Northumbria University
NEWCASTLE

Time-varying relationships between land use and crime: A spatio-temporal analysis of small-area seasonal property crime trends

Matthew Quick [1]

Jane Law [1,2]

Guangquan Li [3]

[1] School of Planning, University of Waterloo, Canada

[2] School of Public Health and Health Systems, University of Waterloo, Canada

[3] Department of Mathematics, Physics and Electrical Engineering, Northumbria University, United Kingdom

Acknowledgements:

We thank the Waterloo Regional Police Service for providing crime data.

Funding:

This research was supported by the Social Sciences and Humanities Research Council of Canada [grant 767-2013-1540].

Time-varying relationships between land use and crime: A spatio-temporal analysis of small-area seasonal property crime trends

Abstract

Neighbourhood land use composition influences the geographical patterns of property crime. Few studies, however, have investigated if, and how, the relationships between land use and crime change over time. This research applies a Bayesian spatio-temporal regression model to analyze twelve seasons of property crime at the small-area scale. Time-varying regression coefficients estimate the seasonally-varying relationships between land use and crime and distinguish both time-constant and season-specific effects. Seasonal property crime trends are commonly hypothesized to be associated with fluctuating routine activity patterns around specific land uses, but past studies do not quantify the time-varying effects of neighbourhood characteristics on small-area crime risk. Results show that, accounting for sociodemographic contexts, parks are more positively associated with property crime during spring and summer seasons, and eating and drinking establishments are more positively associated during autumn and winter seasons. Land use is found to have a more substantial impact on spatial, rather than spatio-temporal, crime patterns. Proposed explanations for results focus on seasonal activity patterns and corresponding spatio-temporal interactions with the built environment. The theoretical and analytical implications of this modeling approach are discussed. This research advances past cross-sectional spatial analyses of crime by identifying built environment characteristics that simultaneously shape both where and when crime occurs.

Keywords

Spatio-temporal, land use, property crime, Bayesian, time-varying coefficient, season

Introduction

Geographical patterns of property crime are influenced by neighbourhood built environment characteristics, including land use (Ceccato et al., 2002; Matthews et al., 2010). Local land use composition shapes the situational conditions necessary for crime offences to occur and is often interpreted through the routine activity theory, which hypothesizes that crimes result from the convergence of motivated offenders, suitable targets, and a lack of capable guardianship in space and time (Cohen and Felson, 1979; Andresen, 2007). Past research has found, for example, that the spatial distribution of property crime is positively associated with non-residential land uses such as commercial uses and public transit stations (Kinney et al., 2008; LaGrange, 1999; Matthews et al., 2010; Weisburd et al., 2012). Despite the routine activity theory proposing a spatio-temporal relationship between land use and crime, or that land use influences both where and when crime offences occur, past small-area research has generally applied cross-sectional spatial analysis methods and has not investigated if, and how, the relationships between land use and crime change over time.

Seasonal crime trends are one of the most robust temporal patterns of crime and are typically observed to be highest during the summer and lowest during the winter (Anderson, 1987; Andresen and Malleson, 2013; Hipp et al., 2004). Proposed routine activity theory explanations focus on spatio-temporal variations in discretionary activities around specific land use types (McDowall et al., 2012). Discretionary routine activities are pursued by choice and vary in both location and temporal frequency, contrasting with obligatory routine activities that are consistent in location and frequency (LeBeau, 1994; Tompson and Bowers, 2015). The difference between high property crime rates during the summer and low rates during the winter, for example, has been attributed to summertime increases in discretionary leisure activities, such as public events and festivals located around parks and open spaces, and around land uses that offer shopping and dining activities (Cohn and Rotton, 2000; Hipp et al., 2004; Sorg and Taylor, 2011).

Often, seasonal crime research has applied time-series methods to analyze longitudinal data for one or many large areas, such as a country or a collection of cities (Breetzke and Cohn, 2012). While these analyses identify generalizable city-level trends, they overlook intra-urban heterogeneity in crime and do not recognize the place-based relationships between crime and the built environment (di Bella et al., 2015; Gorman et al., 2013). In the routine activity theory, it is neighbourhood-scale land use composition that is thought to shape the spatio-temporal distribution of behavioural activity patterns, the availability of physical goods that can be damaged or stolen, and the frequency of convergences between potential offenders and targets (Ceccato et al., 2002; Groff et al., 2014; Groff and Lockwood, 2014). Research exploring small-area crime trends has suggested that land use does influence local crime trends, but inferences are based on descriptive methods such as map comparison between time periods (Andresen and Malleson, 2013; Brunsdon et al., 2009).

This research investigates the time-varying relationships between land use and property crime at the small-area scale. The case study location is the Region of Waterloo, Canada, for twelve seasons from Spring 2011 to Winter 2013-2014. A Bayesian spatio-temporal regression model with time-varying coefficients and random effects is applied. Time-varying coefficients are composed of time-constant and time-changing components and estimate the underlying relative risk of land use and season-specific departures, respectively. This paper begins with a review of past research exploring seasonal crime trends and the relationships between crime and the built environment. Next, Bayesian spatio-temporal regression models are outlined. Seasonally-varying relative risk trends for land use covariates are visualized and explanations for model results are proposed. The theoretical, analytical, and practical implications of this research are discussed and, in conclusion, limitations and future research directions are highlighted.

Literature review

Contemporary research has observed that property crime typically exhibits a recurring trend that is highest during summer seasons and lowest during winter seasons (Breetzke and Cohn, 2012; Hipp et al., 2004). In general, studies have analyzed longitudinal crime data for one large geographical area. Anderson (1987) and Yan (2004), for example, apply analysis of variance methods to find that thefts are higher between April and September in the United States, and that pickpocketing is highest during the summer in Hong Kong, respectively. Linning and colleagues (2016; 2017) apply Poisson and negative binomial regressions between city-level property crime and climatic characteristics, observing a positive association with temperature and a negative association with snowfall.

Time series methods have also been applied to longitudinal crime data for one or many large geographical areas. For example, Cohn and Rotton (2000) identify a positive and statistically significant association between burglary, robbery, and theft rates and the months of June, July, and August, for the city of Minneapolis, Minnesota. Hipp et al. (2004) and McDowall et al. (2012) analyze longitudinal crime data for over eight thousand police unit areas and eighty-eight cities in the United States, respectively, and find that property crimes are highest in summer months after accounting for city temperatures. Notably, Hipp et al. (2004) identify a positive relationship between seasonal property crime oscillations and eating and drinking establishments, but do not consider how this land use influences property crime trends at the small-area scale.

Seasonal routine activities and land use

In a spatio-temporal context, routine activities, or "recurrent and prevalent activities which provide for basic population and individual needs (Cohen and Felson, 1979: 593)," can be distinguished as obligatory or discretionary. Obligatory activities are consistent throughout the year, both in geographical location and temporal frequency, and include household activities located in residential neighbourhoods and occupational activities located in employment areas. Discretionary activities, on the other hand, are pursued by choice and exhibit fluctuating spatio-temporal patterns (Tompson and Bowers, 2015). Generally, research has suggested that discretionary activities are concentrated in indoor locations and in residential areas during autumn and winter seasons, but increasingly occur in outdoor locations and in non-residential areas with public space during the spring and summer (Field, 1992).

