Enhancing Road Traffic Safety: A GIS Based Methodology to Identify Potential Areas of Improvement

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ABSTRACT

It is well known that the major goal of the transportation system is to enhance mobility and crashes are unwanted by-products which have to be minimized while achieving the primary goal. Although general people value travel time more than any other outcomes of transportation system, traffic accidents impose huge economic burden on the society. A detail investigation of the State of California crash statistics showed overrepresentation of fatal, injury, alcohol related crashes, road departure crashes, speeding related crashes in Inland Empire and identified as one of the major transportation issues affecting this region. This seed-grant proposal aimed to investigate the reason behind the high crash statistics in Inland Empire by developing methodologies to identify crash hotspots and detecting the potential areas of safety improvements using Geographic Information System (GIS). However, significant challenges were faced during the research to obtain relevant crash data from Caltrans district 8. Hence the GIS based methodology was developed using data from another real city in the United States. The result of this study showed that spatial dependence plays a strong role in the analysis of road traffic injury crashes. These spatial dependences, accounted through the spatial autocorrelation helped detecting statistically significant clusters of fatal, severe and minor injury as well as pedestrian crashes. These clusters are overlaid with socioeconomic and road network layers to investigate if certain spatial, socioeconomic and traffic related factors are present near statistically significant crash clusters. Once this reconnaissance is completed, a more detailed site investigation is easier to find the contributory factors for fatal, injury and pedestrian crash occurrences.

INTRODUCTION

Identification of crash “hotspots,” “blackspots,” “high risk” or “high collision concentration locations” is a standard practice in departments of transportation throughout the USA to ensure efficient allocation of safety dollars in reducing crash frequencies and severities. There are fairly good numbers of literature focused on methods for identifying “hotspots” utilizing advanced statistical methods such as empirical Bayes (EB) technique (1-6), full Bayes methodology (7-8), simulation methodology (9) and other innovative methods (10). It is now unanimously accepted in safety research that EB technique outperforms any other simplified method of crash hot spot detection— especially the crash counts or rates methodology; nevertheless it is still seen that many cities and departments of transportation use these simplified techniques to rank high crash road segments, ramps and intersections for further improvements. A possible explanation of this statues quo could be the complexity of these mathematical techniques, requiring special training and skills in statistical analysis that often prevent the implementation of these superior methodologies in practice. Additionally, these approaches are not generally combined with any visual tool or mapping software that could help displaying the outcome of these techniques. As a result, these methodologies, although sound and appropriate, have often been under-used by cities and DOTs, and they still depend on their in-house tools (may not be very accurate and sophisticated) to allocate their limited resources to make important decisions about ranking and improving high crash locations. Another drawback noticed in many DOTs is that they do not maintain a GIS crash database, which means they are unable to perform any GIS based crash mapping to detect concentration of high crash locations on their road network. While the GIS based methods may or may not be as superior as EB method, it is at least better than crash count or crash rate methods. Moreover, if overlaid with other layers, the GIS could help associating high crash locations with other crash causal factors, especially factors that are spatial in nature. There are also increasing interest to find the spatial factors affecting road traffic accidents, especially fatal and injury crash occurrence. A major reason for this growing interest is the fact that spatial factors such as land use, population density, population distribution, socio-economic factors as well as environmental factors have strong influences on crash occurrence in addition to the commonly known geometric design elements of roadways.

In transportation safety applications, GIS has been widely used to geo-code accident locations, developing pin maps of crashes and database queries as performed by Levine et al.(11,12), Affum and Taylor (13), Austin et al. (14), Kim and Levine (15) and Miller (16). However, some researchers (11, 12, 16-21) incorporated some of the powerful analytical tools available in GIS software such as buffer, nearest neighbor method, simple density and kernel density estimation method of crash cluster detection to show spatial distribution of crashes at the road network level.

While GIS has been used in these studies not only for visual representation, but to enhance data integration and efficient handling of information from various sources; some of the powerful spatial statistical analysis tools are often under-used in transportation safety analysis. As mentioned earlier, even with the rapid advancement of GIS in the last few decades, some public agencies do not have their crash database in GIS platform, and as a result they are unable to use some of these powerful but straightforward statistical analysis tools available in GIS. Another drawback of not using GIS in crash hotspot detection is the possibility of ignoring important spatial location specific information, which might have strong influence in crash occurrence. For example, spatial features near road networks might influence elevated crashes at a particular location, which will be very hard to detect in the absence of a tool like GIS. However, the good news is that, there are transportation research professionals who are very much interested in exploiting various advanced analytical tools available in commercial GIS software to investigate any association of crashes with spatial features of interest around a transportation network. For example, Flahaut et al. (22) used two different spatial statistical techniques: global autocorrelation index and kernel estimation to identify clusters of road segment crashes in Belgium; Xiao-Qin et al. (23) used hot-spot analysis tools available in GIS to locate snow related crash locations; Bejleri et al. (24) used customized methodologies in GIS to locate road segments and intersections with high pedestrian and bicycle related crashes. In addition to the issue of ignoring possible association of spatial physical and environmental factors by not using GIS, it is also important to mention that very few, if not any, studies consider the effect of spatial site specific factors in detecting hazardous road locations. While the EB method is considered to be efficient in hazardous site detection, researchers often consider the traits of a location, mostly through traffic volumes and sometime through geometric design properties. Although traffic volume is considered to be the single most important exposure variable, it is also well known that spatial location specific factors help explaining unobserved heterogeneity in crash data. For example, in a study, Bauer and Harwood (25) showed that traffic volume related variables could capture 16% to 38% of the variability in crashes, leaving a small (5 to 14%) portion of the variability explained by geometric design variables. However, the unexplained variability (about 40% in this case) could be attributed to both structured as well as unstructured error terms. In another study, Greibe (26) developed prediction models for both road links and junctions and showed that the road link model could capture more than 60% of the systematic variation, but the intersection model had lower explanatory power. Chin and Quddus (27) confirmed like others that traffic volumes are the most important factor, or main effect, predicting crashes. While these studies concluded traffic volume as the primary indicator variables, there are researchers such as Ivan et al. (28) and Ossenbruggen et al. (29) who examined the effect of land use on road segment crashes; Karlaftis and Tarko (30), Noland and Quddus (31) and Aguero-Valverde and Jovanis (32) investigated the effects of demographic patterns and weather on county-level crashes. However, none of these studies had been applied at the intersection level to test if spatial factors have significant influence in high crash location detection. The omission of spatial site specific characteristics could lead to erroneous identification of crash hotspots or black-zones due to the fact that spatial autocorrelation is ignored. The concept of spatial autocorrelation is important when specific attributes of a variable tend to have interdependence over space. This phenomenon is true in case of so called crash hotspots or black-zones, where there are not only high frequency of crashes, but also higher concentration of certain types, maneuvers or other specific attributes of crashes are observed and tend to be overrepresented. In such cases, important information would be lost if spatial dependence of crashes is ignored.

