



# Burglaries Constellations: A New Approach to Deal with Burglaries' Repeat Patterns in Heterogeneous Environments

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## Abstract

Spatiotemporal patterns of repeat victimization in residential burglaries provide valuable insights for predictive applications, though they display increased complexity in large, heterogeneous environments. When the assumed homogeneous areas near prior burglary sites are diminished, the near-repeat pattern becomes restricted. This suggests that burglars may shift to other similar regions, driven by opportunity criteria aligned with criminal behaviour theories. Under this proposed strategy, certain target areas would remain consistently active throughout a burglary wave, leaving behind a detectable "hot trail" on heat maps. By applying Principal Component Analysis (PCA) with varimax rotation for dimensional reduction, we identified these "hot trails" as weighted groupings of cells, termed burglary constellations. Weekly series within these constellations exhibit non-random patterns, facilitating predictive modelling. The resemblance between cells and burglary profiles in each constellation, along with their spatial representation, offers significant information to improve risk prediction and guide preventive policing strategies in large, diverse areas. These findings are consistent with recent criminological studies, suggesting a novel approach in predictive policing frameworks.

**Keywords** Spatiotemporal patterns · Predictive policing · Near-repeat victimization · All-in-one repeat pattern · Optimal Foraging Theory (OFT) · Heterogeneous environment · Principal Component Analysis (PCA)

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## Introduction

### Overview

Predictive policing (Perry et al., 2018) has emerged as an evolving tool aimed at integration with other prominent policing strategies worldwide, such as intelligence-led policing (Ratcliffe, 2008), problem-oriented policing (Borrion et al., 2020; Goldstein, 1990), and evidence-based policing (Brown et al., 2018; Sherman, 1998).

A few years ago, the concept of near-repeat victimization patterns (Farrell & Pease, 1993; M. Townsley, 2003; Pitcher & Johnson, 2011), along with the flag and boost hypotheses applied to residential burglaries (Farrell & Pease, 2017; Tseloni & Pease, 2003), have inspired the development of initial mathematical and statistical models (Mohler et al., 2011; Short et al., 2008) and predictive policing software such as “PRECOBS” and “PredPol” (“PRECOBS Ifmpt—Institut Für Musterbasierte Prognosetechnik”; “Predict Crime | Predictive Policing Software | PredPol”). These near-repeat patterns helped define high-risk areas with elevated chances of repeat incidents following prior burglaries, prompting an increase in police presence under the “hot spots” approach, or “put cops on dots” strategy (Braga et al., 2019b).

Despite years of trials and implementations, the results have often fallen short of expectations (R. A. Berk, 2021; E. Groff & Taniguchi, 2019; Chainey et al., 2018), leading to significant criticism. Some researchers highlight that spatiotemporal patterns are frequently presented with minimal theoretical backing, lacking criminological context (EUCPN, 2017; Kaufmann et al., 2019). Others emphasize that predictive models can be difficult for both officers and the public to understand, raising issues in evaluating their fairness and effectiveness (Bennett Moses & Chan, 2018). Additionally, concerns have been raised about the limited guidance these models provide for officers on responding to high-risk predictions (Ridgeway, 2018), leading to critiques on transparency, potential biases, and ethical implications.

From an operational perspective, predictive policing presents several challenges, including the need for intensified police presence at specific locations and times, often requiring sustained focus over days, weeks, or longer, and significant allocation of resources. This strategy is demanding and necessitates a cultural shift, which may encounter resistance from local police forces due to their reliance on established experience, practices, and intuition rather than guidance from a predictive ‘machine’ (Kaufmann et al., 2019; Bennett Moses & Chan, 2018).

Despite recent criticisms and the lack of consensus on optimal methods and applications, research and development in this area persist, yielding a steady stream of new proposals.

### Literature Review – Optimal Foraging Theory

Optimal Foraging Theory (OFT) (Charnov, 1976; MacArthur & Pianka, 1966), as applied to criminal behaviour (Bernasco, 2009), helps explain near-repeat patterns (Johnson et al., 2009) and may also account for distant crime clusters perpetrated by the same offenders. When dealing with serial criminals, the logic of optimizing risks, costs, and benefits presumably drives them to operate across different territorial areas (or ‘patches,’ in the terminology of Optimal Foraging Theory). Repeatedly targeting a single area diminishes its

most attractive opportunities and heightens the risk of detection; therefore, shifting to new zones for continued near-repeat burglaries becomes an optimal strategy (Summers et al., 2010; Halford, 2023a; Johnson, 2014). This behaviour is further enabled by environmental heterogeneity, which disperses potential targets and complicates the burglars' awareness space, resulting in a broader set of victimized zones that adhere to near-repeat patterns.

The metaphor of the animal world derived from OFT offers appropriate concepts to explain the described criminal behaviour (Bernasco, 2009; Vandeviver et al., 2023). The search for suitable patches to feed, the limited availability of such resources, and the need to manage energy efficiently—all while avoiding detection by predators—are crucial elements in foraging behavior. Deciding when to abandon a patch and move to another, assessing its suitability, and weighing the time and effort required for that movement in pursuit of optimal outcomes are equally important. Prior experience and learned knowledge play a key role in shaping these decisions, as does the nature of the environment—for instance, whether food is abundant or patchily distributed. These considerations closely mirror the patterns observed in the behaviour of serial burglars (Halford, 2023a; Johnson, 2014). In this comparison, the police play the role of the predator, criminals are the prey, and their suitable targets (or victims) are the resources, which, in the case of burglaries, are assumed to be located within neighbourhoods—representing the patches—embedded within larger regions, which function as the habitats.

In ecology, mathematical models have been developed to describe predator–prey interactions (Lima, 2002), the optimal allocation of energy to a patch before abandoning it—such as in the Marginal Value Theorem (MVT) (Charnov, 1976) or the concept of giving-up rate (Halford, 2019)—and the most efficient movement strategies across territory, including random walks and Lévy flights (Johnson, 2014; Vandeviver et al., 2023). From the perspective of mathematical optimisation, three key elements emerge. In criminological terms, these correspond to: *decision*, referring to whether the offender continues to operate in a given area or moves elsewhere; *currency*, understood as the “energy” or capacity of the burglar to continue offending while evading detection and accumulating loot; and *constraints*, which include the availability of suitable targets, the level of security of homes and neighbourhoods, and the presence of law enforcement.

Relying on this framework, we argue that OFT can offer a reasonable explanation for the criminal behaviour of serial home burglars and for the geographic dispersion of non-overlapping hotspots. However, we also highlight key differences in the strategies ultimately adopted by serial burglars, which may diverge from the more ‘animal-like’ logic traditionally associated with OFT.

Also, certain limitations of the OFT and the rational choice perspective (Clarke & Cornish, 1986) add complexity to this model. Although these frameworks explain aspects of criminal behaviour, offenders' decision-making is also shaped by intuition and subjective rewards (Rossmo & Summers, 2022). Moreover, rationality and risk perception may be distorted by the influence of drugs and alcohol (Rossmo & Summers, 2022) or by emotional factors (Van Gelder, 2013).

This study aligns with research advocating for expanding spatial scales in predictive policing, transitioning from microscales to broader, larger-scale approaches (Taylor & Ratcliffe, 2020). In this broader perspective, the spatial unit to be determined is no longer merely a concentric area (such as a square or circle) but rather a network of interconnected spaces. Mathematical and statistical models should evolve to accommodate this added complexity, thereby reflecting a more realistic scenario. While predictions may become less certain or more indeterminate, they should also gain in utility and better align with the common sense, intelligence, and expertise of on-the-ground police forces.

## Research Aim and Hypothesis

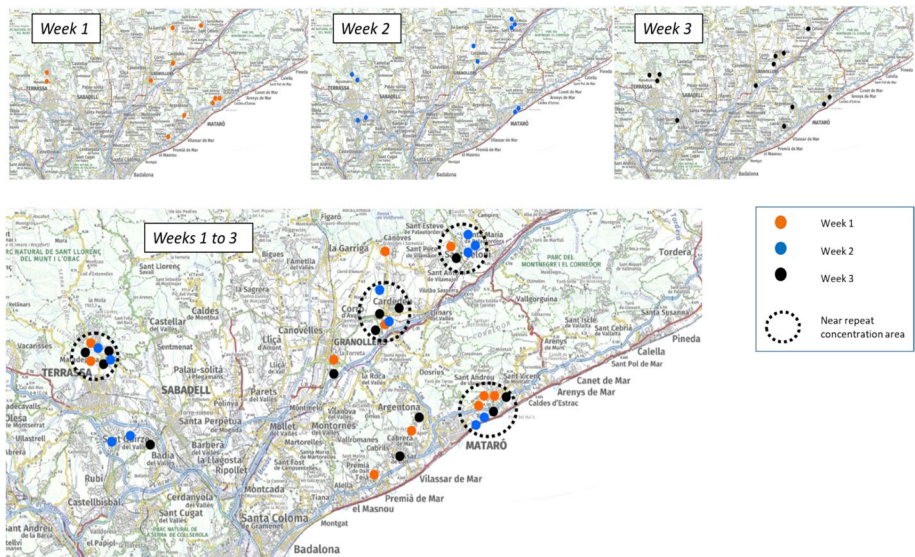
Within this framework, this research aims to introduce a novel approach for predicting burglaries in Catalonia, where near-repeat victimization models (Farrell & Pease, 1993; M. Townsley, 2003) have shown limited applicability (Boqué et al., 2020, 2022). These limitations relate to the heterogeneity of residential areas, which are typically small and dispersed. This distribution compels criminals to spread their activities across multiple areas, either nearby or farther afield.

In Europe, criminal groups involved in burglaries are often internationally composed, displaying complex organizational structures and high specialization, with significant mobility and itinerancy (Wollinger et al., 2018). Studies on crime journey patterns highlight various factors that explain why these distances can be relatively long, supporting this view with similar arguments. There is broad consensus that specialized groups undertake longer journeys to reach areas deemed favourable for burglaries (Van Daele & Vander Beken, 2009; Van Deviver et al., 2015). They may target dispersed areas within a single operation on the same day. The decision-making process typically involves scouting the area a few days in advance, selecting locations based on environmental factors, and applying knowledge from previous burglary experiences. Once in the chosen area, they then decide on the specific residence to target (Nee, 2015; Vandeviver et al., 2015). These groups tend to travel via major roads, such as motorways or dual carriageways, aiming to offset the added costs of longer journeys with a reduced risk of detection and the expectation of higher-value hauls. In remote residential areas, they consider that social control is minimal, and they are less likely to be recognized by local police (Wim Bernasco & Nieuwebeerta, 2005). Studies also suggest that repeat victimization remains a viable pattern for explaining the formation of distant crime clusters, with criminal groups acting serially, alternating between periods of intense activity and inactivity. This inactivity is often justified by the expectation of larger hauls resulting from this operational strategy (Michael Townsley & Sidebottom, 2010).

Research further indicates that most near-repeat burglaries are committed by prolific offenders, frequently sharing the same authorship (Wim Bernasco, 2008; Bernasco et al., 2015; Johnson et al., 2009). An extension of this hypothesis, within the OFT framework, is proposed to explain distant clusters that are repeatedly victimized simultaneously.

This perspective supports the notion that each burglary within these distinct areas or clusters could be viewed as a replica of the broader criminal initiative, fitting into a unified spatiotemporal pattern. It is plausible to assume that environmental heterogeneity reshapes the offenders' awareness space (Brantingham & Brantingham, 1995; Wim Bernasco & Nieuwebeerta, 2005; Curtis-Ham et al., 2020), generating a more intricate 'mental map' with dispersed areas across a wide territory that are attractive targets for burglaries. Additionally, this map would include access routes and the optimal modus operandi for each location, influenced by the burglars' personal experience and possibly that of other groups (Farrell & Pease, 2017; Lantz & Ruback, 2017). Once an area is chosen, offenders select a specific residence, often near or similar to previous targets, thus adhering to near-repeat victimization patterns (K. J. Bowers, 2005; M. Townsley, 2003).

Within this extensive and intricate network, the spatiotemporal pattern connecting all burglaries is referred to as the 'all-in-one spatiotemporal repeat pattern' (Fig. 1), which integrates near-repeat, shift, and co-occurrence patterns. These all-in-one repeats are likely to persist for several weeks, as observed in near-repeat patterns.



**Fig. 1** Illustration of the “all-in-one” spatiotemporal repeat pattern

Figure 1 illustrates the ‘all-in-one’ repeat pattern, hypothetically representing 35 home burglaries over a three-week period. During week 1, burglaries are dispersed without evident concentrations. In weeks 2 and 3, a similar spatial distribution appears, showing initial clustering involving only two or three close-by burglaries. However, when the three weeks are mapped together, four relatively small areas clearly emerge, each repeatedly burglarized and containing 25 of the total 35 burglaries (71%). The all-in-one repeat pattern is typically identified only at the end of a burglary streak, making it challenging to detect while in progress. Preliminary analyses, such as those presented in this study, are necessary to identify this pattern and use it for preventive purposes. If an effective prevention plan had been implemented in the four areas after week 1, the burglaries in weeks 2 and 3 within these high-concentration zones could potentially have been prevented, amounting to 18 home burglaries, more than half of the total incidents.

