Highway Accidents: A Spatial and Temporal Analysis

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A temporal, spatial, and spatial-temporal autocorrelation analysis of highway accidents on the Indiana Toll Road from 1983 to 1987 is presented. Applications of von Neumann's ratio, Moran's I, nearest-neighbor analysis, and a spatial-temporal autocorrelation coefficient to a transportation network situation are illustrated. Applications of these methods to transport network attributes, such as accidents, have not appeared previously. The main objectives are to determine whether these techniques are sensitive enough to distinguish different patterns in the accident distributions and whether these patterns are explainable. The analysis involved 10 sets of accident data, categorized by date of occurrence and location on an east-west roadway. Only 2 of the 10 revealed positive temporal autocorrelation (clustering in time), 5 revealed positive spatial autocorrelation (clustering in space), and between 6 and 9, depending on the method used, revealed positive spatial-temporal autocorrelation (clustering in time and space). These results suggest that observed autocorrelations in accidents are a function of weather conditions or traffic volumes, or a combination of the two.

The spatial, temporal, and spatial-temporal distribution of motor vehicle accidents along a major highway is examined. Although temporal analyses have been undertaken for several years as analysts have sought to predict the number of accidents or fatalities on highways, methods for rigorously analyzing the spatial distribution of events along a highway are not common. Methods for analyzing the spatial and temporal distributions simultaneously on a linear network have not been presented before. Two approaches to this latter problem are examined here. One of these is drawn from the plant ecology and geographical analysis literature and the other has its origin in epidemiology.

CLUSTERING IN TIME AND SPACE

Motor vehicle accidents should occur as a random series in time or space. However, these incidents often cluster temporally and spatially. The existence of temporal clustering is evident during holiday weekends, when the number of accidents and fatalities increases in response to heavier-than-usual traffic volumes. Whether spatial clustering exists is not as obvious.

Temporal Clustering

To determine whether clustering is occurring in a temporal sense, it is necessary to have some notion of an appropriate time interval for data analysis. If temporal distribution is examined at intervals of less than 1 min, the only events to cluster might be those reflecting the same vehicle-to-vehicle collisions and other single-vehicle random events. This information is not without interest, but it does not suggest much to the analyst or policy maker. Therefore, a different temporal scale of analysis is necessary.

The time interval used here is the day. Its use is based on the belief that the number of highway accidents today is, in part, related to the number of accidents that occurred yesterday. Cause is not implicit in such a statement, but rather the recognition that daily accidents are often related to traffic flow volumes or weather conditions, which vary daily, weekly, and seasonally. As a result, temporal autocorrelation exists in these data with variable levels for 1 day not differing a great deal from the level of that variable the following day; that is, similar values tend to cluster in time. Use of a day for the time interval should pick up the influence both of flow volumes and of weather conditions.

Of course, if the major factors influencing temporal autocorrelation are absent, there should not be any clustering of the events in time. For flow volumes and weather conditions, it is possible that increased patrolling by state police and increased maintenance (such as snow removal) could offset some of the expected temporal clustering. Nevertheless, a tendency toward temporal clustering is expected.

Spatial Clustering

Spatial autocorrelation is the tendency for the level of a variable at one location to influence the level of that variable at sites in proximity to the first location. If positive spatial autocorrelation is present, it results in a spatial clustering of similar variable values. This clustering may be caused by many factors. Among these factors are higher traffic volumes in different regions of the transport line, natural or anthropogenic environmental factors (such as fogs) that restrict or interfere with vehicle operation, points of access or egress at which vehicle speeds change, or areas of poor highway design in an engineering sense. A clustering of similar accident values in space would be expected if one or more of these factors are present.

The proper spatial interval for the analysis of spatial autocorrelation in this context is debatable. As explained previously, setting a small interval will result in the clustering only of vehicles in the same incident (automobile-to-automobile collisions), but these data are not of interest here. The use of 0.5-km or similar intervals would be desirable for

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certain environmental events, but this level of detail is uncommon and, as a result, not available. Because of data reporting standards, this analysis uses the 1-mi segment. Most major regional phenomena should be perceptible at this scale, and minor clustering at a lower scale should also be identifiable at the larger scale.

