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Article

Construction and Analysis of Space–Time Paths for Moving Polygon Objects Based on Time Geography: A Case Study of Crime Events in the City of London

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Abstract: Time geography considers that the motion of moving objects can be expressed using space–time paths. The existing time geography methods construct space-time paths using discrete trajectory points of a moving point object to characterize its motion patterns. However, these methods are not suitable for moving polygon objects distributed by point sets. In this study, we took a type of crime event as the moving object and extracted its representative point at each moment, using the median center to downscale the polygon objects distributed by the point sets into point objects with timestamps. On this basis, space–time paths were generated by connecting the representative points at adjacent moments to extend the application scope of space–time paths, representing the motion feature from point objects to polygon objects. For the case of the City of London, we constructed a space–time path containing 13 nodes for each crime type (n = 14). Then, each edge of the space–time paths was considered as a monthly vector, which was analyzed statistically from two dimensions of direction and norm, respectively. The results showed that crime events mainly shifted to the east and west, and crime displacement was the greatest in April. Therefore, space–time paths as proposed in this study can characterize spatiotemporal trends of polygon objects (e.g., crime events) distributed by point sets, and police can achieve improved success by implementing targeted crime prevention measures according to the spatiotemporal characteristics of different crime types.

Keywords: time geography; crime; space–time path; statistical analysis

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1. Introduction

Time geography regards the crime phenomenon as a mobile object whose spatial location changes over time. Crime events during a certain period can be depicted as a point set, where each point corresponds to a specific case. The point set of crime events varies in different periods, indicating that crime phenomena evolve over time. Thus, the footprint of crime phenomena can be represented as a time series of point sets with timestamps. In terms of time geography, this footprint can be substituted by a space–time path. Theoretically, this space-time path can be constructed by extracting and connecting control points [1]: the representative point corresponding to the point set in each period was obtained using the spatial analysis function of GIS (Geographic Information System); representative points at adjacent moments were connected by spatial interpolation. In this way, the footprint of regional crime can be analyzed based on its space–time path.

Yin et al. [2] proposed an approach for modeling the movement of geographical phenomena distributed in areas based on time geography. The approach regarded the COVID-19 pandemic as a mobile object, and a space–time path was constructed for it. Its control points were derived from distributions of the epidemic at each moment through two main steps: (i) rasterizing the distributions of epidemic areas and (ii) extracting element centers of rasters as representative points. This space–time path was used to reveal spatiotemporal patterns of the epidemic, as well as changes in the epidemic that occurred continuously, including its direction and pace of spread. In their results, they used epidemiological statistics to extrapolate the epidemic spread in future based on the space–time path. The representation of moving objects (e.g., the epidemic) possessing polygon distribution characteristics based on the space–time path was proved to be effective.

However, in time geography, studies analyzing moving polygon objects remain confined to constructing space–time paths. In this study, we constructed and statistically analyzed space–time paths of crimes to analyze crime displacement, applying two extensions. First, the construction of space–time paths was extended from the field of infectious diseases to the field of crime. Unlike epidemic data, which are based on predefined region units, crime events data are point sets. For each moment, a representative point of crime events was extracted using the median center and was regarded as a spatiotemporal anchor point. Secondly, compared with other research that only constructed a space–time path, we statistically analyzed the space–time path from perspective of its edges to explore the spatiotemporal pattern and movement law of crime events, including seasonal characteristics and associations between crime types. In addition, norms and directions of edges were measured separately. In this manner, we propose the mathematical foundation of statistically analyzing crime events based on the space–time path, and an approach for crime analysis based on time geography. This approach can effectively visualize and analyze the degree of crime displacement, and provide countermeasures for crime prevention, especially for the development of hotspot policing. Theoretically, it has the potential to be applied to spatiotemporal big data beyond the dataset in this study.

The basic idea of this study is as follows. Firstly, we collected the set of crime points for each period and extracted its representative point as a spatiotemporal anchor point. Secondly, according to the time series of crime point sets, space–time paths composed of spatiotemporal anchor points were generated to realize the connection between crime point sets and time geography. Finally, statistical methods were used to analyze the movement characteristics and spatiotemporal evolution law of crime events. Crime types were divided into groups, to provide support for urban crime prevention.

2. Background

This section introduces the foundations of time geography and its related research, further advancing the contributions of this study.

2.1. Time Geography

Time geography focuses on analyzing spatiotemporal uncertainties of mobile objects based on known spatiotemporal information, applying the principle of spatiotemporal accessibility [3]. It involves two key concepts: space–time path and space–time prism. As shown in Figure 1, the space–time path is a fold line where the trajectory points of the moving object are known. Its straight-line segments connect trajectory points at adjacent moments. The projection of a 3D space–time path expresses the 2D "footprint" and movement trend of a mobile object in geographic space. The space–time path is the basis of the space–time prism and the basic unit of time geography [3]. The space-time prism expresses the potential space–time path set of a moving object between two spatiotemporal anchor points [4,5].

Hägerstrand [3] and Thrift [6] pointed out that all objects occupying a certain space have paths, even inanimate objects. This means that mobile objects include not only classical point objects (e.g., individuals, animals), but also polygon objects, such as typhoons [7] or COVID-19 epidemics [2]. The point object can be geometrically represented as a point, such as a GPS trajectory point or a spatiotemporal point in a travel log [8]. Further, the movement of point objects forms trajectories, which have been widely used in the fields of public health [9], transportation [10], tourism [11], urban planning [12], and animal protection [13].

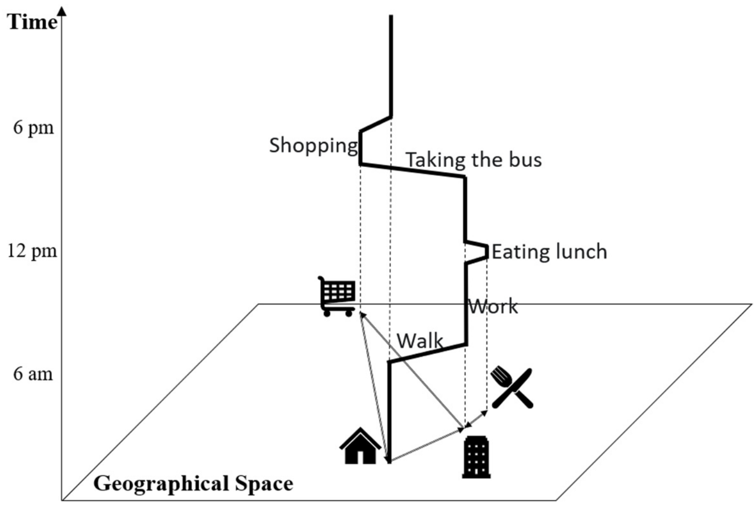


Figure 1. A person's space–time path during a day.

The polygon object can be geometrically represented as a point set or an area. Tian et al. employed trajectory points at the same instant on different dates as a point set to study human behavior [14]. Thus, the position of an individual at any given moment could be described through a point set. Yin et al. [2] stated that the COVID-19 epidemic was a polygon object with particular movement characteristics and that the geographical distribution of infectious diseases expressed its geometric features. They proposed an epidemic space–time path using time geography. The nodes and edges of the epidemic space–time path correspond to representative points of the moving polygon object and lines between them, respectively. These approaches inherit the basic principles of time geography, i.e., analyzing mobile objects' uncertainty based on observed deterministic information. Moreover, the data range for constructing space–time paths was extended from discrete points to discrete polygons. In this way, polygon objects can also generate space-time paths in the same way as point objects so that time geography can be applied in the uncertainty analysis of polygon objects. In the context of time geography, point objects' trajectories have been widely researched [15–17], but polygon objects' trajectories have received less attention, particularly for unseen macroscopic phenomena. Therefore, the time geography framework has great potential for the study of the spatiotemporal uncertainty of polygon objects, which can be used to explore complex spatiotemporal activities (e.g., crime events) or their interaction with their environments.

