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# Evaluating the spatiotemporal clustering of traffic incidents

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ABSTRACT

This research presents both theoretical results regarding the nature of spatiotemporal clustering on a network, and applied outcomes from examining such clustering with regard to traffic incidents. The analysis considers fatal traffic incidents in eastern Fairfax County, Virginia and injury incidents in Franklin County, Ohio. The spatiotemporal analytical methods of Knox and subsequent researchers are reviewed. Specific methods for performing spatiotemporal analysis are outlined, with special attention given to the interpretation of the results for traffic incidents. An argument is made for conducting spatial and temporal cluster analyses independently, in addition to spatiotemporal cluster analysis, a comparative analysis of methods for testing for the significance of spatiotemporal clusters is presented, and suggestions for delineating critical parameters for the Knox statistic are provided.



## 1. Introduction

Understandably, significant attention is dedicated to the occurrence of traffic incidents – particularly those resulting in injuries or fatalities – among the transportation community, and indeed from the public at large. The research in this area has informed the efforts of regulatory authorities in the implementation of measures to reduce the occurrence of traffic incidents in general and traffic injuries and fatalities more specifically. While there are obvious behavioral factors that contribute to traffic incidents, an understanding of the temporal and spatial characteristics coincident with those behaviors can contribute to the prevention of traffic deaths or injuries. Traffic incidents are among those phenomena that demand an understanding of their spatial and their temporal components simultaneously. Two incidents that happen reasonably close to one another in space, but which occur weeks, months, or even years apart are not likely to represent a significant cluster of activities to which remediation efforts should be applied. Similarly, two incidents that occur simultaneously in time, but that are spatially separated, are not likely to be suggestive of an underlying process that can be investigated for traffic incident mitigation. Unfortunately, little is known about the spatiotemporal clustering of traffic injuries and fatalities. While knowledge of the temporal and spatial trends by themselves certainly serve to focus the efforts of law enforcement and safety officials, the combination of those trends can further inform mitigation strategies. This article presents both a series of methods for the examination of spatial, temporal, and spatiotemporal clusters of network-based phenomena and a practical application of those methods to the occurrence of fatal or injurious traffic incidents.

More specifically, the research presented in this article demonstrates methods for the investigation of spatiotemporal clustering when it occurs in network space. This research builds on the seminal work of Black (1991) who examined the spatiotemporal clustering of traffic accidents on a linear highway segment, by extending the methods to apply to the complex road networks typically found in urban areas. Through this extension, this research seeks to contribute to the recent developments in spatial science where Euclidean spatial-analytic methods are extended for application to network space. Moreover, this article presents a comparative analysis of methods for testing for significance of network spatiotemporal clusters, and presents an innovative technique by which to determine appropriate spatial and temporal critical distances for defining spatiotemporal clusters when appropriate critical parameters are unknown.

The structure of the paper is as follows. Section 2 provides a review of both the seminal works and more recent advances in spatiotemporal cluster analysis and in network-based spatial statistics. Section 3 describes two study areas and provides descriptive statistics of the research data. Section 4 discusses the methods used in the examination of temporal, spatial, and spatiotemporal clustering on a network. Section 5 presents the comparative analysis of significance tests and suggestions for delineating critical parameters for those tests. Section 6 provides conclusions and suggestions for future research.

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## 2. Literature review – Spatiotemporal clustering and network spatial statistics

Previous research into spatiotemporal clustering has been pursued most vigorously in the field of epidemiology. Methods for detecting such clusters have successfully informed the medical community about the nature of numerous cancers, limb defects, and neural tube defects (Glass & Mantel, 1969; Knox & Bartlett, 1964; Lloyd & Roberts, 1973; Meighan & Knox, 1965; Roberts, Laurence, & Lloyd, 1975; Smith, Pike, Till, & Hardisty, 1976), among others. Outside of epidemiology, there are intuitive applications of spatiotemporal clustering in criminology, defense intelligence, and in the transportation research discussed here. There have been significant developments in recent decades with regard to examining spatiotemporal clustering; particularly the development of space–time scan statistics (Kulldorff, 2001; Kulldorff, Athas, Feuer, Miller, & Key, 1998; Kulldorff, Heffernan, Hartman, Assuncao, & Mostashari, 2005). However, the method presented in the seminal work of Knox and Bartlett (1964) is still in common use (Kao, Getis, Brodine, & Burns, 2008; McNally, Rankin, Shirley, Rushton, & Pless-Mulloli, 2008; Schmertmann, Assuncao, & Potter, 2010). Knox developed a method for identifying cases of disease that occurred both close in space and close in time. The frequency of cases that occur close to one another in both space and time is referred to as the Knox statistic $X$ or $R$ (the latter term will be used in this research). David and Barton (1966) demonstrated that Knox's conjecture that his statistic followed the Poisson distribution was accurate. Mantel (1967) provided the permutation variance of the Knox statistic, describing how to apply Monte Carlo methods to determine the statistic's significance.

A potentially problematic characteristic of the Knox Method is the requirement to identify measures of closeness, or "critical distances" for both the spatial and temporal distribution of events. While known epidemiological factors may suggest appropriate critical distances in the study of disease clusters, for other applications the critical distances may not be well-defined. Many researchers have suggested techniques to improve this perceived shortfall. David and Barton (1966) proposed their own statistic which compares spatial clusters within subsets of time defined by the average time interval between events. Mantel (1967) proposed the use of reciprocal transformations for the actual space and time labels of cases. Klauber (1971) defined a two-sample spatiotemporal clustering test. These and other similar tests are described in William's (1984) thorough review of continuous space spatiotemporal clustering. Later techniques specific to epidemiology include Baker's (1996) modification of Knox's method (where spatiotemporal clusters were detected within a range of acceptable space and time critical parameters), Jacquez' (1996) k-nearest neighbor method (which specified spatiotemporal clusters based on which points were neighbors in space and time), and a variety of other researchers who developed scan statistics to enable the detection of emerging spatiotemporal clusters (Assunção & Correa, 2009; Kulldorff & Hjalmars, 1999; Rogerson, 2001).

The most recent spatiotemporal methodological advances include a windowed nearest neighbor approach (Pei, Zhou, Zhu, Li, & Qin, 2010), multi-dimensional map algebra (Mennis, 2010), visualizing clusters in a space–time cube (Nakaya & Yano, 2010), the use of bivariate kernel density estimators (Mountrakis & Gunson, 2009), cross k-function analysis (Khan, Santiago-Chaparro, Qin, & Noyce, 2009), and stack-based spatiotemporal clustering (Chang, Zeng, & Chen, 2008). With the exception of Black (1991), Mountrakis and Gunson (2009), and Khan et al. (2009), all of the original spatiotemporal clustering techniques and their most recent counterparts rely on Euclidean distance measures.

Yamada and Thill (2004) illustrated the pitfalls of conducting analysis of network-based phenomena with continuous space measurements with traffic data from Buffalo, NY. Extensive research has demonstrated the validity of using network measures to analyze network-based phenomena and numerous continuous space statistical methods have been extended to network space (Black, 1992; Miller, 1999; Okabe & Satoh, 2006; Okabe, Satoh, & Sugihara, 2009; Okabe & Yamada, 2001; Okabe, Yomono, & Kitamura, 1995; Okabe, Yoshikawa, Fujii, & Oikawa, 1988; Okunuki & Okabe, 2002; Shiode, 2008; Shiode & Shiode, 2009; Yamada & Thill, 2007, 2010). While significant literature exists for the examination of spatiotemporal clustering in Euclidean space, perhaps only one author (Black, 1991) has suggested its implementation in network space.

