Accident Analysis and Prevention 43 (2011) 769–781

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Does street network design affect traffic safety?

Wesley Earl Marshall[a,*], Norman W. Garrick[b]

[a] University of Colorado Denver, Department of Civil Engineering, 1200 Larimer Street, Campus Box 113, Denver, CO 80217, United States
[b] University of Connecticut, Center for Transportation and Urban Planning, Civil & Environmental Engineering, U-37, Storrs, CT 06269-2037, United States

ARTICLE INFO

Article history:
Received 18 September 2009
Received in revised form
28 September 2010
Accepted 24 October 2010

Keywords:
Road safety
Street network
Connectivity
Density
Negative binomial
Sustainable infrastructure
Community design

ABSTRACT

Negative binomial regression models were used to assess the effect of street and street network characteristics on total crashes, severe injury crashes, and fatal crashes. Data from over 230,000 crashes taking place over 11 years in 24 California cities was analyzed at the U.S. Census Block Group level of geography. In our analysis we controlled for variables such as vehicle volumes, income levels, and proximity to limited access highways and to the downtown area. Street network characteristics that were considered in the analysis included street network density and street connectivity along with street network pattern.

Our findings suggest that for all levels of crash severity, street network characteristics correlate with road safety outcomes. Denser street networks with higher intersection counts per area are associated with fewer crashes across all severity levels. Conversely, increased street connectivity as well as additional travel lanes along the major streets correlated with more crashes. Our results suggest that in assessing safety, it is important to move beyond the traditional approach of just looking at the characteristics of the street itself and examine how the interrelated factors of street network characteristics, patterns, and individual street designs interact to affect crash frequency and severity.

1. Introduction

Around the world, 1.2 million people are killed and approximately 50 million people are injured in road crashes (World Health Organization, 2004). In the United States alone, the economic cost of road crashes and injuries exceeds $230.6 billion annually (World Health Organization, 2004). Given the impact of road crashes on the economy and quality of life, it is surprising to note that the road fatality rate in terms of the number of fatalities per population and per miles traveled in the United States continues to fall further and further behind that of other comparable industrialized counties. Less than 40 years ago, there were a dozen major countries with road fatality rates exceeding that of the United States (International Traffic Safety Data and Analysis Group, 2005). As of 2004, every single one of the 29 Organisation for Economic Cooperation and Development (OECD) countries reporting statistics has a lower road fatality rate per population than the U.S., and ten of those countries have rates less than half the U.S. road fatality rate (OECD, 2006). One of those countries, the Netherlands, has brought their road fatality rate over the last 40 years from 25 fatalities per 100,000 population per year to under five, which is less than a third of the current U.S. fatality rate per 100,000 population.

There are a many possible reasons as to why the U.S. is lagging behind the rest of the world when it comes to road safety. One possible explanation that this research will focus on is that we often fail to pay enough attention to overall community design when it comes to safety. For instance, various researchers have shown that street widening projects, typically proposed in order to improve safety and relieve congestion, actually result in a reduction in safety (Noland, 2000; Sawalha and Sayed, 2001; Huang et al., 2002; Dumbaugh, 2006; Swift et al., 2006). In this case, the focus has been too much on assessing how the changes affect individual street segments rather than how those changes might impact the community as a whole. A second example of failing to regard overall community is in how we often attempt to improve safety on residential streets by minimizing the opportunities for through traffic. What is missing is the sense that limiting street connectivity in residential neighborhoods can impact safety elsewhere (Ewing et al., 2002; Ewing and Dumbaugh, 2009).

Hence in this paper, we probe beyond the street, corridor, and neighborhood levels of analyses to determine how aspects of overall community design might affect road safety. More specifically, the goal is to find out more about how characteristics of the street network – in terms of features such as street connectivity, street network density, and street network patterns – are associated with road safety outcomes.

In this research we carry out a spatial analysis of 11 years of crash data in 24 medium-sized California cities. The cities were

* Corresponding author. Tel.: +1 303 352 3741; fax: +1 303 556 2368.
E-mail addresses: wesley.marshall@ucdenver.edu, wesleyemarshall@gmail.com (W.E. Marshall).

0001-4575/$ – see front matter
doi:10.1016/j.aap.2010.10.024

selected from an initial database of over 150 California cities to best represent a geographically diverse collection of 12 medium-sized cities with good safety records and 12 with poor safety records with respect to the number of road fatalities per capita in the transportation system. Street network measures were combined with street characteristics, socioeconomic data, traffic flow information, and over 230,000 individual crash records geo-coded in a Geographic Information System (GIS) database. The analysis was conducted at the U.S. Census Block Group level of geography for over 1000 distinctly populated Block Groups. Statistical negative binomial regression crash models were estimated for three response variables: total number of total crashes, severe injury crashes, and fatal crashes.

By characterizing the street networks of these cities and the representative street design characteristics, the goal is to capture the safety implications of different street network patterns and to account for the potential implications of the street design features while controlling for variables such as vehicle volumes, income levels, and proximity to limited access highways and the downtown area.

2. Background

Over the course of the last century, there has been a dramatic shift in American street patterns and community design. In particular, the U.S. experienced a transition from the traditional gridded street layouts of the first part of the twentieth century to increasingly more dendritic, tree-like street networks of the post-1950s period (Taylor, 2001). In describing these changes, many observers focus on the shape and connectivity of the street networks but typically ignore another factor – street network density – that has progressively decreased over the last half of the century. Despite their fall from favor, connected street networks are widely considered to have some advantages, including directness of travel, more route choice options, and higher network reliability. The trade-off for these advantages – as touted despite the lack of technical evidence by entities such as the Federal Housing Authority (FHA) in the late 1930s with Technical Bulletins No. 5 and 7 (Tunnard, 1963) and the Institute of Transportation Engineers (ITE) with their "Recommended Practice for Subdivision Streets" in 1965 (Southworth and Ben-Joseph, 1997) – is commonly believed to be increased through traffic on local roads and a reduction in safety (Lerner-Lam et al., 1992).

The result was that from the 1950s through the late 1980s, very few new developments in the United States featured a gridded street pattern; instead, hierarchical layouts became the standard (Southworth and Ben-Joseph, 1997). By 1992, this pattern of building hierarchical street networks had started to change with over 50 neo-traditional neighborhood design projects either in the planning stages or in construction (Lerner-Lam et al., 1992). With this influx of more traditional street designs came a small but growing body of research on the pros and cons of different street network structures. Thus far, much of the prevailing research related to street network measures has concentrated on issues such as mode choice, physical activity, and obesity (Ewing and Cervero, 2001). While the explicit relationship between street networks and road safety is beginning to garner more interest, the subject still has not been extensively studied.

An early road safety study from the 1950s by Marks is one of the first to address the perceived safety problems of grid street patterns compared to hierarchical designs (Marks, 1957). Based on 5 years of crash data for 86 residential areas, Marks found almost 8 times more crashes on the gridded streets and 14 times more crashes at the four-way intersections in a grid design than at the T-intersections found in dendritic arrangements. The reason purported for these results was the relationship between increased residential street connectivity and the probability of increased through traffic at higher speeds. Although this study continues to be influential, the researchers paid little attention to some very important considerations such as actual street patterns, the density of these street networks, the potential for crash migration, or the observed levels of crash severity.

Kim et al. (2006) found that the parts of Hawaii with higher populations and more jobs were associated with more crashes when controlling for vehicle volumes. And in a set of papers from a recent 3-year study of street networks and safety in Calgary that also controlled for vehicle volumes, Rifaat and Tay found that street networks comprised of loop and lollipop-type designs were safer than gridded street networks (Rifaat and Tay, 2009, 2010; Rifaat et al., 2009). Conversely, Noland and Quddus found that wards in England with densely populated areas had fewer traffic fatalities and that increased minor street length densities were associated with decreases in slight injuries. In a Virginia study, Lucy and Lewis (2009) found the safest jurisdictions to be those with the highest population density. Ladron de Guevara et al. (2004) found that higher intersection densities in Tucson, Arizona were correlated with fewer fatal crashes and injury crashes but more property damage only (PDO) crashes.