Spatial-Temporal Clustering

Because a scale is available for locating every incident in time and another scale is available for measuring every incident in space, the question is whether there is some method of combining these scales to determine if certain incidents are clustering in time and space. If such a method were available, it might enable researchers to evaluate whether the temporal clustering and spatial clustering were due to the same or different major events. For example, assume that the temporal clustering found in a series of automobile accidents was attributable to holiday travel on weekends during the winter. The presence of spatial clustering might suggest a concentration of this same series of accidents in a given region. The presence of spatial-temporal clustering would reveal that accidents were occurring on the same weekends and sections of the highway and that the two separate distributions are actually a single, interrelated, spatial-temporal distribution. The objective is to identify a method for analyzing this latter type of distribution.

If 1-day time intervals are acceptable for the measurement of temporal autocorrelation and 1-mi spatial intervals are equally acceptable for measuring spatial autocorrelation, then it is reasonable to use these two dimensions to define an area called time-space. In time-space, all events are identifiable as occurring within a certain time period and within a bounded space. If the initial metrics for time and space are unreasonable, the analysis of a time-space with dimensions defined by these metrics will be of little value.

METHODOLOGY

Temporal Autocorrelation Analysis

Statistics for assessing temporal autocorrelation in a data series include the Durbin-Watson statistic and the von Neumann ratio (*1*, pp. 305–307). The von Neumann ratio (Q) was chosen because it was easier to evaluate. For a set of n observations on some variable x arranged in a successive series, the statistic is calculated as follows:

$$Q = \frac{[1/(n-1)] \sum_{i=2}^{n} (x_i - x_{i-1})^2}{(1/n) \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{1}$$

For a large number of observations ($n > 60$), the expected value of Q follows a normal distribution with mean $2n/(n-1)$ and variance $4/n$. Evaluation of the ratio is accomplished in the traditional manner using standard normal deviates on the basis of these values and the calculated Q.

Spatial Autocorrelation Analysis

Analysis of spatial autocorrelation for a linear system, such as a highway, involves the adaptation of conventional autocorrelation techniques used in the analysis of point and areal distributions to linear situations. The statistic of choice in such cases is most often Moran's I (*2–4*). The statistic is calculated as follows:

$$I = \frac{n}{\sum\sum w_{ij}} \frac{\sum\sum w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum(x_i - \bar{x})^2} \tag{2}$$

where

x_i = value of variable x on Line Segment i,
$\bar{x}$ = mean of variable x,
n = number of line segments, and
w_{ij} = weights indicating whether Line Segment i is connected to Line Segment j (= 1) or not (= 0).

For continuous data, the expected value of Moran's I is

$$\mathrm{E}(I) = \frac{-1}{n-1} \tag{3}$$

The variance of I under the assumption of normally distributed data is

$$\mathrm{Var}(I) = \frac{n^2 S_1 - nS_2 + 3\left(\sum\sum w_{ij}\right)^2}{\left(\sum\sum w_{ij}\right)^2 (n^2 - 1)} - \mathrm{E}(I)^2 \tag{4}$$

where

$$S_1 = \frac{1}{2} \sum\sum (w_{ij} + w_{ji})^2 \tag{5}$$

and

$$S_2 = \sum\left(\sum w_{ij} + \sum w_{ji}\right)^2 \tag{6}$$

Although accident data of the type used here are not usually normally distributed, the presence of a large number of observations in the series analyzed makes this assumption tenable. The difference between the expected value of I (from Equation 3) and the calculated value of I (from Equation 2) may be divided by the square root of the variance (see Equation 4) to yield a standard normal deviate, often called a z score, for hypothesis testing.