Based on this review of the literature it is clear that there are unresolved issues with regard to significance testing and critical parameter determination in spatiotemporal cluster analysis, and while there is a strong movement toward recognition of the importance of applying network-based spatial statistics where appropriate, there is little published research delineating the methods for doing so with regard to spatiotemporal cluster analysis. Moreover, there are even fewer studies describing how spatiotemporal clusters of traffic incidents – once identified – can be used to inform mitigation strategies for traffic management. The research in this article addresses each of those issues.

## 3. Study area and data

In order to reach the research goals above, two datasets are employed in addition to several randomly generated realizations. The two study areas are the major road network of Franklin County, Ohio (Fig. 1), and the major road network of Eastern Fairfax County, Virginia (Fig. 2). In the case of Franklin County, injury-causing traffic collisions along major roadways throughout 2009 are considered. Those data were obtained through the Ohio Department of Public Safety's crash request portal (Kennedy, 2010). Within the Franklin County study area, four datasets representing injury-causing traffic collisions are examined, one for each successive 3-month period during 2009. An additional randomly generated dataset is presented for this study area, created using SANET's random points generator tool (Okabe, Okunuki, & Shiode, 2006) to define the event locations on the network, and a random number generator to define event time stamps.

For the Fairfax County dataset, fatality events were extracted from the Fatality Analysis and Reporting System (FARS) Encyclopedia (FARS., 2010). All of the extracted events contained georeferencing information, the date and time of the event, as well as details about the road surface type and condition (dry, wet, etc.). This dataset contains the fatality-causing traffic collisions during the 5-year period between 2004 and 2008 and is complemented by one randomly generated dataset employing the same spatial and temporal constraints as the observed data. Table 1 lists characteristics of each dataset successively. Note the difference in point density between the two study areas.

These two different datasets were chosen purposefully, in that this article is presenting a method that should be applicable across a wide range of potential traffic incident analyses. The clustering of injury-causing incidents may be quite different from that of fatal incidents, which in turn may be significantly different from that of all traffic incidents. Therefore the analyses presented here are performed on datasets that contain different types of incidents (injury-causing vs. fatal), that are located in different areas (Ohio and Virginia) and at different scales, and that occur over different time periods (1 year vs. 5 years).

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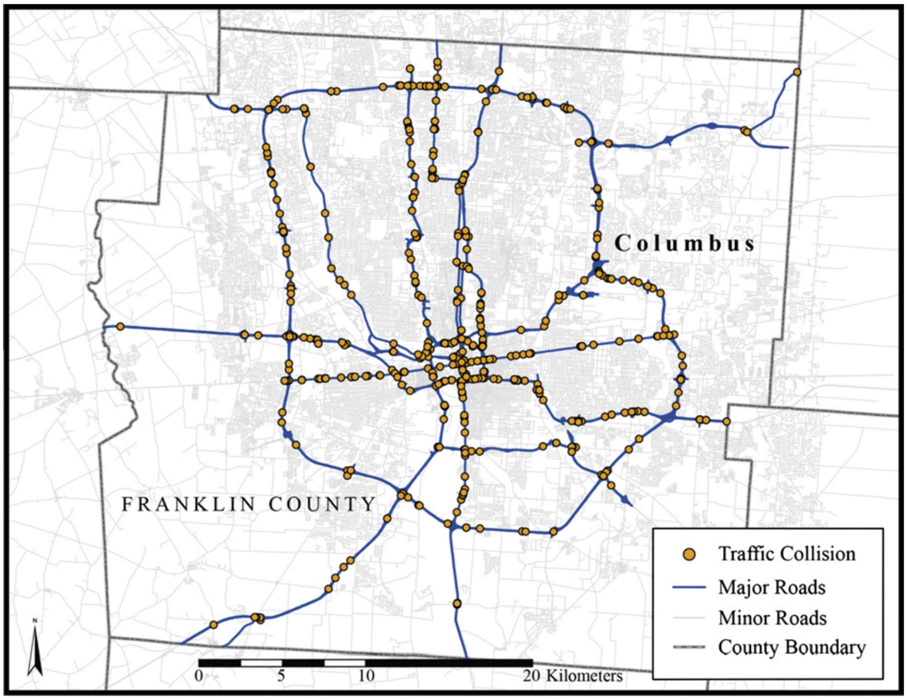


**Fig. 1.** Map of 586 injury-causing traffic collisions on major roads in Franklin County, OH from January to March 2009.

Both the Fairfax Co. and the Franklin Co. data were analyzed using appropriate State Plane coordinate systems based on the 1983 North American Datum. The customary projection associated with these coordinate systems is the Lambert Conformal Conic projection. Although this choice does not permit distance to be preserved everywhere, the parameters of the coordinate systems ensure that distortion to distance will be minimal. In order to conduct analysis of the events in network space, a network dataset was created from the selected major roadways in the study area and an origin–destination matrix was computed for all possible event pairs across the network.

## 4. Analysis of temporal, spatial, and spatiotemporal clustering of traffic incidents

Spatiotemporal cluster analysis is one of many techniques utilized in Exploratory Spatial Data Analysis for geographic pattern recognition (Jacquez, 2008). Recognition of these patterns may illuminate underlying space–time processes. To be explicit, a spatial cluster in this research is a geographic point pattern that demonstrates an excess number of events relative to the expected number of events. Likewise, a temporal cluster is the occurrence of a greater number of events than that expected during a particular time period. A spatiotemporal cluster exists when an excess number of events that occur within some geographic space are also unexpectedly close in time. Practically speaking, while spatial and temporal clusters may exist independently, spatiotemporal clusters indicate a correlation between the spatial and temporal dimension for the given phenomenon. Identifying spatiotemporal clusters may provide valuable insight beyond the determination of exclusively spatial or temporal clusters.

When testing a series of events for spatiotemporal clustering, there is value in first testing for clustering in space and time independently. While clustering in either space or time does not guarantee space–time clustering, it is shown below that the results of the independent tests can guide the inputs to the spatiotemporal tests.

### *4.1. Temporal clustering*

A simple way to test for clustering in time is by considering the time period as a single line in space, and then performing a linear nearest neighbor clustering test. Various linear nearest neighbor tests have been proposed, including those by von Neumann (1941), Pinder and Witherick (1973), Young (1982), and Okabe et al. (1995). Young's and Okabe et al.'s linear nearest neighbor clustering statistics are chosen here, with a comparison of the results from each.

Young's statistic is given by:

$$M = \frac{\sum_{i=1}^{n} M_i}{L}$$

where $i$ is the index of events and $n$ is the total number of events. $M_i$ is the temporal "distance" or time-lag between the point $i$ and its nearest neighbor. $L$ is the "length" of the temporal segment. A value of $M$ close to 0 indicates clustering of the data points, while a value of $M$ close to $n/(n+1)$ indicates dispersion in the data.

The first two moments of $M$ are as follows:

$$E(M) = \frac{n}{2(n+1)}, \quad var(M) = \frac{2n-1}{12(n+1)^2}$$

The $z$-value can be calculated:

$$z = \frac{M - E(M)}{\sqrt{Var(M)}}$$

An alternative test for linear clustering is given by Okabe et al. (1995). That test is derived from the seminal work of Clark and Evans (1954), where the Euclidean distance across space is replaced with the shortest distance along the line segment:

$$R = \frac{\bar{d}}{E(d)} = \frac{\sum_{i=1}^{n} d_i/n}{E(d)}$$

Through this formula the observed average nearest neighbor distance along the line is compared with the expected nearest neighbor distance and the significance of that deviation is determined.

