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Spatio-temporal analysis of crime by developing a method to detect critical distances for the Knox test

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**ABSTRACT**

The present study examined and compared spatio–temporal interaction of the theft of car parts, shop burglary and motorcycle theft in the central business district (CBD) of the city of Zanjan in Iran. The Knox test was selected to detect spatio–temporal interaction. This test has been criticized as being subjective because the selection of critical distances is arbitrary; thus, a method is proposed to detect critical distances in the Knox test using the mean distance, natural breaks classification of nearest neighbour (NN) distance and Ripley’s \(k\) function. Results show obvious differences between the spatio-temporal clusters of the three sets of crimes. They also indicate that changing the spatial cut-offs within a cluster creates different temporal patterns. Of the three criteria for determining critical distances, NN classification based on natural breaks showed more interactions than the other methods.

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**KEYWORDS**

Spatio-temporal analysis; crime clustering; Knox test

1. Introduction

There has been increased concern about developing methods that use spatial analysis to recognize areas of focus for crime (Kennedy \textit{et al.} 2011). Criminal activity tends to be spatially localized in crime hotspots (Sampson and Raudenbush 1999, Eck \textit{et al.} 2005). In these areas, high criminal activity is surrounded by low criminal activity (Johnson \textit{et al.} 1997, Brantingham and Brantingham 1999). Researchers have defined the term ‘hotspots’ differently. Sherman \textit{et al.} (1989) and Eck and Weisburd (1995) tracked hotspot addresses; Taylor \textit{et al.} (1984) and Weisburd and Green (1995) studied hotspot blocks and others have examined clusters of blocks (Block and Block 1995). The use of hotspots to identify problematic areas in urban environments and to determine policing and crime prevention strategies has increased in recent years (Nasar and Fisher 1993, Ratcliffe and McCullagh 1999, Eck \textit{et al.} 2005, Grubesic and Mack 2008). Identifying crime hotspots can aid crime prevention practitioners and police (Ratcliffe 2004).

It is assumed that criminal behaviour requires a convergence in time and space for the likely offender, a suitable target and the absence of a capable guardian (Cohen and Felson 1979, Felson 1994); thus, it is essential to capture accurate temporal information.
Because the existence of likely offenders and suitable targets varies from one location to another throughout the day, crime is neither random nor regularly distributed in time or space (Andresen and Jenion 2004).

While the importance of the combined analysis of spatial and temporal aspects of crime has been emphasized in environmental criminology (Hakim and Shachmurove 1996, Ratcliffe 2002, 2005, 2006), many studies merely consider the spatial element of crime and do not jointly examine spatial and temporal aspects of crime. Recent efforts have shown that space–time regularities for crime are similar, which means the possibility of occurrence of a crime is meaningfully higher within a short temporal and spatial span. Assessment of this spatio–temporal interaction will provide police with critical times and places in which to act to prevent crime.

Spatio-temporal analysis of events is not new. Initial field tests were epidemiological studies of space–time interaction; then these tests have gained widespread applications in a variety of disciplines, especially criminology (Grubesic and Mack 2008, Johnson 2010, Ye et al. 2014). Knox and Bartlett (1964), David and Barton (1966), Mantel (1967), Pike and Smith (1968), Diggle et al. (1995), Jacquez (1996), Baker (1996) and Kulldorff (1997) have all proposed tests for space–time interaction. These are designed to evaluate whether or not cases that are close in space are also close in time and vice versa.

The Knox statistic, the most widely used technique for testing space–time interaction, tests for the presence of a statistically significant cluster within a defined distance and time. It counts the number of pairs of events that are closer in space and time than would randomly occur. Critical distances are used to classify pairs of events as near or far in space and time. The Knox test is an attractive, simple and straightforward way to calculate the test statistic (Kulldorff and Hjalmars 1999); the calculation of index $X$ (number of pairs of time and place) is not complicated. The amount of calculation becomes enormous when there is no specific information about critical distances. The simplicity of the relationship decreases computation time somewhat. Another advantage of this method is that it requires knowledge only about cases with no need for controls. At the same time, some problems exist with the method.

