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Seasonal characteristics of crime: an empirical investigation of the temporal fluctuation of the different types of crime in London

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Abstract

Most types of crimes show seasonal fluctuations but the difference and similarity of the periodicity between different crimes are understudied. Interpreting the seasonality of different crime types and formulating clusters of crimes that share similar seasonal characteristics would help identify the common underlying factors and revise the patterns of patrolling and monitoring to enable sustained management of the control strategies. This study proposes a new methodological framework for measuring similarities and differences in the timing of peaks and troughs, as well as the waveforms of different crimes. The method combines a Poisson state-space model with cluster analysis and multi-dimensional scaling. A case study using twelve types of crimes in London (2013–2020) demonstrated that the amplitude of the seasonal fluctuation identified by this method explained 95.2% of the similarity in their waveforms, while the timing of the peaks covered 87.5% of the variance in their seasonal fluctuation. The high predictability of the seasonal patterns of crimes as well as the stable categorisation of crimes with similar seasonal characteristics enable sustainable and measured planning of police resource allocation and, thereby, facilitates a more efficient management of the urban environment.

Keywords Cluster analysis, Crime seasonality, Multi-dimensional scaling, Trend analysis, Urban sustainability

1 Introduction

Many types of crimes are periodic in that they show seasonal fluctuations in their volume. This tendency is often referred to as *crime seasonality* which can be captured in the form of time-series data with a recurring cycle (Cohen et al., 2003). Crime seasonality has been studied since the mid-nineteenth century (McDowall et al., 2012), because it offers useful insights in several different ways (McPheters & Stronge, 1973). On the theoretical level, studying crime seasonality can help develop theories on their periodicity and identify the underlying cause behind the respective crime (Farrell & Pease, 1994). On the methodological level, it can inform a forecast model for projecting the future volumes of crime and, thereby, enables the local police force to make an informed decision on the scale of crime prevention activities needed in each season (McDowall et al., 2012).

Pursuit of crime seasonality is often motivated by the need to understand the impact of periodic changes in the volume of crime that may induce relevant criminalistic behaviours. Understanding the similarity in

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the periodicity of different crimes will help expand our knowledge base on human behaviours associated with seasonal changes and the respective crime opportunities that emerge in a similar cycle among these crimes. More specifically, identifying a group of crimes that share similar seasonal characteristics could help reveal the risk factors that affect them which, in turn, leads to new insights into the behaviour of the criminals and how they might react to the change of seasons.

In terms of urban management, assessing similarities and differences of the seasonality between different types of crime (especially on how the periodicity of different crimes resonates or opposes with one another) helps coordinate the policing effort to combat such groups of crime by sharing the same policing resources or crime prevention tactics. It would affect many police decisions, such as the short-term deployment for hotspot policing and the long-term redistribution of resources across their precincts (Cohen et al., 2003). The short-term tactics for targeted patrols rely heavily on seasonality projection, as it accounts for up to 50-percent of the changes in crime volume measured at one-month interval (Cohen et al., 2003). As different crimes may peak during different seasons, the police force often find themselves in need of targeting and concentrating their resources on specific types of crime when they become most prevalent. Having a clear idea of the fluctuations in crimes naturally enables the local police force to formulate an efficient and sustainable strategy for managing their finite resource. Understanding the lack of seasonality in some crimes is equally important, as it means the risk of such crimes is perpetual and a fixed resource should be made available. In other words, research on crime seasonality improves our predictive power towards crime forecasting and, for this reason, different aspects of crime seasonality have been studied.

As described in the literature review below, studies on crime seasonality tend to focus on either a detailed analysis and forecasting of a *specific type of crime*, or the measurement and comparison of crime seasonality between *more than one crime type*, often by way of indexing their peaks and troughs. The latter allows us to reflect comparatively on how certain type(s) of crime compare with other crimes in terms of their seasonality. However, only a handful studies have looked at the seasonal resonance and differences across many crimes; and the extent of the similarity and difference between their seasonal characteristics is still understudied. This study aims to develop a methodological framework for classifying crimes by the similarity and differences of their seasonal characteristics in hope of contributing to more efficient and effective policing. Our contributions are in the refinement of the trend extraction method, and construction of groups of crimes that share similar seasonal patterns through cluster analysis and multi-dimensional scaling, whilst also retaining the ability to compare between those within the same group.

2 Literature review

Studies on crime seasonality are many. Some explore the temporal changes across several different crimes (Hird & Ruparel, 2007; McDowall et al., 2012; Andresen & Malleson, 2013; Office for National Statistics, 2013; Linning et al., 2017), while others focus on describing and modelling the fluctuation of specific crime types in each season (e.g. Dong et al., 2017; Ekwall & Lantz, 2022; Stalidis et al., 2018). Empirically, change of season and the weather has been considered to affect the crime volume (Corcoran & Zahnow, 2022); e.g. violent crimes often peak in the summer (Cohn, 1990) and property crimes increase in winter in the global north (Farrell & Pease, 1994). However, little has been studied on the taxonomy of crimes by their seasonal patterns. The following sections offer an overview of the past studies on crime seasonality with a focus on its association with crime theory, as well as the effort on crime categorisation, pursuit of its regional differences, and the methods used for investigating the seasonality of crime.

2.1 Crime seasonality and criminological theories

Crime seasonality is often studied in relation to the criminological theory. Literature suggests that patterns of seasonality depend primarily on the type of crime, and these types are linked to the difference in temperature or the behaviour of the criminals. Quetelet's work (1842) is known as an early example of research into the seasonality of crime. They attributed the increase of crimes in the summer to (1) the increase in pedestrians that leads to greater interactions among people, and (2) the warm weather that reduces people's mental capacity to make rational decision. The former has been developed as *temperature aggression theory* while the latter formed the foundation of *routine activity theory*.

The routine activity theory (Cohen & Felson, 1979) focuses on explaining the seasonal fluctuation of crime through changes in the *opportunities* and *risks* perceived by the criminals. The association between crime seasonality and routine activity theory is often described using time, weather and other seasonal conditions, and how that would affect the human behaviour and change the risk of victimisation at specific seasons, days of the week, or time of day (Ceccato, 2005; Landau & Fridman, 1993; Rotton & Cohn, 2000; Yan, 2004). However, these factors may vary by the region and may be also affected by many other factors. Cohn and Rotton (2000) point out the relevance of routine activity theory towards three property offences: burglary, robbery, and larceny-theft. Furthermore, Cohen and Felson (1979) suggested that fluctuations in crime rates are the result of changes in peoples' activities over the course of the year.