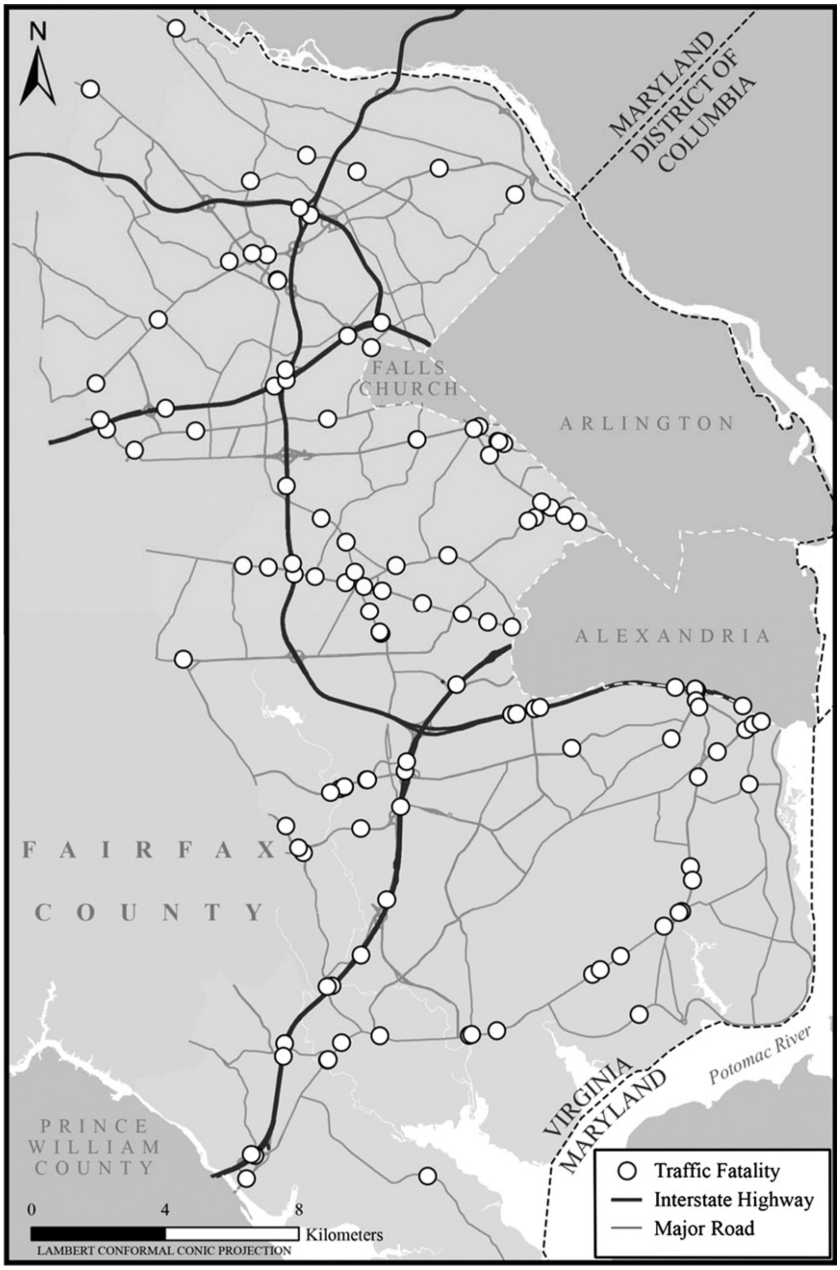


**Fig. 2.** Fatality-causing traffic collisions on major roads in Fairfax County, Virginia, 2004–2008.

**Table 1**
Dataset characteristics.

| Dataset/data sub-set | Total length of network links (km) | Temporal period (days) | Number of events | Spatial (km)/temporal (day) event density |
|---|---|---|---|---|
| Franklin Co. Collisions (January–March 2009) | 930 | 90 | 586 | 0.63/6.51 |
| Franklin Co. Collisions (April–June 2009) | 930 | 91 | 671 | 0.72/7.37 |
| Franklin Co. Collisions (July–September 2009) | 930 | 92 | 653 | 0.70/7.10 |
| Franklin Co. Collisions (October–December 2009) | 930 | 92 | 698 | 0.75/7.59 |
| Random Set (Franklin Co. Network) | 930 | 90 | 698 | 0.75/7.76 |
| E. Fairfax Co. Fatalities (2004–2008) | 950 | 1827 | 125 | 0.13/0.07 |
| Random Set (E. Fairfax Co. Network) | 950 | 1827 | 125 | 0.13/0.07 |

The derivations for the expected value and variance of this statistic are available in Okabe et al. (1995).

Before performing the linear nearest neighbor test for temporal clustering an appropriate temporal interval must be chosen. The choice of intervals along the temporal line at which to capture incident totals can alter the results of the statistics in conceptually the same way as the choice of areal units in 2-dimensional space can influence analyses (commonly termed the Modifiable Areal Unit Problem). However, while there are "empirical suggestions" for choosing areal units in quadrat analysis (Bailey & Gatrell, 1996),

**Table 2**
Temporal interval analysis for traffic collisions in Franklin County, OH, January–March, 2009.

| Time interval | Number of intervals in study period (January–March 2009) | Number of events per interval (586 collisions) |
|---|---|---|
| Month | 3 | 195.33 |
| Week | 12.9 | 45.43 |
| Day | 90 | 6.51 |
| Hour | 2160 | 0.27 |
| Minute | 129600 | 0.005 |

**Table 3**
Results for two linear nearest neighbor statistics given traffic incidents in Franklin County, OH.

| Linear nearest neighbor test | Okabe et al.'s test | Young's test |
|---|---|---|
| Minimum nearest neighbor distance | 0 h | 0 h |
| Maximum nearest neighbor distance | 13 h | 13 h |
| Nearest neighbor distance range | 13 h | 13 h |
| Average nearest neighbor distance | 1.65 h | N/A |
| Expected nearest neighbor distance | 1.87 h | N/A |
| Average nearest neighbor statistic | 0.88 | 0.44 |
| Clustered/random/dispersed | Clustered | Clustered |
| *z*-value | −1.46 | −3.4 |
| Probability (*Q*) | 0.072 | 0.0003 |

no such guideline exists for the temporal case. General rules for determining areal units suggest that excessive variability among event counts should be avoided, while still making the intervals as small as possible to capture the nature of the distribution. One technique for determining a meaningful interval is to divide the total number of events in the dataset by the number of temporal intervals in the study period. This is demonstrated in Table 2. Since the choice of the minute as the temporal interval would lead to many intervals having zero values, and since the choice of the day as the temporal interval would dramatically reduce the number of intervals, hours were chosen as the best and most expedient temporal interval for this study.

A comparison of results for Young and Okabe et al.'s statistics for the test case are given in Table 3. While the two tests use different standardization techniques, the results are nearly identical. Young's test standardizes the statistic by the time period of study (in this case 2160 h), while Okabe et al.'s statistic uses the total number of points in the test distribution, 586. Both tests, however, suggest that the temporal distribution of traffic collisions is slightly more clustered than the expected random temporal distribution and the clustering is statistically significant at the 0.1 level.

