A Bayesian spatial shared component model for identifying crime-general and crime-specific hotspots

Jane Law\textsuperscript{a,b}, Matthew Quick\textsuperscript{c}\textsuperscript{,}\textsuperscript{d} and Afraaz Jadavji\textsuperscript{b}

\textsuperscript{a}School of Planning, University of Waterloo, Waterloo, Canada; \textsuperscript{b}School of Public Health and Health Systems, University of Waterloo, Waterloo, Canada; \textsuperscript{c}School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, USA

\textbf{ABSTRACT}

The spatial patterning of crime hotspots provides place-based information for the design, allocation, and implementation of crime prevention policies and programmes. However, most spatial hotspot identification methods are univariate, analyse a single crime type, and do not consider if hotspots are shared amongst multiple crime types. This study applies a Bayesian spatial shared component model to identify crime-general and crime-specific hotspots for violent crime and property crime at the small-area scale. The spatial shared component model jointly analyzes both violent crime and property crime and separates the area-specific risks of each crime type into one shared component, which captures the underlying crime-general spatial pattern common to both crime types, and one type-specific component, which captures the crime-specific spatial pattern that diverges from the shared pattern. Crime-general and crime-specific hotspots are classified based on the posterior probability estimates of the shared and type-specific components, respectively. Results show that the crime-general pattern explains approximately 81\% of the total variation of violent crime and 70\% of the total variation of property crime. Crime-general hotspots are found to be more frequent than crime-specific hotspots, and property crime-specific hotspots are more frequent than violent crime-specific hotspots. Crime-general and crime-specific hotspots are areas that may be targeted with comprehensive initiatives designed for multiple crime types or specialized initiatives designed for a single crime type, respectively.

\textbf{Introduction}

Crime offences exhibit non-random spatial patterns and often concentrate at hotspot locations (Eck and Weisburd 1995; Ratcliffe and McCullagh 1999; Anselin et al. 2000). Identifying crime hotspots is central to theoretical development, crime prevention policy, and law enforcement resource allocation. From a theoretical perspective, the spatial patterning of hotspots provides exploratory insight into the sociodemographic and built environment characteristics that may explain why high and low levels of crime cluster at specific addresses, street segments, and neighbourhoods (Sherman, Gartin, and Buerger 1989; Hirschfield and Bowers 1997). From a policy development and resource allocation perspective, hotspots are locations that may be suitable for community-based crime prevention strategies, which work to change the local social dynamics, institutions, and organizations that influence criminal behaviour (Herbert and Harries 1986; Tonry and Farrington 1995), and/or geographically focused law enforcement interventions, such as hotspot policing or problem-oriented policing, which aim to modify the places, situations, and opportunities that facilitate crime events (Braga et al. 1999; Ratcliffe 2004; Chainey, Tompson, and Uhlig 2008; Wang 2012).

The most common quantitative methods used to analyse crime hotspots are univariate and identify groups of nearby points or areas that have high levels of one outcome compared to other groups of points or areas that have lower levels of the same outcome (McLaugherty 2015; Wang et al. 2017). Common hotspot methods applied to area-based crime data include local Moran’s I, the Getis-Ord G\textsuperscript{s} statistic, and the spatial scan statistic, for example (Murray et al. 2001; Ratcliffe and McCullagh 1999; Andresen 2009; Nakaya and Yano 2010; Shioda 2011; Ceccato and Dolmen 2011; Li and Radke 2012; Wang 2012). However, because univariate hotspot identification methods focus on only one outcome, they do not account for the underlying data-generating processes shared amongst multiple crime types and do not distinguish between crime-general hotspots, or areas where there are unusually high levels of two or more crime types, and crime-specific hotspots, or locations with unusually high levels of only one crime type (Knorr-Held and Best...
Differentiating the spatial patterns of crime-general and crime-specific hotspots advances understanding of the possible risk factors associated with all, some, or only one type of crime, and provides policy-relevant information for the location, design, and implementation of comprehensive crime prevention initiatives that focus on many crime types and/or specialized initiatives that focus on a single crime type (Weisburd et al. 1993; Haberman 2017).

This study applies a Bayesian spatial shared component model to identify crime-general and crime-specific hotspots of property crime and violent crime at the small-area scale in the Regional Municipality of York, Ontario, Canada. The spatial shared component model jointly analyzes property crime and violent crime and separates the area-specific risk of the crime types into one shared component, which captures the crime-general spatial pattern, and two type-specific components, which capture the residual crime-specific spatial patterns. The crime-general pattern represents the set of processes simultaneously associated with multiple crime types and the crime-specific patterns represent the set of processes associated with only one type. Crime-general and crime-specific hotspots are identified based on the posterior probabilities of the area-specific estimates of the shared and type-specific components having high relative risk, respectively.

Following this introduction, the ecological theories used to explain the spatial clustering of violent crime and property crime are reviewed and the univariate and multivariate methods used to identify crime hotspots in past research are compared. Next, the crime data and the shared component model are detailed, and the results of this study are presented and discussed as they relate to advancing the spatial analysis of multivariate data and informing place-based crime prevention policy. In conclusion, the limitations of this research are discussed and directions for future study are recommended.

**Theories explaining spatial crime clusters**

Broadly, three ecological theories have been used to explain the spatial clustering of crime at the local scale: social disorganization theory, routine activity theory, and crime pattern theory. Social disorganization theory hypothesizes that high levels of crime are due to low informal social control amongst community members (Shaw and McKay 1942). Informal social control is defined as the capacity of residents to realize common values and mobilize to control criminal behaviour, and low informal social control within an area is often characterized by high levels of residential instability, socioeconomic disadvantage, and ethnic heterogeneity ( Sampson and Groves 1989). Widely applied at the small-area and neighbourhood scales, past research has shown that social disorganization theory helps to explain the spatial clustering of many crime types including violent crime and property crime (Andresen 2006; Chamberlain and Hipp 2015).