Proposed routine activity theory explanations for seasonal property crime trends focus on spatio-temporal variations in the convergence of offenders and targets or on the presence of capable guardianship. Focusing on offender and target convergence, past research has suggested that leisure activities occur more frequently during the summer, and that these activities occur at specific non-residential land uses (Hipp et al., 2004; Sorg and Taylor, 2011). For example, increases in shopping, dining, and tourism during summer months are geographically concentrated at commercial and retail stores, eating and drinking establishments, and public transit stations (Hipp et al., 2004; Sorg and Taylor, 2011; Carbone-Lopez and Lauritsen, 2013).

Furthermore, outdoor events in the summer bring together large numbers of people in public spaces such as parks and central business districts, and some proportion of these people may engage in criminal behaviour (Andresen and Malleson, 2013; Cohn and Rotton, 2000; Linning, 2015).

Focusing on the presence of capable guardianship, it has been hypothesized that as discretionary activities shift from residential to non-residential areas in the summer, there are fewer capable guardians in residential neighbourhoods. Consequently, this may increase the attractiveness of property crime targets and the likelihood that criminal opportunities are acted upon (Landau and Fridman, 1993; Linning, 2015). As discretionary activities shift to residential areas during autumn and winter seasons, there is thought to be decreasing frequencies of offender and target convergences in both residential and non-residential areas, increasing levels of guardianship, and consequent decreases in property crime across the study region (Breetzke and Cohn, 2012).

Local seasonal crime trends and land use

While it appears that the land use characteristics of high crime areas are relatively consistent year-to-year (Weisburd et al., 2012: 128), past research contends that the relationships between land use and crime fluctuate seasonally. Andresen and Malleson (2013) compare monthly crime data for census tracts in Vancouver, Canada, and observe that high property crime rates in the summer are located in the central business district or in areas characterized by parks and commercial land uses. Similarly, Linning (2015) observes that streets with increasing property crime counts in the summer are located in central business districts with entertainment and commercial land uses, and Brunsdon et al. (2009) suggest that disorder incidents increase in small-areas with outdoor public spaces during warm temperatures.

Methodologically, small-area studies have been descriptive and have not quantified how the relationships between land use and crime vary over time. Andresen and Malleson (2013) and Linning (2015) compare spatial crime patterns between two seasons, but do not explore how seasonal variations in crime are associated with neighbourhood characteristics. Brunsdon et al. (2009) interpolate spatial crime patterns for time periods and visually compare maps to infer how local changes in disorder vary around built environment features. Sorg and Taylor (2011) apply a cross-sectional regression model to analyze the relationship between street robbery and temperature for three years at the census tract scale, operationalizing month as a binary variable, and observe that small-area commercial and public transit land uses amplify the positive effect of temperature.

Study region and data

The Regional Municipality of Waterloo is located in Ontario, Canada, and is composed of the cities of Waterloo, Kitchener, and Cambridge, and four townships. The geographic unit of analysis is the dissemination area (DA). DAs are the smallest statistical unit that cover the entirety of Canada and have residential populations between 400 and 700. In the study region, there are 707 DAs with an average area of 1.17 km^2.

Reported property crime data was obtained from Waterloo Regional Police Services for twelve seasons from Spring 2011 to Winter 2013-14. Property crimes were the sum of break and enters, thefts under $5,000, thefts over $5,000, motor vehicle thefts, property damage, and graffiti incidents (Cohn and Rotton, 2000; Matthews et al., 2010). Figure 1 shows seasonal property crime trend for the study region. Consistent with past research, property crime was highest in summer seasons and lowest in winter seasons (Anderson, 1987; Hipp et al., 2004). Figure 2 shows the geographical distribution of property crime in Spring 2011 and Winter 2013-14, the seasons with the highest and lowest total property crime counts, respectively. Generally, DAs with high property crime counts are clustered in central areas of the study region during Spring 2011, whereas DAs with high crime counts during Winter 2013-14 are relatively more dispersed.

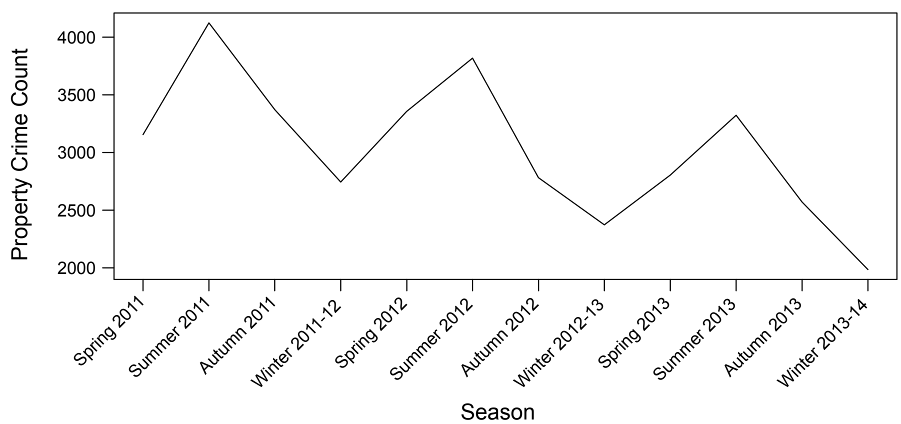

Figure 1. Seasonal property crime trend.