While the tests do provide very similar results, one benefit of using Okabe et al.'s statistic is the ability to observe the average and expected nearest neighbor distance as a function of the temporal interval. From the results here, a basis can be established from which to determine an appropriate range of temporal critical distance values when testing for spatiotemporal clusters (see Section 5).

### 4.2. Spatial clustering on a network

Okabe et al. (1995) extended their linear nearest neighbor clustering test outlined above to the network case where the straight-line distance along a segment is replaced by the shortest-path distance on a network. In order to test for significance in the case of a network comprised of many line segments, Monte Carlo methods are employed using Okabe's SANET software (2006). In the test case of 586 traffic collisions distributed across the major road network of Franklin County, by network space measures, the minimum shortest path distance between any two neighbors is 0 m while the maximum nearest neighbor distance is 7470 m. The average network nearest neighbor distance is 344 m. As a note, this result is almost double the value obtained when calculating the average nearest neighbor distance in continuous space (187 m), highlighting the importance of using network measures for network phenomena.

Fig. 3 displays the results for the nearest neighbor clustering statistic. The expected point distribution and the distributions for significant clustering and dispersion at the 1% and 5% confidence intervals were derived through 1000 Monte Carlo simulations of the probability distribution. While the average network nearest

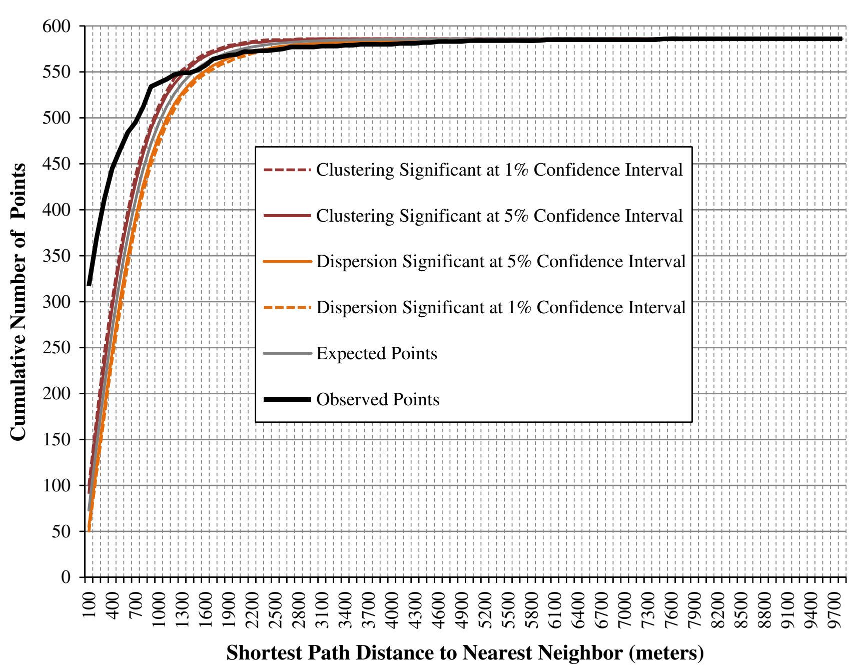


**Fig. 3.** SANET's global auto nearest neighbor distance method results.

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neighbor distance is 344 m, Fig. 3 demonstrates that significant clustering occurs for all of the events whose nearest neighbor is located within 1300 m.

Most importantly, this spatial cluster analysis provides a sense for the scale at which the 586 traffic collisions are spatially dispersed within the Franklin County major road network, in order to inform the spatiotemporal analysis. These findings now provide basis for making decisions about appropriate spatial critical distances when testing for spatiotemporal clusters. Since we know some collisions are collocated and that significant clustering exists up to 1300 m, an acceptable range of appropriate spatial critical distances might exist between 0 and 1300 m. A somewhat more conservative range is represented between the minimum nearest neighbor distance and the mean, or in this case, 0 and 344 m. Further discussion of these limits is provided in Section 5.

**Table 4**
Spatiotemporal clusters, Knox *R*, for the given spatial and temporal critical distance ranges and associated statistical significance for traffic collisions in Franklin County, OH, January–March, 2009.

| Critical spatial distance (m) | Critical temporal distance (h) | Knox-*R* value | Probability (*Q*) |
|---|---|---|---|
| 0 | 0 | 0 | 0.233 |
| | 1 | 1 | 0.498 |
| | 2 | 2 | 0.216 |
| 100 | 0 | 1 | 0.408 |
| | 1 | 2 | 0.291 |
| | 2 | 3 | 0.222 |
| 200 | 0 | 1 | 0.483 |
| | 1 | 2 | 0.413 |
| | 2 | 3 | 0.368 |
| 300 | 0 | 1 | 0.473 |
| | 1 | 2 | 0.489 |
| | 2 | 3 | 0.464 |
| 400 | 0 | *5* | *0.000003* |
| | 1 | *6* | *0.004* |
| | 2 | *8* | *0.005* |

## 4.3. Spatiotemporal clustering

The goal of this research is to examine spatiotemporal clustering among traffic incidents. Given that the Knox method is still in frequent use, we examine it in the context of a network-based transportation application. A detailed explanation of the general Knox method can be found in Cliff and Ord (1981) with examples in Upton and Fingleton (1985). Briefly, the Knox method involves the construction of two event proximity matrices with the dimensions of $n \times n$ for $n$ events. The first matrix defines spatial proximity where a 1 is associated with cell $X_{ij}$ if event $i$ occurred within some critical spatial distance $\delta$ of event $j$ and 0 otherwise. The second matrix defines temporal proximity where a 1 is associated with cell $Y_{ij}$ if event $i$ occurred within some critical temporal distance $\tau$ of event $j$ and 0 otherwise. For both matrices, if $i = j$, then the entry is 0. The Knox statistic is then obtained by the cross-product:

$$R_{\delta\tau} = \sum_{i=1}^{n}\sum_{j=1}^{n} X_{ij} Y_{ij}$$

If no pairs of events are within both the spatial and temporal critical distances the value of $R_{\delta\tau} = 0$. This would represent substantial spatiotemporal dispersion in the dataset. If all pairs of events are within both critical distances, then $R_{\delta\tau}$ will equal the number of pairs of events. This represents the maximum possible spatiotemporal clustering for the dataset. Most commonly the observed value of $R_{\delta\tau}$ will fall between these two extremes, and the observed value is compared to an expected value to determine the significance of the result. For rendering simplicity, $R_{\delta\tau}$ is hereafter written as $R$.

The results of testing for spatiotemporal clusters are presented in Table 4, where the spatial critical distance range was tested at 100 m intervals and the temporal critical distance range at 1 h intervals. For this initial test, the normal approximation will be used, although significance testing is dealt with in more detail in Section 5.