The all-in-one patterns emerge only when repeated multiple times, indicating that the same areas are activated and deactivated in parallel throughout the analysis period. If detected, these patterns are labelled as ‘constellations,’ supporting the hypothesis that a single criminal group is responsible for the burglary streak within each constellation.

Despite these insights and hypotheses concerning criminal behaviour, this study’s data are exclusively spatiotemporal, meaning that details related to the criminal acts themselves cannot be corroborated and remain as explanatory hypotheses. Nevertheless, it is deemed both appropriate and necessary to relate available criminological theory to explain the observed patterns.

This article culminates a series of studies exploring the feasibility of predicting home burglaries in Catalonia. Two prior studies have been published. In the first (Boqué et al., 2020), near-repeat victimization patterns were analysed, revealing limited detection at the microscale but significant detection at the macroscale. A 5 km grid was used to segment the territory, confirming the non-randomness of weekly burglary patterns, which enabled prediction within certain cells meeting specific criteria. In a subsequent study (Boqué

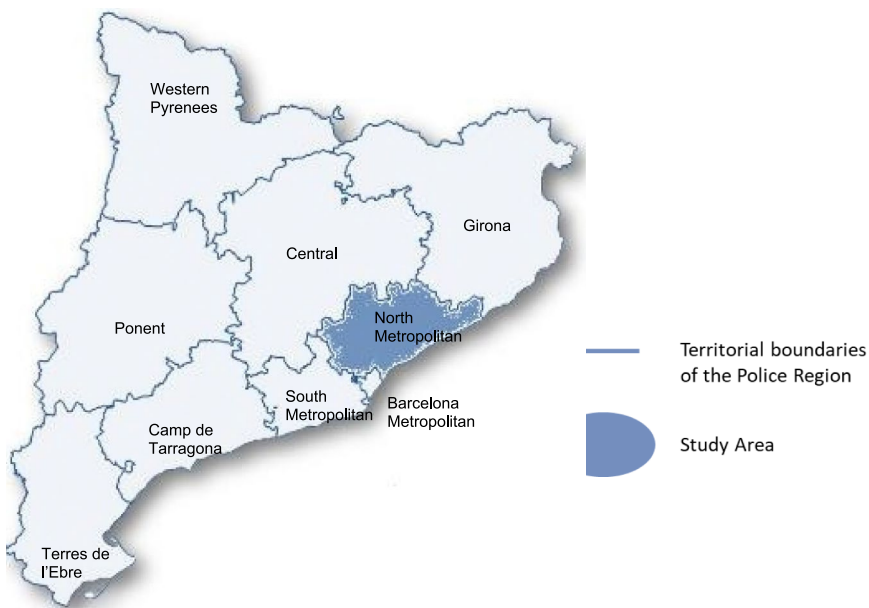
et al., 2022), one of the most advanced current prediction methods, the Integrated Nested Laplace Approximation (INLA) method, was applied. This method facilitates the resolution of models with both spatial and temporal dependencies. Starting from a microscale approach, using cells ranging from 100 to 500 m, the weekly predictive model proved more comprehensive and precise than previous models. However, it revealed that burglaries exhibit both short- and long-distance dependencies, which cannot be fully captured by a single model. Models optimized for short distances employ a continuous approach, whereas models for long distances require 'jumps' and become discontinuous or discrete. Building on the previous two studies, this third article proposes a model to account for dependencies between burglaries in distant areas, supporting the notion that this may be the most effective approach for predicting and preventing home burglaries in geographically heterogeneous environments, such as Catalonia.

## Data and Methodology

### Data Setting

Catalonia is a region in Mediterranean Europe, located on the eastern coast of the Iberian Peninsula and occupying 5.5% of its land area. It is bordered by the Pyrenees and France to the north, the Mediterranean Sea to the east, and Spain to the south and west.

The territory is divided into nine police regions (Fig. 2), each comprising several Basic Police Areas (ABP), which are the primary policing units defined by geographical and



Source: Author's elaboration

Fig. 2 Police Regions (PR) of Catalonia

operational criteria and often include multiple municipalities. These regions are geographically diverse, with the Barcelona Metropolitan Police Region being predominantly urban, while the Western Pyrenees Police Region is mountainous and sparsely populated with small villages.

The North Metropolitan Police Region (NMPR) (Figs. 2 and 3) was selected for detailed study. This region accounts for nearly a quarter of all burglaries in Catalonia and exemplifies the environmental heterogeneity of the area.

Covering 1,864 km<sup>2</sup> and home to 2.2 million residents, this region encompasses diverse areas, including Barcelona suburbs, densely populated towns, extensive industrial zones, major motorways, coastal residential and tourist areas, numerous housing estates, as well as medium-sized towns and rural regions with scattered villages.

The data used in this study consist of reported forced-entry burglaries in Catalonia for the years 2017 to 2019 (see Appendix, Fig. 7), provided by the Catalan Police Force (“Generalitat de Catalunya – Mossos d’Esquadra—Portal Dades Obertes,” n.d.). Each report includes UTM coordinates, a time window (usually within a day) during which the burglary likely occurred, the type of residence targeted (flat, terraced house, detached house or farmhouse), and whether it was a primary or secondary residence.

## Methods

The analytical framework for studying these burglaries involved: (1) dividing Catalonia into 5 km square cells and weekly time intervals, (2) identifying clusters of cells experiencing victimization within the same weeks, (3) analysing the weekly burglary time series associated with these clusters, focusing on their non-random properties, and (4) proposing a new framework for understanding spatiotemporal burglary patterns based on repeat victimization and a novel predictive algorithm.

Burglary coordinates were projected onto a 5 km grid, analysed by weekly series. In 2019, burglaries occurred in 79 NMPR cells, with 52 selected for this study based on a weekly coefficient of variation (CV) over 0.6 and a weekly average above 0.3, thus avoiding excessive global variability from cells with few incidents. These selected cells



Source: Author's elaboration using a map from the Cartographic Institute of Catalonia – ICC

**Fig. 3** Map of the North Metropolitan Police Region (NMPR)

contained 6,692 burglaries, representing 95.8% of all incidents in the region (the remaining 4.2% were located in the 27 cells not included in the analysis).

Principal Components Analysis (PCA) (Pearson K. 1901; Jolliffe, 2002) was used to study the weekly activation patterns across cells, where the variables were the number of burglaries per week in each of the 52 selected cells, with 51 values for each week of 2019,  $Cell_i^t = (B_{i,1}, \dots, B_{i,51})^t, i = 1, \dots, 52$ . (Fig. 4).

This data structure aligns with the approach by Berk and MacDonald (R. Berk & MacDonald, 2009) which examines spatial–temporal relationship between several attributes. However, here the sole variable is the number of burglaries, with the PCA objective being to identify similar temporal profiles among cells.

PCA is a flexible, non-parametric method with minimal data requirements, though it assumes independence of observations. Temporal or spatial dependencies may distort results, creating false correlations. Here, the 5 km cell size largely mitigates spatial dependency effects associated with near-repeat patterns, allowing focus on distant correlations between cells. Any correlation that the PCA finds between cells is due to the temporal profile of the burglaries.

Beyond the results obtained, once the sets of cells frequently targeted by burglars are identified, further explanations can be sought using variables not included in the PCA method, such as the geographical profile of the cells or the presence of highways that may connect them efficiently.

While absolute criteria are not established, it is generally accepted that if the sum of the variance percentages of the principal components exceeds 70% of the total variance, these components provide an adequate representation of the overall variance and, by extension, the underlying problem or model under study. This threshold is often reached with only a few components, allowing the remaining components to be discarded.

For the selected components, the coefficients assigned to each of the 52 cells studied—also referred to as weights—can be interpreted as indicators of the strength of the relationship between each cell and the temporal profile represented by the component, proportional to their correlation. These weights may be positive or negative, reflecting

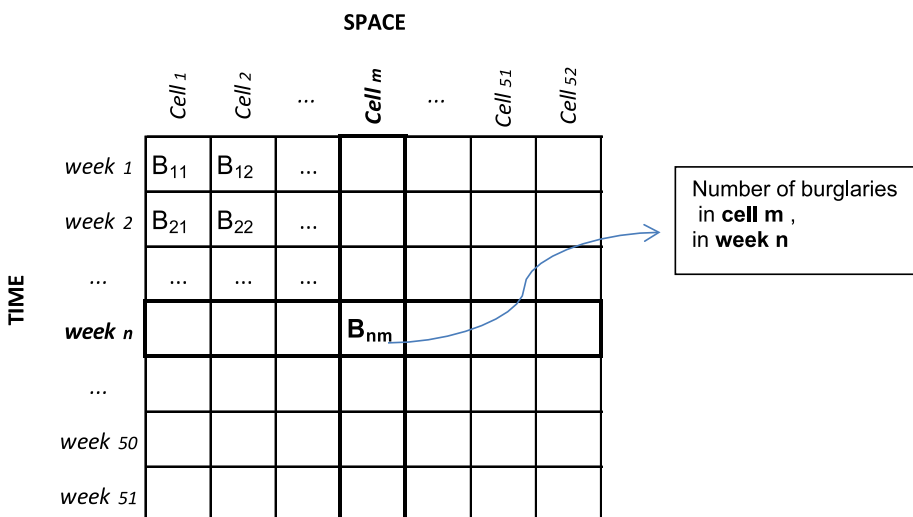


Fig. 4 Spatiotemporal data matrix (weeks x Cells)

the direction of correlation with the temporal profile and indicating the most representative cells for each component in either direction. Cells with near-zero or low absolute values contribute minimal information and can be discarded. Among the remaining cells, a pattern generally emerges: when there is a high burglary count in cells with positive weights, there tend to be fewer burglaries in cells with negative weights. This indicates that both sets of cells convey similar information in opposite directions. Therefore, in this study, only positive weights are considered, with each component represented by a limited number of cells.

To streamline the cell selection process, varimax rotation was applied to minimize the number of high-weight cells within each component, improving interpretability. This approach yielded 'burglary constellations,' representing primary weekly burglary activation patterns in the NMPR and associated cell groups likely to experience concurrent victimization.

It is important to note that this simplification process preserves the independence of the components, even though the correlation between them will be very close to, but not exactly, zero. This is because the few cells that may be shared between two components are not those with the highest weights in either component.

A burglary in a constellation with  $n$  cells is defined by a burglary in any constituent cell, with the total burglaries being the sum across all cells. Constellations thus represent spatial areas with repeat victimization patterns, providing predictive insights.

To this end, the non-randomness of the weekly series was analysed by transforming the weekly burglary counts for a constellation into a binary series of zeros and ones, then applying the runs test. Initially, the mean value serves as the threshold or activation level: if the number of burglaries is equal to or greater than the threshold, a value of 1 is assigned; if lower, a value of 0 is assigned. Using this binary series, the runs test is then applied, which can yield one of the following outcomes (with an associated significance level): a random series, a non-random series due to an excessive dispersion of zeros and ones, or a non-random series due to excessive clustering of zeros and ones. This process is repeated for each constellation, using not only the mean as the threshold but also values slightly above and below the mean.

To validate predictive capability, various activation and deactivation rules for constellations were tested (Table 1) using historical data. For instance, one rule could be to activate a constellation during any week in which the number of burglaries exceeds the previous year's weekly average for that constellation, and to deactivate it when the number of burglaries falls below this average. In this framework, activating a constellation serves as a prediction that burglaries will remain above average in the following week; if this occurs, the prediction is considered successful. Conversely, deactivating a constellation implies a prediction of below-average burglaries in the following week.

To conclude, the general probabilistic framework for burglars' decision-making is outlined, based on the hypothetical assumption of an all-in-one repetition pattern scenario:

**Table 1** Possible rules for activation and deactivation of the constellations

	Activation rule	Deactivation rule
Rule 1	$> \mu$	$< \mu$
Rule 2	$> \mu - \sigma/2$	$< \mu - \sigma/2$
Rule 3	$> \mu + \sigma/2$	$< \mu$
Rule 4	$> \mu + \sigma/2$	$< \mu - \sigma/2$

Within the framework of near-repeat victimization and the spatiotemporal point processes (Diggle, 2005), we assume that the random variable  $X$ , representing the total number of burglaries committed by a burglar or a group of burglars within a specified period in a specific area ( $Z_i$ ), follows a Poisson distribution,  $X \sim \text{Poiss}(\lambda)$ , where  $\lambda$  denotes the weekly burglary intensity (Boqué et al., 2020).

