Integrating Trip and Roadway Characteristics to Manage Safety in Traffic Analysis Zones

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A transportation network is a conglomeration of road–traffic–environment modules and features multicategories of interdependent factors. This mix makes the management of safety in traffic analysis zones (TAZs) explicitly challenging. This study investigated the association between crash frequencies and various types of trip productions and attractions in combination with the road characteristics of 1,349 TAZs of four counties in the state of Florida. Crash safety management of these TAZs is emphasized through prioritizing them by examining the effects of trip and roadway factors on the aggregated crash frequencies. Models were developed separately for total crashes, severe crashes (fatal and severe injury crashes), total crashes during peak hours, and pedestrian- and bicycle-related crashes on the basis of various groups of estimators. It was found that the total crash model and the peak-hour crash model were best estimated by total trip productions and total trip attractions. The severe crash model was best fit by trip-related variables only, and the pedestrian- and bicycle-related crash model was best fit by road-related variables only. The results from this study pave the way for better safety management and the incorporation of safety measures in travel and network planning.

The nature and extent of roadway safety vary widely depending on roadway type and facility, driver characteristics, land use pattern, and various other factors. Considerable research has been conducted to reduce the occurrence of crashes that take millions of lives and cause immeasurable human suffering each year throughout the world. As a crash is associated with a complex interaction of various factors, micro-level crash analysis (e.g., road-specific crash analysis, crash-specific safety analysis, event-specific analysis) can lead to better insight about factors that contribute to crashes. Also, by knowing the factors associated with crash occurrence one can enhance safety-conscious transportation planning and management.

A transportation network is a conglomeration of various sets of road–traffic–environment modules and features by multicategories of interdependent factors. This imposes a challenge in macro-level and aggregate analyses of crashes. Aggregate level considerations are vitally important in transportation planning and have been emphasized in several macro-level studies during the past few years. Macro-level analyses of crash prediction models have been attempted for census block groups; traffic analysis zones (TAZs); census tracts; and counties considering various demographic, socioeconomic, road, and travel characteristics (*1–6*).

The study in this paper was based on 1,349 TAZs of four counties in the state of Florida. This study aims to propose several safety management alternatives for the TAZs by investigating the association between crash frequencies and various types of trip productions and attractions in combination with the road characteristics of the TAZs. In addition, at the transportation planning stage if TAZs are to be defined on the basis of travel demand models, the results of this study point to different approaches when predicting crashes at the zonal level. It is speculated that using trip types to predict crash frequencies will help in understanding the safety consequences at an early stage of transportation planning.

The study examined four response variables: total crashes, severe (fatal and severe injury) crashes, peak-hour crashes, and pedestrian- and bicycle-related crashes per TAZ. Peak periods were estimated on the basis of temporal variations of the aggregated hourly crash frequencies and their association with different trip- and road-related covariates. Also, as both state and nonstate road characteristics within a TAZ were considered in the study, pedestrian- and bicycle-related crashes were of special interest as most of these categories of crashes occur on moderate- to low-speed roadways and streets.

LITERATURE REVIEW

Macro-level crashes have been investigated at various spatial aggregations. The crash models developed in these studies have incorporated different categories of variables in predicting crash occurrences. Amoros and Laumon (*1*) compared traffic safety in several counties in France taking different road types and socioeconomic characteristics into account. Aguero-Valverde and Jovanis (*2*) investigated crash risk for Pennsylvania counties with respect to sociodemographics, weather conditions, transportation infrastructure, and amount of travel. Noland and Oh (*3*) examined the association of various road network infrastructure and some demographic and socioeconomic variables with crashes in the counties of Illinois. Amoros and Laumon (*1*) found significant interaction between county and road type. Other positively associated road-related significant factors in the above-mentioned studies included road mileage and road density (*2*) and number of lanes (*3*). Among demographic variables, Aguero-Valverde and Jovanis (*2*) found that counties with a higher percentage

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of the population below the poverty level and a higher percentage of the population in the age groups 0 to 14, 15 to 24, and over 64 years have significantly increased crash risk. Huang et al. (*7*) concluded that the safety status is worse for areas with lower income and educational levels and a higher unemployment rate compared with relatively affluent areas. Also, counties with higher traffic intensity and population density and a greater degree of urbanization are associated with higher crash risks (*7*). Noland and Oh (*3*) commented that their analysis results did not change much when demographic variables were included, although they found that these variables appear to capture the residual time trend associated with reductions in fatalities and reported crashes.