2.2. Crime Data Characteristics

Crime data include not only suspects' trajectories but also crime records in the predefined regions. The crime records are usually described as a point set on a map. Suspects' trajectories are available from mobile phone records or datasets of registered sex offenders. Crime data can be used for spatial analysis of crime [18] or estimating the activity space of offenders [19].

However, suspects' trajectories are short because police respond to crime events and aim to prevent people from committing further crimes. In addition, concealment of criminal behavior and personal privacy protection [20] make it difficult to obtain public data of suspects' trajectories. Thus, publicly available crime data are typically crime records posted on police departments' official websites, recording the location, time, and other attributes of each case. Crime point sets released by national police departments have been widely used in crime research [21–26]. For example, UCR (uniform crime reporting) has been applied to the study of the spatiotemporal evolution and prediction of crime [27–29].

2.3. Time Geography in Crime Research

In recent years, with the development of the internet, historical criminal records and crime-related data have shown a stepwise expansive growth. Urban crime has become the focus of people's attention in the social context. How to make full use of crime data has become an urgent problem to be solved for social security. The large-scale collection of crime data brings us opportunities and challenges to study the movement characteristics and spatiotemporal patterns of crime. Since crime events have significant temporal and spatial characteristics [30], new methods analyzing crime data need to consider both temporal and spatial dimensions. Time geography is one of these methods. It assumes temporal consistency of criminal behavior [31], which provides a theoretical basis for improving crime prediction, crime association analysis, and reducing recidivism. Applications of time geography in crime research include analysis of crime-related trajectories and crime point sets.

For crime-related trajectories, scholars have used space–time paths and space–time prisms to express uncertainty of crime. Space–time paths can express offenders' activity anchor points (residence, workplace, and other places where they spend a lot of time) and activity routes. Space–time paths of potential victims, offenders, and supervisors in criminal activities can be applied for crime risk assessment through interaction analysis. For instance, Zahnow Renee et al. used activity bundles of space–time paths to describe the "familiar stranger" phenomenon in bus stations and demonstrated its potential to deter criminals [25]. In crime investigations, the disjointed space–time prisms of suspects and victims have been used to check out alibis [32,33], and their intersections indicated the spatiotemporal range where crimes were most likely to occur. Morgan [34] constructed space–time prisms of victims to find out where and when they were most likely stolen from, and verified the effectiveness of applying time geography to analyze crime events by comparing it with a traditional 2D map.

For crime point sets, time geography uses PPA (potential path area) to express uncertainty of crime. For example, Downs [19] used home and work addresses of registered sex offenders in St. Louis to estimate probability PPA for each sex offender and combined them into a density surface to map areas where sex offenders were more frequently present. Downs [35] analyzed activity spaces of sex offenders, using PPT (potential path trees), where PPT is a mapping of PPA in a road network. In general, crime point sets can reflect both the spatial distribution of crime events and their mobility. Therefore, in principle, applications of time geography to crime point sets can use not only PPA or PPT, but also space–time paths.

3. Measurement of Crime Events' Mobility

Centers of point sets have frequently been used to measure qualitative trends of discrete geographic data (e.g., crime and infectious diseases) over time [36,37]. The mobility of such phenomena can be expressed quantitatively by space-time paths composed of these centers. The main task of this section is to establish mapping between crime point sets and space–time paths, which are used to express the mobility of crime events. Through statistical analysis of crime space–time paths, their geometric law was obtained, which was transformed into the motion law of crime events.

3.1. Construction of Space-Time Path Using Crime Point Sets

3.1.1. Extraction of Crime Control Points

As shown in Figure 2, different from a traditional trajectory that only contains one point of a single object at each time, the crime point sets analyzed in this study have several points of many objects in a single time window. Previous research mainly focused on point pattern analysis (e.g., kernel density estimation, standard deviational ellipse, and spatial scan statistics) of crime data, which cannot effectively express crime displacements over time due to high algorithm complexity and time cost. In fact, point pattern is simply one of a group of spatial analysis patterns, which also includes line pattern and plane pattern.

Compared with point pattern analysis, line pattern expresses not only discrete points, but also connections between the points. The addition of such connections can reduce uncertainty of spatial analysis, and improve its accuracy. Therefore, we analyze crime point sets using line pattern, which requires converting the point sets into nodes of lines. The point abstracted from a point set is the control point representing it, which should have spatial, temporal, and attribute information.

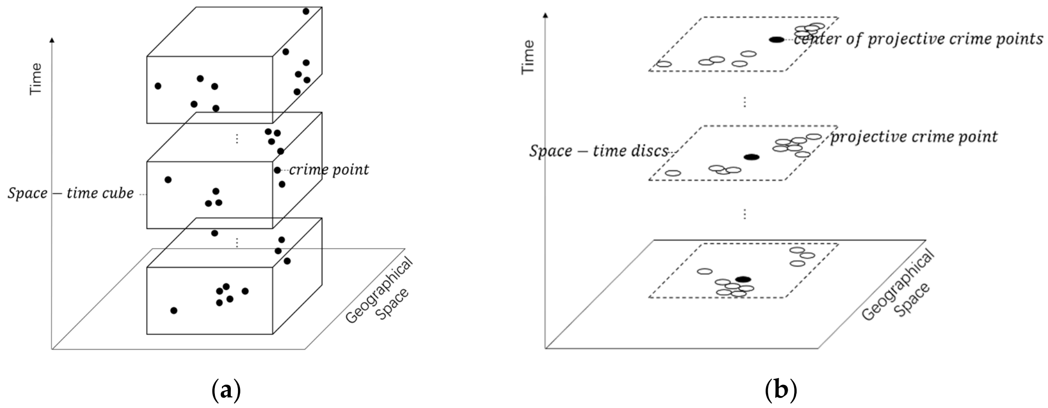


Figure 2. Extraction of crime control points: (**a**) space–time cubes; (**b**) centers of crime events.

To convert multiple points into a single point, the first step is to decrease the dimensionality of raw data, i.e., extracting crime control points. Since the center can reflect the concentration trend of a crime point set, we used center to represent control point. The centers commonly used in geography include mean center, element center, and median center [38]. Mean center is more influenced by outliers than element center and median center. Element center must be an actual data point, but median center can be anywhere, so its square sum of error (SSE) is smaller. Compared with mean center and element center, median center has the advantages of less influence by outliers and less error. Therefore, in this study, we extracted crime control points using median center.

Crime control points have attribute information, i.e., number of crime cases, in addition to spatiotemporal information. In general, adding attribute information can better visualize the trend change in numbers of crime cases, and trajectory clustering can be performed. A center can be expressed as follows:

$$c_{t,k} = (x_{t,k}, y_{t,k}, a_{t,k}) \tag{1}$$

where t denotes time, $t = 0, 1, \ldots, 12$, $t = 0$ for December 2019, and $t = 0, 1, \ldots, 12$ for 12 months of 2020; k denotes crime type; x and y are locations in geographic space; a is attribute information, such as frequency or intensity of crime represented by the control point. Accordingly, the center set of corresponding to crime type k of crime in the whole year is:

$$E_k = \{c_{t,k} \mid t = 0, 1, \ldots, 12\} = \{c_{0,k}, c_{1,k}, \ldots, c_{t,k}, \ldots, c_{12,k}\} \tag{2}$$

The 14 crime types can form a 13 × 14 matrix of center sets:

$$\begin{bmatrix} c_{0,1} & \cdots & c_{0,14} \\ \vdots & \ddots & \vdots \\ c_{12,1} & \cdots & c_{12,14} \end{bmatrix} \tag{3}$$

The above abstraction from discrete point sets to control points achieved two kinds of dimensional reduction. One was to convert discrete point sets distributed in space into spatial points, realizing the conversion from two-dimensional space to 0-dimensional space. The other was to convert one-dimensional time windows where discrete point sets were located into time points, realizing the conversion from one-dimensional time line to 0-dimensional time point. Therefore, the above transformation is essential to convert a three-dimensional space–time cube into a 0-dimensional space–time point, which can simplify the expression and spatial analysis of discrete phenomena.

