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Intra-week spatial-temporal patterns of crime

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Abstract

Since its original publication, routine activity theory has proven most instructive for understanding temporal patterns in crime. The most prominent of the temporal crime patterns investigated is seasonality: crime (most often assault) increases during the summer months and decreases once routine activities are less often outside. Despite the rather widespread literature on the seasonality of crime, there is very little research investigating temporal patterns of crime at shorter time intervals such as within the week or even within the day. This paper contributes to this literature through a spatial-temporal analysis of crime patterns for different days of the week. It is found that temporal patterns are present for different days of the week (more crime on weekends, as would be expected) and there is a spatial component to that temporal change. Specifically, aside from robbery and sexual assault at the micro-spatial unit of analysis (street segments) the spatial patterns of crime changed. With regard to the spatial pattern changes, we found that assaults and theft from vehicle had their spatial patterns change in predictable ways on Saturdays: assaults increased in the bar district and theft from vehicles increased in the downtown and recreational car park areas.

Keywords: Temporal crime patterns; Intra-week crime patterns; Spatial criminology; Spatial point pattern test

Background

Routine activity theory is used to understand criminal events by recognizing the criminal events can only occur when motivated offenders and suitable targets converge in time *and* space with the lack of capable guardians (Cohen and Felson 1979; Felson and Cohen 1980, 1981). As such, a spatial study of criminal events or a temporal study of criminal events will necessarily lead to a partial understanding of any patterns because space and time matter for the emergence of these patterns. In fact, routine activity theory began with the study of crime patterns over time (decades) and was applied spatially at a later date.

One does not have to search for long to come across scores of research studies investigating the spatial patterns of crime. These studies have become increasingly sophisticated with ever-improving data quality and widespread use. The temporal analysis of criminal events, on the other hand, is a far sparser research literature that has not advanced in the same manner as spatial analyses of criminal events: "[the] temporal dimension of crime [has] lagg[ed] behind while advances in crime location geocoding, mapping technology and user competence have allowed the spatial element to flourish" (Ratcliffe 2002, 24). Though this statement is now over a dozen years old, it still rings true today. Moreover, studies that consider both space and time are even fewer. The near-repeat victimization literature is an exception here (Johnson et al. 2007; Morgan 2001; Townsley et al. 2003), as well as a visualization technique for viewing hot spots of crime both temporally and spatially (Townsley 2008).

In this paper we consider spatial and temporal patterns of criminal events. Our analysis focuses on the changing spatial patterns of various crime types for different days of the week employing a spatial point pattern test developed by Andresen (2009). Recent research has investigated this phenomenon in the context of seasonal patterns (Andresen and Malleson 2013a), but this research has not considered intra-week changes in spatial patterns. Our research questions are two-fold: are the spatial patterns of crime the same for different days of the week for different crime types and, are those differences in spatial patterns in "expected" areas? For example, are there more assaults on the weekend in places with drinking establishments? An understanding of these changing spatial patterns over time matters not only for

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theoretical developments, but the application of (situational) crime prevention initiatives.

Theoretical considerations

As stated above, routine activity theory is used to understand the temporal dimension of crime: *when* there are more motivated offenders and suitable targets converging with a lack of capable guardians there will be more criminal events. Because of this, much of the research on temporal crime patterns invokes routine activity theory to explain (changes in) these patterns: change the nature of routine activities and you will change the associated crime patterns. Though there is also the temperature-aggression theoretical framework in this literature (see Hipp et al. 2004), routine activity theory can explain changes in both violent crime and property crime during warmer times of the year, whereas temperature-aggression theory is really only applicable for violent crime. This is particularly evident in some recent research that has investigated the effect of weather on street robbery that found temperature, wind speed, and humidity predicted nighttime and weekend robbery, as predicted; notably, the presence of rain had a negative relationship with robberies on the weekend as would be predicted by routine activity theory (Tompson and Bowers, 2015).

The importance of considering both space and time, however, is best seen considering temporal constraint theory (Ratcliffe 2006). In this theoretical framework, Ratcliffe (2006) puts forth the concept of a time budget that we each have for any given day: we get up at a particular time in the morning, have to be at work at and for a particular time, are expected home at a particular time, and so on. Because of these time constraints within our time budget, we are also constrained in space. This is particularly important for the commission of criminal events if we are expected to be somewhere at a particular time. For example, a youth may leave for a 15-minute walk to school 30 min before s/he has to be there. This allows the student 15 min to commit a criminal event, but also means that s/he cannot travel too far. At the theoretical level, Ratcliffe (2006) generates figures/maps for temporal constraint theory that are very similar to those of the geometric theory of crime that only considers space: paths, nodes, and edges (Brantingham and Brantingham 1981, 1993).

The connection between temporal constraint theory and the geometric theory of crime shows that space and time are not easily separated when considering criminal events. If routine activities change over time, decades for example, we should expect to have a change in crime patterns. However, routine activities change throughout the year. Holidays occur more frequently in the summer months and schools are out for much of that time, and most people will spend more time outdoors when the weather improves (warmer and drier). This is most relevant for the seasonality and crime literature, discussed below. But our routine activities also change throughout the week. For most people who work, their travels to work will most often occur Monday to Friday during the day with leisure activities occurring at night and/or during the weekend—there are, of course, people who do not have a standard work week and work afternoon or evening shifts. However, by definition, if we are spending time at different locations at different times (different seasons or different days of the week), we should expect the spatial patterns of criminal events to change as well.