Overall, the work that has been reported has shown inconsistent results. One set of studies associates more crashes with street networks that exhibit more urban qualities such as more centerline miles of streets, more connectivity, higher populations, and higher population densities (Marks, 1957; Ladron de Guevara et al., 2004; Hadayeghi et al., 2006; Kim et al., 2006; Lovegrove and Sayed, 2006; Rifaat and Tay, 2009). On the other hand, another strand of existing research associates urban places, and the attributes also linked to more urban places (such as increased street network density, street connectivity, mixed land uses, more transit use, and increased population density), with increased safety (Ossenbruggen et al., 2001; Surface Transportation Policy Project (STPP), 2002; Ewing et al., 2003; Environmental Protection Agency, 2004; Pawlovich et al., 2005; Dumbaugh, 2006; Hansen et al., 2007).

Yet another set of studies tended to combine large geographic areas into general categories labeled with terms such as "sprawl" or "smart growth," and a common limitation of road safety studies focusing on an area-wide geographic level is the failure to adequately control for vehicle volumes. For instance in a county-level study, Ewing et al. (2003) found that the 10 counties exhibiting sprawl development were the least safe with respect to the number of traffic deaths per 100,000 population. Similarly, the Environmental Protection Agency issued a report finding that out of 13 metropolitan areas, those more representative of smart growth principles had lower traffic fatality rates (Environmental Protection Agency, 2004). To combat the issue of failing to control for vehicle volumes, some studies have used population and employment as a proxy for this vehicle exposure (Ladron de Guevara et al., 2004). These proxy variables are intended to account for vehicle volumes based on the premise that demand for travel is derived, and traffic flows arise from factors such as people and jobs (Noland and Quddus, 2004). The key problem with this conceptualization is that it fails to sufficiently account for the fact that travel patterns and community design patterns are interrelated, which means that vehicle miles traveled (VMT) is not simply a function of population and employment. For instance, variables such as land use, population density, and street network design have been shown to affect how much driving people do (Cervero and Radisch, 1995; Ewing and Cervero, 2001). Thus, proxy variables based on the relative concentration of population and employment may actually be a better measure of the level of overall activity associated within an area rather that a proxy for vehicle volumes. As a result, our study accounts for *both* actual vehicle volumes as well as a proxy for the level of overall activity. This will help us establish as clear a picture as possible with respect to planning street networks for road safety.

From a street network planning perspective, the key problem is that much of the existing literature fails to account for the fundamental street network measures – street network density, street connectivity, and street patterns – along with street design characteristics. In terms of street network measures, many researchers only take into account a single street network measure such as intersection density. Failing to consider the full range of street network measures limits the potential usefulness of the research. Another issue arises when the scope of a study is restricted to either arterials or local neighborhood roads. For example, some studies have looked at neighborhood-level safety outcomes on street networks that have restricted through traffic or increased traffic calming; the issue is that these same studies often overlook the potential increase in traffic on the arterials and the possibility that crashes no longer occurring on the neighborhoods streets could now be occurring elsewhere and possibly at even higher frequencies (Marks, 1957; Zein et al., 1997). Given these limitations in the existing literature, it is very difficult to fully understand the effect of community design in terms of street network and street characteristics on safety.

3. Overview of study

This research was based upon an initial database of all 473 California cities. We focused on California cities in order to help maintain consistency in the data, especially in comparing injury severity outcomes. From this original database, we selected 24 cities for more a detailed analysis. The first factor in selecting these 24 cities was overall traffic fatality rates. All 473 cities were ranked order by fatality rate from the highest to the lowest. The traffic fatality rate in this database ranged from 0.4 to 23.6 fatalities per 100,000 residents. We then selected 12 cities from the top half with relatively low fatality rates and 12 cities from the bottom half with relatively high fatality rates. The range of fatality rates for the 12 safer cities was 1.3–5.5 fatalities per 100,000 residents compared to a range of 6.0–17.5 for the cities with poorer fatality records. In selecting these 24 cities we also considered, to the extent possible, geography balance and factors such as compatibility in terms of population density and average income. Medium-sized cities were the focus of this research in order to best direct our resources toward cities small enough where we could characterize the structure for many cities but big enough that the individual cities would not be too homogeneous. The following cities were selected:

Safer cities	Less safe cities
Alameda	Antioch
Berkeley	Apple Valley
Chico	Carlsbad
Cupertino	Madera
Danville	Morgan Hill
Davis	Perris
La Habra	Redding
Palo Alto	Rialto
San Luis Obispo	Temecula
San Mateo	Turlock
Santa Barbara	Victorville
Santa Cruz	West Sacramento

Given that the cities were selected on the basis of their fatal crash records, it might seem that one potential explanation for this higher fatality rate in the less safe cities is a higher rate of pedestrian and bicycle fatalities. However, in spite of their overall fatal crash records in the less safe cities, only 33.0% of fatal crashes on surface streets involved pedestrians or bicyclists compared to 44.2% in the safer cities. In light of this difference, the higher fatality rates in the less safe cities are even more notable.

This research was based on 11 years of crash records at the U.S. Census Block Group level of geography. According to the U.S. Census, a Block Group is intended to average 250–500 housing units and vary in area depending on housing density. In our study we have over 1000 distinctly populated Block Groups at an average of approximately 43 Block Groups per city.

3.1. Description of spatial data

3.1.1. Crash data

Fatal crash data from the years 1997 through 2007 was retrieved from the Fatality Analysis Reporting System (FARS) while the non-fatal crash records were obtained from the California Highway Patrol (CHP) for this same period. The FARS data source was used in addition to the CHP source because the FARS data included latitude and longitude information of crash location that was not part of the CHP record, which allowed us to better locate the fatal crashes. California specifies five levels of severity in their database: fatal, severe injury, visible injury, minor injury, and property damage only (PDO). In this study, we generate three statistical crash models for each of the following dependent variables: the total number of crashes; the total number of severe injury crashes not including fatalities; and the total number of fatalities. The three crash models enable us to assess road safety both in terms of overall crash rates and in terms of the impact on human health with the severe and fatal crashes.

Since our goal was to shed light on the potential association between surface street network characteristics and road safety, removing crashes occurring on limited access highways seemed to be a reasonable step. In a previous paper intended to consider the possibility of an association between street networks and road safety as well as determine whether a comprehensive statistical analysis would be needed, we examined safety results for all crashes and then again with the limited access highway crashes excluded (Marshall and Garrick, 2010a). One objective of that paper was to detect the possibility of crash migration; and since the results were similar for both datasets, we felt justified in working without the limited access highway crashes in this paper. For this analysis, we also added a binary variable indicating whether or not the zone was bisected by, or adjacent to, a limited access highway.

Before building the statistical crash models, each crash record was geocoded into the GIS database. Fatal crashes occurring post 2001 were coded using latitude and longitude information. Fatal crashes up until 2001 and all of the non-fatal crashes were geocoded to the nearest intersection on the street where the crash transpired using ArcGIS. The geocoding success rate was as follows for the crashes not occurring on limited access highways (Table 1).

Initially we achieved a geocoding success rate of about 86%. After examining the possible reasons why 14% of the crashes were not successfully located, a second geocoding effort was made using a table of corresponding route numbers and road names to account for the fact that many streets have more than one official name. This brought the overall success rate up to nearly 99%. Compared to other large-scale crash geocoding projects, these results compare very favorably. South Carolina recently geocoded three years of data with an 80% success rate while Riverside County California, in a project funded by the State of California Office of Traffic and Safety, also achieved an 80% success rate (Filian and Higelin, 1996; Sarusua et al., 2008).

3.1.2. Street network data

The street network data was derived from a number of sources including the U.S. Census TIGER line files, the California Spatial Information Library, and the California Department of Transportation (CalTrans) records in an effort to build a GIS street network best representative of what is on the ground. Street network mea-

Table 1
Geocoding results.

	Fatal crashes	Success rate	Non-fatal crashes	Success rate
1997–2007	Successful: 1164 Missed: 17	98.6%	Successful: 237,692 Missed: 3042	98.7%

sures for characterizing both street connectivity and street network density were calculated using ArcGIS. Properly characterizing the street network requires answering three basic questions: how connected are the streets, how compact is the network, and what are the street network patterns. The approach to characterizing these properties will be discussed in the following paragraphs.

With regard to measuring the connectivity of a street network, one common measure is the link to node ratio. Link to node ratio is calculated by dividing the number of links (road segments between intersections) by the number of nodes (or intersections) (Ewing, 1996). The node count represents the total number of intersections including dead ends or cul-de-sacs. For example, adding a dead end cul-de-sac to a street network would add one link and one node to the total count while connecting two existing dead end cul-de-sacs would add one link without adding any additional nodes. Correspondingly, a new dead end would lower the link to node ratio and connecting two dead ends would increase the link to node ratio; thus, the higher the link to node value, the more connected the street network. A score of 1.4 or higher is typically considered to be indicative of a walkable community (Handy et al., 2003); however, it is important to recognize that street connectivity alone does not generate walkability.