Spatial-Temporal Autocorrelation Analysis

Given that it is possible to assess the autocorrelation of the accident data in time and one-dimensional space, the influence of these factors is examined simultaneously. There are two ways that the data could vary. First, the pattern of cases in an area defined by the space and time dimensions can be examined. This method is known as pattern analysis, and the finding of a clustered pattern would infer some type of dependence in the distribution. Second, the extent to which the pattern created by values (in this case, the number of accidents) displays some evidence of organization can be studied. This method is spatial autocorrelation analysis, and a finding of positive spatial autocorrelation would also suggest some type of dependence in the distribution.

A common method for measuring whether clustering exists in a two-dimensional spatial pattern of cases is known as nearest-neighbor analysis. Such a technique could also be used to examine the pattern of cases in time-space. Nearest-neighbor analysis was developed primarily by the plant ecologists Clark and Evans (*5*), although geographers have done a considerable amount of work on this subject since that early research (*6–10*). The measure compares the actual distance of each point to its nearest neighbor in two-dimensional space, with the expected distance to the nearest neighbor being based on a random distribution of points in that space. Division of the former by the latter yields an index for which unity indicates a random distribution, zero represents complete clustering, and a completely dispersed pattern yields a value of approximately 2.15.

Hypothesis testing proceeds by finding the difference between the observed and expected nearest neighbor distances and dividing this value by the expected standard error for a random distribution to yield an index, which is also a standard normal deviate. Symbolically, the observed average distance to the nearest neighbor ($\bar{d}$) is

$$\bar{d} = \sum d_{ij\min}/n \tag{7}$$

where $d_{ij\min}$ is the distance of i to its nearest jth neighbor, and n is the number of points in the distribution. The expected average distance for a random distribution ($\bar{d}_{\text{ran}}$) is

$$\bar{d}_{\text{ran}} = 1/[2(n/A)^{0.5}] \tag{8}$$

where A is the area of surface occupied by the point distribution. The standard error of the mean nearest-neighbor distances is

$$\text{SE}_{\bar{d}} = 0.26136/[n(n/A)]^{0.5} \tag{9}$$

and the standard normal deviate in this case is

$$z = \frac{\bar{d} - \bar{d}_{\text{ran}}}{\text{SE}_{\bar{d}}} \tag{10}$$

Methods for evaluating the pattern of values in space and time fall within the domain of spatial autocorrelation analysis. The methods are not that well developed for time and two-dimensional space. However, for one-dimensional time and one-dimensional space (such as the toll road of interest here), it is possible to use a cross-product statistic attributed to Knox (*11*) and Mantel (*12*).

The technique is described in some detail by Cliff and Ord (*8*) and Upton and Fingleton (*10*). It involves in this case the construction of two event matrices. If there are n events, then the matrices are $n \times n$. For the first matrix (the time matrix), a 1 is included in some Cell t_{ij} if Event i occurred within one time unit of Event j, and 0 otherwise. The second, or space, matrix includes a 1 in Cell s_{ij} if the events occurred within one unit of each other in space, and 0 otherwise. For both matrices, if $i = j$, then the entry is 0. The general cross-product statistic is obtained from the following equation:

$$R = \sum_{i=1}^{n} \sum_{j=1}^{n} t_{ij} s_{ij} \tag{11}$$

If the events are completely independent, then $R = 0$. The expected value of R is

$$\text{E}(R) = \sum_{i=1}^{n} \sum_{j=1}^{n} t_{ij} \sum_{i=1}^{n} \sum_{j=1}^{n} s_{ij}/n(n - 1) \tag{12}$$

Upton and Fingleton (*10*, p.157) provide details on the calculation of variance. The obtained R value can be evaluated with the test statistic, as follows:

$$z = \{[R - \text{E}(R)] - 1\}/[\text{var}(R)]^{0.5} \tag{13}$$

ILLUSTRATIONS

Table 1 presents an illustration of these methods. The first three variables represent three different distributions of 17 events across 40 time periods. The concern goes to the nature of these three distributions. As presented in Table 2, use of the von Neumann ratio reveals that the first variable represents significant positive temporal autocorrelation, the second represents significant negative temporal autocorrelation or dispersion, and the third does not display a significant level of temporal autocorrelation.