Focusing specifically on the situations in which offences occur, routine activity theory proposes that crime offences result from the convergence of motivated offenders, suitable targets, and a lack of capable guardianship in space and time (Cohen and Felson 1979). Routine activity theory research has shown that many crime types are associated with the same set of geographically-varying characteristics (Felson 2008). For example, Andresen (2006) observes that the per cent of young people and the unemployment rate, which is an indicator of motivated offenders, were positively associated with property crimes (automotive theft and break and enter) and violent crime at the small-area scale. Likewise, Roncek and Maier (1991) show that bars and taverns, which are places thought to bring together motivated offenders and suitable targets with a lack of capable guardianship, were associated with higher levels of both property and violent crimes.

Building on the tenets of routine activity theory, crime pattern theory highlights how the interactions between offender activity patterns and features of the built environment lead to clusters of high and low crime at specific locations (Brantingham and Brantingham 2010). Crime pattern theory proposes that the spatial patterning of crime offences is simultaneously influenced by activity nodes, activity paths, and the environmental backcloth (Brantingham and Brantingham 1993); activity nodes are locations used by large populations for routine activities, such as employment, education, or shopping; activity paths are the routes between activity nodes, such as road networks or transit routes; and the environmental backcloth is composed of the broader social, political, and physical contexts in which activity nodes and paths are located (Deryol et al. 2016). While past research has shown that high traffic activity nodes and paths tend to have higher levels of crime than low traffic nodes and paths (Wilcox and Eck 2011), there are differences as to how specific crime types cluster in the urban environment. For example, Kinney et al. (2008) observe that both property crime (motor vehicle thefts) and violent crime (assaults) cluster around regional shopping centres whereas only property crimes tend to cluster around schools and universities.
**Crime-general and crime-specific hotspots**

Social disorganization, routine activity, and crime pattern theories provide the theoretical context for distinguishing between crime-general and crime-specific hotspots as applied to violent crime and property crime. Focusing first on crime-general hotspots, or areas where high levels of multiple crime types are co-located, the clustering of both violent crime and property crime may occur in areas with low informal social control. This aligns with past research showing that the processes hypothesized by social disorganization theory are associated with a number of violent and non-violent crime types (Chamberlain and Hipp 2015; Krivo and Peterson 1996). Routine activity theory and crime pattern theory also support the presence of crime-general hotspots as property crime and violent crime types have been shown to co-cluster around many of the same built environment features. For example, areas located in and around a central business district may be hotspots for property crime and violent crime because there are high densities of commercial land uses with material goods, which can be interpreted as potential property crime targets, as well as high densities of people engaged in employment and leisure activities, which can be interpreted as potential violent crime targets (Nelson, Bromley, and Thomas 2001).

Focusing on crime-specific hotspots, routine activity theory, in particular, highlights how the distribution of crime targets may lead to some locations being hotspots for only one crime type. For example, routine activity theory contends that property crime-specific hotspots may be located in non-residential areas that have many attractive targets, such as in shopping districts where there are many stores with physical goods suitable for theft offences but relatively fewer features likely to facilitate aggressive and violent behaviours (LaGrange 1999; Quick, Li, and Law 2019). Violent crime-specific hotspots, in contrast, may be more likely to occur in residential neighbourhoods that have low informal social control, weak social ties, and few attractive property crime targets. This is supported by differential opportunity theory, which hypothesizes that between-resident social ties and neighbourhood socio-economic characteristics influence crime type composition and crime frequency (Coward and Ohlin 1960; Schreck, McGloin, and Kirk 2009), as well as past social disorganization research suggesting that informal social control has a stronger influence on violent crime than property crime (Ouimet 2000; Haberman 2017; Sampson, Raudenbush, and Earls 1997).

**Methods for analysing spatial crime hotspots**

The most common quantitative methods used to identify spatial crime clusters or hotspots for small-area data are univariate testing-based approaches that analyse a single outcome or crime type, assume a null hypothesis of a random spatial distribution (or no spatial autocorrelation), and identify clusters or hotspots as groups of nearby points or areas that exhibit positive spatial autocorrelation of high crime (Anselin et al. 2000). Perhaps the most frequently applied method to intra-urban crime data in academic research, the local Moran’s I statistic calculates a measure of spatial autocorrelation for a given area and its nearby areas (as specified in an adjacency matrix) and evaluates statistical significance by comparing the local autocorrelation measure to a reference distribution created through random permutations of the study region data (Anselin 1995). Like local Moran’s I, the Getis-Ord \( G^*_i \) statistic calculates a local test statistic for a target area and its nearby areas, and compares this observed value to the expected value calculated based on the distribution of the variable for the study region (Getis and Ord 1992). Hotspots identified via the \( G^*_i \) statistic are areas where the difference between the local value and the expected local value are large and statistically significant. Both local Moran’s I and the \( G^*_i \) statistic have been applied to aggregate crime categories, specifically violent crime and property crime, as well as crime subtypes, including homicide, assault, robbery, burglary, theft, auto theft, and drug crimes (Ratcliffe and McCullagh 1999; Malleson and Andreessen 2015; Quick and Law 2013; Frazier, Bagchi-Sen, and Knight 2013; Haberman 2017; Cohen and Tita 1999; Kennedy, Caplan, and Piza 2011; Li and Radke 2012).