Crash prediction studies at the county level have been thought to suffer from the problem of spatial heterogeneity. Karlaftis and Tarko (*5*) used a stratification scheme to solve this problem to some extent. They used clustering techniques to generate homogeneous groups with similar socioeconomic, traffic, and infrastructure characteristics for the counties of Indiana. Their results showed that models developed for homogeneous clusters of counties were more efficient than the joint models, thus indicating the importance of spatial homogeneity.

Wier et al. (*6*) looked at vehicle–pedestrian injury collisions at 176 San Francisco, California, census tracts, which are spatially disaggregated from the counties. The predictor variables examined in their study included street, land use, and population characteristics and their final model was able to explain about 72% of the systematic variation of the vehicle–pedestrian injury collisions at the census tract level. It was evident from their study that traffic volume was the primary cause of vehicle–pedestrian injury collisions at the area level. Additionally, employee and resident populations, arterial streets without public transit, the proportion of people living in poverty, and the proportion of people age 65 or older were among the other statistically significant predictors.

Noland and Quddus (*4*) analyzed ward-level crash data for England using land use types, road characteristics, and demographic data. Their findings suggested that areas with high employment density had more traffic casualties, more densely populated urbanized areas were associated with fewer casualties, and road length had a positive association with serious injuries. Levine et al. (*8*) examined the zonal relationship between motor vehicle crashes and population, employment, and road characteristics using census block group as the unit of analysis. Their analysis revealed that increased population and miles of major arterials were associated with an increased number of crashes per census block group.

The spatial error resulting from the heterogeneity of spatial aggregation motivated the investigation of macro-level crash analysis at relatively homogeneous zones. It can be argued that the census block, which is the basic zonal unit of the census geography hierarchy in the United States, will have the least amount of spatial heterogeneity. This paper uses TAZ level aggregation to perform the analyses. A TAZ is a spatial aggregation of census blocks and is in part a function of population (*9*). TAZs are thought to have better homogeneity than census blocks as they are special areas delineated by state or local transportation officials particularly for tabulating traffic-related data and are defined as part of the census transportation planning package (*10*).

As cited by You et al. (*11*), the most important criteria used to define TAZs include spatial contiguity, homogeneity, and compactness. Also, TAZs have commonly been considered as a basis for the aggregate modeling process (*12*). Hadayeghi et al. (*13*) studied total and severe crashes at 463 TAZs in the city of Toronto, Ontario, Canada, as a function of socioeconomic and demographic, traffic demand, and network data variables. De Guevara et al. (*14*) developed planning-level crash prediction models for 859 TAZs in Tucson, Arizona, considering demographic, socioeconomic, and roadway characteristics as the predictors.

In this study, safety management of TAZs is emphasized through prioritizing them by examining the effects of various trip and roadway factors on the aggregated crash frequencies at the TAZ level. Also, it is speculated that predicting crash frequencies by using trip types will help in incorporating the safety perspectives during the transportation planning stages as trip types are vitally important in the travel demand modeling process. The modifications of TAZs in Texas are considered during each travel model update when a new base year is established (*15*). Also, travel demand models are used in Florida and around the country to forecast traffic volumes on highways (*16*).

DATA PREPARATION

The study was based on the following four counties of the state of Florida: Citrus, Hernando, Pasco, and Hillsborough. These four counties constitute a total of 1,349 TAZs representing both rural and urban areas. Crash data for the years 2005 and 2006 were used in the study. The geographic information system (GIS) shape files (maps) providing crashes as point entities were collected from the Florida Department of Transportation (DOT). Each point (a crash) in the GIS shape file provided several attributes for the corresponding crash. The roadway characteristics were found from separate GIS shape files provided by Florida DOT. These GIS shape files included roadway segments as line entities. The geographic maps for the study counties were collected from the Florida DOT District 7 Intermodal Systems Development Unit. Each map provided cartographic boundaries of the TAZs within a county. The base spatial unit of the study was TAZ, and the following steps were taken to aggregate variables at the TAZ level:

- The spatial join tool in ArcMap 9.2 (Environmental Systems Research Institute, Inc., Redlands, Calif., 2007) was used to assign crashes to TAZs by joining two GIS shape files: crash map and TAZ cartographic boundary map. It was ensured that both maps had similar GIS coordinate systems.
- The streets were similarly spatially attached to the respective TAZs.
- The spatial join procedure allowed each point (a crash) or line (a roadway segment) feature in the GIS shape files to assign the TAZ identification to which the feature was geographically located.
- The next step was to aggregate crash and roadway attributes at the TAZ level. The attributes tables were exported from ArcMap, and the aggregation was performed with SAS statistical software (Version 9.1.3, Service Pack 3, SAS Institute Inc., Cary, N.C., 2009).
- Therefore, the data set contained all crash and roadway variables aggregated to a TAZ, which was treated as one observation of the data set.

