

Making environmental criminology smarter – A framework for directly measuring routine activities using passively collected geolocation data

Daniel Birks¹, Toby Davies¹, Stijn Ruiter^{2,3},
Timothy C. Hart⁴, Wim Bernasco^{2,5}
and Michael Townsley⁶

Urban Studies

1–19

© Urban Studies Journal Limited 2026



Article reuse guidelines:

sagepub.com/journals-permissions

DOI: 10.1177/00420980261443112

journals.sagepub.com/home/usj

Abstract

We propose novel methods for analysing spatio-temporal tracking data collected via smartphones with the purpose of exploring the extent to which foundational, but as yet untested, assumptions within environmental criminology are observed in real-world behaviour. We provide systematic and replicable methods for identifying and quantifying nodes, trips, visits, paths and activity spaces – key elements of human mobility which underpin the vast majority of theoretical and empirical crime and place-based research. Our approach is illustrated through analyses of data captured from a sample of 16–24 year olds living in urban Australia. Implications for theoretical testing, refinement and extension are discussed.

Keywords

ecological momentary assessment, environmental criminology, GPS tracking, human mobility, routine activities

¹Centre for Criminal Justice Studies, School of Law, University of Leeds, UK

²Netherlands Institute for the Study of Crime and Law Enforcement, Amsterdam, The Netherlands

³Department of Sociology, Utrecht University, The Netherlands

⁴Department of Criminology and Criminal Justice, University of Tampa, FL, USA

⁵Department of Spatial Economics, School of Business and Economics, Vrije Universiteit Amsterdam, The Netherlands

⁶School of Criminology and Criminal Justice, Griffith University, Brisbane, QLD, Australia

Corresponding author:

Daniel Birks, Centre for Criminal Justice Studies, School of Law, University of Leeds, Leeds LS2 9JT, UK.

Email: d.birks@leeds.ac.uk

摘要

我们提出了用于分析智能手机采集的时空追踪数据的新方法，旨在探究环境犯罪学中那些基础性、但尚未得到验证的假设，在现实世界行为中被观测到的程度。我们提供了系统且可复现的方法，用于识别与量化节点、出行、到访、路径和活动空间。这些人类流动性的核心要素，是绝大多数犯罪与空间相关的理论和实证研究的基础。我们通过对澳大利亚城市地区 16 至 24 岁人群样本的采集数据开展分析，阐释了本研究方法的应用。本文探讨了本研究对理论检验、理论完善与理论拓展的启示意义。

关键词

生态瞬时评估、环境犯罪学、GPS 追踪、人类流动性、日常活动

Received: 27 November 2024; accepted: 20 February 2025

Introduction

While crime has generally declined in Western cities since the early 1990s (Farrell et al., 2014), it continues to be an inherent aspect of urban life, imposing significant social costs and influencing collective perceptions of safety and justice. Beyond direct harm to victims, crime can restrict urban residents' freedom to engage in everyday activities and deter investments that are crucial for city development. These dynamics not only impact quality of life but may also generate, reflect or reinforce spatial inequalities: crime affects communities to different degrees, and is concentrated within particular localities (Weisburd, 2015). In this context, understanding how crime shapes – and is shaped by – broader urban processes such as mobility, gentrification and segregation is essential for better understanding the urban condition and the social, economic, and spatial processes that define it.

Environmental criminology proposes that patterns of crime are best understood as the aggregation of numerous situated micro-level interactions between people and their environment. Contemporary understanding

in this domain has been heavily influenced by Cohen and Felson's (1979) routine activity approach and Brantingham and Brantingham's (1981, 1984) geometry of crime and crime pattern theory. These perspectives assert that where and when people spend their time is the key driver in bringing together the essential elements for crime – suitable targets, motivated offenders, and the absence of capable guardianship. The provision of these elements, they argue, is best considered through the lens of everyday activities – the locations people frequently visit (often referred to as routine activity nodes), the pathways that connect them, and the physical, social and economic backcloths within which they are situated (Brantingham and Brantingham, 1984; Brantingham et al., 2016).

This approach has generated powerful heuristics supporting both theoretical and applied efforts to understand the spatio-temporal character of crime (see Wortley and Townsley, 2017). Cohen and Felson's landmark early work, which reconciled increased crime rates post-WWII with systematic changes to routine activities, has

underpinned numerous seminal developments in the field. While deceptively simple, the Routine Activity Approach places everyday activity patterns at the heart of crime opportunity, helping to explain both long term trends and fine-grained patterns of crime. It has informed the logic of hot-spots policing (Sherman et al., 1989) and provided the theoretical foundation for the analyses of spatio-temporal clustering in crime events (Johnson et al., 2007), journey-to-crime patterns (Rossmo, 2000) and offender targeting strategies (Bernasco et al., 2013a).

Despite the prominence of this perspective, however, environmental criminology has consistently been hindered by its inability to directly measure the primary explanatory variable: the routine space-time behaviour of individuals. In the absence of direct observations, research has instead relied upon aggregated measures, such as those which identify sets of places that vary in how often they are frequented. While these variations may reflect their usage by the population as a whole, they do not allow the testing of individual-level theories, which are specified in terms of the way in which an individual's *personal* risk of victimisation or offending is influenced by the structure of their routine behaviours.

Other approaches are individual-focussed, but aggregated over time or activities. For example, many national victimisation surveys measure the frequency of different activities away from home and correlate these indicators with victimisation outcomes (e.g. 'During a typical week, on how many evenings do you go out for fun and recreation?' Osgood et al., 1996: 653). Such approaches are not sufficiently specific, though, to capture the particular settings to which theory refers: what matters is *where* and *when* individuals go out, and whether it is in these settings that victimisation occurs (Lemieux and Felson, 2012).

The lack of measurement is even more pronounced for paths than for nodes: there is scant empirical evidence about how individuals travel *between* places, and specifically the routes they take when doing so. Studies must instead rely on proxy measures (Davies and Johnson, 2015), and are again limited to the aggregate level. Given the theoretical importance of these paths, this significantly limits our ability to verify core theoretical principles.

Recent work by Browning et al. (2021) offers a comprehensive review of the role of mobility in criminological theories and highlights novel data collection strategies, including person-centred strategies such as GPS tracking and space-time budgets as promising tools for measuring human movement. Our contribution to this research field is that we offer a conceptual and computational framework that shows how detailed individual-level raw mobility traces can be translated into core theoretical constructs such as nodes, paths and activity spaces, thereby providing a direct operational bridge between theory and empirical data.

We draw on interconnected advances in the proliferation of smartphone technologies and methods capable of analysing the data they generate. Our goal is to increase the specificity and scalability with which the key explanatory constructs of environmental criminology can be quantified, and thereby refine our understanding of how stylised theoretical concepts are manifested in real-world behaviour. To this end, we outline a reproducible framework for analysing geolocation data collected from smartphones, specifying methods (and providing corresponding tools) to identify and measure key constructs. We illustrate these methods by analysing geolocation data generated by a sample of young people living in Queensland, Australia.

