 1989–2004 largely confirming the previous results of Weisburd et al. (2004), the authors performed a detailed spatial analysis of the trajectory patterns and examined the social ecological characteristics of the areas evidencing high chronic levels of criminal activity. This examination led Weisburd et al. (2012) to develop a model explaining the factors that influenced the developmental trends of micro crime places over time.

Weisburd et al. (2012) spatially analyzed the trajectories identified by the GBTM to see where these clusters were located and to establish whether certain trajectories were more likely to neighbour one another. The results showed that the high crime trajectories were located in the northern section of Seattle, with a particular concentration following a main or arterial road. The southern portion of Seattle evidenced a mixture of different types of trajectories; however, the presence of chronic high crime street segments was particularly evident. The downtown area of Seattle evidenced two interesting geographical trends. The first was a strong degree of clustering for the highest crime rate street segments, and, second, was considerable street-by-street segment variation of differing developmental trajectories. Overall, Weisburd et al. (2012) found that hot spot street blocks were interspersed throughout Seattle, and that high rate streets were often interspersed amongst low rate street segments.

Further, Weisburd et al. (2012) sought to understand *why* certain street blocks evidenced chronic levels of criminal activity versus those that remained relatively crime free. The research revealed that both opportunity and social disorganization related variables evidenced concentrations at the street block level. However, what remained unknown was whether these characteristics were systematically related to certain developmental trajectories. Using a multivariate statistical model (logistic regression), Weisburd et al. (2012) analyzed these variables and their effect on the eight trajectory classifications established by the GBTM. Beginning with variables specific to opportunity theory, the results showed that the presence of high-risk juveniles (motivated offenders) increased the likelihood of a street being in a high rate chronic trajectory twofold. With respect to suitable targets, they found that for every additional employee on a street segment (perhaps representing an industrial/business area), the likelihood of that street showing a high chronic crime pattern increased by 8 %. The presence of a public facility, such as a community centre or high school, within a quarter mile of any given street increased the likelihood that a street segment would be part of a chronically high crime trajectory by 25 %. In addition, the larger the residential population, the more likely a street segment was to be clustered into the chronic high crime pattern. Variables alluding to the convergence of a motivated offender and a suitable target also showed to be significant predictors of high crime chronic street blocks. Specifically, every additional bus stop doubled the likelihood of that particular street evidencing that particular trajectory. Perhaps not surprisingly, any street segment that was an arterial road was also far more likely to be labelled as high chronic in criminal activity. One of the most significant predictors of high chronic crime patterns at the street block level was the percent of vacant land. A 1 % increase in the amount of vacant land increased the likelihood of a street segment being categorized as high chronic by almost 50 %.

The results for the social disorganization variables showed, for example, that a unit increase in the residential property value on a street was associated with a 30 % decrease in the likelihood of that street being labelled as a chronic crime trajectory, whereas the presence of subsidized housing was associated with a 10 % increase. Significant effects were found with the presence of physical disorder and a higher likelihood of a street being in a chronic crime group, as well as with respect to the presence of truant juveniles. Specifically, truant juveniles were found to more than double the likelihood of a street segment being labelled into the chronic crime pattern. Lastly, Weisburd et al. (2012) looked at the percent of active voters on a given street block as an indicator of collective efficacy and found that streets with no active voters relative to all active voters decreased the probability of being on a chronic trajectory group by almost 96 %. Thus, it was concluded that those streets with residents involved in public affairs have far lower levels of criminal activity.

Not only does their research significantly contribute to the utility of examining micro crime places, but it also goes a step further in attempting to explain why such developmental patterns exist; both opportunity theory and social disorganization characteristics were found to be significant. Their research marks the first attempt in spatial criminology to develop an explanatory model for micro crime variation within an urban setting and furthers our understanding of developmental trajectories of criminal places over time.

The seminal work conducted by Weisburd and colleagues on Seattle has offered the field of crime and place tremendous insight into understanding the disproportionate distribution of criminal activity. The research in its entirety, and in particular the GBTM based on street blocks, has never been replicated outside of Seattle. This is a critical junction for this field. If these results can begin to be generalized, its applicability to the wider criminological community and theoretical development may be substantial. This paper accomplishes this by conducting a comparable study of crime and place, based on Weisburd et al. (2004). Based in Vancouver, BC, the conclusions will extend those offered by Weisburd and colleagues with respect to understanding crime and its place in society.

Data and Methods

Vancouver, British Columbia and its Data

Vancouver is situated approximately 200 km north of Seattle. Both cities are located on the Northwest coast of North America and have a similar population size (see Table 1). Additionally, both cities share comparable climates, demographics and are regulated by a municipal police department. Seattle operates the Seattle Police Department and Vancouver, BC operates the VPD. Vancouver is one of the few municipalities in BC that is not policed by the Royal Canadian Mounted Police. One marked difference between the two cities lies in population density; as shown in Table 1, Vancouver is almost half the geographic size of Seattle.

Equally important are the similarities between the two cities with regard to the police data available to conduct a longitudinal examination of crime at micro places. Weisburd et al. (2004) chose the Seattle Police Department because it offered a comprehensive official dataset on crime records in a computerized format. Specifically, Seattle had records of incident reports dating back to 1989; these are records generated by police officers after an initial response to a request for police service. Weisburd et al. (2004) explain that Seattle's police department was guided by a police administrator who was committed to

Table 1 Comparative datasheet on Seattle, WA and Vancouver, BC

Category	Seattle, Washington, USA[a]	Vancouver, BC, Canada[b]
Population	612,000	578,041
Metro population	3,707,400	2,501,699
Population density	2,821 per square km	5,335 per square km
Geographic location	Pacific Northwest, 182 km south of Canadian Border	Pacific Northwest, 53 km north of US border
Land area	217 square km	114 square km
Climate	Moderate with average rainfall of 92 cm per year	Moderate with average rainfall of 119 cm per year
Police Department	Municipal: Seattle Police Department	Municipal: Vancouver Police Department

[a] *Source*: Office of Intergovernmental Relations, City of Seattle, 2011

[b] *Source*: Wikipedia, 2011

research on crime places, that made conducting the study and gaining access to data straightforward. Similarly, the VPD is also known for keeping meticulous computerized records of all police requests for service, their crime category, time and location dating back to the late 1980s.