3.1.2. Construction of Crime Space–Time Paths

The space–time path consists of control points and a sequence of path segments connecting these points. For a given crime type, the control points used to construct crime space–time paths were the median centers. It is worth mentioning that in addition to thre median center, other feature points can be chosen, such as the center of the standard deviation ellipse of a crime point set. Connecting control points with straight lines can generate space–time paths which convert point pattern analysis into line pattern analysis, thus facilitating the expression of displacement patterns of crime events. On the one hand, line pattern analysis increases the connection relationship between points compared with point pattern and can represent semantic relationships between points, including temporal sequential relationships. On the other hand, line patterns add properties such as length and direction and enable study of kinematic characteristics of moving objects (e.g., crime events), including speed, direction, and intensity.

3.2. Geometric Analysis of Crime Space–Time Paths

To facilitate the analysis of these characteristics, we used spatial vectors to solve the analysis problem of the space–time paths. This approach involves three steps. First, we established the connection between space–time paths and spatial vectors, and represented the points and lines involved in the problem with spatial vectors, to turn the space–time path problem into a vector problem. Then, through vector operations, the position relationship, distance, and angle between points and lines were studied. Finally, the results of vector operations were "translated" into the geometric conclusions of space–time paths.

3.2.1. The Vectors of Crime Space-Time Paths

The way to generate a line from two known points is to interpolate between these points in 3D space. Types of interpolation include linear and nonlinear interpolation, such as spline interpolation and Bezier curves. Linear interpolation produces straight lines, which compose a space–time path in classical time geography. This can simply express the movement trend of a moving object, but has a disadvantage that some positions on the straight line may not be reachable for the moving object in reality. Nonlinear interpolation, while generating a more natural curve to represent physical motion, requires additional assumptions about the moving object's behavior [39]. It involves behavioral issues, which are beyond the scope of this measurement theory. Linear interpolation was used in this study to simplify illustration. A line segment consisting of two control points representing crime events can be described as follows:

$$\langle c_{t-1,k}, c_{t,k} \rangle = \overrightarrow{c_{t-1,k}c_{t,k}} \tag{4}$$

where $\langle c_{t-1,k}, c_{t,k} \rangle$ denotes a line segment that connects $c_{t-1,k}$ and $c_{t,k}$ linearly. It can also be represented by a vector. Thus, a crime space-time path includes 13 control points and 12 edges. It can be formalized as:

$$path_k = \{\langle c_{t-1,k}, c_{t,k} \rangle | t = 1, 2, \ldots, 12\} \tag{5}$$

Thus, we can form a 12×14 matrix of edges, which is an extension of the 13×14 matrix center sets:

$$\begin{bmatrix} \langle c_{0,1}, c_{1,1} \rangle & \cdots & \langle c_{0,14}, c_{1,14} \rangle \\ \vdots & \ddots & \vdots \\ \langle c_{11,1}, c_{12,1} \rangle & \cdots & \langle c_{11,14}, c_{12,14} \rangle \end{bmatrix} \tag{6}$$

As shown in Figure 3, $\overrightarrow{c_{t-1,k}'c_{t,k}'}$ is the projective vector of $\langle c_{t-1,k}, c_{t,k} \rangle$ in plane space. It is also called monthly vector in this study and contains two properties: direction and norm. The abstraction from line segments to vectors ignores positional information, making it possible to move the starting point of a segment to a given origin. The monthly vectors reduce the geometric problem of the space–time paths to a vector problem, providing a mathematical basis for statistical analysis of the space–time paths.

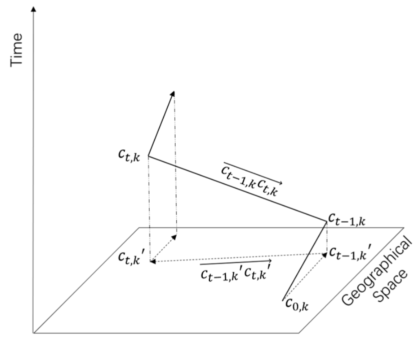


Figure 3. The transformation from a line segment to a monthly vector.

3.2.2. Statistical Analyses of Monthly Vectors

(1) Statistics of norms

Mean, coefficient of variation (CV), and trend analysis were used for statistics of norms. The $Mean_k$ and CV_k can be calculated as follows, respectively:

$$Mean_k = \frac{1}{12}\sum_{t=1}^{12} \| \overrightarrow{c_{t-1,k}'c_{t,k}'} \| \tag{7}$$

$$CV_k = \sqrt{\frac{1}{12}\sum_{t=1}^{12}\left(\| \overrightarrow{c_{t-1,k}'c_{t,k}'} \| - Mean_k\right)} \Big/ Mean_k \tag{8}$$

They can indicate the extent of crime displacement but cannot describe its tendency to spread or contract relative to origin. We denote spread and contraction by positive (+) and negative (−), respectively. As illustrated in Figure 4, with a given origin ($c_{0,k}'$), a difference can be calculated as follows:

$$\Delta d_{\langle t-1,t \rangle,k} = \| \overrightarrow{c_{0,k}'c_{t,k}'} \| - \| \overrightarrow{c_{0,k}'c_{t-1,k}'} \| \tag{9}$$

where, $\overrightarrow{c_{0,k}'c_{t,k}'}$ and $\overrightarrow{c_{0,k}'c_{t-1,k}'}$ are two vectors; $\| * \|$ denotes the norm of vector; $\Delta d_{\langle t-1,t \rangle,k}$ denotes the difference. If $\Delta d_{\langle t-1,t \rangle,k} > 0$, the norm of $\overrightarrow{c_{t-1,k}'c_{t,k}'}$ is positive, otherwise it is negative.

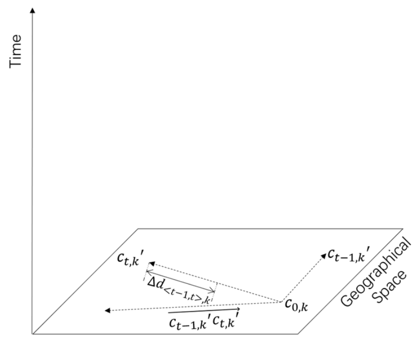


Figure 4. Calculation of the difference about a monthly vector.