This new approach to quantify routine activities, we argue, is at the vanguard of a

new environmental criminology – enabling detailed, reproducible research linking space-time behaviour to individual victimisation risk and societal crime patterns. Ultimately, understanding how these mechanisms give rise to crime will offer insight into this inherent aspect of urban life, and its interdependence with other social processes.

Defining routine activities

Cohen and Felson's (1979) routine activity approach defines routine activities as recurrent behaviours that meet basic needs, such as work, leisure and social interaction, occurring at home, work or other locations. Brantingham and Brantingham's (1981) geometry of crime and crime pattern theory build on this by introducing activity *nodes* (frequently-visited locations like home, work or shopping centres) and *paths* (the routes travelled between these nodes). Collectively, these nodes and paths form an individual's activity *space*, within which they accrue familiarity and build awareness.

Environmental criminology proposes that crime occurs where offenders' activity spaces overlap with the presence of attractive targets. In particular, the geometry of crime and crime pattern theory visually represent likely crime locations as places where offenders, during their routine activities, encounter attractive targets within their awareness space (see Figure 1).

It is hard to overstate the degree to which this depiction of the crime event as a function of routinised movement, and moreover the diagram itself, has influenced environmental criminology. A cursory search of literature finds numerous variations of this diagram in a diverse array of contexts. Yet despite its prominence, with a small number of exceptions (e.g. Curtis-Ham et al., 2023, 2024; Menting et al., 2020), many of the key underlying hypotheses have not been tested directly. To illustrate, while the concept of

activity node is easily explained, there is almost no criminological literature about the extent to which individuals – in their roles as offenders or victims – frequent different *types* of activity node, or the amount of *time* they spend at those locations.

We argue that the primary reason for this is our inability to directly observe individual-level routine activities. Without such observations it is impossible to know (a) whether the model proposed is an accurate depiction of mobility, (b) how it can be refined and (c) the extent to which core elements (e.g. number of nodes) vary across individuals. Such specificity would have implications not only for theory but also for empirical studies of crime and application of their insights to inform crime reduction measures.

Previous measurement of routine activities

As remarked previously, the lack of specificity of many existing victimisation surveys means that they fail to capture the most important dimensions of individuals' routine activities with respect to crime: precisely where and when they spend their time. Where one goes is fundamental for understanding victimisation risk for the simple reason that crime is not evenly distributed (Weisburd, 2015), even among similar places (Eck et al., 2007). The timing of activities is also crucial because crime clusters temporally – by hour, week and season (Felson and Poulsen, 2003). Someone visiting a problem bar on Saturday night will be exposed to more victimisation risk than someone visiting the same bar on Monday afternoon.

Since the early 2000s, research has sought to develop methods capable of capturing more nuanced depictions of person-place-timing interactions. Time-use data-collection instruments, like the Space-Time Budget (STB) questionnaire, have been used in

criminological research to overcome the limitations of previous approaches (Hoeben et al., 2014). The STB is a retrospective pencil-and-paper survey used to collect detailed information about how and when people interact with their proximate environment (Wikström and Butterworth, 2006; Wikström et al., 2012). In structured face-to-face interviews, trained personnel guide respondents to recall – typically at 1-hour intervals – time-use information across several days of the week, including the specific places where they spent their time and their primary activity while there.¹

This approach is time-consuming, relies on accurate long-term recall, and assumes that the participants' primary activities within each hour are relatively static. Despite these threats to validity, however, the STB has been used to produce detailed information about person-place interactions and criminogenic behaviour settings² (Averdijk and Bernasco, 2015; Bernasco et al., 2013; Wikström et al., 2012). A related body of work has also employed manual recording of routine activities from victims of violent crime via geographic information systems (Wiebe et al., 2016). These studies highlight the potential of activity surveys to capture person-environment interactions across criminogenic contexts.

Human dynamics

In recent decades, a new line of research has drawn on large amounts of anonymised location data from smartphones to explore how people move and interact in everyday life. This interdisciplinary field, referred to as 'human dynamics', merges computational methods, network science and social sciences to understand human mobility, and in particular its regularity and predictability. Early work in the field (Gonzalez et al., 2008) showed that individuals' mobility patterns

were inconsistent with existing models that characterised movements as random walks. Observed movements showed much less randomness, with individuals tending to visit a limited number of familiar places, and with their movements displaying a high degree of temporal and spatial regularity (i.e. routines).

The 'exploration and preferential return' model (Song et al., 2010) was developed to account for these regularities. Exploration refers to individuals' tendency to visit new places over time, while preferential return captures the observation that individuals are more likely to return to places they have visited previously (e.g. home, workplace). This model was found to successfully describe patterns of human mobility observed in smartphone data. Subsequently, it has been extended with a social component, demonstrating that individuals are also attracted to places visited by other people (Schläpfer et al., 2021).

Collectively, this review of approaches highlights an opportunity to revisit the way in which core constructs associated with place-based criminology – especially those that have traditionally relied on indirect measures – are operationalised. While STBs provide rich accounts of personal activities, they are resource-intensive and subject to recall limitations. Smartphone-based measurement, which is passive and highly granular, has the potential to transform understanding of these constructs, but has not yet been applied to assess if core assumptions within environmental criminology are observed in real-world behaviour.

Current study

We now set out a systematic approach for quantifying routine activity constructs. Our primary goal is to specify a series of operationalisations capable of measuring characteristics of individual-level patterns of

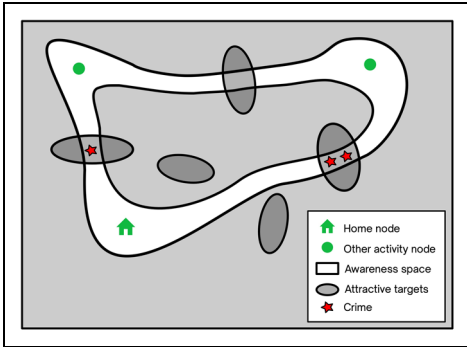


Figure 1. Offender activity space and predicted crime locations according to crime pattern theory (adapted from Brantingham and Brantingham (1981, p. 42)).

human mobility. These operationalisations enable a more specific understanding of individual routine activities, and can also be used to assess how generalisable measures are between individuals, and thus how valid hypotheses implied by the characteristic depiction of routine activities found in Figure 1 might be. To demonstrate these methods, we describe the use of a smartphone app to collect geolocation data from a sample of young adults living in Queensland, Australia.