The second characteristic of the street network that we sought to measure was street network density. Intersection density is one way of characterizing street network density. It is typically measured by the number of intersections per unit area, often a square mile. Intersection density can be calculated separately for major streets and local streets in an attempt to give an indication of the type of intersections that make up the street network. Other typical measures of street network density include average block size, dead end density, and centerline street-mile density as further described in Marshall and Garrick (2009).

We determine street network patterns using an adaptation of Stephen Marshall's concept of macroscopic and microscopic street networks as shown in Fig. 1 (Marshall, 2005). The concept differs from the standard functional classification definitions of arterial, collector, and local roads in that Marshall's system is based upon street network structure. The Macro-level or Citywide Street network distinguishes streets that are generally continuous over a substantial portion of the city that likely service travel from one part of the city to another and, in many cases, trips to or from the city. The Micro-level or Neighborhood Street network generally serves residential neighborhood travel because these streets are on routes not continuous over a significant portion of the city. Marshall defines four types of Citywide Street network types: linear, tributary, radial, and grid; he then combines this with two Neighborhood Street network types: tree and grid.

Marshall presents the chart shown in Fig. 1 in his book as a way to discuss the hybrid types of street patterns and account for the different scales; the chart was not originally intended to serve as a way to classify real street networks (Marshall, 2005). But our preliminary evaluation of this scheme suggested that it would be a good approach for classifying relative differences in street pattern types for our project since we found that it was inclusive of most network types we encountered while at the same time providing a good way of adequately representing the different scales of the street network.

However, in order to transition Marshall's pattern chart into a feasible street pattern classification system, we had to overcome a couple of obstacles. One drawback of Marshall's chart for our purposes was the omission of curvilinear streets. Hence, we added a binary descriptor value stating whether or not the street network was generally curvilinear. Another obstacle of trying to use Marshall's pattern chart in practice is that streets only have two categories: Citywide or Neighborhood. This binary scheme is limiting and not consistent with how places and street networks are often built in practice. As a result, we supplemented Marshall's system with an intermediate type of street that was neither a Citywide Street nor part of the Neighborhood Street network. This intermediate level street enables movement between neighborhoods but is

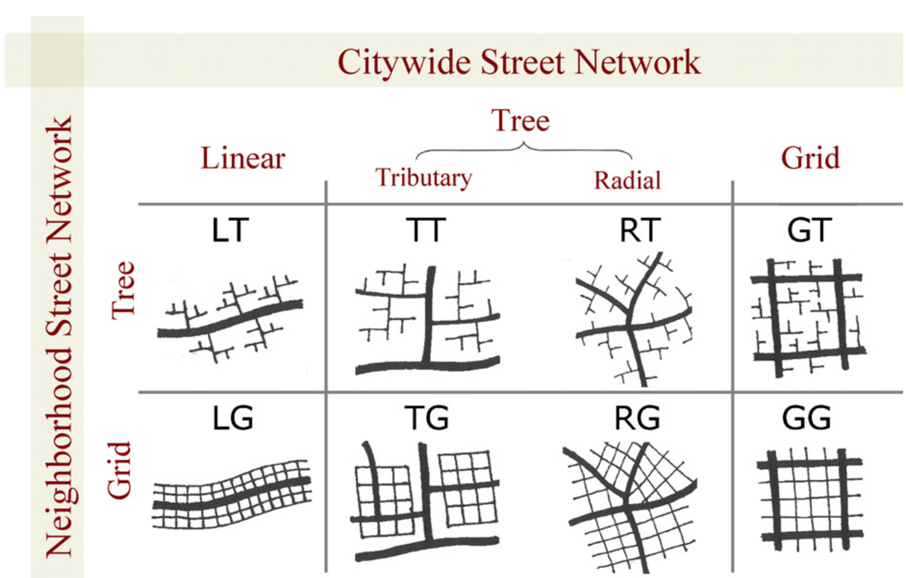

Fig. 1. Citywide–Neighborhood Street network classification system.

Adapted from Marshall (2005).

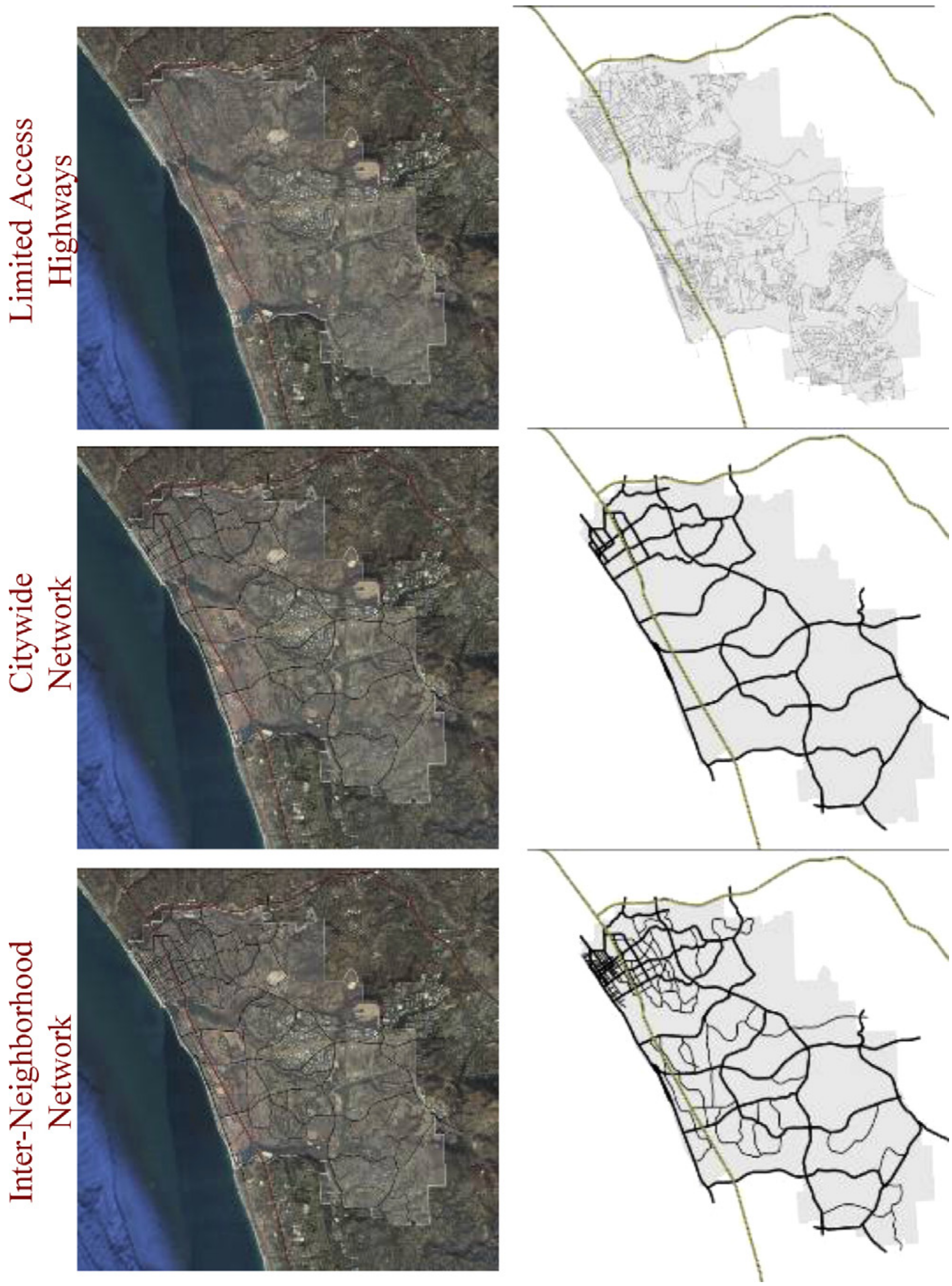

Fig. 2. Citywide–Neighborhood Street network classification in Carlsbad, CA.

not continuous over a substantial portion of the city; accordingly, we labeled these streets the Inter-Neighborhood Streets. The benefit of the Inter-Neighborhood classification is that it better modeled the real-life network structures we were seeing in our cities.

