Article

Urban Analytics and City Science

EPB: Urban Analytics and City Science
0(0) 1–16

DOI: 10.1177/2399808319846904
journals.sagepub.com/home/epb
SAGE

The temporality of place: Constructing a temporal typology of crime in commercial precincts

J Corcoran, R Zahnow and A Kimpton
The University of Queensland, Australia

R Wickes
Monash University, Australia

C Brunsdon
Maynooth University, Ireland

Abstract

Well established in criminological scholarship is the way that crime is neither spatially nor temporally uniformly distributed. Rather crime is distributed in a manner that means it is both particular places and particular times that are subject to the majority of crime events. Furthermore, we know that crime varies over the course of a day and week, with periods of time the same place can function as a crime generator, a crime attractor or as a crime detractor. What is less evident is the way in which some places 'flip' from a largely crime free space to one that provides the necessary preconditions for crime to occur. In this paper we focus on commercial precincts as the context, given their functional importance in our daily lives; providing places of employment, recreation and a locus for social encounters. By spatially integrating crime incident data and census information and employing circular, clustering and spline regression techniques we examine the intensity, tempo and timing of crime in these locales and generate a temporal typology for 2286 commercial precincts across Queensland, Australia.

Keywords

Circular statistics, spline regression, clustering, temporality of place

Corresponding author:
J Corcoran, School of Earth and Environmental Sciences, Queensland Centre for Population Research, The University of Queensland, Queensland, Australia.
Email: jj.corcoran@uq.edu.au

Introduction

Our urban world is comprised of a mosaic of places. Each place has its own intrinsic daily rhythm shaped by population flows (Felson and Boivin, 2015). Population dynamics at places are governed by its form and function along with its location and connection to other features of the urban environment (Lefebvre, 1991). Some places are subject to high population flows throughout the day as individuals enter and exit to fulfil daily routine activities. Other areas, especially those that are largely residential, experience far less daily population flow and may be left largely unpopulated during work/school hours. Daily population flows influence opportunities for crime by facilitating and/or impeding the co-presence or indeed absence of offenders, targets and guardians (Cohen and Felson, 1979; Sutherland and Cressey, 1978).

In the last 30 years we have established a relatively robust understanding of the spatial patterns of crime and place-based risk. According to routine activity theory (RAT) and associated theories, time and space are ‘partners in crime’ so to speak. That is, RAT purports that criminogenic situations arise when a motivated offender and suitable target come together in *time* and *space* in the absence of effective guardianship (Cohen and Felson, 1979). This scholarship has identified places and facilities that tend to experience higher levels of crime, such places are referred to as ‘hotspots’, ‘generators’, ‘attractors’ and ‘risky facilities’ (Brantingham and Brantingham, 1993; Weisburd et al., 2004). Notable risky facilities include bars (Bernasco and Block, 2011; Groff and Lockwood, 2014; Peterson et al., 2000; Roncek and Maier, 1991), schools (Roncek, 2000), greenspaces (Kimpton et al., 2017), commercial areas (Browning et al., 2010; LaGrange, 1999; Taylor et al., 1995) and transit stations (Block and Block, 2000; Block and Davis, 1996; Hart and Miethe, 2015; Irvin-Erickson and La Vigne, 2015).

A smaller body of research reports the temporal rhythms of crime. Historically, time series methods have been applied to explore longitudinal crime trends at larger spatial units. Results demonstrate that annual crime trends exhibit seasonal fluctuations coinciding with regular activities associated with cooler and warmer months of the year (Andresen and Malleson, 2013; Field, 1992; Hipp et al., 2004; McDowall et al., 2012; Uittenbogaard and Ceccato, 2012). Crime events also peak on particular days of the week (Andresen and Malleson, 2015; Haberman et al., 2017; Tompson and Bowers, 2015; Townsley, 2008). Scholars suggest there is a tendency for crime to occur on days and at times when obligatory activities (e.g. school, employment) are limited and individuals have a greater amount of discretionary time (Quick et al., 2017; Tompson and Bowers, 2015). As yet, these assertions have not been tested empirically.

Certainly, we know that legitimate activities at places follow daily temporal patterns, largely reflecting official opening and closing times. Recent work has sought to delve into the nuances of crime temporality at facilities by exploring the distribution of events across segments of the day (Bernasco et al., 2017; Ceccato and Uittenbogaard, 2014; Herrmann, 2015; also see Andresen and Malleson, 2015; Ceccato, 2005; Grubesic and Mack, 2008). For example, Ceccato and Uittenbogaard (2014) identify temporal patterns of crime in Stockholm underground stations noting events peak during the late afternoon and evening ‘rush hour’ when people are travelling home from work or performing unstructured activities (Ceccato and Uittenbogaard, 2014). Yet, even within groups of risky facilities there is a great deal of variation in the timing of legitimate activities that determine population flows and, we suggest, also in the temporality of crime opportunities. For example, while some underground stations will experience very high levels of crime in the evening others will not. Indeed, Eck et al. (2007) propose that crime in a specific geographic area will be highly concentrated within a small number of risky facilities while most will experience little or even no crime (Eck et al., 2007).

The aim of this paper is to extend recent studies of temporal variations in crime at places by focusing on one particular group of risky facilities, *commercial precincts*, and developing a new method capable of delineating a typology based on daily and weekly crime dynamics. We expect this will be dependent on the mix of facilities in the precinct: the legitimate activities the facilities support and their hours of operation as well as broader environmental features of the area and user characteristics. We focus on commercial precincts because they are common across the study site (providing an adequate *n* for analysis) and exhibit heterogeneity in characteristics expected to influence population flows and the temporal distribution of crime (e.g. size, operating hours, legitimate activities hosted at the site and accessibility) (Brantingham and Brantingham, 1998; Ratcliffe, 2004).

To achieve our aim we draw on 12 months of disaggregate crime incident data and census information to identify 2286 commercial precincts in Queensland, Australia before examining the intensity, tempo and timing of drug, property, nuisance and violent crime across these locations. We employ an innovative combination of clustering and circular regression techniques to distinguish different typologies of commercial precincts based on their temporal crime dynamics for specific offence categories.

