Heterogeneity of Crime Distribution

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Urban crimes are not homogeneously distributed but exhibit spatial heterogeneity across a range of spatial scales.

Keywords: spatial association analysis ; spatial heterogeneity ; multiple scale association ; environmental criminology ; living structure

1. Introduction

Understanding the spatial patterns of crime incidents and the relationship with related factors are two core issues in crime analysis [1]. As the distribution of crime incidents is neither random nor homogeneous, the spatial heterogeneity should be considered in crime analysis. By investigating previous studies, it can be learned that spatial heterogeneity has the following three implications. **First**, the spatial heterogeneity of crime can be termed as spatial aggregation or clusters of crime incidents [2]. In other words, the spatial distribution of crime is not randomly distributed but often clustered in some places or regions [3][4][5]. For example, previous studies proved that approximately 50% of crime incidents occurred at only 4.5% of the street segments [4][6]. **Second**, spatial heterogeneity also refers to the variation in relationships across space [7]. Both the direction and strength of the relationship between a response variable (e.g., the crime occurrence) and predictor variables (e.g., the population) may vary with space position [8]. To deal with the spatial heterogeneity in spatial modelling, a widely used model is the geographically weighted regression (GWR) model, which allows the relationship between a response variable and predictor variables to vary across space [9][10]. **Third**, spatial heterogeneity also refers to the inconsistency related with the multiple scales. That is, spatial patterns or relationships analyzed on small spatial units are inconsistent with the results on larger units. Therefore, to investigate the spatial heterogeneity, a fundamental question is to evaluate the impact of spatial units or the scale of analysis [11]. Currently, research on spatial heterogeneity in crime analysis mainly concerns the uneven distribution at the single spatial scale, and the multiscale nature of spatial heterogeneity is seldom considered in studying associated factors for crime occurrence.

Meanwhile, to figure out explanatory factors for the heterogeneous distribution of crime, both theories and models have been developed in past decades. Classical theories include the rational choice theory, routine activities theory, crime pattern theory and geometric theory of crime [12][13][14]. The similarities of these theories are the exploration of the association among crime occurrences, spatial context and human perception. For instance, the geometric theory of crime suggests that the occurrence of crime is likely to happen in situations where an offender’s awareness space overlaps with the areas of criminal opportunities. It emphasizes the influence of the spatial context; that is, offenders tend to commit crimes if they believe the environment provides good opportunities. Researchers also have established some models to quantitatively measure the association between crime occurrence and possible related factors [15][16][17]. In general, the related factors can be categorized into different dimensions, including spatial environment, socioeconomic condition, human activity (mobility) and visual perception about the environment. Instead of being independent of each other, there is a complex association among factors in different dimensions. The complexity mainly lies in two aspects. First, spatial environment is highly correlated with factors in other dimensions, for instance, human mobility. As an important component of spatial environment, the underlying geographic space affects, even shapes, the human activities and urban forms [18][19]. Second, the crime is heterogeneously distributed and the spatial heterogeneity for crime is associated with the multiscale problem. Therefore, the relationship between crime and related factors may vary with scales.

From the perspective of environmental criminology, crime occurrence is a geographic phenomenon. Therefore, spatial properties should be considered in crime analysis. Two well-known spatial properties are spatial dependence and spatial heterogeneity [7][20]. These spatial properties are related with both distribution and relationship (or association).

2. Crime Distribution Pattern

Understanding the spatial pattern of crime is the first step for crime analysis and crime prevention. The basic objective of spatial crime pattern analysis is to find spatial patterns of crime distribution and then use these patterns to help identify the root causes of the crimes and generate strategies for crime prevention [21][22]. One aim of crime distribution pattern analysis is to figure out the spatial dependence structure of crime occurrence. For discrete crime incidents, spatial dependence can be reflected by spatial clusters or concentrations of crime incidents. The spatial heterogeneity related with crime distribution usually refers to the uneven distribution of crime incidents [2]. In this sense, spatial heterogeneity and spatial dependence have a similar meaning, and both spatial dependence and spatial heterogeneity are related with the "law of crime concentration" which states that the majority of crime incidents are distributed in only a small proportion of the spatial units or street segments [4][6]. To figure out the spatial heterogeneity in crime distribution, a widely used approach is spatial hotspot analysis, which aims to pick up spatial areas with higher-than-average incidences of crime [23]. Generally, there are two strategies to detect the spatial hotspots, i.e., the count-based and distance-based methods. For count-based methods, the crime incidents should be aggregated on the specified spatial units, then the spatial statistics such as local Moran's I and Getis-Ord Gi* can be applied [24][25]. The distance-based methods are applied to locations of crime incidents directly and can tell whether the crime incidents are clustered at a given analysis scale (i.e., the distance). Commonly used distance-based methods include the spatial scan statistics, nearest neighbor, Ripley's K and pairwise correlation [26][27][28]. The advantage of count-based methods is that the position of clustered crime can be easily identified via the spatial visualization. However, the distribution pattern of crime is only explored on a single scale. While the distance-based methods (e.g., Ripley's K) can tell whether the crime incidences are clustered at different scales (by setting different distances), they cannot reveal the relationship among different analysis distance. Essentially, a spatial distribution pattern revealed by the distance-based methods is still analyzed at a single scale.

