Spatiotemporal Analyses of Violent Trauma Incidents in Metro Vancouver

Temporal and Socio-Demographic Analysis of Violent Trauma Incidents by Neighbourhood Hotspots and Home-Injury Distance

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GEOG 455 Theoretical and Applied GIS
Spring 2016, Simon Fraser University

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Date of submission: 11 April 2016

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ABSTRACT

Injuries from violent assault are a major healthcare issue and a burden to economic development. Studies show evidence that violent assaults can be linked to features of the urban environment, socio-demographic characteristics, and time. This project examines patterns of violent trauma—injuries that require acute medical care as a result of violent crime—in Metro Vancouver based on home–injury distance (i.e. the distance between a victim's place of residence and their location of injury) and violent trauma hotspots. We define hotspots using an experimental catchment-based approach, combining case density and socio-demographic data on local neighbourhoods. Results show 15 local violent trauma hotspots in Metro Vancouver, occurring along major transit corridors. Consistent with violent trauma literature, our results show temporal patterns in violent trauma incidents, with statistically significant weekly peaks on Saturdays and hourly peaks between 9:00 PM and 3:00 AM. Our results also indicate a statistically significant relationship between victim age and injury mechanism to home-injury distance. Future work involves incorporating qualities of the built environment and platial, qualitative data into our statistical research. Our quantitative approach to defining violent trauma hotspots has limited our number of hotspot observations, which is currently constraining our statistical analyses and limiting our understanding of the socio-demographic characteristics of these hotspots.

1. INTRODUCTION

This project contributes to the understanding of spatiotemporal patterns of violent trauma in Metro Vancouver. Violent trauma is a significant health issue and results in health and other broader social and economic burdens. The objective of this research is to understand temporal, spatial, and socio-demographic patterns of violent trauma to inform future health interventions and prevention strategies aimed at reducing the number of incidents.

In 2014, there were 29,883 police reported incidents of violent assault in British Columbia (BC Ministry of Justice, 2015), of which 15%, 4,500 assaults, were in the City of Vancouver (VPD, 2015). The economic burden of violent assaults in the U.S. reached USD $18-billion in 2010 in medical costs alone (CDC, 2010). The World Health Organization (WHO) classifies interpersonal violence as a major public health issue, and defines violence as the intentional use of physical force against oneself, another person, or against a group that results in or has a high likelihood of resulting in injury, death, psychological harm, maldevelopment, or deprivation (WHO, 2002). The Canadian National Trauma Registry defines interpersonal violent assault as intentionally inflicted injuries (NTR 2011).

Interpersonal violence arises from various behavioural and social factors. Community contexts—such as social network relations and socio-demographic neighbourhood characteristics—as well as personal mindsets determine the presence and complexity of violent acts. Societal frameworks, such as system responsiveness, social and cultural norms, political environment, and economic situations can encourage or inhibit this violence (Krug et al. 2002; Papachristos et al. 2012). Urban areas are a substantial contributor to this kind of interpersonal violent assault. A long history of criminologists have related crime to place, developing an understanding that urban design, land use, features of the built environment, and socio-demographic and socioeconomic environments are decisive factors for the occurrence of crime (Brantingham & Brantingham, 1995). Due to the heterogeneous character of urban spaces, the motivation, type and occurrence of crime differs from neighbourhood to neighbourhood.

Hotspot maps allow easy interpretation and can consider multiple levels of temporal and spatial concentrations at all crime levels (Kidner et al., 2002). Hotspots require a statistically robust form of analysis because clusters of points can be arbitrarily grouped visually—and potentially incorrectly. Hotspot definition varies largely among authors. Crime hotspots have been studied broadly using spatial patterns of violent assault and socioeconomic status (Schuurman et al., 2008; Cusimano et al, 2010; Sparks, 2011; di Bella et al., 2015; Newgard et al., 2015), and particularly on the link between violent assaults and specific features of the urban built environment, such as land use, alcohol serving facilities, traffic, access to and nodes of public transit, and graffiti occurrence (Ashe et al, 2003; Branas et al, 2009; Cunradi et al, 2011; Taylor et al, 2011; Jennings et al., 2013; Walker & Schuurman, 2014; Irvin-Erickson & La Vigne, 2015).

Haas et al. (2015) found that in Toronto about 90% of victims from assaults were injured in a 16km radius from their residence, and Cusimano et al. (2010), that 45.1% of violent assault cases in Toronto occurred between 8:00 PM and 03:59 AM at night. Walker et al. (2014) identified spatiotemporal hotspots of violent trauma incidents in Metro Vancouver and described the hotspots by urban built environment characteristics, hotspot socio-demographics and social deprivation, and victim demographics. However, chances to being injured close to the place of residence depends on patient and injury characteristics (Haas et al. 2015). These findings suggest that violent assault is a complex phenomenon affected by the built environment, temporality, and social conditions.

2. OBJECTIVE

Our study has three objectives: [1] to identify major hotspots of violent trauma in Metro Vancouver, [2] quantify the temporal patterns of violent trauma in Metro Vancouver by month, day of week, and time of day, and [3] test whether various victim-related and case-related variables (e.g. age, sex, mortality, and injury severity and mechanism) are dependent on hotspot locations or the distance from the victim's home to their place of injury.

We hypothesize that: [1] violent trauma hotspots occur in dense neighbourhoods or along major transit routes, [2] violent trauma incidents have temporal patterns at monthly, weekly, and hourly resolutions, peaking during Fall months, weekdays, and midnight hours, and [3] injury and socio-demographic characteristics are dependent on hotspot location rather than by home-injury distance.