In the new context of constellations, after a criminal group decides to initiate a wave of burglaries within the region, they select specific areas to target ("patch choice" in terms of OFT) using a lottery model, such as  $\begin{pmatrix} Z_1 & Z_2 & \dots & Z_n \\ p_1 & p_2 & \dots & p_n \end{pmatrix}$  where  $Z_i$  represent the areas within the constellation and  $p_i$  denotes the probability of each area being chosen, with  $\sum_i^n p_i = 1$ . If  $Y_i$  denotes the number of burglaries committed by this burglar or group within area  $Z_i$ , then the conditioned distribution  $Y_i/X = k$  follows a binomial distribution with parameters  $k$  and  $p_i$ . It can be demonstrated through a straightforward calculation (Appendix, Lemma), that the number of burglaries in area  $Z_i$  follows a Poisson distribution with a parameter equal to  $\lambda p_i$ , that is,  $Y_i \sim \text{Poiss}(\lambda p_i)$ . Therefore, within each region  $Z_i$ , the probabilistic framework would align with near-repeat victimization, with an intensity proportional to the probability of the group selecting it.

Conversely, by the additive property of the Poisson distribution, the total number of burglaries committed by the same criminal group across all selected areas follows the Poisson distribution  $\sum \text{Poiss}(\lambda p_i) = \text{Poiss}(\lambda) \sim X$ . That is, the group's overall intensity is recovered.

In the case of constellations, as they are extensive areas with a high burglary frequency, the Poisson distributions can be well-approximated by the normal distribution.

This approach positions the proposed model as a natural extension of the near-repeat victimization framework within a probabilistic context. Moreover, the model effectively captures the average intensities (frequencies) of burglaries across spatial and temporal dimensions, even though burglaries tend to occur in non-random, clustered patterns (Boqué et al., 2020).

## Results

The principal component analysis allowed us to group the original 52 study cells of the North Metropolitan Police Region into 19 principal components, explaining 80.9% of the total variance in the temporal burglary profiles of these cells. After applying varimax rotation, the output includes the contribution percentage of each component (Table 2) and the standardized contribution of each cell to each component (Appendix, Table 7).

This result was further simplified by excluding cells in each component with relatively low or negative weights. To ensure uniformity, only cells with weights greater than 0.1 were selected (Appendix, Table 8). This simplification characterizes each component with a small subset of cells, typically between 3 and 10, which concentrate the highest positive weights (Table 3, first column). Notably, 2 or 3 cells in each component generally hold the largest weights (Table 3, second and third columns).

We refer to these simplified components as "constellations," which can be represented on a map of hot cells, where each cell's value corresponds to its standardized coefficient (or weight) within the component (Fig. 5).

**Table 2** Percentage of the variance explained by each component after applying varimax rotation

Principal Component	% of the variance	% accumulated
1	6,3	6,3
2	5,5	11,7
3	5,3	17,0
4	4,7	21,7
5	4,6	26,3
6	4,5	30,8
7	4,3	35,1
8	4,2	39,3
9	4,1	43,4
10	4,0	47,4
11	4,0	51,4
12	4,0	55,4
13	4,0	59,4
14	3,8	63,2
15	3,6	66,8
16	3,6	70,4
17	3,6	74,0
18	3,5	77,5
19	3,4	80,9
Period of analysis:		<i>year 2019</i>
Number of cells:		52
Number of weeks:		51
Total burglaries:		6.692

Using this approach, we calculated the series of burglaries within each constellation by summing the incidents in their constituent cells. A statistical summary for 2019 is provided in Table 4.

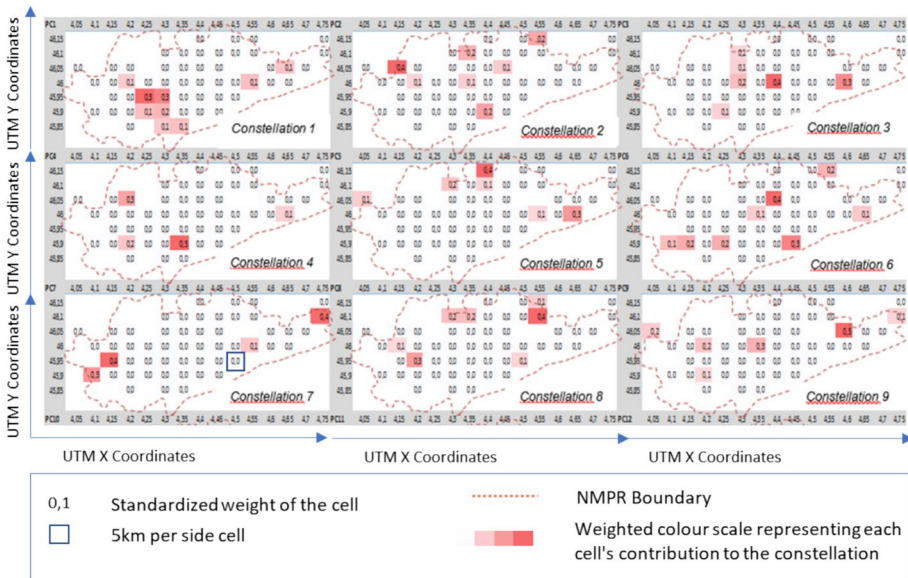
The average number of burglaries in each constellation ( $\mu$ ) is relatively high, with significant weekly fluctuations, reflected in both the standard deviation ( $\sigma$ ) and range, as detailed in the rightmost columns. The final column of Table 4 shows threshold values that can be reached by the weekly burglary series, which may double the value  $\mu + \sigma/2$ . For example, in Constellation 1,  $\mu + \sigma/2$  is 43, while the maximum observed value is 90. In some constellations, this threshold value triples the average ( $\mu$ ); for instance, in Constellation 2, the average ( $\mu$ ) is 16.9, with a maximum of 51.

Examining the profiles of the cells with the highest positive weights in each constellation, with respect to the environment and the type of house victimized, we observed that most cells share specific characteristics (Appendix, Table 9).

For example, in Constellation 1, burglaries predominantly occurred in flats (71.9%) and terraced houses (17.1%), mainly primary residences located in suburban areas. In Constellation 2, burglaries primarily targeted detached houses (45.6%) in upper-class residential areas or housing estates. Constellation 3 was similar, though the targeted areas were more frequently tourist destinations, with properties often serving as secondary residences. Constellation 4 also showed a predominance of burglaries in flats (44.4%) but in upper-class residential areas and housing estates. In Constellation 5, burglaries involved detached

**Table 3** Summary of standardized coefficients weights of PC

	Number of cells with standardized weight > 0.1	Number of cells with standardized weight > 0.2	Number of cells with standardized weight > 0.3
PC 1	9	2	1
PC 2	7	3	1
PC 3	6	2	2
PC 4	4	2	1
PC 5	6	2	2
PC 6	8	2	1
PC 7	4	3	2
PC 8	7	2	1
PC 9	6	2	1
PC 10	8	4	1
PC 11	10	2	1
PC 12	5	2	2
PC 13	5	2	2
PC 14	5	2	1
PC 15	4	3	1
PC 16	5	2	1
PC 17	3	2	2
PC 18	7	2	1
PC 19	7	2	1



**Fig. 5** Map representation of the first 9 constellations for the North Metropolitan Police Region (PCs with standardized weight > 0.1)

**Table 4** Statistical summary of weekly burglaries in the constellations for 2019

Statistical summary of weekly burglaries in the constellations (2019)						
Constellations	#Cells (N)	Mean ( $\mu$ )	SD ( $\sigma$ )	Min	Max	Range
Constellation 1	9	36,0	14,5	18	90	72
Constellation 2	7	16,9	8,5	4	51	47
Constellation 3	6	12,9	6,3	2	33	31
Constellation 4	4	11,7	6,5	4	32	28
Constellation 5	6	7,7	4,4	1	25	24
Constellation 6	8	19,6	7,6	5	45	40
Constellation 7	4	6,4	3,2	1	17	16
Constellation 8	7	19,6	6,4	8	45	37
Constellation 9	6	15,9	6,7	7	36	29
Constellation 10	8	23,2	7,9	14	47	33
Constellation 11	10	22,6	7,4	10	43	33
Constellation 12	5	15,0	6,2	5	36	31
Constellation 13	5	9,4	4,8	1	26	25
Constellation 14	5	4,0	2,6	0	14	14
Constellation 15	4	9,2	4,4	2	19	17
Constellation 16	5	16,3	4,9	7	33	26
Constellation 17	3	5,5	4,6	0	19	19
Constellation 18	7	17,6	6,4	8	38	30
Constellation 19	7	19,0	6,4	8	35	27

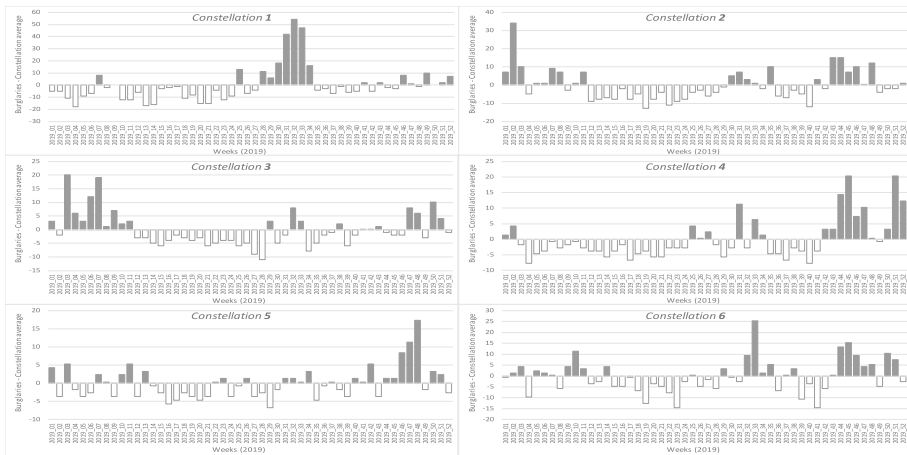
houses (55.3%) situated farther from Barcelona and major cities, on the periphery of the police region. In Constellation 6, urban burglaries were predominant, mostly affecting primary residences (60%) in the centres of medium-sized towns.

For predictive purposes, we assessed the randomness of weekly burglary series within the constellations by applying the runs test to a standardized series. Results indicated that all constellations followed non-random clustering patterns, using the average weekly intensity ( $\mu$ ) as a threshold (Fig. 6 and Appendix, Table 10).

Generally, activation thresholds were found within the interval ( $\mu - \sigma$ ,  $\mu + \sigma$ ). Specifically, wave patterns for thresholds greater than  $\mu - \sigma$  were observed in 14 constellations, thresholds greater than  $\mu - \sigma/2$  in 18 constellations, and thresholds greater than  $\mu + \sigma/2$  in all constellations. For the threshold  $\mu + \sigma$ , the pattern was observed in all constellations except one (Appendix, Table 10).

We analysed the intensity of the weekly repeat pattern in the constellations during 2019. Table 5 presents the prediction success rate based on the activation rules of the constellations, defined as the percentage of weeks in which, when the number of burglaries exceeds the activation threshold, the following week remains above the deactivation threshold. For each rule, Table 5 provides an annual descriptive summary of the types of runs observed in each constellation, including the number of weeks they are active according to the rule, as well as the frequency and duration of the runs.

To assess the stability of the constellations over the years, Rule 4 is taken as a reference, and the runs that would have been generated in the two preceding years are analysed. Table 6 provides a summary using the same metrics as Table 5.



**Fig. 6** Series of values above and below the weekly average of residential burglaries in 2019 for the first six constellations

**Table 5** Annual descriptive summary of the types of runs based on the activation rules of the constellations

Analysis of burglary runs (2019)	Prediction success	Annual frequency per constellation (mean)		
		ACTIVE WEEKS	ACTIVE RUNS	DURATION OF RUNS
Rule 1 ( $> \mu; < \mu$ )	57%	12	5	2 weeks
Rule 2 ( $> \mu - \sigma/2; < \mu - \sigma/2$ )	72%	23	7	4 weeks
Rule 3 ( $> \mu + \sigma/2; < \mu$ )	62%	9	4	3 weeks
Rule 4 ( $> \mu + \sigma/2; < \mu - \sigma/2$ )	82%	16	4	4 weeks

**Table 6** Stability of the constellations over the years 2017 to 2019

	Rule 4 ( $> \mu + \sigma/2; < \mu - \sigma/2$ )	Prediction success	Annual frequency per constellation (mean)		
			ACTIVE WEEKS	ACTIVE RUNS	DURATION OF RUNS
2019	82%	16	4	4 weeks	
2018	87%	17	4	5 weeks	
2017	83%	18	4	5 weeks	

## Discussion

This research sought to uncover the spatiotemporal strategies of burglars, who appear to operate across extensive, heterogeneous environments. Principal Components Analysis (PCA) enabled us to identify what we term ‘constellations’, groups of cells (areas) that tend

to experience victimization simultaneously.

The observation that weekly burglaries within constellations followed non-random wave patterns facilitated predictions based on a system where constellations are activated upon surpassing a predefined threshold and deactivated once they fall below another threshold.

According to Rule 1 (Table 5), if the number of burglaries in a constellation exceeds the annual mean in a given week, it is likely to do so again the following week in approximately half of the cases. In such cases, a two-week run would be generated. This pattern is expected to occur five times per year. To better capture major burglary waves, a stricter activation criterion for constellations can be applied. According to Rule 4 (Table 5), if a constellation is activated in a week when the number of burglaries exceeds  $\mu + \sigma/2$ , it can be guaranteed that in more than 80% of cases, the activation will correspond to a four-week run of high values, remaining above  $\mu - \sigma/2$ . This reliability stems from the recurring pattern of burglary waves, with consecutive runs of high-frequency burglaries followed by runs of lower frequency.