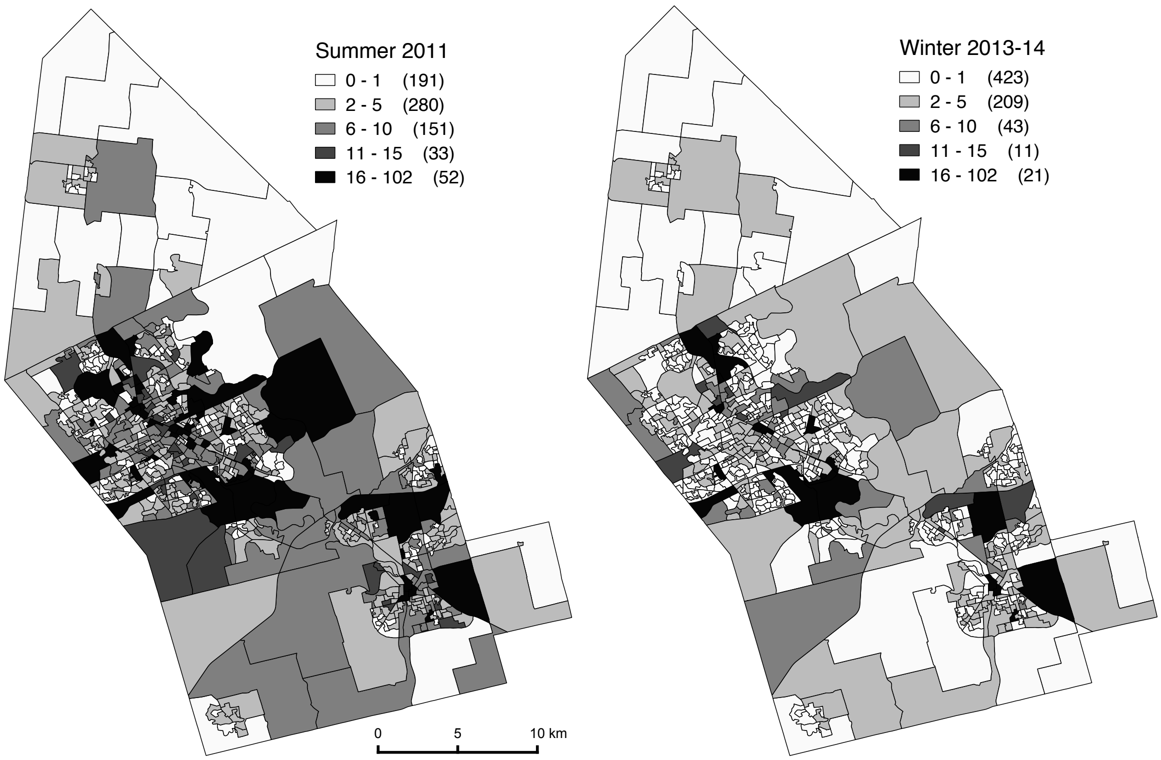

Figure 2. Property crime counts for Spring 2011 and Winter 2013-14. The number of DAs in each class is shown in parentheses.

Table 1 shows descriptive statistics for seasonal property crime counts at the small-area level. Seasons were defined to follow conventional date ranges (i.e., spring and autumn equinoxes, summer and winter solstices) (Table 1). Note that past research has used a variety of seasonal definitions, including monthly (Andresen and Malleson, 2013; Yan, 2004), bi-monthly (Hipp et al., 2004), every three months (Anderson, 1987), and every five months (Landau and Fridman, 1993). For reference, the study region has a continental climate where summer is the warmest (average of 19 °C during the study period), followed by spring (10 °C), autumn (5 °C), and winter (-5 °C).

Table 1. Small-area descriptive statistics for twelve seasons of property crime.

Season	Date Range	Mean	SD	Max	DAs with 0 crime (%)
Spring 2011	March 20 to June 20	4.46	8.67	142	19.66
Summer 2011	June 21 to September 22	5.83	9.82	159	12.31
Autumn 2011	September 23 to December 21	4.77	8.67	128	17.82
Winter 2011-12	December 22 to March 19	3.88	7.43	104	25.88
Spring 2012	March 20 to June 19	4.75	8.43	124	18.81
Summer 2012	June 20 to September 21	5.40	8.57	142	13.86
Autumn 2012	September 22 to December 20	3.94	8.21	112	25.88
Winter 2013-14	December 21 to March 19	3.36	6.73	74	30.98
Spring 2013	March 20 to June 20	3.97	7.20	107	20.09
Summer 2013	June 21 to September 21	4.70	7.98	111	18.95
Autumn 2013	September 22 to December 20	3.64	9.92	82	27.58
Winter 2013-14	December 21 to March 19	2.81	7.07	102	36.07

Eight distinct land use variables were analyzed at the small-area scale: location in a central business district, commercial land use, eating and drinking establishments, government-institutional land use, parks, residential land use, schools, and public transit stations (Andresen and Malleson, 2013; Cohn and Rotton, 2000; di Bella et al., 2015; Kinney et al., 2008; LaGrange, 1999; Linning, 2015; Matthews et al., 2010). Central business districts were delineated by municipally-defined downtown boundaries for the three cities in the study region. Commercial land uses were comprised of retail stores and shopping malls; eating and drinking establishments included restaurants, bars, and pubs; and government-institutional land uses included government buildings and community services. Schools included both elementary and secondary schools, and public transit station density was calculated as the number of bus stations per DA area. Land use data was compiled from the Region of Waterloo, a vector land use database, and Statistics Canada (2012). Land uses that were infrequent at the small-area scale were operationalized as binary variables (Quick et al., 2017; Sorg and Taylor, 2011) (Table 2). DAs may have multiple land use types (e.g., a DA may be located in the central business district and have eating and drinking establishments, commercial land uses, and a park). All land use data was obtained for 2011.

Table 2. Descriptive statistics for built environment and sociodemographic characteristics.

	Mean	SD
Built environment characteristics		
Central business district (binary)	0.02	NA[a]
Commercial (binary)	0.10	NA
Eating and drinking establishments (binary)	0.28	NA
Government-institutional (binary)	0.30	NA
Park (binary)	0.39	NA
Residential (% of DA area)	68.32	33.31
Schools (binary)	0.14	NA
Public transit stations (density per km^2)	18.22	16.43
Sociodemographic characteristics		
Residential population (count)	674.91	470.71

Five-year residential mobility (%)	37.57	17.43
Immigrant residents (%)	21.13	10.79
Index of ethnic heterogeneity (0 to 1)	0.52	0.14
Lone-parent families (%)	16.44	8.38
Low-income families (%)	12.14	11.55
Median income ($)	33,395.57	8,867.95
Young adult population (%)	14.64	5.69

[a] Standard deviations not reported for binary data.

Eight sociodemographic variables were tested to account for neighbourhood disadvantage: residential population, five-year residential mobility, percent of immigrant residents, index of ethnic heterogeneity, percent of lone-parent families, percent of low-income families, median income, and percent young adult population (Table 2) (Craglia et al., 2005; Law and Quick, 2013). Residential population was analyzed as an explanatory variable because property crime may be concentrated in small-areas with mostly non-residential land use (i.e., residential population is not a representative population at risk) and because residential population is a proxy for the number of potential offenders in the routine activity theory (di Bella et al., 2015).

Spatio-temporal analyses

Property crime counts (O_{ij}) for small-area i (1, …, 707) and season j (1, …, 12) were modeled via Poisson distributions with means μ_{ij}. In the Bayesian framework, the Poisson distribution is often used to model infrequent count data at the small-area scale (e.g. Li et al., 2013). Model 1 estimates spatio-temporal property crime risk (μ_{ij}) as the sum of: overall risk (α), spatially structured random effects (s_i), spatially unstructured random effects (u_i), temporally structured random effects (λ_j), and space-time interaction (ϕ_{ij}) (Knorr-Held and Besag, 1998). Random effects terms u_i and s_i account for overdispersion and residual spatial autocorrelation (Haining et al., 2009). Temporally structured random effects (λ_j) capture residual temporal autocorrelation of property crime risk between seasons. Space-time interaction (ϕ_{ij}) captures extra-Poisson variability not accounted for by other model parameters.

$$\log(\mu_{ij}) = \alpha + s_i + u_i + \lambda_j + \phi_{ij} \tag{1}$$

Model 2 adds time-constant regression coefficients (κ) that estimate associations between property crime and neighbourhood sociodemographic and land use characteristics, $x_i^{(1)}$ and $x_i^{(2)}$, respectively. To capture the seasonally-varying influences of land use, regression coefficients associated with land uses are allowed to vary over time (ψ_j) in Model 3. This is informed by previous research observing that sociodemographic characteristics are associated with overall levels of crime, but not seasonal variations (Hipp et al., 2004; Sorg and Taylor, 2011), and assumes that sociodemographic variables only influence the underlying spatial distribution of crime.