3. METHODOLOGY

This project will first identify violent trauma hotspots in Metro Vancouver, including capturing qualitative, socio-economic characteristics of these locations. Second, we will determine whether temporal patterns exists for these hotspots, and whether socio-demographic variables are independent of hotspots. Lastly, we will repeat the same temporal and socio-demographic tests, but instead using home-injury distance (Table 1).

Table 1. Statistical Methodologies for Hotspot and Home-Injury Distance Analysis for Temporal and Socio-Demographic Characteristics

<table>
<tr><th></th><th>Distance Analysis</th><th>Hotspot Analysis</th></tr>
<tr><td>Seasonality</td><td colspan="2">Do the number of violent trauma incidents vary by time?</td></tr>
<tr><td>Month</td><td colspan="2" rowspan="3">Chi-Square Goodness of Fit Test; Expected Proportion Comparisons with Bonferroni Adjusted P-ValuePost Hoc Test</td></tr>
<tr><td>Day of Week</td></tr>
<tr><td>Hour</td></tr>
<tr><td>Independence</td><td colspan="2">Are these variables associated spatially?</td></tr>
<tr><td>Month</td><td colspan="2" rowspan="3">Chi-Square Test; Marascuilo Procedure with Bonferroni Adjusted P-Value Post Hoc Test</td></tr>
<tr><td>Day of Week</td></tr>
<tr><td>Hour</td></tr>
<tr><td>Gender</td><td colspan="2" rowspan="4">Chi-Square Test; Adjusted Standardized Residuals, Marascuilo Procedure with Bonferroni Adjusted P-Value Post Hoc Tests</td></tr>
<tr><td>Age</td></tr>
<tr><td>Expired</td></tr>
<tr><td>Injury Mechanism</td></tr>
<tr><td>Home VANDIX</td><td colspan="2" rowspan="3">Kruskal-Wallis H Test; Mann-Whitney with Bonferroni Adjusted P-Value Post Hoc Test</td></tr>
<tr><td>Injury VANDIX</td></tr>
<tr><td>Injury Severity Score</td></tr>
</table>

3.1. DATA

The project uses three major datasets: the BC Trauma Registry (BCTR), the Vancouver Area Neighborhood Deprivation Index (VANDIX), and land use classifications for Metro Vancouver.

Trauma data from BCTR records cases of people who have been injured by an external cause (i.e. traumatic injury) and have been admitted to a hospital for greater than 48 hours. BCTR collects data from 11 trauma designated hospitals in BC. BCTR data contains injury point location and time; injury mechanism, severity, and mortality (i.e. "expired"); and victim-related information (e.g. age, sex, etc.). Our dataset contains 1271 trauma cases which have been restricted to cases that (a.) were a result of violence or assault, that (b.) occurred in Metro Vancouver between January 1, 2001, and December 31, 2008, and (c.) that had an injury severity score (ISS) of 15 or higher. ISS represents the severity of injuries for several body regions using weighted scores (Baker et al., 1974).

VANDIX provides aggregated information on income, education, demographics, employment, and other variables at a dissemination area level (Bell & Hayes, 2012), and assists us in finding relationships between violent trauma incidents and the socio-demographic characteristics of residential or injury locations of victims. Using VANDIX keeps the methodology of this study consistent with similar studies to produce results that can be compared across studies. Land use classification for Metro Vancouver and public transit data provide neighbourhood and environmental clues on a victim's residential and injury location (Metro Vancouver, 2015).

3.2. HOTSPOT CHARACTERIZATION

In crime and health research, hotspot definition is a highly debated topic and multiple statistical approaches are suggested throughout the literature, ranging from basic Kernel Density Functions and Local indicators of autocorrelation to more complex methodologies, such as machine learning algorithms (Kidner et al., 2002; Chainey et al., 2003; Chainey & Ratcliffe, 2005; Tango, 2010; Torabi & Rosychuk, 2011).

Following Walker et al. (2014), our hotspot analysis is based on kernel point density mapping of incidents within a 600m search radius. This search radius reflects a compromise between walking distance, neighborhood size, and data processing requirements. Kernel point density is a smoothing method that additively applies kernel functions on a set of points in order to determine incident density (Quinn & Keough, 2002). It has been generally proven adequate for crime mapping in Chainey (2013) and Hart (2014).

However, purely quantitative hotspot definitions based on kernel functions risks conflating adjacent incident peaks together merely due to proximity, even though platial characteristics, neighbourhood socio-demographics, and underlying assault motivations may differ. Kernel density, furthermore, tends to visually overestimate very low densities and is not able to distinguish between local and global maxima. Walker et al. (2014) suggest that hotspot determination is contextual and dependent on environmental and demographic factors such as population density or subjective urban characteristics.

For these reasons, our hotspot definition procedure uses an experimental approach derived from watershed analysis. By turning our point density map into an inverted elevation model, we use the metaphor of *flow direction* to identify troughs and ridges of violent trauma incidents. Raster cells of highest density are considered the lowest points. Then, each cell is assigned to a catchment based on a flow direction raster. A flow accumulation raster determines the points of highest inflow, leading to a natural delineation of local violent trauma peaks. This methodology is inspired by a 3D representation of violent trauma for the City of Vancouver (Walker & Schuurman, 2012). It assumes violent trauma incidents to not only be dependent on *places*, but also on *axes*.