These thresholds are adaptable throughout the year to account for seasonal variations and broader crime trends. However, a key limitation in the predictive process lies in accurately identifying the start and end points of these runs. The system requires a significant increase in burglaries during one week to trigger activation starting in the second week. Nevertheless, the objective of this system is to mitigate high-intensity burglary recurrences in the subsequent two to three weeks, thereby breaking the repetition pattern.

These findings support the development of a predictive algorithm structured around the following steps:

1. **Data:** Use at least one year of historical burglary data across the study area.
2. **Spatial and Temporal Structuring:** Divide the area into large cells (several kilometres wide) and use weekly intervals.
3. **Detect Constellations:** Analyse the temporal profiles of burglaries using PCA to group cells with similar activation patterns. Simplify components to derive constellations.
4. **Evaluate Predictive Capacity:** Use the runs test to confirm non-random burglary patterns in each constellation. Exclude constellations lacking this pattern from prediction efforts.
5. **Incorporate Police Intelligence:** Describe the geographic profile of each constellation, noting building types, temporal patterns, access routes, control points, surveillance, etc.
6. **First-Week Prediction:** Assess burglary counts in each constellation from the prior week, focusing on constellations meeting the activation threshold to initiate preventive strategies.
7. **Subsequent Weeks:** Continue monitoring active constellations and, based on resources, apply preventive strategies to newly activated constellations.

This predictive approach diverges from recent microscale-focused models that have sought increasingly narrow spatiotemporal windows. We propose that such models may have been limited in scope, as they constrained prediction capability, restricted police operational flexibility, and overlooked the broader strategic behaviours of burglars. In contrast, the constellations-based approach aims to make broader predictions by identifying correlations across distant areas, offering potential insights into the overarching strategies of criminal groups.

The proposed algorithm strongly aligns with the six-stage model proposed by Dr. Eric Halford in 'Two Sides of the Same Coin' – A Proposed Model for Delivering a Whole

System Serial Crime Reduction Plan (Halford, 2023b), which is grounded in prior research and supported by a robust theoretical framework.

### Criminal Behavioural Implications

An important criminological question remains to be explored: understanding the connection between observed spatiotemporal patterns and criminal behaviour. We hypothesize that these patterns are intentionally generated by criminal groups as an adaptive strategy in heterogeneous environments like Catalonia. The consistency of non-random wave patterns across all constellations supports the notion that the same burglars, or at least a significant portion of them, are active within each constellation. It seems unlikely that distinct criminal groups would systematically coordinate to target similar areas in such a structured manner, thereby producing the well-defined waves observed in this study. If different criminal groups were indeed coordinating or communicating to organize and divide burglary areas over upcoming weeks, one might argue that, to some extent, they function as a single criminal organization or as one coordinated group of burglars.

It is more reasonable to assume that, for example, 2 or 3 active constellations per week are targeted independently by 2 or 3 distinct criminal groups. This suggests that each criminal group would operate within a specific constellation over several weeks, repeatedly targeting the same area and following near-repeat, shift, and co-occurrence patterns. Together, these patterns contribute to the formation of the all-in-one repeat pattern.

The similarity in the profile of residences and victimized environments within each constellation reinforces the assumption that the same burglars are responsible for repeat burglaries in a broader sense and on a larger scale. These individuals make relatively long journeys to seek out similar targets. This behaviour aligns with studies on specialized international criminal groups operating in Europe (Wim Bernasco & Nieuwbeerta, 2005; Nee, 2015; Van Deviver et al., 2015; Wollinger et al., 2018), which demonstrate that burglars often travel considerable distances to commit crimes. Following the rationale of opportunity theory, these offenders assess risks and rewards while tending to revisit places they have previously targeted.

The tendency of co-offenders to target places where their awareness spaces overlap (Lammers, 2018) may also explain the emergence of burglary constellations. Areas most familiar to the majority of burglars are more likely to be repeatedly targeted, gradually becoming chronic hotspots over time. Consequently, these areas gain statistical significance and become predictable.

The “all-in-one” constellation pattern is further supported by the learning processes and accumulated experience of criminal groups (Bernasco et al., 2015; Nee, 2015). Human behaviour may diverge from the animal-based logic of OFT, favouring deliberate strategies – grounded in the Rational Choice Theory perspective – over random movement. Rather than engaging in random walks or Lévy flights to locate new optimal areas (Vandeviver et al., 2023), offenders may rely on a fixed set of familiar zones already identified as suitable for burglary.

In terms of patch choice and the Marginal Value Theorem (MVT), a patch is not abandoned by serial offenders when resources are depleted, but only after an entire wave of burglaries—lasting several weeks—during which the same patch may be revisited. This strategy, developed through years of local offending, involves alternating between patches and making seemingly random shifts across known areas to reduce the risk of detection, ultimately becoming part of the offender’s *modus operandi*. It may be seen as an original solution to the Decision–Currency–Constraint optimisation problem, as formulated within the OFT framework.

It would be interesting to examine whether any animal species exhibiting temporally clustered foraging behaviour has adopted a similar strategy in response to intense predation pressure. Conversely, if no such example is found in the animal world, it would be of great interest—particularly from a policing perspective—to hypothesise what predator strategies may have evolved to counter it.

This approach distinguishes two scale levels corresponding to the decision-making stages burglars might undertake. The first stage involves a large-scale decision, effectively modelled using cells spanning several kilometres to identify areas that will form constellations. The second stage involves a micro-scale decision, defined by cells of a few hundred meters, where near-repeat patterns manifest. A noteworthy aspect is that the large-scale decision represents a singular choice that governs multiple successive micro-scale decisions. Research has demonstrated that this large-scale decision is relatively easy to predict using constellation patterns. As a result, it becomes feasible to forecast which areas are likely to experience increased burglary activity in the coming weeks, although without having precise knowledge of specific locations or times.

### Risk Trigger

Once a burglary wave begins, the location of the initial incidents can be used to identify nearby areas—within a few hundred meters—that are at heightened risk of victimization, based on near-repeat victimization patterns. Additionally, this method enables the prediction of not only repeat burglaries but also potential first-time burglaries in other areas within the constellation. An activated constellation increases burglary risk across all its cells from the very first week, regardless of whether these cells have been previously victimized in the current streak.

### Police Prevention Strategies

From the perspective of constellations, displacement or shift patterns between constellations cells can also be anticipated when intensive prevention operations are implemented in higher-risk cells (Guerette & Bowers, 2009; Ratcliffe & Breen, 2011; Bowers et al., 2011; Wang et al., 2019). It is even possible to predict the routes burglars are likely to use, as well as optimal locations for setting up police checkpoints to intercept their movements. This approach provides a more comprehensive set of information compared to near-repeat predictions, offering law enforcement refined strategies for preventive action.

Several studies have demonstrated that preventive strategies focused on individual hot-spots yield highly positive local outcomes and lead to a diffusion of benefits in surrounding areas, without causing crime displacement (Braga et al., 2019a, b). Another study suggests that "hot spots patrols should be short-term and randomly rotated across hot spots" (Sorg et al., 2017), providing insights into effective ways to patrol constellations at risk.

However, the "all-in-one" pattern challenges the OFT concepts of giving-up rate (the speed or time it takes for burglars to decide to leave a patch) and giving-up density (the amount of resources remaining in a patch when the offender decides to leave). According to our hypothesis, during a burglary wave lasting several weeks, there may be temporary and seemingly random *giving-ups* designed to confuse and hinder police prevention strategies. Therefore, these concepts may need to be redefined under this new formulation—conceived globally—so that preventive actions are planned and coordinated across all cells within the constellation, to achieve the *giving-up* of the entire constellation.

Situational crime prevention measures may also effectively reduce the static risk of burglaries in the long-term. (Addis et al., 2021; Halford et al., 2024). If such prevention measures were effective, they would eliminate the possibility of criminals carrying out near-repeat burglaries, both in immediate geographical proximity and in more distant areas. Given that repeat patterns are a key component in achieving efficiency in the "burglary business," it would be reasonable to expect a dramatic decrease in victimization rates. The risk of detection, combined with the logistical costs and effort required to acquire knowledge for each new burglary, would increase significantly. Consequently, all burglaries would become "initial" or "first-time" incidents, occurring outside the awareness space (in the broader sense) of criminal groups. While there is an optimistically remote possibility that burglars might abandon their activities altogether, such an outcome may be considered unrealistic or unattainable. Nevertheless, this remains the goal of certain "strike hard" initiatives (Chen & Kurland, 2020).

### Geographic Macro-scale

In this study, structuring the territory into constellations allows for an expanded incorporation of new areas into the predictive algorithm. The proposed approach employs 52 cells, each measuring 5 km per side and grouped into 19 constellations. This represents a significant increase compared to the 29 optimal cells—those exhibiting non-random patterns and a coefficient of variation (CV) within the interval [0.7, 1.3]—included in an individual cell predictive model (Boqué et al., 2020). Notably, 95.8% of the region's burglaries in 2019 occurred within these 52 cells. Therefore, implementing effective prevention measures in these areas could substantially reduce the overall number of burglaries in the region.

Other studies have analysed spatiotemporal patterns of crime from a broad perspective, incorporating concepts such as near-repeat victimization and patterns related to the journey to crime and co-occurrence (He et al., 2020; Wang & Zhang, 2020; Wang et al., 2019). Most of these studies focus on urban environments in large cities, typically employing methodologies based on graph theory, data mining, or machine learning. By analysing the relationships between pairs of events based on their spatial and/or temporal proximity, these studies generate networks within grid cells, mapping the interactions between them. It is assumed that the results obtained with previous methodologies and those proposed in this study would be comparable. The potential value of the constellations approach lies in its simplicity—it can be calculated using standard tools—and its integration into a broader theoretical framework supported by new hypotheses on spatiotemporal patterns and criminal behaviour.

### Constellations Stability

Additionally, constellations appear to exhibit long-term temporal stability (Table 6). (Note: The initial intention was to project the constellations from 2019 into 2020 and 2021. However, COVID-19 caused a drastic shift in crime data, rendering those years unsuitable for analysis. Consequently, the preceding years, 2017 and 2018, were used instead to study stability).

It can be observed that the constellations continue to exhibit predictive capacity and a run profile similar to that of 2019 when projected onto the years 2017 and 2018 (Table 6). During these years, governed by Rule 4, the constellations demonstrate an activation predictive power exceeding 80%, with an average of four runs per year lasting between 4 and 5 weeks.

This stability may be attributed to the slow rate of change in environmental factors, as well as in the profiles of houses, neighbourhoods, and populations. However, the knowledge that criminal groups have of these environments, as well as the specialization and type of targets,

can evolve over time (Farrell & Pease, 2017; Lantz & Ruback, 2017). For instance, areas that are frequently victimized may be abandoned in favour of new ones, leading to corresponding changes in the constellations. Such shifts could also be associated with long-term preventive measures, such as enhanced security protocols, the installation of surveillance cameras, or changes to the urban landscape and access routes. Thus, constellations represent a clear example of the interaction between dynamic and static burglary risk factors.

## Limitations

This study has certain limitations. The crime data utilized originates from events reported to the police, which inherently excludes an unknown "dark figure" of unreported crimes. However, in the case of burglaries, this figure is relatively low compared to other types of crimes. Many unreported burglaries may involve attempted or less severe incidents, and given that their spatiotemporal distributions are likely to reflect those of reported burglaries, this limitation does not significantly affect the main conclusions of the study.

Another limitation pertains to the temporal accuracy of reported burglaries. While the specific day and time window (morning, afternoon, or night) is generally recorded, in some instances the event may have occurred over a broader timeframe, occasionally spanning several weeks. Nevertheless, the proportion of such cases is minimal, and the impact on the analysis is mitigated by the use of weekly time intervals.

One limitation of this study is the absence of a sensitivity analysis regarding the spatial unit used—specifically, the 5 km square grid cells—raising concerns related to the Modifiable Areal Unit Problem (MAUP) (Malleson et al., 2019; Johnson et al., 2007). In this case, the choice of cell size was based on prior research conducted in Catalonia (Boqué et al., 2020), which showed that smaller distances reduced the ability to detect near-repeat patterns. In the present study, the aim was to continue detecting that repeat pattern within the cells that were also intended to be linked to one another. The objective was now to identify the pattern at a larger scale, involving a high total number of burglaries, which may have made it more robust and less sensitive to spatial configuration settings.

However, the results may still be sensitive to parameters such as cell size, shape, and grid alignment. Minor adjustments in these factors could influence outcomes depending on the geographical characteristics of the study area. Therefore, any replication of this methodology in other regions should consider testing alternative grid configurations. A simple strategy might involve slightly modifying cell dimensions or shifting the grid, while a more refined approach would involve segmenting the territory into irregular zones based on homogeneous housing types, geographical features, and urban layout.