One challenge of the Knox method is population shift bias (Kulldorff and Hjalmars 1999, Mack et al. 2012), where a test assumes that the population of the study area changes at the same rate across the time period. It is the probability of detecting space–time interaction due to the population shift when there is no space–time interaction of any other kind. Internal migration between different regions, geographically differential emigration or immigration rates, or geographically differential birth or death rates may cause population shift bias. Some studies consider population shift bias only for longer time periods (i.e., years or decades) and assume that shorter periods are unaffected by the problem (Kulldorff and Hjalmars 1999, Aldstadt 2007). Mack et al. (2012) emphasized that population shift bias is a pervasive problem in tests on space–time interaction, even for periods as short as one day. The Knox test has also been criticized for arbitrary selection of critical distances. It is possible to change the temporal and spatial distance and repeat the calculations to maximize the significance of the test statistic, but this creates bias in the procedure (Kulldorff and Hjalmars 1999, Fuchs and Deutz 2002, Grubesic and Mack 2008). Because systematic error (bias) is a directional error that increases when repeating the tests is necessary in the process of research. Researchers generally select spatial and temporal threshold distance values empirically or use
intervals similar to those used by other researchers. Townsley et al. (2003), Johnson and Bowers (2004a), Johnson et al. (2007) and Ye et al. (2014) select spatial thresholds empirically and used 100 m as the critical distances. Also, Johnson and Bowers (2004b) used 201 m as spatial cut-offs in Knox test. Elmes and Roedl (2013) selected 100 m based on a similar interval used by other researchers. In addition, the critical distances used in Grubesic and Mack (2008) were 201 m for comparative purposes with other studies. The critical distances used in their studies correspond to various sub-divisions of a mile (161 m = 1/10 mile, 201 m = 1/8 mile, 268 m = 1/6 mile, 402 m = 1/4 mile, 804 m = 1/2 mile, 1207 m = 3/4 mile, 1609 m = 1 mile). The aim of this study is to modify the way of selecting critical distances and to use crime data to determine critical distances in the Knox test. It could be possible to determine approximate spatial and temporal thresholds for the outbreak of disease, for example, based on previous observation and experience; however, determining these critical distances for a criminal case is a challenge when dealing with the complexity of the factors involved in the occurrence of a crime and lack of accurate data. The present article proposes a method for detecting critical distances for the Knox test using Ripley’s k function and natural breaks classification of nearest neighbour (NN) distance. This study compares the spatio-temporal interaction of three types of crime in the central business district (CBD) of the city of Zanjan in Iran and examined whether significant differences occur between spatio-temporal signatures of these three types of crime.

2. Research setting and data

The study was conducted in the CBD in Zanjan, a middle-sized city located in north-western Iran. The city is the political, economic and educational centre of Zanjan province. It has a population of 386,851 and an area of 76.45 km². The CBD of Zanjan has a population of 32,833 in an area of 2.80 km², with a population density of 11,726 persons per km². This district has four sub-districts that include the historical neighbourhoods of the city.

The current study utilizes an official dataset of three sets of crimes provided by the Zanjan Police Department. Different types of burglary are the highest type of crime in the CBD (Kalantari et al. 2010). The theft of car parts, shop burglary and motorcycle theft were chosen because of showing the greatest degree of spatial clustering. The process of choosing these crimes will be discussed in Section 3.

All reports of theft of car parts, shop burglary and motorcycle theft generated by the city’s 110 reporting system were analysed. In Iran, 110 is the emergency number for the public to call for emergency services, to report crime and request police services. Cohn (1990) discusses the importance of good quality data and, stated that calls for service received by the police could be the most appropriate type of crime data.

Any contact with the police via 110 is automatically recorded in a central system. These data have the address and date information of the crimes. Because they are not digital, they were geo-coded during the study as a single point for each crime and the street names and numbers were translated into mappable (X and Y) coordinates. All efforts were made to maintain the accuracy of the data. The current police callout dataset includes a total of 264 reports of crimes with known locations and occurrence times from 1 January 2011 to 31 December 2011. The units used for the time dimension
were days. Using a 24-h time range means the time stamp recorded is likely to be relatively close to the actual time the incident occurred.

3. Analytical methods

3.1. Nearest neighbour index (NNI)

The NNI was used to choose from among 12 types of crime having the greatest degree of spatial clustering. ArcGIS 10.3 (ESRI 2014) was used to manage, manipulate and analyse the crime observations. NNI is used to test for evidence of clustering (Clark and Evans 1954). It compares the actual distribution of crime data against a dataset of the same sample size with a random distribution. If the NNI result is less than 1, the crime data show evidence of clustering.