$$\log(\mu_{ij}) = \alpha + \kappa x_i^{(1)} + \kappa x_i^{(2)} + u_i + s_i + \lambda_j + \phi_{ij} \tag{2}$$

$$\log(\mu_{ij}) = \alpha + \kappa x_i^{(1)} + \psi_j x_i^{(2)} + u_i + s_i + \lambda_j + \phi_{ij} \tag{3}$$

$$\psi_j = \beta + \gamma_j \tag{3a}$$

Time-varying coefficients (ψ_j) are specified as the sum of a time-constant component (β), which estimates the consistent influence of land use throughout all seasonal time periods, and a time-changing component (γ_j), which estimates season-specific changes in the associations between land use and crime (Model 3a). This coefficient structure assumes that land uses, and the routine activities that occur around them, simultaneously influence the underlying spatial distribution of crime and season-specific increases and decreases in crime. Because land use composition did not change substantially during the study period, land use data was constant for all seasons (i.e., x_i is not time indexed). Model 3 can be extended to tackle research questions where land use changes over time by analyzing land use data as x_{ij}.

In Bayesian hierarchical modeling, model parameters are stochastic and assigned prior distributions. A uniform prior distribution was assigned for α. Normal distributions with mean of 0 and a common unknown variance was specified for u_i. The intrinsic conditional autoregressive prior (ICAR) captures residual spatial autocorrelation and was assigned for s_i (Besag et al., 1991). For the ICAR prior, spatial structure was defined such that areas sharing at least one vertex were considered adjacent. Residual spatial autocorrelation is anticipated because there may be spatially structured risk factors unaccounted for in the model (Tiefelsdorf and Griffith, 2007). Temporally structured random effects (λ_j) were also assigned ICAR prior distributions, where temporal structure was defined via adjacency between neighbouring seasons (Knorr-Held and Besag, 1998). Because seasonal property crime trend is oscillating (Figure 1), this is preferable to prior distributions that constrain time trend to be linear, as in Law et al. (2015). Spatio-temporal interactions (ϕ_{ij}) were assumed to independently follow a normal distribution with mean of 0 and a common unknown variance. This implies that there is no spatial or temporal structure in residuals after accounting for all other components in the model.

Regression coefficients κ and β were assigned vague normal prior distributions and γ_j's were assigned temporal ICAR distributions with the same adjacency specification as the prior on λ_j. We also tested an exchangeable normal prior distribution on γ_j's (no assumption of temporal structure) and obtained nearly identical results. The $Normal_{+\infty} \sim (0, 10)$ distribution was independently assigned as the prior for the standard deviations of the random effects s_i, u_i, λ_j, ϕ_{ij}, and γ_j (Gelman, 2006). Nearly identical results were obtained using two alternative hyperprior distributions assigned on the variances of random effects, *Inverse Gamma* ~ (0.5, 0.0005), and *Inverse Gamma* ~ (0.001, 0.001) (Kelsall and Wakefield, 1999).

Models were fit via the Markov chain Monte Carlo algorithm in WinBUGS v1.4.3. Model convergence occurred after 35,000 iterations and posterior estimates were constructed from two chains run for 50,000 subsequent iterations, where every tenth iteration was retained to reduce autocorrelation of posterior samples. A total of 10,000 iterations were used for obtaining the posterior summary (reported below). Monte Carlo errors for all parameters were below five percent of the corresponding posterior standard deviations, suggesting that the 10,000 iterations were sufficient to approximate the posterior distributions (Lunn et al., 2012). Model fit was evaluated using the Deviance Information Criterion (DIC), where smaller DIC values indicate better model fit (Spiegelhalter et al., 2002).

Results

Model 3 was found to be the best fitting model (DIC results are shown in Table A1). The final spatio-temporal model was obtained by including all κ's and ψ_j's for which the 95% credible interval (CI) was unambiguously positive or negative for at least six seasons (i.e., did not include zero). The 95% CI is the interval that contains the true value of a parameter with 95% probability. Table 3 shows time-constant relative risk estimates of sociodemographic and land use characteristics (exp(κ) for time-constant coefficients and exp(β) for time-varying coefficients as in Model 3), where values greater than one indicate positive associations with property crime.

Figure 3 visualizes the seasonally-varying relative risks ($\exp(\psi_j)$) for land uses associated with property crime.

Table 3. Time-constant relative risk estimates (posterior medians and 95% CI's) for sociodemographic and land use characteristics.

	Relative risk (95% CI)
α	1.56 (1.43, 1.69)
κ_1: Residential population	1.24 (1.16, 1.32)
κ_2: Residential mobility	1.15 (1.07, 1.23)
β_3: Central business district	1.97 (1.28, 3.07)
β_4: Commercial	1.39 (1.13, 1.71)
β_5: Eating and drinking establishments	2.09 (1.81, 2.41)
β_6: Park	1.18 (1.04, 1.34)
β_7: Public transit stations	1.08 (1.01, 1.16)
β_8: School	1.29 (1.08, 1.54)