The Knox test is unique in that – while it is a global test – it is possible to display the pairs of events that contribute to the global

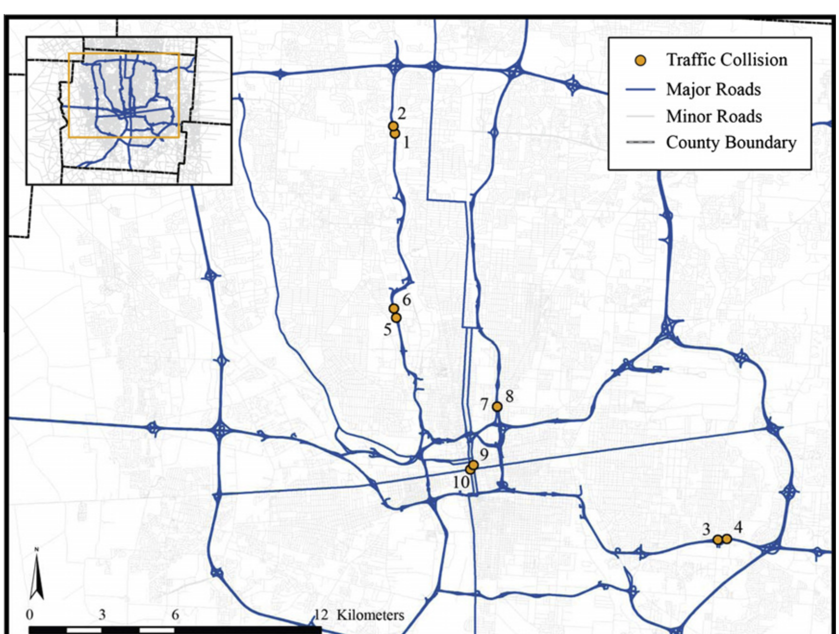


**Fig. 4.** Map of traffic collisions contributing to spatiotemporal clusters defined by a spatial critical distance of 400 m and a temporal critical distance of 0 h in Franklin County, OH, January–March, 2009.

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**Table 5**
Attribute values for incidents contributing to spatiotemporal clusters (Weather Underground, 2009).

| ID | Date | Day of week | Time | Weather |
|---|---|---|---|---|
| 1 | 1/16/2009 | Friday | 4:35:00 PM | Record low temp (−14 degrees) |
| 2 | 1/16/2009 | Friday | 4:15:00 PM | Record low temp (−14 degrees) |
| 3 | 1/20/2009 | Tuesday | 9:00:00 AM | Record low temp (−1 degree) |
| 4 | 1/20/2009 | Tuesday | 9:05:00 AM | Record low temp (−1 degree) |
| 5 | 1/26/2009 | Monday | 12:06:00 PM | Snow |
| 6 | 1/26/2009 | Monday | 12:27:00 PM | Snow |
| 7 | 1/30/2009 | Friday | 6:44:00 PM | Snow |
| 8 | 1/30/2009 | Friday | 6:44:00 PM | Snow |
| 9 | 2/26/2009 | Thursday | 6:45:00 PM | Rain (0.05 in.) |
| 10 | 2/26/2009 | Thursday | 6:13:00 PM | Rain (0.05 in.) |

spatiotemporal clustering. To illustrate this capability, the traffic collisions contributing to the significant spatiotemporal clustering at a critical spatial distance of 400 m and a critical temporal distance of 0 h (events occurring within the same hour) are presented in Fig. 4. The attributes associated with the traffic collisions representing spatiotemporal clusters are presented in Table 5.

An examination of Fig. 4 and Table 5 reveals likely spatial and temporal processes contributing to the observed spatiotemporal clusters. In the case of Fig. 4, the spatiotemporal clusters are located near to major intersections or access/exit ramps to multi-lane highways; locations where vehicles are abruptly changing travel speed and/or lanes. Table 5 indicates that the spatiotemporal clusters occurred during periods of extreme weather in every case, and during weekday rush hour traffic in four out of five clusters. These associated characteristics allow analysts to generate hypotheses regarding the nature of the incident clusters, and to explore mitigation strategies to put into practice.

## 5. Significance testing and critical parameters with the network-based Knox statistic

Two unresolved issues with regard to the Knox statistic are explored in this section. First, the question of the most appropriate significance test for the network based version of the Knox statistic under varying conditions is explored through a comparative analysis of the available methods. Second, since the definition of the critical spatial and temporal distances fundamentally changes the results of the Knox statistic, a formal examination of the ways in which such a decision can be made is presented.

### *5.1. Significance testing for the Knox method*

In statistical testing, perhaps the most important element and greatest challenge is determining the significance of the findings. Generally speaking, statistical significance is based on how closely the observed result compares to the expected result across the known (or assumed) distribution of the test statistic. If the observed result is uncommon when compared to the expected value, it is said to be significant.

The challenge of determining significance is particularly relevant to the Knox method given that this research is expanding the statistic into a new spatial domain (network space). Significance tests for the general Knox method have been developed employing the Chi-square distribution, the normal distribution, and Monte Carlo methods. In this section each significance test is described, and the results of all three tests on the traffic incident datasets are presented for comparison, along with a discussion of multiple testing correction techniques.

#### *5.1.1. Chi-square and Poisson distributions*

Since the pairings derived through the Knox method can be summarized in a two by two contingency table, the Chi-square test has been suggested as a means of testing for the significance of the statistic (Jacquez, 1996; Knox & Bartlett, 1964). The contingency table is established such that all pairs of events in space and time are classified according to the chosen critical space and time distance as either being near or far, for a total of four possible outcomes:

| | | Space | |
|---|---|---|---|
| | | $\leqslant\delta$ | $>\delta$ |
| Time | $\leqslant\tau$ | $a$ | $b$ |
| | $>\tau$ | $c$ | $d$ |

where $\delta$ is the critical spatial distance, $\tau$ is the critical temporal distance, $a$ is the number of spatiotemporal pairs, $b$ is the number of temporal pairs, $c$ is the number of spatial pairs, and $d$ is the number of all other pairs. In the contingency table above, the value of $a$ is the Knox statistic, $R$.

The Chi-square ($\chi^2$) statistic is then calculated by:

$$\chi^2 = \sum_i \sum_j \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

where $O_{ij}$ is the observed value in cells $a$ through $d$ of the contingency table and $E_{ij}$ is:

$$E_{ij} = \frac{W_i \times C_j}{N}$$

with $W_i$ the row sum for the observed value $O_{ij}$, $C_j$ the column sum for the observed value $O_{ij}$, and $N$ the grand total number of paired observations, $a + b + c + d$.

In this instance the probability of finding the calculated $\chi^2$ value may be determined from a Chi-square distribution table with one degree of freedom (Jacquez, 1996). Generally speaking, the higher the $\chi^2$ value, the more rare the result. A large $\chi^2$ value indicates that somewhere in the contingency table, the observed frequencies for a given cell differ markedly from the expected values, although the $\chi^2$ value does not indicate which cell (or cells) contribute to the observed effect. Baker (1996) notes that because a majority of the terms in the $\chi^2$ contingency table will result from the squared differences between observed and predicted numbers of close pairs over distances much larger than the specified critical distances, the power of the $\chi^2$ test is reduced. If the value of $a$ (the Knox statistic) is very small, then it has been demonstrated that the significance of the value may be directly calculated using a single-tailed Poisson distribution where the mean is equal to $E_{ij}$ above (David & Barton, 1966; Knox & Gilman, 1992).

#### *5.1.2. Normal distribution*

The significance test that assumes a normal distribution as the reference distribution has been the most commonly used with the Knox statistic. Developed for the Knox test initially by David and

Barton (1966), the details of the calculations for significance testing according to a normal approximation can be found in Upton and Fingleton (1985). It is generally accepted that when sample sizes are large this is an appropriate distribution for significance testing, although studies by Mielke (1978) and Siemiatycki (1978) identify potential exceptions.