A z-score test statistic can be applied to help increase confidence in the NNI results. This test for statistical significance determines the degree of difference between the actual average NN distance and the average random NN distance (Eck et al. 2005). The z-score is calculated as:

\[ z = \frac{D_{O} - D_{E}}{SE} \]  

where \( D_{O} \), the actual average NN distance, is calculated as:

\[ D_{O} = \frac{\sum_{i=1}^{n} d_{i}}{n} \]  

and \( D_{E} \), the average NN distance in a hypothetical random observation, is calculated as:

\[ D_{E} = \frac{0.5}{\sqrt{n/A}} \]  

where \( n \) is the number of events; \( A \) is the area of the region and \( SE \) is calculated as:

\[ SE = \frac{0.26136}{\sqrt{n^2/A}} \]  

The z-score and p-value, the indicators of significance, are sensitive to the area of study region. To explore a phenomenon over time or, as in the present study, to compare different phenomenon, the study should consider the same area.

3.2. Knox test

Space-time analysis of crime must consider the suitability of the analytical method and data. In the present article, the Knox test was selected to detect spatio-temporal interaction of crimes. This test is a complementary method for hotspot cluster analysis that is well-suited for quantifying both space and time interactions of crime data (Townsley et al. 2003, Grubesic and Mack 2008). It was chosen for this study because it is in widespread use, is simple and straightforward, and uses point data. It is also appropriate for this study, which aims to propose a practical method for determining spatio-temporal thresholds in space–time interaction analysis. Table 1 provides the
spatial and temporal neighbourhood of events for the Knox test (Knox and Bartlett 1964).

Table 1 indicates that the two events show a spatio–temporal interaction if they are close in both space and time. The statistical index for $X$ for this test is calculated as:

$$X = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij}^s a_{ij}^t$$

where $n$ is the number of events, $a_{ij}^s$ is the adjacency in space between $i$ and $j$ events and $a_{ij}^t$ is the adjacency in time between $i$ and $j$ events and:

$$a_{ij}^s = \begin{cases} 1 & \text{if the distance between cases } i \text{ and } j < \delta \\ 0 & \text{otherwise} \end{cases}$$

$$a_{ij}^t = \begin{cases} 1 & \text{if the distance between cases } i \text{ and } j < \tau \\ 0 & \text{otherwise} \end{cases}$$

where $\delta$ is the critical space distance and $\tau$ is the critical time distance.

It is important to understand the critical time and distances in this test because it can determine in which space and time distance the null hypothesis can be rejected or approved. In many studies, $\delta$ is based on field evidence or previous studies. The current study proposes some methods for determining the critical distances based on mean distance, natural breaks classification (Jenks 1977) of the NN distance and Ripley’s $k$ function (Ripley 1977).

ClusterSeer2.5 (ClusterSeer2.5 2015) was used for spatio-temporal analysis. ClusterSeer calculates the null distribution of $X$ (number of pairs in close proximity in both space and time) using either a chi-squared test or Monte Carlo simulation (MCS). The chi-squared test calculates the probability of the classification of events into near-in-space and near-in-time, near-in-space and far-in-time, far-in-space and near-in-time, and far-in-space and far-in-time under the null hypothesis of no clustering. This provides a significance based on comparison of the observed and expected values of $X$ (ClusterSeer2.5 2015). To assess the statistical significance of Knox space–time interactions, a MCS with 999 permutations was performed (Dwass 1957). Each randomly-placed feature point in the study area is considered a permutation. The number of points randomly-placed equals the number of points in the point data. The Knox index calculates observed clusters and the MCS calculates expected clusters based on probabilities derived from the simulation distributions. MCS is usually used when calculating the exact result with a deterministic algorithm is impossible; thus, this method is stochastic (ClusterSeer2.5 2015).