In order to use this adapted classification method in our study, we had to manually classify the entire street network in our 24 cities. Using aerial photographs, we designated the Citywide Streets in each city by selecting streets that were generally continuous across a substantial portion of the city. In other words, the Citywide Street network consisted of those streets that were deemed to be significant connectors between distinct parts of the city. Streets adjacent to or leading to significant commercial or industrial land uses were also considered part of the Citywide Street network. The Inter-Neighborhood Streets were selected to represent connections between adjacent neighborhoods or multiple neighborhoods.

Fig. 2 depicts the process of reclassifying the major and local streets of Carlsbad, California based on the Citywide, Inter-Neighborhood, and Neighborhood Street system using aerial photographs from Google Earth. The top images in Fig. 2 display the limited access highways in Carlsbad. The middle set of images in Fig. 2 depicts the Citywide Street network. This image offers a good indication of what streets would accommodate longer distance travel within Carlsbad and what streets would accommodate traffic coming to or leaving Carlsbad. While most of the Citywide Streets extend across a significant portion of Carlsbad, there were a few additional streets selected in the northwest corner of the city because of their proximity to major commercial land uses. The bottom set of images in Fig. 2 displays the Inter-Neighborhood Streets. Here we can begin to see the roads connecting the different residential neighborhoods of Carlsbad and start to get a better idea of overall street network structure. Using this approach, each Block Group in the database was classified by the predominant street network pattern in that Block Group and the adjacent Block Groups. This process of classifying each Block Group was fairly intuitive to apply, and although the classification system does not accommodate every street pattern possible, it does create a straightforward system for most street patterns. In fact, almost every actual street configuration in our set of cities tended to show one of the characteristic network structures. The only addition we felt was necessary to make sure the actual street networks were representative of the classification scheme was the curvilinear binary variable, as previously described.

Overall, this classification system not only provided a visual representation of the street network, but it also facilitated the creation of more detailed street network measurements. For instance, intersection density can now be broken down by intersection type based on the corresponding intersecting nodes such as Citywide Street network intersections (the intersection of two Citywide Streets) or Citywide Street network – Inter-Neighborhood Street network intersections (the intersection a Citywide Street with an Inter-Neighborhood Street). Furthermore, each crash previously geo-coded into GIS could now be associated with the level of street classification where the crash took place.

One important thing to understand about this Block Group level analysis is that certain features – such as intersection nodes, road segments, and crashes – often sit along the edge of two adjoining Block Groups. When counting these features, GIS can tally the node, road, or crash in question for both Block Groups, neither Block Group, or by manually selecting one Block Group or the other. Other researchers point out that choosing one zone would likely create a bias in the data; on the other hand, opting for attributing the feature to neither area would result in an incomplete picture of what is actually occurring at that level of geography (Tresidder, 2005). As a result, we credit the feature to both Block Groups, a choice that allows us to best compare the data. However, due to this decision, data cannot be aggregated from Block Group level data.

3.1.3. Street level data

For every Citywide street, we collected the following street design characteristics:

- Total number of lanes.
- Curb-to-curb distance.
- Outside shoulder width.
- Inside shoulder width (when median present).
- Raised median width.
- Painted median width.
- On-street parking (0 = no, 1 = yes, 0.5 = along one side of street).
- Bike lanes (0 = no, 1 = yes, 0.5 = along one side of street).
- Curbs (0 = no, 1 = yes, 0.5 = along one side of street).
- Sidewalks (0 = no, 1 = yes, 0.5 = along one side of street).

The data was averaged for the total length of Citywide streets in each Block Group; for instance, a value of 0.6 for a raised median indicates that 60% of the length of Citywide Streets in that particular Block Group has a raised median.

3.1.4. Census data

Census data was collected and analyzed along with the street network data at the census Block Group level of geography. This data included household income levels, demographic information such as age and race, and journey to work data including mode shares and travel time to work. Census 2000 was selected because it was the most appropriate year given the time span of the crash data available (1997–2007).

3.1.5. Exposure data

Vehicle volumes, in terms of VMT, were estimated through the use of Average Annual Daily Traffic (AADT) counts carried out by each city. We geocoded the AADT data to the nearest intersection in a manner similar to the crash records. These points were then joined to the appropriate street segment. The average AADT was then calculated for each street type – Citywide, Inter-Neighborhood, and Neighborhood – and then used to calculate VMT based on total street length by type. Since the number of AADT points on the Neighborhood Streets was relatively low, VMT was estimated on these streets using the CalTrans estimated average AADT value of 845 for local streets. For dead end streets, we used an AADT value of 250. Table 2 contains a summary of the VMT results for each city.

Generally, we would expect that zones with higher VMTs be associated with more crashes. However, VMT only accounts for vehicle travel and does not explicitly convey the level of overall activity – in other words, the total number of people in the area on foot, bike, or traveling by transit and not just those in vehicles. Thus, we used the proxy for vehicle exposure methodology discussed in the background section for what it really seems to be approximating, the activity level associated with each zone. This value was estimated based on the relative levels of population and employment of that zone versus that in other zones and by also taking into account the distance between the target zone and the other zones in the city.

Originally conceived by Daniel Graham and Stephen Glaister, this proxy for exposure uses a simplified gravity model strategy to create a proximate population and proximate employment variable (Graham and Glaister, 2003; Noland and Quddus, 2004). The idea is to establish the relative activity of a zone in terms of the population and employment of that particular zone as well as the population and employment of other zones with respect to the distance between them. The following equation is a proxy for the amount of activity in each zone (Graham and Glaister, 2003; Noland and Quddus, 2004).

$$\mathrm{PP}_i = \sum_j \frac{P_j}{d_{ij}} \qquad \mathrm{PE}_i = \sum_j \frac{E_j}{d_{ij}}$$

In the above equations, PP_i represents the trips generated by Block Group i by the proximate population and PE_i the trips generated by Block Group i by the proximate employment. P_j is the level of population, E_j is the level of employment, and d_{ij} is the centroid-to-centroid distance between zones within each city. The centroid-to-centroid distances are calculated in terms of feet with a distance of 1' used to calculate the intra-zone proxy values. The calculated values are summed to represent a proxy for the overall amount of activity in an area.

The proximate employment and proximate population variables were also used in our study to calculate a proxy for the relative level of mixed land uses by dividing the proxy for employment by the proxy for population. At the Block Group level of geography, this value helped identify the relative mix of employment and population.

3.2. Statistical methodology

The fundamental question we are trying to answer with this research is the following: how are street network measures associated with road safety outcomes? The dependent response variable used to address this question in our statistical analysis is a count of the number of crashes. A conventional linear regression model may not be appropriate for this analysis because of the requirement that the dependent response variable be normally distributed (Long, 1997). To resolve this issue, researchers often rely upon a generalized linear model (GLM) for analyzing count-based crash data. A GLM can be used to account for a non-normal distribution using a link function that relates the linear portion of the model to

Table 2
VMT estimates by city based upon AADT averages by street type.

City	No. of Citywide Street AADTdata points	AADT Citywide Street average	Avg. annual VMT on Citywide Streets	No. of Inter-Neighborhood Street AADT data points	AADT Inter-Neighborhood Street average	Avg. annual VMT on Inter-Neighborhood Streets	Avg. annual VMT on Through Neighborhood Streets	Avg. annual VMT on Dead End Neighborhood Streets	Total avg. annual VMT
Alameda	33	9195	340,567	37	6339	415,536	38,530	4075	798,708
Antioch	46	13,612	657,691	5	3152	207,090	102,468	8170	975,419
Apple Valley	52	5041	571,727	38	1663	184,827	339,919	11,194	1,107,667
Berkeley	37	18,638	881,347	30	12,407	647,700	102,732	3392	1,635,171
Carlsbad	27	15,261	1,065,553	27	6593	385,059	148,464	14,838	1,613,913
Chico	64	12,935	798,415	63	5190	433,002	79,803	9993	1,321,213
Cupertino	22	16,367	409,991	13	5043	134,375	66,813	5671	616,850
Danville	10	18,813	468,624	3	3037	130,385	48,774	11,942	659,725
Davis	46	8163	318,660	29	2477	70,735	54,811	5707	449,912
La Habra	6	19,400	471,304	5	4080	124,319	48,205	3769	647,598
Madera	21	6310	252,380	22	2526	95,007	53,632	3479	404,499
Morgan Hill	12	9571	272,027	7	4430	66,415	53,334	6799	398,575
Palo Alto	18	15,993	797,583	17	7717	323,351	78,070	4894	1,203,899
Perris	37	7485	516,460	11	3817	145,544	72,150	5953	740,108
Redding	57	9059	841,054	67	3730	265,204	168,741	20,191	1,295,190
Rialto	56	8805	619,107	29	3387	109,535	110,206	8107	846,954
San Luis Obispo	17	13,533	549,426	7	3214	70,073	50,694	4577	674,769
San Mateo	15	9792	353,974	65	4355	317,413	73,995	4841	750,223
Santa Barbara	66	11,041	734,980	82	3876	284,925	78,889	7659	1,106,453
Santa Cruz	50	12,268	484,669	55	7703	467,413	47,644	4585	1,004,312
Temecula	30	13,060	724,807	39	16,225	1,144,715	91,018	11,132	1,971,672
Turlock	59	11,209	626,681	50	5187	233,558	64,441	4483	929,163
Victorville	40	14,334	1,461,741	50	4009	493,572	280,346	13,881	2,249,540
West Sacramento	30	7895	297,222	37	2722	147,129	42,007	4333	490,691
Average	35	11,991	604,833	33	5120	287,370	95,654	7653	995,509