3. Crime Association Analysis

Crime pattern analysis just tells where the crime incidences are clustered, the possible influencing factors for the concentration are not clear. In general, influencing factors for crime occurrence may be categorized into four dimensions, i.e., the spatial environment, socioeconomic condition, human activity (mobility) and visual perception about the environment. The concept of spatial environment mainly focuses on the "physical" property of the environment, including the street network [18], typical urban facilities [17] and spatial configurations [29][30]. All these physical properties should be placed in the "space" category, which is therefore termed as underlying geographic space. The socioeconomic conditions focus more on social or economic characteristics of the environment at a special scale, for example, the number of businesses, employees or income at neighborhood level [31][32]. With the availability of mobile phone data or trajectory data, the influence of human activity (or mobility) on crime also is widely investigated [33][34]. Recently, with the development of deep learning and street view image, the influence of visual perception (e.g., living, boring, and disorder) of the environment on crime can also be measured [15][35][36][37]. It should be noted that environment-related and human-related factors are not independent but correlated with each other, especially with the underlying geographic space. For example, as the skeleton of urban form, the street structure affects, even shapes, the human activities, while human activities are closely related to criminal events [18][19]. Previous studies mainly explored the influence of street structure on crime from a single "network" perspective, focusing on the influence of street permeability on human presence or crime occurrence; because street permeability may increase human presence, and both are closely related to public surveillance and criminal activities [8]. However, there is no consensus on the relationship between street structure and crime, and some studies have shown that street permeability can promote crime risk while other studies have drawn the opposite conclusion (i.e., variation in relationships) [38][39]. In addition, the network-based analysis adopted a mechanistic view which treats the geographic space as a collection of lifeless lines at single spatial scale. In geographic space, entities are connected to other things to constitute even larger entities. For example, a set of streets or buildings constitutes a neighborhood, a set of neighborhoods constitutes a city [40]. In other words, representing geographic space as a hierarchy of recursive subspaces could pose more meaning in space cognition and crime understanding [40][41]. However, the influence of the multiscale nature of geographic space on crime occurrence is not seldom evaluated.

When exploring the associated factors for crime distribution, spatial heterogeneity also should be considered, i.e., the variation in relationships across space or scales [7][42]. Currently, different models have been established to explore factors for crime distribution, including the geographically weighted regression (GWR) model and its variants [9][10], negative binomial (NB) regression models, spatial conjunctive analysis of case configurations (CACC) [30] and spatial co-location pattern mining (SCP) methods [17]. Even though GWR is widely used to solve spatial heterogeneity by allowing the relationships between independent and dependent variables to vary by locality, the model is actually based on the linear additive assumption. Meanwhile, it does not work with multipoint data. As for the CACC and SCP methods, the principle of the methods is to discover the co-occurrence of crime and related facilities by constructing a spatial neighborhood, which is achieved by setting a distance threshold. They do not depend on the linear additive assumption and can be applied to explore the complex interaction between crime and multiple facilities. By setting different distance thresholds, spatial association between crime and related factors can be analyzed at multiple scales. However, just like Ripley's K function, spatial association is analyzed at a single scale, in essence.

4. Scale and Spatial Heterogeneity

In fact, the "scale" is an important concept in geography and related science, including environmental criminology. Generally, "scale" refers to both the data scale and analysis scale. While data scale usually is reflected by the data grain and data extent, the analysis scale refers to the spatial units or distances in spatial analysis [43]. In geography, scale matters: changing the analysis scale (e.g., the spatial units) may lead to unexpected or even substantial changes in the results. The scale-related inconsistency is a manifestation of spatial heterogeneity. To solve the multiscale problem, a common practice is to perform analysis at multiple scales of analysis [44]. For example, the widely used Ripley's K function is believed to describe the spatial clustering pattern at multiple scales, which means the function is calculated on the same dataset with different analysis scales (i.e., distances). Although the scale-related problem is also affected by the spatial data distribution (i.e., the data scale), there is seldom research dealing with multiscale analysis regarding the data scale.

As illustrated in the introduction section, spatial heterogeneity has more implications than spatial dependence. Besides non-stationary distribution and variation in relationship, spatial heterogeneity in crime analysis is also related with the multiscale problem. In environmental criminology, the scale-related spatial heterogeneity refers to the fact that there are safe places within bad neighborhoods and dangerous places within good neighborhoods [45]. In previous studies, the spatial heterogeneity in crime analysis mainly concerns the influence of the spatial scale of the analysis (e.g., the spatial units), which in fact refers to the modifiable areal unit problem (MAUP) in geography [11][46]. To deal with the scale-related spatial heterogeneity, the basis is to define an indicator quantifying the degree of spatial heterogeneity and then to find the appropriate spatial scale of the analysis. For example, Andresen proposes a testing methodology that aims to identify the changes in spatial crime patterns at multiple analysis scales [11][47]. In fact, spatial heterogeneity is also closely related to data distribution. Spatial heterogeneity is a global property and exists across multiple data scales [48]. Currently, although spatial heterogeneity is frequently mentioned in crime analysis, studies seldom describe the spatial heterogeneity of crime while considering the multiscale nature of spatial data distribution.

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