About the population-shift bias, Mack et al. (2012) suggested the use of an unbiased approach as proposed by Kulldorff and Hjalmars (1999), which needs to know the
background population and its temporal trends. The present study uses the common version of the Knox test because there is no access to the temporal trends of population in this area. However, because of these reasons, it seems the population shift bias is not a major problem in this study; CBD of Zanjan city includes the homogenous historical district of the city that developing and changing the historical texture is restricted, because of these characteristics, the background population does not increase or decrease so fast in the sub-districts of this area. In addition, the study period in the present study was 1 year, and as Kulldorff and Hjalmars (1999) and Kulldorff (2004) believe that if the study period was only 1 or 2 years, the population shift bias is probably not a major problem, as differential changes in population sizes have not had much chance to accumulate. On the other hand, our study was carried out in a small geographic area and studies show that in small geographic areas, the assumption of a constant population at risk may be valid (Aldstadt 2007). Additionally, studies in which the size of the population shift bias were investigated for the Knox test (Kulldorff and Hjalmars 1999, Mack et al. 2012), the study areas were large (2507 parishes in Sweden, Cincinnati metropolitan area, respectively). Also, Kulldorff and Hjalmars (1999) stated that larger numbers of cases can produce a greater population shift bias for the Knox test, while, in our study there were just 264 cases. Finally, with a comprehensive knowledge about the population dynamics and environmental characteristics of the study area, the common Knox method was selected in this study.

3.3. Methods to determine critical distances

Proposed methods for determining the critical distances for the Knox test in this research are:

3.3.1. Mean distance

In this method, the distance of each point to other points is determined and then the average distances are calculated. This is done for all points and a total mean of distances is calculated. This mean distance can be used as critical distance in the Knox test.

3.3.2. Ripley’s k function

Ripley’s k function investigates the clustering of events by variation in distance. It shows the changes in the clustering or dispersion of the geometric centre of features in relation to variation in the neighbour radius. There are various types of k function; Ripley (1981) formulated function \( L(h) \) as follows which compares the estimated distribution of \( K(h) \) to that consistent with a homogeneous Poisson point process to evaluate clustering:

\[
\hat{L}(h) = \sqrt{\frac{\hat{K}(h)}{\pi}}
\]

For the null hypothesis, \( K(h) = \pi h^2 \), and so \( L(h) = h \). \( K(h) \) is compared for the observed data to that predicted by the null hypothesis by plotting the observed \( L(h) \) against \( f(h) = h \). If the pattern under study shows clustering, \( L(h) \) would exceed the expectation of \( f(h) = h \) at some scales.
$K(h)$ is formulated as follows (Gatrell et al. 1996):

$$K(h) = \frac{R}{n^2} \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} \frac{l_h(d_{ij})}{w_{ij}}$$

(7)

where $R$ is the area of the region of interest, $n$ is the total number of cases, $d_{ij}$ is the distance between the $i$th and $j$th cases, and $l_h(d_{ij})$ is the indicator function which is 1 if $d_{ij} \leq h$ and 0 otherwise. Essentially, it sums the cases within distance $h$ of each location in the dataset (each $i$). $w_{ij}$ is an edge correction factor, the conditional probability that a case is observed in the region, given that it is $d_{ij}$ from the event $i$.

The threshold determined as the boundary of cluster or non-cluster in Ripley’s $k$ function used as the critical distance in this study.

3.3.3. Natural breaks classification (NBC)

Jenks and Caspall (1971) presented this classification algorithm as a method for improving the preparation of thematic maps and as a tool for better visualization of spatial data. NBC is one of the common unsupervised methods in spatial data mapping and geo-visualization (Cao et al. 2014). This algorithm provides an experimental solution for the optimal distribution of classes to minimize the sum of the absolute standard deviation of each category. The algorithm first selects sets of classes and then calculates the absolute deviation from class median. The observations are then transferred to the neighbouring classes to reduce this error.

Forced cycling is carried out for this transmission based on the relationships between observations and the mean of the classes; it is repeated until the total error decreases to a minimum. In forced cycling, observations are transferred to neighbouring classes regardless of the mean of the classes and observations moved. After replacement, the data distribution is tested. If the sum of errors is reduced, the transmission is repeated in the same direction. Forced cycling is performed in both directions from top to bottom classes and vice versa. This process continues until the errors do not reduce further. In this study, this method was used to classify the NN distances and the boundary of classes has been used as critical distances in the Knox test.