the mean of the dependent response variable. Link functions can take various forms – such as log, logit, inverse, or inverse squared – but the purpose is to allow the response variable to relate to the explanatory variables in a nonlinear way (Long, 1997).

Because our crash results were not normally distributed, we initially looked to the Poisson distribution to see if it had the correct distributional properties for a generalized linear regression model (Long, 1997). However, one assumption of the Poisson model is that the variance is equal to the mean, which was not the case for our dataset. Fig. 3 depicts histograms for the total numbers of crashes as well as for the total number of crashes resulting in a fatality. On the x-axis is the number of crashes and on the y-axis is the number of Block Groups with that particular number of crashes. For all our crash data, the variance far exceeded the mean indicating that our data was overdispersed. As a result, we opted for the negative binomial generalized linear regression model, which is a generalized version of the Poisson model and accounts for this overdispersion by introducing a random stochastic component to the log-linear Poisson mean function relationship (Long, 1997; Noland and Quddus, 2004). The following is the negative binomial generalized linear regression model:

$$\ln \tilde{\mu}_i = X_i\beta + \varepsilon_i$$

where μ_i = randomized version of conditional mean of expected crash count of Census Block Group i, X_i = independent predictor variables, β = estimated vector of coefficients representing effects of the covariates, and ε_i = stochastic component representing random error used to account for overdispersion.

Over the last decade, the negative binomial model has become accepted practice for traffic safety researchers conducting statistical testing of crash counts where overdispersion is an issue (Zhou et al., 2009). The negative binomial probability distribution is determined by (Long, 1997):

$$P(y_i|X_i) = \frac{\Gamma(y_i+\nu_i)}{y_i!\,\Gamma(\nu_i)}\left(\frac{\nu_i}{\nu_i+\mu_i}\right)^{\nu_i}\left(\frac{\mu_i}{\nu_i+\mu_i}\right)^{y_i}$$

where Γ = gamma distribution function, ν_i = gamma distribution parameter that affects the shape of the distribution, and y_i = crash count of Census Block Group i. The variance of the negative binomial distribution is (Long, 1997):

$$\mathrm{Var}(y_i|x_i) = \mu_i\left(1+\frac{\mu_i}{\nu_i}\right)$$

If α, the dispersion parameter, begins to approach zero, then a Poisson becomes the appropriate model. The dispersion parameter is related to the gamma distribution parameter as follows (Long, 1997):

$$\nu_i = \alpha^{-1} \quad \text{for} \quad \alpha > 0$$

Using negative binomial generalized linear regression, crash models were built for total crashes and total severe injury crashes not including fatal crashes. This approach had to be slightly modified for the fatal crash model because the fatal crash dataset contained a much larger number of zeros as outcomes than the other datasets, with just over 50% of the Block Groups in our dataset experienced no fatal crashes. This limits the effectiveness of the standard negative binomial regression model (Long, 1997). One methodology frequently used to account for a large number of zero counts in a dataset is to treat that database as if it was made up of two separate datasets. This zero-inflated negative binomial model separately models the large numbers of zeros while still allowing for overdispersion (Lord et al., 2005). Since the first dataset contains only zeros, they are dealt with and predicted with a single independent variable using a Bernoulli probability function (Lord et al., 2005; Erdman et al., 2008). Block Group population was sig-

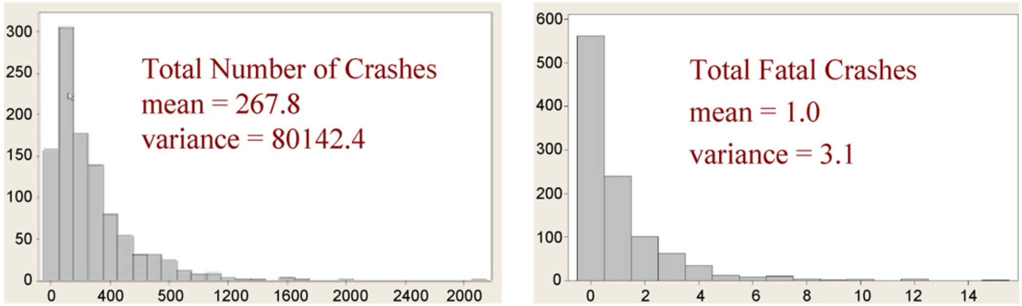

Fig. 3. Histograms for total number of crashes and total fatal crashes.

nificant in predicting Block Groups with zero fatalities; so in the fatal crash model, the nonzero portion of the dataset that experienced more than zero fatal crashes was modeled and analyzed as a standard negative binomial regression model (Lord et al., 2005; Erdman et al., 2008). Also, since the statistical software SAS 9.2 does not permit categorical variables in a zero-inflated negative binomial model, the street classification variable was excluded from the fatal crash analysis.

3.3. *Description of preliminary statistical testing*

The variables used in the final models were selected in an effort to maximize model significance. Models were compared and selected using the AIC value. With respect to multicollinearity, none of the variables used in the final models were highly correlated with one another. Some variables that were *not* included in the models due to the fact that they were highly correlated with another variable that was tested included:
Street network measures.

- Centerline miles of street (total and by type).
- Centerline miles of street per square mile (total and by type).
- Percent of streets by type.
- Connected node ratio.
- Average block size.

Street level data (for citywide streets only)

- Curb to curb distance.
- % of citywide street length with sidewalks.

Miscellaneous

- Population.
- Population density.
- Employment density.
- Mode share data.
- Average travel time to work.

We also tested and analyzed interactions among selected variables. In particular, we tested interactions among street network connectivity, street network density, street network pattern, and Citywide Street design variables. Interactions were generally found not to be significant, but when they were, the effect was in the same direction and at similar levels for all street network patterns. Since

Table 3
Summary statistics of variables at the U.S. census block group level.

Total crash model	Mean	S.D.	Minimum	Maximum
Dependent response variables				
Total number of crashes	272.3	284.3	0	2877
Total severe crashes	4.4	4.4	0	25
Total fatal crashes	1.1	1.8	0	15
Street Network measures				
Intersection density (intersections/sq. mi.)	176.0	98.8	7.9	559.0
Dead end density (dead ends/sq. mi.)	32.0	27.7	0	209.0
Citywide/Inter-Neighborhood intersection density	60.1	68.8	0	523.0
Link to node ratio (# links/# intersections)	1.20	0.20	0.40	2.00
Curvilinear (0, 1)	0.20	0.40	0	1
Street level data for Citywide Streets				
Avg. total number of lanes	3.00	1.10	0	7.00
Avg. outside shoulder width (ft.)	1.70	2.60	0	12.00
% of Citywide Street length with raised median	0.50	0.50	0	1
% of Citywide Street length with painted median	0.40	0.50	0	1
% of Citywide Street length with on-street parking	0.50	0.40	0	1
% of Citywide Street length with bike lanes	0.30	0.30	0	1
% of Citywide Street length with curbs	0.80	0.30	0	1
Exposure				
Vehicle miles traveled (VMT)	30,440	36,586	1475	502,272
VMT standardized from 0 to 1	0.10	0.10	0	1
Proxy for activity	0.30	0.30	0	1
Miscellaneous				
Distance from city center (miles)	1.8	1.4	0.0	9.0
Bisecting or adjacent limited access highway (0, 1)	0.30	0.40	0	1
Income	$57,268	$21,549	$11,956	$128,223
Income standardized from 0 to 1	0.40	0.20	0	1
Proxy for mixed land uses	0.40	0.00	0.30	1

Table 4
Negative binomial (NB) full street network crash models.