We finally use a Getis-Ord G statistics on incident data using the index of social deprivation of the place of injury as a clustering variable (Getis & Ord, 1992), which allows us to detect socially inhomogeneous hotspots. We work with an inverse distance impact, a Manhattan Distance Model as well as a 600m bandwidth on cluster allocation.

Furthermore, we perform qualitative spatial analyses on identified hotspots, including descriptions of places and pictures of the urban built environment. We also qualitatively assess how land use, access to public transit, and the nature of commercial facilities shape these neighborhoods. Understanding the nature of neighbourhoods associated with violent trauma will assist in formulating prevention strategies from an urban planning and design perspective.

3.3. HOME-INJURY DISTANCE CLASSIFICATION

Data preparation includes classifying trauma cases into seven home-injury distance classes using a natural breaks algorithm based on the distance between a victim's' residence and their location of injury. Applying these distance classes, we distinguish between incidents that occur close to the victim's residence and those that occur further away.

3.4. TEMPORAL AND SOCIO-DEMOGRAPHIC ANALYSES

The temporal analyses identifies whether and how violent trauma incidents vary across time among different hotspots and home-injury distances. Chi-square goodness of fit tests are used to determine whether violent trauma incidents are seasonal—in other words, if the frequency distribution of violent trauma incidents differ from an expected, theoretical equal distribution across month, day of week, and hour of day. For statistically significant findings, subsequent post hoc tests are used to identify which months, days of the week, or hours experience a number of violent trauma incidents that are statistically significant above or below than expected. The post hoc tests compare the value of each nominal, temporal variable against the sum of all others (e.g. the expected proportion of violent trauma incidents in one month is 8.33% and the expected proportion for the sum of all other months is 91.67%). Post hoc tests use a Bonferroni adjusted P-value to control the familywise error rate.

Additionally, the socio-demographic analyses identifies whether social or injury characteristics of violent trauma differ by hotspot or home-injury distance. Chi-square tests of independence are used to determine whether age, gender, mortality (i.e. "expired"), and injury mechanism are independent of hotspot or home-injury distance. For statistically significant results, the Marascuilo procedure is used as the first post hoc test to compare which hotspot or home-injury distance pairs are significantly differently. The second post hoc test analyzes adjusted standardized residuals of the chi-square test to determine whether a socio-demographic variable results in an increased or decreased number of violent trauma incidents that are significant different than expected. The Kruskal-Wallis test, a nonparametric one-way analysis of variance, is used to compare whether the medians of ISS, Home VANDIX, and Injury VANDIX are equal among hotspots and home-injury distances. For results that indicate a statistically significant difference, the Mann-Whitney test for between-group comparisons, using a Bonferroni adjusted p-value, determines which hotspots or home-injury distances pairs are significantly different among each other.

3.5. SOFTWARE

Microsoft Excel and SPSS Statistics are used to perform statistical analyses, and ESRI ArcGIS (ESRI, 2014) and Quantum GIS (QGIS Development, 2016) for spatial analyses.

4. RESULTS

4.1. HOTSPOT CHARACTERIZATION

Our hotspot identification procedure provides 15 violent trauma hotspots in the Metro Vancouver area (Fig. 1). A catchment area is considered a hotspot if it exceeds 14 incidents within the studied 7-year period. In rare cases, catchment areas have been merged if they are identified as belonging to the same neighbourhood. One hotspot spreading from Waterfront Station to East Vancouver has been split along Abbot Street based on significantly different social indicators from

Getis-Ord G statistics, suggesting that social indicators should have an impact on hotspot definition.

The major hotspots are characterized by a multitude of factors including: socioeconomic class measured by VANDIX, access to public transportation, perceived security, etc. The majority of hotspots are urban-commercial–based locations that follow the major transit lines from Downtown Vancouver, but hotspots reach as far as Maple Ridge. This may suggest that population density and access to public transportation may be correlated with hotspots.

Our hotspots are labeled (see Fig. 1 for map numbering) as [0] Downtown Eastside-Chinatown, [1] Downtown Granville Street, [2 Downtown Waterfront, [3] Mount Pleasant, [4] Commercial-Broadway, [5] New Westminster, [6] Hastings-Sunrise, [7] Maple Ridge, [8] Joyce-Collingwood, [9] Metrotown, [10] Edmonds, [11] Nanaimo, [12] Broadway-Oak, [13] Downtown Westend, and [14] Surrey.