4. Results and discussion

Because the aim of the study was identifying the spatio–temporal interactions within the clusters, having the greatest degree of spatial clustering was the criteria in the first place. Therefore, clustering analysis was done to examine the spatial distribution of the burglaries. NNI analysis was used to choose for the greatest degree of spatial clustering from among 12 types of crimes. As shown in Table 2, among these 12 types of burglary crimes, only five types had the clustered distribution and the three selected crimes have the greatest degree of spatial clustering. These three types of crime were chosen because they are the most significant for the CBD of Zanjan, they have the lowest NN ratio and they have cluster distributions based on their $z$-scores.

Figure 1a shows the location of Zanjan in north-western Iran and Figure 1b shows the distribution of crime point in the city. Figure 2 shows the distribution of the crimes over the course of a year. The primary temporal distribution of crimes for each day in a year
shows that car parts and motorcycle thefts have a similar distribution pattern. These similarities could be the result of similar crime opportunities and the large number of hot objects in the study area.

4.1. Determination of critical distances using mean distance

The ability to specify time and space thresholds makes the Knox test a flexible tool for the clustering at different spatial and temporal scales. It is possible to hold the space distance constant, and vary the time distance or vice versa and study spatio-temporal clustering crimes.

Where no specific critical distance is present, it is proposed to use the mean distance as the critical distance in the Knox test. Figure 3 shows the $p$-values for critical distance based on the mean distance of the crimes in all sets of crime for a time variation of 1–30
days. In MCS, the $p$-value is used as the relative ranking of the test statistic among the sample values from the Monte Carlo randomization. The $p$-value denotes whether observed values are unusually large or small when compared with a null distribution. This calculation compares the observed value with the upper and the lower tails of the null distribution. In this study, the spatio–temporal interactions have been assessed at the 95% confidence level ($p$-value < 0.05).

Figure 3 shows the differences in spatial and temporal patterns of the three types of crimes. Motorcycle theft on days 3–7 exhibits significant spatio–temporal interaction. Shop burglary exhibits significant spatio–temporal interaction on days 9–13 and 16–19. Spatio–temporal interaction of car part theft was not significant for any day in the specified mean distance. The current study investigated how spatio–temporal interaction varies with critical distances variation. For a better understanding of spatial and temporal patterns of crime, and to compare them, the description of Ripley’s $k$ and NN distances based on NBC methods is followed by detailed analysis of spatio–temporal interaction.
4.2. Determination of critical distances using Ripley’s k function

The results for Ripley’s k function for car parts theft, shop burglary and motorcycle theft are shown in Figure 4. This graph shows calculated \( L \) values (L-points) as black dots, one at each of 10 interpoint distances. All 999 \( L(h) \) functions derived from the MCSs are plotted as grey curves. A green line shows the mean of the simulation functions, and a

**Figure 3.** Knox test results for 30 days. Mean distance for the theft of car parts: 741 m; shop burglary: 565 m; motorcycle theft: 716.

**Figure 4.** Results for Ripley’s k function: (a) the theft of car parts; (b) shop burglary; (c) motorcycle theft.
pair of blue curves outline their upper and lower extent. The identity function, shown as a red line, is partially hidden behind the simulated function curves. The distances from the black curve above the green line identify the cluster distribution. In this study, the black curve crossed the upper blue curve at distances 321 m (for car parts theft), 670 m (for shop burglary) and 231 m (for motorcycle theft), which show the bounder of cluster at 99% confidence level.

Figure 5 shows the spatio-temporal interaction of the crimes based on the Ripley’s $k$ thresholds. The spatio-temporal interaction of car parts theft was of greater significance in a shorter time span than at a longer interval (1–9 days). Spatio-temporal interaction of shop burglary is significant within 10 days. There is no interaction for motorcycle theft at 95% confidence level.

4.3. Determination of critical distances using NBC

For accurate identification of spatio-temporal interaction within a cluster, it is possible to classify each type of crime based on the distance to the nearest object and these values were used as the spatial thresholds for spatio-temporal analysis. NBC can be used for this purpose. The distance to the nearest object for each feature was calculated and the values were classified into five categories based on NBC. Table 3 shows these rates for the three types of crime. These values were extracted from analysis of each cluster of crime and were used as critical distances.

After determining critical distances based on the distance to the nearest object using NBC, the spatio-temporal signature of crimes was used for the Knox test (Figure 6). The general patterns of the three types of crime corresponded to the Ripley’s $k$ curve; however, it is possible to analyse spatio-temporal interaction more accurately for distance within a cluster.

