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# Influence of Places of Resident Activities on Spatial Distribution of Drug-Related Crimes

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**Abstract:** Drug-related crimes have become a common worldwide concern, and studies have considered the influence of different types of land use on such crimes. However, the dynamic visitor flow rate has rarely been taken into consideration when analyzing the cause of drug-related crimes, with most studies only using static population distribution data. Differences between the main factors associated with drug-related crimes on different streets have also rarely been discussed. In this study, the spatial distribution of and factors associated with drug-related crimes were explored from the perspective of residents'daily activities, and the main factors associated with such crimes on different streets were compared and analyzed. The results indicate that drug-related crimes are characterized by significant spatial heterogeneity and clustering; the spatial distribution of drug-related crimes is closely correlated with places of resident activity. More specifically, the denser the distribution of restaurant services and recreational facilities (e.g., cyber cafes and bars) on a street, the more likely drug-related crimes are to occur there. Drug-related crimes on different streets are associated with different factors those on commercial-oriented streets are mainly distributed in areas with dense restaurant services and recreational facilities, while those on streets dominated by industrial parks, residential areas, and woodlands primarily occur where there are high-density traffic facilities and cyber cafes or areas with a high visitor flow rate.

**Keywords:** Drug-Related Crimes, Land Use Type, Dynamic Visitor Flow Rate, Crime Geography

## 1. Introduction

According to the *2018 Report on China's Drug Control Situation*, approximately 275 million people worldwide have used opium, heroin, cocaine, marijuana, ice and other drugs at least once, and nearly 31 million of them have become addicted. Drug abuse not only brings serious harm to the drug users themselves and their families, but is also likely to trigger a number of illegal activities, such as theft. Through recognizing, analyzing, and understanding the spatial distribution of drug-related crimes, we can provide a basis for decision-making to address these issues. This analysis can also offer a data reference for the complete management and planning of urban development.

Environmental criminology has its origins in 19th-century studies of dangerous places. After [1] Jacobs initiated the theory of "eyes on the street," further studies focused on the geography of crime [2]. Empirical findings support Jacobs' perspectives that compact urban characteristics, such as walkability, density, and land-use diversity tend to attract more people onto the streets and generate more interactions between inhabitants, thus nurturing a stronger sense of community and reducing crime by increasing natural surveillance and informal social control [3, 4]. However, there is also relevant criminological literature suggesting that mixed land use exerts a deleterious impact on neighborhood crime by weakening both residents' inclination and effectiveness in performing social control [5, 6]. Specifically, mixed land use can attract more people to the community, while greater population numbers and density likely increase the number of potential offenders and targets, thus leading to more crime and forming more crime hotspots [7-9]. Studies have also found that different types of land use have different degrees of attraction to crime [10, 11]. Different places of interest (POIs), such as retail, abandoned buildings, and gas stations, can attract more criminal activities [12-14]. In geographic criminology, it is increasingly recognized that the appropriate spatial unit of analysis needs to be considered explicitly and carefully chosen [15]. At different spatial scales, crime concentration (specifically, burglary and family theft) differs [16]. Researchers have found that crimes are more concentrated when smaller geographic units were used for analysis, and recent research has focused on addresses [17, 18], street segments [19-22], and houses [23, 24]. There is an internal relationship between drug-related crimes and geographical factors. Most of the targets of drug sales, for example, are drug addicts, so the areas where drug addicts gather will form the main areas for drug sales. Drug traffickers generally choose places with low supervision and a relatively high concentration of buyers. To ensure that the drug caches are not found, safety and concealment of traffic between where drugs are sold and where they are stored are also considered by drug traffickers. Eck compared the characteristics of points with and without drug trafficking in an area of San Diego in the United States and found that places with characteristics including lack of monitoring and easy access are prone to drug-related crimes [25]. Weisburd and Green pointed out that similar drug markets have similar boundaries, which are usually formed by drug trafficking activities in various locations. If there are enough objects near the offender's residence, the dealer usually does not have to travel far between the crime location and residence [26]. Xu used spatial analysis technology to analyze the spatial and temporal distribution characteristics of drug crimes and found a concentrated distribution [27]. Such studies suggest that geographic information can reflect the unique regularity of drug-related crimes [28-30]. In recent years, with rapid social and economic development, population mobility has become increasingly frequent, which has led to the frequent occurrence of urban drug-related crimes. The relationship between residents' activities, urban facilities, and such crimes has become a focus of academic research, but the dynamic visitor flow rate [31-37] has rarely been taken into consideration for the analysis of this association, which tends to use only static population distribution data. Existing studies have also rarely considered whether there are differences in the factors associated with drug-related crimes between different regions. This study therefore explores the spatial distribution of and factors associated with drug-related crimes from the perspective of residents' daily activities and makes a comparative analysis of the main factors related to such crimes on different streets. By understanding the spatial distribution and related factors of drug crimes, we can formulate different prevention and control policies for different streets and achieve more targeted regional management.

## 2. Study Area and Data

### *2.1. Study Area*

This article uses initials to anonymize the study area. District Z of City A was the study area (see Figure 1). As part of a relatively developed coastal city in China. District Z is a fast-developing urban district with convenient transportation and large population mobility within City A. District Z covers an area of 78.75 km$^2$, with an estimated total population of 1,039,900, and it has the largest concentration of drug-related crimes in City A. With many large-area urban villages, District Z is home to traditional crimes, such as violent assault, theft, pornography, gambling, drug abuse, and trafficking, which made it a suitable choice as a study area.