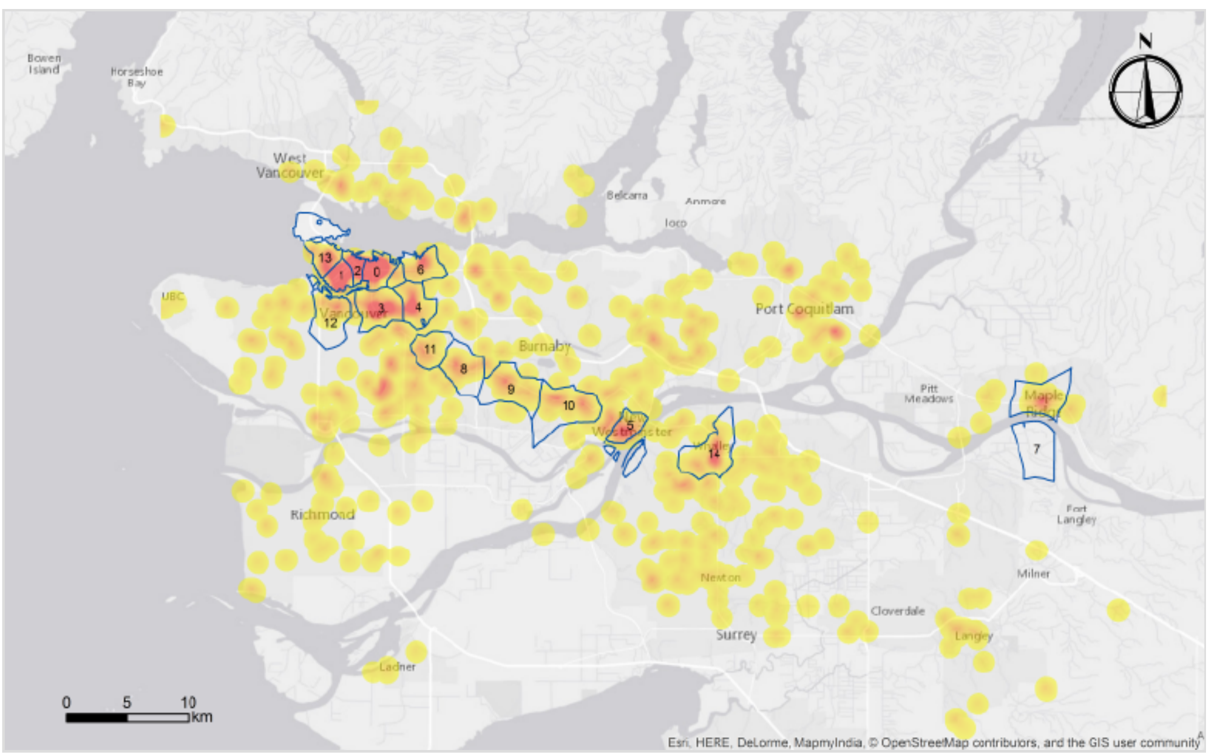

Figure 1. Hotspots Across Metro Vancouver and Violent Trauma Incident Density.

4.2. HOME-INJURY DISTANCE CLASSIFICATION

Six home-injury distance classes have been identified. They represent violent trauma cases that occurred at or close to home, and cases that occurred further away from home. These home-injury distance classes are: 0–0.35km, 0.35-2km, 2-5km, 5–10km, 10–20km, and 20–50km.

4.3. TEMPORAL ANALYSIS

Chi-square goodness of fit tests to determine whether violent trauma incidents are seasonal at monthly, day of week, and hourly scales across hotspots and home-injury distances show temporal trends. Hotspots and home-injury distances share similar temporal patterns: day of week and hour have the greatest effect, while month has a minor one. For hotspots (aggregate and Downtown Eastside-Chinatown) and home-injury distances (aggregate, 0–0.35 km, 2-5 km, 5-10 km, 10-20 km, and 20-50 km), the number of violent trauma incidents are statistically significantly greater than expected, with a confidence level of 0.05, on Saturdays and from 9:00 PM to 3:00 AM. (For a detailed overview of expected and observed counts and p-values for all months, days of week, and hours for each hotspot and home-injury distance class, please refer to appendices i, ii, and iii.)

Table 2. Summary Results of Seasonal Goodness of Fit Tests and and Chi-Square Tests of Independence between Home-Injury Distance and Hotspot vs Socio-Demographic Variables.

	Spatial Analysis Method	Test Variable	Meets Test Assumptions	Degrees of Freedom	Chi-Square	P-Value < 0.05	Cramer's V	Significant Results	Measure of Association
Seasonality	Distance	Month	–	55	58.338	0.354	–	–	–
		Day	–	30	31.411	0.395	–	–	–
		Hour	FAIL						
	Hotspot	Month	FAIL						
		Day	FAIL						
		Hour	FAIL						
Independence	Distance	Age	–	20	59.316	0.000	0.116	Dependent	Very Weak
		Sex	–	5	5.863	0.320	0.073	–	–
		Expired	–	5	4.752	0.447	0.066	–	–
		Injury Mechanism	–	15	15.000	0.000	0.177	Dependent	Weak
	Hotspot	Age	FAIL						
		Sex	FAIL						
		Expired	FAIL						
		Injury Mechanism	FAIL						

Subsequent chi-square tests to determine whether the relative proportion of violent trauma incidences in a month, day, or hour is independent by hotspots or home-injury distance show no statistically significant differences at a 0.05 confidence level among home-injury distances (i.e. "Is the proportion of injuries on Saturday statistically significantly different between 0–0.35 km vs 0.35–2 km?”) (Table 2). Hotspot data was not sufficiently large enough to conduct these chi-square tests.

4.4. SOCIO-DEMOGRAPHIC ANALYSIS

Chi-square tests to determine whether age, sex, mortality (i.e. “expired”), and injury mechanism are independent of hotspot failed to meet the chi-square test requirement for a large enough sample size (Table 2). However, statistically significant results indicate that, out of these four variables, age and injury mechanism are dependent on home-injury mechanism (Table 2). Additionally, Kruskal-Wallis one-way ANOVA on ranks tests show that mean Injury VANDIX is statistically significantly different among hotspots, but ISS and Home VANDIX is not (Table 3). Mean Injury VANDIX, Home VANDIX, and Injury Severity Score was not statistically significantly different among home-injury distances (Table 3).

Table 3. Summary Results of Kruskal-Wallis One-Way ANOVA for Home VANDIX, Injury VANDIX, and ISS.