There are a number of benefits associated with establishing a temporal typography for risky facilities: this approach attends to heterogeneity *within* groups of risky facilities, acknowledges Pareto's Law of concentration (aka 80–20 rule; Eck et al., 2007; Weisburd et al., 2004) and avoids examining facilities at the individual level, an approach that can limit the generalisability and the practical utility of findings. We contend that the typology has utility in its ability to reveal temporal commonalties that can be used to inform the design and deployment of place-based crime prevention. Assessing risk and developing prevention protocols for individual facilities is both time and resource intensive. Developing a typology to identify common patterns and assign individual facilities to a particular sub-group reduces this burden.

Background literature

Scholarly interest in spatial and temporal patterns of crime is not new. Over the last decades criminology has developed a vast theoretical and empirical literature addressing the uneven distribution of crime across place (Bernasco and Block, 2011; Browning et al., 2010; Bruinsma and Johnson, 2018; Kinney et al., 2008; Stucky and Ottensmann, 2009). First introduced in the context of rapid social changes stemming from the Second World War, RAT aimed to explain changes in crime at the national level (Cohen and Felson, 1979). RAT explains the uneven distribution of crime events as a function of the intersection between daily routines and the social and physical environment (Cohen and Felson, 1979). When considered at the aggregate level, the way in which individuals move through space while carrying out their daily schedule has implications for crime. Specifically, RAT proposes that opportunities for crime arise when overlapping activity spaces bring potential offenders and targets together in the absence of effective guardianship (Cohen and Felson, 1979). Particular social and physical environments facilitate or indeed impede the coalescence of these elements. The regularity of daily routines and familiarity with places and situations at the meso (neighbourhood) and micro (individual facility) levels are therefore linked to the propensity for potential offenders to recognise and act on crime opportunities (Brantingham and Brantingham, 1993, 1995).

Risky facilities

Risky facilities, also referred to as crime generators and crime attracters, are places that have a heightened propensity for crime (Eck et al., 2007). Heightened risk at these places is related to their functional purpose which may generate busyness (Wilcox et al., 2004) and/or attract would be offenders by providing easy access to targets (Bernasco and Block, 2011; Brantingham and Brantingham, 1993, 1995; McCord and Ratcliffe, 2009; Taylor et al., 1995; Wuschke and Kinney, 2018). Facilities associated with higher risk of crime include a range of commercial entities such as bars (Bernasco and Block, 2011; Groff and Lockwood, 2014; Peterson et al., 2000; Roncek and Maier, 1991), retail outlets, payday lenders and restaurants (Bernasco et al., 2017; Gordon and Brill, 1996; Kubrin and Hipp, 2016; Smith et al., 2000; Steenbeek et al., 2012).

As common activity nodes, commercial precincts form part of the legitimate awareness space of many people (Wuschke and Kinney, 2018). Common nodes that facilitate the convergence of individual activity spaces are associated with heightened crime risk. However, not all commercial precincts generate equal opportunities for crime, meaning crime risk varies within this group of facilities. Eck et al. (2007) demonstrate the relevance of the 80–20 rule when considering risky facilities of a similar type. The 80–20 rule, also referred to as Pareto's Law or the J-curve, purports the tendency for the majority of crime to occur at a small proportion of facilities. This pattern of concentration is also evident in the distribution of victimisation and offending among victims and offenders, respectively (Eck et al., 2007; Herrmann, 2015; Wuschke and Kinney, 2018).

Taking the concept of crime concentration a step further, intra-facility *temporal* variance in opportunities for crime also exist. Even at spatial crime hotspots, it is unlikely that opportunities for crime are equal across all days of the week and times of the day (Andresen and Malleson, 2015; Haberman et al., 2017; Tompson and Bowers, 2015). Temporal concentrations of crime events at places coincide with place-based regularities in human behaviour that influence co-presence. Largely, these regularities are governed by biological necessities (e.g. sleep, eating), social norms, the legitimate functions of a facility and whether hosted activities are obligatory or discretionary (Bernasco et al., 2017; Hägerstraand, 1970; Quick et al., 2017; Ratcliffe, 2006; Tompson and Bowers, 2015). Temporal patterns of crime at individual facilities will also vary depending on the type of crime considered (Andresen and Malleson, 2013). For example, theft at commercial precincts would likely cluster during business opening hours, especially in the case of retail outlets. In practical terms, potential offenders have much easier access to targets when a store is open compared to when a store is closed, locked and security systems are engaged. However, opportunities for violence or interpersonal crimes may be greater when businesses are closed and there are fewer legitimate users accessing the area to act as guardians. Thus, some facilities are part of a crime hotspot during business hours but comprise a cold spot during other times of the day. While these facilities are part of a spatio-temporal 'hotspot' they are not 'hot dots'; hot dots are micro-locations that experience a stable pattern of concentrated crime over time (Ignatans and Pease, 2018; Pease et al., 2018). Interest in identifying people and places that comprise the 'vital few' hot dots consistently contributing to hotspots over time is emerging in the policing field as a way to maximise the precision of targeted crime interventions (Ignatans and Pease, 2018).

While empirical evidence elucidating the spatiality of crime has grown steadily over the last decades, it is only very recently that scholars have turned their attention to examining the temporal nuances of crime and offending at particular locations. The majority of this work has established support for the routine activities explanation for spatial–temporal variations in crime, reporting that patterns of crime coincide with behavioural regularities and reflect patterns of legitimate use. Andresen and Malleson (2013, 2015) employ a spatial point pattern test to assess seasonal and daily patterns of crime in Canadian neighbourhoods. They demonstrated that the spatial patterns of crime across census tracts and dissemination areas varied by day of the week. Examining temporal trends in robbery at a smaller spatial unit – the street block – Haberman et al. (2017) also found daily fluctuations in spatial patterns of offences across the city of Philadelphia. While some street segments experienced consistently high levels of robbery, others exhibited peaks in robbery at particular times of the day and days of the week resulting in temporal shifts in spatial patterns of robbery at the larger spatial scale.