Empirical evidence for temporal variations in crime patterns

Seasonal crime patterns have been investigated in a variety of different contexts: England (Field 1992; Farrell and Pease 1994), Isreal (Landau and Fridman 1993), the United States (Cohn and Rotton 2000; Rotton and Cohn 2003), Brazil (Ceccato 2005), The Netherlands (van Koppen and Jansen 1999), Scotland (Semmens et al. 2002), and Sweden (Uittenbogaard and Ceccato 2012). Generally speaking, this research has found that the presence and magnitude of seasonal crime patterns varies by crime type and geography. Specifically, property and violent crime types had seasonal patterns, but the lack of a seasonal pattern could sometimes be explained by geography—places with less seasonal variation in climate have less seasonal variation in crime patterns.

More relevant for the current research, however, is a subset of this research that considers the spatial variations of seasonal crime patterns. Generally speaking, this research has found that there have been disproportionate increases in criminal events in places that are of lower socio-economic status: assaults in Texas (Harries and Stadler 1983; Harries et al. 1984), homicide in Brazil (Ceccato 2005), assaults in South Africa (Breetzke and Cohn 2012), and violent crimes in Sweden (Uittenbogaard and Ceccato 2012). Andresen and Malleson (2013a) found that not all crime types exhibit seasonal patterns, but when present such seasonal patterns could be high in magnitude. Moreover, for some crime types (assault, theft, theft from vehicle, and theft from vehicle), summer months had increases in the spatial concentrations of crime in areas frequented more often during the summer months: popular beaches, water activity areas, large parks, and the annual summer fair. Though this is generally an expected result, this is not always the case. For example, Ceccato and Uittenbogaard (2014) report that police statistics in Stockholm show the expected seasonal pattern with increases in criminal events in the summer months, Stockholm Public Transportation data reveal that violent crimes were greatest in the winter months. This was explained by the need of passengers to be indoors at stations in the winter because of low temperatures as well as weather making it more likely for people to leave their cars at home. Both of these situations increase the opportunity for violent criminal events.

Research that investigates daily crime patterns (within the day) is far less common that research investigating seasonal crime patterns, spatial or not. This research includes that of aoristic analysis and related literature (Andresen and Jenion 2004; Ashby and Bowers 2013; Ratcliffe 2000, 2002; Ratcliffe and McCullagh 1998) that attempts to identify missing temporal information in crime data. Another aspect of this research investigates the importance of the "criminological day". Temporally-referenced crime data will be organized along the lines of the calendar day, but this is not realistic for understanding temporal patterns of crime (Felson and Poulsen 2003). Separating criminal events that occur Friday night and Saturday morning with the threshold of midnight may lead to improper inference regarding changing patterns; Felson and Poulsen (2003) recommend that the criminological day begins at 5 am and Tompson and Townsley (2010) recommend 7 am. In other research, Ahlberg and Knutsson (1994) found that there was a major difference between the level of police service and the volume of criminal events based on the hour of the day. Though there may be limitations in the ways in which police officers can be deployed different days of the week, this result is important because research has shown that criminal events are temporally clustered. Consequently, increased levels of policing may be required on different days of the week and different hours of the day. For example, Ceccato and Uittenbogaard (2014) found that reported criminal events on Stockholm's underground transit system are most often between 4 pm and midnight with a peak from 8 to 9 pm; most of these criminal events are violent in nature, with thefts more often occurring in the afternoon—similar results were found by Uittenbogaard and Ceccato (2012) for Stockholm, in general.

Ceccato and Uittenbogaard (2014) also investigated the days of the week and found that weekends had higher crime rates than weekdays on Stockholm's underground transit system, but that difference was not found to be statistically significant. However, when considering Stockholm as a whole, Uittenbogaard and Ceccato (2012) found that both violent crime types (assault and threat) and property crime types (theft, robbery, and burglary) occurred more frequently on the weekend. And Andresen (2014) briefly shows that the patterns of assault change by day of the week, with a greater proportion of assault occurring on the weekend. With clusters of alcohol establishments (places that sell and/or serve alcohol) tending to lead to clusters of violence (Grubesic and Pridemore 2011) and alcohol sales increasing on the weekend, this is not a surprising result. Specifically in the context of the United Kingdom and changes in the timing of alcohol sales, Newton and Hirschfield (2009) found that the impact on violence against person was more pronounced on the weekend as opposed to the weekday—these authors also found that particular alcohol outlets and the immediate spaces around them were important for understanding these changes. However, this spatial dimension is under-investigated and is an obvious next step in this branch of research.

Methods

Data

Crime data and census units of analysis used in the analyses below are for the City of Vancouver, British Columbia, Canada. The Vancouver Census Metropolitan Area (CMA) is the third largest metropolitan area in Canada and the largest metropolitan area in western Canada—currently the population is just over 2.3 million people. In 2001, the year of data under study here, the City of Vancouver had a population of 546 000. In recent years, 1991 – 2001, Vancouver experienced a 16 % growth in its population, and just over 10 % growth 2001 – 2011. The high rate of population growth is often attributed to the 1986 World Exposition on Transportation and Communication. This event garnered Vancouver worldwide attention that has continued because of the most recent 2010 Winter Olympics held in the Vancouver CMA.

Vancouver has experienced a decreasing crime rate prior to the study period, 1991 – 2001, that continues to this day. However, Vancouver's crime rate continues to be substantially higher than the national average. The Vancouver CMA has historically had the highest crime rates among the three largest metropolitan areas in Canada: 11 367 criminal code offences per 100 000 persons in 2001, more than doubling the rate found in Toronto (5381 per 100 000 persons) and almost doubling that in Montreal (6979 per 100 000 persons); the same relative standing held for the 2001 violent crime rate in the Vancouver CMA (1058 per 100 000 persons) in comparison to the Toronto CMA (882 per 100 000 persons) and the Montreal CMA (886 per 100 000), but to a lesser degree. However, these reported differences in crime rates across these three cities has been decreasing in recent years (Kong 1997; Savoie 2002; Silver 2007; Wallace 2003, 2004).