The third cluster detection method used in research to identify local hotspots of one crime type is the spatial scan statistic. The spatial scan statistic uses a scanning window that moves across point locations or small-area centroids to calculate a local test statistic based on the observed and expected crime risks inside of the scanning window at each location. The scanning window changes in size (i.e. increasing in radius up to a constraint) and identifies hotspots as the groups of small-areas or points inside of scanning windows that have high observed to expected ratios (Kulldorff 1997). Like local Moran’s I and the Getis-Ord \( G^*_i \) statistic, the spatial scan statistic has been applied to analyse a number of different crime types, such as robberies, drug offences, burglaries, and auto theft (Quick and Law 2013; Shiode 2011).
**Multivariate cluster detection**

Studies that apply the aforementioned univariate cluster detection methods to explore the similarities and differences between multiple crime types generally compare the locations, shapes, and sizes of hotspots identified from separate analyses. For example, Haberman (2017) applies three univariate hotspot identification methods to eleven crime types and, for each of the methods, quantifies the proportion of street intersections classified as hotspots for one or more crime types. Analysing each crime type separately, however, does not quantify the degree to which multiple crime types are located in the same or nearby locations (Mohan et al. 2011). Five multivariate methods have been proposed to explore the local co-clustering of two or more crime types: the local co-location quotient, the spatial point pattern test, the bivariate local Moran's I, the bivariate and multivariate join count statistics, and principal component analysis.

Given two point datasets (e.g. crime type \(a\) and crime type \(b\)), the local co-location quotient (LCLQ) quantifies the degree to which these patterns are clustered in similar locations by calculating the ratio between the number of type \(a\) points located within a fixed or adaptive bandwidth distance from a type \(b\) point and the number of type \(a\) points within the same bandwidth distance (Cromley, Hanink, and Bentley 2014). The LCLQ allows for spatial non-stationarity in the global co-location quotient proposed by Leslie and Kroenfeld (2011). Applied to analyse the co-location of crime and land use features, Wang et al. (2017) find that residential burglaries are significantly clustered near to entertainment facilities that are located close to, but not in, the CBD in Jiangsu Province, China, and Yue et al. (2017) show that e-bike thefts tend to be co-located with stores, banks, restaurants, and governmental facilities, but not industrial plants, in Wuhan, China. Because the LCLQ is designed to investigate the co-location of point-level data, however, it is not suitable for identifying crime-general hotspots for aggregated count or rate data at the area-level (Cromley, Hanink, and Bentley 2014).

The second method used to assess the co-location of two crime types is the spatial point pattern test. The spatial point pattern test measures the similarity of two geographically referenced point datasets by sampling a subset of points from one dataset (i.e. one crime type), simulating a distribution of crime counts within each area, and calculating the percent of areas for which the second dataset (i.e. the area-specific counts of a second crime type) falls within the confidence intervals generated from the sampled data (Andresen 2009; Malleson and Andresen 2015). The spatial point pattern test provides global information as to the overall similarities of two spatial patterns as well as local information that enables the identification of areas that have similar or dissimilar levels of the two crime datasets. Comparing and contrasting a number of crime types, including aggregated crime categories and specific subtypes, Andresen and Linning (2012) use the spatial point pattern test to show that some crime types have similar spatial patterns, such as commercial robbery and individual robbery, while other crime types do not have similar patterns, such as vehicle theft and robbery.

Extending the univariate local Moran’s I to two variables, bivariate local Moran’s I captures the relationship between the one variable in a given area and the spatial lag of a second variable (i.e. the average of the second variable in adjacent areas) (Lee 2001; Anselin 2019). Co-clusters of the two variables are identified as the areas with high levels of the first variable and the high levels of the spatially lagged second variable (Wang et al. 2017). The bivariate local Moran’s I has been infrequently applied in past crime research, perhaps because it does not account for the in-place (or within-area) correlation structures and overestimates the degree to which two variables are co-located (Anselin 2019). Whereas the bivariate local Moran’s I accommodate continuous variables measured within areas (i.e. crime rate), bivariate and multivariate joint count statistics have been proposed by Anselin and Xun (2019) to assess the co-clustering of two or more binary variables for data that exhibits in-place co-location, or where both variables can have a value of one in a given area, and data that does not exhibit in-place co-location, or where only one of the variables can have a value of one in a given area.

Principal component analysis (PCA) has also been applied to explore the co-location patterns of multiple crime types. PCA is often used to reduce the dimensionality of multivariate datasets and to create principal components, which are combinations of the two or more observed variables, that are not correlated and that maximize the variation of the observed variables. Pope and Song (2015) use PCA to examine the spatial patterning of 30 crime types at the small-area level, creating four principal components that represent contraband crimes, violent crimes, property crimes, and theft-related crimes. Conventional PCA methods, however, do not account for the spatial autocorrelation of principal components between nearby areas.

**Multivariate spatial modelling**

The above univariate and multivariate methods are testing-based insofar as they quantify the local clustering of
one dataset or the local co-clustering of two or more datasets, but do not provide insight into the observed (i.e. covariates) and/or latent (i.e. random effects terms) data-generating processes (Robertson et al. 2010). For example, while the LCLQ helps to identify locations where two crime types are co-located, this method does not consider how the patterning of each crime type is simultaneously explained by crime-general processes, as hypothesized by social disorganization and routine activity theories, or type-specific processes, as suggested by routine activity and differential opportunity theory (see Crime-general and crime-specific hotspots). Multivariate model-based approaches, in contrast, provide a framework for formalizing, testing, and estimating the spatial and/or non-spatial data-generating processes common to multiple variables (Knorr-Held and Best 2001; Held et al. 2005).

Recognizing that the local patterning of many crime types are similar, recent studies have used multivariate models to examine the ways in which multiple crime types are correlated over space and space-time. For example, Liu and Zhu (2017) and Chung and Kim (2018) use Bayesian models featuring the multivariate conditional autoregressive prior distribution to capture the correlations between two and three crime types, respectively. Both of these studies observe that accounting for the between-crime type correlation structures improves model fit compared to separate type-specific analyses. Identifying crime-general spatial patterns using a shared component modelling approach similar to the method applied in this study, Quick, Li, and Brunton-Smith (2018) show that burglary, robbery, vehicle crime, and violent crime share two distinct crime-general patterns, one that is common to all crime types and a second that is common to the theft-related crimes, and Quick, Li, and Law (2019) show that physical disorder, social disorder, property crime, and violent crime share a crime-general spatial pattern and a crime-general time trend.