The number of trip attractions and productions per day per TAZ for 13 categories was collected from the Intermodal Systems Development Unit of District 7 of the Florida DOT. The final data set contained three main categories of variables: crash-related variables, variables pertaining to roadways, and different trip attraction and production rates per TAZ. The complete list and descriptive statistics of responses and predictors are provided in Table 1.

TABLE 1 Description of Variables

Variable Name	Definition	*N*	Mean	Standard Deviation	Min.	Max.
TAZ2004	Traffic analysis zone (in year 2004)	1,349	NA	NA	NA	NA
Crash Severity						
FATAL	Fatal crashes	1,349	0.46	0.849	0	8
SVINJ	Severe injury	1,349	5.07	5.885	0	45
INJ	Injury crashes	1,344	21.13	22.880	0	173
PDO	Property-damage-only crashes	1,344	29.74	38.282	0	310
Response Variables (per TAZ in years 2005–2006)						
Crash_freq	Total number of crashes	1,349	56.20	64.048	0	481
Severe_crashes	Total number of fatal and severe injury crashes	1,349	5.52	6.278	0	47
Peak_crash_freq	Total number of crashes during peak hours	1,217	13.91	14.714	1	110
Ped_bike_crashes	Total number of pedestrian- and bicycle-related crashes	1,349	2.6	4.164	0	50
Independent Variables Related to Roadway Characteristics (total roadway segment length within a TAZ with a posted speed limit)						
seglen15	15 mph	1,349	0.22	0.434	0	4.063
seglen25	25 mph	1,349	8.27	11.729	0	244.595
seglen35	35 mph	1,349	1.40	1.749	0	24.934
seglen45	45 mph	1,349	0.11	0.422	0	6.709
seglen55	55 mph	1,349	0.13	0.621	0	11.248
seglen65	65 mph	1,349	0.22	0.711	0	10.221
SUM_SEG_LEN	All roads	1,349	10.76	14.050	0	265
Intersection	Total number of intersections per TAZ	1,349	12.32	12.055	1	119
Independent Variables Related to Various Trip Productions and Attractions						
HBWP	Home-based work productions	1,349	864.44	940.174	0	8,056
HBWA	Home-based work attractions	1,349	852.97	1,262.400	0	17,788
HBSHP	Home-based shop productions	1,349	889.98	929.371	0	7,363
HBSHA	Home-based shop attractions	1,349	851.82	1,402.270	0	15,842
HBSRP	Home-based social recreational productions	1,349	422.59	436.225	0	3,173
HBSRA	Home-based social recreational attractions	1,349	400.12	649.275	0	8,127
HBSCP	Home-based school productions	1,349	247.14	286.247	0	2,965
HBSCA	Home-based school attractions	1,349	246.75	684.592	0	6,832
HBOP	Home-based other productions	1,349	587.35	614.641	0	4,533
HBOA	Home-based other attractions	1,349	556.74	795.465	0	7,992
NHBWP	Non-home-based work productions	1,349	215.03	299.583	0	3,606
NHBWA	Non-home-based work attractions	1,349	215.03	299.583	0	3,606
NHBOP	Non-home-based other productions	1,349	575.41	860.352	0	10,144
NHBOA	Non-home-based other attractions	1,349	575.41	860.352	0	10,144
LTRKP	Light-truck productions	1,349	268.62	231.951	0	2,264
LTRKA	Light-truck attractions	1,349	268.62	231.951	0	2,264
HTRKP	Heavy-truck productions	1,349	68.76	102.811	0	1,591
HTRKA	Heavy-truck attractions	1,349	68.76	102.811	0	1,591
TAXIP	Taxi productions	1,349	20.26	21.849	0	323
TAXIA	Taxi attractions	1,349	20.26	21.849	0	323
EIP	External–internal productions	1,349	0	0	0	0
EIA	External–internal attractions	1,349	40.21	56.448	0	647
AIRPP	Airport productions	1,349	12.58	34.145	0	540
AIRPA	Airport attractions	1,349	0	0	0	0
COLP	College productions	1,349	79.64	161.303	0	3,234
COLA	College attractions	1,349	38.40	341.085	0	5,069
TOTALP	Total productions	1,349	4,251.79	3,720.230	0	26,741
TOTALA	Total attractions	1,349	4,135.09	5,105.610	0	48,033
logtp	Natural log of TOTALP	1,330	7.86	1.274	0	10.19
logta	Natural log of TOTALA	1,328	7.50	1.642	0	10.78

NOTE: NA = not applicable.