*5.1.3. Monte Carlo simulations*

While originally suggested by Knox and Bartlett (1964), Mantel (1967) provided details for generating a reference distribution for the Knox statistic using Monte Carlo simulations. The process involves the repeated randomization of event labels, then calculating the Knox statistic at each iteration, until enough values have been generated to build an empirical distribution adequate for significance testing. While there is no standard required number of iterations the literature suggests that 1000–10,000 repetitions are sufficient. In order to determine the probability value of the observed Knox statistic, the proportion of the right hand tail of the reference distribution whose simulated Knox values are equal to or greater than the original statistic is calculated.

*5.1.4. Comparisons of significance testing methods*

All of the methods described above were implemented on the Franklin County and Fairfax County traffic incident datasets. The empirical reference distribution generated through Monte Carlo methods is the most easily justifiable given the lack of assumptions it requires. A comparison of the Monte Carlo distribution with the Poisson distribution (see Fig. 5) shows that the Poisson tendency of the Knox statistic persists even when the spatial domain and the phenomenon under study has changed.

Table 6 compares the probability values for the Knox statistic generated across all of the significance testing methods described above, for both the Franklin County and the Fairfax County datasets. For the Monte Carlo test, results are presented for three tests: where time labels are shuffled in the randomization, where space labels are shuffled, and where both time and space labels are shuffled.

From Table 6 it can be noted that although the Poisson distribution and the Monte Carlo distribution displayed in Fig. 5 are nearly identical, the derived probabilities of the observed Knox statistic based on these distributions is different. Moreover, it is apparent that the Knox statistic probability based on the normal approximation most closely resembles the probability based on the Monte Carlo generated reference distribution (where space labels are shuffled). As the Monte Carlo distribution provides the best representation of possible Knox values for a given test, the fact that the normal and Monte Carlo probabilities are similar is further evidence in support of using the normal approximation when an expedient significance test is required.

**Table 6**
Comparison of probabilities for the observed Knox statistic given, the chi-square distribution, the normal distribution, and three distributions generated through Monte Carlo simulation.

| Distribution | Franklin Co. (January–March 2009) $\delta = 400$ m, $\tau = 2$ h; $R \geqslant 8$ | E. Fairfax Co. (2004–2008) $\delta = 1214$ m, $\tau = 7$ days; $R \geqslant 1$ |
|---|---|---|
| Chi-square | 0.022 | 0.254 |
| Chi-square (Poisson) | 0.147 | 0.331 |
| Normal | 0.030 | 0.444 |
| Monte Carlo space shuffled | 0.057 | 0.676 |
| Monte Carlo time shuffled | 0.072 | 0.705 |
| Monte Carlo space and time shuffled | 0.253 | 0.889 |

In the execution of Monte Carlo simulations for the Knox test, the literature suggests that which labels are shuffled is immaterial (Baker, 1996; Jacquez, 1996; Mantel, 1967). Using the data outlined here, it is apparent that shuffling the time labels while the space labels remain fixed, or shuffling the space labels while the time labels remain fixed, provide very similar results. However, if both time and space labels are shuffled concurrently, a very different reference distribution is produced. With this distribution, the probability of obtaining a value of the Knox statistic that is more extreme than the observed value is greater than with either of the single-shuffle distributions. (Figs. 6 and 7). This discrepancy raises questions regarding the generation of the Monte Carlo distributions. Since the test is examining both spatial and temporal clustering simultaneously (with the null hypothesis that there is no significant spatiotemporal clustering), it seems intuitive that both elements should be randomized when determining an underlying distribution. Moreover, since the greater probabilities of larger values of the Knox statistic are found with the space–time randomization, then this method would be one that is more conservative than the other approaches. Questions as to the nature of the exact

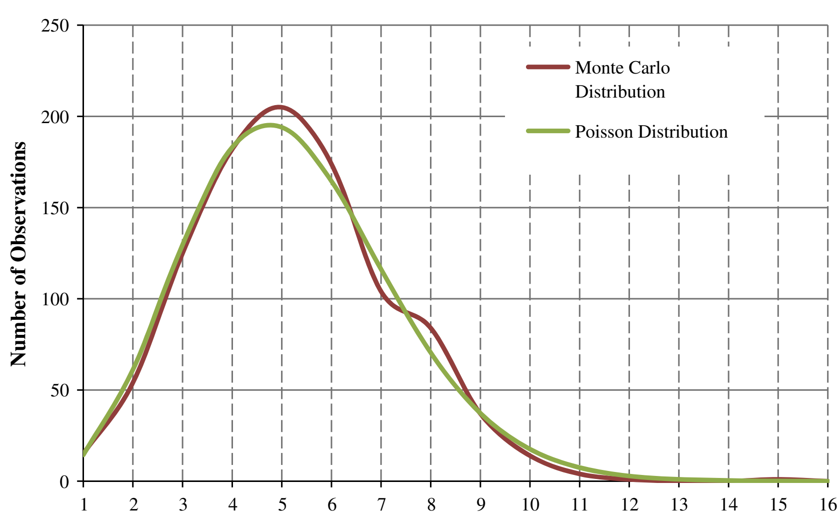


**Fig. 5.** Comparison of the reference distribution generated by 1000 Monte Carlo simulations of spatiotemporal clusters in traffic collisions in Franklin County, OH, January–March 2009, where $\delta = 400$ m and $\tau = 2$ h. The Poisson distribution is generated from the reference distribution mean of 4.24.

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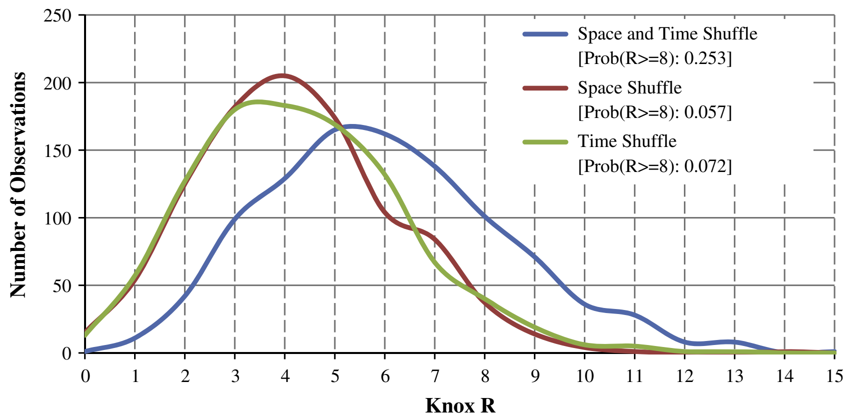


**Fig. 6.** Difference in reference distributions and probabilities generated by 1000 Monte Carlo simulations of the Knox statistic for traffic collisions in Franklin County, OH, January–March 2009, where $\delta = 400$ m, $\tau = 2$ h, and $R \geqslant 8$.

hypothesis being tested, and consequently the power of the significance test deserve more thorough examination than this initial finding allows. This is an area that is open to future research.

*5.1.5. Multiple testing corrections*

In order to maintain statistical rigor when multiple tests are being conducted, methods for adjusting the level at which the observed statistic is determined significant should be considered. Jacquez (2008) suggests that the Bonferroni (Sidak, 1967; Simes, 1986), Holm (1979) or Hochberg (1988) methods may be implemented. While the traditional Bonferroni adjustment involves dividing the desired $\alpha$ by the number of tests performed, or $\alpha/n$, this correction can be seen as excessively conservative and improved methods have been suggested. This research examines the Bonferroni technique and an adjusted method suggested by Simes (1986). Simes (1986) modification orders the probability values of all iterations of the performed test, in descending order, $P_{(1)}, \ldots, P_{(n)}$. The null hypothesis for a given iteration is rejected if:

$$P_{(j)} \leqslant \frac{j\alpha}{n}$$

where $j = 1, \ldots, n$.