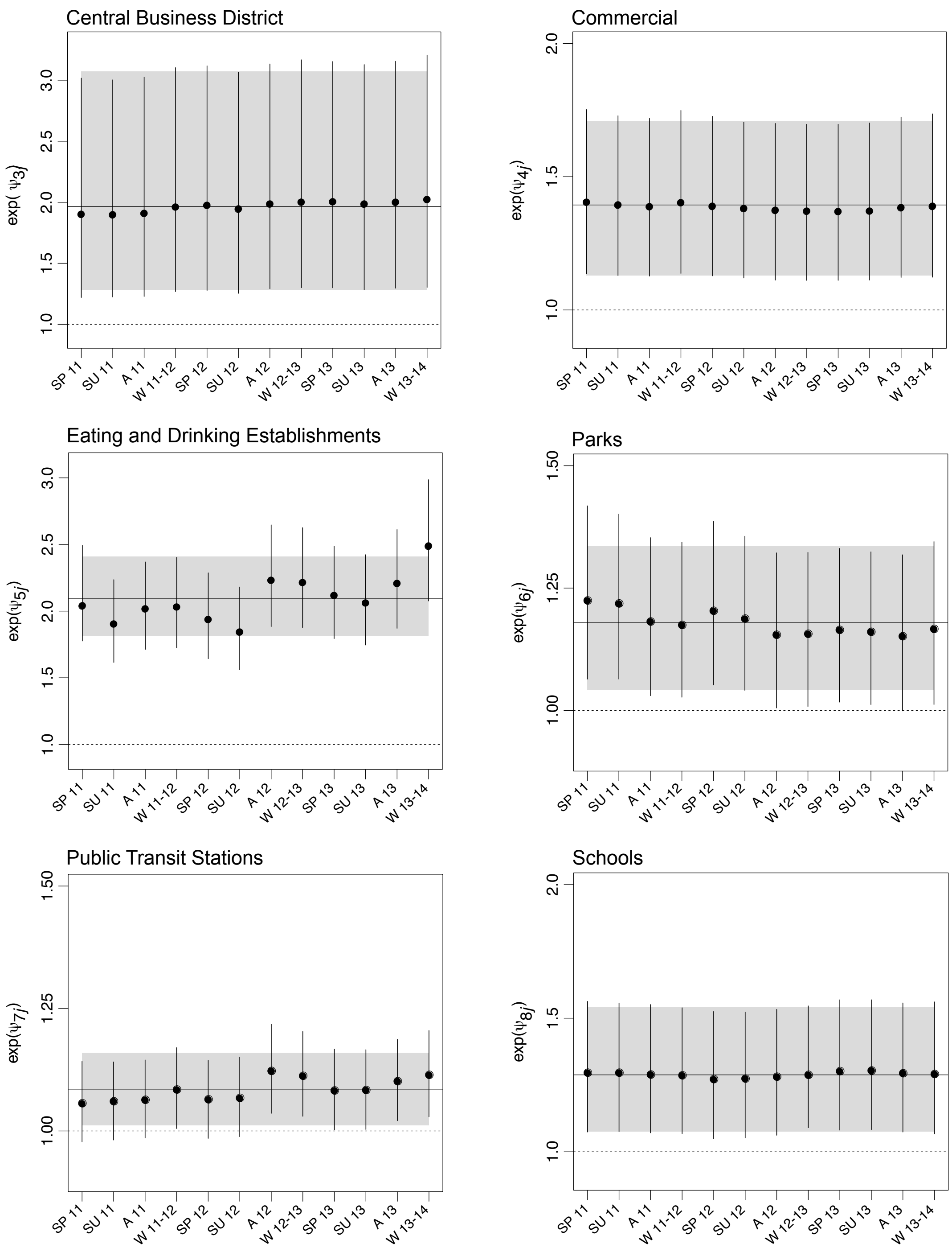

Figure 3. Seasonally-varying relative risks for land uses associated with property crime. Posterior medians are shown as points with corresponding 95% CI's shown as vertical bars. SP represents spring, SU represents summer, A represents autumn, and W represents winter.

Estimates of time-constant relative risks are indicated by horizontal lines with 95% CI indicated by shaded grey. The horizontal dotted line at $\exp(\psi_j) = 1$ indicates no effect of a risk factor on property crime.

Discussion

Controlling for residential population and residential mobility, property crime was found to be associated with six built environment characteristics at 95% CI: location in a central business district, commercial land use, eating and drinking establishments, schools, parks, and public transit stations. All land uses identified in the final model were positively associated with property crime for the twelve seasons analyzed. These land uses have been highlighted in past cross-sectional research exploring the relationships between the built environment and property crime and are commonly interpreted through the routine activity theory (Kinney et al., 2008; Matthews et al., 2010).

Central business districts and commercial land uses are representative of small-areas with high concentrations of material goods that may attract motivated offenders regardless of season. Also, central business districts, commercial land uses, schools, and public transit stations are activity nodes for both obligatory and discretionary activities (LaGrange, 1999). Activity nodes refer to specific locations that attract large numbers of people during routine activities and are anticipated to exhibit positive time-constant associations with property crime. Some proportion of the population moving through these nodes for employment in central business districts, for shopping in areas with commercial land uses, and for commuting through areas with high public transit station density, may offend when situational conditions arise (Brantingham and Brantingham, 2008; Ceccato et al., 2002; Haberman and Ratcliffe, 2015).

Recurring relationships between land use and crime

Focusing on how the relationships between land use and crime change over time, we first classify each seasonally-varying relative risk trend (ψ_j) as recurring or inconsistent. A recurring trend is a seasonally-varying relative risk trend that repeats a four-month pattern for at least two of three four-season cycles (i.e., eight of twelve months). For example, a recurring trend that repeats over three four-season cycles is property crime count for the study region; property crime is highest in all summer seasons and lowest in all winter seasons (Figure 1). An inconsistent trend does not follow a repeating four-month pattern. This classification balances the heterogeneity of small-area spatio-temporal data over twelve seasons, the unconstrained specification of time-changing components (i.e., no oscillating trend imposed on λ_j or γ_j), and past research hypotheses focusing on recurring relationships between land use and property crime.

Based on visual observation of Figure 3, three land uses exhibited recurring seasonally-varying relative risk trends: parks, public transit stations, and eating and drinking establishments. Parks were found to have higher positive associations with property crime during spring and summer seasons than during autumn and winter for the first eight seasons. The relative risk of public transit stations was higher during autumn and winter seasons than spring and summer seasons for all twelve seasons analyzed. Eating and drinking establishments higher positive associations with crime in autumn and winter than in spring and summer for the second and third four-season cycles. Seasonally-varying relative risk trends of central business districts, schools, and commercial land uses were classified as inconsistent.

Generally, recurring relative risk trends appear to change over two time periods, spring/summer and autumn/winter. To quantify this, time-varying coefficients were modified to model recurring trends over two time periods rather than each of the four seasons. In Model 4, ν_j represents modified time-varying coefficients and $x_i^{(3)}$ is eating and drinking establishments, parks, and public transit station land uses. Modified time-varying coefficients resemble Model 3a, however time-constant components were estimated for each four-season cycle (β_k instead of β, where $k = 1, 2$, and 3; $\beta_{k=1}$ corresponds to Spring 2011 to Winter 2011-12). For land uses that have higher relative risk in autumn and winter seasons, $\gamma_j = 0$ if j is in spring or summer and $\gamma_j = \delta$ if j is in autumn or winter. Therefore, δ measures the difference in effect of eating and drinking establishments and public transit stations during the autumn/winter time period compared to β_k, or the effect of these land uses during spring/summer. For parks, $\gamma_j = \delta$ if j is in spring or summer and $\gamma_j = 0$ if j is in autumn or winter. Estimates of $\exp(\delta)$ unambiguously greater or less than 1 indicate a considerable difference in effect between spring/summer and autumn/winter time periods and provide quantitative support for recurring relative risk trends. Vague normal prior distributions were assigned for β_k's and δ_k's.

$$\log(\mu_{ij}) = \alpha + \kappa x_i^{(1)} + \psi_j x_i^{(2)} + \nu_j x_i^{(3)} + u_i + s_i + \lambda_j + \phi_{ij} \qquad (4)$$

Table 4. Posterior medians and 95% CI's of time-varying components that model recurring risk trends between spring/summer and autumn/winter.

	Eating and drinking establishments	Parks	Public transit stations
Spring and Summer 2011	NA[a]	1.14 (1.03, 1.26)	NA
Autumn and Winter 2011-12	1.04 (0.94, 1.15)	NA	1.01 (0.97, 1.06)

Spring and Summer 2012	NA	1.12 (1.01, 1.24)	NA
Autumn and Winter 2012-13	1.24 (1.12, 1.38)	NA	1.09 (1.03, 1.14)
Spring and Summer 2013	NA	1.02 (0.91, 1.14)	NA
Autumn and Winter 2013-14	1.14 (1.02, 1.27)	NA	1.04 (0.99, 1.09)

[a] $\delta = 0$

Table 4 shows the results of modified time-varying components that measure recurring risk trends over two time periods (δ). The relative risk of public transit stations in the autumn/winter exhibited a significant departure from spring/summer during only one time period. This may be attributed to season-specific relative risks for j = 1, 2, 3, 5, and 6 being indistinguishable from zero (95% CI estimates in Figure 2) and suggests that, while public transit stations are associated with overall property crime risk, there is little evidence of a recurring seasonal influence on small-area property crime.