Importantly, past studies applying multivariate modelling approaches to local crime data do not consider how these methods can be used to identify crime-general and crime-specific hotspots. In model-based methods, hotspots are often classified based on area-specific risk estimates and can be applied to specific model parameters via map decomposition (Richardson et al. 2004; Haining, Law, and Griffith 2009), whereas hotspots classified in testing-based approaches are based on rejecting a null hypothesis of no local spatial autocorrelation. Hotspot analysis methods are important for applications to crime prevention policies and programs because they provide location-specific information about where crime is highest and lowest (Chainey, Tompson, and Uhlig 2008). Multivariate hotspot analytical methods, in particular, have the potential to identify and differentiate between areas that should be targeted with comprehensive crime prevention initiatives designed for multiple crime types and areas that should be targeted with specialized initiatives designed for only one crime type (Weisburd et al. 1993; Haberman 2017).

Data and methods

Study region

The Regional Municipality of York is located north and adjacent to Toronto, Ontario, which is Canada’s largest city. In 2006, the study region had a population of 892,712, with nearly 95% of residents living in urban centres such as the cities of Markham, Vaughan, Richmond Hill, and Newmarket. The geographic unit of analysis for this study was the dissemination area (DA). DAs are the set of smallest census areas that cover the entirety of Canada and are delineated such that residential populations are between 400 and 800. The geographical boundaries and population data used in this study were retrieved from the 2006 Statistics Canada census. In total, York Region was composed of 1,128 DAs that had an average population of 791 and an average area of 1.90 km².

Crime data

Property crime and violent crime offence data for 2006 and 2007 were provided by the York Regional Police (YRP). Crime types were classified using Uniform Crime Reporting (UCR) survey codes; violent crimes included offences such as assault, sexual assault, and murder (UCR codes between 1000 and 2000), and property crimes included offences such as break and enter, motor vehicle theft, theft over $5,000, and theft under $5,000 (UCR codes between 2000 and 3000). The location of each crime offence was provided by YRP as a street address and each address was geocoded in ArcGIS 10.0 with a 98% match rate. This exceeds the minimum acceptable match rate of 85% proposed by Ratcliffe (2004). After geocoding, the number of property crimes and violent crimes were summed within each DA. The total counts of each crime type were obtained by summing the 2006 and 2007 counts. The standardized ratios of violent crime and property crime are mapped in Figure 1 (see Appendix A for descriptive statistics). Area-specific standardized ratios were calculated as the observed crime counts within each DA divided by the expected crime counts within each DA. Expected counts were calculated as the overall property crime or violent crime rate for the study region multiplied by the residential population within each DA.
Therefore, the expected crime counts account for the level of crime that would occur in a DA if the crime was distributed proportional to the residential population and control for the different total counts of property and violent crime in the study region. While there are many possible measures of the population at risk, such as daytime/evening populations for violent crimes or the number of theft targets for property crimes, residential population was the only data available for entirety of the study region at the DA scale. Note that conceptualizing and measuring the population at risk is challenging because offenders and targets are mobile over space and time and because quantitative estimates of these moving populations are often not available or accurately inferred using existing data (Kikuchi, Amemiya, and Shimada 2012; Zhang, Suresh, and Qiu 2012).

Exploring the maps of the standardized ratios of property crime and violent crime shows that both crime types had similar spatial patterns: areas with high-standardized ratios (>2) were located in the southwest and southeast of the study region, and areas with low-standardized ratios (<1) were located along the eastern boundary. The similarity of these two patterns is supported by a positive pairwise correlation between the standardized ratios of the two crime types (Pearson’s $r = 0.71$). Contrasting these two patterns, areas located in the north and northwest appear to have higher levels of violent crime than property crime whereas only a few groups of areas have higher levels of property crime than violent crime.

**Multivariate spatial modelling**

The shared component model used to identify crime-general and crime-specific patterns and hotspots are composed of Equations (1)–(4). Let $O_{ik}$ denote the observed crime counts, where $i$ indexes areas ($= 1, \ldots, 1128$) and $k$ indexes crime type ($= 1, 2$). For reference, $O_{i1}$ is the observed violent crime count in area $i$ and $O_{i2}$ is the observed property crime count in area $i$. The crime counts in each area are assumed to be independent Poisson random variables conditional on means $\mu_{i1}$ and $\mu_{i2}$, respectively (Equation (1)). The Poisson model is often used in Bayesian spatial modelling of count data at the small-area scale, where overdispersion and spatial autocorrelation are accounted for via random effects terms (Besag, York, and Mollie 1991; Richardson et al. 2004; Haining, Law, and Griffith 2009). In Equation (2), the Poisson means (on the log scale) are modelled as the product of the type-specific expected crime counts ($E_{ik}$) and the type-specific relative risks ($r_{ik}$). The type-specific expected crime counts are known quantities (as described in Crime data) and the type-specific relative risks, which are conceptually similar to the standardized ratios (Figure 1), are unknown quantities and are estimated in Equations (3) and (4).

\[
O_{ik} \sim \text{Poisson}(\mu_{ik})
\]  

\[
\log(\mu_{ik}) = \log(E_{ik}) \cdot \log(r_{ik})
\]  