Variables	Total crashes (Model 1)			Total severe injury crashes (Model 2)			Total fatal crashes (Model 3)		
	Coefficient	S.E.	β/S.E.	Coefficient	S.E.	β/S.E.	Coefficient	S.E.	β/S.E.
Intercept	2.8929	0.5128	5.64	0.4369	0.5886	0.74	−0.3739	1.6988	−0.22
Street network measures									
Intersection density (intersections/sq. mi.)	−0.0021	0.0004	−5.25	−0.0029	0.0004	−7.25	−0.0068	0.0006	−10.84
Dead end density (dead ends/sq. mi.)	–	–	–	–	–	–	–	–	–
Citywide/Inter-Neighborhood intersection density	0.0011	0.0005	2.20	–	–	–	–	–	–
Link to node ratio (# links/# intersections)	1.0281	0.2092	4.91	0.8677	0.2355	3.68	2.2092	0.3435	6.43
Curvilinear (0, 1)	–	–	–	–	–	–	–	–	–
Street pattern classification									
Tributary-Tree (TT)	0.4197	0.4183	1.00	−0.1802	0.4824	−0.37	–	–	–
Radial-Tree (RT)	0.5466	0.4227	1.29	−0.2351	0.4884	−0.48	–	–	–
Grid-Tree (GT)	0.4074	0.4183	0.97	−0.1089	0.4819	−0.23	–	–	–
Linear-Tree (LT)	0.7656	0.4273	1.79	0.1156	0.4918	0.24	–	–	–
Tributary-Grid (TG)	0.4610	0.4307	1.07	−0.2329	0.4970	−0.47	–	–	–
Radial-Grid (RG)	0.6437	0.4406	1.46	−0.0126	0.5083	−0.02	–	–	–
Grid-Grid (GG)	0.5376	0.4201	1.28	−0.1797	0.4834	−0.37	–	–	–
Linear-Grid (LG) (reference value)	–	–	–	–	–	–	–	–	–
Street level data									
Avg. total number of lanes	0.2509	0.0265	9.47	0.1462	0.0296	4.94	0.1469	0.0439	3.35
Avg. outside shoulder width	–	–	–	–	–	–	–	–	–
% of Citywide Street length with raised median	0.1787	0.0514	3.48	0.1288	0.0583	2.21	–	–	–
% of Citywide Street length with painted median	–	–	–	0.1638	0.0573	2.86	–	–	–
% of Citywide Street length with on-street parking	0.3355	0.0729	4.60	0.3562	0.0848	4.20	–	–	–
% of Citywide Street length with bike lanes	–	–	–	–	–	–	−0.3004	0.1368	−2.20
% of Citywide Street length with curbs	–	–	–	–	–	–	–	–	–
Exposure									
Vehicle miles traveled (VMT) (standardized from 0 to 1)	5.4083	0.5188	10.42	3.5850	0.4735	7.57	–	–	–
log (VMT)	–	–	–	–	–	–	0.2365	0.0824	2.87
Proxy for activity	0.7908	0.1157	6.83	–	–	–	–	–	–
Miscellaneous									
Distance from city center (miles)	−0.1735	0.0208	−8.34	−0.1064	0.0244	−4.36	0.0688	0.0305	2.26
Bisecting or adjacent limited access highway (0, 1)	0.4615	0.0535	8.63	0.2379	0.0592	4.02	–	–	–
Income (standardized from 0 to 1)	−0.9972	0.1441	−6.92	−0.9434	0.1603	−5.89	–	–	–
log (income)	–	–	–	–	–	–	−0.3759	0.1258	−2.99
Proxy for mixed land uses	–	–	–	–	–	–	–	–	–
Dispersion	0.4963	0.0208	23.86	0.4037	0.0312	12.94	0.4929	0.0869	5.67
Inf_intercept	–	–	–	–	–	–	−0.2116	0.4058	−0.52
Inf_Population	–	–	–	–	–	–	−0.0013	0.0004	−3.39
Degrees of freedom	999			1000			1031		
Deviance	1101.5074			1146.2078			–		
Log likelihood	−6376.3547			−2433.3298			−1306.0000		

the overall statistical significance of the models did not increase by including interactions, the interaction terms were not included in the final model shown. Table 3 displays the variables tested in the final crash models.

Also, due to relative magnitude of the vehicle volume counts and average income compared to the rest of the data, these two variables were standardized by subtracting the mean and dividing by the standard deviation using a range of 0–1 in the first two models and by using the log transformation in the zero-inflated negative binomial model. These steps were taken so that the statistical coefficients would not be estimated as zero and the direction of the effects could be observed.

4. Results

The variables tested generally fall into one of three main categories: street network measures, street level data, and exposure. We also created a fourth group of miscellaneous variables tested that includes income, distance from the city center, and whether or not a limited access highway bisects or is adjacent to the zone. The following section presents the results for each category of variable tested.

4.1. Street network measures

Table 4 contains the negative binomial crash model results. The values shown in this table include the estimated coefficient, the standard error, and the ratio of the estimated coefficient over the standard error. This ratio provides an indication of the significance of that particular explanatory variable, with a higher value suggesting higher significance. Results for the independent continuous variables found to be statistically insignificant were not included. Overall, both intersection density and the link to node ratio were significant in all crash models. In fact, we found that increased intersection density was significantly associated with *fewer* crashes across all severity levels while the link to node ratio was significantly associated with *more* crashes. While the street pattern classification variable could not be included in the fatal crash model because SAS 9.2 does permit categorical variables, it was kept in the other two crash models even though it turned out to be insignificant. This was deemed acceptable because including insignificant variables in a negative binomial regression model do not induce bias in cases where the coefficients of other independent variables do not change significantly when the variable is added (Studenmund, 2005). On the whole, we wanted to be sure to account for all three of the fundamental street network measures whenever possible because the overall intent of this work is see how the street network relates to safety outcomes. As well, we wanted to control for the possible effects of street patterns on the dependent crash variables.

Table 5 calculates the percent change in the expected crash count based upon changing the level of a single variable and holding all other variables at their mean in the same manner used in a road safety study set in England by Noland and Quddus (2004). This percent change is based upon the expected number of crashes with respect to the reference value closest to the mean value of that variable and is mathematically the same as elasticity measures but easier to visualize. Looking at the total crash model in Table 5 as an example, the results indicate that dropping intersection density from 144 per square mile (equivalent to a 12-by-12 grid) to 81 (equivalent to a 9-by-9 grid) is associated with on average a 14.15% increase in the total number of crashes in the Block Group when all other variables are held at their mean value. If we increased the intersection density from the reference value of 144 intersections per square mile to 225 (equivalent to a 15-by-15 grid) or 324 (equivalent to a 18-by-18 grid), we would expect a 15.24% and 31.48% *decrease* in total crashes, respectively.

Table 5 also shows that increasing intersection density from 144 to 225 intersections per square mile would result in a 15.6% reduction in total crashes, a 20.9% reduction in severe injury crashes, and a 42.5% reduction in fatal crashes (Models 1, 2, and 3, respectively). The results are even more striking when increasing intersection density to 324 intersections per square mile, where expected crash counts dropped 31.5%, 40.7%, and 70.7% for the three severity levels, respectively. The fact that increased intersection density was associated with a greater drop in more severe crashes is possibly indicative of the role that vehicle speeds play in crash severity. This is a similar to what was postulated in earlier studies such as one by Ladron de Guevara et al. (2004). However, unlike some of these earlier studies, our results show that higher intersection densities are also associated with fewer crashes overall (Rifaat et al., 2009; Rifaat and Tay, 2010). This leads us to believe that higher intersection densities may also play an important role in travel decisions and driver behavior.

Other forms of intersection density tested include dead end density and an intersection density comprised of the combination of the Citywide and Inter-Neighborhood Streets. The Citywide/Inter-Neighborhood intersection density is the *sum* of the following major intersection types divided by square miles:

- Citywide Street network intersections (the intersections of two Citywide Streets).
- Citywide–Inter-Neighborhood Street network intersections (the intersection a Citywide Street with an Inter-Neighborhood Street).
- Inter-Neighborhood Street intersections (the intersection of two Inter-Neighborhood Streets).