The second three variables of Table 1 represent the locations of 17 events along a single dimension, such as a highway, with a length of 40 units. Spatial autocorrelation analyses of these variables also suggest three different types of distributions (see Table 2). The first has a high level of positive spatial autocorrelation (i.e., a clustering of similar values), the second has a high level of dispersion or a uniformity in the distribution of events, and the third is neither clustered nor dispersed but tends toward a random distribution.

Figure 1 shows several possible mappings of the temporal and spatial variables in time-space. In each case the mappings are only two of the possible arrangements that could result when an event's temporal location is linked with its corresponding spatial location. By referring to the marks on the horizontal and vertical axes of the figures, the nature of the one-dimensional temporal and spatial autocorrelation (analogous to the pattern) is revealed. The figure shows that the presence of positive spatial autocorrelation in the location variable and positive autocorrelation in the temporal variable may lead to a clustered distribution (1a) or a dispersed distribution (1b). Furthermore, a dispersed or uniform distribution for these two axes may also lead to a clustered pattern (2a) or a dispersed pattern (2b). Finally, a nearly random distribution of these two axes may result in a clustered pattern (3a) or a dispersed pattern (3b) of incidents in time-space.

Table 3 presents the results of a nearest-neighbor analysis of each of these six mappings in time-space. The nearest-

TABLE 1 SIX EXAMPLES OF SPATIAL AND TEMPORAL LOCATION OF EVENTS

Day or	Temporal			Spatial		
Mile	1	2	3	1	2	3
1	0	0	0	0	0	0
2	0	0	1	1	1	1
3	0	0	0	1	0	0
4	0	1	0	1	1	0
5	0	0	0	1	0	0
6	1	1	0	0	1	0
7	1	0	1	0	0	1
8	1	1	0	0	1	0
9	1	0	0	0	0	0
10	0	1	1	0	1	1
11	0	0	1	0	0	1
12	0	1	1	0	1	1
13	0	0	0	0	0	0
14	1	1	1	1	1	1
15	1	0	0	1	0	0
16	1	1	0	1	1	0
17	1	0	1	1	0	1
18	0	1	1	0	1	1
19	0	0	0	0	0	0
20	1	1	0	0	1	0
21	1	0	0	0	0	0
22	1	1	1	0	1	1
23	1	0	0	0	0	0
24	0	1	0	1	1	0
25	0	0	1	1	0	1
26	0	1	0	1	1	0
27	0	0	1	1	0	1
28	0	1	1	1	1	1
29	0	0	0	0	0	0
30	0	1	0	0	1	0
31	0	0	1	0	0	1
32	0	1	0	0	1	0
33	0	0	0	0	0	0
34	0	1	1	1	1	1
35	0	0	0	1	0	0
36	1	1	0	1	1	0
37	1	0	0	1	0	0
38	1	0	1	0	0	1
39	1	0	1	0	0	1
40	1	0	1	0	0	1

neighbor analysis confirms what is visually apparent from Figure 1. Distributions 1a, 2a, and 3a are clustered, and distributions 1b, are dispersed in the time-space. In other words, the patterns of Mappings 1a, 2a, and 3a reveal the presence of positive spatial autocorrelation, and the patterns of Mappings 1b, 2b, and 3b indicate its absence.

Table 3 also presents the results of a Knox *R* analysis of these six situations. In so doing, it identifies what might be the major shortcoming of this technique. Although the Knox *R* indicates that Distributions 1a and 3a have positive spatial autocorrelation, the test completely fails for Distribution 2a. Although clustering is apparent in this distribution, each case

TABLE 2 ILLUSTRATIVE TEMPORAL AND SPATIAL CASES

Temporal Data Sets	von Neumann Q	z
Distribution 1	.7345	-4.16*
Distribution 2	3.5674	4.79*
Distribution 3	2.2034	.48
Spatial Data Sets	**Moran's I**	**z**
Distribution 1	.5870	3.92*
Distribution 2	-.8601	-5.35*
Distribution 3	-.1029	- .50