Parks were found to exhibit a recurring relative risk trend for two of three spring/summer time periods, specifically 2011 and 2012 (Table 4). This confirms visual observation of seasonally-varying relative risk trends (Figure 2) and supports past descriptive research observing that property crime rates increase during summer months in areas with parks, beaches, and outdoor public spaces (Andresen and Malleson, 2013; Brunsdon et al., 2009; Linning, 2015). Compared to autumn and winter seasons, spring and summer seasons in the study region are warm and discretionary routine activities are more often located outdoor and in and around public parks. Outdoor events situated at parks include festivals, concerts, public celebrations, and recreational sports leagues. From a routine activity perspective, higher levels of these discretionary activities in small-areas with parks during spring and summer seasons suggests corresponding increases in crime opportunities and property crime offences, including thefts from unoccupied vehicles, thefts from nearby stores, or property damage or graffiti (Rotton and Cohn, 2000).

Eating and drinking establishments also show evidence of a recurring seasonal trend, where risk during Autumn/Winter 2012-13 and 2013-14 significantly depart from corresponding spring/summer periods. Throughout the year, eating and drinking establishments, and alcohol serving outlets in particular, are likely to have large numbers of patrons and some proportion may have low self-control related to alcohol consumption (Groff and Lockwood, 2014; Gruenewald et al., 2006). This may be amplified in autumn and winter, when the study region's student population tends to concentrate discretionary leisure activities in areas with many eating and drinking establishments. Note that this finding contrasts with Hipp et al. (2004), who found that eating and drinking establishments were associated with high property crime during the summer for larger geographical units. This relationship should be further explored using data from many cities, specifically focusing on differentiating a generalizable trend from city-specific variations.

While time series analyses have shown that summertime school holidays/closures are associated with higher crime at the municipal scale (Cohn and Rotton, 2000), this research shows that schools do not exhibit a recurring seasonal relationship with property crime. One explanation may be that youth engaging in delinquent activities while not attending school are responsible for property crime increases in the summer, but that offences are concentrated around offender residences or leisure spaces rather than schools (Carbone-Lopez and Lauritsen, 2013). A second explanation may be that land uses that are activity nodes for larger proportions of the population, such as parks and eating and drinking establishments, experience more dramatic spatio-temporal fluctuations in crime opportunities and property crime offences.

Spatio-temporal crime patterns and time-varying regression coefficients

This research is, to the best of our knowledge, the first to apply a Bayesian spatio-temporal model to estimate the time-varying relationships between neighbourhood characteristics and crime at the small-area scale. As such, we reflect on the implications of this research for understanding crime patterns, for interpreting spatio-temporal routine activities, and for applications to urban planning and law enforcement.

Broadly, this research suggests that the built environment has a more substantial influence on spatial, rather than spatio-temporal, crime patterns. Results from Models 3 and 4 show that the magnitude of time-varying components for all land uses are relatively modest compared to time-constant components, and that posterior medians of time-varying regression coefficients were generally within 95% CI's of time-constant components. In Model 3, only two season-specific risk estimates were at least five percent greater than time-constant estimates: eating and drinking establishments during Winter 2013-14 (18.7% greater than time-constant risk) and during Summer 2012 (12.02% less than time-constant risk).

This is further supported by variance partition coefficients (VPC), which quantify the proportion of residual variation explained by spatial random effects, temporal random effects, and space-time interaction in Model 1, and random effects as well as covariates in Models 2, 3, and 4 (Goldstein et al., 2002)[1]. When adding time-constant covariates, the VPC of spatial random effects decreases from 86% in Model 1 to 62% in Model 2, with approximately 15% of the variation explained by land use and 7% of the variation explained by sociodemographic characteristics. When adding time-varying land use covariates in Models 3 and 4, however, the amount of spatio-temporal variability explained by land use characteristics remained at approximately 15% (VPC results are shown in Table A2). Note that adding time-varying covariates also did not change the proportions of variance explained by sociodemographic characteristics and spatial, temporal, and space-time random effects. Land use, therefore, is more important in explaining the spatial variation of crime than the temporal or spatio-temporal variations of property crime across seasons.

From a theoretical perspective, the structure of time-varying coefficients parallels the distinction between obligatory and discretionary activities in the routine activity theory. Time-constant components represent obligatory activities and time-changing components represent season-specific changes in discretionary activities (Tompson and Bowers, 2015). Because time-constant and time-changing components are often similar in magnitude, however, it appears that the degree to which discretionary activities influence small-area property crime is relatively minor. This is not unexpected, as we simultaneously account for sociodemographic characteristics as well as the time-varying effects of multiple land uses, and it is possible that past descriptive research has overstated the role of land use in driving seasonal crime trends. Further, this might be due to the analytical challenge associated with spatio-temporal modeling

[1] The VPC for spatial random effects in Model 1, for example, is equal to the sum of the empirical variances of u_i and s_i divided by the sum of the empirical variances of u_i, s_i, λ_j, and ϕ_{ij}.

of built environment data. We analyzed constant land use data for twelve seasons because land use composition was stable over time, however it is possible that land use is not representative of spatio-temporal variations in discretionary routine activities and, instead, is more suitable for understanding the time-constant or spatial distribution of obligatory activities.

This research informs crime reduction and prevention initiatives in both urban planning and law enforcement. Urban planning, in particular, has the potential to reduce time-constant property crime risk in specific small-areas via modifications to the built environment (Johnson et al., 2008). One strategy may be to limit future development of high risk land uses in neighbourhoods with high time-constant property crime risk, however, because many land uses found to be associated with property crime are desirable amenities and serve important functions, a better option may be to implement crime prevention through environmental design standards (CPTED). CPTED aims to influence offender decision-making by increasing perceptions of capable guardianship. In a spatio-temporal context, urban planners should consider how the physical characteristics and activity functions of land uses change over time. For example, urban planners and designers should ensure that foliage and event-related infrastructure in parks during the summer does not obscure the natural surveillance provided by vehicular traffic, passersby, and park users (Loukaitou-Sideris et al., 2001; Iqbal and Ceccato, 2016).

Compared to the relatively permanent built environment modifications that result from land use planning and urban design, law enforcement can change the spatial and temporal distribution of resources in anticipation of recurring seasonal crime trends (Johnson et al., 2008). The results of this research suggest that the geographical distribution of law enforcement resources should be relatively consistent throughout the year and target neighbourhoods that have land uses with high time-constant relative risks. Temporally, moderate amounts of law enforcement resources may be cycled between areas with parks in the spring/summer and areas with eating and drinking establishments in the autumn/winter. Public awareness campaigns and targeted policing initiatives may prevent and deter crime, influencing time-constant and season-specific crime risk targeted small-areas and the study region as a whole.