Sample

This study analyses the space-time behaviour of a sample of young adults living in the Brisbane Metro area of Queensland, Australia. Brisbane is the third most populous city in Australia, with a population of approximately 2.7 million in 2023. Study participants were recruited via online social media; ads were posted on Facebook and Instagram from 20 February through 1 March 2017 and targeted 18-to-24 year-olds living within Brisbane. A total of 95 individuals responded to the ad campaign, met eligibility requirements, and were enrolled in the study.

Data

Data were collected from participants over a period of 30 days during March 2017,³ using a smartphone app called Sense.DAT (Mobidot, 2017) which passively tracks participants' geographical locations. Participants were required to download and install the app on their own smartphone (either Android or iOS) as part of the study's eligibility requirements. The Sense.DAT app was designed for mobility research and had been used in several studies outside criminology (e.g. Geurs et al., 2015; Suijs et al., 2015).

To conserve battery, Sense.DAT utilises movement-initiated measurement, where data recording begins when a participant's device senses a 'significant change in location' (Mobidot, 2017). The app captures the location of the device (in coordinates) at 1-second intervals, using the phone's GPS sensor, until movement ceases. Temporal gaps in observations can thus be interpreted as either stationary at any time or a loss of battery or signal.

Quality

Data were collected from 61 of 95 eligible participants at least once during the 30-day study period (64% participation). Of these 61 participants, 44 were recorded on at least 21 unique days over the month (46% completion). The remainder of the paper presents analyses of data generated by these 44 individuals only. Collectively, these participants generated 1.1 million timestamped location measurements—henceforth referred to as waypoints – describing 48,754 km of travel distance.

Method

We now outline methods to derive measurements of key constructs from these data. We do this in stages: after examining nodes, we analyse the trips between them, and the

paths taken during these trips. At each stage, we provide pseudo-code for the steps required to translate raw waypoint data into these core constructs and present an illustrative application of the method to our sample. In doing so, we propose several approaches for summarising these measures amongst a cohort of individuals, while also assessing the degree to which participants differ in their spatial behaviours.

Constructs

Nodes

Our first core construct is the routine activity *node*. In the literature, this is conceptualised as a place repeatedly frequented by an individual, such as a home, workplace or social setting. We define it here simply as a location that is repeatedly visited, and identify such cases by applying the following approach to each participant's waypoint observations:

1. For each waypoint, calculate the distance in time (*delta_t*) and space (*delta_d*) to the next waypoint.
2. Identify all waypoints where *delta_t* is greater than *stationary_time_threshold* (default = 10 minutes). Of this subset, identify waypoints where *delta_d* is less than *stationary_space_threshold* (default = 100 m) and classify these as *stops*.

The first step identifies all waypoints where the device has not generated data for an extended period. This implies that it is either: (a) stationary or (b) moving but has lost signal or power. The second step is intended to ensure that only the former case is identified as a stop.⁴

3. Apply the clustering algorithm DBSCAN, which identifies groups of points that lie within a given distance of each other, to all stop points. This is

applied with maximum radius *node_radius* (default = 100 m) and size *node_visit_freq* (default = 2), meaning that it identifies locations where multiple stops have occurred within close proximity. Each of these locations is considered to be an activity node and the corresponding stops are tagged as node visits.

The output of this process is clearly dependent on the various parameter values used. Some parameters, such as *stationary_time_threshold* and *stationary_space_threshold*, likely have minimal impact. The former distinguishes between brief pauses and extended stops; the latter ensures that GPS noise or minor movement within a location does not lead to false node splits. Default values for these parameters are acknowledged to be arbitrary, informed by exploratory data analysis and pragmatic judgement. Other parameters may have a larger influence, and indeed greater conceptual significance. An example of this is *node_visit_freq*: how often a location must be visited to be considered a routine activity node.

Because the number of observed days varies across participants, we standardise the procedure by specifying a fixed *visit_regularity* – which specifies that a routine activity node must be visited at least once every D days, on average – and use this to derive the corresponding *node_visit_freq* for each participant. If *visit_regularity* is four days, for example, then a participant observed for 24 days would be required to have stopped at a location six times, whereas a participant observed for 28 days would require seven stops.⁵

As expected, the less often a node is required to be visited, the more nodes will be identified for each participant (see Figure 2(a)). Half of participants have three or fewer locations that they visit at least once every four days, but the median number of locations visited every two weeks was eight (essentially, all locations visited more than

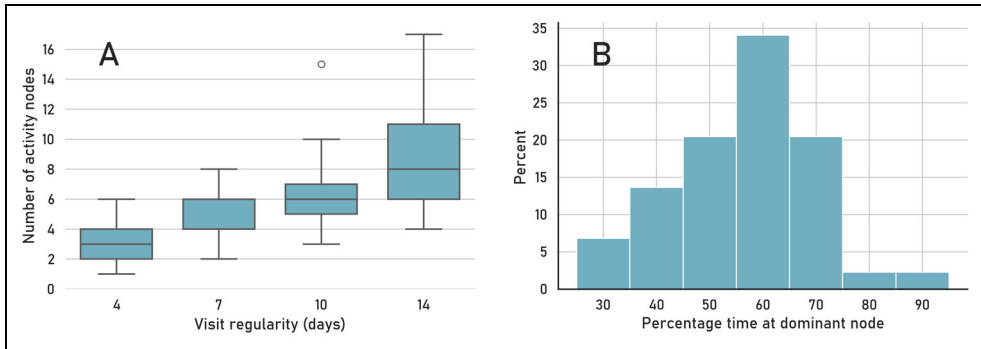


Figure 2. (a) Boxplots showing the variation in number of activity nodes identified per individual for a range of possible values of the *visit_regularity* parameter. Boxes represent interquartile range; horizontal lines indicate median and (b) proportion of time spent by participants at their most-visited node.

once). The extent of variation within each category also indicates that the range of places frequented is much greater for some participants than others.

While the dependence on *visit_regularity* is clear, there is little basis on which to select a particular value. The term ‘routine’ is not defined in concrete terms within literature, and no fixed value would be universally meaningful. For concreteness, here we explore the case where *visit_regularity* is equal to 10 days (i.e. routine activity nodes are those that are visited at least every 10 days, on average).

The activity nodes identified for each individual are, of course, not equal and some will be visited more than others. Most immediately, all individuals would be expected to have a highly-dominant ‘home’ location, and this is indeed the case. As shown in Figure 2(b), most participants spend more than half their time at their dominant node, though there is substantial variation across participants.

There is also a high level of variation in the extent to which other nodes are visited. Figure 3 shows the distribution of time spent across activity nodes for two example participants (the dominant node is omitted in

both cases). The participants illustrate contrasting cases: both have seven activity nodes, but while participant A (Figure 3(a)) has a relatively concentrated distribution of activity, participant B’s (Figure 3(b)) is more even. These differences likely reflect differences in lifestyles: the node which dominates A’s (non-home) activity may be a work or study location, whereas B has more spatially diffuse activities.