By definition, temperature aggression theory (Anderson et al., 2000) only accounts for the increase in violent crime. However, it can inform other expanded models that incorporate additional factors affected by the temperature. For instance, the social effect is predicated on a needs-based view of property crime (Falk, 1952) and suggests that seasonal unemployment and increased living expenses affect the levels of criminal activity at different times of year (Gorr et al., 2003). The fact that aggressive crimes increase in summer is certainly not new (Breetzke & Cohn, 2012; Cohn, 1990; Rotton & Cohn, 2000, 2003, 2004). Part of the fluctuations in crime volume can be indeed attributed to changes in the temperature or the amount of daylight that may induce crime opportunities (Anderson & Anderson, 1984), but the impact of the temperature and climate seems to reflect differently from one crime to another. For instance, some crimes peak in summer when the pedestrians flow frequently during daytime and houses are left empty with open windows; while others are more prevalent during the winter season with long dark hours and cold weather in the northern hemisphere where there is a small number of pedestrians or potential witnesses (van Koppen & Jansen, 1999). Hird and Ruparel (2007) found that common and indecent assaults peak in the summer in the United Kingdom. Similarly, Breetzke and Cohn (2012) noted the general consensus among researchers on the positive association between temperature and aggression (Anderson et al., 2000; Cohn & Rotton, 1997).

These studies suggest that increase in temperature triggers aggressive behaviour and violent crimes, yet other studies have reported different or contradicting results. For instance, burglary tends to peak in the summer in Northern America (Chimbos, 1973; Cohn & Rotton, 2000; McDowall et al., 2012), while others found that residential burglary in England peaks in winter—Farrell and Pease (1994) suggest burglary reaches peak in February and March, whilst Office for National Statistics (2013) points to November and December. Similarly, Cohn and Rotton (2000) found that robbery peaked in summer, while McDowall et al., (2012) found that all crimes other than robbery peaked in summer. It shows that the *regularity* and *periodicity* of changes in human behaviour and the amount of crime opportunities can be also explained by the change in the outdoor temperature, which in turn implies that routine activity theory itself is subject to temperature changes. These contradicting outcomes are found for a variety of reasons. For instance, some studies suggest the amplitude or the amount of the seasonal fluctuation is smaller for cities in a warmer climate and, conversely, seasonality is more prominent in a colder climate (Hipp et al., 2004). Also, Linning (2015) suggested that: (a) property crimes show distinct temporal peaks in humid continental climates (e.g. Ottawa) and not in temperate areas (e.g. Vancouver); and (b) regardless of climate, micro-spatial patterns of property crime remain relatively consistent across the year. However, Dodge and Lentzner (1980) and Dodge (1988) proposed that crime seasonality depends upon the types of crime. The varying outcomes of the studies pursued at the intersection of crime seasonality and criminological theory suggest that crimes are prone to regional variation, and they do not necessarily conform to the theoretical framework. It would help to establish a framework for systematically finding the seasonality of different crime types and the similarity groups they form.

2.2 Categorisation of crimes

Classification of crimes into a set of groups or categories have been attempted before, yet the broadness of these categories has made it challenging to discuss the detailed nuance of similarities in their seasonal fluctuation. Many such studies focus on classification by the distinct crime types only, dividing everything broadly into assault or property crimes. Also, these groups are often defined a priori or follow the classification suggested by the local police force. For instance, Hird and Ruparel (2007) reported to the UK Office for National Statistics about the seasonal patterns of 25 different crime types and classified them into three categories: (1) crimes with peaks in the summer months and troughs in the winter months; (2) crimes with peaks in the winter months and troughs in the summer months; and (3) those with regular peaks and troughs that are not led by seasons. These categories are derived by observing their changes in graphs, as opposed to systematic analysis of their trend and seasonality. It means that the process of grouping the crimes is prone to subjectivity, and the extent of similarity between those within the same group also remains unclear.

While these broad distinctions can still help from the policing and criminalistic standpoint (e.g. the first category involves violence and/or are motivated by personal reasons, whereas the latter is triggered by financial gains), different crime types are likely to have different seasonal fluctuation as well as volume (e.g. common assault is much more frequent than homicide). In other words, aggregating several crime types together may in fact lead to unclear and potentially misleading conclusion about the similarity and differences in the seasonal fluctuation of crimes categorised into the same group.

Some of the recent studies recognise this shortfall and are conducted against finer categories or on individual crimes. For instance, Linning et al., (2017) divided property crimes into four distinct crime types, which offered a clearer understanding on their different nuances. Different climate variables affect certain crime types more than other crimes, thus advocating the importance of analysing and comparing the volume of each type of crime individually. Other studies include categorisation of a variety of violent and property crime types across the city of Pittsburgh, Pennsylvania in square grid units (Cohen et al., 2003), as well as a report to the US Department of Justice (Dodge, 1988) which looks at the seasonality of crime victimisation across 4 types of violent crimes, 5 types of larceny and 5 types of burglary, concluding that crimes with similar amplitude of fluctuation could have very different month-to-month patterns. Andresen and Malleson (2013) also analysed seven types of crimes individually (assault, burglary, robbery, sexual assault, theft, theft from vehicle and theft of vehicle). They found that some patterns that emerged from the individual crime type contradicted the overall trends. The results show that the spatial patterns of the various crime types are different from season to season.

2.3 Regional variation in the crime seasonality

The seasonal patterns of the same type of crime may be considerably different between different countries and regions Andresen and Malleson (2015). Also, Yan's work on the seasonality of property crime (Yan, 2004) suggested that the crime seasonality is different in Hong Kong when compared with situations in the UK and EU. Regional difference can be found even within the same nation. For instance, Michael and Zumpe (1983) reported that only five of the 16 American cities they studied showed statistically significant rhythms in the fluctuation of robbery cases and that they peaked in November–December. On the other hand, McDowall et al. (2012) found distinct seasonal peaks for motor vehicle theft over a 24-year period across 88 American cities.