Regarding patch choice, this study did not incorporate geographical information layers into the configuration of the constellations, as it relied solely on the time and place data of burglaries. The analysis of similarities in the profiles of residences was conducted subsequently, while the geographical environment was interpreted using maps and local knowledge of the territory. This approach was adopted deliberately, as the development of valid geographic layer configurations for policing and crime analysis should be conducted ad hoc, grounded in the principles of crime concentration and opportunity. Historical data represents the optimal foundation for such configurations (Bogucki et al., 2020).

Another limitation of this study concerns the lack of empirical data to support the proposed hypotheses on criminal behaviour related to serial crimes and serial offenders. The analysis relies exclusively on theoretical reasoning and observed spatiotemporal patterns, without access to offender identification in police-resolved cases. This absence limits the

ability to empirically validate the crime-linking assumptions underlying the model. Nonetheless, previous empirical research on domestic burglars has identified inter-crime distance and target selection as key indicators for linking burglary events (Halford, 2023a), which reinforces the theoretical foundation of our approach. Even so, future research should aim to incorporate offender-based data to enable more robust crime-linking analyses and allow for further testing of the proposed spatiotemporal foraging patterns.

## Conclusions

Broadening the theoretical framework of predictive models from near-repeat victimization to the more general Optimal Foraging Theory (OFT) has expanded the modelling perspectives of predictive policing and its implementation, aligning them more closely with recent studies on criminal behaviour and, ideally, with the intuition and experience of law enforcement practitioners. In this process, the problem to be addressed has become more complex; however, it has been demonstrated that simple statistical tools can uncover newly proposed spatiotemporal patterns and anticipate burglary risks across vast and heterogeneous territories.

The main innovation of the constellations approach lies in its ability to provide both global and local predictions simultaneously—across the entire territory of interest and within specific locations that are currently being, or are likely to be, victimized—by integrating the static and dynamic components of the phenomenon.

Burglary constellations may reflect burglars' typical preferences regarding where and when they commit their crimes. Their existence might be surprising, as it suggests that burglars repeatedly follow the same crime "program," targeting the same locations, the same types of residences, and likely using the same routes to commit these offenses. Moreover, these crime "programs" appear to be consistent or highly similar across different criminal groups operating within the territory. Consequently, external factors—such as the environment, the type of residence, the rationality underlying criminal behaviour, the psychological mechanisms shaping burglars' awareness spaces, and their tendency to repeat past experiences—may explain the existence of constellations in heterogeneous spaces.

Police intelligence can enhance the predictive insights derived from constellations by interpreting their representation on the map. This approach offers valuable information for designing preventive strategies, identifying potential routes that burglars might use, understanding the profiles of the residences likely to be targeted, and delineating specific high-risk areas within cells that require heightened protection. The stability of the constellations provides police forces with the necessary time to incorporate this additional intelligence, refining it week by week with updated tactical and operational information.

This predictive approach transcends a purely regional perspective. Systematic and planned burglary activities across multiple areas simultaneously emerge as the most plausible explanation for the spatiotemporal distribution of burglaries observed in Catalonia and, by extension, in other heterogeneous spaces common throughout much of Europe. In such environments, the "all-in-one repeat" pattern has been proposed as a reference spatiotemporal model.

This model extends the concept of repeat burglaries from nearby areas to distant but similar locations previously selected by criminal groups, introducing what could also be described as "near-far repeat" patterns. When aggregated by weeks and areas, this pattern tends to conform to a simple probabilistic model, akin to a lottery system, aligning with the constellations and their weighted cells. This criminal behaviour is well explained by Optimal Foraging

Theory (OFT) and the role of awareness space in offenders and co-offenders, positioning the proposed model as a natural extension of the near-repeat victimization model.

Future research should explore this approach in other territories and environments, particularly across Europe. Specifically, the aim should be to confirm, refute, or refine hypotheses regarding whether the same offenders or criminal groups are responsible for waves of burglaries within a specific constellation. Additionally, studies simulating criminal behaviour (Birks et al., 2012; E. R. Groff et al., 2019) could provide further validation of this approach.

The observed stability of the data, consistently revealing similar Poisson distributions for burglary intensity with comparable means year after year, underscores the challenges faced by law enforcement in developing effective preventive strategies. The constellation approach has the potential to disrupt these dynamics. The findings of this study suggest the possibility of breaking criminal groups' operational patterns in such environments. However, there are few precedents and significant uncertainties surrounding this possibility (Hardyns & Rummens, 2018; Taylor & Ratcliffe, 2020).

Furthermore, it is important to acknowledge that success in applying these models would inherently disrupt current patterns, thereby challenging the accuracy of future predictive models. Consequently, it seems logical that both the predictive models and methodologies must remain flexible, serving as adaptable analytical tools rather than rigid frameworks. Moreover, active participation from police forces in this analytical and experimental process is crucial to ensure operational sensibility, correct interpretation of results, and enhanced utility in planning preventive strategies (Hardyns & Rummens, 2018).

This study has demonstrated the potential to enhance crime prediction and prevention by incorporating new spatiotemporal patterns and employing cost-free methodologies. These tools are not based on artificial intelligence, nor do they need to be, and require only a limited amount of data to achieve meaningful progress. We advocate for police analysts to build upon these findings, refine them further, and implement them in practice wherever feasible.

## Appendix

Lemma:

$$\left. \begin{array}{l} X \sim \text{Poiss}(\lambda) \\ Y_i / X = k \sim \text{Bin}(k, p_i) \end{array} \right\} \Rightarrow Y_i \sim \text{Poiss}(\lambda p_i)$$

Proof:  $P(Y_i = y) = \sum_{k=0}^{\infty} P(Y_i = y, X = k) = \sum_{k=0}^{\infty} P(Y_i = y | X = k) P(X = k) =$

$$= \sum_{k=y}^{\infty} \binom{k}{y} p^y (1-p)^{k-y} \left( \frac{e^{-\lambda} \lambda^k}{k!} \right) \quad (\text{conditional probability is 0 if } k < y)$$

$$= \frac{(p\lambda)^k}{k!} e^{-\lambda} \sum_{k=y}^{\infty} \frac{1}{(k-y)!} ((1-p)\lambda)^{k-y} = \frac{(p\lambda)^k}{k!} e^{-\lambda+(1-p)\lambda} = \frac{(p\lambda)^k}{k!} e^{-p\lambda} \blacksquare$$

Fig. 7 Weekly Reported Home Burglaries in the North Metropolitan Police Region—NMPR (2017–2019)

**Table 7** Standardised weights of each PC after the varimax rotation

Cells	PC—Varimax Standardised																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Cell1	-.007	.075	-.093	.167	-.032	.071	-.089	-.038	.127	.015	-.032	.092	-.031	-.027	-.007	-.090	-.105	.003	.043
Cell2	.109	.023	-.006	.030	-.221	.011	-.016	-.139	.040	-.091	-.005	-.033	-.090	.036	.176	.296	.079	.024	.062
Cell3	.132	-.043	-.025	.005	-.011	-.059	-.007	.066	-.091	.022	-.142	.181	-.181	.011	.061	.025	.083	.069	-.097
Cell4	-.005	-.009	.021	-.037	.035	.354	.033	.000	-.058	-.059	-.019	.018	.085	.052	-.051	.003	.006	-.019	.034
Cell5	-.015	.045	-.018	-.021	.040	-.030	-.068	.103	-.159	.204	.170	-.154	.098	-.004	-.065	.133	-.028	-.033	-.127
Cell6	.325	-.019	-.007	-.072	.007	-.051	-.002	.062	.059	-.052	.018	-.028	-.010	-.009	-.048	-.072	-.072	-.036	-.007
Cell7	-.019	-.030	-.031	.000	.027	.014	-.077	.119	.003	.005	-.005	-.009	.012	.001	-.474	.021	-.058	.046	.110
Cell8	.265	.019	.041	.015	.029	-.065	.083	-.034	-.023	-.003	-.010	.029	-.015	-.091	.000	.037	-.066	.021	-.017
Cell9	.024	.008	.000	.019	-.051	.194	-.066	-.005	.014	.005	-.024	-.003	-.114	.039	-.028	.038	-.169	.127	-.129
Cell10	.016	.239	.027	.043	.060	.059	-.051	-.019	-.117	.042	.071	-.075	-.021	.077	-.037	.088	-.164	-.180	-.046
Cell11	-.019	-.069	-.056	-.105	-.039	.066	-.033	.009	.037	-.033	.034	.487	.027	-.084	.010	-.013	-.041	-.088	-.007
Cell12	.062	.068	-.024	.049	-.126	-.102	.001	.286	.088	-.058	.125	-.047	.035	-.017	-.059	-.150	-.086	.115	.016
Cell13	.154	-.048	-.002	.087	.030	.084	-.102	.002	.001	.155	-.011	-.188	.068	-.053	.053	-.098	.068	-.241	-.074
Cell14	.133	-.063	.119	-.197	-.035	.190	.029	.013	-.074	-.009	.211	-.025	.021	.170	.005	.055	.008	.135	.102
Cell15	.102	.105	.070	-.110	.014	.008	-.019	-.165	.197	.185	-.193	.011	.088	-.031	-.283	-.042	.024	.067	-.147
Cell16	-.077	.036	.009	.088	.033	.031	.099	-.024	-.064	.207	.095	.063	-.011	.104	.035	-.187	-.004	.095	-.046
Cell17	.072	.006	-.001	.040	.075	.017	.003	-.025	.040	-.023	.031	-.091	.370	-.060	.030	-.057	-.040	.022	.112
Cell18	-.032	-.137	.014	.467	-.041	-.005	-.027	.068	-.022	.000	-.071	-.165	.015	.004	.015	.034	.059	-.026	.119
Cell19	-.010	.082	.310	-.164	.023	.014	-.041	.037	.010	-.093	-.023	.001	-.010	-.058	-.001	.128	-.097	.061	-.169
Cell20	.134	-.024	.067	.030	.109	-.048	.137	-.035	.030	-.121	.159	-.026	-.098	-.001	.018	-.041	.095	.025	.139
Cell21	-.060	.198	.015	.025	-.005	-.148	.076	.189	-.053	.014	-.103	.010	.116	-.026	.055	.064	-.019	-.085	.032
Cell22	.027	-.035	.030	.011	.060	-.080	-.089	.040	.056	-.077	.067	.082	-.089	.011	.000	.005	.153	.095	.049
Cell23	.021	-.029	-.075	-.070	-.071	.023	-.040	-.003	.075	.401	-.089	-.016	-.114	.051	-.010	-.019	.068	-.085	.036
Cell24	-.002	.004	.114	.058	-.066	-.077	.076	-.027	-.026	.237	.107	.095	.025	-.005	-.015	-.001	-.247	.082	-.011
Cell25	-.135	-.045	.037	.002	-.083	.292	-.079	.067	.078	.071	.025	.024	.036	-.103	.161	.068	-.013	-.011	.020

**Table 7** (continued)

		PC—Varimax Standardised																		
Cells	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	
Cell26	-.006	.395	-.100	-.088	.025	-.070	.004	-.009	-.125	-.035	-.030	-.022	-.054	-.057	-.004	-.043	.048	.127	-.007	
Cell27	-.031	.120	-.043	-.089	.015	.114	.079	-.130	.261	-.090	.107	.034	.067	.049	-.036	.029	.042	-.067	.043	
Cell28	.058	-.001	-.062	.062	.023	-.008	.365	-.019	.136	-.039	-.050	-.032	.069	.051	.119	.036	.021	-.093	-.019	
Cell29	.120	.005	.048	-.027	.024	-.081	.050	.038	-.039	-.114	-.060	.166	-.038	-.422	.055	-.034	-.015	-.045	-.002	
Cell30	.034	.029	-.124	-.078	.080	.044	.009	.080	.070	.036	.002	.020	.051	.020	.129	.047	.027	.208	.054	
Cell31	-.061	-.018	.087	.087	-.016	-.044	.034	.014	-.054	.009	-.076	.302	-.051	-.021	.016	.018	-.014	-.095	.204	
Cell32	-.084	.130	.041	.014	.009	.004	.007	-.047	.039	.101	-.032	-.078	.190	-.240	.069	.066	.006	.061	.099	
Cell33	.026	-.129	.405	.064	-.014	.028	-.071	-.024	-.092	.012	.042	-.077	.058	-.047	-.029	-.039	-.016	-.014	-.106	
Cell34	.067	-.013	.175	.083	-.037	-.074	-.033	-.127	.098	.113	-.049	-.157	-.071	.008	.022	.007	.326	-.080	-.033	
Cell35	-.001	.027	-.113	.016	-.041	.059	.058	-.097	.038	-.033	-.119	.199	.123	.272	.240	-.100	.018	.006	.076	
Cell36	.053	-.107	.105	-.027	.165	.019	.018	.185	-.065	.021	-.121	-.041	-.177	.061	.023	-.220	.065	-.039	.076	
Cell37	-.080	-.019	-.055	-.008	-.061	.005	.041	-.001	-.031	-.003	.027	.024	.054	.011	.025	.001	.473	.081	.010	
Cell38	.029	-.004	-.017	-.126	.062	-.038	.375	.002	.003	-.012	-.037	.063	-.055	-.080	.018	.026	.021	.113	.048	
Cell39	-.049	.050	.022	.280	-.004	-.068	-.001	-.006	-.107	-.032	.142	.060	.074	-.018	-.005	.036	-.020	-.058	-.149	
Cell40	-.035	.019	.035	-.023	-.017	.004	.032	.032	-.064	-.037	.046	-.108	.038	.051	-.081	-.096	.075	.540	.030	
Cell41	.088	.039	.045	.042	.114	-.186	-.042	-.112	.067	-.022	-.055	.016	-.035	.218	.036	.121	.031	.049	-.052	
Cell42	-.010	.222	-.017	-.129	-.108	.173	-.042	.142	.010	-.234	-.030	-.047	-.100	.135	-.045	-.144	.020	-.100	-.153	
Cell43	.036	-.082	-.121	-.010	.139	-.024	-.167	.014	.166	-.034	.106	.010	-.065	-.064	.173	.042	-.251	-.017	-.100	
Cell44	-.064	-.054	.051	-.033	-.071	.042	.019	.039	.026	-.057	.009	.071	.362	.024	-.060	.085	.068	.031	-.092	
Cell45	-.001	-.136	-.067	-.003	-.084	-.005	.033	.078	.518	.055	-.035	-.017	.039	-.003	-.016	.027	-.016	-.038	-.070	
Cell46	-.057	-.065	-.035	.136	.300	.123	.081	.068	-.111	.002	.088	-.101	-.001	-.149	.031	.013	.060	-.119	-.012	
Cell47	-.017	-.079	-.039	.000	-.030	.081	-.008	.444	.012	-.010	.007	-.009	-.005	-.095	-.104	.032	-.016	.005	.010	
Cell48	-.063	-.018	-.013	.025	.057	.042	.044	.050	.038	.015	-.081	-.017	.027	-.001	-.052	.435	.003	-.112	-.024	
Cell49	-.036	-.028	-.120	.050	-.041	.004	.001	.061	-.057	.011	-.023	.057	.012	-.009	-.050	-.035	.005	.036	.577	