With this background, the primary aims of this research were:
1) First of all, to develop a GIS based crash hotspot detection methodology by utilizing spatial statistical analysis tool available in GIS, and
2) To identify association with spatial locational factors that has strong influence on crash occurrence.

IDENTIFICATION OF SPATIAL CONCENTRATION OF CRASHES USING GIS

There are several analytical tools available in GIS to analyze point features such as road traffic crash occurrences. Two of the very common point pattern detector tools available in GIS are i) quadrant analysis or the density analysis tool and ii) the nearest neighbor analysis tool. In recent years Kim and Levine (15) used nearest neighbor method to detect clusters of pedestrian crashes. They developed standard deviational ellipse of each of the nearest neighbor clusters and the number of points these ellipses contain to measure the dispersion and orientation of the points around the mean center of the clusters. Pulugurtha et al. (21) utilized the concept of quadrant or grid based analysis to compute crash density/ concentration as a measure to detect crash hot spots. In doing that they used two different techniques of density estimation, such as a) simple, and b) kernel density estimation tools available in Arc GIS toolbox. As expected, kernel density methodology provided higher accuracy of hot spot detection due to its sophisticated mathematical algorithm as opposed to the simple density computation method. After computing the densities, these researchers developed a composite score of high crash location ranking by combining three different methods: crash frequency, crash density and crash rates method. Sando et al. (33) also utilized a nearest neighbor algorithm for crash pattern detection, and compared the merits of this methodology with other statistical techniques such as regression analysis, neural network and Bayesian techniques. These authors suggested that in the absence of a priori knowledge about probability distribution of the count patterns; a nearest neighbor is very effective.

While density analysis and nearest-neighbor analysis are commonly used in point pattern detection, both density and nearest-neighbor analysis treat all points i.e. crashes in this case, as if they are the same. In other words, these two methods analyze only the location of the point, but not their attributes. Spatial statistical tools on the other hand take both the location of the crash and their attributes into account. As a result it is considered to be more powerful as it takes not only the location of the crash into account, but also the activities happening at a particular location. Specifically, spatial autocorrelation analysis assesses the extent to which the value of a variable X at a given location i, is related to the values of that variable at contiguous/neighboring locations. Hence the basic concept of spatial autocorrelation is related to the interdependence of a specific attribute over space. Clearly, this is the main idea behind investigating high crash concentration locations, i.e. to identify locations with unusually high numbers of specific types of crashes. The assessment of spatial correlation involves analyzing the degree to which the value of a variable for each location co-varies with values of that variable at nearby locations (22). When the level of co-variation is higher than expected, contiguous locations have similar values and autocorrelation is positive. When the level of co-variation observed are negative, high values of the variable are contiguous with low values and the autocorrelation is negative. The lack of significant positive or negative co-variation suggests the absence of spatial autocorrelation. To quantify the spatial correlation, two popular indices: *Geary's Ratio* and *Moran's I* are generally used. These are known as global method of assessing spatial autocorrelation, and they measure and test if patterns of point distributions are clustered or dispersed in space with respect to their attribute values. In this context, it is important to mention that both *Geary's Ratio* and *Moran's I* measure autocorrelation for interval or ratio data. Most analysts favor *Moran's I* as its distributional characteristics are more desirable and this index has greater general stability and flexibility. *Moran's I* index is defined as

$$I = \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_i \sum_j w_{ij}}$$

where w_{ij} is the weights representing proximity relationships between location i and neighboring location j, x_i is the value of the interval or ratio variable X at locations i, $\bar{x}$ the mean of all x_i's, n the total number of locations, i = 1, 2, ………..,n and j = 1, 2, ………..,n and $s^2 = \sum_i (x_i - \bar{x})^2 / n$, a measure of sample variance. In case of point pattern detection, generally the weight w_{ij} is often used as the inverse of the distance between two points i and j. This is derived from first law of geography that suggests larger weights to points that are close and smaller weights to points that are far apart. Hence w_{ij} is generally defined as $1/d_{ij}^{\delta}$, where δ may be taken any appropriate value such as 0.5, 1.0, 1.5, 2.0 or any other number based on specific characteristics or empirical evidence associated with geographic phenomena in question. Many empirical studies in spatial autocorrelation have shown that a δ value of 2.0 for the exponent of distance indicates a stronger reduction in the importance of the points located further away, making spatial association stronger with closest neighbors. Hence a widely acceptable value of δ = 2.0 has been adopted in this study.

In terms of choice between *Geary's Ratio* and *Moran's I* index, the major difference between *Geary's Ratio* and *Moran's I* is that in case of *Geary's Ratio* the numerator consists of the square of the difference in attribute values for point i and point j such that $(x_i - x_j)^2$ is considered instead of the measure $(x_i - \bar{x})(x_j - \bar{x})$ in case of *Moran's I*.

While this global method of assessing spatial autocorrelation existed for longer time, there are also Local Indicators of Spatial Association (LISA) such as local version of *Moran's I*. This index is used to indicate the level of spatial autocorrelation at the local scale, i.e. a value of the index is calculated for each spatial unit i. The local Moran statistic for unit i is defined as

$$I_i = (x_i - \bar{x}) \sum_i w_{ij} (x_j - \bar{x})$$

Similar to global *Moran's I*, a high value of *local Moran* indicates clustering of similar values and a low value means a clustering of dissimilar values of a variable. The cluster analysis tool available in GIS provides estimation of *local Moran's* values and the associated Z scores for all locations in the study area. The Z score represents the statistical significance of the index value, i.e. whether the apparent similarity (or dissimilarity) in values between the feature and its neighbors is greater than one would expect simply by chance. A high positive Z score for a feature indicates that the surrounding features have similar values and help finding locations with specific type of crash concentration. A low negative Z score for a feature indicates the feature is surrounded by dissimilar values. Once these Z scores are calculated, it is possible to identify statistically significant spatial locations with high crash concentration.

APPLICATION OF THE METHODOLOY TO DETECT HIGH CRASH INTERSECTIONS

The methodology described in previous sections is applied to detect crash concentration location of a real city in the USA. While the focus of this study is to detect high crash locations with fatal, severe injury and minor injury crashes, the methodology could be applied to detect any other crash types. In the following sections, descriptions of the data used are discussed first, followed by the application of spatial statistical techniques in GIS to detect crash concentration locations, and discussion of the findings.