Differences in the distribution of activity across nodes evidently represent a further basis to discriminate between the behaviours of different participants. To study how the extent of concentration varies, we first summarise each participant’s distribution by computing its associated Gini coefficient. The Gini coefficient ranges between 0 and 1 and measures the extent to which a given quantity is concentrated within a population – here the extent to which time is concentrated within activity nodes. A value of 0 corresponds to a perfectly equal distribution (time spent equally at all nodes), while 1 represents extreme concentration (all activity at one node).

Figure 3(c) shows the distribution of these values across our sample (excluding dominant nodes). Our results demonstrate there is

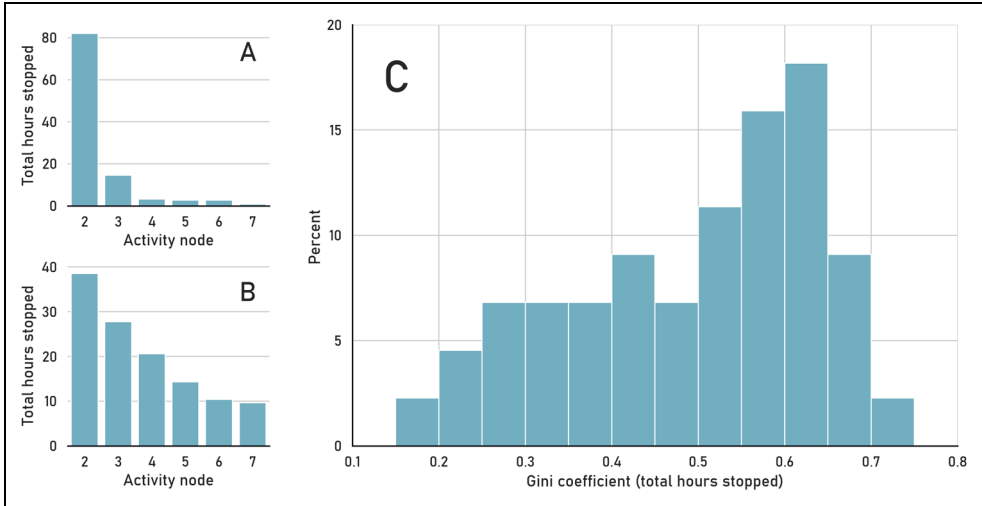


Figure 3. (a) and (b) Distribution of time across activity nodes for two example participants and (c) distribution of Gini coefficients across sample.

no single archetype for how participants distribute their time, with the sample containing a mixture of individuals between the two extremes, as exemplified by participants A (Gini = 0.28) and B (Gini = 0.69).⁶ Encouragingly, the level of concentration is relatively consistent across different values of *visit_regularity* – the Gini coefficients obtained using 10-day regularity have Spearman’s correlations of 0.90 and 0.86 respectively with their 7- and 14-day counterparts. In other words, individuals who have a concentrated activity pattern do so regardless of the definition of activity node used.

Trips

Having examined the locations where individuals spend substantial amounts of time (stops), and the locations where they do so regularly (activity nodes), we now consider behaviour between stops. In doing so, we are implicitly considering another aspect of the general structure proposed by the geometry

of crime: the links formed between activity nodes during travel between them.

In this study, we define a *trip* as a specific sequence of movements between any pair of consecutive stops (as defined above); that is, between the point at which an individual begins moving after a previous stop and the point at which they next stop moving. While our empirical construct of a trip refers to individual instances of movement, it is conceptually related to the idea of paths in environmental criminology, which describe how routine movements between activity nodes contribute to awareness spaces and shape opportunity structures (Brantingham and Brantingham, 1984). Examining trips therefore reveals not only which places participants travel between, how often, and the extent to which such movements involve routine activity nodes, but also the connecting paths, which themselves form part of activity and awareness spaces.

Most participants complete between three and five trips per day, on average, with none taking more than six. This is broadly

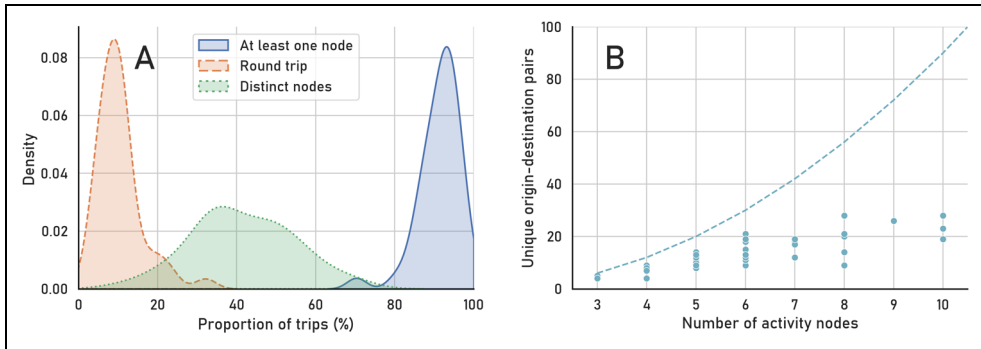


Figure 4. (a) Proportions of trips of different types, (b) number of unique origin-destination pairs realised, as a function of the number of nodes. The dotted line shows the maximum number of possible pairs for each value.

consistent with visiting two places from home – the outward and return journeys would count as separate trips – though more circuitous journeys are also possible. Individuals are fairly similar in this respect – almost all engage in some travel, but few make large numbers of trips.

We can also examine where individuals tend to travel. Figure 4(a) shows the proportion of trips which (i) either start or end at an activity node (i.e. feature at least one node), (ii) start and end at the same activity node (i.e. a round trip – an individual leaves a node, moves for a period, then returns to the same node) and (iii) start and end at distinct activity nodes (i.e. a journey from one node to another). For most individuals, the vast majority of trips involve at least one activity node, but only a small proportion of these return to the same node without stopping. The proportion of trips between distinct activity nodes shows much more variability: while most participants have 30%–50% of this type, the distribution ranges from around 10%–70%. The remaining trips will involve travel between an activity node and a non-routine stop location.

Trips between activity nodes are of particular interest, since they play a prominent role within the geometry of crime. For any

individual, travel can – in principle – take place between any pair of activity nodes, and so the number of potential journeys is large. Not all of these journeys will be taken, however, and some will be taken more frequently than others.

Figure 4(b) shows the number of origin-destination pairs between which at least one trip was observed, as a function of the individual's number of activity nodes. Individuals with more nodes have more potential pairs: the dotted line shows the number of possible combinations. While the number of observed pairs does increase for individuals with more nodes, however, it does not do so proportionally. This is, of course, unsurprising: individuals would not realistically travel between every possible pair of locations. More likely is that the most important activity nodes (e.g. home, university, work) are densely connected, but that additional nodes only attract a modest number of additional connections (e.g. to home).