METHODOLOGY

Crash frequencies are non-negative integers, which are not normally distributed. It has been widely accepted that a Poisson or negative binomial (NB) model has the ability to estimate the relationships between the number of crashes and covariates. The underlying assumption of the Poisson distribution of variance equal to the mean is often violated in the crash count data. Most of the time, crash observations have a greater variance than their mean and therefore the data are overdispersed. NB models take this overdispersion into account. The NB distribution is characterized by the following mean–variance relationship of a practical observation, Y:

$$\mathrm{Var}(Y) = \mu + \alpha\mu^2 \tag{1}$$

where $\mu = E(Y)$ (expectation of Y) and α is the overdispersion parameter. The presence of overdispersion is adjusted by the log-linear relationship between the expected number of crash counts in an observation unit i, μ_i, and the covariates X_i (*4*).

$$\ln(\mu_i) = X_i\beta + \epsilon_i \tag{2}$$

where β is the estimated coefficient vector and ϵ is the random error term representing the effect of omitted unobserved variables. NB has the following general form of probability mass function.

$$\Pr(Y = y_i) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(y_i + 1)}\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i}\left(\frac{1}{1+\alpha\mu_i}\right)^{1/\alpha} \tag{3}$$

where Γ (.) = gamma function and $\alpha > 0$. Poisson regression is a limiting condition of NB regression while $\alpha \rightarrow 0$. Wide application of NB regression models as found in the road safety literature (*4, 13, 14, 17–22*) implies acceptable practice in modeling crash frequencies and therefore is thought to be appropriate to use in this study.

DISCUSSION AND RESULTS FROM MODEL ESTIMATES

Each model was estimated separately for various trip generations (productions and attractions), roadway characteristics, and considering the combined effect of trip- and road-related variables. The variables that were statistically significant at the 95% confidence level were retained in the models. The following response variables were considered: total number of crashes (Model A), severe (fatal and severe injury) crashes (Model B), total peak-hour crashes (Model C), and pedestrian- and bicycle-related crashes (Model D). As in the study by Wang and Abdel-Aty (*23*) and the temporal variations of the aggregated hourly crash frequencies on weekdays, peak hours were defined as 7:00 to 9:00 a.m. and 3:30 to 6:30 p.m.

The NB model estimates for four categories of crashes that consider trip-related predictors only are presented in Table 2. To capture the combined effects of various trip productions and trip attractions per TAZ, models were estimated with only two variables: natural logarithmic transformation of total trip productions and total trip attractions per TAZ. The transformations were applied to minimize heteroskedasticity in the data. Table 3 provides different model estimates and goodness of fit for the four developed models considering

TABLE 2 NB Models of Total Crashes, Severe Crashes, Peak-Hour Crashes, and Pedestrian- and Bicycle-Related Crashes with Trip-Related Predictors Only

	Total Crash (Model A)		Severe Crash (Model B)		Peak-Hour Crash (Model C)		Pedestrian- and Bicycle-Related Crash (Model D)	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	3.3661	0.0466	1.1714	0.0462	2.0335	0.0436	0.1118	0.0709
HBWA	–0.0005	0.0001	–0.0004	0.0001	–0.0005	0.0001	–0.0004	0.0001
HBWP					0.0004	0.0001		
HBSHA	0.0001	0	0.0001	0	0.0006	0.0001		
HBSRA					–0.0009	0.0002		
HBSRP	–0.0078	0.0012			–0.0064	0.0009	–0.0122	0.0016
HBSCP	0.0008	0.0002						
HBOA					–0.0003	0.0001		
HBOP	0.005	0.0009			0.0044	0.0007	0.0084	0.0012
LTRKP	0.002	0.0008	0.0022	0.0002			0.0032	0.001
HTRKP	–0.001	0.0004	–0.0011	0.0004			–0.0026	0.0009
EIA	0.0091	0.0032	0.0054	0.0025	0.0137	0.0019		
AIRPP	0.011	0.0016			0.0069	0.0013	0.0158	0.0022
COLP	0.0005	0.0002					0.0009	0.0004
NHBWP							0.0008	0.0002
α	0.9608		0.8646		0.6634		1.5448	
logL (intercept model)	265,585.71		7,497.97		33,239.06		1,499.53	
logL (full model)	265,748.88		7,603.84		33,402.56		1,627.37	
Deviance value/DF	1.164		1.1366		1.0738		1.03	
Pearson chi-square value/DF	1.211		1.0962		1.2167		1.0123	

NOTE: SE = standard error; logL = log likelihood; DF = degree of freedom.