Data Used

Current growth and expansion of the Inland Empire along with the historically high crash statistics in this region, definitely seeks thorough investigation crash statistics and potential areas of safety enhancement and this was the primary aim of the seed grant project. To perform this task crash data were requested from the Inland Empire region, from Caltrans district 8. While some data were obtained from Caltrans in the beginning of the project, the team was unable to receive any further data instead of continued requests. Due to the absence of the required dataset, the research team went ahead and developed the methodology using crash data from a real city in the USA. The data used in this study are obtained from three different sources, including: a) crash data, b) spatial characteristics, and c) demographic data. The study sites examined in the study are signalized intersections including four-legged and T- junctions.

Crash data

The crash data for this study are obtained from the Accident Location Identification System database maintained by a western State. The database contains all of the micro-level information about crashes, such as the type of crash, severity, time of occurrence, crash location and description of sites, vehicle maneuvers before a crash, direction of movement of the vehicle prior to the crash, information about the people involved in the crash (both driver and passenger information), as well as vehicle information. For this study crash data from 2001 to 2004 at signalized intersections are collected and analyzed. Previous research on crash hot-spot identifications (9) suggests that an average of three years crash data should be used to detect high crash concentration locations. This minimizes abnormal fluctuation of crashes for a certain year as well as regression to the mean effect often described in safety literature. As a result a combined crash data from three year time period were used in this study and the data are categorized as intersection-related crashes if a crash occurred within the curb-line limits of the intersection, or if it occurred within the influence area of the intersection, defined as within 250 ft along any leg of the intersection (from the intersection center point).

Demographic and socioeconomic data

To investigate the spatial association of crash occurrence, demographic distribution of a location is very important to investigate. In case of pedestrian and bicycle related crashes it is generally assumed that people involved in crashes live or work at that place. While no such assumption could be made in case of other crash types, population density and demographic distribution could be associated with specific crash attributes. For example, if certain regions have higher than average young population and at the same time statistically significant clusters of crashes are involved with young inexperienced drivers, special investigation should be needed at those locations. Also, findings from previous research indicate crashes tend to be clustered in regions with high poverty. This study uses census track population density data, socio-economic data such as the percentage of populations below poverty and age distribution data to create surface data in raster GIS. These layers are then overlaid with crash clusters to detect any special association.

Spatial variables

Besides crash data, demographic distribution and socio-economic data, some spatial variables that are used in this study are locations of schools and drinking establishments. While one might question the inclusion of these two particular spatial variables in this study; they are considered because they span the range of what might be considered to be truly causal or surrogate of causal variables in traffic safety. It is of interest to investigate if spatial features such as schools or drinking establishments like bars and pubs have strong influence in pedestrian crash occurrence. While, it is not claimed, that the spatial variables are perfect measures for the underlying causal mechanisms, but it is believed that all variables are capturing the effect of underlying causal mechanisms even if not directly causal.

While school-zone related data was directly obtained from the County, finding the locations of drinking establishments was not as straightforward. First of all, the availability of a GIS layer representing all the drinking locations did not exist. Secondly, the available GIS tiger files show the locations of establishments with liquor licenses; however, these may not be locations where people go, spend time and drink alcohol. For example, many supermarkets obtain liquor licenses, however it is unlikely that alcohol purchased at these locations will also be consumed there. To deal with this problem, addresses of bars and pubs were identified from the yellow pages. Then geo-coding service in GIS was used to locate those addresses on street map and a new layer was created showing the location of bars and pubs as a point. These two layers are overlaid with crash layers and demographic distribution layers to reveal their association with crash hot spots.

The spatial statistical method in GIS

To examine the spatial pattern of crashes this study focused on fatal, severe and minor injury crashes rather than total number of crashes. Also pedestrian crashes are examined to check their patterns. As mentioned earlier, spatial autocorrelation method is advancement over quadrant or nearest neighbor methods of spatial pattern detection as it takes not only the location of points but also the attributes of the locations into account. As a result, this is a useful technique to detect locations with higher than average probability of injury crash occurrence— crashes involving huge economic burden for any jurisdiction. To perform this task, spatial autocorrelation coefficient using *Moran's I* index and associated Z-score are computed for fatal and injury crashes. As mentioned already, a high positive Z score for a feature indicates that the surrounding features have similar values. Hence the locations where fatal and injury crashes have Z-scores of >=2 are locations with statistically significant crash clusters at the α =0.05 level. These intersections are extracted from the original analysis and are displayed in Figure 1. From this figure, it is quiet clear that there are four main regions in the City, i.e. northern, eastern, middle and southern part where fatal and injury crashes are concentrated. Once these regions are investigated closely, it is identified that in all these four zones, pedestrian fatal crash clusters are located within quarter mile radius of schools near the intersections. However, no such strong association is observed in case of severe or minor pedestrian crashes. Also a close look at Figures 2, 3, 4 and 5 indicates that vehicle related fatal crash clusters are not very close to schools or even bars or pubs. On the other hand, severe and minor crashes that are not related to pedestrian tend to be clustered near bars and pubs. From these maps it is also observed that each zone 1 and 2 consists of at least one intersection that has cluster of fatal, severe as well as minor injury crashes, and they are eventually close to bars and pubs. When these crash clusters are compared with population density (Figure 6) and poverty distributions (Figure 7), it is generally observed that crash clusters are present in medium to high density locations and not so much in locations with lower population densities. However, crash clusters seem to have a weak correlation with poverty in this study. For example, the zone 2 in Figure 7 represents very high population below poverty than zone 1, 3 and 4, but zone 3 is associated with large numbers of crash clusters of any type. Hence, it is hard to conclude the correlation between poverty and crash clusters in this study. However, from these crash distributions it is quite clear that zone 2 and zone 3 requires much attention in terms of safety enhancement. Finally, the crash clusters are overlaid with two different age distributions, age 15-24 (Figure 8) and age 65 and up (Figure 9). While Figure 8 did not indicate any positive correlation with young population and crash clusters, Figure 9 shows that elderly are involved in crashes in locations with medium to high elderly population. As teenage and young drivers tend to be overrepresented in crash data and elderly population have the highest involvement rate in terms of number of crashes per mile driven, these are the two population distributions are investigated in details. The result of these map analyses shows that crash involvements of young drivers are somewhat sporadic but are often near spatial features such as schools and pubs. However, further investigations of specific locations are needed before establishing any correlation with crash clusters and specific age groups.