This way, the norm of a monthly vector can be expressed as:

$$norm_{t,k} = \begin{cases} \|\overrightarrow{c_{t-1,k}c_{t,k}}\|, & \Delta d_{\langle t-1,t\rangle,k} > 0 \\ -\|\overrightarrow{c_{t-1,k}c_{t,k}}\|, & otherwise \end{cases} \quad (10)$$

where $norm_{t,k}$ denotes the trend and intensity of crime displacement. Each crime space-time path has 12 $norm_{t,k}s$ which represent the spread or contraction of crime events relative to the origin. Therefore, the integrated norm of all crime types in one month can be quantitatively calculated as follows:

$$\overline{norm}_t = \frac{1}{14}\sum_{k=1}^{14} norm_{t,k} \quad (11)$$

(2) Statistics of directions

The direction of a monthly vector is defined as $\theta_{t,k}$ which is zero due east and increases counterclockwise. The statistics of directions include frequency statistics and directional mean ($Mean\theta_t$). We divided the frequency statistics described by rose diagrams into statistics for each crime type and statistics for all crime types. The $Mean\theta_t$ describes the directional mean of all monthly vectors in a month. It can be calculated as follows:

$$Mean\theta_t = \begin{cases} \arctan\left(\frac{\sum_{k=1}^{14}\sin\theta_{t,k}}{\sum_{k=1}^{14}\cos\theta_{t,k}}\right), \sum_{k=1}^{14}\sin\theta_{t,k} \geq 0 \; and \sum_{k=1}^{14}\cos\theta_{t,k} > 0 \\ 180 - \arctan\left(\frac{\sum_{k=1}^{14}\sin\theta_{t,k}}{\sum_{k=1}^{14}\cos\theta_{t,k}}\right), \sum_{k=1}^{14}\sin\theta_{t,k} \geq 0 \; and \sum_{k=1}^{14}\cos\theta_{t,k} < 0 \\ 180 + \arctan\left(\frac{\sum_{k=1}^{14}\sin\theta_{t,k}}{\sum_{k=1}^{14}\cos\theta_{t,k}}\right), \sum_{k=1}^{14}\sin\theta_{t,k} < 0 \; and \sum_{k=1}^{14}\cos\theta_{t,k} < 0 \\ 360 - \arctan\left(\frac{\sum_{k=1}^{14}\sin\theta_{t,k}}{\sum_{k=1}^{14}\cos\theta_{t,k}}\right), \sum_{k=1}^{14}\sin\theta_{t,k} < 0 \; and \sum_{k=1}^{14}\cos\theta_{t,k} > 0 \end{cases} \quad (12)$$

3.2.3. Geometric Conclusion of Crime Space-Time Paths

Based on the statistical analyses of crime space–time paths, movement parameters such as direction and velocity (norm) of crime displacement can be obtained. Using the geometric information, the integrated crime space–time path that reflects the movement characteristics of all crime types in an area can be constructed. It consists of three parts: (i) the origin (median center of $\{c_{0,1}, c_{0,2}, \ldots, c_{0,14}\}$); (ii) the integrated norm for each month ($\overline{norm}_t$); and (iii) the directional mean for each month ($Mean\theta_t$).

Routine activity theory has become a theoretical framework for study of the seasonal fluctuations of crime, but it has generally ignored crime events' geographical distribution; that is, it does not consider the seasonal spatial variations of crime [40]. To solve the problem, this study analyzed spatial changes of crime events over time from the geographic dimension, based on the geometric characteristics of crime space–time paths, and realized the "translation" from the statistical characteristics of space–time paths to the laws of crime displacement. Within the framework of routine activity theory, this approach can provide support for exploring crime patterns across time and space, as well as for the deployment of patrol resources. It can also help answer questions such as, "How much did each crime type, or all crime types, vary geographically in a region during different periods?". In addition, we consider the impact of the COVID-19 pandemic on crime movement patterns.

4. Experiments

4.1. Data Source and Its Preprocessing

The dataset utilized in this work is open source, legitimate, and authoritative [41] and was obtained from the British police's official website (https://data.police.uk, accessed on 18 March 2022). The published data include only the month of crime cases, with no date or hour information. This study analyzed the dataset at the finest time granularity possible, i.e., months. Fourteen crime types were defined in this website, and all of them were used in this study. The dataset includes 14 crime types: antisocial behavior, bicycle theft, burglary, criminal damage and arson, drugs, other crime, other theft, possession of weapons, public order, robbery, shoplifting, theft from the person, violence and sexual offences, and vehicle crime. We analyzed four aspects of crime records: time (month), longitude, latitude, and type of crime.

Given that the City of London (2.6 km^2) is more developed and provides better information than other places, this study relied on its crime records. Analyzing the latest data is conducive to increasing the value of results. Relatively new data from December 2019 to December 2020 were used in our work; these were the most recent data available when this study started. Moreover, in 2020, the COVID-19 pandemic caused a large degree of crime displacement, making hotspot policing work difficult. Analyzing the dataset from this period is more conducive to demonstrating how crime space–time paths can visualize and analyze these displacements, for crime prevention. Data preprocessing was performed using Python 2.7 and ArcMap 10.2; the steps were as follows: removing missing data, grouping, cropping, and format conversion.

Figure 5 shows the processed crime data. The number decreased from 6816 to 5845 after preprocessing, and the average number of cases per crime type was 418. Other thefts accounted for the largest number of cases (1067). The case numbers for possession of weapons were the least (only 54). Figure 5b depicts the temporal information of crime events in comparison to Figure 5a. Cesium 1.93 was used for 3D display of the preprocessed crime data. One intuitive approach is to connect the points of a crime type in different months using a path. However, a crime type may have non-unique points in each month, making it difficult to construct a crime space–time path.

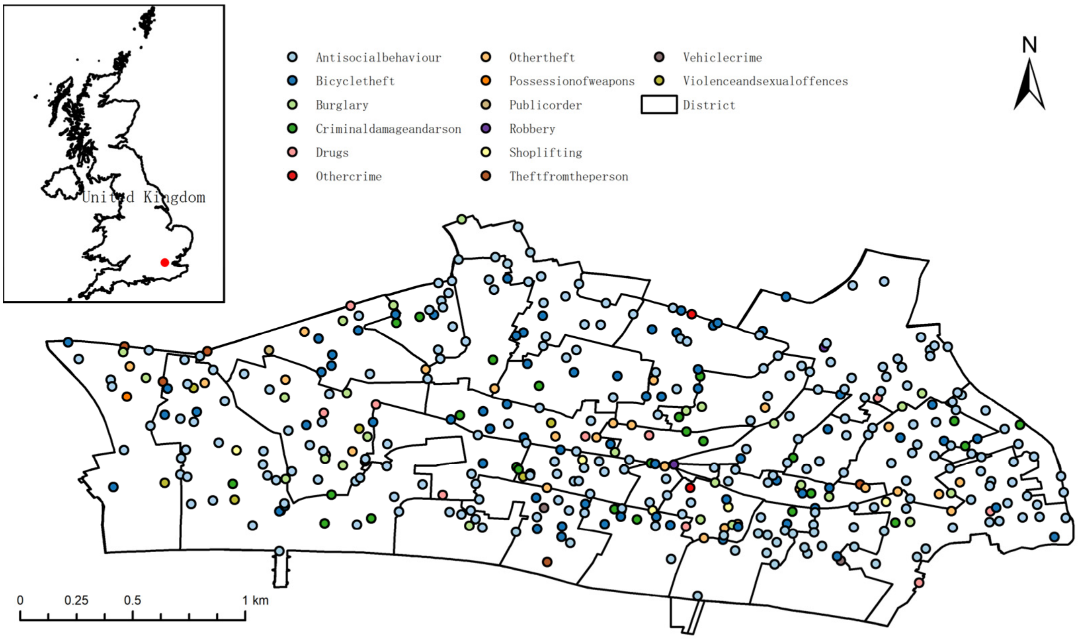
4.2. Construction of Crime Space-Time Paths