Focusing on temporal crime patterns at a particular group of facilities, Ceccato and Uittenbogaard (2014) examined temporal patterns of crime in Stockholm's underground transit system at three temporal units: season of the year, day of the week and hour of the day. Counter to their expectations that crime would peak during summer, crime events were highest during the winter months. This may be related to greater crowd density on stations when individuals are seeking protection from the weather in cooler months. There was also evidence that crime was higher on weekends than weekdays and, in particular, between the hours of 4 pm and midnight when stations are experiencing peak periods of legitimate use. Quick et al. (2017) report similar findings. They examined seasonal variations in the relationship between land use and property crime across six groups of risky facilities. Property offences at parks consistently peaked during summer/spring while offences at transit stations and eating and drinking establishments were highest in winter and autumn. There was no evidence of seasonality in property offences at commercial areas, schools or in the central business district. They suggest differences in the influence of season on property crime across facilities are associated with consistent versus changing ('seasonal') target availability. Similarly, Haberman and Ratcliffe (2015) identified a moderating influence of time of the day on the relationship between risky facilities and crime. Robbery was associated with parks only during the daytime when parks are used for legitimate activities. Likewise, the relationship between pawn shops and increased crime risk was only apparent during the afternoon when the shops were open for legitimate business.

Recently, Bernasco et al. (2017) applied the RAT framework to examine variations in street robbery across days of the week and hours of the day at risky facilities across Chicago. They found limited support for the assertion that crime at places exhibits significant temporal variability. Other studies have also failed to find evidence that place-based crime risk changes over the course of the day (Breetzke and Cohn, 2013; Hart and Miethe, 2015). So why the conflicting findings? While previous studies represent a significant contribution to the literature, missing from their research is a consideration of *heterogeneity* in crime risk within a group of risky facilities of similar type. The ubiquitous 80–20 rule must be considered when examining temporal patterns of crime at risky facilities of similar types. Analyses of crime across all schools, retail outlets or bars within a meso-level geographic unit (e.g. neighbourhood or census block) would fail to highlight temporal signatures of the minority of places that host the majority of the crime. As it is not possible, or useful, to devise time signatures for individual blocks or facilities, instead we propose that for a particular group of facilities we can impart a classification system based on the temporal distribution of risk across a 24 hour period to inform the allocation of regulatory resources and place management strategies.

To effectively regulate co-presence in shared spaces requires an understanding of the temporal patterns of crime opportunities. Current practices in urban planning, design and place regulation assume invariance in temporal patterns of crime across facilities of a particular type within a larger geographic unit, typically looking at aggregate counts

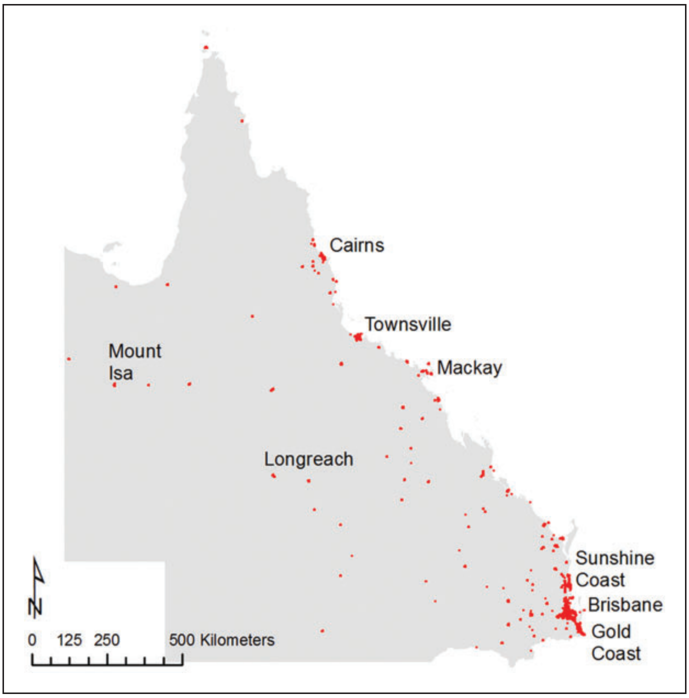

Figure 1. Commercial precincts across Queensland, Australia.

of crime for a month or year. Underdeveloped is our understanding of variations in temporal crime patterns across groups of facilities of similar type. Focusing on the most troublesome places *and times* will have greater impacts on crime across the community than distributing prevention and response efforts to all places and times. Understanding place–time crime dynamics can inform both formal security responses and informal place management strategies.

Case study context, data and methods

The State of Queensland forms the study context (Figure 1). Using the smallest geographic unit of the 2016 census, the mesh block[1] (ABS, 2016), a total of 2286 commercial precincts were identified across Queensland. These precincts range in size from 1600 to 9,142,500 square metres and represent a broad spectrum of commercial developments from a small strip of shops to large regional shopping centres. Crime incident data were procured from the Queensland Police Service for a 12-month period (1 January to 31 December 2016) in order to temporally align with the 2016 census data. Four crime types form the focus of investigation: drug crimes, property theft, property damage and public nuisance.[2]

Of the 291,713 total crime incidents in Queensland (for our four crime types) during 2016, 18.96% (55,317) were located in commercial precincts (representing just over 1% of the State's land cover), of which there were 5781 drug crimes, 29,587 property thefts, 3870 incidents involving property damage and 16,079 recorded public nuisances (Figure 2).

Cluster analysis on our crime data is performed using partitioning around medoids (PAM), the most common form of k-medoid clustering. PAM is employed to partition a

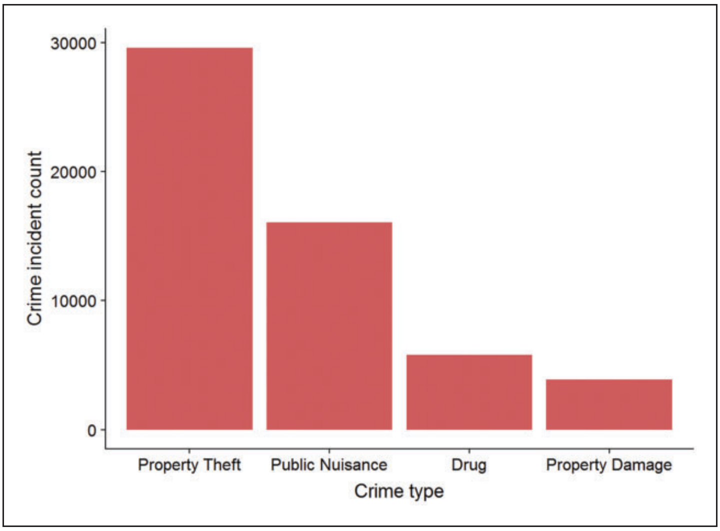

Figure 2. Count of crimes in commercial precincts.

set of objects into k number of clusters through searching for what Rousseeuw and Kaufman (1990) term *representative objects*. Subsequent to identifying the set of representative objects that describe a given data set, clusters are formed through assigning each object to their closest representative object. One particularly useful feature of PAM is its ability to robustly capture cluster centres, which is especially important in situations where objects poorly align to clusters (Van der Laan et al., 2003).