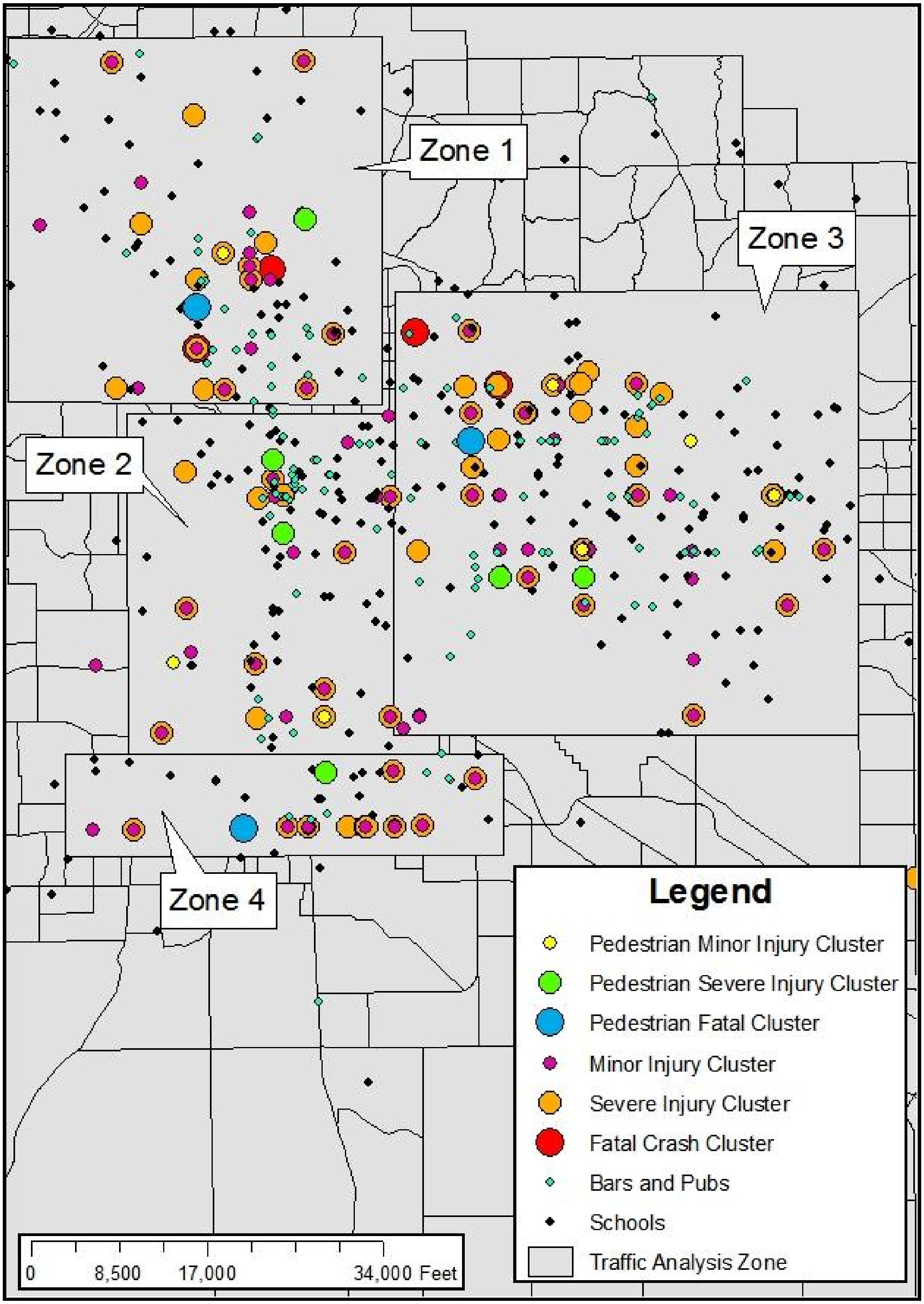

Figure 1: Distribution of crash clusters with schools and bars and pubs.