* significant at .01 (z > | 2.58|)

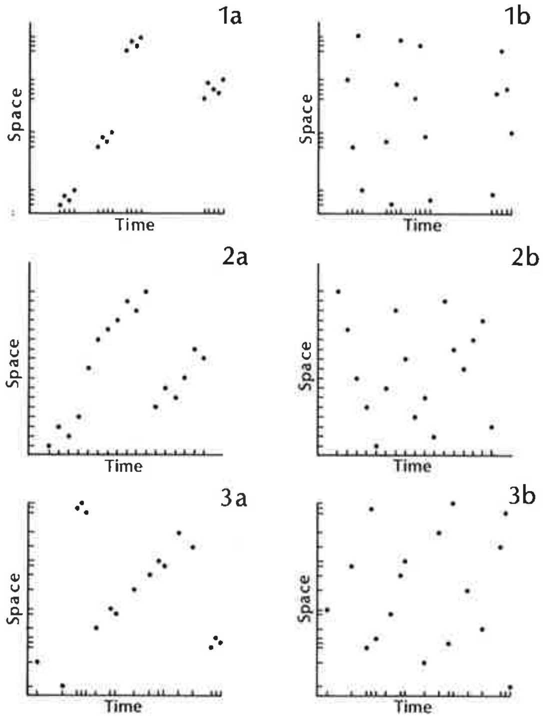

FIGURE 1 Possible two-dimensional mappings of spatial and temporal events.

is more than one unit away from each other case in time and space. This finding demonstrates how critical the definition of nearness is in using this test. The other distributions (1b, 2b, and 3b) reveal an absence of positive spatial-temporal autocorrelation, as expected.

Of the various distributions, the ones that are of primary interest for analysis or policy reasons are those that display positive spatial autocorrelation in one dimension, positive temporal autocorrelation, and positive spatial-temporal autocorrelation, or a clustering in time-space, as assessed by nearest neighbor analysis. Random distributions would imply no major regional or temporal influences. A dispersed or nearly uniform pattern is an unlikely, though not impossible, distribution for most transport-related phenomena.

STUDY AREA AND DATA

The empirical situation of interest here is the spatial and temporal distribution of motor vehicle accidents along the Indiana Toll Road from 1983 through 1987. This toll road is a limited-access trafficway in the northern part of Indiana extending 156 mi between Illinois and Ohio (see Figure 2). The trafficway consists of an eastbound roadway and a westbound roadway.

The motor vehicle accident data are perhaps best thought of as traffic incidents. The incidents recorded may be minor and involve suspected personal injury or damage to a single item (e.g., a vehicle, a sign, or a guardrail) in excess of $500. The data also record incidents involving fatalities, but these reports are a small minority of those in this data base. The data used are recorded by day of the year and toll road milepost. The former allows an analysis of temporal autocorrelation over 365 days (366 days in 1984), whereas the latter permits a spatial autocorrelation analysis across the 156 days.

For the spatial-temporal analysis, the two scales above defined a two-dimensional time-space surface. On this surface an accident receives a space coordinate and a time coordinate corresponding to the milepost and day on which the accident occurred. Events that occurred near each other in time and space will appear close to each other on the time-space surface. If the analysis suggests a clustering of events, it is reasonable to infer the existence of a certain amount of spatial-temporal autocorrelation.

RESULTS OF ANALYSIS

The results of the temporal autocorrelation analysis are presented in Table 4 as von Neumann Q statistics and standard normal deviates. Of the 10 data sets analyzed, only 2 demonstrated a significant amount of temporal autocorrelation. The implications of this finding are numerous and range from very successful patrolling practices to uniqueness in the type of data used. It is common practice for the Indiana State Police to increase the level of patrolling during holiday periods in an attempt to decrease motor vehicle accidents. The toll road is not a typical highway in that it receives heavier use during