The regional difference may also arise from the difference in the social environments including deprivation and the demographical composition. Harries et al. (1984) used findings from a study by Lewis and Alford (1975) to assist in the designing of a neighbourhood-level study of seasonality and assault. When considering the spatial context across neighbourhoods, they discovered that areas with deprivation "showed a more distinct summer peak of assaults than did other neighborhoods" (Harries et al., 1984, p.601). Similarly, Andresen and Malleson (2015) reported a disproportional increase in criminal events in places that are of lower socio-economic status. Breetzke and Cohn (2012) also found that the seasonal effect of assault was greatest in socially deprived neighbourhoods for all assault types (except for indecent assault) in the city of Tshwane, South Africa. In particular, deprived neighbourhoods had higher assault rates in summer, whereas in winter, assault rates were more evenly spread across all neighbourhoods. On the other hand, Breetzke (2016) stratified the neighbourhoods by the level of deprivation and concluded that significant peaks in property crime were observed in the third quintile (i.e. the middle class) roughly every 75 days. It could be that different neighbourhoods exhibit unique crime periodicities and these differences are driven by social deprivation. These studies suggest that seasonal fluctuations have both environmental and social components, which collectively can lead to different seasonal patterns from one location to another. It calls for a robust categorisation framework of crime seasonality which can be applied to data from any region.

2.4 Reviews on the methodology

Studies on the methodology of seasonality analysis has been also pursued rigorously. Broadly, they are divided into (1) exploratory analysis of the seasonal signature through the patterns of fluctuation and the timing of peaks and troughs, (2) regression modelling designed for revealing the contributing factors (i.e. what causes the seasonality of crimes), and (3) other forms of modelling approaches that focus on the decomposition of crimes into the long-term trend, the seasonal cycles and the residual. As each group of methods is designed for different purposes, their utility and validity depend on the scope of the respective analysis. Block (1984) notes that outcomes of analyses and their capacity to address the pertinent question of "Is crime seasonal?" would depend on the type of methods and the statistical criteria used for making that decision (Block, 1983). In the following, we will review the existing range of methods for analysing seasonality of crimes with a focus on their capacity to decompose the temporal trend of each crime and measure the similarity in their seasonal characteristics.

Methods that measure and analyse the seasonal patterns in an exploratory fashion vary in their approaches but are often designed in the form of an index with which to measure the crime seasonality (Castle & Kovacs, 2021; Farrell & Pease, 1994). For instance, McPheters and Stronge (1973) developed seasonal indices to test the seasonality of crime, and their method consisted of several analyses including those of the variance and the moving average. More recently, Andresen (2016) developed a spatial point pattern test and developed similarity index *S* for pair-wise comparison between the days of the week and the types of crime for the similarity in their crime patterns in each area, with their peaks and troughs being categorised with respect to the four seasons. Finally, the report from Office for National Statistics (2013) followed on Hird and Ruparel's work (2007) and labelled its method 'M7' statistic, which is a type of seasonality index that indicates the presence of seasonality. While these indices can be utilised as a proxy for measuring crime seasonality, they are not designed to compare the similarity of seasonal fluctuation of crimes.

Another group of studies investigates the association between the seasonal patterns of crimes and those of relevant factors. Their aim is to identify the underlying factors for the seasonal changes of each crime, and to estimate their individual effects by predicting them through some form of regression analysis. For instance, van Koppen and Jansen (1999) focused on the regression modelling of the variation in the number of commercial robbery. Similarly, Breetzke and Cohn (2012) carried out temporal regression analysis for each deprivation quintile with months as predictors. Linning et al. (2017) used weather and time as predictors to examine whether different weather and temporal variables had a distinctive impact on a specific type of offences. Carbone-Lopez and Lauritsen (2013) used the four seasons as predictors in their time-series regression models and estimated the seasonal differences in violent crime victimisation rates. Cohn and Rotton (2000) performed hierarchical regression analyses to extract the independent variables including meteorological variables (temperature, precipitation, cloud cover), time dummy variables and aperiodic variables; of which temperature emerged as a significant predictor of property offences. Finally, Yan (2004) applied regression modelling and analysis of variance (ANOVA) on crime data from Hong Kong and reported the absence of seasonality in burglary and total theft, but with a winter peak for commercial theft and mild increase of snatching and pickpocketing in summer. These results are markedly different from the seasonal patterns of property crimes reported for UK data (Hird & Ruparel, 2007), which compounds the notion of regional variation of crime seasonality. However, the association between different types of crimes was not clarified in these studies, as regression modelling is aimed for explaining and forecasting the seasonal fluctuations of crime, rather than categorising crimes by their similarity.

Other studies propose models designed for the decomposition of the changes in crime volumes and further analysis of their seasonal patterns. They range from the classical decomposition model for separating the long-term trends and the seasonal fluctuations, to Fourier analysis for identifying the periodicity of the seasonal fluctuation (Breetzke, 2016). For instance, Landau and Fridman (1993) used a stochastic model called SARIMA (Seasonal, Auto-Regressive Integrated Moving Average) (McCleary et al., 1980). It expands on the Box-Jenkins-type autoregressive moving average method (Box & Jenkins, 1976) and incorporates seasonal correlation. However, it does not provide coefficients for the individual months of the cycle (Brockwell & Davis, 2002). Also, the US Census Bureau and Statistics Canada developed a decomposition method called X-11 which separates the seasonal fluctuations into the long-term trend, the seasonal fluctuation and the random element, much like the classic decomposition model but is smoother and more robust (Dagum, 1980; Dagum & Bianconcini, 2016). Block (1983) compared some of these different methods: namely, the ARIMA stochastic model, Census X11, moving average, component seasonality method, and correlogram; and proposed a periodic regression analysis (PRA) (Block, 1984). Similarly, Cohen et al. (2003) developed a seasonality model that extends the classical decomposition of time series using a multivariate, cross-sectional, fixed-effect model which is designed to interact with indices of urban ecology informed by major crime theories. McDowall et al. (2012) also proposed a panel extension of the classic time-series decomposition (Brockwell & Davis, 2002; Mills, 2003) while Dong et al. (2017) decomposed the fluctuation of crime volume into the long-term trend and the seasonal fluctuations using moving window average. While these methods enable us to decompose the changes in crime counts, they are not linked to the measurement of similarity between the waveforms from different crimes.

In summary, a wide range of methods have been developed for the purpose of interpreting the seasonal fluctuation of specific crimes, yet a systematic comparison between these crimes is yet to be established. Given these backgrounds, this study will propose a new methodological framework for comparing and categorising crimes by their seasonal characteristics. To understand its mechanics, we will apply the proposed method to empirical crime data from London with the aim to measure the frequency, the magnitude and the regularity of their seasonality and, thereby, investigate which types of crimes share similar patterns of seasonal fluctuation and how such seasonal fluctuations compare between the different groups of crimes.