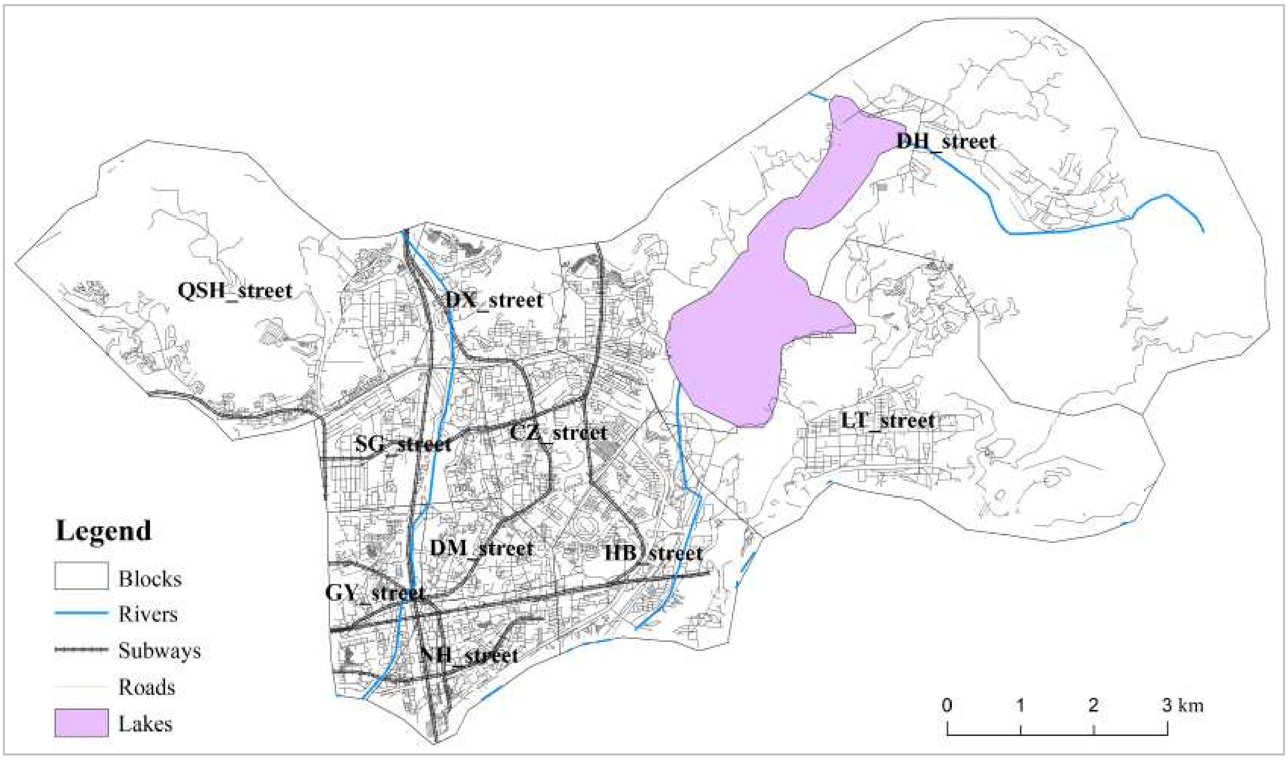


***Figure 1.*** *Study area.*

### *2.2. Data*

#### *2.2.1. Case Data*

The drug-related crime data in this paper were composed of records of emergency calls received by the police and were obtained from the City A Public Security Bureau in 2017. The drug-related crimes analyzed in this paper refer to all kinds of drug crimes (including smuggling, trafficking, transporting, manufacturing, and illegally possessing drugs). Through preliminary screening, 5,287 drug crime incidents were identified; each crime had a clear case address and case category, as well as including the coordinates and time of the crime. Before the formal analysis, criminal cases outside the study area were manually corrected based on the case address description and removed. Incompletely recorded cases were also removed. After processing, the data from 5,233 drug-related crimes were considered.

#### *2.2.2. Traffic Data*

The traffic data primarily covered information regarding bus stations, subway stations, and roads. The road data came from a 2018 high-definition satellite map provided by BIGEMAP, and the road vector data of District Z were obtained by vectorization and clipping. Information for the bus stations and subway stations was obtained through the 2018 API of Amap using Python code from 2018; data from this source was then cropped to get the District Z bus station point data and subway station data. Table 1 shows the cropped traffic data for District Z.

#### *2.2.3. Resident Activity Data*

Resident activity data largely included location information for resident activities and the dynamic visitor flow rate. In this paper, the land type for the residential activities was classified by POI data, which refer to the point with the name, category, longitude, and latitude (i.e., navigation map information). POI data were also obtained through the API of Amap using Python code. Simple pre-processing was performed to eliminate invalid POI data, and locations for resident activities were divided into eight land-use types according to the daily travel of the residents [38] (see Table 1). The dynamic traffic data for this study were obtained using Tencent and Python code. The Tencent travel data came from the Tencent location big data service window (http://heat.qq.com/index.php). Based on the large number of users of Tencent products, this service records the real-time location of active users of Tencent products such as QQ (800 million users), WeChat (350 million users), Qzone (600 million users), Tencent Games (200 million users), and Tencent website (130 million users), with a coverage of about 99.3% of the total population in China; this means that this data can accurately reflect the spatial distribution of the population in the study area. Network crawling of the real-time location data of users had certain restrictions on the size and amount of data obtained. Therefore, based on the restrictions, we selected November 12, 2018 as the data extraction node. November 12 was a normal workday, so it was likely representative of typical patterns. Using Python code, we obtained suitable travel thermal data in District Z for 23 periods from 01:00 to 24:00 on November 12, 2018, with a time interval of 10 minutes. The higher the thermodynamic value, the denser the population (see Figure 2).