(1) Method

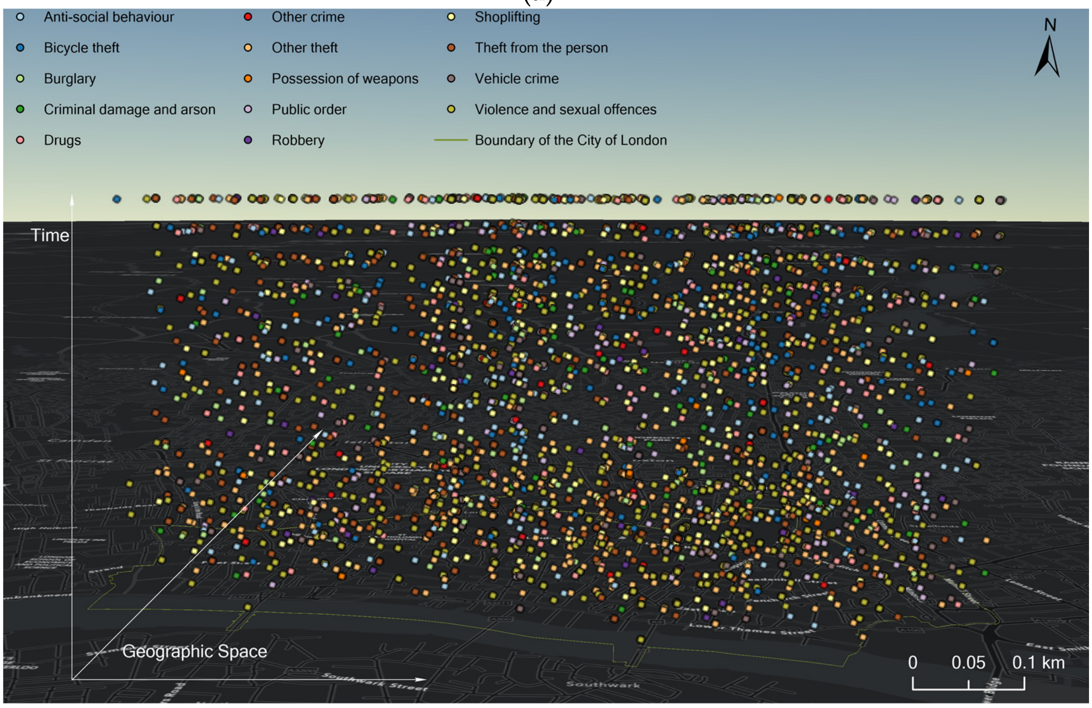
By connecting a crime type's control points, which are the median centers of crime point sets, the crime space–time path for this crime type can be constructed. Each median center includes spatial location (longitude, latitude), timestamp (month), and attribute (number of cases). Thus, the movement of a crime type can be represented by a crime space–time path composed of 13 control points and connecting lines between them. The vertical direction represents the time interval. Because the time dimension and space dimension are independent in the 3D space and have different scales, the scale of the time dimension is somewhat arbitrary. In this study, one month corresponds to 0.1 km in the vertical direction.

(2) Results

Figure 6 depicts crime space–time paths which express crimes' spatiotemporal patterns. The nodes and edges represent the center and displacement (both intensity and direction) of crime events. As illustrated in Figure 6, crime space–time paths were not straight lines, meaning that crime centers swung with the seasons, and the swing amplitude had a certain seasonality. Furthermore, different crime space–time paths were not identical, meaning that the spatiotemporal characteristics of different crime types were also not the same. The visualization of crime space–time paths on maps can help us understand the interaction patterns between different crime types in an area, such as random, attractive, or repulsive relationships [15]. It can also support the study of interactions between crime and environment, including geography or society. For example, an offender may commit multiple crimes in his or her surroundings [42], resulting in complex dependencies between crime types [20], which manifests as a tendency to attract each other along space–time paths. It is obvious from the above that joint analysis of crime space–time paths can contribute to revealing and discovering the general characteristics and patterns of crime events in an area, thereby offering a more complete description of crime.



(**a**)



(**b**)

Figure 5. Crime data after preprocessing: (**a**) 2D; (**b**) 3D.

4.3. Statistical Analysis of Crime Displacement Characteristics

The crime displacement characteristics include temporal (e.g., seasonality), spatial (e.g., distance and directionality), and spatiotemporal dimensions (e.g., velocity).

(1) Method

In geographical space, crime space–time paths had 168 monthly vectors (14 crime types $\times$ 12 edges). Each monthly vector is specified by norm and direction. It can be expressed by two parameters in the polar coordinate system: polar diameter and polar angle.

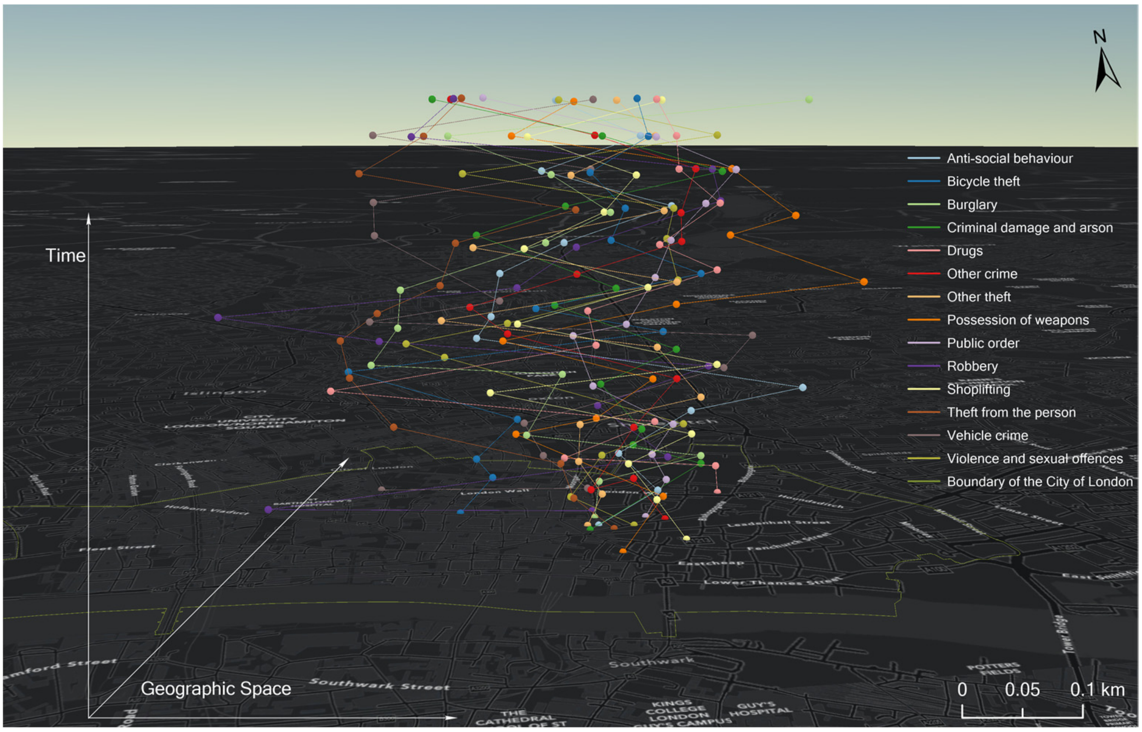


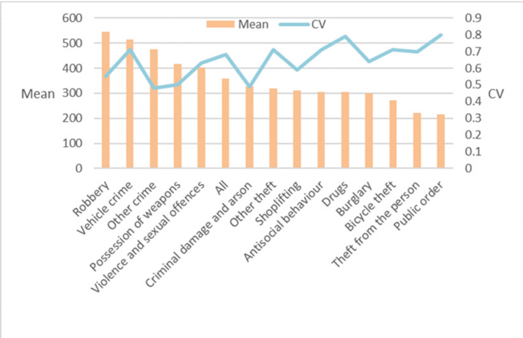
Figure 6. Crime space-time paths.