The VPD keeps computerized records of each call-for-service that had reached their dispatch centre. Each call from the public or police initiated call was noted by the dispatcher with the following details entered into the VPD system: the category of the incident (e.g. robbery), date, time, time it was dispatched to the police, location, priority level of the call, district location and whether the location was situated in the city's downtown eastside area. For the purposes of this paper, the years 1991–2006 were chosen for analysis. The following 22 calls-for-service categories were selected for inclusion and were subsequently geocoded for street segment analysis: arson, assault, assault in progress, attempted break and enter, attempted theft, break and enter, break and enter in progress, drug arrest, fight, alarm, holdup, homicide, purse snatching, robbery, robbery in progress, shoplifting, stabbing, stolen vehicle, sexual assault, theft from vehicle, theft and theft in progress. These data were further narrowed down by excluding calls-for-service that were either located at an intersection, were specified as having occurred at the police precinct or did not specify any known location. The decision to exclude those incidents occurring at intersections is supported by Weisburd et al. (2004) where intersections are noted as not belonging to any particular street segment and technically could be linked to four different ones.[2] The final sample size for the VPD dataset was 1.08 million calls for service from 1991 to 2006. These data were geocoded with a 98 % hit rate, well above the threshold identified by Ratcliffe (2004).

From 1991 to 2006, the highest volume of crimes was seen in 1996, with 89,143 calls for service to the VPD. Conversely, the lowest level of crime was noted at the most recent year of 2006, with only 46,079 calls for service. Overall, criminal activity for the above mentioned 22 categories decreased by almost 40 %, 48 % from its peak in 1996—a similar downward trend to that of many other major cities in North America and Europe during the

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[2] For Vancouver, approximately 25 % of calls-for-services amongst the 22 index crimes examined from 1991 to 2006 were located at intersections and subsequently excluded from the analyses.

same time frame (Ouimet 2002; Mishra and Lalumière 2009; Levitt 2004; Farrell et al. 2011). Table 2 displays the comparison between the Weisburd et al. (2004) data and the Vancouver data.

On average, 40 % of street blocks in Vancouver did not experience any calls-for-service during the 16-year study period. This establishes that all criminal activity (i.e. for the crimes analyzed) was located on only 60 % of all possible streets throughout the city (approximately 7,724 out of 12,980). Additionally, only 7.8 % of streets evidenced 60 % of all the criminal activity, 34 % of streets exhibited 1–4 calls for service, 18 % experienced 5–15 calls for service and 5 % experienced 16–50 calls for service. Approximately 3.6 % of street segments experienced over 50 calls for service during this 16-year period. Tentatively, these results indicate that criminal activity is concentrated at the street segment level throughout Vancouver and that this concentration is stable over time.

Trajectory Analysis Methods

Nagin and Land (1993), in the context of the criminal career debate, pioneered the use of trajectory analysis in criminology. Most often termed 'group-based trajectory model' (GBTM), this semi-parametric statistic is used to identify a distinct subgroup of individuals following a similar pattern of change over time on a given variable (Andruff et al. 2009).

GBTM assumes independence between repeated measures over time for each observation. With regard to its application in the crime and place literatures this means, for example, that the number of crimes for a group of streets in one particular trajectory for 1 year (e.g. 1995) is completely independent of the number of crimes on those same streets for the following year (e.g. 1996). This assumption may be problematic. In addition, GBTM does not account for any spatial autocorrelation. In terms of the crime data for this study, the crime count for the '300 block of Kingsway' is completely independent of the crime count from its neighboring blocks, the 200 or 400 block of Kingsway. This assumption may be problematic because criminal activity does not exist in a geographic silo; rather, problematic streets are often directly adjacent to one another due to mirroring neighborhood qualities. GBTM assumes that the variance seen between different trajectories is a reflection that these groups are completely distinct subpopulations. For example, if one were to extrapolate this statistical assumption to the Weisburd et al. (2004) findings, it would infer that Seattle was comprised of 18 entirely distinct subpopulations of street segments that exist independently of one another and evidenced unique crime patterns over time. One must view these results with caution, as the chosen model for GBTM is based on the best, most stable Bayesian Information Criteria (BIC) score, and may not necessarily reflect the true 'reality' of distinct subpopulations of crime volume throughout a city.

Perhaps the most notable challenge of GBTM is the inability of the application Proc Traj, a program that operates within SAS, to accommodate counts greater than 50—the software truncates these cases to 50. Weisburd et al. (2004) discusses this difficulty by stating that previous studies employing GBTM did not note concern over this as the variable of interest for many of these studies was the number of convictions for individual offenders, and coming across more than 50 would be a rarity. However, when applying GBTM to crime counts of street segments, the prevalence of cases greater than 50 is inevitably larger. This affected only 1 % of Seattle's street segments over the 14-year period, but the Vancouver dataset has approximately 3.6 % (468 of 12,980) street segments with at least one entry above 50.

K-means is a non-parametric statistical technique that is also used to analyse longitudinal data with the goal of identifying clusters of cases that share similar traits (Genolini

Table 2 Comparative details of Seattle PD and Vancouver PD data

Category	Weisburd et al. (2004) and Seattle police data	Vancouver police data
Years included	1989–2002 (14 years)	1991–2006 (16 years)
Data source	Incident reports	Calls-for service reports
Sample size	1.5 million incident reports	1.08 million calls-for-service
Unit of analysis	Street segments	Street segments
Number of street segments	29,849	12,980
Location exclusions	Intersections, police precinct and places without a geographic identifier	Intersections, police precinct, and 'no known location'
Crime decline over study period	−24 %	−40 %

and Falissard 2010), originally developed by Calinski and Harabasz (1974). The k-means statistic has been used in the criminological literature. Huizinga et al. (1991) implemented the k-means statistic to examine the offending trends of 1,530 Denver youth over a 2-year period (1987–1988). In a more recent article, Mowder et al. (2010) implemented the k-means statistic to explore the resilience of 215 male and female juvenile offenders who were committed to a juvenile facility.

