Collaborative Sciences Center for
ROAD SAFETY

FINAL REPORT

Integrating spatial safety data into transportation planning processes

December 2019

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Acknowledgement of Sponsorship

This project was supported by the Collaborative Sciences Center for Road Safety, www.roadsafety.unc.edu, a U.S. Department of Transportation National University Transportation Center promoting safety.

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. CSCRS-R15	**2. Government Accession No.**	**3. Recipient's Catalog No.**
4. Title and Subtitle: Integrating spatial safety data into transportation planning processes		**5. Report Date** December 2019 **6. Performing Organization Code**
7. Author(s) Christopher R. Cherry, Amin M. Hezaveh, Louis Merlin		**8. Performing Organization Report No.**
9. Performing Organization Name and Address University of Tennessee, Knoxville Civil and Environmental Engineering 324 JD Tickle Building Knoxville TN 37996-2313 Florida Atlantic University School of Urban & Regional Planning Florida Atlantic University 777 Glades Road, SO 284I Boca Raton, FL 33431		**10. Work Unit No.** **11. Contract or Grant No.**
12. Sponsoring Agency Name and Address United States Department of Transportation		**13. Type of Report and Period Covered** **14. Sponsoring Agency Code**
15. Supplementary Notes Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.		

16. Abstract

Travel demand models enable us to forecast the state of the transportation system under different scenarios such as changes to demand, transportation infrastructure and policies. By using a wide array of performance measures, planners can evaluate scenarios and compare their performance including but not limited to regarding cost, mobility, and emission with base scenario. Despite previous attempts to integrate road safety into planning models, one area that needs further attention is the safety of road users (instead of road entities) and how changes in travel patterns due to changes in transportation infrastructure and demographics affect the safety of road users.

To compare the safety performance of scenarios, we developed an HBA Safety Performance Function (HSPF). Similar to the traditional SPF that estimates the expected safety of a road entity, HSPF estimates the expected safety of road users in a particular traffic analysis zone (TAZ) based on their average trip frequency, trip length and modal splits. The main report focuses on developing the HSPF and evaluation of two scenarios based on the Nashville Metropolitan area travel demand model. Findings indicated that HSPF could be used to evaluate and quantify the safety impact of travel demand alternatives and it is strongly correlated with the travel characteristics of the road users at the TAZ level. To illustrate how HBA can be integrated into travel demand models as well as other relevant sources of data, we present four case applications. Each application illustrates different applications of the HBA to explore factors affecting road safety.

17. Key Words		18. Distribution Statement	
Home Based Approach; Safety Peformance Function; Travel Demand Models; Planning; Scenario Analysis			
19. Security Classif. (of this report)	**20. Security Classif. (of this page)**	**21. No. of Pages**	**22. Price**
Unclassified	Unclassified		

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Contents

Executive Summary

Travel demand models enable us to forecast the state of the transportation system under different scenarios such as changes to demand, transportation infrastructure, and policies. By using a wide array of performance measures, planners can evaluate scenarios and compare their performance including but not limited to cost, mobility, and emissions with base scenarios. Despite previous attempts to integrate road safety into planning models, one area that needs further attention is the safety of road users (instead of road segments or intersections) and how changes in travel patterns due to changes in transportation infrastructure and demographics affect the safety of road users.

Unlike the majority of road safety studies, in this report we attributed traffic crashes to the home address of the road users following an approach that is more consistent with public health approaches. We defined the Home-Based Approach as ***the expected number of crashes that road users who live in a certain geographic area experience during a specified period***. Furthermore, we measured the HBA crash frequency at the traffic analysis zone (TAZ) level. Using HBA enables us to measure both travel demand characteristics and safety at the TAZ corresponding to the residential address of the road users. As a result, HBA enables us to explore the relationship between travel demand and road safety of the road users (i.e., vulnerable road users, drivers, drivers and passengers, all road users).

The HBA can be used in evaluation, forecasting tools, and scenario analysis. To compare the safety performance of scenarios, we developed an HBA Safety Performance Function (HSPF). Similar to traditional SPFs that estimate the expected safety of a road entity, HSPF estimates the expected safety of road users in a particular TAZ based on their average trip frequency, trip length and modal splits. Those travel demand factors are predicted by travel demand models. To maintain brevity, the main report focuses on developing the HSPF and evaluation of two scenarios based on the Nashville Metropolitan area travel demand model as individual case studies. Findings indicate that HSPF could be used to evaluate and quantify the safety impact of alternative travel demand scenarios that are strongly correlated with travel characteristics of the road users at the TAZ level.