Equation (3) estimates the relative risk of violent crime as the sum of the expected violent crime counts ($\log(E_{i1})$), a type-specific intercept ($\alpha_1$), a spatial shared component ($\delta \theta_i$), a set of type-specific spatially structured random effects terms ($s_{ij}$), and a set of type-specific unstructured random effects terms ($u_{ij}$). Equation (4) estimates the relative risk of property crime as the sum of the expected property crime counts ($\log(E_{i2})$), a type-specific intercept ($\alpha_2$), a spatial shared component
\((1/\delta(\theta))\), a set of type-specific spatially structured random effects terms \((s_{i2})\), and a set of type-specific unstructured random effects terms \((u_{i2})\) (Knorr-Held and Best 2001; Held et al. 2005). In Equations (3) and (4), the intercepts capture the average crime risks for the study region and the shared components capture the correlations between violent crime and property crime. The sum of \(s_{i2}\) and \(u_{i2}\) captures the type-specific spatial patterns that depart from the crime-general pattern and represent latent processes associated with only violent crime (Equation (3)) or only property crime (Equation (4)). In particular, the type-specific spatially structured random effects terms \((s_{i2})\) account for between-area spatial autocorrelation and risk that is explained by spatial processes amongst groups of nearby DAs and the type-specific unstructured random effects terms \((u_{i2})\) account for overdispersion and risk that is explained by within-area non-spatial processes (Besag, York, and Mollie 1991).

\[
\log(\mu_{i1}) = \log(E_{i1}) + a_1 + \delta \theta_i + s_{i1} + u_{i1}
\]

\[
\log(\mu_{i2}) = \log(E_{i2}) + a_2 + (1/\delta) \theta_i + s_{i2} + u_{i2}
\]

The shared components in Equations (3) and (4) are composed of a scaling parameter \((\delta\) or \(1/\delta\)) and a set of shared spatially structured random effects terms \((\theta_i)\). The shared random effects terms capture the crime-general spatial pattern common to both crime types and the scaling parameters allow each crime type to have a unique association with the crime-general spatial pattern. The shared component assumes that violent crime and property crime are associated with one or more of the same data-generating processes, which is supported by the crime-general mechanisms highlighted by social disorganization and routine activity theories, the positive correlation between violent crime and property crime (see Crime data), and the visual similarities observed in Figure 1.

For interpretation of the shared component, a value of \(\delta\) close to one indicates that violent crime and property crime have a similar magnitude of association with the crime-general pattern (i.e. if \(\delta = 1\), then \(1/\delta = 1\)) whereas a large positive value of \(\delta\) indicates that violent crime has a stronger association with the crime-general pattern than property crime (e.g. if \(\delta = 2\), then \(1/\delta = 0.5\)). Areas with high risk due to the crime-general pattern will have estimates of \(\exp(\theta_i) > 1\) at the 95% credible interval (95% CI)\(^1\) and areas with low risk due to the crime-general pattern will have estimates of \(\exp(\theta_i) < 1\) at the 95% CI. Likewise, areas with high risk due to the crime-specific patterns will have estimates of \(\exp(s_{i2} + u_{i2}) > 1\) at 95% CI and areas with low risk due to the crime-specific patterns will have estimates of \(\exp(s_{i2} + u_{i2}) < 1\) at 95% CI.

### Hotspot identification

In Bayesian statistical models, all unknown parameters are estimated as probability distributions (i.e. \(a_k, \delta, \theta_i, s_{ik}\), and \(u_{ik}\)) in Equations (3) and (4). A common hotspot identification approach in the Bayesian modelling framework uses these distributions to quantify the probability that one or more model parameters exceed a researcher-specified threshold. This is referred to as the posterior probability (Richardson et al. 2004). Following past studies using Bayesian modelling approaches to identify local crime hotspots, crime-general hotspots were evaluated based on the posterior probability of the shared random effects being greater than one \((\Pr(\exp(\theta_i) > 1 | \text{data}))\) and crime-specific hotspots were evaluated based on the posterior probability of the type-specific random effects being greater than one \((\Pr(\exp(s_{ik} + u_{ik}) > 1 | \text{data}))\) (Law, Quick, and Chan 2014, 2015; Li et al. 2014). Unlike univariate and multivariate testing-based hotspot identification methods, this shared component approach accounts for uncertainty in the area-specific risk estimates and allows for hotspots to be classified based on different thresholds that may reflect strategic priorities, crime prevention capabilities, and resources availability, for example.

In this study, three thresholds were used to identify and rank crime-general and crime-specific hotspots: 0.8, 0.9, and 0.95 (Richardson et al. 2004). Higher threshold values represent stronger evidence that an area is a hotspot. For example, if the risk due to the crime-general spatial pattern is very high in area \(i\) (i.e. a large proportion of the posterior distribution of \(\exp(\theta_i)\) is greater than one), then \(\Pr(\exp(\theta_i) > 1 | \text{data})\) will likely be greater than 0.8 and this area will be classified as a crime-general hotspot. In contrast, if the risk due to one of the type-specific components is close to one (i.e. approximately 50% of the posterior distribution of \(\exp(s_{ik} + u_{ik})\) is less than one), then \(\Pr(\exp(s_{ik} + u_{ik}) > 1 | \text{data})\) will be close to 0.5 and this area will not be classified as a crime-specific hotspot.

### Prior distributions and model fitting

All prior distributions specified for this modelling approach are detailed in Appendix B, however, two prior distributions are of note. First, each set of spatially structured random effects terms \((\theta_i, s_{i1},\) and \(s_{i2}\)) were assigned an intrinsic conditional autoregressive prior distribution (ICAR) with an unknown common variance \((\sigma^2_0, \sigma^2_1,\) and \(\sigma^2_2\)). The ICAR prior imposes a spatially smoothed risk surface and captures spatial autocorrelation between
adjacent areas as specified by a queen-contiguity adjacency matrix (Besag, York, and Mollie 1991). Second, the logarithm of the scaling parameter (i.e. log(δ)) was assigned a normal distribution with a mean of 0 and a variance of 0.17. This prior assumes that both δ and 1/δ are positive, which is supported by the positive correlations between the two crime types (see Crime data). This prior also assumes that the ratio of the two scaling parameters (i.e. δ/(1/δ)) is between 0.2 and 5 with 95% probability (Knorr-Held and Best 2001). This was confirmed based on the results showing that this ratio was greater than 0.2 and less than 5 at the 95% CI. Note that estimating one scaling parameter (δ) for one outcome variable and assigning the inverse to the second outcome variable improves model identifiability compared to estimating separate scaling parameters for each outcome (Lawson 2009; Knorr-Held and Best 2001).