Limitations and future research

One limitation of this research is that land use composition is operationalized to represent behavioural routine activity patterns. Future research should investigate data that directly captures both spatial and temporal dimensions of routine activities, such as sales data from commercial retail stores (Weisburd et al., 2012), statistics on park users or transit ridership (Loukaitou-Sideris et al., 2001), or mobile phone and social media data that captures business check-ins (Hanaoka, 2016; Jacobs-Crisioni et al., 2014). It may also be interesting to explore spatio-temporal crime patterns during longer processes of metropolitan or neighbourhood change, for example modeling the time-varying effects of changing sociodemographic characteristics related to gentrification (Kirk and Laub, 2010; Papachristos et al., 2011).

A second limitation of this research is that time-varying relationships between land use and crime are estimated for the entire study region. Modeling seasonal relative risk trends for the study region improves understanding of the processes influencing spatio-temporal crime patterns, but may overlook geographically and temporally-focused variations in crime. For example, outdoor events hosted in one park that increase property crime in nearby neighbourhoods for a small period of time may be obscured in this spatio-temporal model. In future research, the time-varying relationships between neighbourhood characteristics and crime should be investigated at the small-area level using regression coefficients vary over both space and time. One approach would be to develop Bayesian spatially- and temporally-varying coefficient models, which may resemble the non-Bayesian method proposed by Fotheringham et al. (2015).

Related, we assume that sociodemographic characteristics do not influence seasonal variations of crime. While this is supported by past time-series research analyzing property crime trends using the routine activity theory (Hipp et al., 2004), it is possible that neighbourhood crime trends are influenced by neighbourhood disadvantage and residential mobility, for example. Studies have shown that violent crimes tend concentrate in disadvantaged neighbourhoods during the summer, as explained by the interactions between uncomfortably high temperatures, aggression, and disadvantage (Harries et al., 1984; Rotton and Cohn, 2004). The time-varying coefficients used in this study would be useful for exploring how the relationships between violent crime and sociodemographic contexts vary over time. Finally, the results of this research should be taken in context of the modifiable areal and temporal unit problems (Openshaw, 1984; Cheng and Adepeju, 2014). The time-varying relationships between land use and crime will exhibit different trends depending on how seasonal time periods and small-area units are defined and alternative operationalizations of spatial and temporal units should be further investigated.

References

Anderson CA (1987) Temperature and aggression: Effects on quarterly, yearly, and city rates of violent and nonviolent crime. *Journal of Personality and Social Psychology* 52(6): 1161–1173.

Andresen MA (2007) Location quotients, ambient population, and the spatial analysis of crime in Vancouver, Canada. *Environment and Planning A* 39(10): 2423–2444.

Andresen MA and Malleson N (2013) Crime seasonality and its variations across space. *Applied Geography* 43: 25–35.

Besag J, York J and Mollie A (1991) Bayesian image restoration with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics* 43(1): 1–59.

Brantingham P and Brantingham P (2008) Crime pattern theory. In: Wortley R and Mazerolle L (eds) *Environmental Criminology and Crime Analysis*. Portland, Oregon: Willan Publishing, pp. 78-93.

Breetzke GD and Cohn EG (2012) Seasonal assault and neighborhood deprivation in South Africa: Some preliminary findings. *Environment and Behavior* 44(5): 641–667.

Brunsdon C, Corcoran J, Higgs G and Ware A (2009) The influence of weather on local geographical patterns of police calls for service. *Environment and Planning B* 36: 906–926.

Carbone-Lopez K and Lauritsen J (2013) Seasonal variation in violent victimization: Opportunity and the annual rhythm of the school calendar. *Journal of Quantitative Criminology* 29: 399–422.

Ceccato V, Haining R and Signoretta P (2002) Exploring offence statistics in Stockholm City using spatial analysis tools. *Annals of the Association of American Geographers* 92(1): 29–51.

Cheng T and Adepeju M (2014) Modifiable temporal unit problem (MTUP) and its effect on space-time cluster detection. *PLoS ONE* 9(6). Epub 27 June 2014 DOI: 10.1371/journal.pone.0100465.

Cohen LE and Felson M (1979) Social changes and crime rate trends: A routine activity approach. *American Sociological Review* 44(4): 588–608.

Cohn EG and Rotton J (2000) Seasonal trends and property crimes in Minneapolis, 1987-1988. A moderator-variable time-series analysis of routine activities. *Journal of Environmental Psychology* 20: 257–272.

Craglia M, Haining R and Signoretta P (2005) Modelling high-intensity crime areas: Comparing police perceptions with offence/offender data in Sheffield. *Environment and Planning A* 37(3): 503–524.

di Bella E, Corsi M, Leporatti L and Persico L (2015) The spatial configuration of urban crime environments and statistical modeling. *Environment and Planning B* 44(4): 647–667.

Field S (1992) The effect of temperature on crime. *British Journal of Criminology* 32(3): 340–351.

Fotheringham AS, Crespo R and Yao J (2015) Geographical and temporal weighted regression (GTWR). *Geographical Analysis* 47(4): 431–452.

Gelman A (2006) Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis* 1(3): 515–533.

Goldstein H, Browne W and Rasbash J (2002) Partitioning variation in multilevel models. *Understanding Statistics* 1(4): 223–231.

Gorman DM, Gruenewald PJ and Waller LA (2013) Linking places to problems: geospatial theories of neighborhoods, alcohol and crime. *GeoJournal* 78: 417–428.

Groff ER and Lockwood B (2014) Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of Research in Crime and Delinquency* 51(3): 277–314.

Gruenewald PJ, Freisthler B, Remer L, LaScala EA and Treno A (2006) Ecological models of alcohol outlets and violent assaults: Crime potentials and geospatial analysis. *Addiction* 101: 666–677.

Haberman CP and Ratcliffe JH (2015) Testing for temporally differentiated relationships among potentially criminogenic places and census block street robbery counts. *Criminology* 53(3): 457–483.

Hanaoka K (2016) New insights on relationships between street crimes and ambient population: Use of hourly population data estimated from mobile phone users' locations. *Environment and Planning B*. Epub ahead of print 10 October 2016 DOI: 10.1177/0265813516672454.

Haining R, Law J and Griffith D (2009) Modelling small area counts in the presence of overdispersion and spatial autocorrelation. *Computational Statistics and Data Analysis* 53(8): 2923–2937.

Harries KD, Stadler SJ and Zdorkowski RT (1984) Seasonality and assault: Explorations in inter-neighborhood variation, Dallas 1980. *Annals of the American Association of Geographers* 74(4): 590-604.

Hipp JR, Bauer DJ, Curran PJ and Bollen KA (2004) Crimes of opportunity or crimes of emotion? Testing two explanations for seasonal change in crime. *Social Forces* 82(4): 1333–1372.

Iqbal A and Ceccato V (2016) Is CPTED useful to guide the inventory of safety in parks? A study case in Stockholm, Sweden. *International Criminal Justice Review* 26(2): 150–168.

Jacobs-Crisioni C, Rietveld P, Koomen E and Tranos E (2014) Evaluating the impact of land-use density and mix on spatio-temporal urban activity patterns: An exploratory study using mobile phone data. *Environment and Planning A* 46(11): 2769–2785.