Two illustrative cases are shown in Figure 5. In each case, nodes are connected if a trip took place between them, and the thickness of the arrows corresponds to the frequency of trips. The individual shown in Figure 5(a) has a relatively sparse pattern

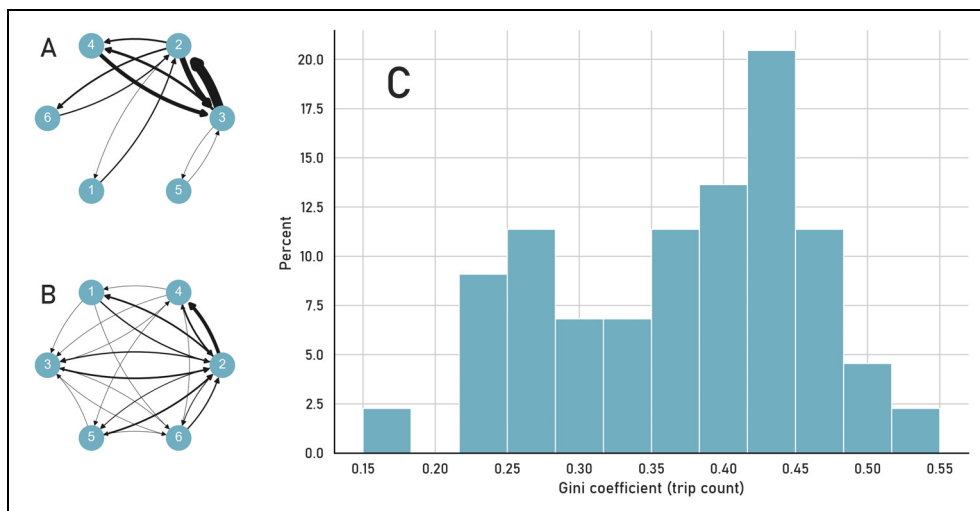


Figure 5. (a) and (b) Inter-node trip frequencies for two example participants and (c) distribution of Gini coefficients for inter-node trip frequencies.

of connections, but with a high frequency of travel between three particular nodes. The individual in Figure 5(b), on the other hand, has many more connections, but less concentrated activity on any particular pairing. The first individual is likely to have a high degree of familiarity with a small number of routes, while the second travels more routes, but less routinely.

This concentration of trips can also be summarised using the Gini coefficient, as shown in Figure 5(c). Again, the sample includes a range of behaviour types: some whose movements are dominated by a few highly-regular trips; others whose movements are much more diverse; and many more in between. These results are relatively robust to the definition of activity nodes: the Gini coefficients obtained for 10-day regularity have Spearman's correlations of 0.88 and 0.76 with their 7-day and 14-day counterparts. This implies that individuals with concentrated travel patterns do so regardless of precisely how nodes are defined. The association is weaker (0.63) with 4-day regularity,

but this typically includes many fewer possible trips.

Visits

The frequency and accuracy with which individuals' movements are recorded means that their movements can be examined with a high degree of granularity. In particular, it is possible to identify the routes that are taken when travelling between stops, and therefore the places that are visited during through-travel, rather than just those at which individuals stop. These routes are especially important theoretically, because a key idea is that visits in the course of routine travel are important for both victimisation (through exposure to crime risk) and offending (through the accrual of awareness).

Importantly, the granularity of the data allows us to identify the particular streets that individuals used when travelling between locations. To do this, however, the data must first undergo a pre-processing step, known as *map-matching*. Map-

matching is the process of converting raw GPS data – recorded in terms of coordinates only – to a path through street segments on the road network. This involves two fundamental steps: (1) matching each waypoint to a location on the street network and (2) identifying the paths between successive locations. In this study, we used open-source street network data from OpenStreetMap.

Map-matching is a non-trivial task, because the spatial errors inherent in GPS data mean that the segment that is closest to a given waypoint may not be the one on which the participant was actually located. Simply matching waypoints to the nearest segment can result in unrealistic routes, and alternative approaches must be used—here we used the approach proposed by Lou et al. (2009)—the algorithm is described in full in the paper, but the key steps can be summarised as:

1. For each waypoint, the C closest segments (Euclidean distance) are identified.
2. For each of these street segments, the closest point on the segment to the waypoint is found. These C candidate points are assigned a quality score based on their distance from the waypoint – closer points receive a higher score.
3. For all pairs of successive waypoints P and Q , each of P 's candidate points is paired with each of Q 's, and the shortest network path between the two is found. This is also given a transmission score based on the similarity between the path distance and the Euclidean distance between the two waypoints.
4. The algorithm identifies the sequence of candidate points and transitions between them which maximises the overall score. This corresponds to a path through the network, which is then considered to be the matched path.

This map-matching is applied to all trips, so that each trip is represented as a path through the network. Each path can be seen as a sequence of visits to segments as they are traversed.

Paths and activity spaces

In keeping with prior analysis, there is substantial variation in the distance travelled by individuals: average distances per day are evenly distributed between 10 and 60 km. The average trip length also shows variation around its mean of approximately 11 km, though to a lesser degree: this suggests that much of the variation seen in daily distance is due to differences in the number of trips undertaken.

Of greater significance than the distances travelled, however, is analysis of the paths themselves. For each individual, the processed data provides a record of all visits to each street segment within the study area, along with the timing at which they occurred. Figure 6(a) shows the frequency of visits to each segment for an example participant – for privacy reasons, we show data collected by one of the study authors, not part of the sample – giving a high-level overview of their overall activity space. In the plot, red polygons denote activity nodes and street segments are coloured based on number of visits.

The example activity space shows several regularities that are reflective of the sample. The first is that only a small proportion of segments were visited during the study period. Figure 6(b) shows the number of segments visited at least once during the study period, showing that most individuals visited 2000–5000 unique segments; approximately 1%–2% of all streets within the study area. This figure is even lower if restricted to segments that were visited more than once: for most individuals, around half their visited segments were only visited once.