The Bayesian multivariate shared component model, which was composed of Equations (1)–(4), was fit using the Markov chain Monte Carlo (MCMC) algorithm in WinBUGS v.1.4.3 (Lunn et al. 2000). Two MCMC chains were initiated at dispersed starting values and the convergence of model parameters was monitored by trace plots and Gelman–Rubin statistics. For each chain, 20,000 iterations were discarded as burn-in and an additional 20,000 iterations, thinned by 10 to reduce autocorrelation of the MCMC samples, were retained for posterior inference.

Results
Table 1 shows the results of the multivariate shared component model. The scaling parameters, which quantify the relative association between each crime type and the crime-general spatial pattern (the set of shared spatially structured random effects terms), were both found to be close to one. This indicates that violent crime and property crime had a relatively similar influence on the underlying crime-general pattern. One explanation for this is that both property crime and violent crime were analysed as standardized ratios and had similar scales centred near one (see Appendix A). If the crimes were analysed as counts without expected counts used as offsets or as rates with a common population at risk or denominator, for example, then the more frequent crime type could have a larger scaling parameter and a greater relative influence on the crime-general pattern (Quick, Li, and Law 2019).

The magnitude of the empirical variances of the two sets of type-specific random-effects terms helps to understand the relative importance of the spatial and non-spatial processes for understanding the crime-specific spatial patterns. For both violent crime and property crime, the largest empirical variances were attributed to the shared component (Table 1). This indicates that the crime-general spatial pattern was relatively more important for understanding the overall distribution of both crime types than the crime-specific patterns. Of the two type-specific components, the empirical variance of the unstructured random effects terms was larger than the empirical variance of the spatially structured random effects terms for both crime types (Table 1). Note that when variance terms are estimated to be near to zero, the corresponding random effects parameters can be interpreted as having little explanatory importance. This suggests that there was little spatial autocorrelation exhibited by either crime-specific pattern after accounting for the crime-general spatial pattern.

Variance partition coefficients (VPC) provide an alternative approach to understanding how the crime-general and crime-specific patterns explain the overall patterning of violent crime and property crime (Goldstein, Browne, and Rasbash 2002). For example, the VPC quantifying the proportion of total variation of violent crime explained by the crime-general pattern is equal to the empirical variance of δθ divided by the sum of the empirical variances of δθ, s1i, and u1i. Likewise, the VPC quantifying the proportion of total variation of property crime explained by the crime-general pattern is equal to the empirical variance of (1/δ)θi divided by the sum of the empirical variances of (1/δ)θi, s2i, and u2i. In this study, the shared component representing the crime-general spatial pattern captured 81% (95% CI: 74–89%) of the total variation of violent crime and 70% (95% CI: 64–77%) of the total variation of property crime. In contrast, the type-specific components explained less than 30% of the total variation of both crime types, with

| Table 1. Results of the multivariate shared component model. The posterior medians of model parameters are shown with 95% CIs in parentheses. |
|--------------------------------|-----------------|-----------------|
| Violent crime | Property crime |
| Intercept (exp(β0)) | 0.71 (0.68, 0.73) | 0.61 (0.59, 0.63) |
| Scaling parameter | 1.02 (0.96, 1.08) | 0.98 (0.93, 1.04) |
| Empirical variances of random effects terms |  |  |
| Shared component | 0.56 (0.48, 0.65) | 0.52 (0.44, 0.60) |
| Type-specific spatially structured component | 0.01 (0.001, 0.05) | 0.01 (0.002, 0.05) |
| Type-specific unstructured component | 0.11 (0.07, 0.16) | 0.21 (0.16, 0.25) |
the unstructured type-specific random effects terms accounting for more than 90% percent of this type-specific variability.

**Crime-general and crime-specific patterns and hotspots**

Figure 2 maps the crime-general spatial pattern and the two crime-specific spatial patterns. The crime-general pattern captures the underlying risk surface common to both violent crime and property crime and the crime-specific patterns capture the risk for each type that diverges from the crime-general pattern. Visually, the crime-general pattern is representative of the similarities between the violent crime and property crime patterns shown in Figure 1, with areas of high risk concentrated in the southwest and in the north of the study region. Focusing on the crime-specific patterns, violent crime and property crime had a relatively similar number of areas with a high relative risk (\(\exp(s_{ik} + u_{ik}) > 1\)), with 506 areas for violent crime and 518 areas for property crime. Property crime exhibited greater variation of type-specific relative risks, with a minimum estimate of 0.46 (95% CI: 0.22–0.93) and a maximum estimate of 6.60 (95% CI: 1.00–10.82). This compares with violent crime, which had a minimum type-specific risk estimate of 0.61 (95% CI: 0.33–1.10) and a maximum of 2.49 (95% CI: 1.53, 4.20). Visually, areas with high violent crime-specific risk were dispersed throughout the study region whereas areas with high property crime-specific risk were clustered primarily in the southwest.

Crime-general and crime-specific hotspots are visualized in Figure 3. Of the three hotspot types, crime-general hotspots were the most frequent (34.8% of all areas), followed by property crime-specific hotspots (15.5%) and violent crime-specific hotspots (9.6%). There were also a number of areas that had overlapping hotspot classifications; approximately 10% of areas were both crime-general and property crime hotspots, 7% of areas were both crime-general and violent crime hotspots, and 15 areas (1.3% of all areas) were identified as crime-general, violent crime-specific, and property crime-specific hotspots (Figure 3).