Johnson SD, Lab SP and Bowers KJ (2008) Stable and fluid hotspots of crime: Differentiation and identification. *Built Environment* 34(1): 32–45.

Kelsall JE and Wakefield JC (1999) Discussion of 'Bayesian models for spatially correlated disease and exposure data' by Best NG, Arnold RA, Thomas A, Waller L and Conlon EM. In: *Bayesian Statistics 6* (eds JM Bernardo, JO Berger, P Dawid and AFM Smith), Oxford University Press: Oxford, pp.131–156.

Kinney JB, Brantingham PL, Wuschke K, Kirk MG and Brantingham PJ (2008) Crime attractors, generators, and detractors: Land use and urban crime opportunities. *Built Environment* 34(1): 62–74.

Kirk DS and Laub JH (2010) Neighborhood change and crime in the modern metropolis. *Crime and Justice* 39(1): 441–502.

Knorr-Held L and Besag J (1998) Modelling risk form a disease in time and space. *Statistics in Medicine* 17: 2045–2060.

Landau SF and Fridman D (1993) The seasonality of violent crime: The case of robbery and homicide in Israel. *Journal of Research in Crime and Delinquency* 30: 163–191.

LaGrange TC (1999) The impact of neighborhoods, schools, and malls on the spatial distribution of property damage. *Journal of Research in Crime and Delinquency* 36: 393–422.

Law J and Quick M (2013) Exploring links between juvenile offenders and social disorganization at a large map scale: a Bayesian spatial modeling approach. *Journal of Geographical Systems* 15(1): 89–113.

Law J, Quick M and Chan PW (2015) Analyzing hotspots of crime using Bayesian spatiotemporal modeling approach: A case study of violent crime in the Greater Toronto Area. *Geographical Analysis* 47(1): 1–19.

LeBeau JL (1994) The oscillation in police calls to domestic disputes with time and the temperature humidity index. *Journal of Crime and Justice* 17(1): 149–161.

Li G, Haining R, Richardson S and Best N (2013) Evaluating the No Cold Calling zones in Peterborough, England: Application of a novel statistical method for evaluating neighbourhood policing policies. *Environment and Planning A* 45: 2012–2026.

Linning SJ (2015) Crime seasonality and the micro-spatial patterns of property crime in Vancouver, BC and Ottawa, ON. *Journal of Criminal Justice* 43: 544–555.

Linning SJ, Andresen MA and Brantingham PJ (2016) Crime seasonality: Examining the temporal fluctuations of property crimes in cities with varying climates. *International Journal of Offender Therapy and Comparative Criminology* Epub ahead of print 17 March 2016 DOI: 10.1177/0306624X16632259.

Linning SJ, Andresen MA, Ghaseminejad AH and Brantingham PJ (2017) Crime seasonality across multiple jurisdictions in British Columbia. *Canadian Journal of Criminology and Criminal Justice* 59(2): 251–280.

Loukaitou-Sideris A, Liggett R and Iseki H (2001) Measuring the effects of built environment on bus stop crime. *Environment and Planning B* 28: 255–280.

Lunn D, Jackson C, Best N, Thomas A and Spiegelhalter D (2012) *The BUGS Book: A practical introduction to Bayesian analysis*. London, United Kingdom: Chapman and Hall/CRC Press.

Matthews SA, Yang T-C, Hayslett-McCall KL and Ruback RB (2010) Built environment and property crime in Seattle, 1998-2000: A Bayesian analysis. *Environment and Planning A* 42(6): 1402–1420.

McDowall D, Loftin C and Pate M (2012) Seasonal cycles in crime, and their variability. *Journal of Quantitative Criminology* 25: 389–410.

Openshaw S (1984) The modifiable areal unit problem. *Geo Abstracts*, University of East Anglia.

Papachristos AV, Smith CM, Scherer ML and Fugiero M (2011) More coffee, less crime? The relationship between gentrification and neighborhood crime rates in Chicago, 1991 to 2005. *City and Community* 10(3): 215–240.

Quick M, Law J and Luan H (2017) The influence of on-premise and off-premise alcohol outlets on reported violent crime in the Region of Waterloo, Ontario: Applying Bayesian spatial modeling to inform land use planning and policy. *Applied Spatial Analysis and Policy* 10(3): 435–454.

Rotton J and Cohn EG (2004) Outdoor temperature, climate control, and criminal assault: The spatial and temporal ecology of violence. *Environment and Behaviour* 36(2): 276–306.

Smith WR, Frazee SG and Davison E (2000) Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of diffusion of street robbery as a diffusion process. *Criminology* 38(2): 489–524.

Spiegelhalter DJ, Best NG, Carlin BP and van der Linde A (2002) Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society B: Statistical Methodology* 64(4): 583–639.

Statistics Canada (2012) North American Industry Classification System (NAICS) Canada 2012. Available at: http://www.statcan.gc.ca/eng/subjects/standard/naics/2012/index (accessed 9 August 2016).

Tiefelsdorf M and Griffith DA (2007) Semiparametric filtering of spatial autocorrelation: the eigenvector approach. *Environment and Planning A* 39: 1193–1221.

Tompson LA and Bowers KJ (2015) Testing time-sensitive influences of weather on street robbery. *Crime Science* 4:8.

Weisburd D, Groff ER and Yang S-M (2012) *The criminology of place: Street segments and our understanding of the crime problem*. Oxford, United Kingdom: Oxford University Press.

Yan YY (2004) Seasonality of property crime in Hong Kong. *British Journal of Criminology* 44: 276–283.

Appendix

Table A1. Model fit diagnostics.

Model	Description of covariates	$\overline{D}$ [a]	p_D [b]	DIC [c]
1	No covariates	29,884	2,571	32,455
2	Time-constant sociodemographic and land use covariates	29,893	2,559	32,452

3	Time-constant sociodemographic covariates and time-varying land use covariates	29,934	2,512	32,446
4	Time-constant sociodemographic covariates and two-season recurring land use covariates	29,921	2,517	32,439

[a] $\overline{D}$ is the posterior mean of the deviance and represents goodness of fit.

[b] p_D is the effective number of parameters and represents model complexity.

[c] DIC = $\overline{D} + p_D$

Table A2. Variance partition coefficients. Posterior medians and 95% credible intervals are shown.

Model	$u_i + s_i$	λ_j	ϕ_{ij}	Sociodemographic characteristics	Land use characteristics
1	0.86 (0.84, 0.87)	0.05 (0.04, 0.06)	0.10 (0.08, 0.11)	NA	NA
2	0.62 (0.58, 0.65)	0.06 (0.05, 0.08)	0.11 (0.10, 0.13)	0.07 (0.04, 0.10)	0.15 (0.11, 0.18)
3	0.61 (0.57, 0.65)	0.08 (0.06, 0.09)	0.11 (0.09, 0.12)	0.07 (0.04, 0.09)	0.15 (0.11, 0.20)
4	0.62 (0.58, 0.65)	0.07 (0.05, 0.09)	0.11 (0.09, 0.13)	0.07 (0.04, 0.10)	0.14 (0.10, 0.18)