As a non-parametric statistic, k-means does not require data to fit a specific distribution, and is able to accommodate larger counts better than the GBTM in Proc Traj. Genolini and Falissard (2010) stress that when the k-means statistic is supplemented by GBTM, the researcher is given a thorough picture of longitudinal patterns within a large dataset and if the two statistics reveal comparable results, one can be very confident in the validity of the clusters identified. As such, we employ both techniques here.

Results

Group-Based Trajectory Model (GBTM)

The application of the GBTM to the Vancouver dataset found that only the 7-group solution evidenced stability—the 7-group solution converged to the same solution when the initial starting values were altered. Therefore, the seven-group solution was chosen as the final model for this study.

The yearly averages for each Trajectory are displayed in Fig. 1. The data showed that all but one Trajectory (Trajectory 3) evidenced a decrease in the average number of crimes occurring at the street segment level. In particular, Trajectories 2 and 4 showed an almost 50 % decrease in the average crime count over the 16 year period. Trajectory 3 showed a slight increase in the average crime count, however, this increase was marginal, from an average of 0.05 crimes per year in 1991 to an average of 0.06 crimes per year. As is evident in the discussion below, this did not constitute an 'increasing trajectory'. Perhaps most interesting from Fig. 1 is the uniformity of the longitudinal trends at the street segment level. Although the trajectories have differing initial intercepts, they evidenced similar slopes over time. This means that the variation in the average crime counts from 1991 to 2006 is comparable for each trajectory.

To further discern the patterns from Fig. 1, Trajectories 1 through 7 were broken into categorical groups. A linear curve was fitted to the average number of crimes at each time

point for each trajectory. This created seven linear trends that could be identified as increasing, decreasing or stable in nature depending on their slope. This process was replicated from Weisburd et al. (2004) whereby if a slope value for a trajectory was less than −0.2, it was classified as 'decreasing'; if a slope value for a trajectory was greater than −0.2 to +0.2, it was classified as 'stable' and if a slope value for a trajectory was greater than +0.2 it was classified as 'increasing'. This led to the identification of only two classifications: a stable group (see Fig. 1a) and a decreasing group (see Fig. 1b).

Trajectories 1, 2 and 3 evidenced a stable trajectory. Together, these three stable trajectories represent 70 % of all the street blocks throughout Vancouver. This suggests that the majority of street segments did not follow the general declining crime trend. Despite the fact that Trajectories 1 and 2 showed negative slopes, their range was very small and could not be categorized as decreasing in nature. It is also important to note that these trajectories showed low-valued intercepts ranging from 0.04 to 3.36. This means that for 70 % of street segments in Vancouver, the crime volume was relatively low to begin with in 1991 and due to the marginal change over time; these low levels of crime remained stable over the 16-year period. Trajectories 4, 5, 6 and 7 were all classified as showing a decreasing trend with slopes ranging from −2.068 to −0.237. These trajectories constitute almost 30 % of the segments examined throughout Vancouver. Figure 1b displays the results for the decreasing groups and shows the average crime count for each year for each trajectory. When considering the intercepts, the greatest range within these decreasing trajectories from an average low of 7.32 crimes in 1991 for Trajectory 4 to an average high of almost 90 crimes in 1991 for Trajectory 7. As these trajectories harbor the fewest number of streets, this finding shows that very few trajectories were responsible for the majority of criminal activity in Vancouver during the study period. Additionally, the low magnitude slopes continue to support the finding that crime volume patterns are consistent over time at the street block level.

In 1991, Vancouver recorded 76,963 calls for service (amongst the categories analysed). Sixteen years later in 2006, this had declined to 46,079, representing a 40 % reduction in calls for service to the VPD. While the decreasing street segments account for the overall drop in recorded crime over the 16-year period in Vancouver, stable and decreasing trajectories show a comparable pattern of overall decline during the study period. That is, both trajectories evidence a decline in recorded crime with decreasing trajectories declining 39 % and stable trajectories also decreasing 40 % from 1991 to 2006. This indicates that all areas throughout Vancouver evidenced similar declines in crime volume at the street segment level and that the decline in crime seen for the city overall cannot necessarily be attributed to one 'high crime area'. The decreasing trajectories (that account for only 30 % of all street segments) are clearly the driving force behind the overall crime drop based on volume. However, this crime drop has been a phenomenon across the entire city.

K-Means Results

The k-means statistic identified a four-group model, based on the Calinski Criterion scores. Trajectory 1 depicts 'very low crime' counts for each street segment over the study period, 93.7 % of the sample. Trajectory 2 depicts 'low crime' volumes over the study period, 5.5 % of the sample. Trajectories 3 and 4 depict 'high crime' and 'very high crime' street segments, respectively, and encompass the patterns not discernible through the SAS Proc Traj methodology, due to the requirement to truncate any street segment above 50. The results for Trajectory 3 are the 'high crime' street segments constitute 0.8 % of the sample
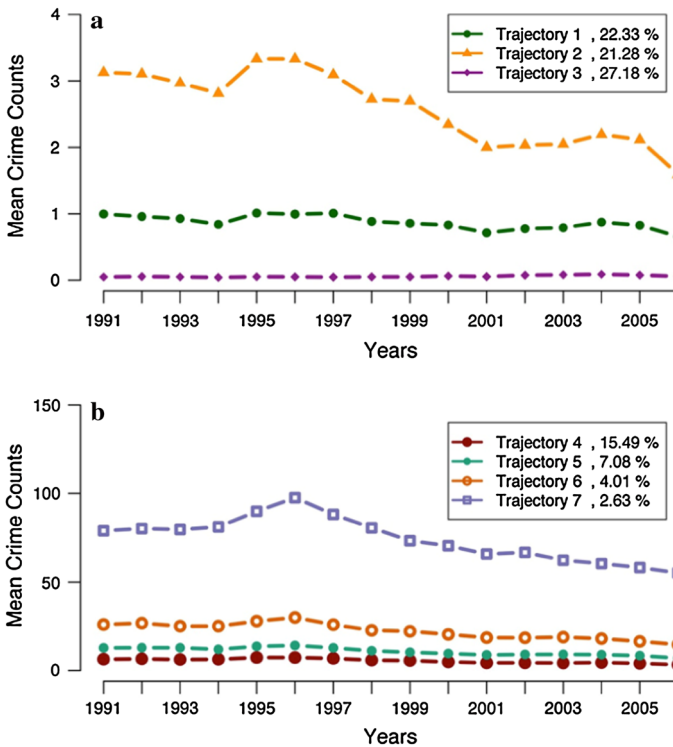
Fig. 1 **a** Stable trajectories, GBTM. **b** Decreasing trajectories, GBTM