TABLE 3 NB Models of Total Crashes, Severe Crashes, Peak-Hour Crashes, and Pedestrian- and Bicycle-Related Crashes with Total Trip Production and Attractions

	Total Crash (Model A)		Severe Crash (Model B)		Peak-Hour Crash (Model C)		Pedestrian- and Bicycle-Related Crash (Model D)	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	1.4541	0.1607	−0.9455	0.1903	0.2019	0.1747	−3.7349	0.323
logtp	0.1035	0.0335	0.2196	0.0351	0.1161	0.0329	0.4131	0.054
logta	0.2218	0.0257	0.1135	0.0278	0.1863	0.0256	0.1661	0.0408
α	0.963		0.8577		0.7258		1.5825	
logL (intercept model)	265,585.71		7,497.97		33,239.06		1,499.53	
logL (full model)	264,869.66		7,616.1565		33,276.37		1,627.2998	
Deviance value/DF	1.1542		1.134		1.0815		1.0305	
Pearson chi-square value/DF	1.3745		1.0616		1.4075		1.1639	

total trip production and attractions. Table 4 presents estimates of crash models with road-related predictors only. Finally, models estimated considering all variables (both trip and road related) are presented in Table 5.

Total Crash Model

Model A retained 10 independent variables while assessing the association with trip-related variables only (Table 2). No non-home-based trips were found significant at the 95% confidence level. The total-crash-trip-only model (Table 2) showed a negative association with home-based work attractions, home-based social recreational productions, and heavy-truck productions. Drivers often travel with their families and children in social recreational trips and are usually more careful in such conditions. For home-based work attractions, travelers may drive more cautiously.

The second model for total crashes was developed using total trip productions and total trip attractions only (Table 3). This model provided a better model fit than the first model on the basis of log likelihood and deviance value per degree of freedom (DF). As mentioned previously, logarithmic transformation of total trip productions and attractions was used. Both covariates were positively associated with the number of total crashes per TAZ. As the number of trips (attractions and productions) increases, exposure of traffic is thought to increase, and high exposure tends to increase the total number of crashes. Hadayeghi et al. (*13*) found a similar association between vehicle kilometers traveled and total crashes per TAZ in the city of Toronto. Also, a positive estimate for vehicle miles traveled was found by Karlaftis and Tarko (*5*) while investigating significant variables for crashes involving aged drivers in counties of Indiana.

The third model was developed considering road-related predictors only (Table 4). Five variables were found to be significant, among which the sum of roadway segment lengths with a 25-mph posted speed limit was found to be negatively associated with total crashes. On the contrary, the total segment length with higher posted speed limits (35, 45, and 65 mph) and total number of intersections per TAZ were found to be positively associated with total crashes. The association between higher speed and crash propensity has been well recognized in road safety studies (*24–26*). Intersections can

TABLE 4 NB Models of Total Crashes, Severe Crashes, Peak-Hour Crashes, and Pedestrian- and Bicycle-Related Crashes with Road-Related Predictors Only

	Total Crash (Model A)		Severe Crash (Model B)		Peak-Hour Crash (Model C)		Pedestrian- and Bicycle-Related Crash (Model D)	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	3.2512	0.0496	0.9522	0.0507	2.0908	0.0464	0.33	0.0729
seglen25	−0.0112	0.0025			−0.0082	0.0021		
seglen35	0.0539	0.0241	0.1205	0.0219			−0.0598	0.0297
seglen45	0.2956	0.0824	0.2527	0.0704	0.1394	0.0702		
seglen55			0.1019	0.0435				
seglen65	0.2852	0.0496	0.2386	0.044	0.1817	0.0455		
Intersection	0.0452	0.0031	0.0304	0.003	0.036	0.0027	0.048	0.0044
α	0.9399		0.8021		0.7193		1.8179	
logL (intercept model)	265,585.71		7,497.97		33,239.06		1,499.53	
logL (full model)	265,765.97		7,646.6		33,355.04		1,567.3662	
Deviance value/DF	1.1574		1.128		1.0745		1.0181	
Pearson chi-square value/DF	1.0263		1.0787		1.1575		1.0748	

TABLE 5 NB Models of Total Crashes, Severe Crashes, Peak-Hour Crashes, and Pedestrian- and Bicycle-Related Crashes with All Predictors