The results of both the traditional and the modified Bonferroni correction techniques are shown in Table 7. The strictness of the traditional Bonferroni adjustment is readily apparent when compared to the results of the modified adjustment.

*5.2. Establishing critical parameters for the Knox method*

Unlike spatiotemporal studies in epidemiology, where critical parameters can be defined by the known etiology of disease, for the case of traffic incidents, critical parameters may be relative to the spatial and temporal processes involved at the area and time of study. Therefore, it is recommended to test a range of possible critical distances (as above) to determine more holistically how spatiotemporal clustering is present in the data. However, since multiple tests across those ranges of critical distances will in turn demand multiple-testing correction techniques, it is desirable to identify the smallest possible range of critical parameters that reveal the presence of clustering. While methods have been published for identifying the most significant result within a given range of spatiotemporal parameters (Baker, 1996), methods for determining an acceptable range of values when they are unknown have not. One method for determining this range is to perform nearest neighbor distance calculations (as in Section 4) on the spatial and temporal components of the datasets. The lower bound for the parameter range is intuitively the minimum nearest neighbor distance, as no pair of events can be closer together. The value in question is the upper bound.

Table 8 contains the results of tests for clustering in the spatial and temporal dimensions as described in Section 4. Tables 9–11 show the results of spatiotemporal tests where the minimum, average, and maximum nearest neighbor distances, respectively, were used as critical parameters for both space and time. For most

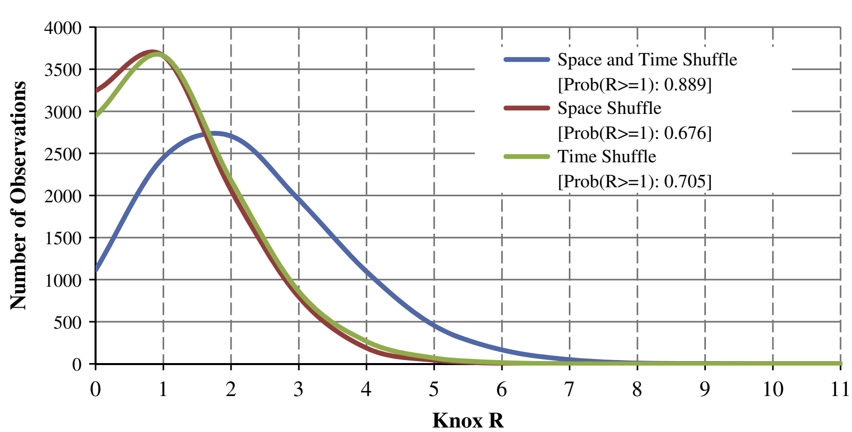


**Fig. 7.** Difference in reference distributions and probabilities generated by 10,000 Monte Carlo simulations of the Knox statistic for traffic collisions in E. Fairfax County, VA, 2004–2008 where $\delta = 1214$ m, $\tau = 7$ days, and $R \geqslant 1$.

**Table 7**
Spatiotemporal clusters, Knox *R*, for the given spatial and temporal critical distance ranges and associated statistical significance for traffic collisions in Franklin County, OH, January–March, 2009. Italicized values are significant where $Q \leqslant$ the Bonferroni correction for $\alpha = 0.05$.

| Critical spatial distance (m) | Critical temporal distance (h) | Knox-*R* value | Probability (*Q*) | Modified Bonferroni correction for $\alpha = 0.05$ | Traditional Bonferroni correction for $\alpha = 0.05$ |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 0.233 | 0.020 | 0.003 |
| | 1 | 1 | 0.498 | 0.050 | 0.003 |
| | 2 | 2 | 0.216 | 0.013 | 0.003 |
| 100 | 0 | 1 | 0.408 | 0.030 | 0.003 |
| | 1 | 2 | 0.291 | 0.023 | 0.003 |
| | 2 | 3 | 0.222 | 0.017 | 0.003 |
| 200 | 0 | 1 | 0.483 | 0.043 | 0.003 |
| | 1 | 2 | 0.413 | 0.033 | 0.003 |
| | 2 | 3 | 0.368 | 0.027 | 0.003 |
| 300 | 0 | 1 | 0.473 | 0.040 | 0.003 |
| | 1 | 2 | 0.489 | 0.047 | 0.003 |
| | 2 | 3 | 0.464 | 0.037 | 0.003 |
| 400 | 0 | 5 | *0.000003* | *0.003* | *0.003* |
| | 1 | 6 | *0.004* | *0.007* | 0.003 |
| | 2 | 8 | *0.005* | *0.010* | 0.003 |

**Table 8**
Results of nearest neighbor cluster analysis for the spatial and temporal dimensions.

| Nearest neighbor distance results | Spatial dimension | Temporal dimension |
|---|---|---|
| Franklin County Collisions (January–March 2009) | Clustered | Clustered |
| Franklin County Collisions (April–June 2009) | Clustered | Clustered |
| Franklin County Collisions (July–September 2009) | Clustered | Clustered |
| Franklin County Collisions (October–December 2009) | Clustered | Clustered |
| Random set (Franklin County Network) | Random | Random |
| Eastern Fairfax County Fatalities (2004–2008) | Clustered | Random |
| Random set (Fairfax County Network) | Random | Random |

**Table 9**
Comparison of the Knox statistic and associated probabilities calculated using the minimum nearest neighbor distance in space and time as the critical parameters. Italicized values indicate $Q \leqslant \alpha = 0.05$.

| Minimum nearest neighbor distance | Spatial (m) | Temporal | Knox *R* | Prob (*Q*) |
|---|---|---|---|---|
| Franklin County Collisions (January–March 2009) | 0 | 0 h | 0 | – |
| Franklin County Collisions (April–June 2009) | 0 | 0 h | 0 | – |
| Franklin County Collisions (July–September 2009) | 0 | 0 h | 2 | *0.000* |
| Franklin County Collisions (October–December 2009) | 0 | 0 h | 2 | *0.012* |
| Random Set (Franklin County Network) | 12 | 0 h | 0 | – |
| Eastern Fairfax County Fatalities (2004–2008) | 12 | 0 d | 0 | – |
| Random Set (Fairfax County Network) | 112 | 0 d | 0 | – |

of the non-random datasets, when the average nearest neighbor distance was used as the critical parameter for space and time, the spatiotemporal statistic was significant. Therefore, it seems appropriate to use the range of values between the minimum and average nearest neighbor distances as an initial range of inputs for spatiotemporal critical parameters, based on the assumption that if the upper bound of the range is significant, then it is possible that values below this bound will be significant as well. If this range does not produce a significant test result, then the next logical range to consider is between the average nearest neighbor distance (lower bound) and maximum nearest neighbor distance (upper bound). By limiting the critical distance parameters in this way, the impact of the Bonferroni correction is minimized.