The criminal event data used in the analyses below are from the Vancouver Police Department's Calls for Service Database (VPD-CFS Database) that is generated by its Computer Aided Dispatch (CAD) system. The VPD-CFS Database is the set of all requests for police service that are made directly to the VPD, allocated through the 911 Emergency Service, and calls for service made internally by VPD members. The VPD-CFS Database contains the location and the complaint code/description for each call. Each call contains two codes: the initial complaint code and a complaint code filed by the officer on the scene with the latter taken to be correct. Some may consider the VPD-CFS Database a proxy for actual criminal event data because not all calls for service represent actual violations of the criminal code. Consequently, CFS data have been considered police activity data instead of criminal event data. From the complete CFS data, the crime types of: all crimes, assault, burglary, robbery, sexual assault, theft, theft of vehicle, and theft from vehicle are all analyzed below—the category of all crimes is the aggregate of the other seven crime types, plus drug arrests, prostitution, shoplifting, homicide, and arson. The geocoding procedure used for the current data generated a match rate of 94 %. Because this match rate exceeds the minimum acceptable match rate generated by Ratcliffe (2004) and that improper address records appear to be random, the analysis is undertaken with little concern for spatial measurement error. Total counts by the day of the week of both aggregate and disaggregate data used are presented in Table 1.

Spatial units of analysis

The analysis below is performed using census tracts and the dissemination areas from the Statistics Canada Census of Population. Census tracts are relatively small and stable geographic areas that typically have a population that ranges from 2500 to 8000, and an average of 4000 persons. Dissemination areas, more similar in size to the census block group from the census in the United States, are smaller than census tracts, containing approximately 400–700 persons; these spatial units of analysis are typically composed of one or more blocks. The City of Vancouver has an area of approximately 115 km^2, 110 census tracts (CTs) and 1011 dissemination areas (DAs), defined by Statistics Canada. Of course, despite the fact that our analysis is undertaken at two spatial scales of analysis, all of the results below are subject to the modifiable areal unit problem (Fotheringham and Wong 1991; Openshaw 1984). However, our choice to analyze census tracts and dissemination areas was made because these are the most common spatial units used in this literature. Criminological research in this area has shown that the modifiable areal unit problem can have impacts on the analysis but does not necessarily impact the qualitative nature of the results (Andresen and Malleson 2013b; Wooldredge 2002). We are not investigating the modifiable areal unit problem, *per se*, but just wanted to ensure our results were not sensitive to the choice of spatial unit of analysis.

Spatial point pattern test

In order to investigate the similarity of spatial point patterns for different days of the week, a testing methodology that identifies changes in spatial crime patterns must be employed. Specifically, we are interested in a test that is locally-based such that we can identify *where* any changes are occurring. Andresen's (2009) spatial point pattern test, and its corresponding index, provides such a testing method because it can be used to identify changes or differences in the spatial patterns of crime. We are unaware of any other such test that identifies statistically significant change at the local level that can be mapped. This spatial point pattern test was developed and used in a criminological context (Andresen 2009), but has been used to investigate: changing patterns of international trade (Andresen 2010), the stability of crime patterns (Andresen and Malleson 2011), the spatial impact of the aggregation of crime types (Andresen and Linning 2012), the spatial dimension of the seasonality of crime (Andresen and Malleson 2013a), the role of local analysis in the investigation of crime displacement (Andresen and Malleson 2014), and the comparison of open source crime data and actual police data (Tompson et al. 2015).

Andresen's (2009) spatial point pattern test is an area-based point pattern test that is concerned with the similarity between two different spatial point patterns at the local level. This spatial point pattern test is not concerned with null hypotheses of random, uniform, or clustered distributions. However, if random, uniform, or clustered point pattern distributions are generated it may be used for this purpose as well. Andresen's (2009)

Table 1 Counts of crime types by day of the week

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
All Crime	10343	10142	9604	9604	9604	9067	8798	67,163
Assault	685	659	711	711	831	862	768	5,227
Burglary	2230	2123	1856	1829	1829	1723	1776	13,354
Robbery	199	215	170	184	182	211	166	1,325
Sexual assault	61	82	79	59	49	73	59	462
Theft from vehicle	2973	2829	2613	2559	2469	2199	2361	18,021
Theft	1879	1856	1738	1820	1820	1395	1300	11,820
Theft of vehicle	1031	951	931	911	917	1004	951	6,696

spatial point pattern test is available at no cost in a graphical user interface: < http://code.google.com/p/spatialtest/>. The test is computed as follows:

1. Nominate a base dataset (assaults, for example) and count, for each area, the number of points that fall within it.
2. From the test dataset (burglary, for example), randomly sample 85 % of the points, with replacement. As with the previous step, count the number of points within each area using the sample. This is effectively a bootstrap created by sampling from the test dataset.
3. Repeat (2) a number of times (300 is used here).
4. For each area in the test data set, calculate the percentage of crime that has occurred in the area. Use these percentages to generate a 99 % nonparametric confidence interval by removing the top and bottom 0.5 % of all counts (2 from the top and 2 from the bottom in this case). The minimum and maximum of the remaining percentages represent the confidence interval. It should be noted that the effect of the sampling procedure will be to reduce the number of observations in the test dataset but, by using *percentages* rather than the *absolute counts*, comparisons between data sets can be made even if the total number of observations are different.
5. Calculate the percentage of points within each area for the base dataset and compare this to the confidence interval generated from the test dataset. If the base percentage falls within the confidence interval then the two datasets exhibit a similar proportion of points in the given area. Otherwise they are significantly different (Andresen and Malleson 2013a).