We perform an isometric log ratio (ILR) transform to allow for the fact that precincts can vary in size, and so rather than working directly with counts, proportions of each crime in a precinct are considered (Egozcue et al., 2003). Such quantities are constrained to add up to 1 for each precinct (or 100 if percentages are used) and also to be not less than zero. These constraints can distort the distance metrics used in PAM to assess similarity of crime type composition. Essentially there is one degree of freedom less than the number of crime types and less variability in the distribution of proportions when some are close to zero or one. The ILR transform takes the proportions as an m-dimensional vector and maps them on to an *unconstrained* $m-1$ dimensional vector space. The definition of the transform is relatively complicated, but details are given in the Egozcue paper cited above. Furthermore, an R package offering a function for carrying out the transformation ('compositions') is documented in Van den Boogaart and Tolosana-Delgado (2008). Distances between vectors in the transformed space are not subject to the distortions mentioned above and are a better foundation for the cluster analysis.

To visualise the results of the cluster analysis in the form of radar plots, cyclic splines are fitted. These have a roughness penalty, and satisfy $f(x) = f(x + c)$, $f'(x) = f'(x + c)$ and $f''(x) = f''(x + c)$ where $c = 24 \times 7 = 168$ hours.

Results and discussion

The cluster analysis reveals distinct weekly cluster types that are each specific to a particular crime type (Figure 3). For example, for drug crimes the four distinct types might be described in the following way: Type 1, *multimodal weekend peak*, displays a particular

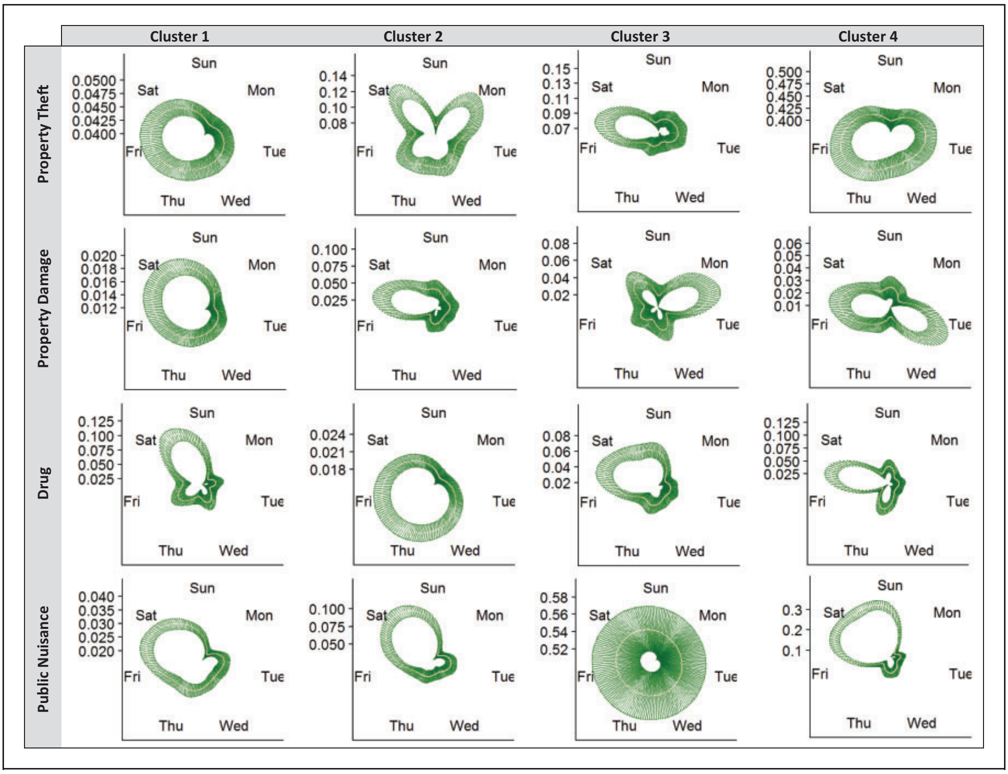

Figure 3. Weekly cluster types for each crime with 95% error bars.

predominance of crimes during both weekend days. Type 2, *low uniform*, wherein the full weekly cycle is characterised by low crime. Type 3, *high uniform*, is characterised by moderate to high levels of crime through most of the week with a peak Friday evening. Type 4, *multimodal weekday and weekend peak*, is characterised by two main peaks, a smaller one in the early hours of Thursday morning and a larger one on Friday night. Plotting the four cluster types with their 95% error bars at each observation indicates that for each cluster and crime type, error is acceptable, with the exception of cluster 3 for nuisance crimes. In this particular case, cluster 3 represents just 14 commercial precincts that are subject to 24.9% of all public nuisance crimes. Table 1 provides a full assessment of commercial precinct membership by cluster and crime type.

The geography of cluster types for drug crimes (Figure 4) reveals an interesting mix of cluster membership across the study context. The two map panels at the bottom of Figure 4 show this mix of cluster membership in Brisbane (left) and within Brisbane's Central Business District (CBD) and surrounds (right). Both maps highlight the way in which the temporality of crime in spatially adjacent commercial precincts can be very different. For example, of the 106 commercial precincts that are depicted in the Brisbane CBD and surrounds (Figure 4, bottom right), all four temporality types are represented (Type 1 (36), Type 2 (21), Type 3 (34), Type 4 (15)) and display no systematic spatial patterning; rather there exists is a relatively spatial dispersed patterning. This is confirmed through a test for spatial autocorrelation wherein Moran's I[3] values for each of the cluster types reveal either relatively weak positive spatial autocorrelation (clusters 2 and 3, with I values of 0.04 ($p = 0.00$) and 0.184 ($p = 0.00$), respectively), or spatially random patterns (clusters 1 and 4,

Table 1. Number (and proportion) of commercial precincts by crime and cluster type.