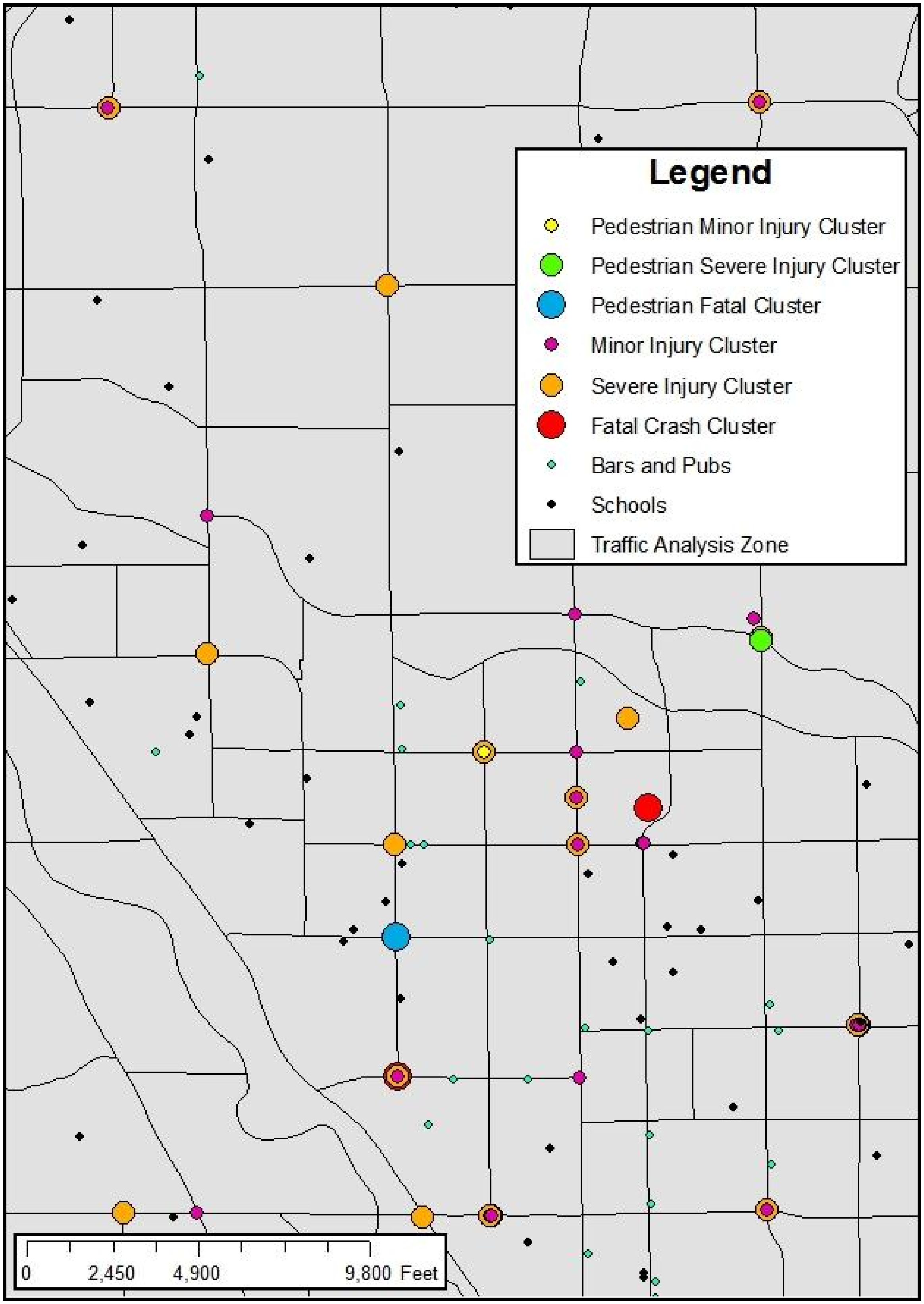

Figure 2: Distribution of crash clusters with schools and bars and pubs, Zone 1.

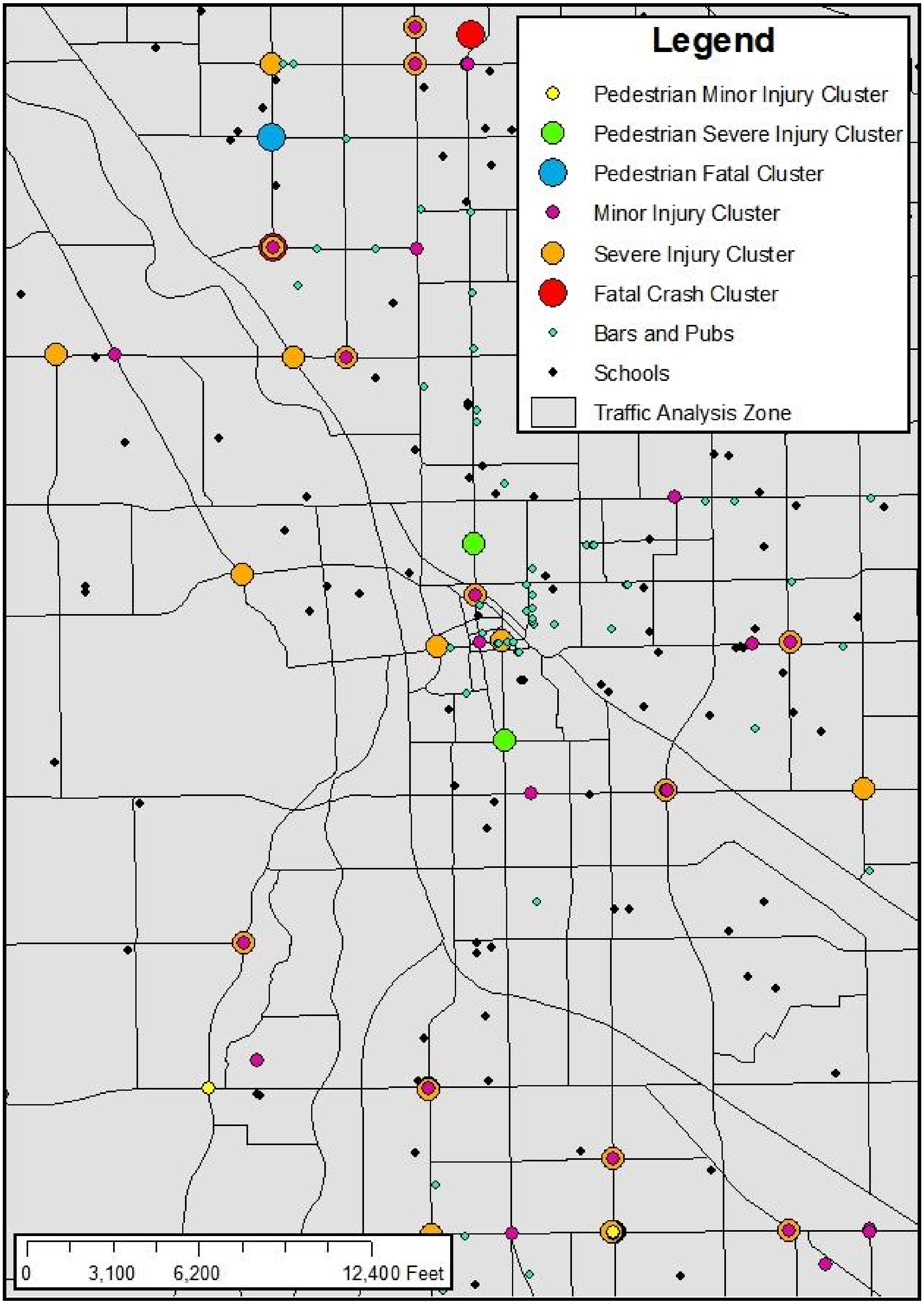

Figure 3: Distribution of crash clusters with schools and bars and pubs, Zone 2.