To illustrate how HBA can be integrated into travel demand models as well as other relevant sources of data, we present four applications of integrating safety into planning models. Each application illustrates different ways HBA can be used to explore factors affecting road safety. In addition to our work focused on Nashville in the core report, our applications span different geographies including three analyses in a smaller Tennessee city, Knoxville, and one state wide analysis. The geographic resolution for the Nashville cases and the three Knoxville applications are TAZ-level analysis. Similarly, the statewide analysis also uses census-level data. These applications are finer resolution than most other studies that tend to focus on zip-code levels of resolution.

HBA Application 1: Factors influencing road users' likelihood of involvement in traffic crashes at the zonal level.

In this application, we developed a model to predict the expected number of traffic crashes in the Knoxville Metropolitan area based on the information at the TAZ level as well as the output of the travel demand model. Knoxville MPO travel demand patterns are slightly different from Nashville MPO in that the region is more dependent on personal vehicles for commuting. Nevertheless, the Home-Based Approach was able to capture the relationship between the travel demand model outputs, demographic variables, and road users' safety. The model's estimate indicates that average zonal (i.e., TAZ) travel activity has a significant positive association with the HBA crash rate. This also holds for interstate and arterial vehicle miles traveled (VMT), intersection density, the percentage of roads with sidewalks, percentage of areas near bus stations, and the number of workers per household. On the other hand, median household income, population density, and VMT on low-speed roads have significant negative associations with HBA crash rate.

HBA Application 2: Exploring the economic impact of traffic crashes at the zonal level

Similar to the first application, in this study we used the Knoxville MPO travel demand model. To incorporate injury severity, we measured the Economic Cost of traffic Crashes (ECC) and the Comprehensive Cost of traffic Crashes (CCC) at the zonal level by using the monetary value of the person-injury cost. HBA method was able to explain the relationship between transportation network characteristics, demographic information, and the economic burden of crashes. Furthermore, we measured the Gini coefficient for the economic burden of traffic crashes which indicated the presence of inequal distribution of the burden of traffic crashes.

HBA Application 3: Factors influencing cost of traffic crash at the traffic analysis zone level: incorporating spatial effects

Unlike the previous two applications, we used spatial regression models to incorporate the presence of spatial autocorrelation in the analysis. Findings indicate that spatial autocorrelation exists in the study area. The presence of spatial autocorrelation and superiority of the spatial autoregressive regression compared to the spatial error model implies the economic cost of traffic crashes in one TAZ is affected by the traffic safety of the adjacent TAZs. Findings are discussed in line with road safety literature.

HBA Application 4: A statewide geographically weighted regression to estimate the comprehensive cost of traffic crashes at a zonal level

In this application, we are using United States census data as an input for statewide analysis of factors influencing the burden of traffic crashes at the State level. Furthermore, we used a Geographically Weighted Poisson Regression (GWPR) model to show spatial variation of the coefficient at the census tract level. Poisson and GWPR models were used to analyze the data. The GWPR model was more suitable compared to the global model to address spatial heterogeneity. Findings indicate the population of people over 60-years-old, the proportion of residents that use non-motorized transportation, household income, population density, household size, and metropolitan indicators have a negative association with CCCAZ. Alternatively, VMT, vehicle per capita, percent educated over 25-years-old, population under 16-years-old, and proportion of non-white races and individuals who use a motorcycle as their commute mode have a positive association with CCCAZ.

To conclude, integrating safety explicitly into planning models requires planning-oriented data resolution and planning approaches. Most planning approaches rely on generation of travel demand from activity generators (homes and destinations). We can translate safety data from the location of the crash to the home of the crash participants, effectively developing crash generation models that are oriented toward travel demand analysis methods. From a practitioner perspective, integrating safety into planning processes explicitly and proactively includes safety as a measure of effectiveness of various transportation investment strategies. It also allows for more nuanced equity and environmental justice analysis to assure that negative safety outcomes and countermeasures are fairly distributed. The work here presents novel analytical approaches to account for spatial heterogeneity in crash rates and outcomes. The methods presented here and new and future approaches can improve the predictive power of safety models, including new geographically sensitive approaches to estimating safety burden within planning processes.