	Total Crash (Model A)		Severe Crash (Model B)		Peak-Hour Crash (Model C)		Pedestrian- and Bicycle-Related Crash (Model D)	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	0.9755	0.1476	−1.3272	0.1881	−0.099	0.169	−3.672	0.314
seglen25	−0.014	0.002	−0.011	0.0026	−0.0112	0.0019		
seglen35	0.0599	0.0212	0.1381	0.0217	0.1762	0.0654	−0.1124	0.0257
seglen45	0.3408	0.0755	0.3093	0.0644				
seglen55			0.1722	0.0432				
seglen65	0.3413	0.046	0.2616	0.0402	0.2171	0.042		
Intersection	0.0336	0.0029	0.0191	0.0028	0.0279	0.0025	0.0365	0.004
logtp	0.125	0.0296	0.224	0.0341	0.144	0.0317	0.421	0.0522
logta	0.1815	0.023	0.0867	0.0257	0.1436	0.0242	0.1012	0.0393
α	0.7651		0.6582		0.6105		1.4044	
logL (intercept model)	265,585.71		7,497.97		33,239.06		1,499.53	
logL (full model)	265,040.86		7,746.89		33,379.04		1,673.87	
Deviance value/DF	1.1406		1.1309		1.0697		1.0309	
Pearson chi-square value/DF	1.2615		1.045		1.3443		1.0729	

also experience an increase in certain types of crashes, particularly rear-end crashes. In general, crashes may increase at intersections because of complicated maneuvers, and therefore a higher number of intersections within a TAZ could lead to an increase in total crashes. Finally, total crashes were tested for all variables (both trip- and road-related predictors) and model estimates are provided in Table 5. Among the seven significant variables, five belonged to roadway characteristics; the remaining two were log of total trip productions and log of total trip attractions. Interestingly, the five significant roadway variables were the same as in the third model (Table 4), which was developed for the road-related predictors only, and the direction of their respective estimates was the same in both models. Log of total trip productions and log of total trip attractions were positively associated with the total number of crashes per TAZ. This result conforms to the trip effects as exposure measures from the standpoint that one extra trip will generate an additional count in traffic volume.

On the basis of log likelihood, deviance value per DF, Pearson chi-square value per DF, and model parsimony, the total crash model was found to be best fit by total trip productions and total trip attractions (Table 3).

Severe Crash Model

Model B was developed considering severe crashes (fatal and severe injury crashes) as the response variable. The trip-only model (Table 2) for severe crashes retained five significant variables, among which home-based work attractions and heavy-truck productions were negatively associated with the increase in severe crashes. Most of the work-related trips are made during peak hours, which are usually congested and thus speeds are relatively low compared with off-peak hours. This possibly lowers the severity of crashes. Heavy-vehicle drivers are usually skilled drivers and are professionally trained to cope with unexpected situations in the road–traffic environment, which may help explain the decreasing the number of severe crashes.

Total trip production and attraction models for severe crashes (Table 3) provided almost similar goodness of fits compared with the trip-only model (Table 2). The log likelihood, deviance value per DF, and Pearson chi-square value per DF for the total trip severe crash model (Table 3) were slightly greater than those for the trip-only model for severe crashes (Table 2).

The severe crash model with the road-related predictors (Table 4) had five significant variables at the 95% confidence level. The sum of roadway lengths with 35-, 45-, 55-, and 65-mph speed limits were positively associated with severe crashes. This is theoretically acceptable as higher speeds tend to be associated with more severe crashes as previously mentioned. The severe crash model using all predictors (road- and trip-related variables; Table 5) retained eight significant variables, of which only the sum of the roadway lengths with a 25-mph speed limit had a negative estimate. This means that the increase in roadways with a 25-mph posted speed would reduce the number of severe crashes within a TAZ. This is easily explained because severe crashes are less likely to occur at reduced speeds. Among the four models discussed in this section, it was found that the severe crash model was best described by trip-related variables only (Table 2).