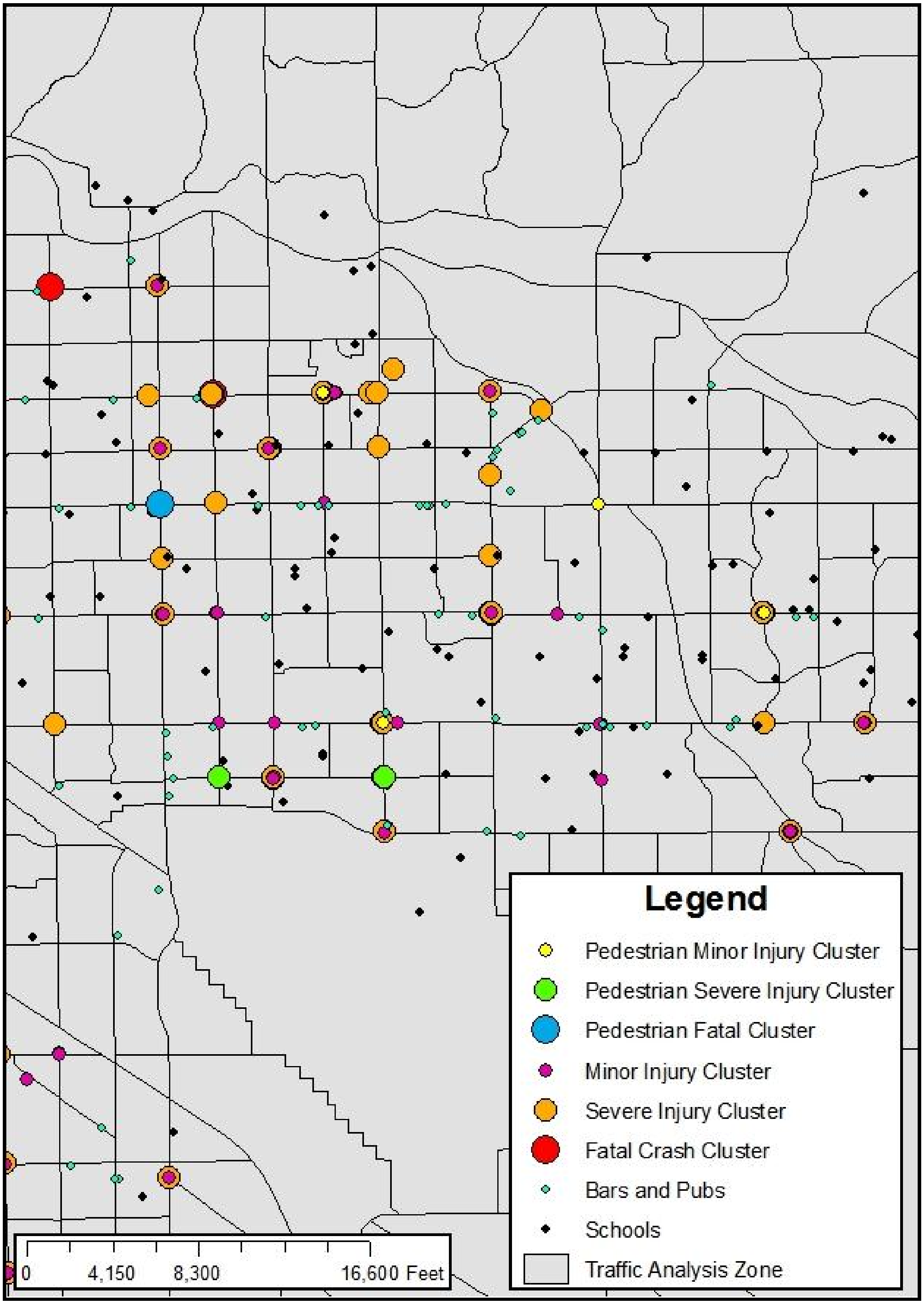

Figure 4: Distribution of crash clusters with schools and bars and pubs, Zone 3.

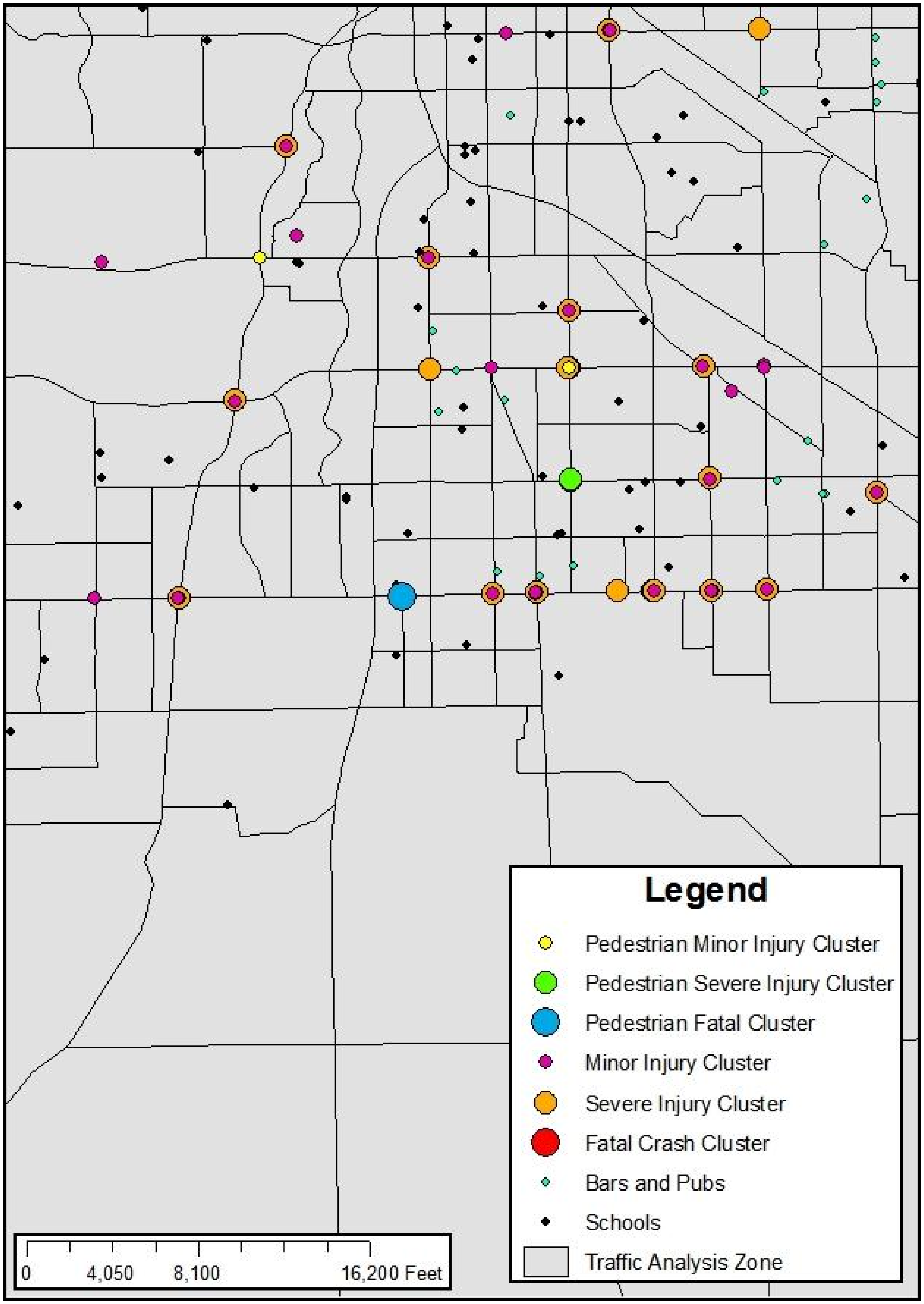

Figure 5: Distribution of crash clusters with schools and bars and pubs, Zone 4.