Introduction

Travel demand forecasting and modeling remain important tools in the analysis of transportation plans, projects, and policies. Travel demand modeling is essential and useful for modeling transportation systems in the future under different circumstances. Performance measures are used by planners to evaluate travel demand models; they are used for several purposes: among them are accountability, efficiency, effectiveness, communication, clarity, and improvement (Pickrell and Neumann 2000). According to Federal Highway Administration, performance measurement can be defined as a process of assessing progress toward achieving predetermined goals, including information on the efficiency with which resources are transformed into goods and services (outputs), the quality of those outputs (how well they are delivered to clients and the extent to which clients are satisfied) and outcomes (the results of a program activity compared to its intended purpose), and the effectiveness of government operations in terms of their specific contributions to program objectives (Shaw 2003).

Vehicle-miles of travel, vehicle-hours of travel, link-based volume-to-capacity ratios, travel speeds, emission, accessibility to jobs, and accessibility to public transit are among the most frequently used performance measures in transportation system analysis (Cambridge Systematics 2012). More advanced metrics such as travel time reliability; intersection-based, area-based, or multimodal levels of service; hours of delay; or hours of congestion require both the input data and the model functions to calculate the measure for both a current base year and any horizon years (Cambridge Systematics 2012). Performance measures enable planners to compare and rank alternatives and make an informed decision for choosing the best alternative.

One of the areas that have received less attention is the safety assessment of transportation planning. Safety planning encompasses the idea that safety issues can be brought into earlier stages of the transportation planning process. Historically, safety has primarily been considered in the design phases of transportation projects or afterward when crash analyses are conducted and hot spots are identified (de Leur and Sayed 2003). The approach of safety planning, on the other hand, suggests that safety considerations can be integrated even into the earliest stages of the transportation planning process. This potentially includes which types of transportation projects get selected and built, where they are built, and even potentially land use planning decisions (Schwetz, Reiff, and Chatterjee 2004) and other transportation policy decisions such as travel demand (Pirdavani et al. 2012b).

Another goal of safety planning is to forecast a baseline of expected crash rates against which progress can be measured (S. Washington 2006). According to S. Washington (2006), safety is often considered by transportation officials to be a concept that is best handled during the project design process or left to enforcement agencies. Relatively little thought was given to how safety could be considered early in the planning process so that resulting plans, operations strategies, policies, and institutional partnerships would incorporate safety not as an afterthought, but rather as an integral part of an agency’s capital investment, operations, and daily management programs.

Future crash counts are determined not just by infrastructure, but also by underlying changes in population demographics as well as travel demand. Road safety studies tend to specify the presence of disparities across road user type, income, race, and ethnicities; for instance, the crash fatality rate is approximately double in low- and middle-income countries compared to high-income countries (World Health Organization 2015). This trend also holds within-country; several studies in the United States reported that vulnerable road users (i.e., pedestrians and bicyclists) and lower-income neighborhoods have higher fatality rates compared to motorized road users and wealthier neighborhoods (Clark 2003; Marshall and Ferenchak 2017; Romano, Tippetts, and Voas 2006). In rural areas, the fatality rate tends to be several times higher than in urban areas (Blatt and Furman 1998; Marshall and Ferenchak 2017). Additionally, some ethnic groups such as Hispanics, African-Americans, and Native Americans have both higher crash rates (Mayrose et al. 2005; Braver 2003; Campos-Outcalt et al. 2003; McAndrews et al.

2013; Mayrose and Priya 2008) and fatality rates (Schiff and Becker 1996; Baker et al. 1998; Harper et al. 2000).

The challenges of safety planning include the problem that transportation safety analysts are trying to analyze the safety impacts of infrastructure or infrastructure changes that have not been built yet. For this reason, predictive models are often used. Crash prediction models can be used to forecast the expected impacts of certain defined infrastructure changes at the zonal level for specific type of crashes (e.g., Cai et al. 2017; Gomes, Cunto, and da Silva 2017; Hadayeghi et al. 2006; Hezaveh, Arvin, and Cherry 2019; Pirdavani et al. 2012a; Wang et al. 2016). The advantage of zonal-level safety prediction models compared to the models that predict crashes at the entity level (e.g., road segment, intersection) is that a wider variety of planning variables can be accounted for including demographics, travel demand, and land use variables (Mohammadi, Shafabakhsh, and Naderan 2018; Naderan and Shahi 2010). While it is not impossible to consider land use in a segment level model, land use composition, demographic variables, street network variables, and any of a variety of outputs from travel demand models can be used in a zonal-level planning analysis.