Peak-Hour Crash Model

The peak-hour crash model (Model C) presented in Table 2 revealed that home-based work attraction and home-based social recreational productions and attractions had negative estimates. The possible effects of home-based work attractions and home-based social recreational productions have been previously explained. The coefficient for the home-based work productions, external–internal attractions, and airport productions were positive and significant. Perhaps a desire to reach the destination quickly generates such positive correlations. Airport trips could also be related to nonfamiliar travelers (rental cars). Home-based other trip attractions and productions were retained in the model with opposite signs in their estimates. An explanation for such cases is difficult at the macro-level crash analysis. For the combined model (Table 5) of peak-hour crashes, six variables were found significant at the 95% confidence level, among which only the sum of roadway lengths with a 25-mph posted speed limit had a negative estimate. Similar to Model B, the sum of roadway lengths with posted speed limits of 35 and 65 mph were positively associated with peak-hour crashes. The peak-hour crash model with road-related predictors (Table 4) also had the sum of roadway lengths with a 25-mph posted speed limit estimate negatively associated with the peak-hour crash frequency. The other three significant variables of the road-only model were the sum of roadway lengths with 45- and 65-mph posted speed limits and the total number of intersections per TAZ, all with positive signs. The hasty attitude of commuters to avoid peak-hour congestion or to reach home or work places early or on time is an inherent characteristic of peak-hour driving. This may increase crashes at or near intersections and on high-speed (e.g., ≥45 mph) roads. On the basis of goodness-of-fit for the full model, it was suggested that peak-hour crashes were best described with total trip productions and total trip attractions (as in Table 3).

Pedestrian- and Bicycle-Related Crash Model

Pedestrian- and bicycle-related crash models (Model D) developed considering trip-related variables only (Table 2) provided goodness of fits similar to those for Model D in Table 3 (i.e., total trip productions and attractions model). Only two independent variables—total roadway segment lengths with 35-mph speed limit and total number of intersections per TAZ—were significant in the pedestrian and bicycle crash model developed for road predictors only (Table 4). The total roadway segment length with a 35-mph speed limit was negatively associated, whereas the estimate of total number of intersections per TAZ was positive and the highest among the four models (Table 4), which indicates that pedestrians and bicyclists tend to be more involved in crashes at or near intersections. The combined effect model (Table 5) for pedestrian- and bicycle-related crashes had three significant positive predictors—log of total trip productions, log of total trip attractions, and number of intersections per TAZ—while the total roadway length with a 35-mph speed limit was negatively associated with pedestrian- and bicycle-related crashes as in Table 4. Assessing the goodness-of-fit statistics showed that the pedestrian- and bicycle-related crash model was best fit by the road-related predictors only (Table 4).

MANAGING TRAFFIC ANALYSIS ZONE SAFETY

Because of resource constraints in the transportation industry, there is always a need to prioritize hazardous sites or locations for safety treatments. A similar concept can be applied for TAZs. Thus, this study investigates a way to prioritize TAZs for safety management.

A traditional way is to look at the frequencies of these crashes in different TAZs. As TAZs vary widely in size, normalizing each of these crashes per mile of road would provide a standardized risk among the study TAZs. Figure 1 shows the frequency of severe crashes per mile of road at different TAZs. This map can easily be used to identify TAZs where safety management for severe crashes is most necessary. A similar map may be produced for other types of crash of interest.

The alternative to identify TAZs that require particular safety conscious attention from the authorities is to consider the factors identified to be significantly associated with each of these crashes. The analyses in the previous section revealed the significant factors associated with total, severe, peak-hour, and pedestrian- and bicycle-related crashes. For example, among the trip variables, home-based shop productions, light-truck productions, and external–internal attractions were positively associated with severe crashes (Table 2). Among roadway factors, the highest positive association for severe crashes was found for total roadway lengths with 45- and 65-mph speed limits (Tables 4 and 5). This clearly indicates a need to emphasize safety treatments in TAZs with longer miles of roads that have 45- and 65-mph posted speed limits. Also, safety authorities may prioritize safety issues with TAZs with higher home-based shop productions, light-truck productions, and external–internal attractions.

Similar analogies can be drawn for total, peak-hour, and pedestrian- and bicycle-related crashes. Among several positively associated factors for total crash frequency, roadway lengths with 45- and 65-mph posted speed limits were the highest (Tables 4 and 5). Therefore, safety treatment at TAZs with more miles of such roads is expected to reduce severe crashes as well as overall crash frequency.

Three home-based trip variables (work productions, shop attractions, and other productions) had positive associations with peak-hour crashes. Therefore, zones that generate a high number of such trips should be considered for safety management strategies. Also, peak-hour crashes were found to be positively associated with roadway lengths with 35-, 45-, and 65-mph posted speed limits.

The number of intersections per TAZ was the common factor associated with every type of crash investigated in this study. Intersections by their own unique nature demand special attention and have been emphasized in the safety literature.

CONCLUSION

This paper analyzed various trip types and roadway characteristics to analyze crash frequencies per TAZ. The results reveal that total trip productions and total trip attractions provide a better model fit for the total and peak-hour crashes. On the other hand, severe crashes were best associated with different trip-related variables, whereas the pedestrian- and bicycle-related crash model was best described by the roadway characteristics of a TAZ. This is a significant conclusion that might indicate that different approaches to zonal level analysis should be considered on the basis of type or severity of crashes being estimated.