Geographically, the crime-general hotspots were often grouped in relatively large clusters, such as the areas located in the north, in the southwest, and in central areas of the study region (all with \(\Pr(\exp(\theta_i) > 1 \mid \text{data}) \geq 0.95\)). This can be explained by the shared random effects terms being specified as a set of spatially structured random effects terms that borrow strength from adjacent areas to estimate a spatially smoothed risk surface (see Prior distributions and model fitting). In comparison, violent crime-specific and property crime-specific hotspots were typically composed of only a small number of areas and were scattered throughout the study region. This supports the results indicating that the type-specific unstructured random effects accounted for a larger proportion of variation than the

![Figure 2](image-url) Figure 2. Crime-general (\(\exp(\theta_i)\)) and crime-specific spatial patterns (\(\exp(s_{ik} + u_{ik})\)).
type-specific spatially structured random effects, and accordingly, this study suggests that the non-spatial within-area processes influencing only property crime or only violent crime were relatively more important than the type-specific spatial processes shared amongst nearby areas (Table 1). Because this study controlled for the different total counts of violent crime and property crime via the expected crime counts (Equation (2)), the larger number of property crime-specific hotspots can be attributed to the shared component explaining a smaller proportion of variation of property crime (70% compared to 81% for violent crime) and, therefore, a larger number of areas having unusually high (and low) property crime-specific risks.

Discussion

This study has applied a Bayesian spatial shared component model to identify crime-general and crime-specific hotspots for property crime and violent crime at the small-area scale. The multivariate shared component model used in this paper jointly analyzes two crime types and separates the area-specific risks of the crime types into a shared component, which captures the crime-general spatial pattern, and type-specific components, which capture the crime-specific spatial patterns that diverge from the crime-general pattern. Crime-general and crime-specific hotspots were classified using the posterior probabilities of the shared and type-specific components. This study found that both violent crime and property crime had similar associations with the underlying crime-general pattern, that the crime-general pattern explained the largest proportion of variation for both crime types, and that crime-general hotspots were more frequent than both types of crime-specific hotspots.

The shared component modelling approach illustrated in this study provides a framework for quantifying the spatial and non-spatial correlation structures between multiple variables and for differentiating the data-generating processes that are crime-general, or shared amongst multiple crime types, and crime-specific, or unique to each crime type. This contrasts with existing univariate and multivariate cluster detection methods, which test for local spatial autocorrelation of one variable or more than one variable but do not provide insight into if and how the processes associated with crime patterns are crime-general and/or crime-specific. For example, compared to the separate application of univariate cluster detection methods to each crime type and classifying crime-general hotspots as the overlapping areas identified as clusters for both property crime and violent crime, the shared component model applied in this study estimates the crime-general relative risk for all-areas in the study region; allows for the crime-general pattern to be spatially autocorrelated.
and to be differentially influenced by each crime type; uses the crime-general relative risk estimates to identify crime-general hotspots; and enables researchers and analysts to classify hotspots based on multiple different thresholds after accounting for uncertainty of the area-specific risk estimates.

From a theoretical perspective, analysing crime-general and crime-specific hotspots strengthens inference regarding how the urban environment influences multiple crime types simultaneously. The results of this study suggest that the spatial patterns and hotspots of violent crime and property crime arise from similar data-generating processes at the small-area scale, as shown by the shared component explaining the largest proportion of variation of both crime types and by the crime-general hotspots being more frequent than the type-specific hotspots. While this has been observed in past social disorganization and routine activity research that compares the results of many univariate analyses (Ceccato, Haining, and Signoretti 2002; Andresen 2006; Chamberlain and Hipp 2015), this study provides quantitative evidence that the local patterns of violent crime and property crime were relatively more similar than different at the study region scale. Note that, while including risk factors is not common in hotspot analyses, this multivariate shared component model can be extended to include covariates (Quick, Li, and Brunton-Smith 2018; Quick, Li, and Law 2019) and future research focused on explaining the differences between crime-general and crime-specific patterns should look to include covariates that operationalize social disorganization, routine activity, and crime pattern theories, and examine how these risk factors influence the location of crime-general and crime-specific hotspots.

Classifying crime-general and crime-specific hotspots via a Bayesian spatial shared component model also provides information relevant to the design, allocation, and implementation of crime prevention policies and programs at both the study region and small-area scales. Because crime-general hotspots were found to be more common than both types of crime-specific hotspots, the results of this study suggest that law enforcement resources at the study region scale be focused on comprehensive policies and programs that address the geographically situated processes associated with criminal behaviour, broadly defined, rather than the geographically situated processes associated with only one crime type. Comprehensive interventions may look to prioritize addressing the factors common to multiple crime types, specifically informal social control, as hypothesized in social disorganization theory, and the convergence of motivated offenders, suitable targets, and a lack of capable guardianship, as outlined in routine activity theory. Groff (2015) draws parallels between these two concepts and suggests that interventions focused on changing offender perceptions of what constitutes appropriate behaviour in a given place may be effective for overall crime reduction. A focus on comprehensive interventions at the study region scale is also supported by the finding that a majority of crime-general clusters had very strong evidence of being a hotspot, with 60% of all crime-general hotspots having posterior probability estimates greater than 0.95 (Figure 3).