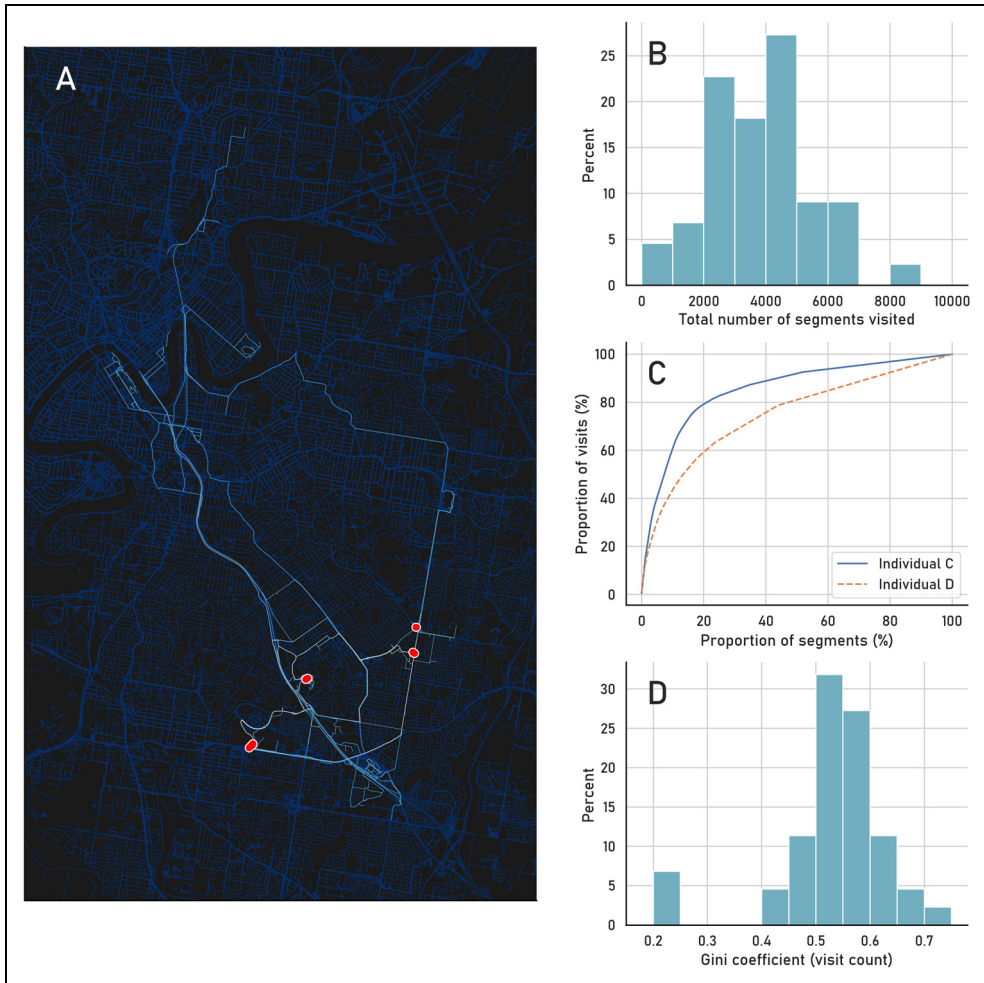


Figure 6. (a) Example activity space, with street segments coloured according to visit frequency, (b) distribution of number of segments visited, (c) concentration of visits for two example participants and (d) distribution of Gini coefficients for segment visit frequency.

If the number of segments visited is taken as a measure of the ‘size’ of an individual’s activity space, it is again clear that there is substantial variation. One possibility is that this is simply a function of overall activity; however, there is no correlation between the number of trips taken and the number of segments visited. In particular, some individuals make many trips but have relatively small activity spaces, implying that either (a)

their trips use the same segments repeatedly or (b) their trips are especially short. Conversely, some individuals travel little but cover a large area.

The tendency to traverse the same streets repeatedly can be seen by examining the concentration of visits across segments. Figure 6(c) shows concentration curves for two contrasting individuals, both of whom visit a similar number of segments overall. For

individual C, the 20% most-visited segments account for 80% of all visits, but for individual D this figure is only 60%. Again, this concentration can be summarised for each individual by calculating the Gini coefficient (individuals C and D have values 0.7 and 0.49 respectively) – see Figure 6(d). Again, the wide degree of variation across individuals is apparent: some repeatedly visit the same segments, while others show a more diverse pattern of visits.

Discussion

This article introduces novel methods for analysing spatio-temporal tracking data collected via smartphones with the purpose of exploring the extent to which foundational, but as yet untested, assumptions within environmental criminology are observed in real-world behaviour. We provide systematic and replicable methods for identifying and quantifying several key elements of the depiction of routine movement which underpins the vast majority of crime and place research.

The findings from our sample of young people in urban Australia demonstrate that, while the almost ubiquitous and implicitly homogenous depiction of routine movement – based on Cohen and Felson's (1979) routine activity approach and Brantingham and Brantingham's (1981) geometry of crime and crime pattern theory – offers considerable face validity, it may mask important nuances. Our results provide empirical granularity to the concept of the activity space by showing that: (i) some nodes are visited more than others, (ii) inter-node travel accounts for only a fraction of trips, (iii) travel only occurs between some node-pairs and (iv) some paths are traversed more frequently than others. Collectively, these findings suggest that routine activity spaces are not a flat plane of uniform activity, but rather a prioritised hierarchy of locations and routes. Moreover, there is also

considerable variation in key features – the number of nodes, and the extent of concentration – between individuals, even within our relatively small and homogeneous sample. Such variation, we suggest, may well be reconcilable with key criminological constructs. To illustrate, drawing on Lemieux and Felson (2012) and Ruiter and Bernasco (2018), we might hypothesise that the risk of victimisation increases with time spent away from activity nodes, particularly in settings with low guardianship, such as public spaces or while on foot. While our data do not distinguish between such contexts or travel modes, this framing suggests that there may be considerable variability in victimisation risk across our small sample of participants. Similarly, following Brantingham and Brantingham (1984), we might expect offenders to favour targets located along familiar routes. This could imply that individuals with more diverse travel patterns contribute to a broader spatial distribution of potential target areas, though such interpretations remain necessarily tentative given the nature of our current data, which do not include measures of victimisation or offending.

Aside from their implications for understanding crime, our findings unveil new insights into the structure of urban life. Our approach of disaggregating routine movements into their constituent components has shown the micro-level patterns which reflect how urban spaces are experienced by individuals. These have clear implications for understanding the character of particular places: their social composition results from the superposition of diverse individual activity spaces, each reflecting a lifestyle embedded in space. Our findings show the complexity of these patterns, while also offering a means to further reconcile them with other urban phenomena. The granularity of the analysis enables the exploration of how activities might intersect in different types of places – such as residential areas,

transit hubs, or recreational zones – and future work might focus on this by taking a place-centred, rather than individual-centred, approach.

One key challenge to our study like any other that relies on passively collected data is self-selection bias, whereby individuals willing to share geolocation information may differ systematically from those who do not – for example, in terms of age, digital literacy, or attitudes toward privacy. These differences may affect observed patterns of routine activity and limit the extent to which findings can be generalised. Recognising this limitation is crucial, particularly when findings are used to inform policy or intervention design. Future research should explore how to characterise and, where possible, correct for this bias – whether through design, analytic techniques, or by incorporating complementary data sources.