TABLE 3 ILLUSTRATIVE SPATIAL-TEMPORAL CASES

Time-Space Data Sets	Nearest Neighbor Index	z	Knox Statistic	z
Mapping 1a	.386	- 4.85*	10	3.09*
Mapping 1b	1.374	2.95*	0	.71
Mapping 2a	.725	- 2.17**	0	0.00
Mapping 2b	1.375	2.96*	0	0.00
Mapping 3a	.602	- 3.14*	12	10.56*
Mapping 3b	1.466	3.68*	0	- .47

* significant at .01 (z > 2.58)

** significant at .05 (z > 1.96)

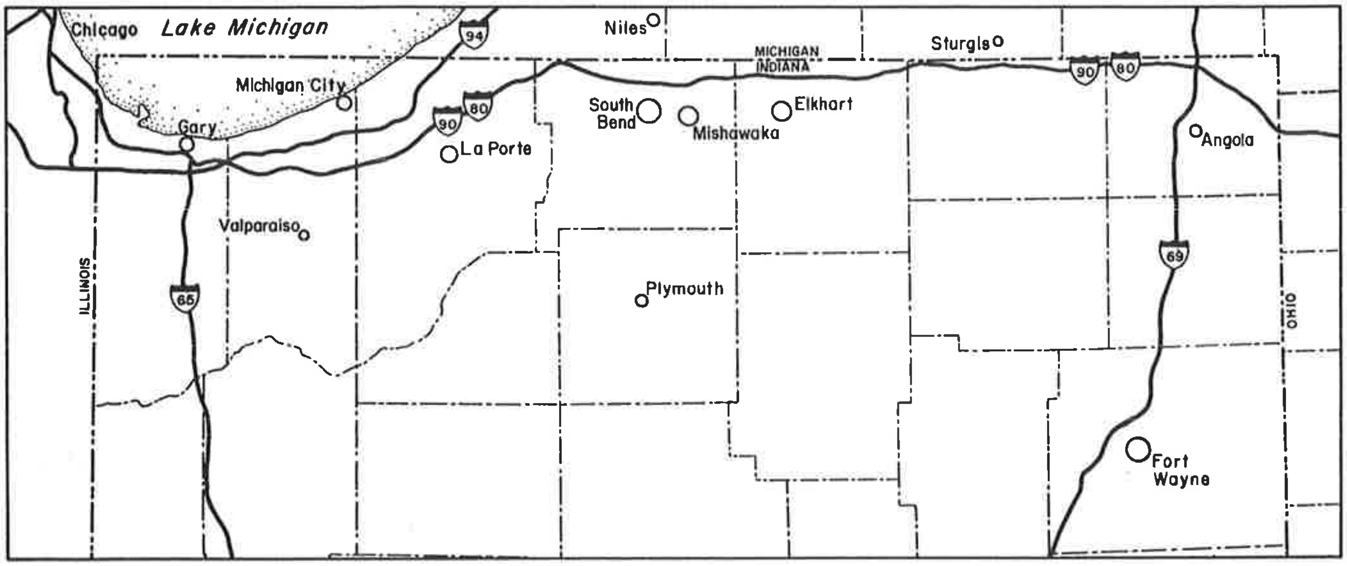

FIGURE 2 Location of Indiana Toll Road (I-80 and I-90) in northern Indiana.

weekdays with commuters and truckers, and relatively light weekend traffic. Nevertheless, a temporal clustering during weekdays is also not apparent.

The spatial autocorrelation analysis did reveal a significant amount of positive spatial autocorrelation (at the .05 significance level) for 5 of the 10 data sets analyzed. This result may reflect an underlying influence of heavier traffic volumes in the western part of the state due to the Chicago metropolitan area. It may also represent a greater number of accidents due to the mixing of traffic moving at different speeds, because the western part of this highway has a greater number of entrances and exits from the toll road than does the eastern end.