The spatial point pattern test operates in such a way to create variability in one dataset by sampling at 85 % in order to generate nonparametric confidence intervals for statistical testing: comparing this test dataset to a baseline spatial distribution. As such, statistically significant changes/differences can be identified at the local level.

The output of the test has two components. The first component is a global parameter that ranges from 0 (no similarity) to 1 (perfect similarity). This index of similarity, S, is calculated as follows:

$$S = \frac{\sum_{i=1}^{n} s_i}{n},$$

where s_i is equal to one if the two spatial patterns are similar in spatial unit i and zero otherwise, and n is the total number of spatial units. Consequently, the S-Index represents the proportion of spatial units that have a similar spatial pattern within both the baseline and test datasets. With values ranging from zero to unity, a decision must be made: at which point are two spatial point patterns considered "similar"? There is no established rule of thumb in this context, but the literature considering multicollinearity in a regression context is instructive. When considering the variance inflation factor (VIF) and multicollinearity in a regression context, a VIF that ranges from 5 to 10, or greater, may be considered potentially problematic (O'Brien 2007). If this were considered within a bivariate context, a correlation that ranges from 0.80 to 0.90 may be considered potentially problematic. Because of this, we consider the value of 0.80 is used to indicate two spatial point patterns are similar. However, it is important to note that this is not a dichotomous choice as to whether two patterns are similar or not; rather, 0.80 is used as an approximate indicator of when we have confidence in the results for similarity.

Second, the spatial point pattern test generates output that can be mapped to show where statistically significant change occurs. Consequently, census tracts and dissemination areas that have statistically significant changes on particular days may be mapped in order to identify any spatial patterns in the differences of the two spatial point patterns. Though this spatial point pattern test does not meet the requirements to be considered a local indicator of spatial association (LISA, see Anselin 1995), this spatial point pattern test is similar to LISA statistics in that the output can be mapped for subsequent analysis.

Results and discussion

Before the analysis turns to the results and output of the spatial point pattern test, the proportions of criminal events on each day of the week for each crime type are shown in Fig. 1. Figure 1a shows the proportions during the week for all crime, as defined above. Clearly, criminal events in general are more common during the week than on the weekend. In fact, the beginning of the week has a greater proportion than the rest of the week. It should be noted, however, that the range in these proportions is not great, 13–15.5 %.

Assault, Fig. 1b, shows the opposite temporal pattern: these criminal events are most infrequent at the beginning of the week and most common on Friday, Saturday, and Sunday—the impact of Sunday is likely due to assaults occurring "Saturday night" but after midnight. Burglary, that includes both residential and commercial burglary, follows the same pattern as all crime, but with more variation: 13–17 %. For this particular crime type, such a temporal pattern would be expected, as residents would be more likely to be at home guarding their

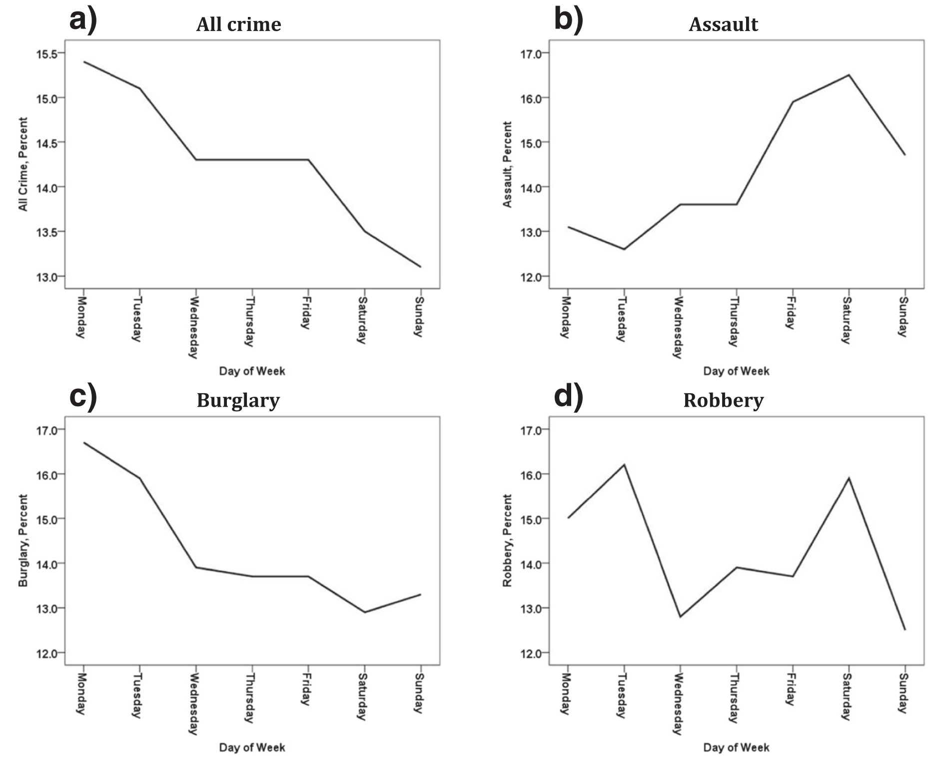

Fig. 1 Intra-week temporal patterns of crime. **a** All crime. **b** Assault. **c** Burglary. **d** Robbery. **e** Sexual assault. **f** Theft from vehicle. **g** Theft. **h** Theft of vehicle

property on the weekend. Robbery and sexual assault, Fig. 1d and e respectfully, do not appear to have any temporal pattern with peaks in these figures occurring both during the week and the weekend.