Spatial Analysis Method	Test Variable	Degrees of Freedom	Chi-Square	P-Value < 0.05	Significant Results
Distance	Home VANDIX	5	3.661	0.599	–
	Injury VANDIX	5	3.729	0.589	–
	Injury Severity	5	2.673	0.750	–
Hotspot	Home VANDIX	14	19.332	0.153	–
	Injury VANDIX	14	312.097	0.000	Dependent
	Injury Severity Score	14	13.155	0.514	–

There is sufficient evidence at a 0.05 significances level that age differs by home–injury distance, $c^2(20, N = 1103) = 59.32$, $p = 0.00$, with a very weak measure of association, Cramer’s $V = 0.12$ (Table 2). Although the chi-square test shows that true age proportions differ, the Marascuillo post hoc test—used to compare the proportions of one age group among different distances—can not identify with sufficient confidence which pairs of home–injury distances differ.

A second post hoc test, using adjusted standardized residuals and a Bonferroni corrected p-value, compares which proportions are significantly different than expected among all age and home-injury distance pairs. At a 0.05 significance level corrected for 30 comparisons, there is a significantly lower proportion of violent trauma incidents for 20–29 year olds within 0–0.35 Km (expected 38% vs observed 25%, p 0.0007 < 0.0017), and a higher proportion for 20–29 year olds within 20–50 Km (expected 38% vs observed 48%, p 0.0011 < 0.0017) and for 40–49 year olds within 0.35-2 Km (expected 20% vs observed 32%, p 0.0008 < 0.0017) (Table 4).

As well, there is also sufficient evidence at a 0.05 significance level that injury mechanisms differs by home–injury distance, $c^2(15, N = 1043) = 97.77$, $p = 0.00$, with a weak measure of association, Cramer's V = 0.18 (Table 2). The Marascuillo post hoc test shows significant difference in the proportions of firearm-related violent trauma incidents across distance, but no significant differences in proportions among assault-, cutting-, and stabbing-related violent trauma incidents.

Table 4. Distance vs Age Chi-Square Test, Observed and Expected Counts, Adjusted P-value < 0.0017.

		20-29	30-39	40-49	50-59	60+	Total
0-0.35 Km	Observed	35	24	36	28	17	140
	Expected	53	28	28	19	11	
	P-Value	0.0007	0.3191	0.0776	0.0247	0.0352	
0.35-2 Km	Observed	30	24	37	18	7	116
	Expected	44	24	23	16	9	
	P-Value	0.0044	0.9140	0.0008	0.5877	0.4754	
2-5 Km	Observed	50	38	35	32	10	165
	Expected	63	34	33	23	13	
	P-Value	0.0274	0.3459	0.7062	0.0260	0.3901	
5-10 Km	Observed	101	48	38	21	16	224
	Expected	85	46	45	31	17	
	P-Value	0.0142	0.6406	0.1860	0.0292	0.7232	
10-20 Km	Observed	103	52	45	34	15	249
	Expected	95	51	50	35	19	
	P-Value	0.2120	0.7976	0.3581	0.9105	0.2580	
20-50 Km	Observed	100	38	31	20	20	209
	Expected	79	42	42	29	16	
	P-Value	0.0011	0.3960	0.0340	0.0457	0.2619	
Total		419	224	222	153	85	1103

With 95% confidence, the proportion of firearm-related violent trauma incidents was significantly higher within the 0–0.35 Km home–injury distance (32.21%) compared to either 2–5 Km (7.79%), 5–10 Km (6.76%), 10–20 Km (6.96%), and 20–50 Km (4.43%) home–injury distances (Table 5). The second post hoc test using adjusted standardized residuals and a Bonferroni corrected p-value confirms the first post hoc results: at a 0.05 significance level corrected for 24 comparisons, there is a significantly higher proportion of firearm-related violent trauma incidents within 0–0.35 Km (expected 10% vs observed 32%, p 0.0000 < 0.0021) (Table 6). However within 0–35 Km, there is a lower than expected proportion of assault-related violent trauma incidents (expected 53% vs observed 40%, p 0.0018 < 0.0021) (Table 6).

Table 5. Distance vs Injury: Significantly Different Pairs of Proportions, P-value < 0.05.

Firearm		0-0.35 Km	0.35-2 Km	2-5 Km	5-10 Km	10-20 Km	20-50 Km
		0.32	0.11	0.08	0.07	0.07	0.04
0-0.35 Km	0.32			✗	✗	✗	✗
0.35-2 Km	0.11						
2-5 Km	0.08	✗					
5-10 Km	0.07	✗					
10-20 Km	0.07	✗					
20-50 Km	0.04	✗					

At a 0.05 significance level, median Injury VANDIX are statistically significantly different between different hotspots, $c^2(14, N = 662) = 312.1$, $p = 0.00$ (Table 3). However, a subsequent pairwise comparison using Dunn's procedure with a Bonferroni correction for all 15 hotspots, a total of 105 pairs, is still required to determine which hotspots pairs are sufficiently different among each other.

Table 6. Distance vs Injury Chi-Square Test: Observed and Expected Counts, Adjusted P-value < 0.0021.