3 Data and methodology

3.1 Data

The dataset used as a case study comprises monthly crime records of all 12 types of crimes recorded across Greater London, U.K. between June 2013 and February 2020. They are anti-social behaviour (ASB), bicycle theft, burglary, criminal damage and arson, drugs, robbery, possession of weapon, public order, shoplifting, theft from the person, vehicle crime, and violence and sexual offence. These 12 crime types comprise the main categories of crime in UK. The dataset starts from 2013, as the current classification of crime types was introduced then, and the datasets from the preceding years did not have a direct correspondence with the 12 crime types used as the crime types from 2013 onward. It offers a good range of temporal patterns in that the overall number of crimes in London has been on the decline for the last 20 years, yet seasonal fluctuations persist across different crimes with patterns varied by crime types.

3.2 Methodology

The process of extracting the seasonal characteristics of crimes and deriving clusters by their similarity requires the following three steps:

1 Decomposition of the crime count trajectory into the long-term trend, the seasonal fluctuation and the residual term and their smoothing to enable analysis of each component;
2 Categorisation of crimes by similarity of their seasonal waveforms or the timing of their seasonal peaks through clustering analysis; and
3 Comparison between the groups by means of multi-dimensional scaling to understand the extent of similarity among them.

3.2.1 Poisson state-space model

As mentioned earlier, the temporal fluctuation in the volume of crime can be decomposed mainly into the long-term trend of the criminal activities, and the short-term, recuring seasonality of crime. To ensure stability of measurement across different crimes that vary in their volume and the frequency of their seasonal fluctuations, a Poisson state-space modelling (Helske, 2017) will be used in this study. It is analogous to the classical decomposition-type, a common forecasting method for estimating seasonality of a single univariate time series (Makridakis & Wheelwright, 1978). It mechanically removes the temporal variation and extracts the long-term trend and the seasonal fluctuation. Unlike many other models currently in use, the flexibility of a state-space model offers more resilience; i.e. the outcomes are less affected by the scale difference in the volume of crime between each crime type (e.g. burglary occurs twice as frequently as robbery does, and is a magnitude greater in frequency compared to possession of weapons, but we still wish to compare them all). It also copes better with the difference in the number of days in each month.

The Poisson state-space model estimates a state at time t by comparing it against the observation as follows:

State Model (t: Time Stamp, ε_t^*: Gaussian noise)

$$\text{Long term Trend Component}: \alpha_t = 2\alpha_{t-1} - \alpha_{t-2} + \varepsilon_t^\alpha \tag{1}$$

$$\text{Short term Seasonal Component}: s_t = -\sum_{d=1}^{11} s_{t-d} + \varepsilon_t^s \tag{2}$$

Observation Model (y_t: Crime count, u_t: number of days at the t th month)

$$y_t \sim \text{Poisson}\left(y_t \mid u_t \exp(\alpha_t + s_t)\right) \tag{3}$$

where $\exp(\alpha_t + s_t)$ denotes the expected number of crimes per day consisting of the long-term trend component α_t and the short-term seasonal component s_t. The mean values in the state space model are then smoothed and simulated using a Kalman-filtering package KFAS (Kalman Filter and Smoother) to control the noise and, thereby, to clarify the patterns of the long-term trend or the short-term seasonal component (Helske, 2017).

3.2.2 Clustering analysis

Once the decomposition is completed, the degree of similarity in the temporal footprints of different crimes will be measured by using two different methods to derive a dissimilarity matrix between crime types: (1) L_1-distance which retains the timing of the peaks and troughs when comparing their seasonality with those of other crimes, and (2) Dynamic Time Warping (DTW) (Müller, 2007) which moves the temporal footprints to explore the similarity in the shape of the time-series waveforms from different crimes, regardless of the timing of their peaks and troughs. The former is achieved by standardising the components to account for the difference in the timing of peaks and troughs. The latter remains unstandardised but slides the data along the temporal dimension to synchronise the peaks and the trough of crimes and, thereby, help compare the amplitude of the seasonal fluctuations.

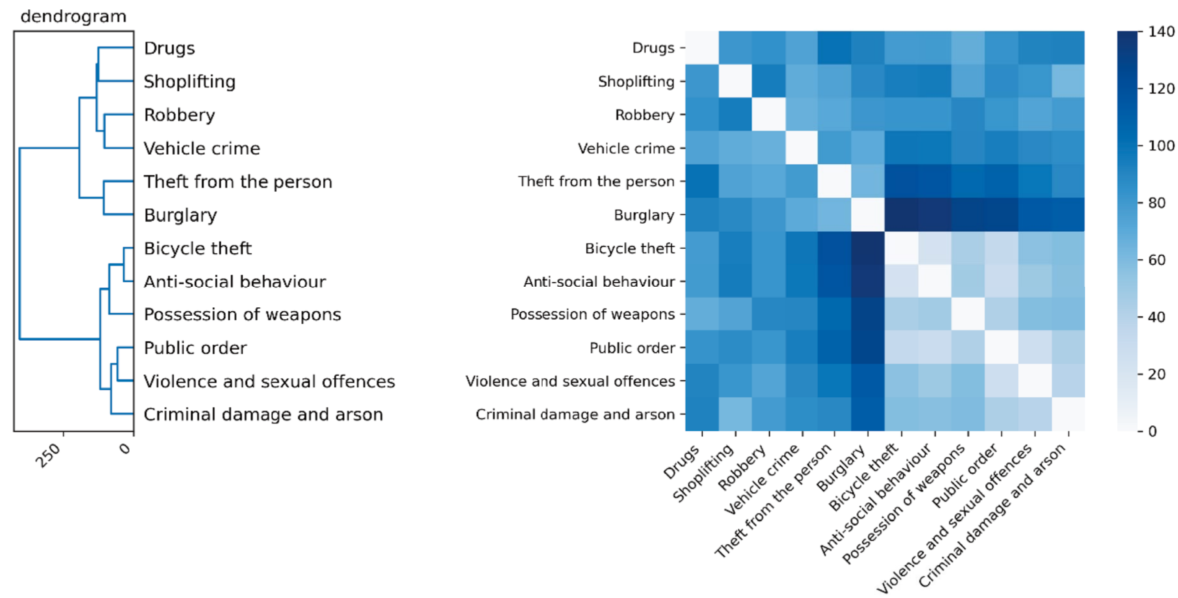
3.2.3 Multi-dimensional scaling

Finally, we investigate the spread of seasonal characteristics among different crimes by applying multi-dimensional scaling (MDS) on the time-series data from all crimes. MDS is adopted for its capacity to compare simultaneously the amplitude and the timing of the peak season across all crime types and to measure the relative distance between the crimes. Data from each type of crime is transformed into a one-dimensional space, both in terms of their waveform and the peak season to reproduce the dissimilarity matrix among crimes. The extent of dissimilarity will be measured in percentages to indicate the goodness of fit. Suppose that crime types i and j are dissimilar from each other by D_{ij} and their Euclidean distance measured through MDS in a one-dimensional space is d_{ij}. The dissimilarity index will be expressed as