The theft of car parts has significant interaction at relatively shorter distances and within shorter time intervals. The interaction decreased when the period increased,
especially for shorter distances, but the interaction increased at times for larger distances. The convergence of shorter intervals with shorter distances of crime occurrence indicates the seriousness of the hotspots and types of crime. Unlike the theft of car parts, shop burglary has significant interaction for relatively long spans of time (12–30 days) at some critical distances. The spatio–temporal interaction of motorcycle theft varied from that of the other two crime types and spatio–temporal interaction existed at almost all spans of time and at all distances, although no interaction was noted for days 8–14, 23 and 26. The scattered distribution of abandoned motorcycles in the study area confused the pattern for this offense.

The interaction for shop burglary was subject to fluctuations as, at all distances except 678 m, the interaction increased as the time span increased. Fluctuation in motorcycle theft reached a maximum, but lost interaction at most of the specified thresholds; however, at shorter distances, it exhibited significant space–time interaction. The theft of car parts showed the highest statistical significance for spatio–temporal interaction. In other words, spatio–temporal interactions for this type of crime were significant at wider ranges.

Table 3. Critical distances for distance to nearest object using NBC, Ripley’s k function and mean distance.

<table>
<thead>
<tr>
<th>Critical distance</th>
<th>Theft of car parts</th>
<th>Shop burglary</th>
<th>Motorcycle theft</th>
</tr>
</thead>
<tbody>
<tr>
<td>NBC</td>
<td>25</td>
<td>23</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>55</td>
<td>54</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>97</td>
<td>103</td>
<td>128</td>
</tr>
<tr>
<td></td>
<td>149</td>
<td>198</td>
<td>172</td>
</tr>
<tr>
<td></td>
<td>228</td>
<td>459</td>
<td>288</td>
</tr>
<tr>
<td>Ripley’s k function</td>
<td>321</td>
<td>670</td>
<td>231</td>
</tr>
<tr>
<td>Mean distance</td>
<td>741</td>
<td>565</td>
<td>716</td>
</tr>
</tbody>
</table>

Figure 7 shows the last step of testing for spatio-temporal hotspots. The Knox-based spatio–temporal interaction tests for spatial and temporal cut-offs with the lowest p-values are shown in the CBD of Zanjan. The circles denote the area of space–time interaction. Figure 7a shows the Knox test for spatio–temporal interaction for the theft of car parts. The minimum period for occurrence of the theft of car parts was 3 days (the theft of car parts occurred at least every 3 days inside the circle). One cause of frequent car parts theft in this area is the lack of parking lots, which forces vehicle owners to park their vehicles on the streets, increasing the opportunity for theft. Another important cause is the commercial land use in the study area. It is a significant destination for work or business and attracts a large number of vehicles from other parts of the city every day.

Figure 7b shows the results of the Knox test for spatio–temporal interaction of shop burglary. The minimum period for occurrence of shop burglary was 10 days, which was longer than for car parts theft. An important factor in the spatio–temporal interaction of shop burglary is that the area is located in the traditional bazaar of Zanjan. Figure 7c show Knox test for spatio–temporal interaction of motorcycle theft. The period of repeating motorcycle theft is 6 days, which is longer than car parts theft but shorter than shop burglary. As a result, car parts theft has more spatio-temporal interaction than the other two types. After car parts theft, shop burglary has more spatio–temporal interaction while motorcycle theft has less spatio–temporal interaction in the study area.
The similar patterns for motorcycle theft and car parts theft arise from the similar natures of the offenses, although their frequencies are not the same. The different pattern for shop burglary results from the different nature of the crime.

Figure 6. Spatio-temporal signature using NBC for: (a) the theft of car parts; (b) shop burglary; (c) motorcycle theft.
different distribution of crime targets and existence of a commercial landscape. The month of March coincides with Nowruz, the Persian New Year’s Day. Sales for this national holiday reach a peak in the days prior. The bazaar and shopping centres attract many shoppers and the stores are full of merchandise, which motivates offenders.

4.4. Comparing space–time interaction in the proposed methods

Factors such as urban texture, access, network of streets, criminal targets and the abilities of police affect the patterns of spatio-temporal distribution. It is best to obtain these thresholds from the criminal data of each study. In the current study, the critical distances were based on: (i) the mean distance of the crime; (ii) classification of NN distances based on NBC and (iii) the distance extracted from Ripley’s $k$ function for days 1–30.