**Table 7** (continued)

		PC—Varimax Standardised																	
Cells	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Cell50	,030	,095	,027	-,116	,441	-,047	,026	-,110	-,055	-,063	-,046	-,019	,030	,047	-,088	,015	-,088	,024	-,054
Cell51	-,013	-,030	-,028	-,014	-,036	,011	-,058	,005	-,003	,011	,434	,014	,001	,005	,017	-,069	-,014	,012	-,043
Cell52	-,059	,015	-,121	,081	,037	,149	,263	-,014	,056	,027	,126	-,072	-,063	-,172	-,217	-,217	,080	-,008	-,100

**Table 8** Standardised weights of the PC varimax after simplification process

		Constellations																		
Cells		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Cell1					0,17															
Cell2	0,11															0,18	0,30			
Cell3	0,13												0,18							
Cell4						0,35														
Cell5							0,10				0,20	0,17				0,13				
Cell6	0,32																			
Cell7							0,12													0,11
Cell8	0,27																		0,13	
Cell9							0,19													
Cell10													0,24							
Cell11																				0,11
Cell12								0,29				0,12		0,49						
Cell13	0,15										0,16									
Cell14	0,13						0,19					0,21			0,17				0,14	0,10
Cell15	0,10									0,20	0,18									
Cell16											0,21				0,10					
Cell17														0,37						0,11
Cell18																				0,12
Cell19																	0,13			
Cell20	0,13					0,11		0,14				0,16								0,14
Cell21									0,19					0,12						
Cell22																				0,15
Cell23											0,40									
Cell24				0,11							0,24	0,11								
Cell25							0,29													0,16

**Table 8** (continued)

Cells	Constellations																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Cell26		0,40																	0,13
Cell27		0,12				0,11			0,26		0,11								
Cell28							0,37		0,14						0,12				
Cell29	0,12											0,17							
Cell30												0,30						0,21	
Cell31													0,19						0,20
Cell32										0,10									
Cell33			0,40																
Cell34			0,18							0,11							0,33		
Cell35												0,20	0,12	0,27	0,24				
Cell36			0,11		0,16			0,18											
Cell37																	0,47		
Cell38							0,38											0,11	
Cell39				0,28							0,14								
Cell40																			0,54
Cell41					0,11														
Cell42		0,22				0,17		0,14						0,22		0,12			
Cell43					0,14				0,17		0,11			0,13					
Cell44													0,36						
Cell45									0,52										
Cell46				0,14	0,30	0,12													
Cell47								0,44											
Cell48															0,44				
Cell49																			0,58

**Table 8** (continued)

		Constellations																		
Cells		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Cell150						0,44														
Cell151												0,43								
Cell152							0,15	0,26				0,13								

**Table 9** Architectural and Usage Profiles of Burgled Residences in the First Six Constellations – Percentage Relative to Total Burglaries Within Each Cell\*

Cells (utmX/utm Y)	weight	1st residence—Terraced house/Row house	1st residence—Detached single-family house	1st residence—Lodging facility/Small accommodation unit	1st residence—Rural farm-house/Iso-lated rural dwelling	1st residence—Apartment/Multi-family housing unit	2nd residence—Terraced house/Row house	2nd residence—Detached single-family house	2nd residence—Rural farm-house/Iso-lated rural dwelling	2nd residence—Apartment unit/Multi-family housing unit	Total burglaries during 2019	Environmental description of the top-weighted cells in the constellation
<b>Constellation 1</b>												
4,3/45,85	0,4	6,4%	0,9%	0,0%	0,0%	91,5%	0,3%	0,0%	0,0%	0,9%	329	Suburban areas
4,35/45,85	0,5	16,9%	0,3%	0,0%	0,0%	81,1%	1,0%	0,0%	0,0%	0,7%	307	
4,25/45,95	0,9	22,0%	5,8%	0,0%	0,0%	69,1%	1,5%	1,2%	0,0%	0,4%	259	
4,3/45,95	0,8	23,4%	2,9%	0,4%	0,0%	70,7%	1,7%	0,0%	0,0%	0,8%	239	
4,3/45,9	0,5	16,6%	13,1%	0,0%	0,6%	66,9%	1,1%	1,1%	0,0%	0,6%	175	
4,2/46	0,3	16,2%	8,1%	0,0%	0,6%	74,0%	0,0%	1,2%	0,0%	0,0%	173	
4,25/45,9	0,5	25,6%	16,3%	0,0%	0,0%	56,4%	1,7%	0,0%	0,0%	0,0%	172	
4,7/46,05	0,3	14,8%	18,8%	0,0%	0,7%	38,3%	3,4%	11,4%	2,0%	10,7%	149	
<b>Total</b>		<b>17,1%</b>	<b>6,6%</b>	<b>0,1%</b>	<b>0,2%</b>	<b>71,9%</b>	<b>1,2%</b>	<b>1,3%</b>	<b>0,2%</b>	<b>1,4%</b>	<b>1803</b>	
<b>Constellation 2</b>												
4,2/45,9	0,4	15,3%	34,3%	0,0%	0,0%	47,1%	0,8%	2,2%	0,0%	0,3%	359	upper class residential areas
4,4/45,9	0,6	26,6%	47,2%	0,0%	0,9%	21,1%	0,5%	2,8%	0,0%	0,9%	218	
4,35/46,1	0,5	16,9%	61,0%	0,0%	1,5%	5,1%	3,7%	11,0%	0,7%	0,0%	136	
4,15/46,05	0,9	7,6%	79,7%	0,0%	0,0%	4,2%	0,8%	6,8%	0,0%	0,8%	118	
4,35/46	0,4	24,8%	24,8%	0,0%	0,0%	42,9%	1,9%	2,9%	1,0%	1,9%	105	
4,45/46,05	0,4	15,7%	48,3%	0,0%	0,0%	28,1%	0,0%	6,7%	0,0%	1,1%	89	
4,55/46,15	0,5	17,0%	37,7%	0,0%	3,8%	37,7%	1,9%	1,9%	0,0%	0,0%	53	
<b>Total</b>		<b>18,0%</b>	<b>45,6%</b>	<b>0,0%</b>	<b>0,6%</b>	<b>29,4%</b>	<b>1,2%</b>	<b>4,4%</b>	<b>0,2%</b>	<b>0,6%</b>	<b>1078</b>	

Table 9 (continued)

Constellation	Cells (utmX/utm Y)	weight	1 st residence—Terraced house/Row house	1 st residence—Detached family house	1 st residence—Lodging facility/Small accommodation unit	1 st residence—Rural farm-house/Iso-lated rural dwelling	1 st residence—Apartment unit/Multi-family housing unit	2nd residence—Terraced house/Row house	2nd residence—Detached single-family house	2nd residence—Rural farm-house/Iso-lated rural dwelling	2nd residence—Apartment unit/Multi-family housing unit	Total burglaries during 2019	Environmental description of the top-weighted cells in the constellation
Constellation 3	4,6/46	0,7	19,7%	15,0%	0,0%	0,0%	35,4%	8,8%	10,9%	1,4%	8,8%	147	Touristic places
	4,3/46,05	0,3	16,1%	53,2%	0,0%	0,0%	14,5%	1,6%	14,5%	0,0%	0,0%	124	
	4,4/45,95	0,4	23,3%	58,9%	0,0%	0,0%	4,4%	2,2%	10,0%	0,0%	1,1%	90	
	4,4/46	0,8	23,0%	54,0%	0,0%	1,1%	20,7%	0,0%	0,0%	0,0%	1,1%	87	
	4,3/46	0,5	24,7%	56,8%	0,0%	2,5%	8,6%	1,2%	6,2%	0,0%	0,0%	81	
Const. 4	4,3/46,1	0,4	2,9%	71,0%	0,0%	0,0%	7,2%	1,4%	17,4%	0,0%	0,0%	69	upper class residential areas
	Total		<b>18,7%</b>	<b>47,3%</b>	<b>0,5%</b>	<b>0,0%</b>	<b>17,4%</b>	<b>3,2%</b>	<b>10,0%</b>	<b>0,3%</b>	<b>2,5%</b>	<b>598</b>	
	4,2/45,9	0,5	15,3%	34,3%	0,0%	0,0%	47,1%	0,8%	2,2%	0,0%	0,0%	359	
	4,35/45,9	0,9	18,1%	29,7%	0,0%	2,6%	44,5%	1,3%	3,9%	0,0%	0,0%	155%	
	4,2/46,05	0,7	15,9%	41,3%	0,0%	0,0%	28,6%	4,8%	6,3%	0,0%	0,0%	63	
Total		<b>16,1%</b>	<b>33,8%</b>	<b>0,0%</b>	<b>0,7%</b>	<b>44,4%</b>	<b>1,4%</b>	<b>3,1%</b>	<b>0,0%</b>	<b>0,0%</b>	<b>0,5%</b>	<b>577</b>	

**Table 9** (continued)

Constellation	Cells (utmX/utm Y)	weight	1 st residence—Terraced house/Row house	1 st residence—Detached family house	1 st residence—Lodging facility/Small accommodation unit	1 st residence—Rural farm-house/Iso-lated rural dwelling	1 st residence—Apartment unit/Multi-family housing unit	2nd residence—Terraced house/Row house	2nd residence—Detached single-family house	2nd residence—Rural farm-house/Iso-lated rural dwelling	2nd residence—Apartment unit/Multi-family housing unit	Total burglaries during 2019	Environmental description of the weighted cells in the constellation
Constellation 5	4,45/46,1	0,3	18,4%	58,8%	0,0%	1,5%	5,9%	1,5%	12,5%	0,7%	0,7%	136	Far from major cities, periphery of the police region
	4,2/45,85	0,3	7,7%	80,2%	0,0%	0,0%	2,2%	1,1%	8,8%	0,0%	0,0%	91	
	4,3/46,1	0,4	2,9%	71,0%	0,0%	0,0%	7,2%	1,4%	17,4%	0,0%	0,0%	69	
	4,4/46,1	0,4	24,6%	38,6%	0,0%	0,0%	22,8%	3,5%	8,8%	0,0%	1,8%	57	
	4,05/46,05	0,4	5,9%	51,0%	0,0%	2,0%	3,9%	3,9%	33,3%	0,0%	0,0%	51	
	4,65/46	0,6	47,6%	19,0%	0,0%	0,0%	11,9%	14,3%	2,4%	2,4%	2,4%	42	
Const. 6	4,4/46,15	0,9	21,6%	24,3%	0,0%	0,0%	48,6%	0,0%	5,4%	0,0%	0,0%	37	Urban areas of medium-sized towns
	Total		<b>16,4%</b>	<b>55,3%</b>	<b>0,0%</b>	<b>0,6%</b>	<b>11,0%</b>	<b>2,9%</b>	<b>12,8%</b>	<b>0,4%</b>	<b>0,6%</b>	<b>483</b>	
	4,4/46,05	0,8	14,8%	4,7%	0,0%	0,3%	75,1%	1,3%	0,7%	0,3%	2,7%	297	
	4,15/45,9	0,5	13,5%	21,3%	0,0%	0,0%	56,5%	2,2%	4,8%	0,0%	1,7%	230	
	4,25/45,9	0,4	25,6%	16,3%	0,0%	0,0%	56,4%	1,7%	0,0%	0,0%	0,0%	172	
	4,45/45,9	0,6	33,9%	6,5%	0,0%	0,0%	48,4%	4,0%	1,6%	0,0%	5,6%	124	
4,65/46	0,3	47,6%	19,0%	0,0%	0,0%	11,9%	14,3%	2,4%	2,4%	2,4%	42		
Total			<b>20,9%</b>	<b>12,4%</b>	<b>0,0%</b>	<b>0,1%</b>	<b>59,5%</b>	<b>2,7%</b>	<b>1,8%</b>	<b>0,2%</b>	<b>2,3%</b>	<b>865</b>	