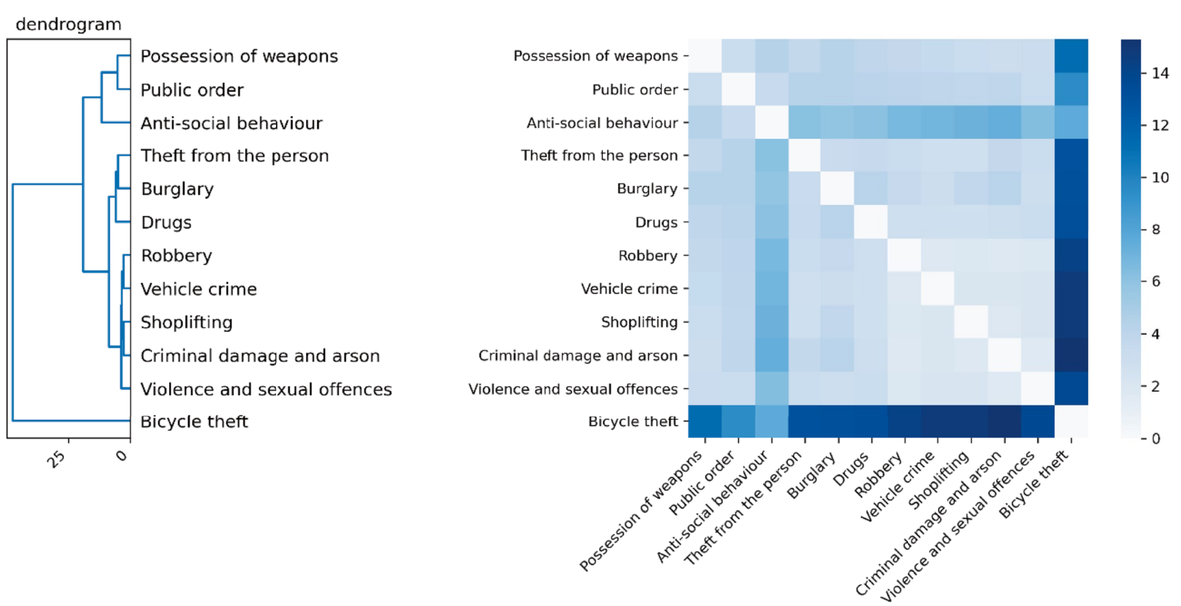
$$\text{Dissimilarity index} = \sum_{i,j} \left(d_{ij} - D_{ij}\right)^2 / \sum_{i,j} D_{ij}^2 \tag{4}$$

4 Analysis and results

The seasonality decomposition and the subsequent clustering of the groups of crimes revealed several interesting insights into the association between the types of crime,



(a) Clustering analysis by the similarity of the timing of peaks and troughs.



(b) Clustering analysis by the similarity of the waveform of their seasonal fluctuation.

Fig. 1 Outcomes of clustering analysis of the 12 types of crime in London. (**a**) measures the similarity in the timing of their peaks and troughs, while (**b**) looks at the similarity of the waveform of their fluctuation, regardless of the timing of the peak. (**a**) Clustering analysis by the similarity of the timing of peaks and troughs. (**b**) Clustering analysis by the similarity of the waveform of their seasonal fluctuation the weather and season, as well as the long-term trend.

Figure 1 shows the outcome of clustering analysis. The dendrograms on the left illustrate the order of clustering between crimes based on the similarity in their seasonal fluctuations (e.g. both bicycle theft and ASB peak and trough at very similar timing), while the dissimilarity matrices on the right show the difference in the timing of the peaks and troughs between all pairs of crimes (Fig. 1(a)) and that of the amplitude and the overall pattern of the wave forms (e.g. possession of weapons and public order have similar amplitude and wave forms) (Fig. 1(b)). Specifically, in Fig. 1(a), we derived similarities and differences of their time-series using L1-distance whereby the timing of the peaks and troughs were retained for the purpose of identifying groups of crime that share similar seasonal tendencies in the timing of their peaks. It shows a clear distinction between crime types that are active in the summer months and the others (either active in winter or with unclear seasonal fluctuation). On the other hand, Fig. 1(b) indicate the grouping of crimes using Dynamic Time Warping (DTW). It compares the shape and the amplitude of the wave form between different crimes, irrespective of the timing of their peaks. The difference in the outcomes of the two cluster analyses is subtle but the former seems to be affected by the criminalistic behaviours (induced in part by the weather), while the latter seems to reflect the nature of the crimes which determines the magnitude of the change in their amplitude.

Similarity between the long-term trend of crimes was also investigated (Fig. 2). Results are broadly categorized into four groups: (1) fluctuation: crimes exhibit fluctuations with no long-term changes; (2) decline-increase: those with initial decrease followed by recent increase

Fig. 2 Grouping of the 12 types of crime in London by the form of their long-term trend

but no long-term growth; (3) steady-increase: those increasing steadily; and (4) decline-steady-increase: those with initial decrease followed by recent increase and show long-term growth in their volume.

While the crimes within each group do not necessarily share a similar pattern of seasonal fluctuations, the four crimes in the third group (steady-increase type)—namely public order, shoplifting, violence and sexual offences, possession of weapons—have either low or unclear seasonal fluctuation, and the fourth group (decline-steady-increase) also consists mainly of those with weak or unclear seasonal fluctuation. In other words, crimes that are persistent and show mild but gradual increase in London tend to be less affected by the season. The fact that these crimes are not dissuaded by the seasonal fluctuation nor the recent policing effort in London suggests that the crime opportunity for the offenders remains rife for these categories of crimes across the year and have seen a marginal increase in such opportunity.