Thus, while our results serve primarily to illustrate our proposed analytical approach and may not generalise beyond this context, we argue that these types of data and the methods introduced here for analysing them present unprecedented opportunities for advancing both theoretical and empirical efforts within environmental criminology. This research is beyond the reach of this article, but we hope that the tools provided here enable or inspire these efforts to enhance the specificity with which the relationship between human movement and crime can be understood.

Opportunities

First, fine-grained space-time data, such as those analysed here, allow for empirical tests of hypotheses that have seldom, if ever, been directly tested. Combining measures of key theoretical concepts with measures of crime would enable subsequent tests of theory previously inaccessible to empirical methods. To illustrate, the proposition that crimes are

more likely to occur along individuals' routine paths has remained a principal assumption in the geometry of crime and crime pattern theory for over 40 years. To the best of the authors' knowledge, however, this assumption has never been directly tested. Large-scale observation of these paths, such as demonstrated here, enables such a test.

By extension, the ability to measure these key constructs promotes the articulation of hypotheses with greater specificity. Many common hypotheses are expressed only in general terms, such as the assertion that individuals usually commit crimes – and are victimised – within their activity spaces. Such statements can be made much more specific, by expressing the proposed relationship between risk and key quantities, such as how regularly or recently a place is visited. How much more likely is crime in a place that is visited more frequently than one that is visited less frequently, for example?

Similarly the availability of individual data that are not only spatially but also temporally fine-grained makes it possible to engage with the temporal aspects of offender-target convergences. With a few exceptions (e.g. van Sleeuwen et al., 2021), most prior research has focussed on offender-target convergence in space, and has ignored that crime requires motivated offenders and unguarded attractive targets to converge both in space and in time.

Core theories of environmental criminology may also be extended by linking space-time data to other aspects of human activity. Examples include activity node functions (e.g. home, work, leisure), activity types (e.g. socialising, working), travel modes (e.g. walking, driving), social contexts (e.g. alone, with peers) and physical states (e.g. heart rate, intoxication). Combining these measures would enable the formulation of new hypotheses linking situational and contextual factors. Here, a trade-off exists between the ease with which detailed mobility data

can be passively collected via smartphones, and the inability of such data to capture contextual information, such as the nature of interactions and specific activities participants are engaged in. We believe there is considerable potential in combining this approach with traditional means such as space-time budgets, or indeed in exploring the passive collection of such data (e.g. via Bluetooth). Furthermore, intelligence data collected by police forces could provide useful contextual information about offenders' interactions and behaviours around activity nodes (Curtis-Ham et al., 2024).

Practical implications

Finally, one of the key goals in undertaking this study was to provide a prototype analytical framework which could be used by others. To this end, all program code required to replicate the analyses detailed above can be found at <https://github.com/tobydavies/MakingEnvCrimSmarter>. Importantly, while the approach was applied to data collected via the Sense.DAT app, it was designed with minimal data requirements – requiring only coordinates, timestamps and unique participant identifiers. It should therefore also be applicable to data collected from other sources, such as other phone tracking applications, mobile service providers, and Google location history or equivalents. While it may be necessary to tailor the implementation (e.g. by adjusting parameters), this means our approach should be replicable across settings.

Challenges

Despite their potential value, the nature of both the data and the behaviour under study do present significant challenges. The first of these relate to privacy. While mobility data do not include personal characteristics, individuals' spatial patterns are highly distinctive

and therefore present risks of deductive re-identification (De Montjoye et al., 2013). As a result of these concerns, local lawmakers and ethical committees may have good reasons to block this type of data collection, or prospective participants may be unwilling to enrol. Furthermore, the sensitivity of location data limits opportunities for engaging with open science practices, notably sharing research data.


One possible mitigation is to modify the data to enhance privacy (e.g. by adding noise, or through spatial aggregation); however, such approaches compromise the informational value of data. Another potential solution is the firewalling of individual-level data from researchers. In this model, researchers never directly access individual-level traces; instead, analytical code is deployed to a secure platform which only returns aggregate outputs. Such approaches do present challenges in terms of model testing and validation, but they offer a viable means to derive insights from these data while reducing privacy concerns.


Finally, perhaps the most serious challenge for the data analysed here is relating it directly to criminal behaviour and victimisation. Both victimisation and offending are rare, and the latter is usually covert; only two studies have ever linked individuals' fine-grained spatio-temporal behaviour to their criminal behaviour (Griffiths et al., 2017; Rossmo et al., 2012). While our approach cannot directly overcome this challenge, a key principle of the routine activities approach is that there is no fundamental distinction between the activities of offenders and non-offenders – indeed, offenders spend most of their time not offending – and so general insights should still be applicable for understanding offending. These may be of value even without a direct situational link between movement data and crime data: previous studies have demonstrated that space-time behaviour captured


via STB can predict future offending locations (Bernasco, 2019). The overt nature of victimisation means that it is more straightforward: data can be used to examine the influence of mobility on whether, as well as where and when, victimisation occurs (Ruiter and Bernasco, 2018).


More generally, we hope that the widespread use of smartphones and the ability to develop new specific measures from the data they routinely collect will encourage researchers to devise studies that capture new and powerful insights in scientifically and ethically robust ways. Perhaps even making environmental criminology a little smarter.


ORCID iDs

Daniel Birks  <https://orcid.org/0000-0003-3055-7398>

Toby Davies  <https://orcid.org/0000-0002-9677-2579>

Stijn Ruiter  <https://orcid.org/0000-0003-2872-2710>

Timothy C. Hart  <https://orcid.org/0000-0003-3274-3661>

Wim Bernasco  <https://orcid.org/0000-0002-3385-0883>

Ethical considerations

Our study received ethical clearance from the Griffith University Human Research Ethics Committee (GU Ref: 2016/829) on 1 February 2017. All prospective participants were presented with an information sheet on the study's landing page, detailing the purpose, potential risks, data usage and storage protocols. Participants provided informed consent by selecting an option to proceed.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This project was supported by the Griffith Criminology Institute Pilot Project Fund.

Declaration of conflicting interests

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

Notes

1. For a comprehensive review of the STB methodology, see Hoeben et al. (2014).
2. Another important advantage of the STB is that it also records activities and the presence of others, which the geotracking methods used in the current study are unable to do.
3. During this period, a number of events took place that may have influenced activity patterns, including several major concerts and sports fixtures, as well as the landfall of Cyclone Debbie on 28 March, which brought heavy rainfall and localised disruption.
4. It is acknowledged that this analysis assumes participants typically carry their phones; occasions where devices are left behind (e.g. at home, in vehicles or at certain venues) may influence the detection and interpretation of stops.
5. Strictly, we apply the ceiling function after dividing the number of observed days by *visit_regularity*: with a regularity of four days, a participant observed for 25 days would therefore be required to have stopped seven times.
6. The Gini coefficient is a measure of statistical dispersion representing inequality within a distribution. It is calculated as $G = \frac{\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j|}{2n^2 \bar{x}}$, where x_i and x_j are individual values in the distribution, n is the number of observations, and \bar{x} is the mean value. To provide context for these values, in fields such as economics, where the Gini coefficient is used to measure income inequality, values of 0.2–0.3 correspond to relative equality, 0.4–0.5 are regarded as indicative of high inequality, and values exceeding 0.5 suggest severe disparity. Applied here to the distribution of time spent across activity nodes, similar magnitudes indicate that a large share of time is concentrated in a relatively small number of locations rather than being evenly spread.