Road safety definition in engineering analysis is best specified as "*the number of accidents (crashes) by kind and severity, expected to occur on the entity during a specified period.*"(Hauer 1997, 24) This definition attributes road safety to the location of the crashes (i.e., entity). Consequently, this concern has led to improvements in the geometric design or operations of transportation facilities, a traditional responsibility of transportation agencies. As a result, most strategies target engineering solutions and design of the road infrastructure rather than focusing on the road users and their characteristics.

Furthermore, police crash reports as the main source of road safety analysis only record limited information about road users involved in traffic crashes including age, gender, road user type, seating position, safety equipment use (e.g., helmet, seat belt), driving license status, and road users' violations (e.g., distraction, speeding, DUI) (MMUCC 2012). Although this information provides a valuable contribution to safety science, this information about road users seems trivial compared to the substantial role of road users in traffic crashes. By using the traditional definition of road safety that attributes safety to the location of traffic crashes, it is challenging to measure and attribute the burden of crashes in areas where individuals reside.

Unlike engineering approaches in road safety analysis, in epidemiology and public health studies, residential characteristics of the population play an important role, and usually the issue of interest (i.e., the health problem) is typically attributed to the residential address of a population such as neighborhood, city, state, or country. This is also the case for travel demand models. In travel demand models such as the four-step model or activity-based models, transportation planners measure and study the travel behavior of the road users based at the traffic analysis zone corresponding to the home address of the road user (Kanafani 1983). Travel demand models and other sources of data such as Census data are valuable sources of data, and using them in road safety analysis would provide a complete picture of road safety (Cherry et al. 2018).

Remarkably, most demand for transport is a derived demand (Kanafani 1983) and varies substantially based on the origin of the travelers and the regional economy. This variation in travel demand reflects the traveler's sociodemographic and economic factors, and travelers' multimodal accessibility to their destination, among other things (Kanafani 1983; Cervero and Kockelman 1997). This variation in transportation demand can be measured by a comparison of the travel characteristics at the zonal level such as trip frequency, average trip length, and mode choices. We hypothesize variation in travel demand strongly correlates with the safety of the individuals living in a city, that is, residents with lower (motorized) travel demand bear a smaller crash and injury burden.

To tie traffic crashes to the home addresses of the individuals in this study, we took an epidemiological approach to a road safety analysis by looking at travel behavior surrounding the home addresses of the road users involved in traffic crashes –i.e., a Home-Based Approach (HBA). HBA enables us to evaluate and compare transportation planning alternatives based on their safety performance. This study has several objectives:

1- To introduce an index (HBA) for measuring road safety that attributes traffic crashes to the road users instead of road entities.
2- Develop a safety performance function to explore the correlation between travel demand and the safety of road users.
3- Estimate and compare the safety of long-term planning models by using proposed HSPF.

Furthermore, to illustrate how HSPF can aid in the evaluation of transport safety analysis, we present four applications of the HBA. Each application illustrates different approaches and advantages to evaluate the safety performance of travel demand models.

Methodology

Home-Based Approach Definition

The definition of the road safety that is used in most studies that use crash data (e.g., safety performance function, crash severity analysis, crash modification factor development) is best specified as "*the number of accidents (crashes) by kind and severity, expected to occur on the entity during a specified period.*"(Hauer 1997, 24) This definition attributes the road safety to the location of the crashes (i.e., entity) rather than individuals who had a direct role in traffic crashes (i.e., pedestrians, bicyclists, motorcyclists, and drivers).

To tie traffic crashes to the home addresses of the individuals in this study, we will use the home address of the road users who were involved in a traffic crash. A residential address is one of the crucial data elements the police officer records at the crash scene (MMUCC 2012). Furthermore, using the home address to collect information of the road users to collect data elements regarding sociodemographic and travel behavior is a common practice in urban travel demand analysis (Kanafani 1983) but is not often used in road safety analysis due to privacy concerns and geocoding challenges.