Figure 3 shows results from clustering analysis of the seasonal fluctuation with respect to the timing of their peaks (i.e. outcomes from Fig. 1(a)). They were split into three different groups: (1) peaks in summer, (2) peaks in winter, and (3) unclear or weak seasonality. For instance, both bike theft and ASB have a distinct peak in summer, while burglary and theft-from-the-person show moderate increase in winter. They reflect the offender's behaviour and broadly conform to the routine activity theory. For instance, the significant rise in bike theft in the summer can be attributed to the increased use of bikes during

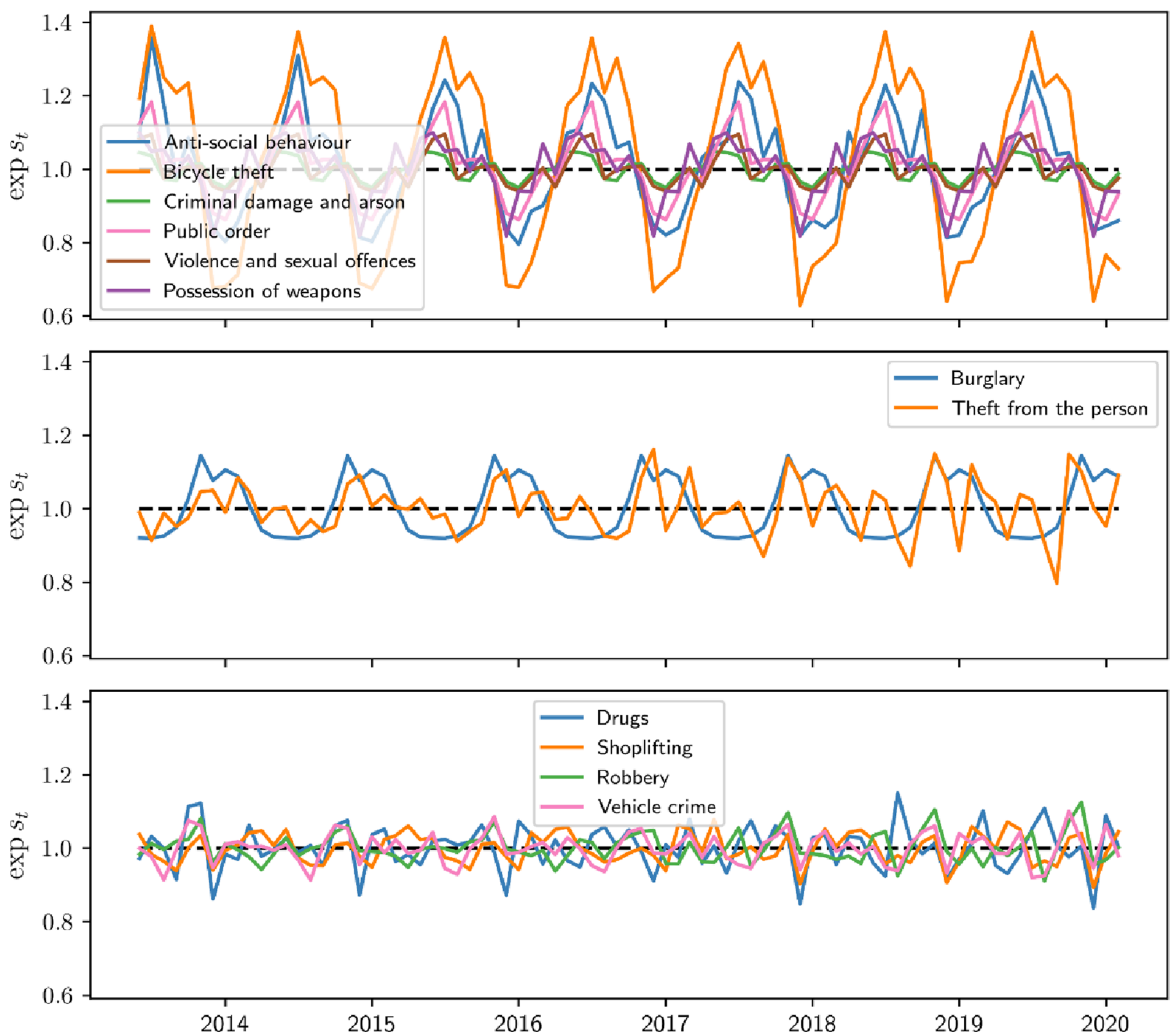


Fig. 3 Grouping of the 12 types of crime in London by the timing of their peaks and troughs

the warmer season, as it also increases the number of motivated offenders and suitable targets. On the other hand, drugs, shoplifting, commercial robbery and theft from vehicle are linked to quick cash and remain stable across the seasons. The stability of their volume across different seasons also likely owes to the ample number of targets and the offenders for these types of crime that do not change significantly by the season.