The spatial-temporal analysis consisted of a nearest-neighbor analysis of the motor vehicle accidents on a time-space surface and a spatial temporal autocorrelation analysis using Knox's statistic. The results of the nearest-neighbor analysis are presented in Table 5, which reveals a significant amount of clustering in 6 of the 10 data sets analyzed. Assuming comparability of the z scores between the one-dimensional spatial and temporal autocorrelation and the two-dimensional nearest-neighbor analysis, six of the two-dimensional cases

TABLE 4 VON NEUMANN'S Q STATISTIC, MORAN'S I STATISTIC, AND CORRESPONDING z SCORES

Year	Indices	Eastbound	Westbound
1983	Q (z)	1.80 (-2.01)**	1.84 (-1.57)
	I (z)	.1270 (1.67)	.1573 (2.05)**
1984	Q (z)	1.76 (-2.33)**	1.87 (-1.29)
	I (z)	.2098 (2.71)*	.1219 (1.60)
1985	Q (z)	1.95 (- .49)	1.85 (-1.47)
	I (z)	.1638 (3.13)**	.3177 (3.81)*
1986	Q (z)	1.84 (-1.62)	2.01 (.01)
	I (z)	.0862 (1.16)	.1133 (1.50)
1987	Q (z)	2.02 (.17)	1.90 (-1.02)
	I (z)	.1505 (1.97)**	.0789 (1.07)

* significant at .01 (z > 2.58)

** significant at .05 (z > 1.96)

TABLE 5 SPATIAL-TEMPORAL NEAREST-NEIGHBOR AND KNOX *R* ANALYSIS

Year	Roadway	n	NN Index	z	Knox-R	z
1983	East	337	.915	-2.99*	66	5.11*
1983	West	290	.877	-4.00*	46	3.57*
1984	East	323	.884	-4.00*	64	4.62*
1984	West	311	.964	-1.22	56	4.91*
1985	East	368	.938	-2.26**	68	4.15*
1985	West	353	.891	-3.92*	76	4.98*
1986	East	335	1.007	.26	24	.03
1986	West	340	.910	-3.17*	64	5.55*
1987	East	394	.973	-1.03	52	2.77*
1987	West	335	.976	- .83	52	3.71*

* A significant z for a two-tailed test at the .01 level is > ¦2.58¦.

** A significant z for a two-tailed test at the .05 level is > ¦1.96¦.

are stronger than their one-dimensional counterparts. This finding is to some extent consistent with the combining of the low-level temporal autocorrelation with the low one-dimensional positive spatial autocorrelation.

The level of temporal autocorrelation was the highest for roadways East-83, West-83, East-84, West-85, and East-86, although only two of these were significant. Of these five, the first four are strong in the two-dimensional analysis. Eastbound traffic in 1985 was having incidents that significantly clustered in space, but not time, and combining the two increased the level of clustering. Westbound traffic in 1986 that was not significantly clustered in time or space was significantly clustered in time-space. In four cases (West-84, East-86, East-87, and West-87) the nearest-neighbor analysis revealed no significant clustering in time-space.

Plots of three of these distributions are shown in Figures 3–5, where each box represents a traffic incident. The eastbound traffic incidents of 1983 are plotted in Figure 3. Notable attributes of this figure are (a) the vertical array of symbols at approximately Day 80 across the entire length of the tollway, (b) the clustering of incidents between Mileposts 0 and 25 through the entire year, (c) the vertical array of incidents between Days 350 and 365, and (d) a clustering of incidents around Day 150 between Mileposts 90 and 100. Of these four attributes, the first and third appear to be a function of snow and ice conditions according to climatological records, and the second appears to be related to the generally higher traffic volume near Chicago (which increases the probability of an incident). The reason for the clustering noted at Day 150 is not apparent, although its occurrence on Memorial Day suggests a traffic volume situation. The first three patterns are also evident in the westbound traffic of 1983 (see Figure 4), which is consistent with the regional weather pattern explanation offered. The fourth pattern does not appear in the westbound traffic.

As noted previously, regional weather conditions play a major role in the development of spatial clustering. Snowfall, snow coverage, ice, and rainfall are evident in the mapped data. There was also a period of several days in October 1987 when a clustering of incidents occurred near South Bend.