The Citywide/Inter-Neighborhood intersection density was only significant in the total crash model (Model 1). In this case, a greater density of Citywide/Inter-Neighborhood intersections was associated with more total crashes. Dead end density did not turn out to be significant in any of models.

The link to node ratio was included as characterization of street network connectivity. In terms of street connectivity, an increase in the link to node ratio (increased street connectivity) is associated with an overall *increase* in crashes for all severity levels. Table 5 shows that increasing street connectivity from a link to node ratio of 1.25–1.4 would result in an expected 16.7% increase in total crashes, a 13.9% increase in severe injury crashes, and a 39.3% increase in fatal crashes.

4.2. Street level data

Of the street level characteristics collected along all the Citywide Streets in all 24 cities, the average number of lanes, which was highly correlated with the average curb-to-curb distance, was significant in all of our models. More lanes resulted in an increase to the expected number of crashes across all severity levels. The average total number of lanes on the Citywide Streets had one of the higher levels of statistical significance with respect to safety of all the variables in our dataset. The results also suggest that more travel lanes are associated with a greater effect on the total number of crashes than on the fatal or severe injury crashes. One possible explanation is the chance that more of the property damage only and minor injury crashes result from lane changes along streets with more lanes.

The width of the outside shoulder was not significant in any model. The presence of raised medians and painted medians both seemed to have similar effects in our results. A higher percentage of Citywide Streets with a raised medians or painted median was

Table 5
Percent change in expected crash counts per U.S. census block group – Full Street network crash models.

Variables %	Total crashes (Model 1) % Change	Severe crashes (Model 2) % Change	Total fatal crashes (Model 3) % Change
Intersection density			
81	14.15%	20.05%	53.75%
144 (reference value)	–	–	–
225	−15.64%	−20.94%	−42.48%
324	−31.48%	−40.67%	−70.74%
Link to node ratio			
1.1	−14.29%	−12.20%	−28.21%
1.25 (reference value)	–	–	–
1.4	16.67%	13.90%	39.29%
1.55	36.13%	29.73%	94.02%
Total no. of lanes on Citywide Streets			
2 (reference value)	–	–	–
4	65.17%	33.96%	34.15%
6	172.81%	79.46%	79.95%
Bisecting or adjacent limited access highway (0, 1)			
0 (reference value)	–	–	–
1	58.65%	26.86%	–
Distance from city center (miles)			
0	41.48%	23.71%	−12.86%
1	18.95%	11.23%	−6.65%
2 (reference value)	–	–	–
3	−15.93%	−10.09%	−7.12%
4	−29.32%	−19.17%	14.75%
% of Citywide Street length with on-street parking			
0% (reference value)	–	–	–
50%	18.26%	19.49%	–
100%	39.86%	42.79%	–
% of Citywide Street length with bike lanes			
0% (reference value)	–	–	–
50%	–	–	−14.29%
100%	–	–	−26.53%

significantly related to increasing overall crash totals and severe injury crashes. Raised medians and painted medians were not significant in the fatal crash models. This suggests that the increased presence of a median in these cities does not seem to be having a statistically significant effect on more severe crash types.

Increasing the percentage of Citywide Streets with on-street parking was associated with *more* total crashes and severe crashes, but there was no significant association between on-street parking and fatalities. This suggests that the presence of on-street parking may influence vehicle speeds, and in turn, crash severity. The other street level variables tested were the percent of Citywide Streets with curbs (which was very highly correlated with sidewalks) and those with bike lanes. Whether or not there were vertical curbs on the Citywide Streets was not significant in any of the models. The presence of bike lanes however was significant only in the fatal crash models. Overall, having bike lanes along the Citywide Streets was associated with a decrease in the expected number of fatal crashes. Comparing the difference between a Citywide Street network with no bike lanes versus a Citywide Street network complete with bike lanes showed that the presence of bike lanes would be associated with 31% fewer fatal crashes.

4.3. Exposure

In controlling for exposure, we used both the calculated vehicle volumes in terms of VMT as well as a proxy for the level of activity. As described in Section 3.1, the proxy for the level of activity is not intended to approximate VMT but rather the level of activity supported by each place in terms of their relative concentrations of population and employment. Overall, increased VMT was significantly associated with an increase in total crashes as well as total severe crashes; however, VMT did not turn out to be correlated with the number of fatal crashes. This lack of a significant association between VMT and fatal crashes suggests that while traffic volumes are an important factor in the overall number of crashes, traffic volumes do not influence the expected number of fatal crashes as much as street network measures (such as intersection density) or street design characteristics (such as the number of lanes).

With regard to controlling for the proxy for activity in terms of population and employment, it turned out to be significant only in the total crash model where increased activity was correlated with an increase in only the expected number of total crashes.

4.4. Other variables

In terms of the variables tested that we have not already discussed, income was statistically significant in all the models. In every case, higher income levels were associated with a reduction in the expected number of crashes. Also, the distance from the city center played an interesting role. Being closer to the city center was significantly associated with more total crashes and total severe crashes. However, the closer a Block Group was to the city center, the fewer the expected number of fatal crashes. Table 5 shows that the area near the downtown district of a city, when compared to the average Block Group, has on average 40% more total crashes but 12% fewer fatal crashes. We speculate that this has to do with lower vehicle speeds in areas closer to the city center.

Proximity to a limited access highway resulted in more total crashes and more severe injury crashes. This result suggests that it might be worthwhile to investigate on-ramp and off-ramp locations as well as the prospect of a speed differential between cars leaving the highway and those already on the street network. This proximity to limited access highways variable was not significant in the fatal crash model. Also, the proxy for mixed use was not significant in any of the models.

5. Conclusion

The goal of this study was to assess how street network characteristics affect road safety. Using a spatial GIS analysis together with a novel approach to classifying street network patterns, our research showed that both street network and street characteristics are significantly correlated with road safety outcomes. The basis for this analysis was over 230,000 individual crash records geo-coded in a GIS database in over 1000 census Block Groups in 24 California cities.

In conducting this study, we controlled for variables such as street patterns, vehicle volumes, activity levels, income levels, proximity to limited access highways and to the downtown area. In general, areas with lower incomes or those that are adjacent to a limited access highway tended to have more crashes; also, being in closer proximity to the downtown area resulted in more total crashes but fewer fatal crashes.

We found that street networks with high intersection densities correlate with fewer crashes across all severity levels. The lower crash rates on networks with higher intersection densities might be due to differences in travel patterns in denser, more urban environments. This is supported by the fact that neighborhoods with higher intersection densities also tended to have a lower percentage of people who chose to drive to work. It is also worth noting that increasing intersection density from the average value to the highest value was associated with an expected 30% decrease in total crashes but with more than a 70% drop in fatal crashes. In other words, the effect of increased intersection density was much more pronounced for fatalities than for less severe injuries. This suggests that one factor at work might be lower vehicle speeds on the street networks with higher intersection densities.

Conversely, we found that increased street connectivity is significantly associated with an increase in crashes of all severities. The negative effect of the link to node ratio may be due to increased traffic conflicts associated with more connectivity. It is also important to keep in mind that highly connected street networks have the capacity to dissipate congestion from arterials, which allows cities to build arterials with fewer travel lanes and less travel on the City-wide street network and be associated with lower crash rates. Also, our previous research showed higher street connectivity (as well as intersection density) to be associated with more walking, biking, and transit use. So in trying to strike the right balance with the varying goals of a transportation system, it will be interesting to eventually determine how different levels of street connectivity for different modes will impact safety.

We found that street network characteristics played a major part in safety outcomes on the streets in our study. More specifically, the statistical crash models gave us two important results concerning the street network: first and foremost, increased street network density in the form of intersection density was correlated with fewer crashes across all severity levels; and secondly to a lesser extent, increased street connectivity in the form of the link to node ratio was associated with more crashes across all severity levels when all other factors are kept constant. However, it is important not to interpret these results in isolation since these two characteristics of the street network are also associated with other factors that impact safety. For instance, increased intersection density, increased street connectivity, as well as the type of street pattern are associated with much higher levels of walking, biking, and transit use (Marshall and Garrick, 2010b). Overall, these results suggest that we must move beyond the narrow focus of just looking at the characteristics of the individual street and start to consider how street network measures interact with street design characteristics in terms of building a safer and more sustainable transportation system.