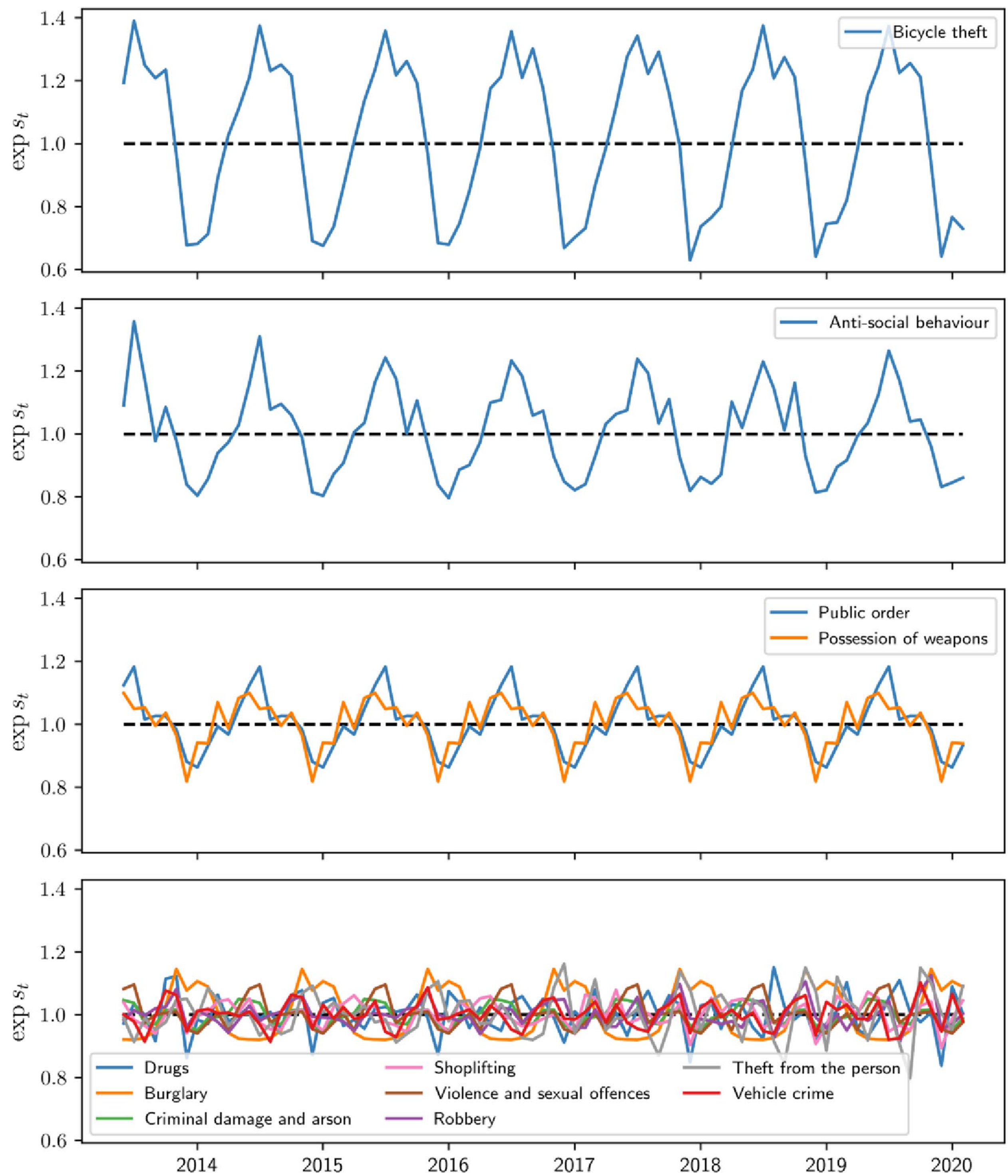


Fig. 4 Grouping of the 12 types of crime in London by the amplitude of their seasonal fluctuation

In contrast, grouping the crimes by their amplitude and waveform (as shown in Fig. 4) resulted in four categories: (1) very high fluctuation (e.g. bike theft), (2) high fluctuation, (3) medium fluctuation, and (4) low fluctuation. Interestingly, neither the timing of the peaks nor the waveform of the seasonality seems to have clear association with the volume of the crime itself; rather, i.e. crimes that record a high overall volume do not necessarily result in high seasonal fluctuation. These results confirm the findings reported by Hird and Ruparel (2007).

It is unclear if the contrast between bike theft (peaking in the summer) and the residential burglary (ripe in winter) means that the same group of offenders are operating in different season (i.e. stealing bikes in summer and breaking an entry into properties in winter), and would require qualitative data on the offenders' identity.

Finally, MDS was carried out against the amplitude of seasonal fluctuation and that of the peak seasons. The results are shown in the form of a scatterplot in Fig. 5. The dissimilarity indexes defined in Eq. (4) was 4.8% for the fluctuation and 12.5% for the peak seasons. It shows that the amplitude of the seasonal fluctuation plays a key role in explaining 95.2% of the dissimilarity in their waveforms. It can be interpreted as the intensity of the seasonality of crime. Similarly, timing of the peak and the trough were found to explain 87.5% of the variance in their seasonal fluctuation which can be interpreted as the annual profile of the respective crime.

The scatterplot can be also interpreted as having the extremity of the amplitude on the horizontal axis and the season of the year on the vertical axis. The result is an inverse proportional association between the two; i.e. activities that require planning and are more frequent in winter (e.g. burglary) are more consistent in their volume across the year; while unplanned activities that prevail in summer (e.g. bike theft, ASB) have more prominent peaks and troughs. It extends our understanding of the routine activity theory in that the volume of the crimes is not determined solely by the volume of targets, offenders and guardians, but are also affected by the weather.

5 Discussion

The outcomes revealed several interesting points on crimes recorded in London:

- Six out of 12 crime types reach their peak in the summer months, all of which showing clear and moderate to high level of fluctuation. The Office for National Statistics (2013) states that, broadly speaking, it is the warm weather and the longer days in the summer that are likely luring out the offenders to spend more time outdoors, whilst the open windows and the absence of residents at home induce prop-

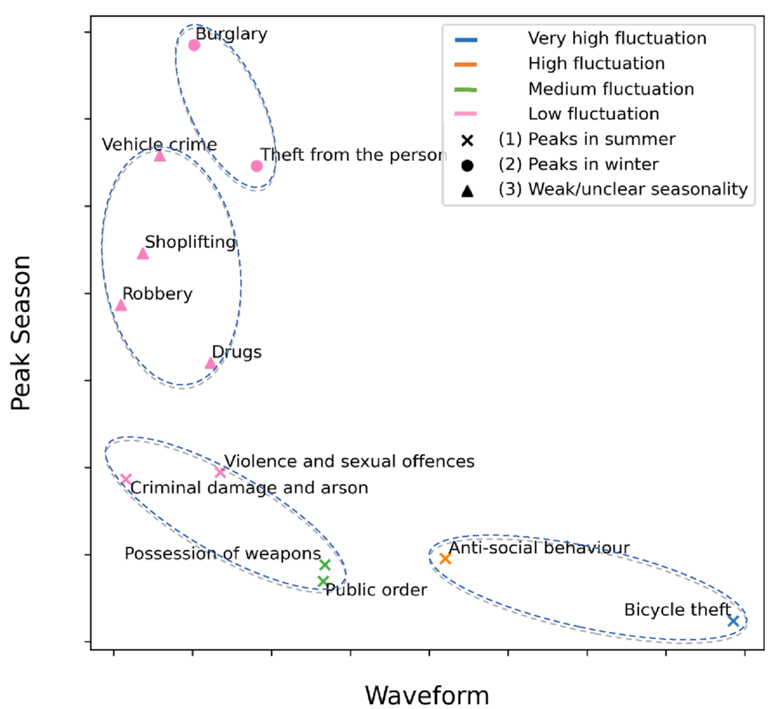


Fig. 5 Scatterplot of the crime seasonality of the 12 types of crimes in London derived by multi-dimensional scaling. The horizontal and the vertical axes respectively correspond to the amplitude and the timing of the peak season

erty crimes. Our study was able to identify the finer difference among the summer-peaking crimes and concluded that some of the prominent peaks in the summer were observed among non-property crimes. Bicycle theft showed particularly prominent peaks in the summer months, followed by ASB. While both are susceptive to changes in weather, they seem to be more directly affected by the at-risk population.