Figure 6: Crash clusters with population density, schools, and bars and pubs.

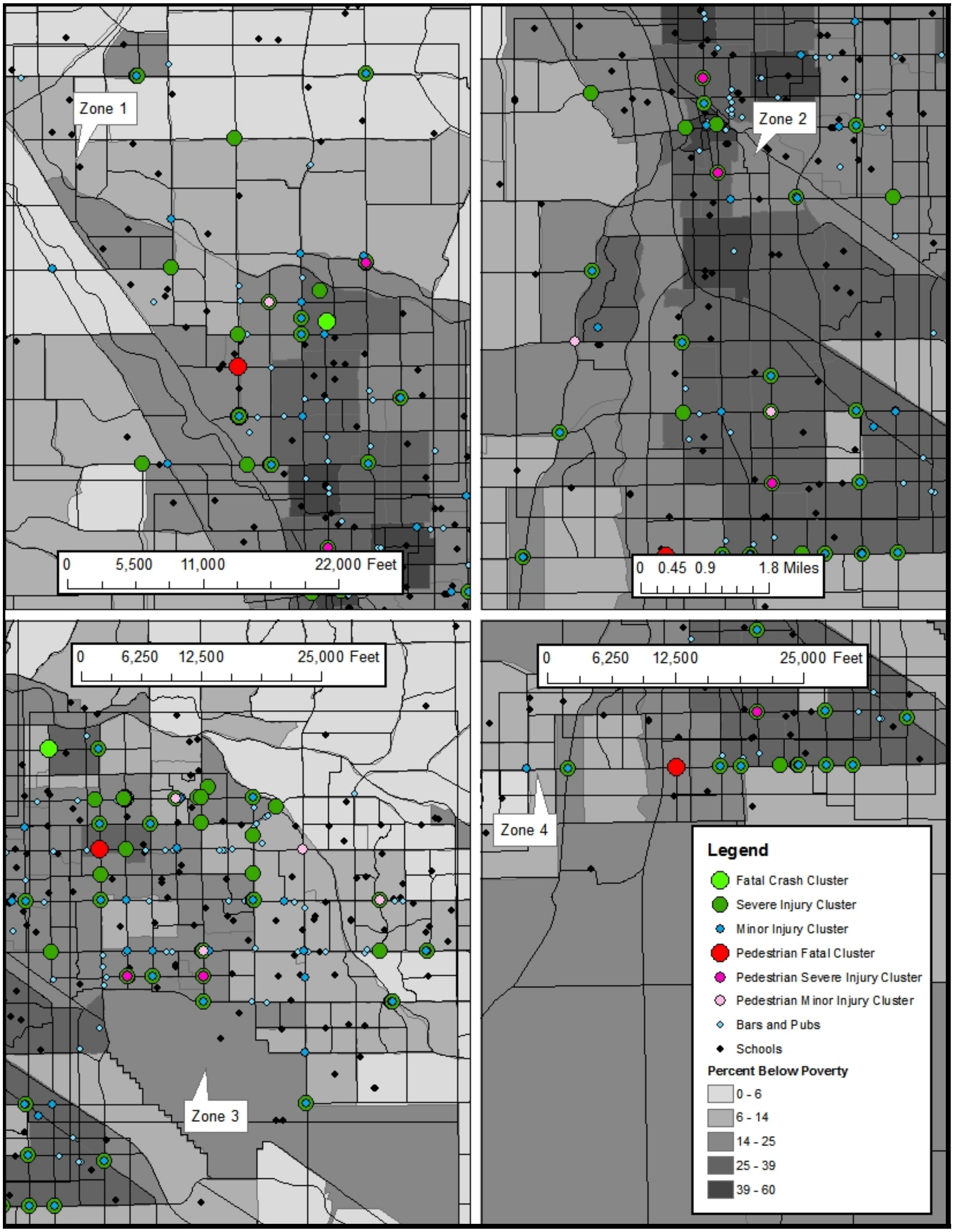

Figure 7: Crash clusters with percent below poverty, schools, and bars and pubs.