		Assault	Stab	Cut	Firearm	Total
0-0.35 Km	Observed	56	36	1	44	137
	Expected	73	44	6	14	
	P-Value	0.0018	0.1106	0.0293	0.0000	
0.35-2 Km	Observed	68	28	4	12	112
	Expected	60	36	5	12	
	P-Value	0.0963	0.0837	0.7184	0.8665	
2-5 Km	Observed	81	51	10	12	154
	Expected	82	50	7	16	
	P-Value	0.8482	0.7953	0.1282	0.2745	
5-10 Km	Observed	117	65	11	14	207
	Expected	110	67	9	21	
	P-Value	0.3005	0.7796	0.3812	0.0641	
10-20 Km	Observed	116	85	13	16	230
	Expected	123	74	10	24	
	P-Value	0.3226	0.0813	0.2206	0.0615	
20-50 Km	Observed	118	71	5	9	230
	Expected	108	65	9	21	
	P-Value	0.1250	0.3483	0.1656	0.0023	
Total		556	336	44	107	1043

5. DISCUSSION

BCTR data, central to our study, is systematically gathered and verified. However, we believe that data recording protocols could be biasing our results. For example, patients undergoing outpatient treatment or who stay in hospitals for less than 48 hours are not captured in our data. Also, ISS information could be misleading of actual injury severity because it requires two distinct body regions to be severely injured in order to assign a score greater than 15. And, analysis on victim expiry is limited by the fact that a patient's location of residence is not registered in case of death—eliminating expired patients from our analyses.

This project is data driven and highly exploratory. The catchment area metaphor has not yet been applied in crime hotspot definition before and has not been robustly validated. As well, as the complementary G statistics shows, this methodology does not sufficiently incorporate environmental and socioeconomic neighbourhood characteristics when defining hotspots. However, our hotspot results are generally in line with Andresen (2007), Walker et al. (2014) and VPD (2015), suggesting validity of our experimental methods through external comparisons.

Our way of data categorization based on natural breaks in home-injury distance is arbitrary, just as any other method had been. We believe that natural breaks lead to distance classes that reflect the most common radii of human mobility. 350 m is believed to be the distance of direct neighbourhood, whereas distances to up to 20 km reflect a common human geo-social radius (Phithakkitnukoon et al., 2012). Different classification schemes will lead to a different significance pattern of results.

Considering statistical methods, hotspot examination is limited through small sample sizes for most spatial areas. Significant statements can be made on a maximum of the four most represented hotspot locations. The remaining ten hotspots do not feature a sufficient number of incidents in order to run required statistical tests (e.g. chi-square requiring more than 20% of samples to have an expected value of at least 5), so that only descriptive statistics could have been presented. Changing our statistical approach towards Fisher's Exact Test for significance could overcome this challenge. A larger amount of samples would equally resolve the problem. However, this would include an extension of the observed time period or a different hotspot resolution, which would then break spatial accuracy.

Despite these challenges, our project provides noticeable results on the distribution and characteristics of violent trauma in Metro Vancouver. As expected, hotspots of violent trauma tend to be located in areas with higher population density. Moreover, major transit axes can be identified within those (e.g. Kingsway and Millennium Skytrain Line). This finding is in line with

Andresen (2007) who suggests an increased potential of interpersonal crime in higher density areas and along transit because of higher risk of personal conflicts. Knowledge about our study region reveals that our method is not yet able to capture hotspot differences based on the urban environmental setup. It also produces artifacts in hotspot areas that require manual adjustment. Hotspot determination supported by environmental scans (Schuurman, 2009) could enhance our study at this point.

Temporal patterns exist on all temporal resolutions, but are not universally strong. Contradicting our hypothesis, Fall months are no peak for violent trauma and monthly patterns in general can only show potential trends towards late Summer months. Daily and hourly patterns are broadly in line with Walker et al. (2014). Regardless of distance, more people get injured during nighttime hours and on weekends. The irregularity of incidents that occur at or close to the victims' home may be explained by the fact that those are rather caused by longer term interpersonal conflicts. Regarding hotspots, results are most meaningful on a global level, whereas hotspots suffer from data insufficiency. However, trends in examined hotspots do not differ largely.

The underrepresentation of 20 to 29 year old people in the 0 to 0.35 km distance class may imply that longer term interpersonal conflicts are less dominant in that age group. Their overrepresentation in the 20 to 50km class suggests that younger people have a higher willingness to travel further to places that bear the risk to being assaulted. The overrepresentation of 40 to 49 year olds in the 0.35 to 2km distance class would need further research on the actual victims' characteristics. A higher granularity in our study compared to Haas et al. (2015) could explain that results in the latter seem to be more meaningful. In terms of injury mechanisms, Haas et al. (2015) finds a median distance between 0.1 and 2.2 miles related to potentially assault-related injuries, whereas our study suggests that most assaults occur further than 2km from the victims' homes. The high proportion of firearm attacks at or close to home could be explained by the Canadian culture of not carrying arms in public. Our finding that gender is independent of place and distance to home is different from assumptions made in Walker (2014).

With regard to Walker (2014) and Haas et al. (2015), our study increases the level of detail considering hotspots and distance from home to place of injury classification. Although not conclusive in all dimensions due to data limitations and although found relations tend to be weak, our results are still meaningful for that kind of complex social phenomenon. Against our expectations, distance classes led to more significant results than hotspots. Our study did not account for the link between qualitative environmental elements and the actual incidents. This is a point to improve during further research.

6. CONCLUSION

This study contributes to defining and characterizing hotspots of violent trauma in Metro Vancouver. It enhances previous studies using an adapted approach to consider both empirical case data and socio-demographic indicators. We see the study's relevance in providing information on assault prevention and emergency response. Incorporating more qualitative information on the built environment, we see potential relevance in urban design for creating safer public spaces. Findings on temporal patterns of violent trauma extends precedent studies in terms of resolution and may particularly contribute to emergency service allocation. Results on case- and victim-based information indicates potentially more vulnerable population groups and points at possible measures of information and prevention. Overcoming the challenge of data availability, meaningful statements can also be made on a spatial level.