and averaged 113 crimes across the 16-year period. Trajectory 4 depicts the 'very high crime' street segments, and is arguably the most interesting result. This group is comprised of only nine street segments, averaging 359 crimes over the 16-year study period. All trajectories are shown in Fig. 2.

To further categorize the four-group model identified through k-means, the groups were classified as either decreasing or stable trajectories according to the methodology in Weisburd et al. (2004). Trajectory 1 exhibited a stable trajectory, with a slope of −0.098. The number of calls for service on these street segments did show a decline over the 16-year period from 37,043 in 1991 to 20,131 in 2006, however, the slope of −0.098 would register as a stable trajectory, according to Weisburd et al.'s (2004) standards. One potential explanation for the minimal slope value may be that this group consists of 93.6 % or 12,160 street segments and the large numbers in this group may minimize the effects of the decline in calls for service over the study period. In 1991, the stable trajectory group, comprised of the majority of street segments (93.6 %) and evidenced an average of 3.35 calls for service and declined to an average of 0.09 crimes each year.

Trajectories 2, 3 and 4 were classified as decreasing trajectories, according to Weisburd et al.'s (2004) criteria. The data show all three trajectories decreasing in crime volume over the study period, with more significant slopes compared to the stable trajectory. Trajectory 2 shows that in 1991, 5.49 % of street segments evidenced an average of 38.69 calls for service, with an average yearly decline of 1.03 calls for service until 2006. These 713 street segments evidenced 25,175 calls for service in 1991 and declined to 15,360 by 2006.
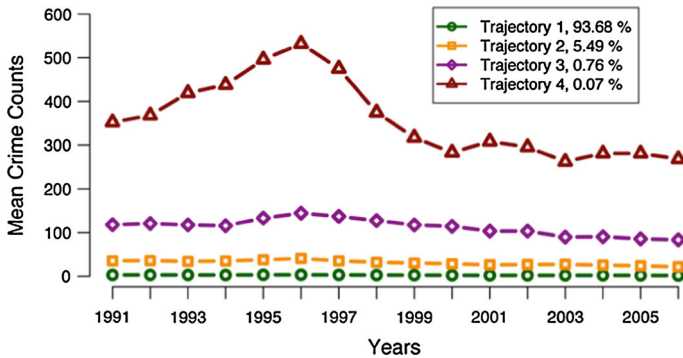
Fig. 2 Trajectories 1 through 4 identified by the k-means statistic

Trajectory 3, comprised of 98 street segments evidenced an average of 134.82 calls for service in 1991 with an average decline of 2.95 crimes per year until 2006. This involved 11,575 crimes in 1991, with a decline to 8,177 by 2006. Trajectory 4, comprised of only nine street segments evidenced an average of 454.99 calls for service in 1991 with a yearly average decline of 12.74 crimes until 2006. These street segments evidenced 3,170 calls for service in 1991 with a decline to 2,411 crimes by 2006.

Overall, all four trajectories identified by the k-means statistic evidenced a decline in calls for service throughout the 16-year study period. Similar to the GBTM analysis, the overall crime drop in Vancouver is being driven by a small percentage of street segments, because of volume; however, the k-means results similarly show that crime has been decreasing across most of the city.

K-Means Visualization

The statistical results of this analysis revealed two main findings. First, crime is concentrated at the street block level. Both the GBTM and the k-means methods show that the vast majority of blocks evidence minimal crime, while a select few harbor a disproportionate amount of criminal activity. Secondly, it appears that the varying levels of concentration evidence stability over time. That is, the streets with no crime, low crime, moderate and high levels of crime remain as such for long periods.

What is not known is the geographic distribution of these crime trajectories throughout Vancouver. Are the street blocks evidencing moderate and high levels of crime uniform throughout the city or clustered in specific areas? Weisburd et al. (2012) and Groff et al. (2010) present visualization maps depicting the location of the trajectory classifications were produced. It is argued for simplicity purposes that the k-means results are preferable when visualizing the geographic distribution of blocks that show low levels of crime versus those evidencing higher volumes.