Role of funding source

Funding for this research was obtained through the Dwight D. Eisenhower Transportation Fellowship program and the New England University Transportation Center. The funding sources played absolutely no role in the study design nor any collection, analysis, or interpretation of the data.

References

Cervero, R., Radisch, C., 1995. Travel Choices in Pedestrian Versus Automobile Oriented Neighborhoods. The University of California Transportation Center, University of California at Berkeley.

Dumbaugh, E., 2006. The design of safe urban roadsides: an empirical analysis. In: Transportation Research Board 85th Annual Meeting, Washington, D.C.

Environmental Protection Agency, 2004. Characteristics and Performance of Regional Transportation Systems. Environmental Protection Agency, Washington, D.C.

Erdman, D., Jackson, L., et al., 2008. Zero-Inflated Poisson and Zero-Inflated Negative Binomial Models Using the COUNTREG Procedure. SAS Institute, Inc., Cary, NC.

Ewing, R., 1996. Best Development Practices: Doing the Right Thing and Making Money at the Same Time. APA Planners Press, Washington, D.C.

Ewing, R., Cervero, R., 2001. Travel and the Built Environment: A Synthesis. Transportation Research Record: Journal of the Transportation Research Board 1780, 87–114.

Ewing, R., Dumbaugh, E., 2009. The Built environment and traffic safety: a review of empirical evidence. Journal of Planning Literature 23 (4), 347–367.

Ewing, R., Pendall, R., et al., 2002. Measuring Sprawl and its Impact. Environmental Protection Agency, S.G. America. Washington, D.C.

Ewing, R., Schieber, R., et al., 2003. Urban sprawl as a risk factor in motor vehicle occupant and pedestrian fatalities. American Journal of Public Health 93, 1541–1545.

Filian, R., Higelin, J., 1996. Traffic Engineering in a GIS Environment: Highlighting Progress of the County of Riverside Geographic Information System Based Accident Records System. From http://gis.esri.com/library/userconf/proc95/to050/p029.html.

Graham, D., Glaister, S., 2003. Spatial variation in road pedestrian casualties: the role of urban scale, density and land-use mix. Urban Studies 40 (8), 1591–1607.

Hadayeghi, A., Shalaby, A.S., et al., 2006. Temporal transferability and updating of zonal level accident prediction models. Accident Analysis and Prevention 38 (3), 579–589.

Handy, S., Paterson, R., et al., 2003. Planning for Street Connectivity: Getting from Here to There. Planning Advisory Service Report 515, American Planning Association.

Hansen, G., Garrick, N., et al., 2007. Variation in free-flow speed due to roadway type and roadside environment. In: Transportation Research Board 86th Annual Meeting, Washington, D.C.

Huang, H.F., Stewart, R., et al., 2002. Evaluation of Lane Reduction “Road Diet” Measures on Crashes and Injuries. Transportation Research Record 1784, pp. 80–90.

International Traffic Safety Data and Analysis Group, 2005. Traffic Deaths per 100,000 Population in Individual Representations Since 1970. From http://www.cemt.org/irtad/.

Kim, K., Brunner, I.M., et al., 2006. Influence of Land Use, Population, Employment, and Economic Activity on Accidents. Transportation Research Record. Journal of the Transportation Research Board 1953, 56–64.

Ladron de Guevara, F., Washington, S.P., et al., 2004. Forecasting Crashes at the Planning Level: Simultaneous Negative Binomial Crash Model Applied in Tucson, Arizona. Transportation Research Record 1897, 191–199.

Lerner-Lam, E., Celniker, S.P., et al., 1992. Neo-traditional design and its implications for traffic engineering. ITE Journal 62 (1), 17–25.

Long, J.S., 1997. Regression Models for Categorical and Limited Dependent Variables. SAGE Publications, Thousand Oaks.

Lord, D., Washington, S.P., et al., 2005. Poisson Poisson-gamma and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory. Accident Analysis and Prevention 37 (1), 35–46.

Lovegrove, G., Sayed, T., 2006. Macro-level collision prediction models for evaluating neighbourhood traffic safety. Canadian Journal of Civil Engineering 33 (5), 609–621.

Lucy, W.H., Lewis, L., 2009. Danger of Traveling: The Safest and Most Dangerous Cities and Counties in Metropolitan. University of Virginia, Virginia.

Marks, H., 1957. Subdividing for traffic safety. Traffic Quarterly Institute of Transportation Engineers (July), 308–325.

Marshall, S., 2005. Streets & Patterns. Spon Press, New York.

Marshall, W., Garrick, N., 2009. The shape of sustainable street networks for neighborhoods and cities. In: Congress for the New Urbanism XVII, Denver, CO.

Marshall, W., Garrick, N., 2010a. Considering the role of the street network in road safety: a case study of 24 California cities. Urban Design International Journal 15 (3), 133–147.

Marshall, W., Garrick, N., 2010b. The effect of street network design on walking and biking. Transportation Research Record (in press).
Noland, R., 2000. Traffic fatalities and injuries: are reductions the result of 'improvements' in highway design standards? In: Transportation Research Board 80th Annual Meeting, Washington, D.C.
Noland, R., Quddus, M., 2004. A spatially disaggregate analysis of road casualties in England. Accident Analysis and Prevention 36 (6), 973–984.
Organisation for Economic Co-operation and Development (OECD), 2006. Quality of Life: Transport. OECD Factbook, Paris.
Ossenbruggen, P., Pendharkar, J., et al., 2001. Roadway safety in rural and small urbanized areas. Accident Analysis and Prevention 33 (4), 485–498.
Pawlovich, M., Li, W., et al., 2005. Iowa's experience with "Road Diet" measures: impacts on crash frequencies and crash rates assessed following a Bayesian approach. In: Transportation Research Board 84th Annual Meeting, Washington, D.C.
Rifaat, S.M., Tay, R., 2009. Effects of Street Patterns on Injury Risks in Two-Vehicle Crashes. Transportation Research Record 2120, 61–67.
Rifaat, S.M., Tay, R., 2010. Effect of street pattern on road safety: are policy recommendations sensitive to different aggregations of crashes by severity? In: Transportation Research Board 89th Annual Meeting, Washington, D.C.
Rifaat, S.M., Tay, R., et al., 2009. Effects of neighborhood street patterns on traffic collision frequency. Journal of Transportation Safety & Security 1 (4), 241–253.
Sarusua, W., Ogle, J. H., et al., 2008. Location, Location, Location: Using GPS to Identify Crash Location—South Caroline Experience. TRB 87th Annual Meeting Compendium of Papers DVD.
Sawalha, Z., Sayed, T., 2001. Evaluating safety of urban arterial roadways. Journal of Transportation Engineering 127 (2), 373–378.
Southworth, M., Ben-Joseph, E., 1997. Street and the Shaping of Towns and Cities. McGraw-Hill, New York.
Studenmund, A.H., 2005. Using Econometrics: A Practical Guide, 5th edition. Addison-Wesley, Boston, MA.
Surface Transportation Policy Project (STPP), 2002. Mean Streets 2002: Pedestrian Safety, Health and Federal Transportation Spending. From http://www.transact.org/pdfs/ms2002/meanstreets2002.pdf.
Swift, P., Painter, D., et al., 1998. Updated 2006 residential street typology and injury accident frequency. In: Congress for the New Urbanism VI, Denver, CO.
Taylor, J., 2001. Transportation and Community Design: the Effects of Land Use and Street Pattern on Travel Behavior. From http://www.sustainable-communities.agsci.ubc.ca/bulletins/TB_issue_11_Transportation_edit.pdf.
Tresidder, M., 2005. Using GIS to Measure Connectivity: An Exploration of Issues. School of Urban Studies and Planning. Portland State University, Portland, OR.
Tunnard, C., 1963. Man-Made America. Yale University Press, New Haven.
World Health Organization, 2004. World Report on Road Traffic Injury Prevention.
Zein, S.R., Geddes, E., et al., 1997. Safety Benefits of Traffic Calming. Transportation Research Record. Journal of the Transportation Research Board 1578, 3–10.
Zhou, H., Ivan, J., et al., 2009. Safety effects of exclusive left turn lanes at unsignalized intersections and driveways. In: Transportation Research Board 88th Annual Meeting, Washington, D.C.