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APPENDIX I:

Monthly Seasonality Goodness of Fit Test

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Metro Van	Expected: 104	98	76	99	99	102	112	110	132	99	126	94	99	1246
	P-Value	0.5499	0.0043	0.6203	0.6203	0.8509	0.4025	0.5273	0.0039	0.6203	0.0231	0.3135	0.6203	
0-0.35 Km	Expected: 12	9	16	11	14	12	12	10	9	7	17	12	11	140
	P-Value	0.4148	0.1851	0.8385	0.4755	0.9188	0.9188	0.6103	0.4148	0.1536	0.1029	0.9188	0.8385	
0.35-2 Km	Expected: 10	9	5	9	7	6	11	7	14	6	16	14	12	116
	P-Value	0.8228	0.1170	0.8228	0.3703	0.2180	0.6542	0.3703	0.1455	0.2180	0.0334	0.1455	0.4331	
2-5 Km	Expected: 14	8	9	8	12	20	12	14	26	13	19	7	17	165
	P-Value	0.1053	0.1809	0.1053	0.6221	0.0783	0.6221	0.9439	0.0006	0.8327	0.1392	0.0573	0.3600	
5-10 Km	Expected: 19	18	14	21	21	21	20	19	23	18	16	18	15	224
	P-Value	0.8720	0.2593	0.5727	0.5727	0.5727	0.7472	0.9358	0.2948	0.8720	0.5191	0.8720	0.3754	
10-20 Km	Expected: 21	24	16	25	18	16	20	29	26	19	21	19	16	249
	P-Value	0.4562	0.2761	0.3298	0.5283	0.2761	0.8635	0.0585	0.2287	0.6882	0.9543	0.6882	0.2761	
20-50 Km	Expected: 17	20	9	15	14	12	23	23	21	21	18	13	20	209
	P-Value	0.5179	0.0352	0.5453	0.3925	0.1752	0.1623	0.1623	0.3698	0.3698	0.8839	0.2690	0.5179	

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
All Hotspots	Expected: 55	51	35	55	56	57	58	58	76	51	70	45	50	662
	P-Value	0.5579	0.0046	0.9813	0.9067	0.7966	0.6903	0.6903	0.0034	0.5579	0.0370	0.1528	0.4675	
DTES-Chinatown	Expected: 16	19	11	14	11	22	16	19	22	11	18	15	15	193
	P-Value	0.4475	0.1855	0.5874	0.1855	0.1233	0.9827	0.4475	0.1233	0.1855	0.6177	0.7778	0.7778	
Downtown Granville St	Expected: 7	7	2	8	8	7	12	8	10	3	14	6	4	89
	P-Value	0.8730	0.0378	0.8230	0.8230	0.8730	0.0788	0.8230	0.3218	0.0903	0.0116	0.5869	0.1901	
W Hastings St-Waterfront		Does not meet chi-square test assumptions												57
W Broadway	Expected: 5	1	3	3	5	3	8	6	12	2	5	6	6	60
	P-Value	0.0617	0.3502	0.3502	1.0000	0.3502	0.1611	0.6404	0.0011	0.1611	1.0000	0.6404	0.6404	
Commercial-Broadway		Does not meet chi-square test assumptions												34
New Westminster														30
E Hastings St														20
Maple Ridge														18
Joyce-Collingwood														23
Metrotown														23
Kingsway														28
Nanaimo St-Kingsway														15
Oak St-Broadway														16
Downtown Westend														24
Surrey														32

APPENDIX II:

Day of Week Seasonality Goodness of Fit Test

		Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total
Metro Van	Expected: 178	133	151	129	161	197	271	204	1246
	P-Value	0.0003	0.0288	0.0001	0.1687	0.1240	0.0000	0.0353	
0-0.35 Km	Expected: 20	19	24	22	16	19	17	23	140
	P-Value	0.8091	0.3340	0.6291	0.3340	0.8091	0.4687	0.4687	
0.35-2 Km	Expected: 17	9	14	15	16	19	32	11	116
	P-Value	0.0445	0.4951	0.6767	0.8795	0.5193	0.0000	0.1393	
2-5 Km	Expected: 24	16	19	15	25	27	35	28	165
	P-Value	0.0921	0.3091	0.0565	0.7506	0.4456	0.0110	0.3245	
5-10 Km	Expected: 32	26	25	23	28	33	54	35	224
	P-Value	0.2519	0.1814	0.0857	0.4450	0.8486	0.0000	0.5668	
10-20 Km	Expected: 36	25	30	22	27	39	63	43	249
	P-Value	0.0556	0.3130	0.0140	0.1206	0.5347	0.0000	0.1785	
20-50 Km	Expected: 30	18	18	18	28	39	50	38	209
	P-Value	0.0191	0.0191	0.0191	0.7135	0.0707	0.0001	0.1075	

		Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total
All Hotspots	Expected: 95	65	89	65	84	105	152	102	662
	P-Value	0.0010	0.5360	0.0010	0.2403	0.2467	0.0000	0.4093	
DTES-Chinatown	Expected: 28	18	25	23	31	24	44	28	193
	P-Value	0.0490	0.5968	0.3470	0.4806	0.4625	0.0007	0.9298	
Downtown Granville St	Expected: 13	6	8	10	9	13	25	18	89
	P-Value	0.0420	0.1533	0.4110	0.2605	0.9310	0.0002	0.1093	
W Hastings St-Waterfront	Expected: 8	6	7	3	6	10	17	8	57
	P-Value	0.4173	0.6653	0.0516	0.4173	0.4821	0.0008	0.9569	
W Broadway	Expected: 9	7	10	3	9	14	9	8	60
	P-Value	0.5621	0.5982	0.0398	0.8744	0.0452	0.8744	0.8330	
Commercial-Broadway		Does not meet chi-square test assumptions							34
New Westminster									30
E Hastings St									20
Maple Ridge									18
Joyce-Collingwood									23
Metrotown									23
Kingsway									28
Nanaimo St-Kingsway									15
Oak St-Broadway									16
Downtown Westend									24
Surrey									32

APPENDIX III:

Hourly Seasonality Goodness of Fit Test

Distance Hourly Seasonality Goodness of Fit Post Hoc Test: Observed Counts, Adjusted P-value < 0.0021

		12	13	14	15	16	17	18	19	20	21	22	23	0	1	2	3	4	5	6	7	8	9	10	11	Total
Metro Van	Expected: 47	22	23	22	37	26	31	33	47	44	70	99	100	92	133	115	72	56	20	24	11	5	9	13	16	1120
	P-Value	0.0002	0.0004	0.0002	0.1483	0.0020	0.0191	0.0410	0.9602	0.6901	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.1628	0.0001	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	
0-0.35 Km	Expected: 5	3	2	1	5	3	3	7	8	7	12	8	9	8	6	9	13	7	3	2	1	0	0	2	2	121
	P-Value	0.3530	0.1664	0.0660	0.9849	0.3530	0.3530	0.3730	0.1783	0.3730	0.0015	0.1783	0.0717	0.1783	0.6628	0.0717	0.0003	0.3730	0.3530	0.1664	0.0660	0.0218	0.0218	0.1664	0.1664	
0.35-2 Km		Does not meet chi-square test assumptions																								116
2-5 Km	Expected: 6	4	2	4	1	5	4	3	4	9	10	16	18	12	8	12	7	10	4	3	2	0	4	1	4	147
	P-Value	0.3804	0.0886	0.3804	0.0344	0.6424	0.3804	0.1971	0.3804	0.2354	0.1097	0.0000	0.0000	0.0153	0.4390	0.0153	0.7180	0.1097	0.3804	0.1971	0.0886	0.0115	0.3804	0.0344	0.3804	
5-10 Km	Expected: 9	4	4	4	5	5	7	6	7	5	13	19	25	26	24	22	10	5	8	4	3	1	1	2	2	212
	P-Value	0.0967	0.0967	0.0967	0.1877	0.1877	0.5286	0.3301	0.5286	0.1877	0.1521	0.0005	0.0000	0.0000	0.0000	0.0000	0.6884	0.1877	0.7746	0.0967	0.0450	0.0071	0.0071	0.0188	0.0188	
10-20 Km	Expected: 9	4	3	5	8	9	6	3	8	6	10	21	19	20	35	21	15	14	3	3	2	1	0	2	4	222
	P-Value	0.0778	0.0358	0.1535	0.6746	0.9331	0.2750	0.0358	0.6746	0.2750	0.8011	0.0001	0.0011	0.0003	0.0000	0.0001	0.0535	0.1106	0.0358	0.0358	0.0149	0.0056	0.0019	0.0149	0.0778	
20-50 Km	Expected: 8	4	3	1	10	2	7	5	5	6	8	18	12	16	31	33	10	7	2	5	1	0	0	2	1	189
	P-Value	0.1584	0.0760	0.0123	0.4392	0.0325	0.7501	0.2953	0.2953	0.4949	0.9637	0.0002	0.1332	0.0031	0.0000	0.0000	0.4392	0.7501	0.0325	0.2953	0.0123	0.0041	0.0041	0.0325	0.0123	

Hotspot Hourly Seasonality Goodness of Fit Post Hoc Test: Observed Counts, Adjusted P-value < 0.0021

		12	13	14	15	16	17	18	19	20	21	22	23	0	1	2	3	4	5	6	7	8	9	10	11	Total
All Hotspots	Expected: 24	7	12	15	16	16	14	15	24	26	42	49	44	43	64	65	43	29	16	14	9	3	5	7	9	587
	P-Value	0.0003	0.0101	0.0507	0.0806	0.0806	0.0308	0.0507	0.9246	0.7502	0.0003	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001	0.3482	0.0806	0.0308	0.0014	0.0000	0.0001	0.0003	0.0014	
DTES-Chinatown	Expected: 7	4	6	8	6	3	3	7	7	11	15	18	13	9	18	14	11	7	3	4	4	0	1	2	2	176
	P-Value	0.2086	0.6150	0.8014	0.6150	0.1021	0.1021	0.8999	0.8999	0.1666	0.0038	0.0001	0.0326	0.5295	0.0001	0.0119	0.1666	0.8999	0.1021	0.2086	0.2086	0.0057	0.0169	0.0442	0.0442	
Downtown Granville St		Does not meet chi-square test assumptions																								74
W Hastings St-Waterfront																										51
W Broadway																										53
Commercial-Broadway																										32
New Westminster																										28
E Hastings St																										20
Maple Ridge																										14
Joyce-Collingwood																										21
Metrotown																										22
Kingsway																										24
Nanaimo St-Kingsway																										14
Oak St-Broadway																										14
Downtown Westend																										16
Surrey																										27