Based on the k-means statistics, Fig. 3 displays the location for each of the four trajectory groups, showing the street-by-street variability. The vast majority of areas are marked with streets that are low in criminal activity and remained low. These streets are marked by the grey, thin lines for the "low stable trajectory". The significant presence of these blocks is not surprising as this trajectory constitutes 93.68 % or 12,160 street segments.
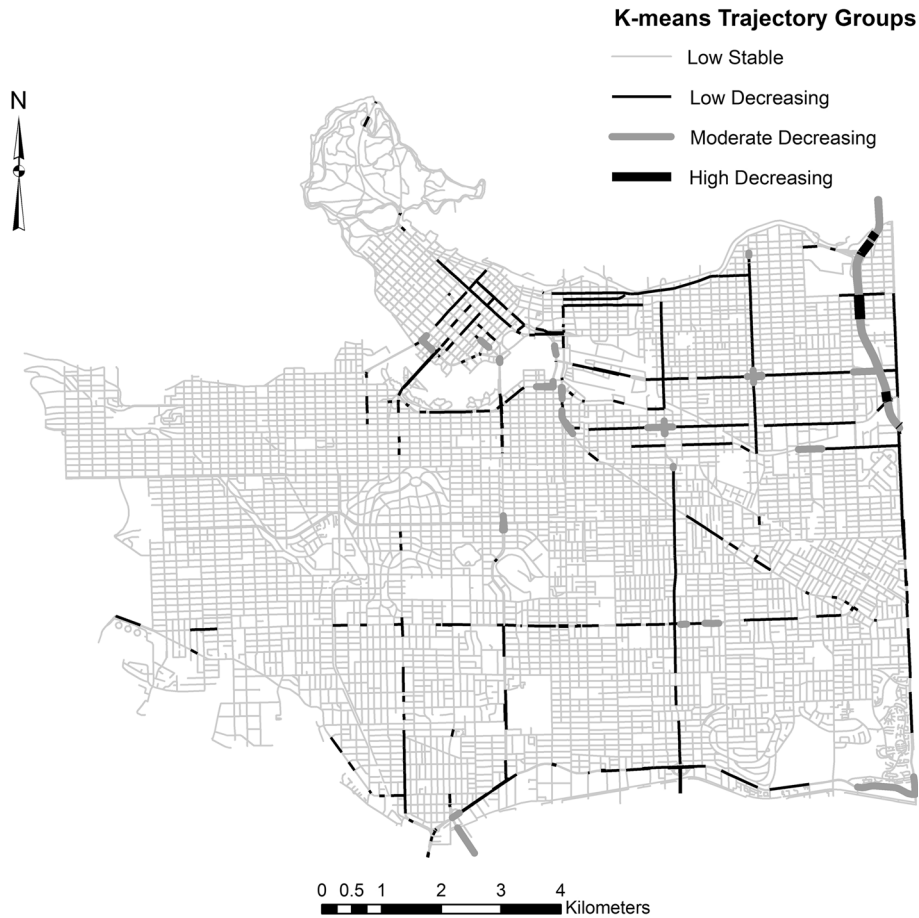
Fig. 3 Spatial distribution of k-means trajectories

Upon close inspection, one can see that the low decreasing street blocks (as marked with a thin black line) are largely located on arterial roads. This means that these busy streets did not evidence a large amount of criminal activity to begin with, but did show a notable decline over the study period. It is also clear from Fig. 3 that the western portion of the city, that is the most affluent, exhibits only the low stable trajectory streets. Conversely, it is only the eastern portions of the city, in particular the northeast portion, that harbor the higher crime street blocks.

The northeast part of Vancouver shows the greatest heterogeneity in terms of a mixed presence of crime volume trajectories. The northeast area iccludes the highest crime trajectory area known as 'Hastings Sunrise'. This area has mixed land use between residential and industrial locations and is arguably less affluent than its neighboring areas to the west. In addition, this area also shows that all the high crime volume streets directly neighbor low stable blocks with low and moderate decreasing blocks interspersed in between. It is interesting to note that this area is marked with many arterial roads such as Hastings Street,

Boundary Road, and McGill Street and an entrance onto the Trans-Canada highway. This area also hosts the Pacific National Exhibition (PNE) each year. The PNE is a large-scale public event that includes a fair, concert events and amusement park rides. It runs each year throughout the summer and early fall and brings a significant volume of people to the Hastings Sunrise area.

Of great interest is the lack of high crime street blocks in the downtown eastside area of Vancouver. The downtown area of Vancouver, particularly the eastside portion, is notoriously known for being riddled with drug problems and incivilities. The surprisingly low levels of crime volumes at the street block level may be due to the fact that the police primarily patrol this area to increase their presence and prevent criminal activity from getting out of hand. It may be the case that the drug charges are higher in this area overall, but when compared to overall levels of criminal activity, this area may be less active in evidencing index crimes and more active in behaviors not captured by the dataset. The presence of the low decreasing street blocks in the downtown eastside area may also be a result of the specialized attention this area is given by the VPD.

The southwest portion of Vancouver, that includes the Oak Street Bridge, is noted as including a moderate decreasing trajectory in its southbound lane, but a low decreasing trajectory in its northbound lane. This indicates that the bridge has seen an overall decline in criminal activity, but exhibits varying levels of crime in each direction. The southeast portion of Vancouver exhibits the moderate crime trajectory identified at the bottom portion of the map. This is located along Marine Way and is a stretch of road mostly marked with forest, but also industrial activity.

This map does offer a clear picture of both the heterogeneity and the homogeneity of crime patterns on street blocks. The street segments evidence a heterogeneous pattern in that varying crime volumes neighbor one another throughout the city. This is known as a steep crime gradient (Groff et al. 2010). Throughout the majority of Vancouver, one can see stable street blocks adjacent to various decreasing street segments. Conversely, the homogeneity of both the low stable and high decreasing street blocks is evident. The former is clustered in the western portion of Vancouver, whereas the latter is entirely segregated within the northeast corner of the city. They underscore the importance of examining crime at micro places, as aggregate geographic analyses would have masked these variations.

Discussion

When comparing the two cities, the results show a strong concentration of criminal activity. Vancouver's distribution of criminal activity at the street block level was comparable to that of Seattle's. Of particular interest is the fact that for both cities, 100 % of the crime was located on only 50–60 % of all street blocks. Also, half the criminal activity was evidenced on only 4.5–7.8 % of street blocks. The street blocks with the highest levels of crime, defined as showing more than 50 incidents or calls for service through the study period encompassed only 1 % of all possible streets in Seattle and only 3.6 % of all streets in Vancouver—see Table 3.

Overall, both cities showed considerable concentrations of criminal activity over their respective study periods and the results for Vancouver's criminal activity at the street block level was comparable to that of Seattle. The results showed that street blocks throughout Vancouver evidenced significant tendencies towards certain levels of criminal activity and

Table 3 Descriptive statistical results of crime concentrations on street blocks

Category	Weisburd et al. (2004) and Seattle, WA[a]	Vancouver, BC
Included years	1989–2002	1991–2006
Dataset categories	All incident reports	Index crimes
Most common crimes	50 % property, 17 % prostitution	41 % property, 24.5 % theft from auto
Mean number of crimes per block	3.6	5.25
Percent decline in crime	24	40
Percent of blocks with all crime	50	60
Percent of blocks with half the crime	4.5	7.8
Percent with more than 50 crimes	1	3.6
Percent of blocks with 1–4 crimes	34.5	34

[a] Percent of blocks with varying proportions of crime are represented as averages based on data presented in Weisburd et al. (2004)

that these proportions remained stable for long periods of time. What was not clear was whether it was the same street blocks evidencing the same proportions from 1 year to the next.