To address the shortcoming of the location-based approach definition, in this study we will define the Home-Based Approach (HBA). In the HBA, we attribute traffic crashes to the home address of the road users. And in this way, we define the Home-Based Approach (HBA) crash frequency as ***the expected number of crashes that road users who live in a certain geographic area experience during a specified period.*** It should be noted that the measurement unit of the HBA crash frequency is the number of crashes per year per resident of a geographic unit.

Considering the availability of the travel demand model as the finest geographical unit for studying transportation demand analysis and travel behavior, we used the traffic analysis zone (TAZ) as the geographic unit for this analysis. The TAZ is the conventional unit of analysis in travel demand modeling and is used to aggregate individual households and premises into manageable geographies for modeling purposes (Ortuzar and Willumsen 2002). Furthermore, we measured HBA crash frequency of multiple road users including vulnerable road users (i.e., pedestrian and bicyclists), drivers, vehicle occupants (i.e., driver and passenger), and all road users (vehicle occupants and vulnerable road users).

Crash Data and Geocoding Addresses

Overall, 2,026,666 individuals were involved in 694,276 traffic crashes between 2014-16 in Tennessee. The Home address of the road users involved in traffic crashes who reside in the Nashville metropolitan region was extracted from Tennessee Integrated Traffic Analysis Network (TITAN) crash database. We used the Bing application program interface (Bing 2019) services to geocode the addresses, and only those geocoded addresses that had an accuracy level of premises (e.g., property name, building name), address-level accuracy, or intersection level accuracy were used for the analysis.

Nashville Travel Demand Model

In order to develop HSPF, in this study we used the travel demand model of the Nashville Metropolitan area which is an activity-based model. Nashville metropolitan has a total population of 1.5 million across 2,816 TAZs. This region is anchored by the city of Nashville but also includes several urbanized areas outside the city. The travel demand model is an activity-based model that simulates household and person travel choices at a microzone-level on a minute-by-minute basis (RSG 2016).

The population of a TAZ to some extent represents its residents' miles traveled in the transportation system. As population increases, we expect to see higher miles traveled in the network. However, the population variable does not capture the number of trips generated by residents of a geographic area nor their trip length (e.g., activity). Some studies focused on modeling the crash frequency of a TAZ based on the location of traffic crashes used trip generation models as a vector to reflect the activity of one TAZ (Mohammadi, Shafabakhsh, and Naderan 2018; Naderan and Shahi 2010; Abdel-Aty, Siddiqui, and Huang 2011; Dong, Huang, and Zheng 2015; Dong et al. 2014). Although trip generation provides information regarding the activity of the road users, it fails to capture trip length. A more inclusive variable for estimating the economic cost of traffic crashes at a zonal level needs to consider both trip length and trip frequency simultaneously.

To compare travel demand for different areas and incorporate them in the analysis, we developed average miles traveled (AMT) for each mode of transportation. The travel demand model provides a trip tour for each person in a family. Each family is further assigned to a certain TAZ. To generate a total exposure metric, we estimate AMT by mode (m) for residents of TAZ i:

$$Average\ Miles\ Traveled_{mi} = \frac{\sum_f \sum_p d_{mi_{fp}}}{Pop_i} \qquad \text{Equation 1}$$

where Pop_i and f respectively correspond to the population and number of families in the i^{th} TAZ and p represent persons in each family unit. **Table 1** presents the descriptive statistics of the miles traveled by each mode for the study area. AMT for motorized road users was substantially higher than for transit, walk, and bike.

Table 1 Descriptive statistics of miles traveled in the system at the TAZ level

Road user type	Mean	Std. Err.	[95% Conf. Interval]
All road user	27.96	0.96	26.07-29.85
Drivers only*	33.85	1.18	31.53-36.17
Motorized vehicle** (i.e., passenger(s) + driver)	35.45	1.23	33.04-37.86
Walk & Bike	0.56	0.03	0.50-0.62
Transit	1.04	0.04	0.96-1.11

* Weighted average of single, two, and three occupant vehicles: Drivers A = 1 * $AMT_{\text{Single vehicle}}$ + $^1/_2\ AMT_{2\text{ occupants}}$ + $^1/_3\ AMT_{3\text{ occupants}}$
** Average of single, two, and three occupant vehicles: Drivers AMT = $AMT_{\text{Single vehicle}}$ + $AMT_{2\text{ occupants}}$ + $AMT_{3\text{ occupants}}$

Modeling Approach

To evaluate safety at zonal level traditionally, count data models are commonly utilized owing to the nature of traffic crashes that are measured as non-negative integers in a specific period of time (Anastasopoulos and Mannering 2009). Likewise, the HBA crash frequency is a non-negative integer. Hence the models that would be used must follow the nature of count models.