At the local scale, the 15 areas concurrently identified as crime-general hotspots, property crime-specific hotspots, and violent crime-specific hotspots are areas where law enforcement may look to initiate comprehensive programs focused on all crime types. One example may be a community consultation programme that brings together law enforcement and residents to identify issues of local importance and increase participation in crime prevention. These types of community-centred initiatives may also help to uncover why high levels of property crime and high levels of violent crime are correlated and strengthen resident-based informal social control, which has been shown to be associated with many different crime types (Braga and Schnell 2013). Areas classified as only property crime-specific or violent crime-specific hotspots, on the other hand, maybe suitable for interventions targeted to type-specific behaviours and contexts. One approach is situational crime prevention, which attempts to prevent and deter crime through reducing the physical opportunities for offending and increasing the likelihood that an offender will be caught by the police (Clarke 1980). For example, target hardening initiatives that increase security and surveillance of material goods in stores or homes in areas identified as property crime-specific hotspots may be effective at reducing opportunistic property crime offending in these areas, but may be less effective at reducing aggressive and violent behaviours in areas classified as violent crime-specific hotspots (Herbert and Harries 1986; Clarke 1997).

Limitations and future research

One limitation of this study is that the crime data does not account for crime events that are unreported to police or all spatial dimensions of criminal behaviour. For example, it is possible that datasets measuring crime calls-for-service or crime victimization, or datasets representing offender residences or crime harms may exhibit different correlation structures and different shared patterns than those identified in this study (Curtis-Ham and Walton 2017). Future work may look to integrate two or more of these datasets in a multivariate shared component model, explore the similarities and
differences amongst the different types of crime data, and identify locations that have high risks of offences, offenders, and harms.

A second limitation of this study is that only property crime and violent crime types were made available to the researchers by YRP, yet past research has shown that specific crime subtypes exhibit different spatial patterns than these two broader categories (Andresen and Linning 2012). As such, the results of this study may not reflect the spatial patterns and hotspots identified when analysing more specific crime subtypes. When data is accessible, future studies should explore the crime-general and crime-specific patterns amongst all, or subsets of, multiple different crime subtypes, however, this will likely require more complex and potentially intractable models that better account for sparse spatially correlated data, such as joint zero-inflated or hurdle models (Feng and Dean 2012). Past research has also suggested that different operationalizations of the population at risk impact the identification of crime hotspots (Andresen 2011) and so future studies should explore how populations inferred via remote sensing of ambient daytime/evening populations, tracking of individual or aggregate activity spaces, or geolocated social media activity impact the location of crime-general and crime-specific hotspots (Andresen 2011; Kikuchi, Amemiya, and Shimada 2012; Malleson and Andresen 2015; Downs 2016).

Future research should also explore how local crime-general and crime-specific spatial patterns change over time. Extending the spatial multivariate shared component model to space-time data at annual, seasonal, monthly, daily, and hourly scales would allow researchers and practitioners to identify emerging crime-general and crime-specific hotspots and design location- and time-specific policies for multiple crimes or only one crime. A spatiotemporal shared component modelling approach would also provide a framework for evaluating the effects of place-based crime prevention policies and programs on crime-general and crime-specific processes as well as the corresponding diffusion or displacement of crime (Hall and Liu 2009). Additionally, to overcome the limitations of data aggregation within areas (Zhang, Suresh, and Qiu 2012), studies should consider developing shared component models for micro-scale or point-based data that can accommodate crime events recorded for street intersections, street segments, or addresses.

**Note**

1. The 95% credible interval is the interval that contains the true value of a parameter with 95% probability. In Bayesian statistics, credible intervals are analogous to confidence intervals in frequentist statistics.

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No potential conflict of interest was reported by the authors.

**ORCID**

Matthew Quick [http://orcid.org/0000-0002-1112-9323](http://orcid.org/0000-0002-1112-9323)

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### Appendix A. Descriptive statistics for violent crime and property crime (2006–2007) at the dissemination area (DA) level

|                  | Violent crime | Property crime |
|------------------|--------------|---------------|
| Total count      | 10,970       | 38,959        |
| Mean             | 9.72         | 34.53         |
| Standard deviation | 18.31       | 106.19        |
| Minimum          | 0            | 0             |
| Maximum          | 379          | 2,721         |
| Standardized ratio * | 1.01         | 0.98          |
| Mean             | 1.27         | 2.14          |
| Standard deviation | 39.88       |               |

*The standardized ratios were calculated as the observed crime counts divided by the expected crime counts (see Crime data).*

### Appendix B. Prior distributions for Equations (3) and (4)

Improper uniform priors were assigned to the two type-specific intercepts ($\alpha_1$ and $\alpha_2$). The two sets of type-specific unstructured random effects terms were assigned normal distributions with means of zero with common unknown type-specific variances, $\sigma^2_{u1}$ and $\sigma^2_{u2}$.

The two sets of type-specific spatially structured random effects terms were each assigned intrinsic conditional autoregressive prior distributions (ICAR) with a common unknown type-specific variance, $\sigma^2_s$. The shared random effects terms ($\theta_i$) were also assigned an intrinsic conditional autoregressive prior distribution (ICAR) with an unknown variance, $\sigma^2_{\theta}$ (Held et al. 2005). In the ICAR model, the posterior means of $s_{ik}$, for example, are equal to the average of the posterior means of the $s_{ik}$’s in adjacent areas and the variance is the equal to $\sigma^2_s/n$, where $n$ is the number of adjacent small-areas specified in the areal adjacency matrix. As such, the $s_{ik}$’s account for local spatial autocorrelation of crime between nearby areas, and areas with many neighbouring areas have more precise estimates of $s_{ik}$ than areas with few adjacent areas (Besag, York, and Mollie 1991). A queen-contiguity adjacency matrix was used to define the spatial structure of the study region.

For the variance parameters of the random effects terms, *Inverse Gamma* (1.0, 0.01) distributions were assigned for $\sigma^2_{u1}$, $\sigma^2_{u2}$, $\sigma^2_s$, and $\sigma^2_{\theta}$ (Held et al. 2005). To ensure that this prior distribution did not substantially influence the results of this study *Inverse Gamma* (0.1, 0.1) and *Inverse Gamma* (0.01, 0.01) distributions were also tested (Lunn et al. 2000; Ancelet et al. 2012). The results for all sensitivity tests were nearly identical to the results presented in this study.