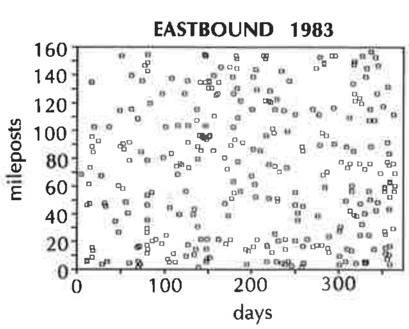

FIGURE 3 Time-space plot of accidents on Indiana Toll Road: eastbound roadway, 1983.

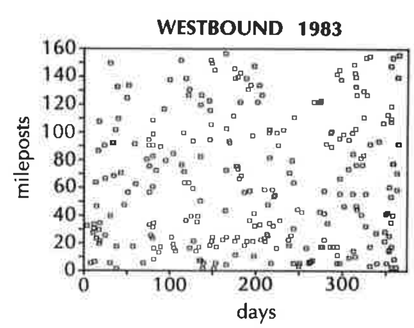

FIGURE 4 Time-space plot of accidents on Indiana Toll Road: westbound roadway, 1983.

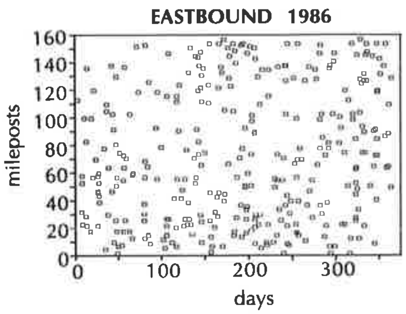

FIGURE 5 Time-space plot of accidents on Indiana Toll Road: eastbound roadway, 1986.

Local climate records indicate a record number of fog days during that month.

Figure 5 shows the eastbound traffic of 1986. It is included primarily because it represents a random distribution in time-space. Large areas of this time-space have no incidents, whereas in other areas there is an occasional overlapping of two or, on rare occasions, three incidents. Such a pattern is typical of a random two-dimensional distribution. From a safety analyst's perspective, this pattern is a desirable one.

Table 5 also presents the results of the Knox *R* spatial-temporal analysis of accident values. These results differ substantially from those of the nearest neighbor analysis and suggest a much stronger level of spatial-temporal autocorrelation in the pattern of values. The two methods are in perfect agreement in the nearly random pattern of data for eastbound traffic of 1986, but otherwise the Knox *R* analysis indicated highly significant spatial-temporal autocorrelation in every case.

The spatial-temporal results should not be viewed as conflicting. The nearest-neighbor analysis is examining the pattern of events in time-space. The Knox analysis is examining the similarity (autocorrelation) in the pattern of events in time and the pattern of events in space. From a residual analysis perspective, the Knox approach may be more useful; from an accident analysis perspective, the nearest-neighbor approach seems to yield more useful results.

POLICY IMPLICATIONS

Each of the situations analyzed implies the need for or the success of some public safety policy. Whether or not the traffic on the Indiana Toll Road is typical, the absence of significant temporal autocorrelation in motor vehicle accidents is a desirable attribute. This success may be attributable to policing, good road maintenance (snow removal or highway surface maintenance), or a good traffic use pattern.

The presence of spatial clustering implies that all is not perfect with this system. Weather conditions in given regions may create the spatial clustering of accidents, but clustering would then be expected to appear in the temporal analysis and it does not. The clustering may simply result from increases in accidents because of increases in traffic volume. One possible policy response might be to use on- and off-ramps to control traffic volumes. The spatial clustering may also be caused by poor highway design.

The time-space analyses, as reflected by the nearest-neighbor analyses, suggest only a few instances in which a tendency toward temporal clustering is combining with spatial clustering to make insignificant concentrations appear significant. The implications might be that poor weather conditions over a few time periods are combining with poorly designed ramps and resulting in the identification of a stronger level of clustering. The ability to identify such situations suggests that this approach to time-space analysis deserves further study.

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