	Cluster membership				Total number of commercial precincts
	1	2	3	4	
Property theft	1200 (76.7%)	185 (11.8%)	117 (7.5%)	62 (4.0%)	1564 (68.4%)
Property damage	950 (83.7%)	55 (4.8%)	46 (4.1%)	84 (7.4%)	1135 (49.7%)
Drug	68 (6.1%)	890 (80.3%)	89 (8.0%)	62 (5.6%)	1109 (48.5%)
Public Nuisance	938 (81.7%)	144 (12.5%)	14 (1.2%)	52 (4.5%)	1148 (50.2%)

with I values of 0.02 ($p = 0.50$) and -0.02 ($p = 0.94$), respectively). Examination of the geography of cluster types for the other crime categories reveals a similar story. That is for all cluster types either weak positive spatial autocorrelation or spatially random patterns exist (Table 1).

Taken together the results suggest that crime in commercial precincts is for the large part precinct specific and is a likely reflection of the characteristics of the site that include accessibility, opening hours and regulation. For example, while some commercial precincts remain open to the public after closing hours, others have security screens that restrict the entry of individuals after stores have closed. As such, we would argue that these site-specific features act to either permit or restrict the flow of temporary populations at certain times of the day and in doing so regulate the co-presence of potential targets, offenders and guardians. Thus, the design of commercial precincts is critical in conditioning both the number of individuals in the space and the mix of legitimate and non-legitimate users. Further, the spatial patterning of cluster types is likely a consequence of the multiple functions of commercial places. For example, Type 2 (property theft), Types 3 and 4 (property damage) and Type 4 (drug crimes) precincts display multi-modal weekday and weekend peaks which may be indicative of their multiple functions such as late night shopping during the week as well as forming part of a night time entertainment district during weekends.

The variation in crime at fine spatial scales (such as the individual address or street segment), commonly referred to in the literature as 'micro places' is well established in criminological scholarship (Braga et al., 2010; Weisburd et al., 2004). Whereas the focus of much of this literature has been to understand crime at fine spatial scales, here we place the focus on the temporality of crime and argue the need to consider this dimension in alliance with space in order to unpack the crime narrative within and across places. Revealing the way in which the temporality of crime varies across places is particularly important because increasing population density, the demise of the universal 9 to 5 work day and shifts towards a 24 hour economy, are bringing together a greater diversity of potential offenders, victims and targets in particular places across longer periods of the day and night (here we focus on commercial spaces). Further, in many of these places the regulatory responsibilities straddle private security and police during times when the legitimate users (commercial operators and customers/clients) are not present. This means that it is even more important to have a targeted approach to prevention and response so the role of security and police can be clearly articulated.

The differences we capture in our typology of commercial precincts are likely a reflection of daily population flows and, in the case of commercial facilities, in large part mirror the opening hours of these places. From the demographic scholarship we know that there exists a large shift in population numbers from one area of a city to another throughout the day (Charles-Edwards, 2016; Dobson et al., 2000; Novák and Sýkora, 2007; Shen, 2002). This area of research remains an emerging area of interest as new methods and sources of data

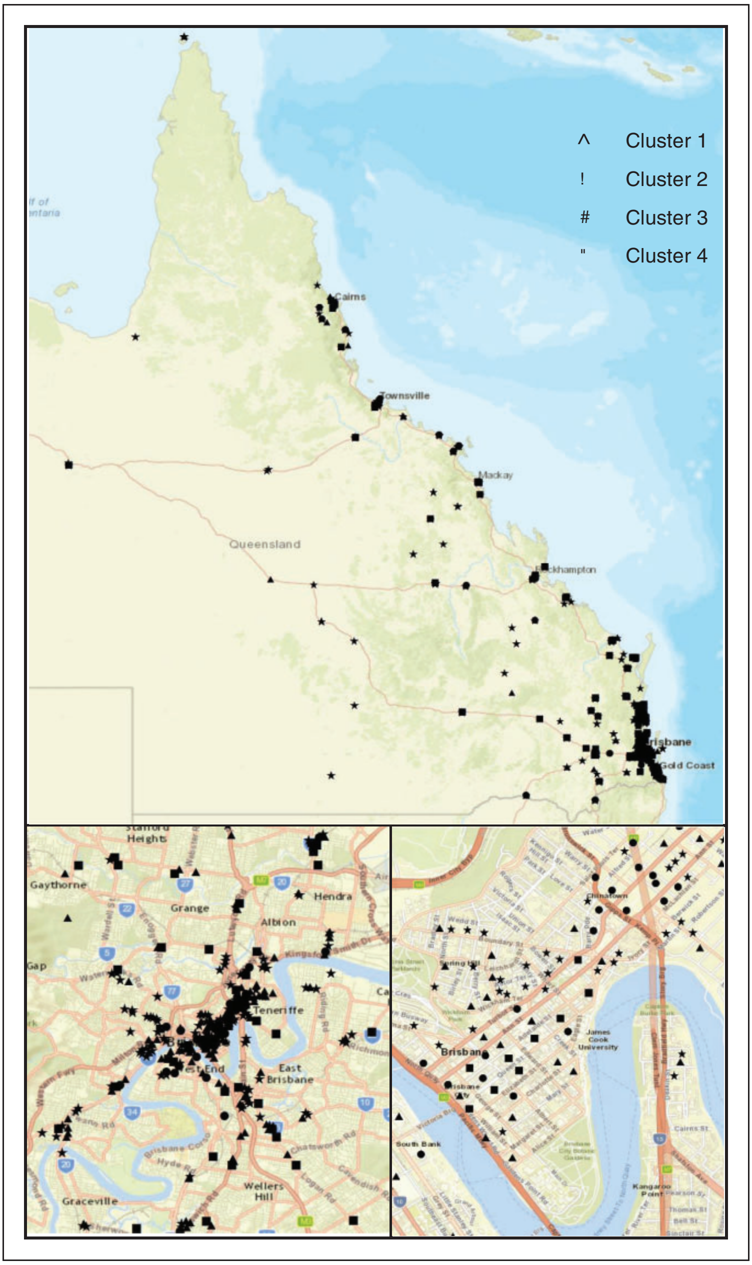

Figure 4. The geography of cluster types (drug crimes).

become available through which temporary populations can be estimated at progressively finer spatial and temporal scales (Kontokosta and Johnson, 2017). The recent availability of mobile phone-based data and the use of smartphone applications would appear promising in its capacity to offer high resolution coverage of a metropolis (Ahas et al., 2010; Birenboim and Shoval, 2016); however, data confidentiality issues are arguably the greatest hindrance to its broader application for temporary population estimation.