The $p$-values varied dramatically for the different spatial and temporal thresholds. Table 4 is based on the frequency of $p$-values < 0.05 as the criteria for evaluation and comparison of the methods used in this study. Most interactions for all three types of crime fall into the critical distances obtained for the NN distance classification specified in NBC (mean column), followed by the thresholds for mean distance, and thresholds for Ripley’s $k$ function. The most spatio–temporal interactions were observed for shop burglary (total mean column) followed by the theft of car parts and motorcycle theft. As seen, changes in the number of significant interactions do not follow a specific trend when the intervals for the spatial thresholds are increased or decreased.

Figure 7. Knox test for spatio–temporal interaction of: (a) the theft of car parts (critical distance: 228 m, critical time: 3 day); (b) shop burglary (54 m, 16 day); (c) motorcycle theft (288 m, 6 day).
Three major conclusions were drawn according to the aims of the study:

(1) The use of common critical distances from previous studies or those chosen empirically may not show the maximum number of interactions and that the interactions were lower than the observed number. In some studies, 100 m was used as the normal critical distances (Townesley et al. 2003, Johnson and Bowers 2004b, Elmes and Roedl 2013). The results of the present study showed that at distances approaching 100 m (97 m for the theft of car parts and 103 m for shops burglary), the interactions strongly decreased compared to other thresholds. It can be concluded that the suggested intervals for the study of spatio–temporal interactions in the Knox test cannot be trusted for every location and crime.

(2) The critical distances at which maximum spatio–temporal interactions occur can differ greatly from one crime to another. For instance, the greatest interaction in the theft of car parts occurs at greater distances (228 m), but most interactions for shop burglary occurred at shorter distances (54 m). Using a specific critical distances for all types of crime could overlook large aspects of real behaviour.

(3) Of the three criteria for determining critical distances, NN distance classification based on natural breaks method showed many more interactions than the other methods. Table 5 indicates that this method, with a mean of 12.6, is more than twice the mean number of interactions for the average distance for a crime and more than triple the average for Ripley’s k function.

Table 4. Frequency of significant interactions at different intervals for 1–30 days periods.

<table>
<thead>
<tr>
<th>Crime</th>
<th>Distance</th>
<th>Frequency for 1–30 days periods (p &lt; 0.05)</th>
<th>Mean</th>
<th>Total mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theft of car parts</td>
<td>NBC distance: 25 m</td>
<td>17</td>
<td>16.6</td>
<td>8.9</td>
</tr>
<tr>
<td></td>
<td>NBC distance: 55 m</td>
<td>17</td>
<td>16.6</td>
<td>8.9</td>
</tr>
<tr>
<td></td>
<td>NBC distance: 97 m</td>
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5. Conclusion

The present study examined and compared the spatio–temporal interactions for the theft of car parts, shop burglary and motorcycle theft for the CBD of Zanjan. The results showed that different patterns of crimes occur within different time intervals within a spatial cluster. The study of these thresholds increases understanding of criminal behaviour for each type of crime. While no significant difference was found in the spatial scales, evaluation of each cluster at different time spans based on the critical distances within each cluster reveals different patterns. Understanding these differences can reduce crime in urban areas. Most importantly, the presence of a rigorous method for identifying spatio–temporal interactions of thefts have a meaningful influence on crime prevention. The findings of this study indicate that the use of crime data at the micro level (in this case) to determine critical distances in the Knox test offers better results than conventional or experimental detection of thresholds. In terms of results that have already been published, it seems there is really no way of knowing how reliable the results are without reanalysing the data using proposed methods. We recommend that the data be reanalysed using the proposed methods in this study to examine the spatio–temporal interactions. The present study treats spatial distance and temporal distance separately, but there are methods that integrate spatial distance and temporal distance. Huang et al. (2010) extended the traditional geographically weighted regression model with temporality into a geographically and temporally weighted regression (GTWR). The spatio-temporal distance in their study integrates spatial distance and temporal distance in a linear manner. However, further research is required to evaluate these methods by using integrated spatial and temporal distances, repeating them for other types of crime in different areas and utilizing other methods of clustering, distance classification and threshold detection.

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References