Theft from vehicle, Fig. 1f, also has the same general temporal pattern as all crime, decreasing as the week progresses. Theft, Fig. 1g, also has this pattern, but the temporal pattern is far more stark. Monday to Friday there is very little variation with the proportions ranging from 15 to 16 %. However, for Saturday and Sunday this proportion drops to a range of 11–12 %. Theft of vehicle, Fig. 1h, at first glance has a temporal pattern similar to that of all crime with a spike on the weekend as well. However, given the high proportion of criminal events occurring on Monday, this may be a result of our using midnight as the beginning of the day rather than the criminological day discussed by Felson and Poulsen (2003) or Tompson and Townsley (2010). This is left as a direction for further research.

Turning to the results of the primary analysis, the spatial point pattern test, the global results for the census tracts are reported in Table 2. The S-Indices reported in Tables 2 and 3 compare the individual days to the rest of the days in the week: Monday with Tuesday to Sunday, for example; however, other tests were implemented that investigated the similarity of two different days (Monday and Friday, for example) with qualitatively similar results. It should be immediately clear that none of the S-Index values are close to approaching the threshold of 0.80 to be considered similar. The S-Index values range from 0.38 to 0.60, indicating that the spatial point patterns of the individual days are significantly different from the rest of the week. Some of the S-Index values were similar in ways that led to our investigation of two specific days. For example, in the case of sexual assault, Friday and Saturday had identical S-Index values and we were curious if this was because these two days differed from the rest of the week in the same way—similarly for theft from vehicle on Thursday and Friday with identical S-Index values. However, upon investigation of these, and other, day combinations it was found that there was not a high degree of similarity. Consequently, these days differed in their spatial patterns from the rest of the week to the same degree but in different places.

The global results for the spatial point pattern test considering dissemination areas, Table 3, is essentially the same as the results presented in Table 2 aside from the results for robbery and sexual assault. In the cases of these two crime types, the S-Index values are approaching the threshold value of 0.80, indicating a high degree of similarity. However, particularly in the case of sexual assault, one could easily argue that the spatial patterns for the individual days are similar to the rest of the week. In fact, when comparing specific days to one another in these cases the S-Index values approach 0.90, definitively crossing the threshold value of 0.80, discussed above. In other research using this spatial point pattern test, Andresen and Malleson (2011) found that geographically smaller units of analysis had greater values for the S-Index and this was because of the large number of zero values in dissemination areas for both point patterns being tested. However, as evidenced by the other crime types, this is not the case, generally speaking, for these analyses. In fact, if any pattern is present the S-Index values are generally lower in the analyses of dissemination areas. In the current case, these high S-Index values for dissemination areas are likely due to the high degree of concentration of criminal events for these crime types in Vancouver: all robberies and sexual assaults in Vancouver reported to the police occur in 5.32 and 2.99 % of street segments, respectively (Andresen and Malleson, 2011). We do not consider the street segment in our analyses, but the high degree of concentration is still present for these crime types.

Mappable results for all of the spatial point pattern tests performed in Tables 2 and 3 are available, but two of those maps show particularly interesting results. Figure 2, assaults on Saturday versus the rest of the week, shows that Saturday has increased concentrations of assaults in the east side of the city as well as a large cluster for Saturday in the downtown/bar and skid row areas that are located in the northern peninsula of the city. Though there are no immediately obvious reasons for the increased concentrations of criminal events in the eastern portion of Vancouver, the increased concentrations of assault in the downtown/bar and skid row areas is no surprise.

The results for theft from vehicle on Saturday versus the rest of the week are shown in Fig. 3. A similar pattern is present for theft from vehicle with an increased concentration of criminal events in the eastern portion of Vancouver and the downtown area. The cluster in the downtown area has shifted west compared to the assaults output that is closer to the shopping area of downtown, comparing Figs. 2 and 3, with the addition of an increased concentration around the perimeter of Stanley Park, the large area at the end of the northern peninsula of the city. This area in Stanley Park contains the one road around the park itself with a number of parking areas. Similar to the mapped results of assaults, such a pattern of increases on Saturdays is expected, based on the research questions stated above. However, it is important to note that the changes in the spatial patterns do not always occur in an expected pattern. Figure 4 shows the results for burglary on Mondays versus the rest of the week. In this case, there is no obvious pattern for Monday versus the rest of the week—the weekly peak of burglaries occurred on Monday, but similar results are present for other burglary comparisons. As such, though there are some results that exhibit expected patterns, this is not monolithic.

Conclusion

In this paper we have investigated the differences in spatial and temporal patterns of criminal events for a number of different crime types. We found that all crime types aside from robbery and sexual assault had rather distinctive temporal patterns as the week progressed. Though one could argue that robbery and sexual assault had no such distinctive patterns, with peaks on Tuesday and Saturday (robbery) and Tuesday/Wednesday and Saturday (sexual assault), this could mean that robbers and sexual offenders are on the prowl on these particular day; alternatively, two types of robbers and sexual offenders could have distinctive temporal patterns. Moreover, there may be something distinctive about the victims of robbery and sexual assault that lead to such a pattern because of the similarity across these two crime types.