A key consideration in studies incorporating a time component is the choice of temporal unit. To date the crime literature has examined seasonal variations across the year (McDowall et al., 2012), variations across days of the week (Andresen and Malleson, 2015) and to a lesser extent differences between day and night time crime (Ceccato and Uittenbogaard, 2014). However, there tends to be an inverse relationship between the degree of aggregation in the spatial and temporal components; when larger spatial units are used, temporal units tend to be smaller. The opposite is also true. In this paper we use the location and timing of crime at the finest space-time granularity that is possible with the data available, that is by hour of day and by mesh block. In doing so, allied with the application of our temporal typology method, we reject the assumption that temporal patterns of crime across facilities in a geographic area are homogeneous and align with Eck et al.'s (2007) finding that the timing and intensity of crime across risky facilities of a similar type is heterogeneous.

A number of limitations associated with the input data and the results need noting. First, offence types occurring within commercial precincts are diverse and go beyond the four presented herein. Given this, re-running the clustering method for each independent crime type would be useful to reveal the way in which drug offences might differ in their temporal signature to assault or robbery, for example. The second limitation relates to the temporal accuracy of the crime data. Previous research has highlighted the way in which the officially recorded time of a crime may not be reflective of the actual time the crime occurred and that this precision varies by crime type (Ratcliffe, 2002). As such it is reasonable to assume that for the four crime types used in this study that the time associated with each recorded crime varies in precision and is reflective of whether witnesses were present at the time of a crime and if these witnesses reported the incident to the police as it was unfolding or were at least able to report an accurate event time. We do know that for some crimes such as robbery, the difference between the recorded time of the offence and the actual time can be a matter of seconds, whereas burglary can be as much as weeks in situations where home owners return from a period away to find their place burgled (Ratcliffe, 2002). In lieu of any alternate data (such as accident and emergency records or information from social media feeds such as Twitter or Facebook) through which we can triangulate crime timings, we need to treat the results with some degree of caution as it relates to temporal precision.

The development of our temporal clustering methodology paves the way for several avenues of future research. First, is the collection of data that helps us to estimate the way that crime intersects with the temporary populations present within and across our commercial facilities. Given that many commercial precincts offer free Wi-Fi coverage this would appear to be a promising data source to begin to unpack the temporary population–crime relationship (Charles-Edwards and Bell, 2013). Second, is to model the determinants of cluster membership to ascertain the extent to which built and natural environmental features in alliance with socio-demographic characteristics play a role in generating crime opportunities. Third, is to apply our methodology to other situational contexts and land use types to reveal the extent to which the cluster types identified for commercial facilities in Queensland, Australia exist elsewhere as it relates to their spatial and temporal dynamics.

Conclusions

In this paper we have developed a new method to construct temporal typologies of crime. With a focus on the 2286 commercial facilities across the State of Queensland, Australia our method distinguished four distinct cluster types. Interestingly, the geographic patterning of these four cluster types shows that the temporality of crime in spatially adjacent commercial facilities can be very different. This is likely reflective of daily population flows, business hours as well as the local security presence and physical design of these locales – all features that contribute to crime opportunities. The capacity to segment facilities based on patterns of crime in this way has direct utility in both the allocation of finite policing resources to specific locales at specific times identified as crime prone, as well as in the development of common crime prevention initiatives to apply across locations considered to be members of the same cluster type.

The practical implications of this research go beyond criminal justice responses to crime prevention and management wherein we suggest that the findings can inform urban planners and local building management authorities on how to best utilise 'mixing' of facilities to optimise the presence of legitimate users of commercial precincts and minimise unnecessary encounters between likely or motivated offenders (illegitimate users) and targets when security, police or informal guardians are not present. Identification of a precinct's typology can reveal its crime opportunity profile and associated prevention action, thus avoiding the necessity for costly and time consuming individual site analyses. For example, in our study, crime prevention initiatives in precincts that are members of clusters 3 and 4 should target theft with a particular focus on Friday evenings. Focusing interventions on peak crime types and 'hot' times has the greatest potential to impact overall crime rates which in turn can positively affect public perceptions of the precinct, improve feelings of safety and increase patronage. Identification of a precinct's typology can also help to manage, and set priorities within, a local area's situational crime prevention strategy for planners and developers. In situations where evenings are identified as the crime 'hot' time, lighting may be the top priority for physical environmental approaches to safety. In areas where property damage is revealed as the most common problem, CCTV and target hardening approaches, including access control during particular hours, could be appropriate approaches. These examples demonstrate that a key benefit of the method we present here for capturing temporal signatures of crime at places is the direct transferability of the research outcomes to practice.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was funded by the Australian Government through the Australian Research Council Discovery project scheme, DP150101293.

ORCID iD

J Corcoran https://orcid.org/0000-0003-3565-6061

Notes

1. It should be noted that the land use ascribed to a mesh block is an indicator of the main planned land use. A mesh block is formed from an aggregation of individual land parcels.
2. Theft includes both theft and the handling of stolen goods, public nuisance includes good order offences and illegal alcohol consumption, drug crimes include consumption and dealing, and property damage includes unlawful entry and arson.

3. Moran's I values were computed using the total number of crimes recorded in a given commercial precinct, by cluster type. The distance metric was inverse distance squared and row standardisation was employed.

References

Ahas R, Aasa A, Silm S, et al. (2010) Daily rhythms of suburban commuters' movements in the Tallinn metropolitan area: Case study with mobile positioning data. *Transportation Research Part C: Emerging Technologies* 18(1): 45–54.

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

Andresen MA and Malleson N (2015) Intra-week spatial-temporal patterns of crime. *Crime Science* 4(1): 1–11.