Group-Based Trajectory Model Results

The GBTM found more than twice the number of distinct developmental trajectories of micro crime places in Seattle versus Vancouver—see Table 4. Vancouver had seven crime trajectories at the street block level, whereas Seattle had eighteen. This is not surprising considering the difference between the two datasets. Weisburd et al. (2004) analyzed all criminal activity reported in Seattle ($n = 1.5$ million reported crimes) versus 22 index property and violent offences analyzed for Vancouver ($n = 1.08$ million reported crimes). This may have led to the statistical program identifying a larger number of developmental trajectories throughout Seattle as more crime may have lent itself to greater variability and/ or patterns at the street block level. What is more interesting though is that despite the large differences in the number of trajectories between the two studies, they both share marked similarity in the nature and type of trajectories identified. Both datasets identified the majority of trajectories as either stable or decreasing in nature, with Vancouver solely consisting of these two categories. The stable trajectories accounted for the vast majority of street blocks throughout both cities. Seattle saw 84 % of its street blocks classified as stable in nature and Vancouver had 70 % of its streets labelled as stable. Additionally, both studies showed that stable street segments could be categorized as low crime.

From 1989 to 2002, Seattle experienced a 24 % decline in crime incidents. Weisburd et al. (2004) stressed that it was the 14 % of street segments identified as decreasing that

Both cities had decreasing trajectories as their second largest group identified by the GBTM method; however, Vancouver has twice as many compared to Seattle. This may be due to the fact that Vancouver did not evidence any increasing trajectories. Seattle's decreasing trajectories included the street blocks with the highest crime counts, with the highest showing an average of 96 crimes for 1989. Vancouver's decreasing trajectories also involve the highest crime blocks, with one trajectory showing an average of 89 crimes for 1991. The decreasing trajectories show the largest overall range in criminal activity for both cities.

From 1989 to 2002, Seattle experienced a 24 % decline in crime incidents. Weisburd et al. (2004) stressed that it was the 14 % of street segments identified as decreasing that

Table 4 Comparison of the GBTM Results

Category	Weisburd et al. (2004) and Seattle, WA	Vancouver, BC
Final model	18 group solution	7 group solution
Number of stable trajectories	8	3
Percent of all street blocks (stable)	84 %	70 %
Range of y-intercepts (stable)	+0.03 to +7.5	+0.04 to +3.36
Range of slopes (stable)	+0.07 to +0.14	−0.1 to +0.002
Number of decreasing trajectories	7	4
Percent of all street blocks (decreasing)	14 %	30 %
Range of y-intercepts (decreasing)	+4.3 to +96	+7.3 to +89.8
Range of slopes (decreasing)	−2.1 to −0.2	−2.0 to −0.23
Number of increasing trajectories	3	NA
Number of all street blocks (increasing)	2 %	NA
Range of y-intercepts (increasing)	−0.3 to +15.55	NA
Range of slopes (increasing)	+0.3 to +2.3	NA

were responsible for this decline. In contrast, all but one of the seven trajectories identified within the Vancouver dataset showed negative slopes. Almost the entire city, even those street segments labelled as stable in nature, evidenced declines in calls-for-service. From 1991 to 2006 Vancouver saw a 40 % decrease in the 22 index crimes measured. Unlike the findings from Seattle, it became clear that this decline in criminal activity was more widespread throughout Vancouver and almost all street blocks would have played a role in this change over time, but because of crime volumes the crime drop in Vancouver was still driven by a small percentage of street segments similar to Seattle.

Weisburd et al. (2004) discussed the surprising homogeneity in crime patterns uncovered by the GBTM method. Specifically, it was highlighted that, "the main purpose of trajectory analysis is to identify the underlying heterogeneity in the population. What is most striking, however, is the tremendous stability of crime at places" (p. 298). Seattle's low crime trajectories remained low throughout the study period and the same trend was evident amongst the higher crime trajectories, regardless of their classification. For example, Weisburd et al. (2004) highlight that the highest rate trajectory begins at almost 95 incidents and only decreases to an average of 75 crimes by the end of the study period; as such, it remained the highest rate trajectory. The developmental patterns identified for Vancouver's street blocks are concordant with the Weisburd et al. (2004) findings of overall homogeneity. The fitted slopes evidenced by the decreasing trajectories between the two cities are almost identical in their values and minimal range, showing that despite the classification of 'decreasing', these street blocks remained relatively stable over time. Vancouver's decreasing trajectories vary significantly in terms of their intercept values; however, these levels do not change dramatically over the study period, for each of the 4 decreasing patterns identified.

GBTM Versus K-Means Results

Table 5 displays the results generated by the GBTM versus that of the k-means statistic. Both identified the majority of street blocks as evidencing stable crime patterns. The difference is that the GBTM identified three separate distinct subgroups of stable street

Table 5 Comparison of GBTM versus k-means results

Category	GBTM	K-means
Final model	7 group solution	4 group solution
Number of stable trajectories	3	1
Percent of all street blocks (stable)	70 %	94 %
Range of y-intercepts (stable)	+0.04 to +3.36	+3.35
Range of slopes (stable)	−0.1 to +0.002	−0.098
Number of decreasing trajectories	4	3
Percent of all street blocks (decreasing)	30 %	6 %
Range of y-intercepts (decreasing)	+7.3 to +89.8	+38.6 to +455
Range of slopes (decreasing)	−2.0 to −0.23	−12.74 to −1.03

segments, despite their highly comparable y-intercepts and slopes. These stable trajectories have slopes that range from only −0.1 to +0.002, thus it is questionable as to whether their separate identification is of practical use in discerning micro crime patterns. In contrast, the k-means method grouped all the street blocks showing stable tendencies into one trajectory, accounting for 94 % of the city's segments. This is arguably more efficient.