**Table 10**
Comparison of the Knox statistic and associated probabilities calculated using the average nearest neighbor distance in space and time as the critical parameters. Italicized values indicate $Q \leqslant \alpha = 0.05$.

| Average nearest neighbor distance | Spatial measure (m) | Temporal measure | Knox *R* | Probability (*Q*) |
|---|---|---|---|---|
| Franklin County Collisions (January–March 2009) | 344 | 1.65 h | 5 | 0.073 |
| Franklin County Collisions (April–June 2009) | 305 | 1.44 h | 10 | *0.000* |
| Franklin County Collisions (July–September 2009) | 301 | 1.47 h | 9 | *0.000* |
| Franklin County Collisions (October–December 2009) | 276 | 1.34 h | 7 | *0.003* |
| Random Set (Franklin County Network) | 495 | 1.56 h | 0 | – |
| Eastern Fairfax County Fatalities (2004–2008) | 1214 | 7 d | 1 | 0.444 |
| Random Set (Fairfax County Network) | 1318 | 7.27 d | 0 | – |

**Table 11**
Comparison of the Knox statistic and associated probabilities calculated using the maximum nearest neighbor distance in space and time as the critical parameters. Italicized values indicate $Q \leqslant \alpha = 0.05$.

| Maximum nearest neighbor distance | Spatial measure (m) | Temporal measure | Knox *R* | Probability (*Q*) |
|---|---|---|---|---|
| Franklin County Collisions (January–March 2009) | 7470 | 13 h | 449 | 0.062 |
| Franklin County Collisions (April–June 2009) | 5516 | 15 h | 408 | 0.192 |
| Franklin County Collisions (July–September 2009) | 5396 | 21 h | 551 | 0.311 |
| Franklin County Collisions (October–December 2009) | 5224 | 20 h | 749 | *0.001* |
| Random Set (Franklin County Network) | 3236 | 16 h | 96 | 0.285 |
| Eastern Fairfax County Fatalities (2004–2008) | 8447 | 40 d | 83 | *0.048* |
| Random Set (Fairfax County Network) | 8685 | 29 d | 55 | 0.359 |

Note that, as expected, the randomly generated datasets do not demonstrate spatial or temporal clustering in Table 8. Nor do they demonstrate any significant spatiotemporal clustering in Tables 9–11. While this may be obvious, it reinforces the supposition that

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independent clustering in space and time is related to spatiotemporal clustering. This also reinforces the importance of testing for clustering in space and time independently prior to proceeding with a spatiotemporal analysis. Although significant spatiotemporal clusters may exist when spatial and temporal clusters do not, a researcher may not wish to invest the time in a spatiotemporal cluster analysis if there is an absence of clustering in both space and time independently.

## 6. Conclusions and future research

Among the contributions of this research are both practical and theoretical elements. With regard to the former it has been shown that the spatiotemporal clustering of traffic incidents can be successfully examined (a) when spatial and temporal analyses in isolation accompany the spatiotemporal analysis in order to derive value from all potential components of clustering, (b) when appropriate network measures of clustering are employed, (c) when logical critical parameters for the tests are determined, and (d) when robust and justifiable significance testing is performed. Further, the research presented in this article demonstrates that the Knox test for spatiotemporal clustering can be used to identify and visualize specific observations that contribute to spatiotemporal clustering (if it is present). In the case of the empirical study presented here, law enforcement and safety officials may choose to dedicate additional resources to explain why the spatiotemporal clustering is occurring at the specified location and time, and subsequently what measures might be implemented to mitigate the specific traffic risks in the future. Moreover, a general method was presented for determining logical critical distance ranges for spatiotemporal cluster analysis based on the results of independent tests of spatial and temporal clustering.

With regard to more general theoretical contributions several observations have been made with regard to the distribution of the Knox statistic when applied to traffic incidents. It has been shown that the distribution of the Knox statistic on a network generated through Monte Carlo simulation with space labels randomized is closely approximated by the Poisson distribution. Moreover, shuffling either space or time labels provides a similar distribution. However, it has also been shown that shuffling both space and time labels generates a significantly different distribution. This raises questions regarding what significance test ought to be used by researchers who do not choose to generate their own empirical distributions. Although additional research on a range of traffic incident datasets should be performed, these initial results suggest that a normal distribution most closely matches the empirical distribution generated through the randomization of space labels. If the randomization of both space and time labels is accepted as a more reasonable assumption for generating empirical distributions, then it appears that the Poisson distribution may be a better choice. This was clear in the Franklin County case, while none of the regular distributions was a close match to the space–time randomized distribution in the Fairfax County case.

As may be expected, these findings have generated significant questions that are worthy of future research. With regard to the determination of ranges for critical parameters (for which a logical basis is established here), it may be possible to limit these ranges further, thus limiting the number of tests that would need to be performed. Along these same lines, additional work could better inform the choice of temporal intervals, in much the same way as empirical work has led to guidelines for determining areal extents in other types of analysis.

Additionally, one of the improvements in continuous spatiotemporal cluster analysis is the result of work regarding population shift bias (Klauber & Mustacchi, 1970; Kulldorff & Hjalmars, 1999; Mantel, 1967). In terms of network spatial statistics, the topic of addressing the population-at-risk has been raised in the context of the network K-function, although not with regard to temporal clustering (Yamada & Thill, 2004). It may be that the network-based equivalent of population shift bias is a traffic flow bias. Traffic flow across the network may have a real effect on the significance of observed spatiotemporal clustering, especially in congested urban areas where traffic flow fluctuates at regular temporal intervals. While reliable traffic flow information over short time scales has historically been difficult to obtain, this is changing due to advances in traffic monitoring technologies, and therefore this is likely to be a fruitful area for future research.

This is related to issues regarding the nature of the spatial platform on which incident data exist, since it has been shown that assumptions of spatial extent can influence the underlying distributions of the derived statistics (Thomas, 1996). Therefore, future research into spatial considerations such as network edge effects and data aggregation may provide further insight into the nature of traffic incidents. Further, the presence of variable values associated with either the incidents themselves (e.g. damage values or severity values) or the segments of the network (e.g. aggregated incident values) may encourage the development and use of spatio-temporal network autocorrelation as an extension of the work of Black (1992) and Black and Thomas (1998). This network extension of the Knox test is a global test, meaning it describes the distribution of points throughout the entire study area, without addressing the significance of local clusters. The extension of network-based spatiotemporal cluster analysis to the local case statistic appears to be a research area yet to be addressed, but one which could provide valuable insight for traffic collision analysis (Moons, Brijs, & Wets, 2009).

Finally, the choices of statistics used here for independent temporal and spatial cluster analysis were based on assumptions about the representations of the temporal and spatial domains. That is, the choice of Young's and Okabe's linear clustering statistics was made based on the notion that time of events (more specifically the time of traffic incident occurrence) is best represented as a straight line. Similarly, Okabe's network-based spatial clustering statistic is chosen under the assumption that a network is the best representation of the spatial domain on which traffic incidents occur. Although the network choice for spatial representation is well-supported by recent literature, the nature of the temporal domain may need more examination. It is well-known that some traffic patterns are cyclical; e.g. rush-hours, day-of-week patterns, or seasonal patterns. Future work should examine the ways in which underlying temporal domains and the critical distances within them can influence the results of spatiotemporal clustering analyses. Other modeling efforts have chosen to model space and time as analogous variables in two-dimensional real space (Diggle, Chetwynd, Häggkvist, & Morris, 1995).

Most importantly, it is hoped that the presence of a rigorous method for identifying spatiotemporal clusters in traffic accidents can have a meaningful influence on the prevention of traffic injuries and fatalities. It is hoped that the addition here of methods that allow investigation of spatiotemporal patterns will provide some contribution to the field of traffic management, and to spatial analysis more generally.

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