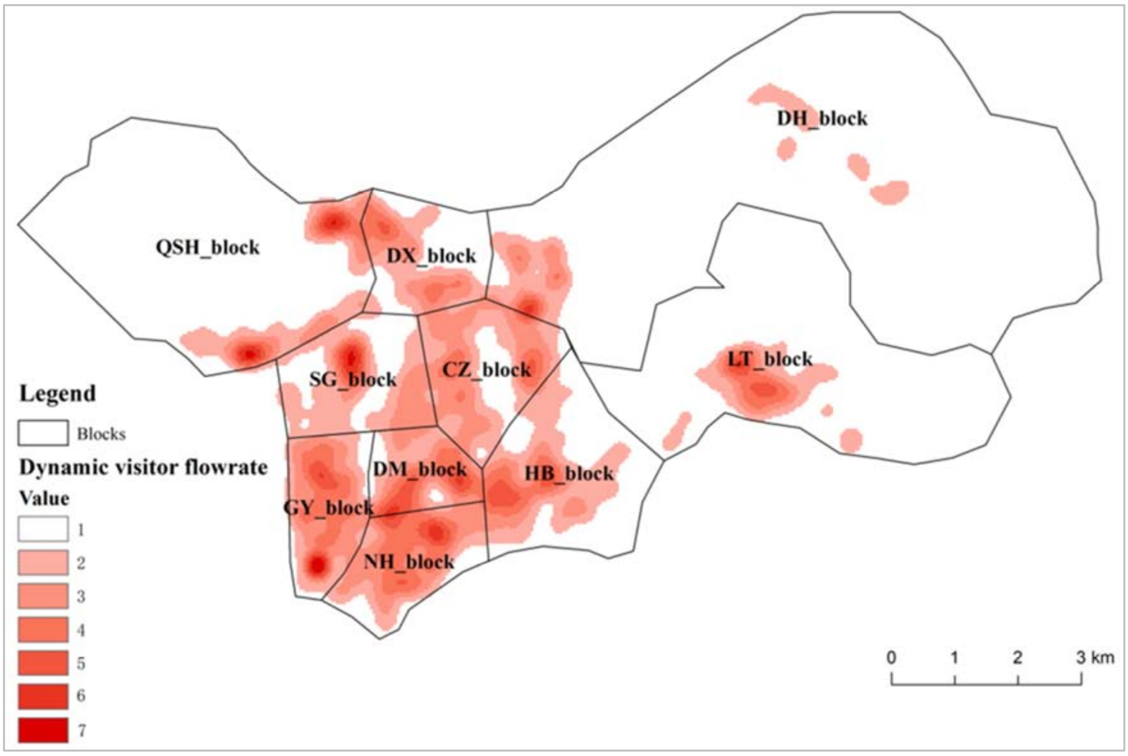


***Figure 2.*** *Heat map of the dynamic visitor flow rate.*

***Table 1.*** *Description of variables.*

| Variables | Mean | Std dev. | Min | Max | Description |
|---|---|---|---|---|---|
| Total number of drug-related crime cases within blocks | 523.3 | 851.6 | 15 | 2724 | The number of drug-related crimes in the blocks was taken as the dependent variable |
| Traffic data within blocks | | | | | The numbers for three types of traffic data were taken as the independent variables. Further, data about bus stations and subway stations were obtained by counting the number of facilities in the block. The road network density was obtained by calculating the ratio of the total length of all of the roads in the block to the total area of the block. |
| Bus stations | 216.8 | 61.2 | 135 | 264 | |
| Subway stations | 3.7 | 2.5 | 0 | 8 | |
| The road network density (km/km$^2$) | 19.4 | 8.3 | 4.6 | 30.5 | |
| Locations of resident activities within blocks | | | | | The numbers for eight types of locations of resident activities data were taken as the independent variables. The data were obtained by counting the number of facilities within the block. |
| Markets | 4.6 | 2.1 | 2 | 9 | |
| Shopping malls | 84 | 50.8 | 35 | 840 | |
| Restaurant services | 363.8 | 244.2 | 162 | 987 | |
| Karaoke TV establishments (KTVs) | 7 | 9.1 | 0 | 32 | |
| Cinemas | 3 | 2.7 | 0 | 9 | |
| Bars | 13 | 21.0 | 0 | 74 | |
| Cyber cafes | 8 | 6.1 | 3 | 25 | |
| Accommodation services | 304.2 | 165.5 | 117 | 709 | |
| Average value of the dynamic visitor flow rate within blocks | 930.6 | 254.9 | 590 | 1477 | The dynamic visitor flow rates were taken as the independent variables. The daily average visitor flow density value for each block was obtained by calculating the 24-hour dynamic visitor value of the blocks. |

## 3. Methods

In this study, the factors associated with drug-related crimes were primarily explored from the perspective of residents' daily activities. Research has shown that the most comfortable walking distance for most people is 300–500 m [39]. Hence, to facilitate matrix calculation, a 21 (row) × 31 (column) grid was generated according to the size of the study area, with each grid being 500 m × 500 m, to ensure the data accuracy and spatial distribution continuity of drug-related crimes. We used the Geodetector method to explore and analyze the differences in the main associated factors present on different blocks (see Table 1). Figure 3 shows the specific process.