The number of decreasing trajectories identified by both statistics is also comparable. GBTM identified four versus three decreasing trajectories for the k-means statistic. Both statistics also found that the decreasing trajectories evidenced the highest rate street segments. However, that is where the similarities end. The results from the k-means saw only 6 % of Vancouver's street segments classified as decreasing in nature compared to 30 % with GBTM. The range of intercept values is also significantly larger for the k-means statistic. The reason for this is clearly due to the statistic's ability to account for values greater than 50. The decreasing street blocks for the k-means range from 38.6 to 455, whereas the highest rate trajectory identified by the GBTM was 90, however, anything above 50 would not have been included as part of the calculations for the final model solution.

The notable differences observed in the statistical values between the two statistics underscores the importance of implementing an alternative trajectory analysis, such as k-means, when one's dataset includes cases greater than 50. The fitted linear slopes evidenced by the k-means technique also show an astoundingly larger range compared to the GBTM method. GBTM evidenced a range in slope values of −2.0 to −0.23 for all four decreasing trajectories, whereas the k-means statistic saw this range expanded from −12.74 to −1.03. And these slopes were applied to only 6 % of street segments. Thus, the k-means statistic was extremely useful in not only accounting for the highest rate street segments, but also capturing the significant range of these high rate trajectories over time.

Regardless of the significant differences in the statistics produced between the GBTM method and k-means, it is important to underscore that both methods tell a very similar story pertaining to the overall developmental patterns of micro crime places. Both showed that Vancouver's street blocks were, for the majority, either crime free or had low levels of criminal activity and that these patterns remained largely stable over time. Both statistics also showed a minority of streets with high crime activity that decreased during the study period. Thus, despite the differences between the two cluster analysis techniques, both methods confirmed five main findings for Vancouver:

1. Crime is concentrated in nature.
2. Most street blocks have low crime levels that remain that way over time.
3. The chronic high crime streets exist on very few street blocks.
4. The highest crime rate streets showed substantial declines over the study period.
5. All street block trajectories evidenced declines in crime volume, but a relatively small percentage of these street blocks are driving the crime drop in Vancouver.

An obvious question to pose at this point is: how can these two methods both tell such similar stories when their statistics are so different? The reason why the statistics are so different is most likely, as stated above, rooted in the k-means method being able to account for values greater than 50. However, it is clear that this limitation of GBTM does not change the qualitative nature of the results. This is analogous to a statistical method that is used inappropriately and biases the parameter estimates but does not change their signs. In this situation, the general story is similar, but the details (magnitudes) change. This is an important implication for other studies that have used GBTM: if a study area has a sufficiently large number of street segments with more than 50 crimes, based on the results presented above truncating these values at 50 does not serious bias the statistical output.

Implications of the Results

There are a number of implications that emerge from this research. First and foremost, using two different methodologies in a different city we were able to replicate the research of Weisburd and colleagues—though there are some differences between the two cities, the overall result is generalizable here. This is important because there are so few crime and place studies that investigate crime across entire municipalities. These studies, however, have shown incredible concentrations within their respective cities: Minneapolis, MN (Sherman et al. 1989), Seattle, WA (Groff et al. 2010; Weisburd et al. 2004, 2009, 2012), Vancouver, BC (Andresen and Malleson 2011), and Ottawa, ON (Andresen and Linning 2012). In all of these cases 50 % of crime is accounted for in approximately 5 % of street segments. In analyses that considered individual crime types, this concentration of crime can be even greater (Andresen and Malleson 2011; Andresen and Linning 2012).

This repeated finding regarding the concentration of crime at places has led Weisburd et al. (2012) to put forth the law of crime concentrations. Based on the results presented above, and with the other work on Vancouver by Andresen and Malleson (2011), we cannot deny that this law holds for Vancouver, BC. Though more research needs to be undertaken to further corroborate this law of crime concentrations, the evidence presented thus far is quite strong. This clearly implies that the (best/easiest) opportunities for crime are located in very particular places. The implications for crime prevention here are obvious. As stated by Sherman et al. (1989), it is far easier to modify the routine activities of places than of people. Consequently, there is a need for a better understanding of those places that generate vastly disproportionate volumes of crime. If we can modify how people routinely use those places (changing the routine activities of places) the potential for crime reduction is significant.

With regard to where the various trajectories are located, there is another similarity with the results presented here and present in Weisburd et al. (2012). In Seattle, Weisburd et al. (2012) found a clear indication of the clustering of the various trajectories. However, the clustering was not always a "typical" form of spatial clustering. Most often, when spatial clustering is presented (particularly in the case of crime hotspots), there is an epicenter or

peak followed by radial distance decay. Though this pattern is present in the maps shown in Weisburd et al. (2012), there is also the presence of linear clustering along particular streets. This is clearly present in Fig. 3 showing the 4 k-means trajectories for Vancouver. The low stable street segments comprise the vast majority of Vancouver, but the low, moderate, and high decreasing street segments exhibit very obvious linear clustering along the primary north–south and east–west routes within Vancouver. In fact, in many cases, multiple trajectory classifications are along the same route and contiguous to one another. This result only adds to the usefulness of having so few moderate and high crime street segments to address in the context of crime prevention activities, discussed above.

Conclusion

The purpose of this analysis was to expand the research of crime and place by replicating the seminal work of Weisburd et al. (2004) outside of Seattle. Over one million calls-for-service from the VPD from 1991 to 2006 were analyzed at the street segment level to determine whether micro crime places in Vancouver evidenced developmental trajectories. Using two separate statistical methods, a trajectory analysis was conducted, identifying the following:

Crime on Vancouver's street blocks is highly concentrated.

The results showed that 100 % of all criminal activity was located on only 60 % of street blocks. The highest concentrations of criminal activity, defined as streets evidencing over 50 crimes on average per year, were found on only 2 % of blocks.

These crime concentrations remained relatively stable over time.