The results of the spatial point pattern tests, at both spatial units of analysis, showed that each day of the week had spatial patterns that were distinct from the rest

Table 2 Spatial point pattern test output, S-Indices, census tracts

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
All crime	0.555	0.527	0.555	0.564	0.564	0.555	0.555
Assault	0.482	0.491	0.518	0.509	0.60	0.409	0.536
Burglary	0.545	0.509	0.564	0.591	0.491	0.527	0.545
Robbery	0.491	0.382	0.427	0.455	0.391	0.445	0.491
Sexual Assault	0.464	0.436	0.455	0.409	0.418	0.418	0.455
Theft from vehicle	0.582	0.536	0.582	0.545	0.545	0.473	0.445
Theft	0.527	0.555	0.418	0.582	0.464	0.427	0.527
Theft of vehicle	0.527	0.518	0.500	0.527	0.573	0.445	0.518

Baseline comparison is all days aggregated less the day under analysis

Table 3 Spatial point pattern test output, S-Indices, dissemination areas

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
All crime	0.516	0.497	0.501	0.506	0.497	0.511	0.485
Assault	0.505	0.492	0.496	0.499	0.521	0.505	0.515
Burglary	0.451	0.467	0.442	0.474	0.458	0.461	0.457
Robbery	0.738	0.739	0.729	0.749	0.728	0.738	0.737
Sexual Assault	0.785	0.795	0.784	0.780	0.777	0.790	0.782
Theft from vehicle	0.454	0.484	0.476	0.499	0.455	0.425	0.411
Theft	0.464	0.474	0.428	0.464	0.442	0.411	0.416
Theft of vehicle	0.461	0.464	0.430	0.429	0.443	0.444	0.458

Baseline comparison is all days aggregated less the day under analysis

of the week for each crime type except for robbery and sexual assault. The lack of any patterned differences, temporal or spatial, for robbery and sexual assault is likely due to the fact that these crime types are highly concentrated in space and are also relatively rare in the police records.

It is important to state that this study is not without its limitations. First, we analyze criminal events that are reported to the police. Consequently, we must assume that the spatial and temporal patterns (and their changes) reported here are representative of all such criminal events. Second, because of data restrictions we are not able to use the criminological day, but use the calendar day. Future research should consider this to investigate the possibility of sensitivity in the results. And third, we only used one method of analysis to investigate this

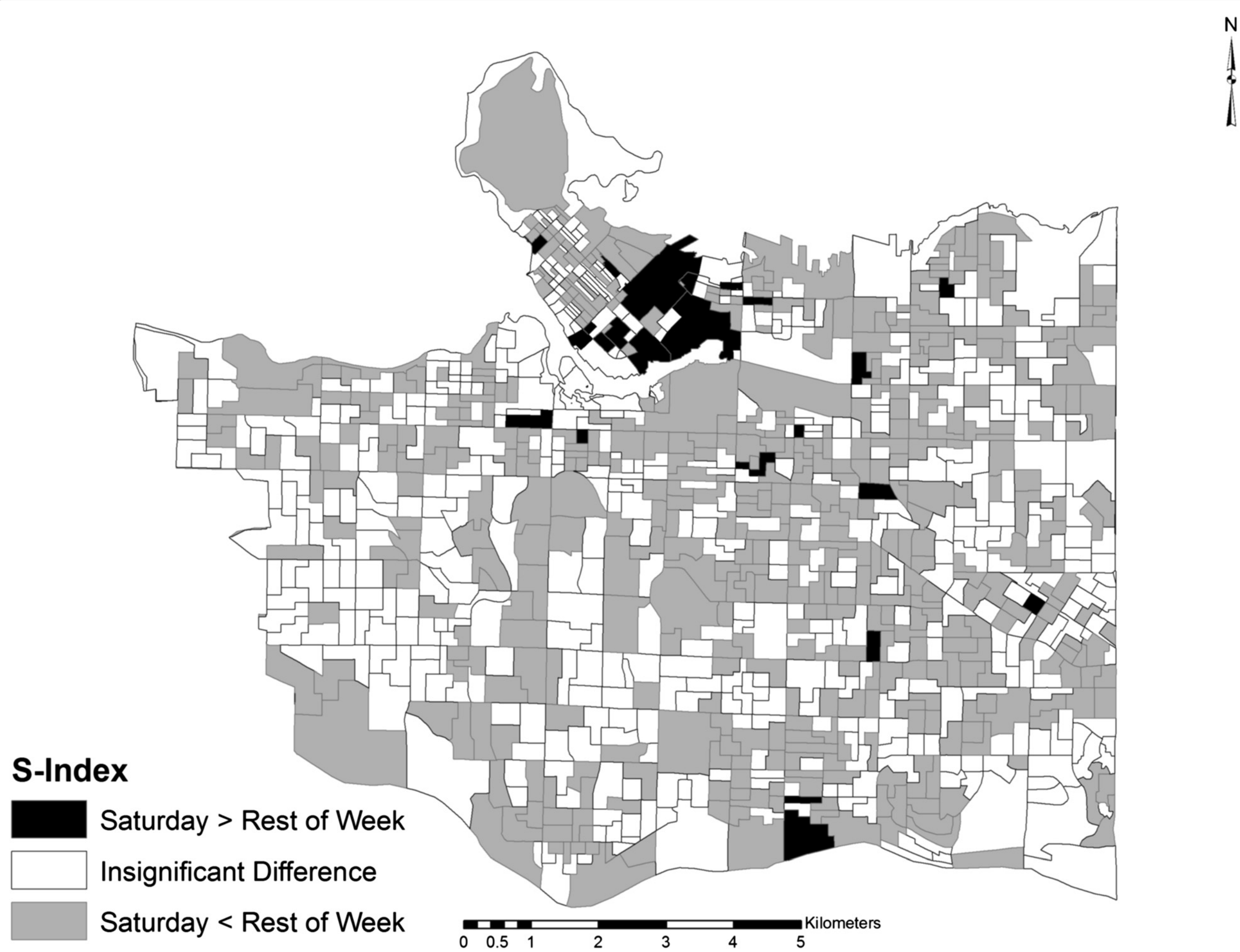

Fig. 2 Spatial point pattern test output, assault, dissemination areas, Saturday versus rest of the week