\* Note: Some cells are shared by multiple constellations but have a high weight in only one of them. These overlaps may distort the profiles shown in the table, as the cells with the highest weight in a constellation do not necessarily correspond to those with the highest number of burglaries over the course of the year

**Table 10** Runs test for the standardized series of weekly burglaries in the

Runs test	Const. 1	Const. 2	Const. 3	Const. 4	Const. 5	Const. 6	Const. 7	Const. 8	Const. 9	Const. 10	Const. 11	Const. 12	Const. 13	Const. 14	Const. 15	Const. 16	Const. 17	Const. 18	Const. 19	
Total cases	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260
Test Value	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50	-1,50
Number of runs	15	18	7	13	7	23	13	9	15	8	20	15	13	1	23	17	1	9	25	
Z	-4,50	-1,92	-4,10	0,40	0,21	0,73	-1,99	-3,13	0,46	-1,92	-2,80	-1,62	-1,99	-5,61	-5,61	0,53	-3,13	0,80	0,80	
Sig. asympt. (bilateral)	,000	,055	,000	,691	,837	,466	,046	,002	,644	,055	,005	,106	,046	,000	,000	,597	,002	,426	,426	
Test Value ( $\mu - \sigma$ )	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00	
Number of runs	41	48	54	55	54	48	52	61	58	50	52	69	51	77	67	65	47	47	51	
Z	-4,35	-3,32	-1,30	-3,01	-3,52	0,07	-3,74	-2,66	-4,21	-3,10	-4,69	-1,40	-2,15	-1,81	-2,08	-0,56	-0,80	-1,74	-2,83	
Sig. asympt. (bilateral)	,000	,001	,193	,003	,000	,945	,000	,008	,000	,002	,000	,162	,032	,070	,038	,574	,421	,081	,005	
Test Value ( $\mu - 0,5\sigma$ )	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50	
Number of runs	74	78	86	71	93	98	113	90	72	91	86	91	90	92	107	98	102	75	79	
Z	-5,44	-5,22	-4,30	-6,39	-3,83	-2,54	-1,22	-3,67	-6,69	-4,30	-4,49	-4,20	-2,23	-4,17	-1,68	-2,11	-2,74	-5,71	-5,33	
Sig. asympt. (bilateral)	,000	,000	,000	,000	,000	,011	,224	,000	,000	,000	,000	,000	,026	,000	,093	,035	,006	,000	,000	
Test Value ( $\mu$ )	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
Number of runs	84	88	89	76	93	105	117	86	81	83	87	99	103	108	106	100	92	91	87	
Z	-5,68	-5,16	-4,87	-6,77	-4,50	-3,19	-1,67	-5,50	-6,06	-5,96	-5,24	-3,83	-2,86	-2,84	-2,95	-3,55	-3,67	-4,61	-5,47	
Sig. asympt. (bilateral)	,000	,000	,000	,000	,000	,001	,095	,000	,000	,000	,000	,000	,004	,005	,003	,000	,000	,000	,000	
Test Value ( $\mu + 0,5\sigma$ )	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	

Table 10 (continued)

Runs test	Const. 1	Const. 2	Const. 3	Const. 4	Const. 5	Const. 6	Const. 7	Const. 8	Const. 9	Const. 10	Const. 11	Const. 12	Const. 13	Const. 14	Const. 15	Const. 16	Const. 17	Const. 18	Const. 19
Number of runs	75	69	59	68	81	77	81	67	69	81	71	83	83	79	90	86	68	77	78
Z	-3,50	-5,52	-5,89	-5,28	-3,29	-3,30	-4,05	-5,64	-6,56	-3,75	-4,79	-3,09	-2,97	-1,82	-1,84	-3,67	-3,68	-3,82	-3,53
Sig. asympt. (bilateral)	,000	,000	,000	,000	,001	,001	,000	,000	,000	,000	,000	,002	,003	,069	,066	,000	,000	,000	,000
Test Value ( $\mu + \sigma$ )	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Number of runs	49	41	53	46	49	57	53	53	43	49	49	47	51	59	70	58	54	45	62
Z	-3,37	-6,43	-4,01	-4,72	-4,72	-3,32	-3,50	-2,62	-6,35	-3,95	-3,67	-2,93	-1,77	-1,05	-2,57	-3,09	-2,97	-4,44	-2,92
Sig. asympt. (bilateral)	,001	,000	,000	,000	,000	,001	,000	,009	,000	,000	,000	,003	,076	,292	,010	,002	,003	,000	,003
Test Value ( $\mu + 1,5\sigma$ )	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50	1,50
Number of runs	29	25	35	22	23	35	31	33	39	39	33	25	33	33	42	29	29	29	24
Z	-3,35	-4,64	-2,54	-7,80	-5,03	-3,08	-2,42	-1,49	-2,08	-2,08	-1,49	-3,29	-1,49	-2,79	-0,96	-1,11	-4,97	-4,97	-2,16
Sig. asympt. (bilateral)	,001	,000	,011	,000	,000	,002	,015	,135	,037	,037	,135	,001	,135	,005	,337	,268	,000	,000	,031

**Authors' Contributions** All jointly participated in the study design and decision-making of the analytical strategy and contributed significantly to the revision of the manuscript and the contribution of intellectual content. More specifically:

**Pere Boqué:** Data curation, Methodology, Software, Writing- Original draft preparation. **Laura Serra:** Conceptualization, Methodology, Software, Writing- Reviewing and Editing. **Marc Saez:** Methodology, Validation, Writing- Reviewing.

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**Data Availability** The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Ethics Approval and Consent to Participate** All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

**Conflict of interest** The authors declare no conflicts of interest.

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## References

- Addis, N., Evans, A., & Malleson, N. (2021). Burglars as optimal foragers: Exploring modern-day tricks of the trade. *Crime Prevention and Community Safety*, 23(4), 359–380. <https://doi.org/10.1057/s41300-021-00125-x>
- Bennett-Moses, L., & Chan, J. (2018). Algorithmic prediction in policing: Assumptions, evaluation, and accountability. *Policing and Society*, 28(7), 806–22. <https://doi.org/10.1080/10439463.2016.1253695>
- Berk, R. A. (2021). Artificial intelligence, predictive policing, and risk assessment for law enforcement. *Annual Review of Criminology*, 4(1), 209–237. <https://doi.org/10.1146/annurev-criminol-051520-012342>
- Berk, R., & MacDonald, J. (2009). The dynamics of crime regimes. Article. *Criminology*, 47(3), 971–1008. <https://doi.org/10.1111/j.1745-9125.2009.00161.x>
- Bernasco, W. (2008). Them again?: Same-offender involvement in repeat and near repeat burglaries. *European Journal of Criminology*, 5(4), 411–431. <https://doi.org/10.1177/1477370808095124>
- Bernasco, W., & Nieuwebeerta, P. (2005). How do residential burglars select target areas? : A new approach to the analysis of criminal location choice. *British Journal of Criminology*, 45(3), 296–315. <https://doi.org/10.1093/bjc/azh070>
- Bernasco, W., Johnson, S. D., & Ruiter, S. (2015). Learning where to offend: Effects of past on future burglary locations. *Applied Geography*, 60, 120–129. <https://doi.org/10.1016/j.apgeog.2015.03.014>
- Bernasco, W. (2009). Foraging strategies of homo criminalis: Lessons from behavioral ecology. *Crime Patterns and Analysis*, 2(1), 5–16. <http://www.eccajournal.org/V2N1S2009/Bernasco.pdf>
- Birks, D., Townsley, M., & Stewart, A. (2012). Generative explanations of crime: Using simulation to test criminological theory. *Criminology*, 50(1), 221–254. <https://doi.org/10.1111/j.1745-9125.2011.00258.x>
- Bogucki, R., Milczek, J. K., & Miziula, P. (2020). A simple crime hotspot forecasting algorithm. In *Proceedings of the 2020 Federated Conference on Computer Science and Information Systems (FedCSIS)* (pp. 23–26). <https://doi.org/10.15439/2020F5>

- Boqué, P., Marc, S., & Laura, S. (2022). Need to go further: Using INLA to discover limits and chances of burglaries' spatiotemporal prediction in heterogeneous environments. *Crime Science*, *11*(1), 1–22. <https://doi.org/10.1186/S40163-022-00169-W/FIGURES/15>
- Boqué, P., Serra, L., & Saez, M. (2020). 'Surfing' burglaries with forced entry in Catalonia: Large-scale testing of near repeat victimization theory. *European Journal of Criminology*, *18*(6), 748–767. <https://doi.org/10.1177/1477370820968102>
- Borrion, H., Ekblom, P., Alrajeh, D., Borrion, A. L., Keane, A., Koch, D., Mitchener-Nissen, T., & Toubaline, S. (2020). The problem with crime problem-solving: Towards a second generation pop? *British Journal of Criminology*, *60*(1), 219–240. <https://doi.org/10.1093/bjc/azz029>
- Bowers, K. J. (2005). Domestic burglary repeats and space-time clusters: The dimensions of risk. *European Journal of Criminology*, *2*(1), 67–92. <https://doi.org/10.1177/1477370805048631>
- Bowers, K. J., Johnson, S. D., Guerette, R. T., Summers, L., & Poynton, S. (2011). Spatial displacement and diffusion of benefits among geographically focused policing initiatives: A meta-analytical review. *Journal of Experimental Criminology*, *7*(4), 347–374. <https://doi.org/10.1007/s11292-011-9134-8>
- Braga, A. A., Turchan, B., Papachristos, A. V., & Hureau, D. M. (2019a). Hot spots policing of small geographic areas: Effects on crime. *Campbell Systematic Reviews*, *15*(3), e1046. <https://doi.org/10.1002/cl2.1046>
- Braga, A. A., Turchan, B. S., Papachristos, A. V., & Hureau, D. M. (2019b). Hot spots policing and crime reduction: An update of an ongoing systematic review and meta-analysis. *Journal of Experimental Criminology*, *15*(3), 289–311. <https://doi.org/10.1007/s11292-019-09372-3>
- Brantingham, P., & Brantingham, P. (1995). Criminality of place - crime generators and crime attractors. *European Journal on Criminal Policy and Research*, *3*(3), 5–26. <https://doi.org/10.1007/BF02242925>
- Brown, J., Belur, J., Tompson, L., McDowall, A., Hunter, G., & May, T. (2018). Extending the remit of evidence-based policing. *International Journal of Police Science and Management*, *20*(1), 38–51. <https://doi.org/10.1177/1461355717750173>
- Chainey, S. P., Curtis-Ham, S. J., Mark Evans, R., & Burns, G. J. (2018). Examining the extent to which repeat and near repeat patterns can prevent crime. *Policing*, *41*(5), 608–622. <https://doi.org/10.1108/PJPSM-12-2016-0172>
- Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, *9*(2), 129–136. [https://doi.org/10.1016/0040-5809\(76\)90040-X](https://doi.org/10.1016/0040-5809(76)90040-X)
- Chen, P., & Kurland, J. (2020). The impact of “Strike Hard” on repeat and near-repeat residential burglary in Beijing. *ISPRS International Journal of Geo-Information*, *9*(3), 150. <https://doi.org/10.3390/ijgi9030150>
- Clarke, R. V., & Cornish, D. B. (1985). Modeling offenders' decisions: A framework for research and policy. In M. Tonry, & N. Morris (Eds.), *Crime and justice: An annual review of research* (Vol. 6, pp. 147–185). University of Chicago Press. <https://doi.org/10.1086/449106>
- Curtis-Ham, S., Bernasco, W., Medvedev, O. N., & Polaschek, D. (2020). A framework for estimating crime location choice based on awareness space. *Crime Science*, *9*(1), 1–14. <https://doi.org/10.1186/s40163-020-00132-7>
- Diggle, P. J. (2005). *Spatio-temporal point processes: Methods and applications*. Johns Hopkins University, Department of Biostatistics, Working Paper 78. <https://biostats.bepress.com/jhubiostat/paper78/>
- Farrell, G., & Pease, K. (1993). Once bitten, twice bitten: Repeat victimisation and its implications for crime prevention. In *Police research group, crime prevention unit series, paper no. 46*. Home Office. [https://popcenter.asu.edu/sites/default/files/problems/burglary\\_home/PDFs/Farrell\\_Pease\\_1993.pdf](https://popcenter.asu.edu/sites/default/files/problems/burglary_home/PDFs/Farrell_Pease_1993.pdf)
- Farrell, G., & Pease, K. (2017). Preventing repeat and near repeat crime concentrations. In *Handbook of crime prevention and community safety*. <https://doi.org/10.4324/9781315724393>
- Generalitat de Catalunya – Mossos d'Esquadra. (n.d.). Open data – Mossos d'Esquadra. [https://mossos.gencat.cat/ca/els\\_mossos\\_desquadra/indicadors\\_i\\_qualitat/dades\\_obertes/](https://mossos.gencat.cat/ca/els_mossos_desquadra/indicadors_i_qualitat/dades_obertes/). Accessed 5 May 2025.
- Goldstein, H. (1990). *Problem-oriented policing*. McGraw-Hill. <https://www.ojp.gov/ncjrs/virtual-library/abstracts/problem-oriented-policing-1>
- Groff, E., & Taniguchi, T. (2019). Quantifying crime prevention potential of near-repeat burglary. *Police Quarterly*, *22*(3), 330–359. <https://doi.org/10.1177/1098611119828052>
- Groff, E. R., Johnson, S. D., & Thornton, A. (2019). State of the art in agent-based modeling of urban crime: An overview. *Journal of Quantitative Criminology*, *35*(1), 155–193. <https://doi.org/10.1007/s10940-018-9376-y>
- Guerette, R. T., & Bowers, K. J. (2009). Assessing the extent of crime displacement and diffusion of benefits: A review of situational crime prevention evaluations. *Criminology*, *47*(4), 1331–1368. <https://doi.org/10.1111/j.1745-9125.2009.00177.x>
- Halford, E. (2023a). Linking foraging domestic burglary: An analysis of crimes committed within police-identified optimal forager patches. *Journal of Police and Criminal Psychology*, *38*(1), 127–140. <https://doi.org/10.1007/s11896-022-09497-8>