Australian Bureau of Statistics (2016) Australian Statistical Geography Standard (ASGS): Volume 1 – Main structure and greater capital city statistical areas, July 2016. Catalogue number: 1270.0.55.001. Available at: http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016?OpenDocument (accessed 6 October 2017).

Bernasco W and Block B (2011) Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency* 48(1): 33–57.

Bernasco W, Ruiter S and Block R (2017) Do street robbery location choices vary over time of day or day of week? A test in Chicago. *The Journal of research in crime and delinquency* 54(2): 244–275.

Birenboim A and Shoval N (2016) Mobility research in the age of the smartphone. *Annals of the American Association of Geographers* 106(2): 283–291.

Block RL and Block CR (2000) The Bronx and Chicago: Street robbery in the environs of rapid transit stations. In: Mollenkopf J (ed) *Analyzing Crime Patterns: Frontiers in Practice*. London: Sage, pp.147–148.

Block RL and Davis S (1996) The environs of rapid transit stations: A focus for street crime or just another risky place? In: Clarke RV (ed) *Preventing Mass Transit Crime*. Monsey, NY: Criminal Justice Press, pp.237–257.

Braga AA, Papachristos AV and Hureau DM (2010) The concentration and stability of gun violence at micro places in Boston, 1980–2008. *Journal of Quantitative Criminology* 26(1): 33–53.

Brantingham PL and Brantingham PL (1993) Environment, routine and situation: Toward a pattern theory of crime. *Advances in Criminological Theory* 5(2): 259–294.

Brantingham P and Brantingham P (1995) Criminality of place. *European Journal on Criminal Policy and Research* 3(3): 5–26.

Brantingham PL and Brantingham PJ (1998) Mapping crime for analytic purposes: Location quotients, counts, and rates. *Crime Mapping and Crime Prevention* 8: 263–288.

Breetzke GD and Cohn EG (2013) Burglary in gated communities: An empirical analysis using routine activities theory. *International Criminal Justice Review* 23(1): 56–74.

Browning CR, Byron RA, Calder CA, et al. (2010) Commercial density, residential concentration and crime: Land use patterns and violence in neighborhood context. *Journal of Research in Crime and Delinquency* 47(3): 329–357.

Bruinsma GJ and Johnson SD (eds) (2018) *The Oxford Handbook of Environmental Criminology*. Oxford: Oxford University Press.

Ceccato V (2005) Homicide in Sao Paulo, Brazil: Assessing spatial-temporal and weather variations. *Journal of Environmental Psychology* 25(3): 307–321.

Ceccato V and Uittenbogaard AC (2014) Space–time dynamics of crime in transport nodes. *Annals of the Association of American Geographers* 104(1): 131–150

Charles-Edwards E (2016) The estimation of temporary populations in Australia. In: Wilson T, Charles-Edwards E and Bell M (eds) *Demography for Planning and Policy: Australian Case Studies*. Cham: Springer, pp.31–49.

Charles-Edwards E and Bell M (2013) Estimating the service population of a large metropolitan university campus. *Applied Spatial Analysis and Policy* 6(3): 209–228.

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

Dobson JE, Bright EA, Coleman PR, et al. (2000) LandScan: A global population database for estimating populations at risk. *Photogrammetric Engineering and Remote Sensing* 66(7): 849–857.

Eck JE, Clarke RV and Guerette RT (2007) Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. *Crime Prevention Studies* 21: 225.

Egozcue JJ, Pawlowsky-Glahn V, Mateu-Figueras G, et al. (2003) Isometric logratio transformations for compositional data analysis. *Mathematical Geology* 3(35): 279–300.

Felson M and Boivin R (2015) Daily crime flows within a city. *Crime Science* 4(1): 31.

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

Gordon CL and Brill W (1996) The expanding role of crime prevention through environmental design in premises liability. National Institute of Justice Research in Brief. Available at: https://www.ncjrs.gov/pdffiles/cptedlia.pdf (accessed 16 April 2019).

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.

Grubesic TH and Mack EA (2008) Spatio-temporal interaction of urban crime. *Journal of Quantitative Criminology* 24(3): 285–306.

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

Haberman CP, Sorg ET and Ratcliffe JH (2017) Assessing the validity of the law of crime concentration across different temporal scales. *Journal of Quantitative Criminology* 33(3): 547–567.

Hägerstraand T (1970) What about people in regional science? *Papers in Regional Science* 24(1): 7–24.

Hart TC and Miethe TD (2015) Configural behavior settings of crime event locations: Toward an alternative conceptualization of criminogenic microenvironments. *Journal of Research in Crime and Delinquency* 52(3): 373–402.

Herrmann CR (2015) The dynamics of robbery and violence hot spots. *Crime Science* 4: 33. DOI: 10.1186/s40163-015-0042-5

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

Ignatans D and Pease K (2018) Crime concentrations: Hot dots, hot spots and hot flushes. In: Bruinsma GJ and Johnson SD (eds) *The Oxford Handbook of Environmental Criminology*. Oxford: Oxford University Press, pp.664–690.

Irvin-Erickson Y and La Vigne N (2015) A spatio-temporal analysis of crime at Washington, DC metro rail: Stations' crime-generating and crime-attracting characteristics as transportation nodes and places. *Crime Science* 4(1): 14.

Kimpton A, Corcoran J and Wickes R (2017) Greenspace and crime: An analysis of greenspace types, neighboring composition, and the temporal dimensions of crime. *Journal of Research in Crime and Delinquency* 54(3): 303–337.

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

Kontokosta CE and Johnson N (2017) Urban phenology: Toward a real-time census of the city using Wi-Fi data. *Computers, Environment and Urban Systems* 64: 144–153.

Kubrin CE and Hipp JR (2016) Do fringe banks create fringe neighborhoods? Examining the spatial relationship between fringe banking and neighborhood crime rates. *Justice Quarterly* 33(5): 755–784.

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(4): 393–422.

Lefebvre H (1991) *The Production of Space*. Oxford: Blackwell Publishers.

McCord ES and Ratcliffe JH (2009) Intensity value analysis and the criminogenic effects of land use features on local crime patterns. *Crime Patterns and Analysis* 2(1): 17–30.

McDowall D, Loftin C and Pate M (2012) Seasonal cycles in crime, and their variability. *Journal of Quantitative Criminology* 28(3): 389–410.