- Burglary and thefts-from-the-person peak in the winter months, especially in November. It confirms the observations made by other studies about the dimmer and shorter days, less witnesses on streets, and people likely to be carrying around more cash in the run-up to Christmas (Office for National Statistics, 2013). However, this tendency is reversed in Chicago where residential burglary and theft on streets are ripe during the summer months (Towers et al., 2018). The clue seems to lie with the severity of weather during winter where the cold temperature and the snow-cover restrict the activities of burglars', whereas winter in London is milder and less restrictive to the criminals.
- Crimes with weak or unclear seasonality generally have low fluctuation but with multiple small peaks across the year and a dip in December. These crimes (shoplifting, robbery, drugs and vehicle crimes) are habitual and persistent in nature. While unconfirmed, these crimes may be triggered by criminals with a drug or alcohol addiction or other demand for quick cash (Office for National Statistics, 2013). They are likely to be unplanned and can be only tackled by reducing the crime opportunities; e.g. remain visible to witnesses and do not leave possessions unattended.

These findings indicate that the groups of crimes sharing similar seasonal fluctuations may be linked by the criminalistic opportunities associated with crime opportunity theory and the wider environment criminology. For instance, bike theft, vehicle crimes and burglary are often treated in the same category of crimes, yet their seasonality shows a marked contrast. Results from MDS also confirm the grouping of crime types that are brought together by the relevant crime opportunities and offenders' behaviour in that some groups are more prone to the weather condition while others are stable and persistent across the year. Increase in ASB, violence and sexual offences, weapons possession, public order and arson in the summer months confirms findings from other studies that reported the association between temperature and aggression. The significant peaks observed in bike theft and ASB in summer suggest that these two crimes are linked particularly strongly to the warmer, sunnier weather that leads to increased crime opportunities. On the other hand, persistent crimes with weak or unclear seasonality, namely drugs, shoplifting, robbery and vehicle crime, seem to be triggered by the need for cash on the criminals' side and are less affected by the weather. Given these groupings, we can confirm that the peaks and the troughs are formed by the combination of the criminalistic behaviour and crime opportunities, which in turn reflects the extent that each group of crimes is affected by the weather and the temperature.

The methodological framework proposed in this study enables us to (1) separate the groups of crimes with respect to two different components; namely the timing of the peaks/troughs and the extent of amplitude, and (2) indicate the contributing factors for their separations by measuring the similarity in their seasonal fluctuation using MDS. Results from cluster analysis are hierarchical in that it reports the order of clustering and their distance from the others, thus allowing us to reclassify the groups of crimes into sub-groups for further analysis of their seasonal characteristics. Identifying groups of crimes that share similar seasonal characteristics, especially those that may not have been previously linked to one another, could lead to new insights into the motivation behind and opportunities for different types of crimes. This was an exploratory, proof-of-concept analysis that applied a new analytical framework for interpreting a set of crime data from London, and it can be applied more widely towards analysing other areas and larger sets of crimes. Similarly, interpretation of the underlying factors requires comparative analysis of data between multiple regions to accumulate more evidence towards the understanding of the patterns of crime across time and map them against the existing criminological theory.

In terms of the impact on policing strategies, categorising the crime types with respect to their seasonal patterns helps estimate how much attention is needed for each group of crimes at a specific time of the year and how strongly they may be affected by the weather. For instance, tackling vehicle theft requires a short-term but intensive deployment of resources because of its high amplitude, whereas crimes that are as perpetual as drugs and shop lifting require long-term operation such as stop-and-search. While the peaks and troughs for each crime may have been known empirically, a systematic understanding of the amount of fluctuation, their timing as well as the similarity in the seasonality between crimes were previously understudied. Insights from this study are expected to form the first step towards the local police forces to strategise their prevention and intervention actions across different crimes.

6 Conclusion

This study investigated the similarity and differences of the seasonal fluctuations between different types of crimes. They were measured and compared against each other with respect to the timing of their peaks as well as the magnitude of their fluctuations. The results showed a wide variation in their patterns of seasonal changes, ranging from those aggravated during the summer months with perhaps more impulse, to those increasing in the winter months with more calculated actions, as well as those with less clear patterns of seasonality. As mentioned earlier, 95.2% of the similarity in their waveforms were explained by the amplitude of the seasonal fluctuation, while 87.5% of the timing of the peaks covered the variance in their seasonal fluctuation. This shows the high predictability of seasonal patterns of the seasonality of individual crime type, which leads to better planning of the police forces in the year cycle, along with the a priori knowledge to target specific types of crimes that are "in season." It enables a more controlled management of the urban environment to reduce urban risks and maintain sustainable and efficient policing. As discussed on the outset, seasonal fluctuations in the volume of crime have been previously studied for several different crime types. However, a systematic investigation of the similarities and differences of the seasonal characteristics across all crime types in a dataset was not conducted until now, and this study offers fresh insights into their association in that respect. These findings will help local police forces to plan their patrol routines more efficiently by targeting the groups of crime sharing similar seasonal patterns which in turn could help build a more sustainable city in terms of the wellbeing and security of the residents.

As discussed earlier, this study would benefit from a follow-up investigation using datasets from different cities in the UK as well as those from other parts of the world, especially those with different climatic and environmental conditions to examine whether the results bear any similarity in the grouping of the crime types and their seasonal characteristics. The method proposed in this study could be applied for comparing the seasonality of the same crime type from different parts of the world. Another possibility is to take a modelling approach to explain and predict crime occurrences using the seasonal characteristics identified in this study and other confounding factors. While this study does not address the geographical aspect of crime occurrences, findings on the crime seasonality could be utilised alongside the risk factors linked with specific locations (e.g. the socio-economic profiles of the neighbourhood, build environment and the physical environment, including climate change and extreme weather) to model and predict the surge in each group of crimes. Finally, crime seasonality can be linked to the spatial distribution of crimes where the spatial–temporal patterns of the different types of crimes can be measured and clustered by their characteristics. There is emerging literature on crime colocation whereby the spatial colocation of crimes is measured with respect to the similarity of their spatial patterns. Exploring the similarity in the spatial and temporal periodicity between different crimes would help the police force formulate an efficient intervention strategy for deploying their resource in areas of highest risks and during the peak seasons to fight against a group of crimes that shares common spatial–temporal traits. Further research in this domain is eagerly awaited.

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Authors' contributions
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Declarations

Competing interests
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