- Halford, E. (2023b). 'Two sides of the same coin' - A proposed model for delivering a whole system serial crime reduction plan. *Policing (Oxford)*, 17, 1–14. <https://doi.org/10.1093/police/paad026>
- Halford, E., Giannoulis, M., Condon, C., & Keningale, P. (2024). Do hotspot policing interventions against optimal foragers cause crime displacement? *International Journal of Law, Crime and Justice*, 77(March), 100654. <https://doi.org/10.1016/j.ijlcrj.2024.100654>
- Halford, E. S. (2019). *Exploring the behaviour of foraging burglary offenders and predictive police interventions to prevent and reduce their offending* (Doctoral dissertation). University of Central Lancashire. <https://clock.uclan.ac.uk/29245/>
- Hardyns, W., & Rummens, A. (2018). Predictive policing as a new tool for law enforcement? Recent developments and challenges. *European Journal on Criminal Policy and Research*, 24(3), 201–218. <https://doi.org/10.1007/s10610-017-9361-2>
- He, Z., Tao, L., Xie, Z., & Chong, Xu. (2020). Discovering spatial interaction patterns of near repeat crime by spatial association rules mining. *Scientific Reports*, 10(1), 1–12. <https://doi.org/10.1038/s41598-020-74248-w>
- Johnson, S. D. (2014). How do offenders choose where to offend? Perspectives from animal foraging. *Legal and Criminological Psychology*, 19(2), 193–210. <https://doi.org/10.1111/lcrp.12061>
- Johnson, S. D., Summers, L., & Pease, K. (2009). Offender as forager? A direct test of the boost account of victimization. *Journal of Quantitative Criminology*, 25(2), 181–200. <https://doi.org/10.1007/s10940-008-9060-8>
- Johnson, S. D., Birks, D. J., McLaughlin, L., Bowers, K. J., & Pease, K. (2007). *Prospective crime mapping in operational context: Final report*. Home Office Online Report 19/07. Home Office. <https://www.ojp.gov/ncjrs/virtual-library/abstracts/prospective-crime-mapping-operational-context-final-report>
- Jolliffe, I. T. (2002). *Principal component analysis* (2nd ed.). Springer. <https://doi.org/10.1007/b98835>
- Kaufmann, M., Egbert, S., & Leese, M. (2019). Predictive policing and the politics of patterns. *British Journal of Criminology*, 59(3), 674–692. <https://doi.org/10.1093/bjc/azy060>
- Lammers, M. (2018). Co-offenders' crime location choice: Do co-offending groups commit crimes in their shared awareness space? *British Journal of Criminology*, 58(5), 1193–1211. <https://doi.org/10.1093/bjc/azx069>
- Lantz, B., & Ruback, R. B. (2017). A networked boost: Burglary co-offending and repeat victimization using a network approach. *Crime and Delinquency*, 63(9), 1066–1090. <https://doi.org/10.1177/0011128715597695>
- Liagre, F., Strategic and Policy Officer, & EUCPN Secretariat. (2017). *Recommendation paper on predictive policing*. European Crime Prevention Network (EUCPN). [https://eucpn.org/sites/default/files/document/files/10.\\_recommendation\\_paper\\_predictive\\_policing\\_update\\_0.pdf](https://eucpn.org/sites/default/files/document/files/10._recommendation_paper_predictive_policing_update_0.pdf)
- Lima, S. L. (2002). Putting predators back into behavioral predator-prey interactions. *Trends in Ecology and Evolution*, 17(2), 70–75. [https://doi.org/10.1016/S0169-5347\(01\)02393-X](https://doi.org/10.1016/S0169-5347(01)02393-X)
- MacArthur, R. H., & Pianka, E. R. (1966). On optimal use of a patchy environment. *The American Naturalist*, 100(916), 603–609. <https://doi.org/10.1086/282454>
- Mallesen, N., Steenbeek, W., & Andresen, M. A. (2019). Identifying the appropriate spatial resolution for the analysis of crime patterns. *PLOS ONE*, 14(6), e0218324. <https://doi.org/10.1371/journal.pone.0218324>
- Mohler, G. O., Short, M. B., Brantingham, P. J., Schoenberg, F. P., & Tita, G. E. (2011). Self-exciting point process modeling of crime. *Journal of the American Statistical Association*, 106(493), 100–108. <https://doi.org/10.1198/jasa.2011.ap09546>
- Nee, C. (2015). Understanding expertise in burglars: From pre-conscious scanning to action and beyond. *Aggression and Violent Behavior*, 20, 53–61. <https://doi.org/10.1016/j.avb.2014.12.006>
- Pearson, K. (1901). Pearson, K. 1901. On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, 2, 559–572.
- Perry, W., McInnis, B., Price, C., Smith, S., & Hollywood, J. (2018). *Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations*. *Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations*. <https://doi.org/10.7249/rr233>
- Pitcher, A. B., & Johnson, S. D. (2011). Exploring theories of victimization using a mathematical model of burglary. G. Rengert, E. Groff, & J. Eck. (Eds.), *Journal of Research in Crime and Delinquency*, 48(1), 83–109. <https://doi.org/10.1177/00224278103884139>
- PRECOBS Ifmpt - Institut Für Musterbasierte Prognosetechnik. (n.d.). Accessed March 20, 2018. <http://www.ifmpt.de/>
- Predict Crime | Predictive Policing Software | PredPol. (n.d.). Accessed March 20, 2018. <http://www.predpol.com/>

- Ratcliffe, J. (2008). *Intelligence-led policing*. Willan. <https://books.google.es/books?id=iPxLvGAAACA AJ>
- Ratcliffe, J. H., & Breen, C. (2011). Crime diffusion and displacement: Measuring the side effects of police operations. *Professional Geographer*, 63(2), 230–243. <https://doi.org/10.1080/00330124.2010.547154>
- Ridgeway, G. (2018). Policing in the era of big data. *Annual Review of Criminology*, 1, 421–449. <https://doi.org/10.1146/annurev-criminol-062217-114209>
- Rossmo, D. K., & Summers, L. (2022). Uncertainty and heuristics in offender decision-making: Deviations from rational choice. *Journal of Criminal Justice*, 81(January), 101923. <https://doi.org/10.1016/j.jcrimjus.2022.101923>
- Sherman, L. W. (1998). Evidence-based policing. In *Ideas in American policing*. Police Foundation. <https://www.policinginstitute.org/publication/evidence-based-policing/>
- Short, M. B., D’Orsogna, M. R., Pasour, V. B., Tita, G. E., Brantingham, P. J., Bertozzi, A. L., & Chayes, L. B. (2008). A statistical model of criminal behavior. *Mathematical Models and Methods in Applied Sciences*, 18(supp01), 1249–67. <https://doi.org/10.1142/S0218202508003029>
- Sorg, E. T., Wood, J. D., Groff, E. R., & Ratcliffe, J. H. (2017). Explaining dosage diffusion during hot spot patrols: An application of optimal foraging theory to police officer behavior. *Justice Quarterly*, 34(6), 1044–1068. <https://doi.org/10.1080/07418825.2016.1244286>
- Summers, L., Johnson, S. D., & Rengert, G. F. (2010). The use of maps in offender interviewing. In W. Bernasco (Ed.), *Offenders on offending: Learning about crime from criminals* (pp. 246–272). Willan Publishing. <https://www.ojp.gov/library/publications/use-maps-offender-interviewing-offenders-offending-learning-about-crime>
- Taylor, R. B., & Ratcliffe, J. H. (2020). Was the pope to blame? Statistical powerlessness and the predictive policing of micro-scale randomized control trials. *Criminology and Public Policy*, 19(3), 965–996. <https://doi.org/10.1111/1745-9133.12514>
- Townsend, M. (2003). Infectious burglaries. A test of the near repeat hypothesis. *British Journal of Criminology*, 43(3), 615–633. <https://doi.org/10.1093/bjc/43.3.615>
- Townsend, M., & Sidebottom, A. (2010). All offenders are equal, but some are more equal than others: Variation in journeys to crime between offenders. *Criminology*, 48(3), 897–917. <https://doi.org/10.1111/j.1745-9125.2010.00205.x>
- Tseloni, A., & Pease, K. (2003). Repeat personal victimization: ‘Boosts’ or ‘flags’? *British Journal of Criminology*, 43(1), 196–212. <https://doi.org/10.1093/bjc/43.1.196>
- Van Daele, S., & Vander Beken, T. (2009). Out of step? Mobility of itinerant crime groups. In P. C. van Duyne, S. Donati, J. Harvey, A. Maljevic, & K. von Lampe (Eds.), *Crime, money and criminal mobility in Europe* (pp. 43–70). Wolf Legal Publishers. [https://www.researchgate.net/profile/Klaus-Von-Lampe/publication/45179107\\_Crime\\_money\\_and\\_criminal\\_mobility\\_in\\_Europe/links/56eefc7a08aed17d09f85d0e/Crime-money-and-criminal-mobility-in-Europe.pdf](https://www.researchgate.net/profile/Klaus-Von-Lampe/publication/45179107_Crime_money_and_criminal_mobility_in_Europe/links/56eefc7a08aed17d09f85d0e/Crime-money-and-criminal-mobility-in-Europe.pdf)
- Van Gelder, J. L. (2013). Beyond rational choice: The hot/cool perspective of criminal decision making. *Psychology, Crime and Law*, 19(9), 745–63. <https://doi.org/10.1080/1068316X.2012.660153>
- Van Deviver, C., Van Daele, S., & Van Der Beken, T. (2015). What makes long crime trips worth undertaking balancing costs and benefits in burglars journey to crime. *British Journal of Criminology*, 55(2), 399–420. <https://doi.org/10.1093/bjc/azu078>
- Vandeviver, C., Neutens, T., van Daele, S., Geurts, D., & Beken, T. V. (2015). A Discrete spatial choice model of burglary target selection at the house-level. *Applied Geography*, 64, 24–34. <https://doi.org/10.1016/j.apgeog.2015.08.004>
- Vandeviver, C., Neiryck, E., & Bernasco, W. (2023). The foraging perspective in criminology: A review of research literature. *European Journal of Criminology*, 20(2), 626–652. <https://doi.org/10.1177/14773708211025864>
- Wang, Z., Liu, L., Zhou, H., & Lan, M. (2019). Crime geographical displacement: Testing its potential contribution to crime prediction. *ISPRS International Journal of Geo-Information*, 8(9), 1–12. <https://doi.org/10.3390/ijgi8090383>
- Wang, Z., & Zhang, H. (2020). Construction, detection, and interpretation of crime patterns over space and time. *ISPRS International Journal of Geo-Information*, 9(6), 339. <https://doi.org/10.3390/ijgi9060339>
- Wollinger, G. R., Querbach, M., Röhrig, A., König, A., & Isenhardt, A. (2018). *Offender organization and criminal investigations with regard to organised residential burglary: Results of an international expert survey* (Research Report No. 147). Kriminologisches Forschungsinstitut Niedersachsen e.V. (KFN). [https://kfn.de/wp-content/uploads/Forschungsberichte/FB\\_147%20en.pdf](https://kfn.de/wp-content/uploads/Forschungsberichte/FB_147%20en.pdf)