The Poisson model and negative binomial models are two common model specifications for count data. The main difference between these two specifications is the restriction of equality of the mean and variance ($E[n_i] = Var[n_i]$) of the observations. In the case of traffic crashes, this assumption usually is not met. To take account for the inequality of mean and variance, the more generalized negative binomial model is proposed:

$$\lambda_i = exp\ (\beta X_i + \varepsilon_i) \qquad \text{Equation 2}$$

where $Exp(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance α. The addition of this term allows the variance to differ from the mean ($Var[n_i] = E[n_i] + \alpha E[n_i]^2$). The negative binomial probability density function has the form:

$$P(n_i) = \left(\frac{\frac{1}{\alpha}}{\left(\frac{1}{\alpha}\right) + \lambda_i}\right)^{\frac{1}{\alpha}} \frac{\Gamma\left[\left(\frac{1}{\alpha}\right) + n_i\right]}{\Gamma\left(\frac{1}{\alpha}\right) n_i!} \left(\frac{\lambda_i}{\left(\frac{1}{\alpha}\right) + \lambda_i}\right)^{n_i} \qquad \text{Equation 3}$$

where, $\Gamma(.)$ is a gamma function. In the negative binomial model, if the value of α approaches zero, the negative binomial model yield to the Poisson model. Therefore, the negative binomial model is appropriate when the value of the dispersion parameter (α) significantly differs from zero (S.P. Washington, Karlaftis, and Mannering 2010). Additionally, we measured elasticity effects for each variable. Elasticity can be interpreted as the percent effect a 1% change in a variable has on the severity outcome probability (Khorashadi et al. 2005).

Traditionally, in road safety analysis, traffic volume is used as the exposure variable, usually in the form of traffic count, Vehicle Miles Traveled (VMT), Daily Vehicle Miles Traveled (DVMT), or VMT by road classification (Aguero-Valverde and Jovanis 2006; Hadayeghi, Shalaby, and Persaud 2010; Li et al. 2013; Rhee et al. 2016; Pirdavani et al. 2012c, 2012a; Pirdavani et al. 2013; Hosseinpour et al. 2018). Since we are estimating the number of crashes of the road users in one TAZ, in this study, we will use the population of the TAZ as the exposure variable for the regression analysis.

Scenario Analysis

In order to determine if countermeasures are reducing the number of crashes, we can forecast expected crash frequency or crash rates at the zonal level, and those forecasts can be used in turn as a benchmark against which to measure progress on improving safety (S. Washington 2006).

In this study, we assessed two scenarios based on travel demand in the year 2033. The base business-as-usual scenario[1] (EC[2]-2033) does not include major changes and only considers the development of the existing transportation infrastructures without substantial changes in the public transit system. Alternatively, the second scenario for illustration (Transit-2033) focuses on large investments in a mass transit system. The plan reflects the proposed 2018 ballot initiative to expand transit and includes 26 miles of light rail and 25 miles of bus rapid transit as well as additional funding for local buses and the existing Nashville commuter rail line. **Figure 1** presents the abstract representation of the proposed changes in the transportation network (Let's Move Nashville 2017). This proposed scenario was projected