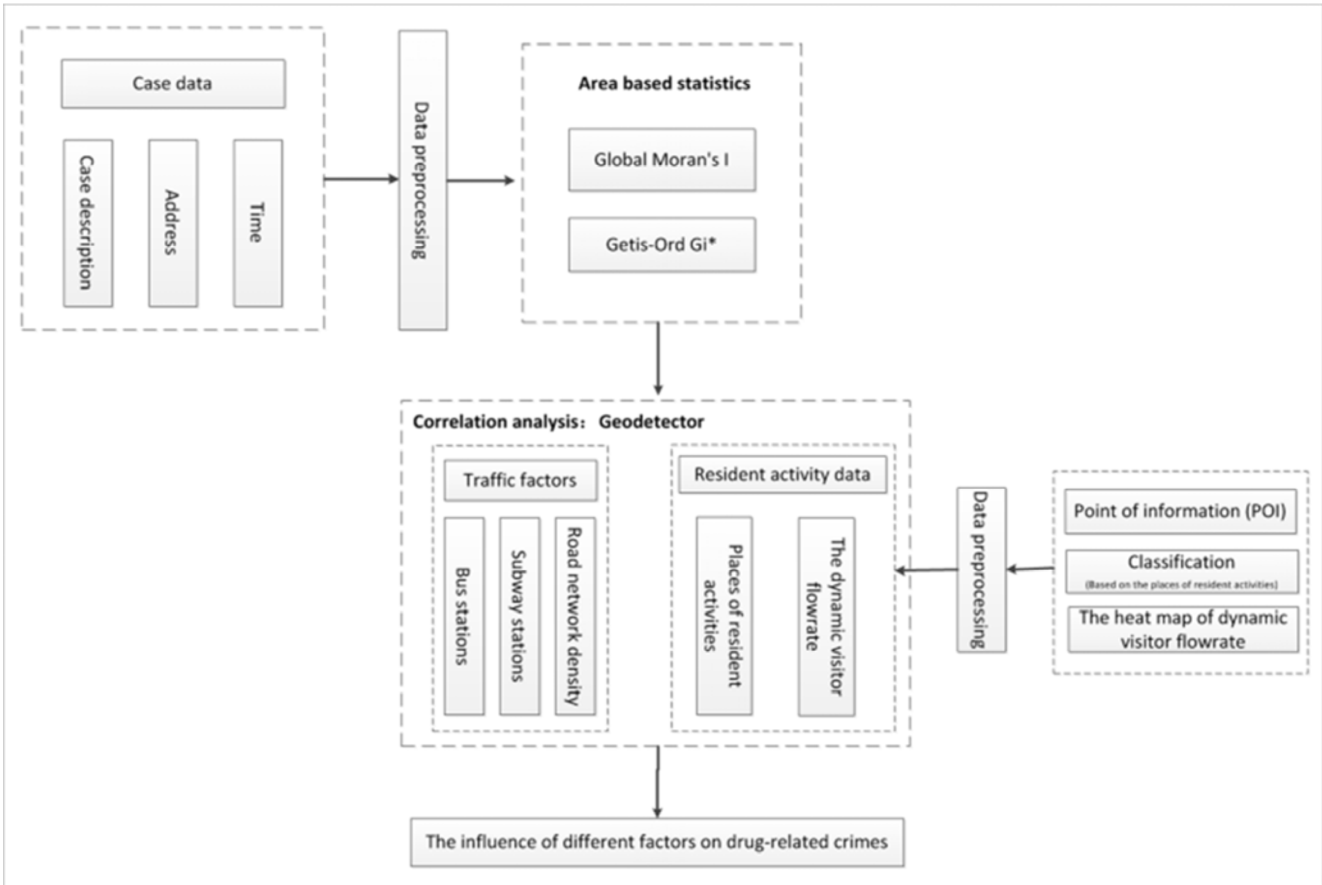


***Figure 3.*** *Flow map of the methodology.*

### 3.1. Global Moran's I

Proposed by Moran in 1948, Global Moran's I reflects spatial adjacency or the similarity between the attribute values of adjacent regional units. The degree of spatial autocorrelation is represented by Global Moran's I, which can be calculated using Equation (1):

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \omega_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where Zi denotes the difference between an attribute value of event i and its average value, ωi,j is the weight between event i and event j, and n is the number of events. Global Moran's I ranges from −1 to +1. The closer the value is to −1, the greater the difference between the units or the less concentrated the distribution. The closer the value is to 1, the closer the relationship between the units, and the more similar these units are to each other (high-value aggregation or low-value aggregation). If the value is close to 0, there is no correlation between units [40].

### 3.2. Getis-Ord Gi*

Getis-Ord Gi* was specifically used to calculate the clustering of crime hot spots. By calculating the local G statistic of each element in the weight set, the location where the high-value or low-value elements cluster was determined using Equation (2):

$$G_i^* = \frac{\sum_{j=1}^{n} \omega_{i,j} x_j - \bar{X}\sum_{j=1}^{n} \omega_{i,j}}{S\sqrt{\frac{[n\sum_{j=1}^{n} \omega_{i,j}^2 - (\sum_{j}^{n} \omega_{i,j})^2]}{n-1}}} \tag{2}$$

where $x_i$ is the attribute value of element $j$, $\omega_{i,j}$ is the spatial weight between elements $i$ and $j$, $n$ is the total number of elements, and

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{3}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{4}$$

The Gi* returned by each element is the *Z* statistic value. For statistically significant positive Z values, the higher the Z value, the more significant the clustering effect of the hot spots. For statistically significant negative *Z* values (the lower the *Z* value) the closer the cold spots are clustered. The so-called cold spots are areas with a significantly lower concentration of criminal acts than the surrounding areas.

### 3.3. Geodetector

The spatial distribution of drug-related crimes is restricted by different spatial and geographic factors. Geodetector can effectively identify different geographical factors and the impact of the interaction between different geographical factors on drug-related crimes. The principle is to test the coupling of the two spatial distributions—that is, attribute and factor spatial differentiation [41]. The Geodetector *q* statistic can be used to measure spatial heterogeneity, identify explanatory factors, and analyze the interaction among variables. The *q* value was calculated as follows:

$$q = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{m} n_i \sigma_i^2 \tag{5}$$

where $q$ is the index of factor X on drug-related crime Y, the variance of Y is composed of *m strata (i=1, 2, …, m)*, $\sigma^2$ is the variance of drug-related crimes in the entire region, *n* represents the number of samples in the study area, *m* denotes the number of secondary regions, and $\sigma_i^2$ is the variance of the number of drug-related crimes in secondary regions. When $\sigma_i^2 \neq 0$, the model is tenable. $q \in [0, 1]$; when $q = 0$, the number of drug-related crimes is not affected by the factors. The larger the value for $q$, the greater the factor's explanatory power. The explanatory effect is best when $q = 1$.

There were two reasons we chose Geodetector to analyze factors correlated with drug crimes. First, the sample size was under 30 for analysis of the factors associated with drug-related crimes in the block, but a sample size greater than 30 is needed for multiple regression, but Geodetector can detect correlations when the sample size is under 30 and achieve the accuracy that other models need a larger sample size to achieve. Second, the correlation between drug-related crime and the surrounding environment is complex, not simply linear and there is a strong correlation between independent variables. The commonly used correlation coefficient analysis method must make linear assumptions, but Geodetector makes no linear assumption for the variable because it belongs to the category of variance analysis. The value of *q* reflects the explanatory percentage of independent variable *x* to dependent variable *y*(*100 * q*)%. Unlike multiple regression analysis, the Geodetector model is not affected by the collinearity of multiple independent variables; however, it should be noted that any continuous factors needs to be discretized. The advantages and disadvantages of the discretization algorithm directly affect the accuracy of the evaluation results. The independent variables and dependent variable in this paper are discrete factors, so we used Geodetector to carry out the correlation analysis.

# 4. Results

## *4.1. Spatial Distribution of Drug-Related Crimes*

Global Moran's I was used to analyze the sites of drug-related crimes in District Z; the resulting value was 0.7210, which indicates a significant spatial correlation. The value of *Z* was 16.6360, which is much larger than the critical *Z*-score of 2.58 at a confidence level of 99%. Therefore, the spatial distribution of drug-related crimes in District Z of City A was characterized by a clustering pattern.

Getis-Ord Gi* was applied to analyze drug-related crime sites in District Z; the results are shown in Figure 4. The drug-related crimes in the district were relatively concentrated and principally clustered on GY_block, DM_block, and NH_block (the larger the GiZSore, the more significant the clustering effect of the hot spots). According to the statistics, there are 371 grid cells in District Z, while drug-related crime hot spots were found in only 24 cells (about 6%), which were associated with 17.4% of the population. There were 4,839 drug-related crimes altogether in these hot spots, accounting for 92.5% of the total crimes in the study area. Approximately 92.5% of drug-related crimes in District Z occurred in only 6% of the region, indicating significant spatial heterogeneity and clustering.