Novák J and Sýkora L (2007) A city in motion: Time-space activity and mobility patterns of suburban inhabitants and the structuration of the spatial organization of the Prague metropolitan area. *Geografiska Annaler: Series B, Human Geography* 89(2): 147–168.

Pease K, Ignatans D and Batty L (2018) Whatever happened to repeat victimisation? *Crime Prevention and Community Safety* 20(4): 256–267.

Peterson R, Krivo L and Harris M (2000) Disadvantage and neighborhood violent crime: Do local institutions matter? *Journal of Research in Crime and Delinquency* 37(1): 31–63.

Quick M, Law J and Li G (2017) Time-varying relationships between land use and crime: A spatio-temporal analysis of small-area seasonal property crime trends. *Environment and Planning B: Urban Analytics and City Science*. Epub ahead of print 4 December 2017. DOI: 10.1177/2399808317744779. First Published December 4, 2017

Ratcliffe JH (2002) Aoristic signatures and the spatio-temporal analysis of high volume crime patterns. *Journal of Quantitative Criminology* 18(1): 23–43.

Ratcliffe JH (2004) The hotspot matrix: A framework for the spatio-temporal targeting of crime reduction. *Police Practice and Research* 5(1): 5–23.

Ratcliffe JH (2006) A temporal constraint theory to explain opportunity based spatial offending patterns. *Journal of Research in Crime and Delinquency* 43: 261–291.

Roncek D (2000) Schools and crime. In: Goldsmith V, McGuire P, Mollenkopf J, et al. (eds) *Analyzing Crime Patterns: Frontiers of Practice*. London: Sage, pp.153–165.

Roncek DW and Maier PA (1991) Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of 'hot spots'. *Criminology* 29(4): 725–753.

Rousseeuw PJ and Kaufman L (1990) *Finding Groups in Data*. Hoboken, NJ: Wiley Online Library.

Shen J (2002) A study of the temporary population in Chinese cities. *Habitat International* 26(3): 363–377.

Smith WR, Frazee SG and Davison S (2000) Furthering the integration of routine activity theory and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology* 38(2): 489–523.

Steenbeek W, Völker B, Flap H, et al. (2012) Local businesses as attractors or preventers of neighborhood disorder. *Journal of Research in Crime and Delinquency* 49(2): 213–248.

Stucky TD and Ottensmann JR (2009) Land use and violent crime. *Criminology* 47(4): 1223–1264.

Sutherland EH and Cressey DR (1978) *Criminology*. 10th ed. Philadelphia, PA: Lippincott.

Taylor RB, Koons BA, Kurtz EM, et al. (1995) Street blocks with more nonresidential land use have more physical deterioration: Evidence from Baltimore and Philadelphia. *Urban Affairs Review* 31: 20–136.

Tompson LA and Bowers KJ (2015) Testing time-sensitive influences of weather on street robbery. *Crime science* 4(1): 8.

Townsley M (2008) Visualising space time patterns in crime: The hotspot plot. *Crime Patterns and Analysis* 1(1): 61–74.

Uittenbogaard AC and Ceccato V (2012) Space-time clusters of crime in Stockholm, Sweden. *Review of European studies* 4(5): 148–156.

Van den Boogaart GK and Tolosana-Delgado R (2008) "Compositions": A unified R package to analyze compositional data. *Computers and Geosciences* 4(34): 320–338.

Van der Laan M, Pollard K and Bryan J (2003) A new partitioning around medoids algorithm. *Journal of Statistical Computation and Simulation* 73(8): 575–584.

Weisburd D, Bushway S, Lum C, et al. (2004) Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology* 42(2): 283–322.

Wilcox P, Quisenberry N, Cabrera DT, et al. (2004) Busy places and broken windows? Toward defining the role of physical structure and process in community crime models. *Sociological Quarterly* 45(2): 185–207.

Wuschke K and Kinney JB (2018) Built environment, land use and crime. In: Bruinsma G and Johnson S (eds) *The Oxford Handbook of Environmental Criminology*. New York: Oxford University Press, pp.475–496.

J Corcoran is Professor in Human Geography within the School Earth and Environmental Sciences at The University of Queensland, Australia and the director of the Queensland Centre for Population Research. His research interests lie in the fields of Population Geography, Spatial Science and Regional Science. His publications cover topics including human mobility and migration, human capital, and social problems each of which has a focus on quantitative methods. He is the co-editor of Australian Population Studies and Secretary of the Applied Geography Commission.

R Zahnow is a Lecturer in Criminology at the School of Social Sciences at the University of Queensland. Renee has expertise in spatial and longitudinal analyses; she has applied these skills to examine a range of social problems including crime, disorder, substance use and community regulation. Renee's research focuses on place-based patterns of crime and victimisation; she is particularly interested in understanding the link between the regularities of daily human mobility, social and behavioural norms and the propensity for crime and deviance.

A Kimpton is a postdoctoral research fellow within the School Earth and Environmental Sciences at The University of Queensland, Australia, and his research interests include social sustainability, place, urban mobility and land use, data science, and urban analytics. Topics explored within his publications include social equity, place attachment, crime, greenspace, land use classification, circular statistics, and urban mobility.

R Wickes is an Associate Professor in Criminology in the School of Social Sciences at Monash University in Melbourne, Australia. Her research focuses on demographic changes in urban communities and their influence on community regulation, crime and disorder. She has published in journals such as Criminology, Journal of Research in Crime and Delinquency, Social Forces, Journal of Quantitative Criminology, Urban Studies, American Journal of Community Psychology among others. She is the lead investigator of the Australian Community Capacity Study, a multisite, longitudinal study of place.

C Brunsdon is Professor of Geocomputation, and Director of the National Centre for Geocomputation at Maynooth University, Ireland. Prior to this, Chris was Professor of Human Geography at the University of Liverpool in the UK, before which he worked in the Universities of Leicester, Glamorgan and Newcastle, all in the UK. Chris has degrees from Durham University (BSc Mathematics) and Newcastle University (MSc Medical Statistics, PhD in Geography). His research interests lie in spatial data analysis, spatial statistics and geocomputation, focusing on reproducible approaches, health data analysis and the analysis of crime patterns.