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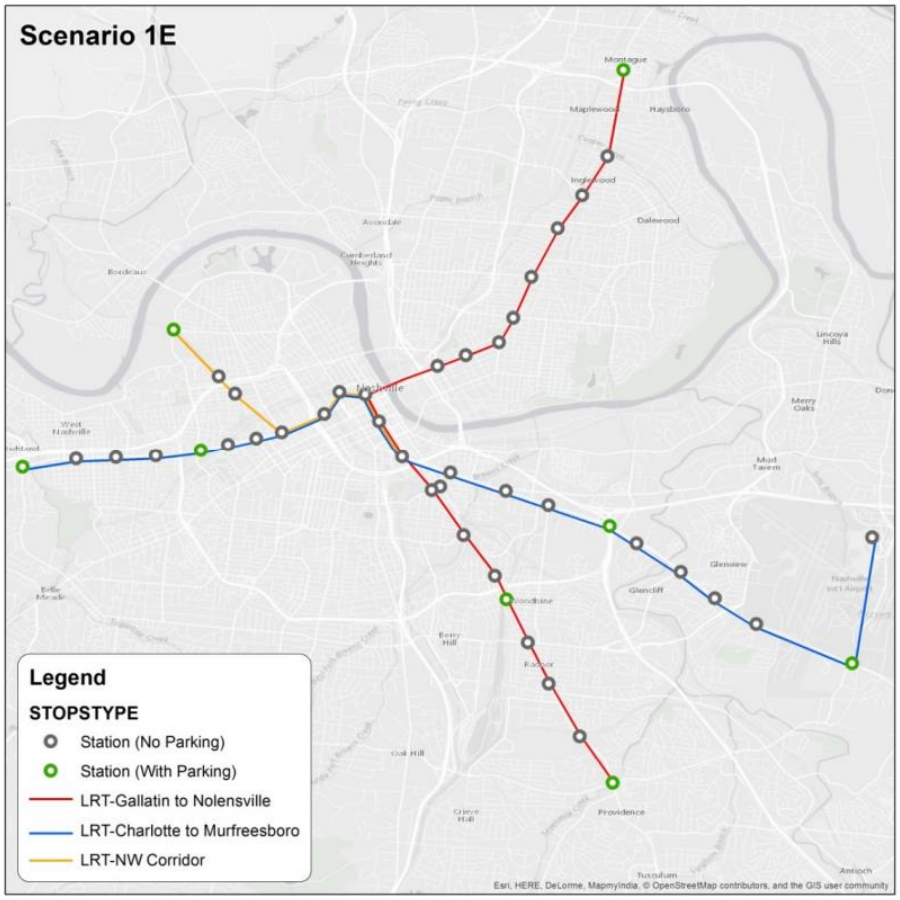
[1] Or no build scenario

[2] Existing condition

to increase from 35,600 today to anywhere between 114,500 and 131,000 by 2040 (Let's Move Nashville 2017).



Source: HDR Engineering

Figure 1 Transit lines in the proposed scenario

Results

Predicting Crash Frequency

After geocoding the home addresses of the road users, we found that 366,144 (i.e., drivers, passengers, pedestrians, and bicyclists) had a home address in the Nashville metropolitan area. After assigning individuals to the TAZ corresponding to their home address, we measured HBA crash frequency for different road users. Table 2 presents the average HBA crash frequency by road user type at the TAZ level. Figure 2 presents the HBA crash frequency distribution over the average miles traveled as well as the empirical probability distribution function (PDF) and the empirical cumulative distribution function (CDF) of the HBA distinct to different transportation modes.

Figure 3 and Figure 4 also present the HBA crash frequency at the zonal level in Nashville MPO. The spatial distribution of the HBA indicates that the HBA crash frequency is less in the central area of the Nashville MPO compared to the decentralized areas. More urbanized areas with higher population density are in centralized areas. It should be noted that 55% (1,389) TAZs had zero pedestrian or bicycle-related crashes. On the other hand, there were no populated TAZs with zero crashes for all other HBA crash types.

Table 3 presents the correlation between AMT (by transportation modes) and HBA crash frequency. All the correlations are significant (*p-value* < *0.05*). Considering the correlation between average miles traveled and HBA crash frequency, we found that Walk and Bike has a relatively lower correlation compared to other modes of transportation.

Table 2 HBA crash frequency by road user type between 2014-16

HBA Crash Frequency	Mean	Std. Err.	[95% Conf. Interval]
All road user	145.07	2.65	139.86-150.27
Driver	110.21	2.01	106.27-114.14
Motorized road user	144.27	2.64	139.10-149.45
Vulnerable road user	0.79	0.02	0.75-0.84