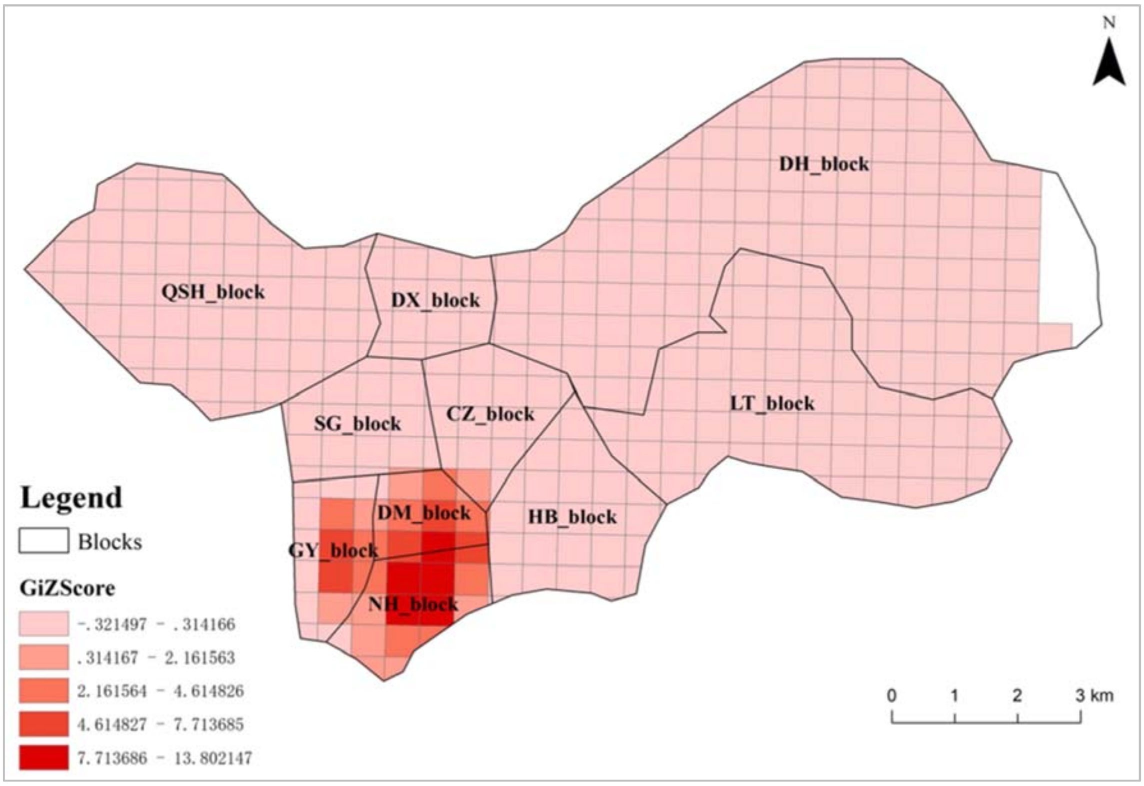


***Figure 4.*** *The results of the Getis-Ord Gi*.*

## *4.2. Global Factors*

Geodetector showed that different independent variables had different degrees of association with the number of drug crimes on the block. According to their degree of association with this dependent variable, the top five independent variables—restaurant services, cyber cafes, bars, accommodation services, and dynamic visitor flow rate—out of 12 were selected as the main associated factors (see Table 2). These five factors all had a *P* value of less than 0.0001. Restaurant services had the strongest explanatory power (0.6270), accounting for 62.70% of the distribution of drug-related crimes ($P < 0.0001$). The other factors had less explanatory power. Among them, the explanatory power of cyber cafes (0.5880) and restaurant services (0.6270) was similar, and there was a relatively small difference between the explanatory power of bars (0.5092) and that of accommodation services (0.4904).

***Table 2.*** *The main factors associated with drug-related crimes under the global investigation.*

| Case type | Main associated factors (Top five) | | | | |
|---|---|---|---|---|---|
| | (Level of significance: $P < 0.0001$) | | | | |
| **Drug-related** | **Restaurant services** | **Cyber cafes** | **Bars** | **Accommodation services** | **Dynamic visitor flow rate** |
| | 0.6270 | 0.5880 | 0.5092 | 0.4904 | 0.4275 |

The interactions between various factors, were mutually strengthening; that is, the main associated factors correlated with each other for mutual enhancement. Such interaction explained more than a single factor. The main associated factors and the other factors were tested in pairs to calculate the degree of correlation ($q$ value), and the three factors with the highest $q$ values were selected as the main correlated factors (see Table 3).

***Table 3.*** *Main related factors of the associated factors.*

| Case type | Main associated factor | Main related factor 1 (q values) | Main related factor 2 (q values) | Main related factor 3 (q values) |
|---|---|---|---|---|
| Drug-related | Restaurant services | Cyber cafes 0.7239 | KTVs 0.7238 | Shopping malls 0.7201 |
| | Cyber cafes | Bars 0.8575 | Shopping malls 0.8204 | KTVs 0.7977 |
| | Bars | Cyber cafes 0.8575 | Accommodation services 0.7820 | KTVs 0.7208 |
| | Accommodation services | Bars 0.7820 | KTVs 0.7417 | Cyber cafes 0.7037 |
| | Dynamic visitor flow rate | Cyber cafes 0.7513 | KTVs 0.7041 | Restaurant services 0.6940 |

Note: Frequently appearing factors are shown in bold.

Overall, the main associated factors for drug-related crimes were often correlated factors of the main factors. This was especially the case for cyber cafes and bars (0.8575). Additionally, karaoke TV establishments (KTVs) and cyber cafes were the most frequently correlated among the main associated factors. Based on the global analysis, the places where drug-related crimes are concentrated are often places with densely distributed restaurant services and recreational facilities that can gather a large number of people.

### *4.3. Associated Factors of Each Block*

With blocks in District Z as the statistical unit, the main associated factors for drug-related crimes on different blocks were comparatively analyzed (see Table 4). The results showed that on DM_block, DX_block, GY_block, and NH_block, all of the associated factors tended to have a strong power in explaining the distribution of drug-related crimes. On DM_block, DX_block, and GY_block, the main associated factors were similar, most of which were shopping malls, restaurant services, accommodation services, and the dynamic visitor flow rate. Recreational facilities (KTVs, bars, and cyber cafes), shopping malls, and restaurant services were the main associated factors on NH_block. On other blocks, the explanatory power of various factors was relatively low, but the main associated factors mostly included restaurant services, accommodation services, and dynamic visitor flow rate. In other words, on the blocks where drug-related crimes were weakly related to various factors, the explanatory power of restaurant services, accommodation services, and dynamic visitor flow rate on drug-related crimes was relatively weak; however, they were still the most correlated factors for drug-related crimes.