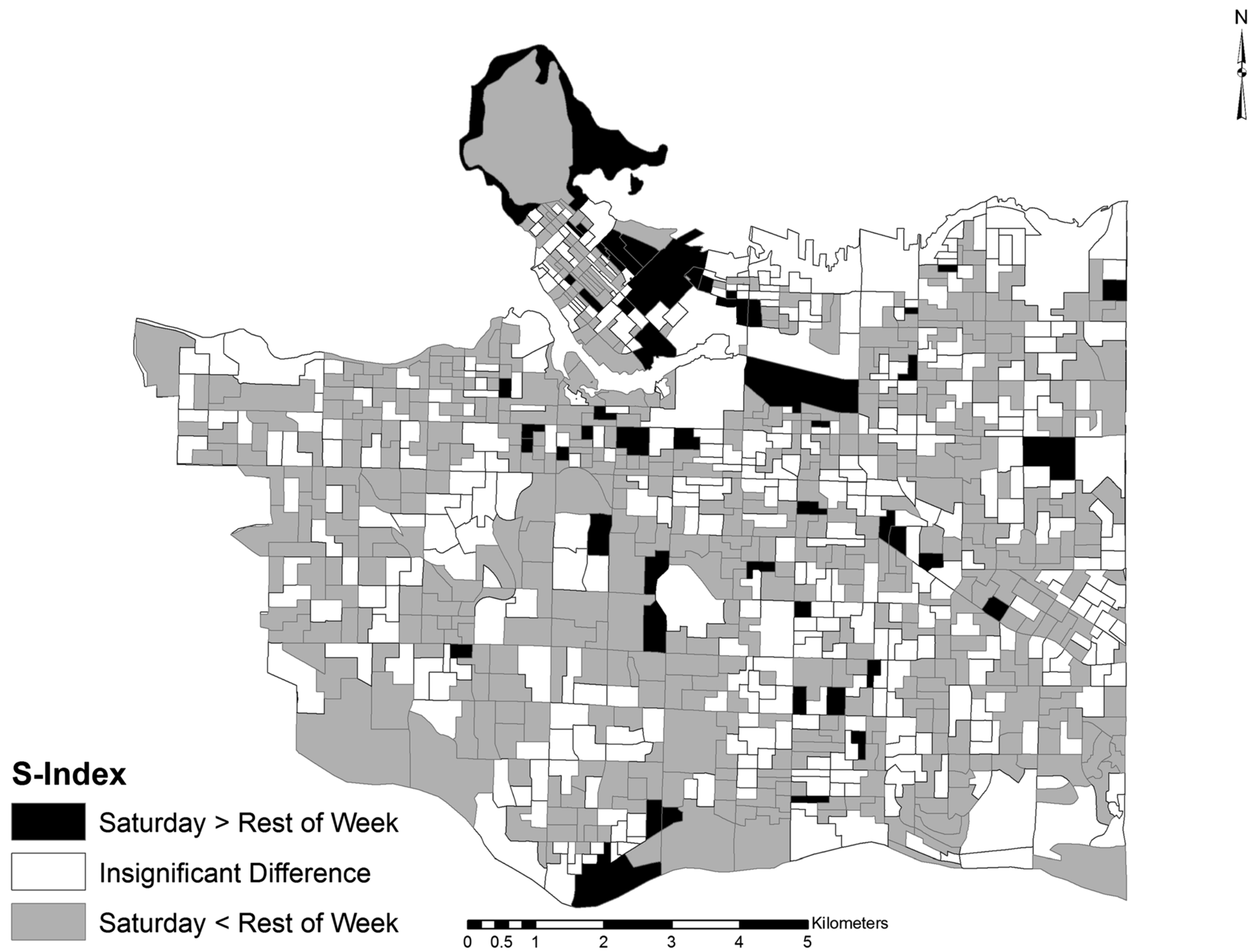

Fig. 3 Spatial point pattern test output, theft from vehicle, dissemination areas, Saturday versus rest of the week

phenomenon. Though, as stated above, we are not aware of another statistical test that allows us to directly answer our research questions, other statistical methods may provide different results.

These results clearly show that for most crime types under analysis there are distinctive temporal and spatial patterns for different days of the week. As stated above, such a (set of) result(s) are important in the context of situational crime prevention. If a researcher or practitioner is going to implement a crime prevention initiative knowing when *and* where those criminal events occur is going to prove to be critical information. Based on the results presented above, the knowledge of when and where cannot be separated because where you implement a crime prevention initiative is going to change depending on when you implement a crime prevention initiative. As such, the analyses of both dimensions will be critical for the success of any crime prevention initiative.

But these results are also important for the purposes of theory. If we are testing theory based on aggregated data of some form (temporally or spatially) any confirmation or rejection of theoretical hypotheses may be in error. For example, because of the existence of distinct spatial patterns on different days of the week for all crime types that do not have high degrees of spatial concentration, the aggregation of the individual days may generate a spatial pattern that has little theoretical value. And similarly for the temporal aggregation of criminal event data. Consequently, whether a researcher or practitioner is interested in crime prevention or theoretical testing they must at least consider the importance of space *and* time in their analyses.