In addition, the study results conform to the trip effects as a traffic exposure measure. However, considering trips as an exposure measure has certain limitations as the trips vary in length and time. The other exposure measures were not readily available for the TAZs used in this study. A few signs of the variable estimates for aggregate level models were difficult to explain. This particular issue has been reflected in the road safety literature; for example, De Guevara et al. (*14*) argued that for the data aggregated to the TAZ level a theoretically defensible fatal crash model is proved to be the most difficult to find. Also, it is recommended that investigation of the spatial relationship, if any, among the neighboring TAZs be considered in future research.

This study approach bears the potential for developing proactive and reactive safety countermeasures in transportation safety planning. Reactive safety countermeasures can be applied by transportation officials for built-up areas. High-risk zones can be identified according to crash distribution per TAZ. These zones may be considered in

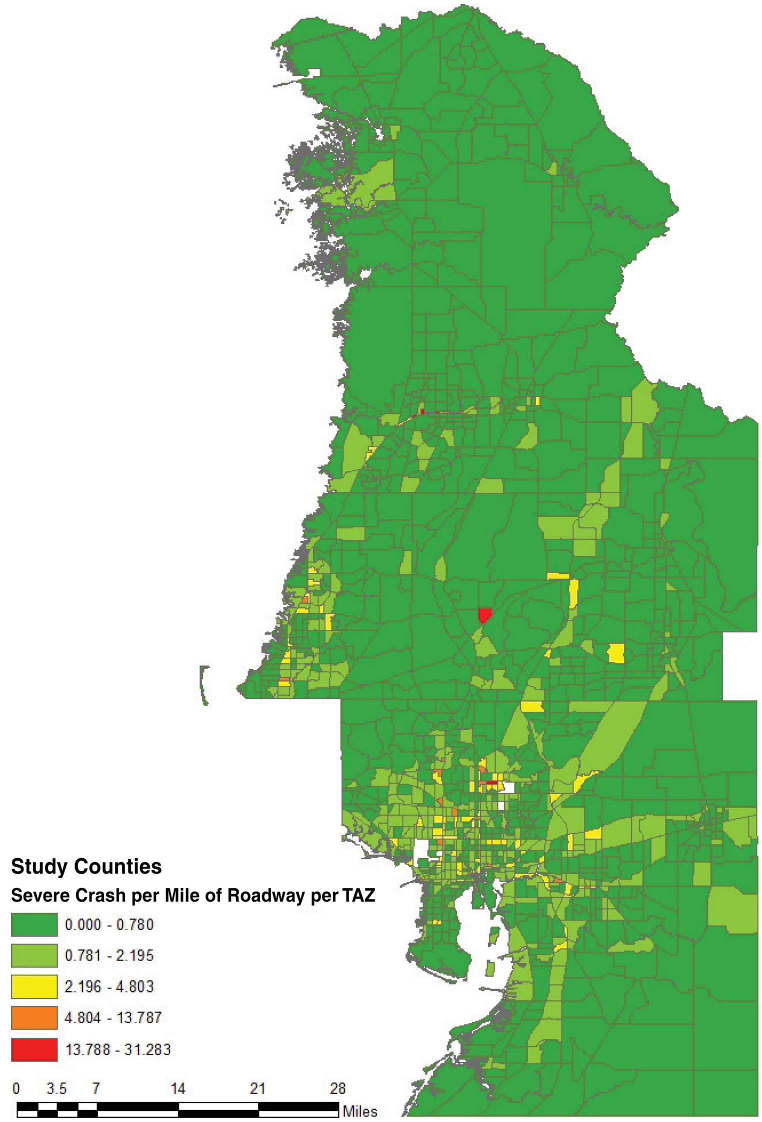

FIGURE 1 Distribution of severe crashes per mile of roadway per TAZ.

allocating safety funds. The identified significant factors would give decision makers, engineers, and planners a head start in enhancing safety features on the street network, if necessary. Proactively, the contributing factors identified as associated with different types of crashes may be built into a transportation network with appropriate safety measures. Therefore, the study approach helps in examining crash-specific factors to undertake necessary safety treatments at a zonal level for any particular crash type.

This paper evaluated safety management strategies, mostly in the form of identifying safety problems and contributing factors at the zonal level. TAZs could be identified for specific strategies to improve safety through better planning and management.

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