References

- Averdijk M and Bernasco W (2015) Testing the situational explanation of victimization among adolescents. *Journal of Research in Crime and Delinquency* 52(2): 151–180.
- Bernasco W (2019) Adolescent offenders' current whereabouts predict locations of their future crimes. *PLoS One* 14(1): e0210733.
- Bernasco W, Block R and Ruiter S (2013a) Go where the money is: Modelling street robbers' location choices. *Journal of Economic Geography* 13(1): 119–143.
- Brantingham PL and Brantingham PJ (1981) Notes on the geometry of crime. In: Brantingham PJ and Brantingham PL (eds) *Environmental Criminology*. Sage Publications, pp. 27–54.
- Brantingham PJ and Brantingham PL (1984) *Patterns in Crime*. Prentice Hall.
- Brantingham PJ, Brantingham PL and Andresen MA (2016) The geometry of crime and crime pattern theory. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*, 2nd edn. Routledge, pp. 119–136.
- Browning CR, Pinchak NP and Calder CA (2021) Human mobility and crime: Theoretical approaches and novel data collection strategies. *Annual Review of Criminology* 4(1): 99–123.
- Cohen L and Felson M (1979) Social change and crime rate trends: A routine activity approach. *American Sociological Review* 44(4): 588–608.
- Curtis-Ham S, Bernasco W, Medvedev ON, et al. (2023) Relationships between offenders' crime locations and different prior activity locations as recorded in police data. *Journal of Police and Criminal Psychology* 38: 172–185.
- Curtis-Ham S, Bernasco W, Medvedev ON, et al. (2024) Familiar locations and similar activities: Examining the contributions of reliable and relevant knowledge in offenders' crime location choices. *International Criminal Justice Review* 35(1): 9–28.
- Davies T and Johnson SD (2015) Examining the relationship between road structure and burglary risk via quantitative network analysis. *Journal of Quantitative Criminology* 31(3): 481–507.
- De Montjoye YA, Hidalgo CA, Verleysen M, et al. (2013) Unique in the crowd: The privacy bounds of human mobility. *Scientific Reports* 3(1): 1376.
- Eck JE, Clarke RV and Guerette RT (2007) Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. In: Farrell G, Bowers K, Johnson SD, et al. (eds) *Crime Prevention Studies*. Willan, pp. 225–264.
- Farrell G, Tilley N and Tseloni A (2014) Why the crime drop? *Crime and Justice* 43(1): 421–490.
- Felson M and Poulsen E (2003) Simple indicators of crime by time of day. *International Journal of Forecasting* 19(4): 595–601.
- Geurs KT, Thomas T, Bijlsma M, et al. (2015) Automatic trip and mode detection with move smarter: First results from the Dutch mobile mobility panel. *Transportation Research Procedia* 11: 247–262.
- Gonzalez MC, Hidalgo CA and Barabasi A-L (2008) Understanding individual human mobility patterns. *Nature* 453: 779–782.
- Griffiths G, Johnson SD and Chetty K (2017) UK-based terrorists' antecedent behavior: A spatial and temporal analysis. *Applied Geography* 86: 274–282.
- Hoeben EM, Bernasco W, Weerman FM, et al. (2014) The space-time budget method in criminological research. *Crime Science* 3: 12.
- Johnson SD, Bernasco W, Bowers KJ, et al. (2007) Space-time patterns of risk: A cross national assessment of residential Burglary victimization. *Journal of Quantitative Criminology* 23(3): 201–219.
- Lemieux AM and Felson M (2012) Risk of violent crime victimization during major daily activities. *Violence and Victims* 27(5): 635–655.
- Lou Y, Zhang C, Zheng Y, et al. (2009, November) Map-matching for low-sampling-rate GPS trajectories. In: *Proceedings of the 17th ACM SIGSPATIAL international conference on advances in geographic information systems* (pp. 352–361).
- Menting B, Lammers M, Ruiter S, et al. (2020) The influence of activity space and visiting frequency on crime location choice: Findings from an online self-report survey. *British Journal of Criminology* 60(2): 303–322.
- Mobidot BV (2017) SENSE.Dat (Version 1.3.5) [Mobile application software].

- Osgood DW, Wilson JK, O'Malley PM, et al. (1996) Routine activities and individual deviant behaviour. *American Sociological Review* 61(4): 635–655.
- Rossmo DK (2000) *Geographic Profiling*. CRC Press.
- Rossmo, D. K., Lu, Y., & Fang, T. B. (2012). Spatial-temporal crime paths. In *Patterns, prevention, and geometry of crime* (pp. 16–42). Routledge.
- Ruiter S and Bernasco W (2018) Is travel actually risky? A study of situational causes of victimization. *Crime Science* 7: 10.
- Sherman LW, Gartin PR and Buerger ME (1989) Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology* 27(1): 27–56.
- Schläpfer M, Dong L, O'Keeffe K, et al. (2021) The universal visitation law of human mobility. *Nature* 593: 522–527.
- Song C, Qu Z, Blumm N, et al. (2010) Limits of predictability in human mobility. *Science* 327: 1018–1021.
- Suijs L, Wismans LJJ, Krol L, et al. (2015) Phantom jam avoidance through in-car speed advice. *Transportation Research Procedia* 8: 227–236.
- Van Sleeuwen SE, Ruiter S and Steenbeek W (2021) Right place, right time? Making crime pattern theory time-specific. *Crime Science* 10: 2.
- Weisburd D (2015) The law of crime concentration and the criminology of place. *Criminology* 53(2): 133–157.
- Wiebe DJ, Richmond TS, Guo W, et al. (2016) Mapping activity patterns to quantify risk of violent assault in urban environments. *Epidemiology* 27(1): 32–41.
- Wikström PH and Butterworth DA (2006) *Adolescent Crime: Individual Differences and Lifestyles*. Willan Publishing.
- Wikström PH, Oberwittler D, Treiber K, et al. (2012) *Breaking Rules: The Social and Situational Dynamics of Young People's Urban Crime*. Oxford University Press.
- Wortley R and Townsley M (2017) *Environmental Criminology and Crime Analysis*, 2nd edn. Routledge.