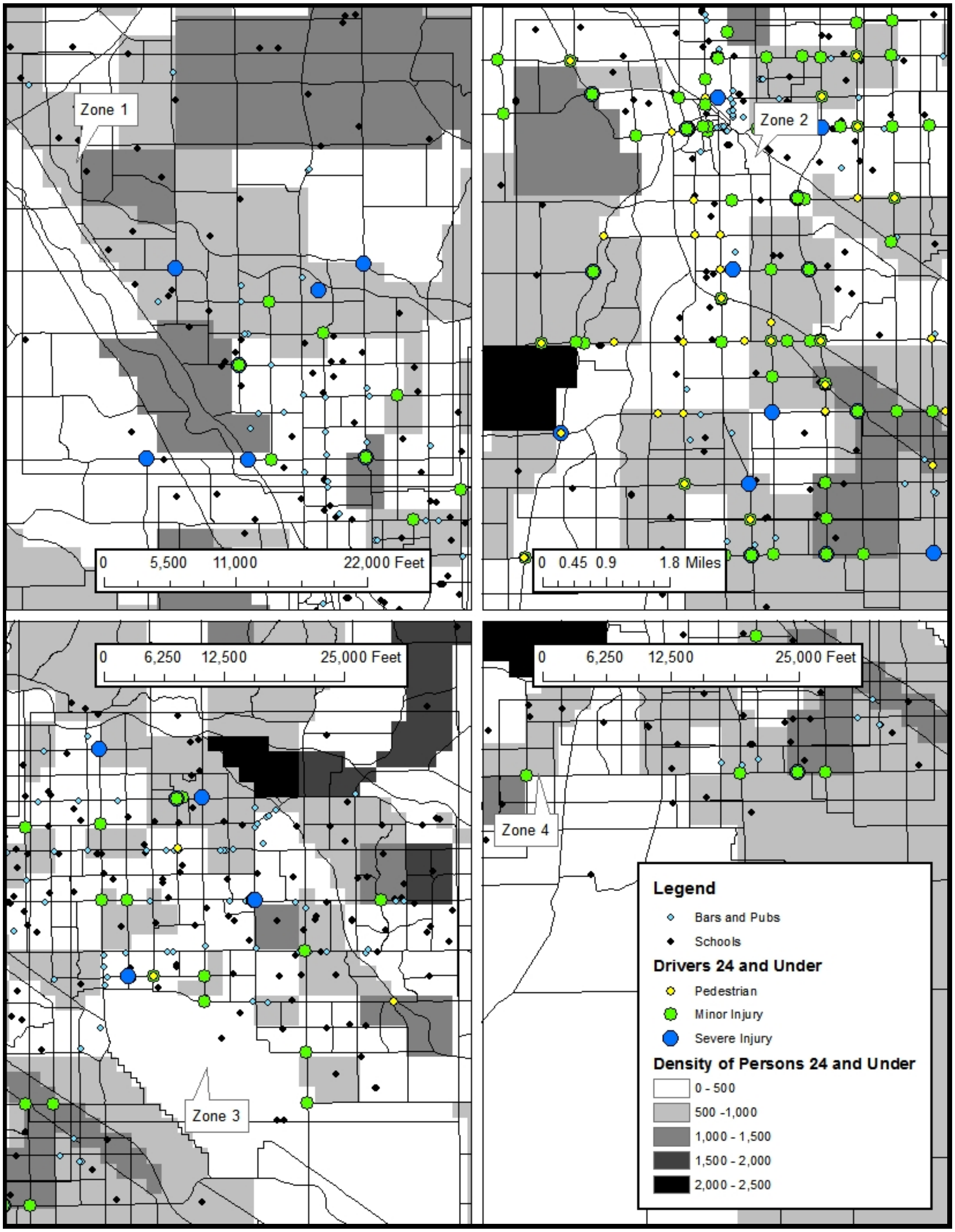

Figure 8: Crash clusters by drivers age 24 and under with density of persons age 24 and under, schools, and bars and pubs.

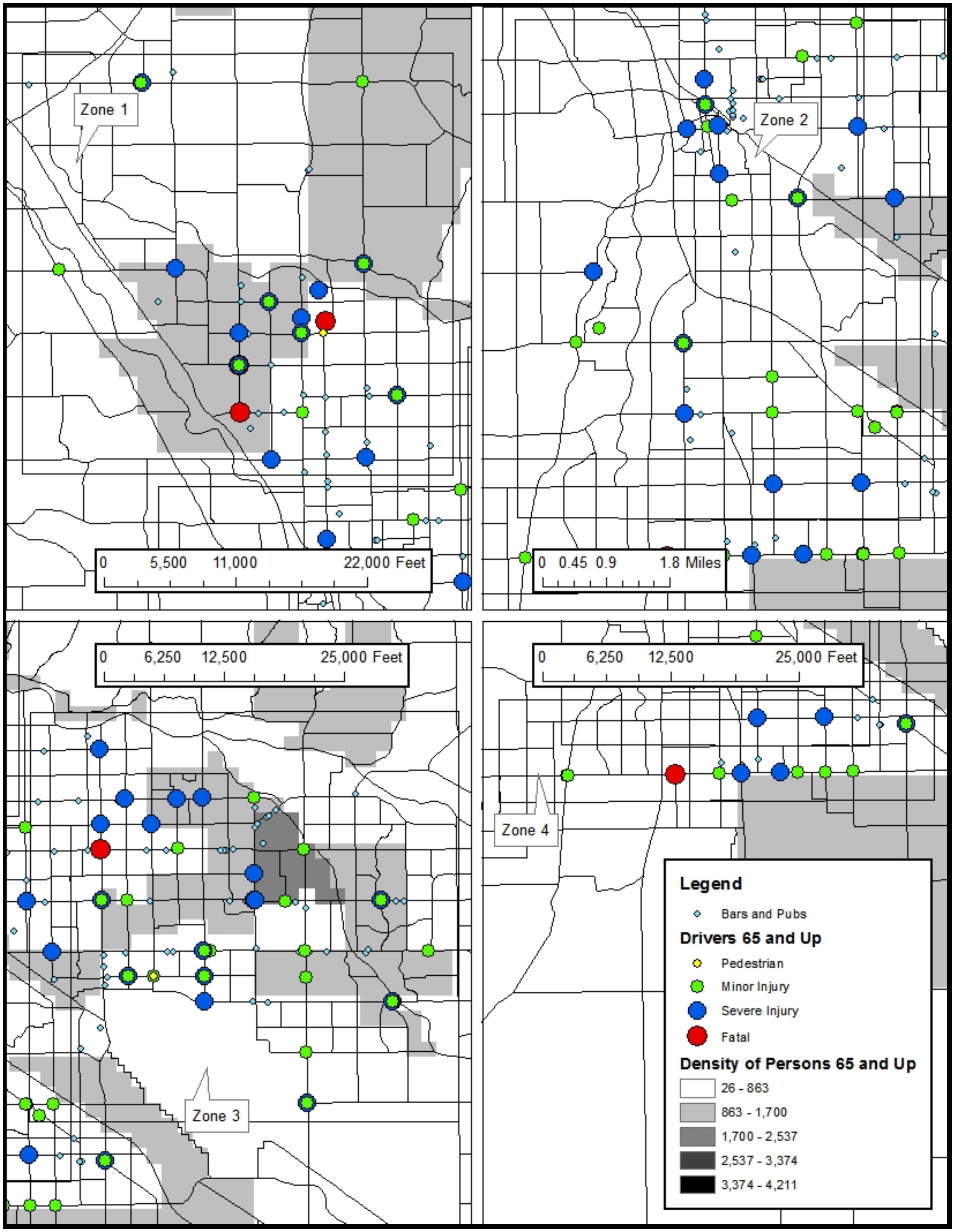

Figure 9: Crash clusters by drivers age 65 and up with density of persons age 65 and up and bars and pubs.

CONCLUSIONS

This study develops a GIS based methodology for fatal, injury and pedestrian crash cluster mapping and analysis using crash data and various spatial, demographic and socioeconomic data available from a real city in the USA. The cluster detection in this study used readily available spatial autocorrelation tools in GIS to identify crash clusters. As a result, this method is straightforward to apply but at the same time accurate in meaning that crash clusters are not just detected by frequency or crash concentration/density but by investigating the spatial correlation of the crash attributes. Statistical significance of these created clusters is also checked with Z-statistics. Once these clusters are mapped, subjective judgments are used to detect clusters that are associated with spatial attributes such as schools, bars and pubs, population density, age distribution and poverty data. The output map analysis indicates that there are some correlations with school locations and pedestrian crashes as well as bars and pubs with minor and severe crashes related to vehicles. In addition some common patterns of higher number of minor and severe injury clusters are observed across locations with high density populations, but correlation with socioeconomic distribution such as percentage of people below poverty or age distribution are not very significant. Once these maps are created and checked, they may help local transportation agencies to understand issues of fatal, injury and pedestrian crashes so that further site specific investigations are possible to enhance safety.

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