Endnotes

[1]An 85 % sample is based on the minimum acceptable hit rate to maintain spatial patterns, determined by Ratcliffe (2004). Maintaining the spatial pattern of the complete data set is important so we used this as a benchmark for sampling. An 85 % sample was for the purposes of generating as much variability as possible while maintaining the original spatial pattern. Also note that "replacement" in this context refers to subsequent

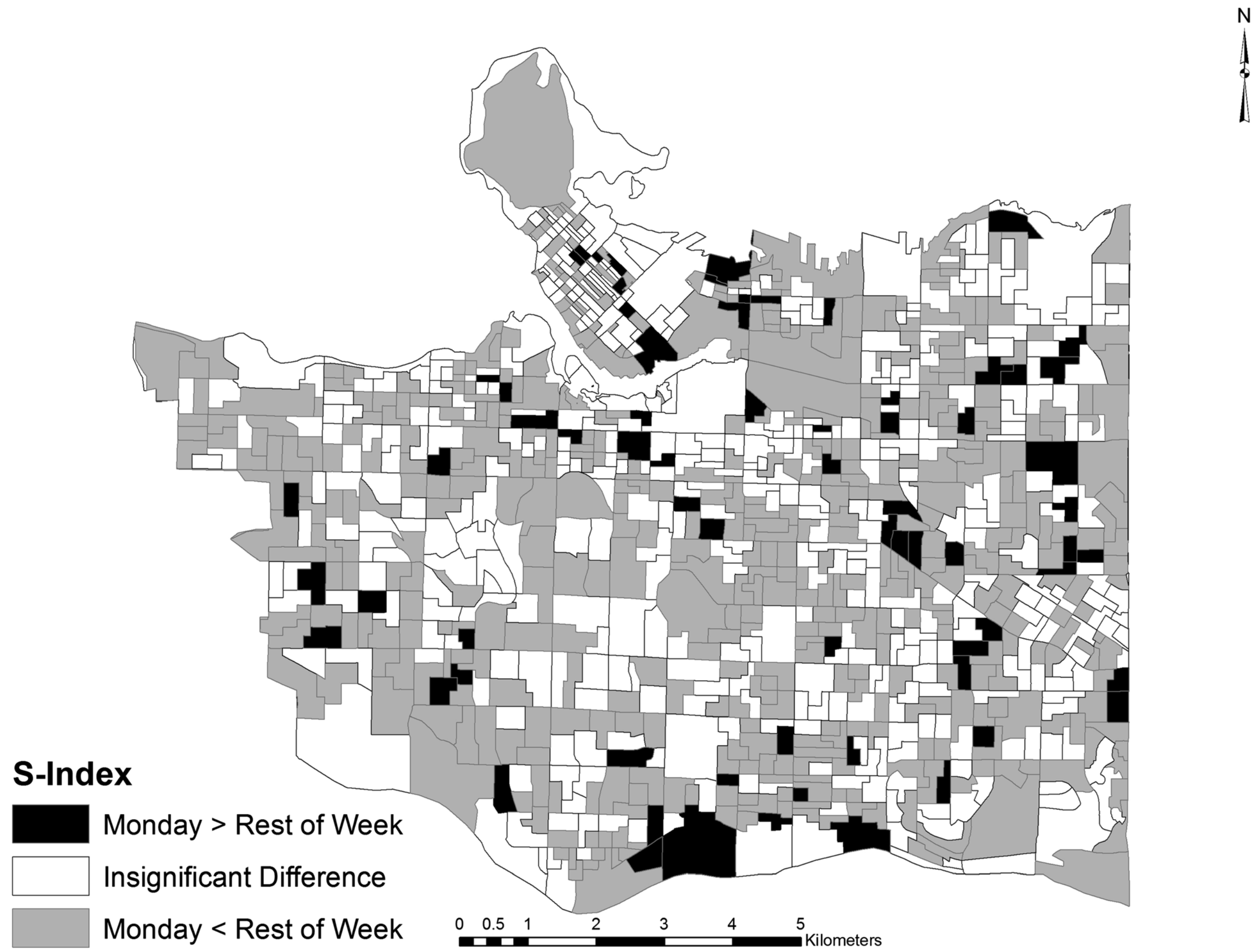

Fig. 4 Spatial point pattern test output, burglary, dissemination areas, Monday versus rest of the week

samples; any one point may only be sampled once per iteration in this procedure to mimic Ratcliffe (2004).

[2]Though some Monte Carlo research has used 50 repeated samples (Davis and Keller, 1997), early Monte Carlo experiments in the statistical literature achieved good results with as few as 20 repeated samples (Hope, 1968). We use 300 repeated samples here to err on the side of caution and because it provides convenient cut-off values when generating the confidence interval, as discussed in step 4.

[3]Previous research using this test has used a 95 % confidence interval. However, because of the large number of statistical tests performed here, in the context of a Bonferroni correction, we have increased this confidence interval to 99 %.

[4]The program written to perform the test uses double precision that has at least 14 decimal points when dealing with numbers less than unity. The smallest number that we have to deal with in the current analysis (regardless of scale) is 0.000030498. This is well within the limits of double precision.

[5]According to Anselin (1995), a LISA statistic is to have a mathematical relationship with a corresponding global statistic: Moran's *I* and local Moran's *I*, for example.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
MA and NM were involved in the design of the research study. MA prepared and analysed the data and prepared the first draft of the manuscript. NM participated in the development of the statistical methods and subsequent writing of the manuscript. Both authors read and approved the final manuscript.

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