The 3D space–time paths showed the dynamic movement of crime centers, but they are cluttered, as illustrated in Figure 6, making it difficult to extract useful information such as movement patterns and interactions [43,44]. The monthly vectors, similar to the marginal distributions, can be analyzed using dimensionality reduction, i.e., considering one parameter while ignoring the effect of another. For the norms, $Mean_k$ and CV_k were calculated for each crime type according to Equations (7) and (8). Then, in order to analyze the trends of crime displacement, the symbol of each norm was determined in accordance with Equation (9), where "+" denotes spread and "−" denotes contraction. Finally, the integrated norm of all crime types in one month was calculated according to Equation (11). For the directions, the average direction of all monthly vectors in each month was calculated according to Equation (12).

The statistical heterogeneity of norms and directions can provide a quantitative basis for differentiated crime prevention.

(2) Statistical results of norms

As shown in Figure 7, norms can be used to analyze some indicators of crime displacement and to classify crime types. Figure 7a shows statistical information, including the $Mean_k$ and CV_k of norms for each crime type. $Mean_k$ characterizes the size of displacement for each crime type. The larger it is, the greater displacement of crime between months, and vice versa. CV_k characterizes the stability of displacement for each crime type. The smaller its value, the stronger stability of crime displacement, i.e., the smaller gap between norms of monthly vectors in different months. In addition, we also calculated the $Mean_{all}$ and CV_{all} of all crime types. Figure 7a indicates that the corresponding $Mean_k$ and CV_k of different crime types varied greatly. With the decrease of $Mean_k$, CV_k tended to increase, and the two showed a "scissor" shaped distribution, meaning that the lower $Mean_k$, the more sensitive CV_k is to outliers of norms, and vice versa.



(**a**)

	$CV_k < CV_{all}$	$CV_k > CV_{all}$
$Mean_k < Mean_{all}$	I Burglary Criminal damage and arson Shoplifting	II Antisocial behaviour Bicycle theft Drugs Other theft Public order Theft from the person
$Mean_k > Mean_{all}$	III Other crime Possession of weapons Robbery Violence and sexual offences	IV Vehicle crime

(**b**)

Figure 7. Analysis of norms: (**a**) $Mean_k$ and CV_k of crime types; (**b**) division of crime types.

Figure 7b shows the division of crime types based on $Mean_k$, CV_k, $Mean_{all}$ and CV_{all}. Based on the size relationships, 14 crime types can be divided into 4 groups. There were three crime types in Group I: burglary; criminal damage and arson; and shoplifting. There were six crime types in Group II: antisocial behavior; bicycle theft; drugs; other theft; public order; and theft from the person. Group III had four crime types: other crime; possession of weapons; violence and sexual offences; and robbery. Group IV had one type: vehicle crime. As can be seen from Figure 7b, the number of crime types in each group is uneven. There were more crime types in Group 2 and Group 3 than the others, i.e., CV_k was inversely proportional to $Mean_k$, which was consistent with the "scissor" distribution.

Table 1 lists specific response steps that should be taken for each group. For Group I, the norms were generally small and narrowly distributed, and monthly crime displacements were small and stable. Thus, police departments should actively supervise the hotspots of these crime types. Crime hotspots are often used to indicate areas where crime events are clustered in geographic space [45]. For Group II, the norms were generally small but widely distributed, and monthly crime displacements were small and fluctuant. Thus, police departments should not only supervise the hotspots of these crime types, but also focus on the months when crime displacement is large. For Group III, due to the large and stable monthly crime displacement, the norms were generally large and narrowly distributed, i.e., the crime displacement remained high throughout the year. Thus, rather than limiting forces to crime hotspots, police need to deploy resources across a broader area and increase inter-regional coordination among departments to systematically use crime information to prevent crime. For Group IV, the norms were generally large and widely distributed. Therefore, the scope of police resource allocation should be broad in general, and its location should be adjusted in time. The above measures are based on studies showing that measures for crime prevention mainly depend on crime type [46], and crime hotspots shift significantly over time [47]. It can be inferred that effective hotspot policing needs to consider not only the changes in crime hotspots over time but also different crime types [48], so that police resources can be matched to specific crime hotspots.

Table 1. Corresponding responses for each crime group.

	$CV_k < CV_{all}$ The norms distribute narrowly, and stability is strong.	$CV_k > CV_{all}$ The norms distribute widely, and stability is week.
$Mean_k < Mean_{all}$ The norms and crime displacements are generally small.	Crime hotspots should be actively regulated.	Crime hotspots should be monitored intensively in months when crime displacement is small, but not in other months.
$Mean_k > Mean_{all}$ The norms and crime displacements are generally large.	Police resources should be expanded beyond hotspots.	The scope of police resource allocation should be broad in general, and its location should be adjusted with time.

(3) Statistical results of changes in norms over time

Figure 8 shows rose diagrams of changes in norms over time for crime types' monthly vectors. For each crime type, the norms had obvious heterogeneity, i.e., the magnitude of norms varied over time, and the months in which the maximum value appeared were different. In terms of morphology, there were crime types with unipolar morphology, such as antisocial behaviour, which shifted significantly in just one month. Bipolar morphology, such as for violence and sexual offences, refers to a significant change in two months. Multipolar morphology, such as for vehicle crime, indicates significant displacements over many months. Figure 8 denotes the trend of any monthly vector's endpoint relative to its starting point. Each crime type shows an alternating distribution of spread (red) and contraction (green). There was no crime type that continued to spread or contract over a prolonged time.