***Table 4.*** *The main associated factors of drug-related crimes for each block.*

| Block | Main associated factors (Top five) (Level of significance: P < 0.0001) | | | | |
|---|---|---|---|---|---|
| CZ_block | Cinemas 0.3288 | Accommodation services 0.328 | Restaurant services 0.3214 | Dynamic visitor flow rate 0.2559 | Bars 0.2368 |
| DH_block | Dynamic visitor flow rate 0.0801 | Restaurant services 0.0660 | Bus stations 0.0434 | Shopping malls 0.0362 | Road network density 0.0312 |
| DM_block | Bus stations 0.9034 | Cyber cafes 0.8957 | Accommodation services 0.6812 | Shopping malls 0.5724 | Dynamic visitor flow rate 0.5373 |
| DX_block | Shopping malls 0.9506 | Dynamic visitor flow rate 0.9259 | Cyber cafes 0.7135 | Restaurant services 0.6666 | Accommodation services 0.5556 |
| GY_block | Cyber cafes 0.8007 | Dynamic visitor flow rate 0.6625 | Road network density 0.3729 | Shopping malls 0.2196 | Accommodation services 0.2076 |
| HB_block | Dynamic visitor flow rate 0.7053 | Restaurant services 0.6328 | Cinemas 0.5965 | Accommodation services 0.5912 | Cyber cafes 0.3986 |
| LT_block | Dynamic visitor flow rate 0.5822 | Accommodation services 0.4585 | Restaurant services 0.3211 | Shopping malls 0.1923 | Bus stations 0.1548 |
| NH_block | KTVs 0.8693 | Bars 0.8377 | Cyber cafes 0.709 | Shopping malls 0.7915 | Restaurant services 0.7911 |
| QSH_block | Dynamic visitor flow rate 0.4446 | Restaurant services 0.3062 | Cyber cafes 0.2283 | Road network density 0.1744 | Accommodation services 0.1658 |
| SG_block | Cyber cafes 0.3234 | Bars 0.3182 | Accommodation services 0.2376 | Road network density 0.2136 | Dynamic visitor flow rate 0.2012 |

There appeared to be a mutually strengthening interaction between the factors associated with drug-related crimes on each block was detected (see Table 5); that is, the main associated factors correlated with each other for mutual enhancement. On DM_block, the main associated factors were also the primary correlated factors. Restaurant services and recreational facilities (bars, KTVs, and cyber cafes) were the most frequently correlated factors among the main associated factors, indicating that areas on DM_block where drug-related crimes were relatively concentrated usually had densely distributed restaurant services and recreational facilities. On DX_block, restaurant services and the dynamic visitor flow rate were the most frequently correlated factors among the main associated factors, indicating that drug-related crimes were often concentrated in places where people gather. On GY_block, the main associated factors were closely related to traffic factors (e.g., the density of bus stations and road networks) and the density of recreational facilities (KTVs, bars and cyber cafes), which means that convenient transportation and concentrated recreational facilities were the primary factors that led to the clustering of drug-related crimes on GY_block. On NH_block, among the main associated factors, recreational facilities (KTVs, bars, cyber cafes and cinemas), were the correlated factor that appeared most frequently, indicating that the main reason for the aggregation of drug-related crimes on NH_block was the existence of many such facilities. Because the correlation coefficient of the main associated factors of drug-related crimes was comparatively low on the other blocks, only the first correlated factors, which are few in number (see Table 5) are discussed here. On CZ_block and DH_block, the main associated factors were most closely correlated with traffic factors (the density of bus stations and road networks). On HB_block and LT_block, they were most closely correlated with the dynamic visitor flow rate while on QSH_block and SG_block, they were most closely related to cyber cafes.

***Table 5.*** *Main factors related to the associated factors.*

| Case type | Main associated factor | Main related factor 1 (q values) | Main related factor 2 (q values) | Main related factor 3 (q values) |
|---|---|---|---|---|
| CZ_block | Cinemas | KTVs 0.9078 | Restaurant services 0.9058 | Subway stations 0.8895 |
| | Accommodation services | Road network density 0.955 | Restaurant services 0.9437 | KTVs 0.9366 |
| | Restaurant services | Bus stations 0.9783 | Accommodation services 0.9437 | Dynamic visitor flow rate 0.9117 |
| | Dynamic visitor flow rate | Road network density 0.92 | Restaurant services 0.9117 | KTVs 0.8944 |
| | Bars | Bus stations 0.7513 | Cinemas 0.7041 | Accommodation services 0.6194 |
| DH_block | Dynamic visitor flow rate | Road network density 0.135 | Restaurant services 0.1151 | Bars 0.1041 |
| | Restaurant services | Road network density 0.1177 | Dynamic visitor flow rate 0.1151 | Accommodation services 0.0964 |
| | Bus stations | Road network density 0.132 | Dynamic visitor flow rate 0.1012 | Restaurant services 0.0953 |
| | Shopping malls | Dynamic visitor flow rate 0.092 | Restaurant services 0.0855 | Bus stations 0.0826 |
| | Road network density | Dynamic visitor flow rate 0.135 | Bus stations 0.132 | Restaurant services 0.1177 |
| DM_block | Bus stations | Bars 0.9812 | Accommodation services 0.9703 | Shopping malls 0.9703 |
| | Cyber cafes | Road network density 0.9824 | Restaurant services 0.9703 | Accommodation services 0.9703 |
| | Accommodation services | Restaurant services 0.9703 | KTVs 0.9703 | Bus stations 0.9703 |
| | Shopping malls | Road network density 0.9803 | Bars 0.9802 | Restaurant services 0.9704 |
| | Dynamic visitor flow rate | Bus stations 0.9347 | Restaurant services 0.9347 | Markets 0.9347 |
| DX_block | Shopping malls | Restaurant services 0.9824 | Bars 0.9675 | Dynamic visitor flow rate 0.9567 |
| | Dynamic visitor flow rate | Road network density 0.9856 | Restaurant services 0.983 | Shopping malls 0.9567 |
| | Cyber cafes | Shopping malls 0.9567 | Cinemas 0.9567 | Dynamic visitor flow rate 0.9566 |
| | Restaurant services | Dynamic visitor flow rate 0.9568 | Shopping malls 0.9567 | Accommodation services 0.9435 |
| | Accommodation services | Restaurant services 0.9435 | Dynamic visitor flow rate 0.9327 | Shopping malls 0.9214 |
| GY_block | Cyber cafes | Bus stations 0.9846 | Restaurant services 0.9808 | Bars 0.9671 |
| | Dynamic visitor flow rate | Bus stations 0.9998 | Bars 0.9996 | Cyber cafes 0.9524 |
| | Road network density | KTVs 0.9996 | Cyber cafes 0.8874 | Accommodation services 0.8811 |
| | Shopping malls | Bars 0.9568 | Cyber cafes 0.9567 | Road network density 0.6272 |
| | Accommodation services | Bars | Dynamic visitor flow rate | Road network density |