The vast majority of street blocks were identified as having stable developmental trajectories over the study period. This means that the volume of criminal activity seen on street blocks throughout the majority of Vancouver did not change substantially from 1991 to 2006. Additionally, all of the street blocks labelled as stable evidenced minimal levels of crime. In sum, of the 60 % of streets harbouring criminal activity, the majority showed low criminal activity and remained that way over 16 years.

Vancouver's street blocks show significant geographic variability.

The spatial distribution of street block trajectories throughout Vancouver strongly supports the tenet that micro crime places must be analyzed to both understand the variability of criminal activity and to further progress on crime prevention. The current analysis showed that crime levels and the extent to which they are likely to remain stable versus change varies substantially from one block to the next. Results showed blocks low in crime adjacent to blocks with the highest crime rates; results also showed street blocks with stable trajectories neighboring those that decreased in nature. Thus, we cannot discount the spatial unpredictability of criminal activity evidenced at micro places. The research from this analysis indicates that high levels of criminal activity vary from one street to the next. As such, there was no evidence found that would support the notion of a "bad area"; perhaps only, "bad streets".

In their book, Weisburd et al. (2012) questioned whether their results regarding developmental crime patterns are generalizable outside of Seattle. It is argued here that they are. In general, the overall results are remarkably similar in terms of the three main findings as specified above. However, Vancouver did not evidence any increasing

trajectories, whereas Seattle did. In fact, both sets of trajectory analyses conducted only yielded stable and decreasing developmental patterns throughout Vancouver's street blocks.

Weisburd et al. (2012) implored other researchers to replicate their work in other jurisdictions to assess the generalizability of the data stemming from Seattle. It is argued that "this is essential if we are to build a science of the criminology of places" (p. 219). This analysis answers that call with a replication of the seminal work published in 2004. And we now wish to echo the call made by Weisburd et al. (2012) and hope to generate enthusiasm for more scholars to assess the longitudinal patterns of micro crime places at the street block level using the same methodology. It is hoped that this expansion of research on micro crime places will lead to a further understanding of the criminology of place.

References

Andresen MA, Linning SJ (2012) The (in)appropriateness of aggregating across crime types. Appl Geogr 35(1–2):275–282

Andresen MA, Malleson N (2011) Testing the stability of crime patterns: implications for theory and policy. J Res Crime Delinq 48(1):58–82

Andruff H, Carraro N, Thompson A, Gaudreau P, Louvet B (2009) Latent class growth modelling: a tutorial. Tutor Quant Methods Psychol 5(1):11–24

Bernasco W, Block R (2011) Robberies in Chicago: a block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. J Res Crime Delinq 48(1):33–57

Braga AA, Hureau DM, Papachristos AV (2011) The relevance of micro places to citywide robbery trends: a longitudinal analysis of robbery incidents at street corners and block faces in Boston. J Res Crime Delinq 48(1):7–32

Brantingham PJ, Brantingham PL (1991) Environmental criminology. Waveland Press, Prospect Heights

Brantingham PJ, Dyreson DA, Brantingham PL (1976) Crime seen through a cone of resolution. Am Behav Sci 20(2):261–273

Calinski T, Harabasz J (1974) A dendrite method for cluster analysis. Commun Stat 3(1):1–27

Elragal A, El-Gendy N (2012) Trajectory data mining and the need for semantics. European, Mediterranean and Middle Easter Conference on Information Systems, June 7–8, Munich, Germany

Farrell G, Tseloni A, Mailley J, Tilley N (2011) The crime drop and the security hypothesis. J Res Crime Delinq 48(2):147–175

Genolini C, Falissard B (2010) KmL: k-means for longitudinal data. Comput Stat 25(2):317–328

Groff ER, Weisburd D, Yang S (2010) Is it important to examine crime trends at a local "micro" level? A longitudinal analysis of street to street variability in crime trajectories. J Quant Criminol 26(1):7–32

Huizinga D, Esbensen F, Weiher AW (1991) Are there multiple paths to delinquency? J Crim Law Crim 82(1):83–118

Levitt SD (2004) Understanding why crime fell in the 1990s: four factors that explain the decline and six that do not. J Econ Perspect 18(1):163–190

Mishra S, Lalumière M (2009) Is the crime drop of the 1990s in Canada and the USA associated with a general decline in risky and health-related behavior? Soc Sci Med 68(1):39–48

Mowder MH, Cummings JA, McKinney R (2010) Resiliency scales for children and adolescents: profiles of juvenile offenders. J Psychoeduc Assess 28(4):326–337

Nagin DS, Land KC (1993) Age, criminal careers and population heterogeneity: specification and estimation of a nonparametric, mixed Poisson model. Criminology 31(3):327–362

Ouimet M (2002) Explaining the American and Canadian crime "drop" in the 1990s. Can J Criminol 44(1):33–50

Ratcliffe JH (2004) Geocoding crime and a first estimate of a minimum acceptable hit rate. Int J Geogr Inf Sci 18(1):61–72

Robinson WS (1950) Ecological correlations and the behavior of individuals. Am Sociol Rev 15(3):351–357

Sherman LW, Gartin PR, Buerger ME (1989) Hot spots of predatory crime: routine activities and the criminology of place. Criminology 27(1):27–56

Weisburd D, Bushway S, Lum C, Yang S (2004) Trajectories of crime at places: a longitudinal study of
    street segments in the City of Seattle. Criminology 42(2):283–322
Weisburd D, Bruinsma GJN, Bernasco W (2009a) Units of analysis in geographic criminology: historical
    development, critical issues, and open questions. In: Weisburd D, Bernasco W, Bruinsma GJN (eds)
    Putting crime in its place: units of analysis in geographic criminology. Springer, New York, pp 3–31
Weisburd D, Morris NA, Groff ER (2009b) Hot spots of juvenile crime: a longitudinal study of street
    segments in Seattle, Washington. J Quant Criminol 25(4):443–467
Weisburd D, Groff ER, Yang S (2012) The criminology of place: street segments and our understanding of
    the crime problem. Oxford University Press, New York