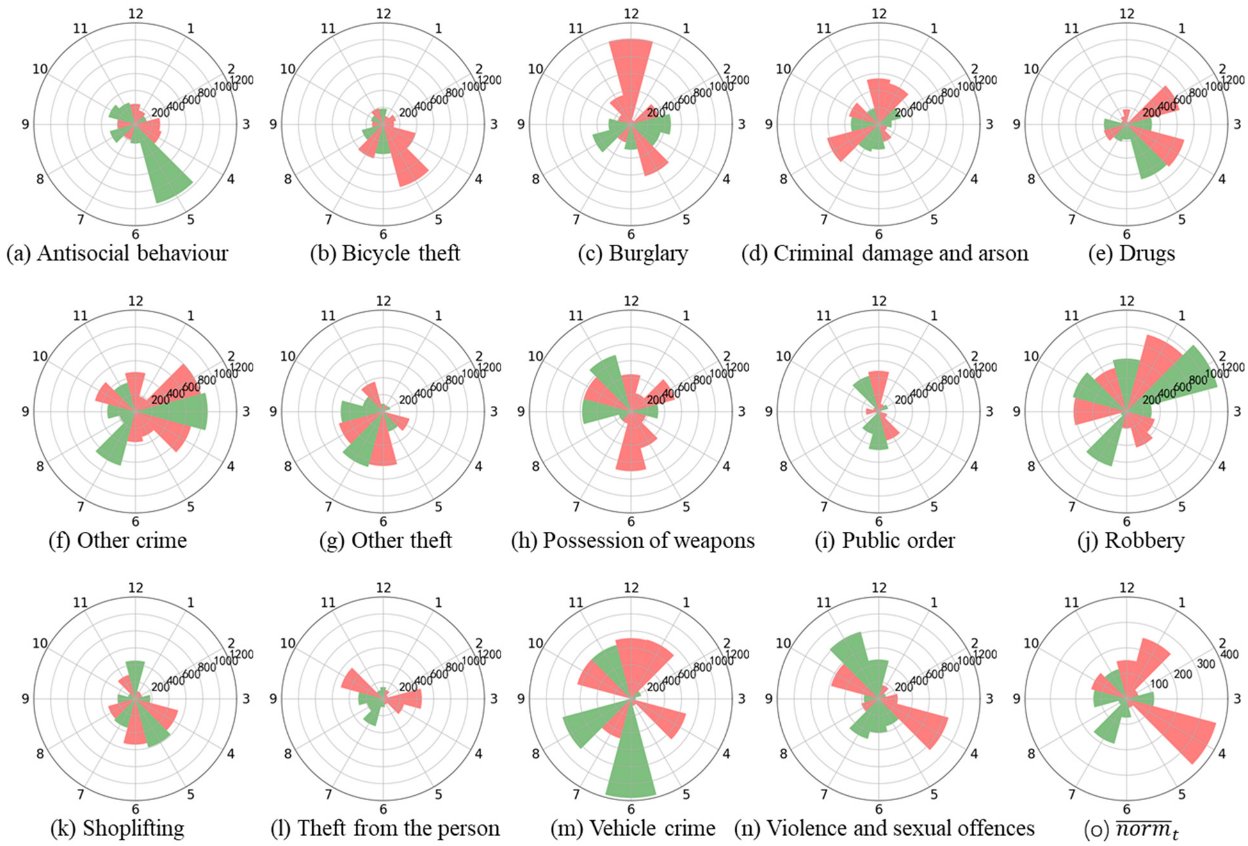
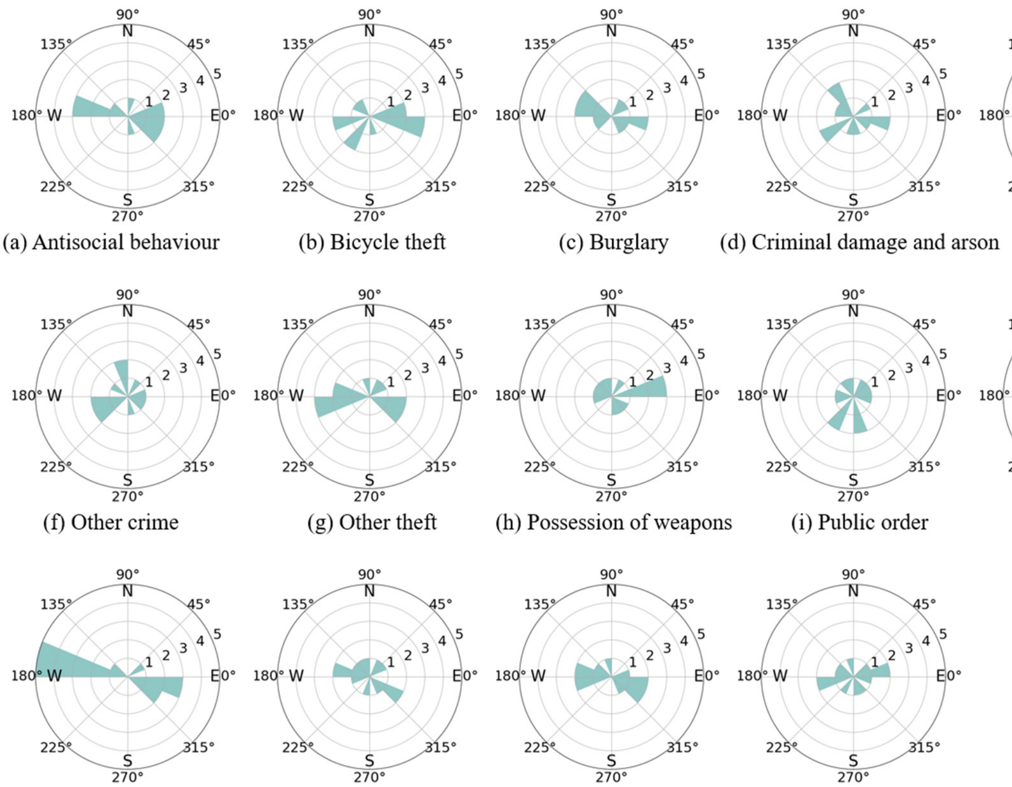


Figure 8. Statistics of norms (12 angles correspond to 12 months. The polar diameters represent norms, where the red indicates spread and the green indicates contraction.).

Figure 8o is a synthesis of other rose diagrams, showing that crime displacement in the City of London is bipolar, i.e., crime events spread in spring and winter but contracted in summer and autumn. This is because, in temperate climates, the long and cold nights of winter or spring are spent mostly indoors, with limited outdoor activities. There are fewer potential victims in an area, which forces offenders to move and seek more opportunities to commit crimes, leading to an increase in the norms and spread of crime. In summer and autumn, the nights are shorter and the weather is warm [49], so people spend more time outdoors and their activity spaces are larger, which increases the number of potential victims, leading to a decrease in norms and contractions of crime displacement. As shown in Figure 8o, the spread trend of crime displacement was most significant in April, which may be related to the COVID-19 epidemic lockdown policy in that month, i.e., the closure of public places (e.g., bars and schools) and working from home [50] that contributed to the spread of crime. This heterogeneity provides the basis for real-time adjustments in hot-spot policing, because crime events are seasonal [51,52].

(4) Statistical results of directions

Figure 9 illustrates the frequency of monthly vector directions, including the rose diagrams for 14 crime types, where 360 degrees is divided equally into 16 subregions; the polar angle indicates the direction of monthly vector; the polar diameter indicates the frequency of monthly vectors in the corresponding subregion. For each crime type, the frequency of directions had obvious anisotropy, that is, it varied with the direction and the maximum occurred at different angles. The morphological discontinuity of the rose diagrams was obvious. Some crime types showed a unipolar trend. For example, possession of weapons showed a single direction of crime displacement. In addition, violence and sexual offences showed a bipolar trend, shifting mainly in two directions. For multipolar crime types such as drugs, the main directions of displacement were multiple and not obvious. However, temporal information was ignored in the distribution of monthly vector directions.



(a) Antisocial behaviour (b) Bicycle theft (c) Burglary (d) Criminal damage and arson (e) Drugs (f) Other crime (g) Other theft (h) Possession of weapons (i) Public order (j) Robbery (k) Shoplifting (l) Theft from the person (m) Vehicle crime (n) Violence and sexual offences

Figure 9. Statistics of directions.

(5) Statistical results of changes in directions over time

Figure 10 shows the linear overlay of 14 rose diagrams (Figure 9) for each season, reflecting the time-variant characteristics of crime events in the City of London. The polar diameter of the rose diagram for any season was the sum of the corresponding polar diameters in Figure 9. Accordingly, the rose diagram of a year was the sum of all polar diameters in Figure 9. As can be seen from Figure 10, the displacement direction of crime events in the City of London had obvious variability. There was a distinct polarity throughout the year, i.e., oscillations along the east and west directions. In winter, spring, and autumn, crime events shifted mainly along the east and west directions, while in summer they moved mainly in the east direction. This means that the deployment of police resources should also be along the east and west directions, and resources should be deployed to the east in the summer.