| Case type | Main associated factor | Main related factor 1 (q values) | Main related factor 2 (q values) | Main related factor 3 (q values) |
|---|---|---|---|---|
| | | 0.9848 | 0.8855 | 0.8811 |
| | Dynamic visitor flow rate | Cinemas<br>0.9934 | Accommodation services<br>0.8417 | Markets<br>0.8417 |
| | Restaurant services | Markets<br>0.8886 | Cinemas<br>0.8605 | Road network density<br>0.8066 |
| HB_block | Cinemas | Dynamic visitor flow rate<br>0.9934 | Restaurant services<br>0.8605 | Shopping malls<br>0.799 |
| | Accommodation services | Dynamic visitor flow rate<br>0.8417 | Shopping malls<br>0.8171 | Cinemas<br>0.768 |
| | Cyber cafes | Dynamic visitor flow rate<br>0.748 | Restaurant services<br>0.7304 | Markets<br>0.6967 |
| | Dynamic visitor flow rate | Restaurant services<br>0.9291 | Accommodation services<br>0.9246 | Road network density<br>0.6554 |
| | Accommodation services | Dynamic visitor flow rate<br>0.9246 | Road network density<br>0.9244 | Bus stations<br>0.9158 |
| LT_block | Restaurant services | Dynamic visitor flow rate<br>0.9291 | Road network density<br>0.9266 | Bus stations<br>0.9218 |
| | Shopping malls | Dynamic visitor flow rate<br>0.6268 | Accommodation services<br>0.479 | Road network density<br>0.454 |
| | Bus stations | Restaurant services<br>0.9218 | Accommodation services<br>0.9158 | Dynamic visitor flow rate<br>0.6368 |
| | KTVs | Cyber cafes<br>0.9972 | Bars<br>0.9972 | Road network density<br>0.9962 |
| | Bars | KTVs<br>0.9972 | Cyber cafes<br>0.9958 | Cinemas<br>0.9932 |
| NH_block | Cyber cafes | KTVs<br>0.9972 | Bars<br>0.9958 | Cinemas<br>0.9958 |
| | Shopping malls | KTVs<br>0.9798 | Cinemas<br>0.9792 | Bars<br>0.9403 |
| | Restaurant services | Cinemas<br>0.9933 | Cyber cafes<br>0.9518 | Bus stations<br>0.9146 |
| | Dynamic visitor flow rate | Cyber cafes<br>0.8921 | Bus stations<br>0.7414 | Restaurant services<br>0.6894 |
| | Restaurant services | Cyber cafes<br>0.8522 | Dynamic visitor flow rate<br>0.6894 | Bus stations<br>0.5011 |
| QSH_block | Cyber cafes | Dynamic visitor flow rate<br>0.8921 | Restaurant services<br>0.8522 | Accommodation services<br>0.8176 |
| | Road network density | Cyber cafes<br>0.8156 | Bus stations<br>0.7133 | Dynamic visitor flow rate<br>0.4786 |
| | Accommodation services | Cyber cafes<br>0.8176 | Bus stations<br>0.4692 | Dynamic visitor flow rate<br>0.466 |
| | Cyber cafes | Accommodation services<br>0.9829 | Bus stations<br>0.9826 | Dynamic visitor flow rate<br>0.9801 |
| | Bars | Cyber cafes<br>0.8598 | Markets<br>0.8004 | Dynamic visitor flow rate<br>0.7646 |
| SG_block | Accommodation services | Cyber cafes<br>0.8921 | Bus stations<br>0.8522 | Bars<br>0.8176 |
| | Road network density | Cyber cafes<br>0.9829 | Bus stations<br>0.8059 | KTVs<br>0.5504 |
| | Dynamic visitor flow rate | Cyber cafes<br>0.9801 | Bars<br>0.7646 | Bus stations<br>0.6744 |

Note: Frequently appearing factors are shown in bold.

## 5. Discussion

By conducting a global analysis of drug-related crimes using Moran's I index, we found that they feature strong spatial autocorrelation; that is, there is a significant aggregation phenomenon in the distribution of drug-related crimes. The local index Gi* was used to carry out a hot spot analysis of drug-related crimes. According to the analysis, there are 371 grid cells in District Z, and we found drug-related crime hot spots in only 24 cells (about 6%). There were altogether 4,839 drug-related crimes in these hot spots, accounting for 92.5% of the total crimes in the study area. In other words, about 92.5% of drug-related crimes in District Z occurred in only 6% of the region; which indicates the presence of clear hot spots for drug-related crimes [42, 43], This means that, with efforts on drug control being constantly strengthened, drug traffickers are becoming increasingly cautious and choose locations with slack supervision and relatively concentrated buyers. Moreover, because drug-related crimes involve high risk, criminals tend to commit crimes in places with a higher success rate but a lower risk coefficient, so these crimes are characterized by significant spatial heterogeneity and clustering. Drug-related crimes are not irregular. Eck argued that drug-related crimes often occur in places with characteristics such as lack of monitoring and easy access. Xu used big data integration analysis and determined that about 30% to 40% of drug crimes are concentrated in less than 5% of police service areas. And J Hibdon found a high degree of concentration of drug calls across all street segments in Seattle. Due to the influence of geographical location, natural and economic conditions, different cultural levels, and inconsistent anti-drug efforts in different regions, there are differences in the spatial distribution of drug-related crimes. Understanding this spatial distribution can help to deter drug-related crimes effectively.

By analyzing the global associated factors of drug-related crimes, we found that restaurant services (0.6270) and recreational facilities (cyber cafes, 0.5880; bars, 0.5092) have the strongest explanatory power; that is, restaurant services were able to explain 62.70% of the distribution of drug-related crimes at a confidence level of 99.99%, while cyber cafes and bars were able to explain 58.80% and 50.92%, respectively, of the distribution at a confidence level of 99.99%. Moreover, the interaction between various factors appears to be mostly mutual strengthening. The most frequent correlated factors are KTVs, cyber cafes, and bars, suggesting that the concentration of drug-related crimes is closely related to locations of resident activities and that the areas with concentrated distribution of drug-related crimes are usually where restaurant services and recreational facilities are densely distributed [44]. Featuring long business hours, mixed populations, and a lack of standardized management, these places are the main breeding grounds for drug-related crimes. The denser the distribution of restaurant services and recreational facilities (e.g., cyber cafes and bars) in an area, the more likely drug-related crimes are to occur in that area, which further supports the viewpoint that criminal acts are closely correlated with geographical factors [45]. Studies have found that the drug markets were not randomly distributed and were particularly likely to form near schools.

In District Z (10 blocks), drug-related crimes on DM_block, DX_block, GY_block, and NH_block were strongly correlated with the locations of resident activities, while such a correlation was relatively weak for the remaining blocks. DM_block, GY_block, and NH_block are close to each other; with a large number of commercial department stores, squares, and shopping malls, these are the most economically prosperous blocks in District Z, resulting in a high population density throughout the day. Although DX_block also has shopping malls and squares, the block covers a smaller area and is less prosperous than DM_block, GY_block, and NH_block, and drug-related crimes are accordingly less concentrated. The remaining blocks are mostly dominated by industrial parks, buildings, residential areas, and woodlands, where there are fewer services to attract people, so the concentration of drug-related crimes is accordingly relatively low. The main associated factors of drug-related crimes vary from one block to another, because the main functional facilities differ. On commercially oriented blocks (DM_block, GY_block, DX_block, and NH_block), drug-related crimes are mainly distributed in areas with dense restaurant services and recreational facilities, which can gather a large number of people. Blocks dominated by industrial parks and residential areas (CZ_block, SG_block, HB_block, and LT_block) are equipped with convenient transportation, and drug-related crimes are mainly distributed in areas with dense transportation facilities and cyber cafes as well as a high dynamic visitor flow rate. On woodland-based blocks (QSH_block and DH_block), residents' daily activities are restricted, and there are fewer places where crowds gather, so drug-related crimes are mainly found in areas where transportation facilities and cyber cafes are densely distributed.

Drug-related crimes do not happen irregularly. Their spatial distribution shows an obvious aggregation—that is, there are "crime hotspots." This spatial distribution is also closely correlated with places of resident activity. Specifically, the denser the distribution of restaurant services and recreational facilities (e.g., cyber cafes and bars) on a street, the more likely drug-related crimes are to occur. Moreover, affected by the geographical location, natural conditions, economic conditions, different cultural levels, and inconsistent anti-drug efforts, the characteristics of drug crimes differ widely by region. Countermeasures should be put forward according to the facilities on different streets. On commercially oriented blocks (DM_block, GY_block, DX_block, and NH_block), drug-related crimes are mainly distributed in areas with dense restaurant services and recreational facilities; it is necessary to strengthen the key investigations of KTVs, bars, and other entertainment places within the jurisdiction, conduct surprise inspections, urge those in charge and the employees of all entertainment places to comprehensively strengthen drug-control management, standardize the system of responsibility for drug control, and resolutely prevent such places from becoming hideouts for drug abuse and drug trafficking activities. On blocks dominated by industrial parks and residential areas (CZ_block, SG_block, HB_block, and LT_block), drug-related crimes are primarily found in areas with high-density traffic facilities and cyber cafes or areas with a high visitor flow rate, so it is necessary to strengthen detection at bus and subway stations, as well as strengthening anti-drug publicity and preventive education among key groups such as residents and employees in the jurisdiction. For woodland-based blocks (QSH_block and DH_block), drug-related crimes mainly happen in areas where traffic facilities and cyber cafes are densely distributed, so it is necessary to increase the deployment of the police force, increase the frequency of public security patrols, and enhance the role of surveillance to deter crime in those areas. It is important to grasp the geographical differences in drug crimes and rationally allocate resources to reduce the crime rate and provide people with a safe and secure urban environment.

# 6. Conclusions

Based on the 2017 data on drug-related crimes in District Z of City A, spatial analysis and geographical factors were used to analyze the distribution of drug-related crimes and associated factors in District Z from the perspective of residents' daily activities. Three main conclusions were drawn. First, drug-related crimes are characterized by significant spatial heterogeneity and clustering. About 92.5% of drug-related crimes in District Z occurred in only 6% of the region. Second, the spatial distribution of drug-related crimes is closely related to the locations of resident activities. Locations supporting different resident activity have different explanatory power on the concentration of drug-related crimes. Restaurant services (0.6270) and recreational facilities (cyber cafes, 0.5880; bars, 0.5092) have the strongest explanatory power, so the more densely restaurant services and recreational facilities (e.g., cyber cafes and bars) are distributed in an area, the more likely drug-related crimes are to occur in that area. Third, the distribution of drug-related crime varies from block to block. On commercially oriented blocks (DM_block, GY_block, DX_block, and NH_block), drug-related crimes mainly occur in areas with dense restaurant services and recreational facilities; on blocks dominated by industrial parks and residential areas (CZ_block, SG_block, HB_block, and LT_block), such crimes are primarily found in areas with high-density traffic facilities and cyber cafes or areas with a high visitor flow rate; while on woodland-based blocks (QSH_block and DH_block), drug-related crimes mainly happen in areas where traffic facilities and cyber cafes are densely distributed.

In this study, the factors associated with drug-related crimes were quantitatively analyzed based on the dynamic visitor flow rate from the perspective of residents' daily activities, to determine how the distribution of such crimes is affected by different locations. The associated factors were also comparatively analyzed for different blocks, providing a reference for reasonably allocating police resources. In the future research work, we will carry out supplementary research from two aspects. On the one hand, we will refine the locations of resident activities to further explore the areas where drug-related crimes are more concentrated and distributed. On the other hand, it is to supplement the sex, age, education and other related factors of the criminal, to further enrich the research. Based on the conclusions reached in this study, by rationally allocating police resources to major places crowded with people, it would be possible to crack down effectively on drug-related crimes, reduce their incidence, and provide urban residents with a more comfortable and healthier living environment. Attaching importance to spatial prevention and control is a fundamental and effective way to alleviate or fundamentally solve the problem of urban crime.

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