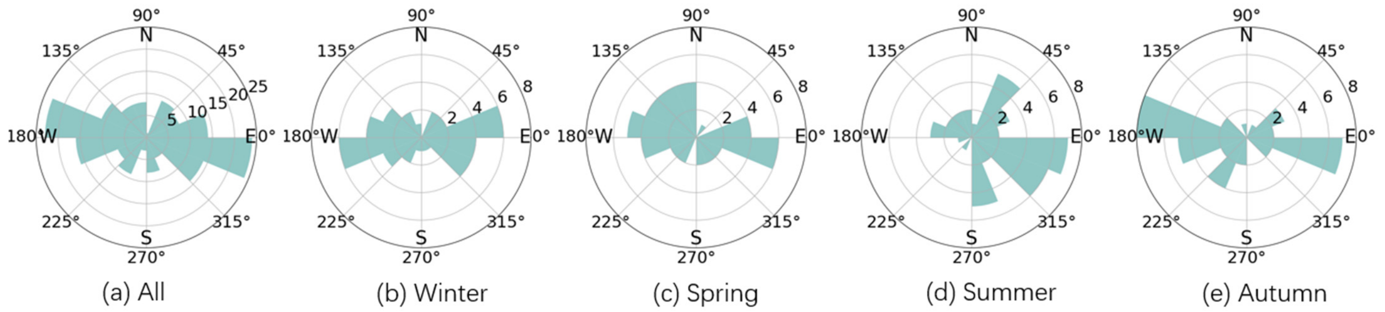


Figure 10. Statistical results of changes in direction over time.

Figure 11 shows the integrated crime space–time path, which characterizes the overall trend of crime events in a region. The norm and direction of each edge were calculated according to Equations (11) and (12), respectively. According to Figure 11, crime centers shifted to some extent every month. Initially, they were mainly distributed in the east of the City of London, and gradually deviated to the northeast over time. The residential areas on the west side were bypassed, possibly due to the natural community surveillance effect that discouraged crime.

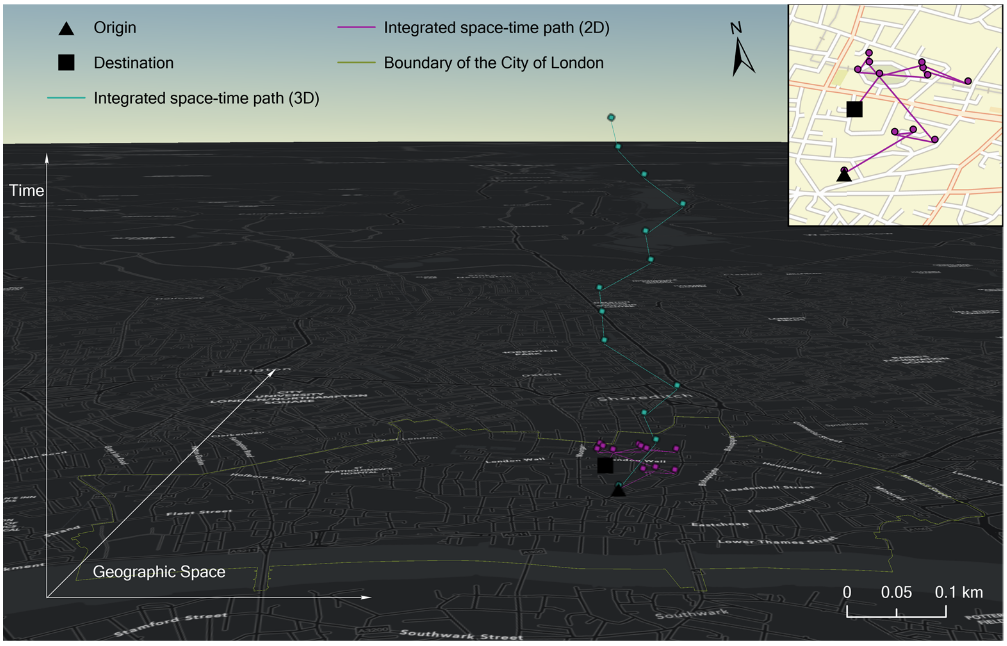


Figure 11. Integrated space-time path for all crime events.

5. Conclusions and Discussion

In this study, crime space–time paths were constructed for the City of London. The realistic significance of its movement parameters was statistically analyzed to understand crime displacement in the region. According to the norms and directions of monthly vectors, a dimensionality reduction approach was adopted to analyze the spatiotemporal characteristics of crime events. Firstly, considering the differences in the $Mean_k$ and CV_k of crime types, the 14 crime types were divided into 4 groups (Figure 7b), and corresponding suggestions were given for each group (Table 1). On this basis, the changes in norms over time were analyzed from the perspective of monthly vectors (Figure 8). Secondly, through the statistical analysis of directions, it was found that the directions of crime displacement were obviously heterogeneous, mostly in the east and west directions. Furthermore, the characteristics of directions were analyzed from the perspective of seasonal differences, and we found that crime events shifted in a particular direction in summer (Figure 10). Finally, an integrated crime space–time path was constructed for the City of London (Figure 11), revealing the characteristics of crime events in general.

These results affirm the practical application of space–time paths in the study of crime point sets. Its theoretical implications are outlined in the following: A crime point set at each moment corresponds to a space–time disc from the perspective of time geography, so that the spatial distribution sequence of crime events can be converted into a sequence of space–time discs. This approach breaks through the limitation that the space-time disc sequence in classical time geography can only be constructed based on anchor points. Space–time path is another key concept of time geography, in addition to space–time disc, which can quantitatively describe the movement characteristics of geographical phenomena and their interaction patterns. Control points constituting a crime space–time path can be transformed from the crime point sets. The approach proposed in this study enables time geography to be applied to point sets. Compared with point pattern analysis, it is a faster and more reliable method for visualization and analysis of point sets.

The contributions of this study include extending the application of the time geography framework from discrete points for point objects to discrete point sets for polygon objects, and combining crime space–time paths with routine activity theory to reveal the crime movement patterns in a region. Through experiments, we illustrated the effectiveness of crime space-time paths in quantifying the spatiotemporal patterns of crime displacement, which is important for the effective implementation of hotspot policing.

This study classified crime types according to the degree of crime displacements. In future work, we can consider more factors (such as the number of crimes, the direction of crime displacements, the spatial distribution range of crimes, etc.) to divide them into different spatial and temporal patterns, which will make the grouping of crime types more interpretable and contribute to crime prevention. In addition, this study mainly considered temporal factors, such as seasons in regard to temperature and sunshine duration, but did not consider the built environment and demographic characteristics when explaining the patterns of crime displacement. Future work needs to incorporate more factors to explain the movement patterns of crime events in a more refined and comprehensive manner.

As far as the practical application of the approach proposed in this work was concerned, some specific parameters or algorithms needed to be specified, and these choices had an impact on the results. First, we the used median center to extract the representative point from a crime point set. In fact, the representative points may be hotspots in addition to centers, and the choice depends on the research objective. Since a crime point set contains non-unique hotspots, the median center was chosen in this study.

Second, the time interval of monthly vectors needed to be specified. The time span of a crime point set represented by a center is one month. The monthly vector is the connection between two centers at adjacent moments, and in some sense it has no time interval. In this study, we specified that the time of each center corresponded to the last day of each month, so that the logical time interval of monthly vectors was one month.

Third, the origin needed to be specified when calculating the symbol of norms (Equation (9)). Similar to the reference system, different origins may produce very disparate results. The origin was the starting point of each space–time path. In addition to the starting point, the origin can also be the center of all control points. The purpose of choosing the starting point was to facilitate analysis of the trend of crime displacement relative to the first month.

Finally, the number of subregions for rose diagrams (Figure 9) required specification. Geographic space can usually be divided into 4, 8, 16, 32 direction subregions. As with the raster scale, the larger the number of subregions, the higher the accuracy. Too many or too few subregions are not conducive to the statistical analysis of directions. Given that there are 12 monthly vectors of a space–time path, 16 direction subregions are sufficient.

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