Table 3 Correlation between HBA crash frequency and average miles traveled

		HBA Crash Frequency				Average Miles Traveled				
		All Users	Drivers	Motor-ized Road Users	Vulner-able	All users	Drivers only	Motor-ized Road Users	Transit	Walk & Bike
HBA Frequency	All road user	1.00		-	-	-	-	-	-	-
	Driver	1.00	1.00	-	-	-	-	-	-	-
	Motorized road user	1.00	1.00	1.00	-	-	-	-	-	-
	Vulnerable road user	0.61	0.61	0.61	1.00	-	-	-	-	-
Average Miles Traveled	All users	0.14	0.15	0.14	0.09	1.00	-	-	-	-
	Drivers only	0.14	0.14	0.14	0.08	1.00	1.00	-	-	-
	Motorized Road Users	0.14	0.15	0.14	0.09	1.00	1.00	1.00	-	-
	Transit	0.14	0.14	0.14	0.09	0.97	0.97	0.97	1.00	-
	Walk & Bike	0.09	0.09	0.09	0.05	0.78	0.78	0.77	0.82	1.00

All correlations are significant

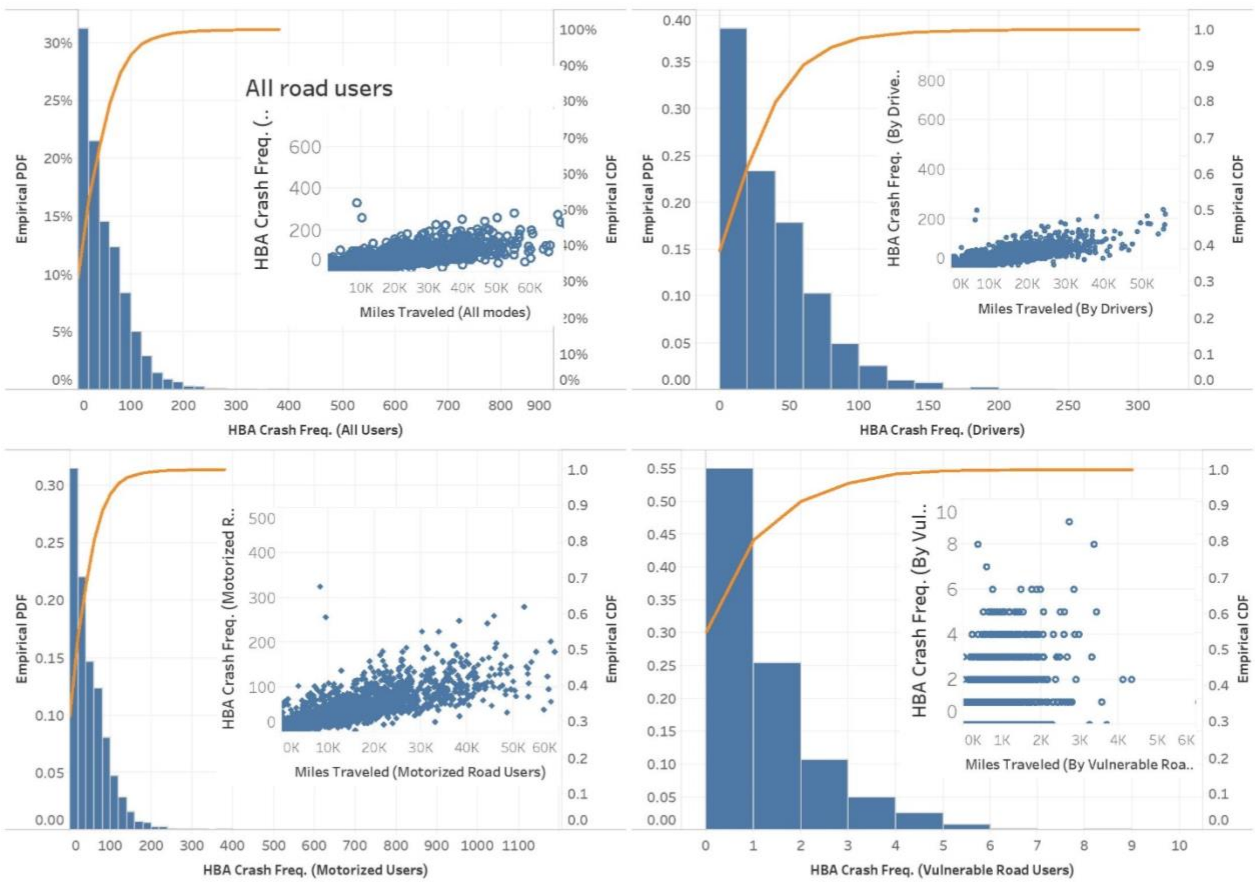


Figure 2 VMT and HBA crash frequency by different road users' type

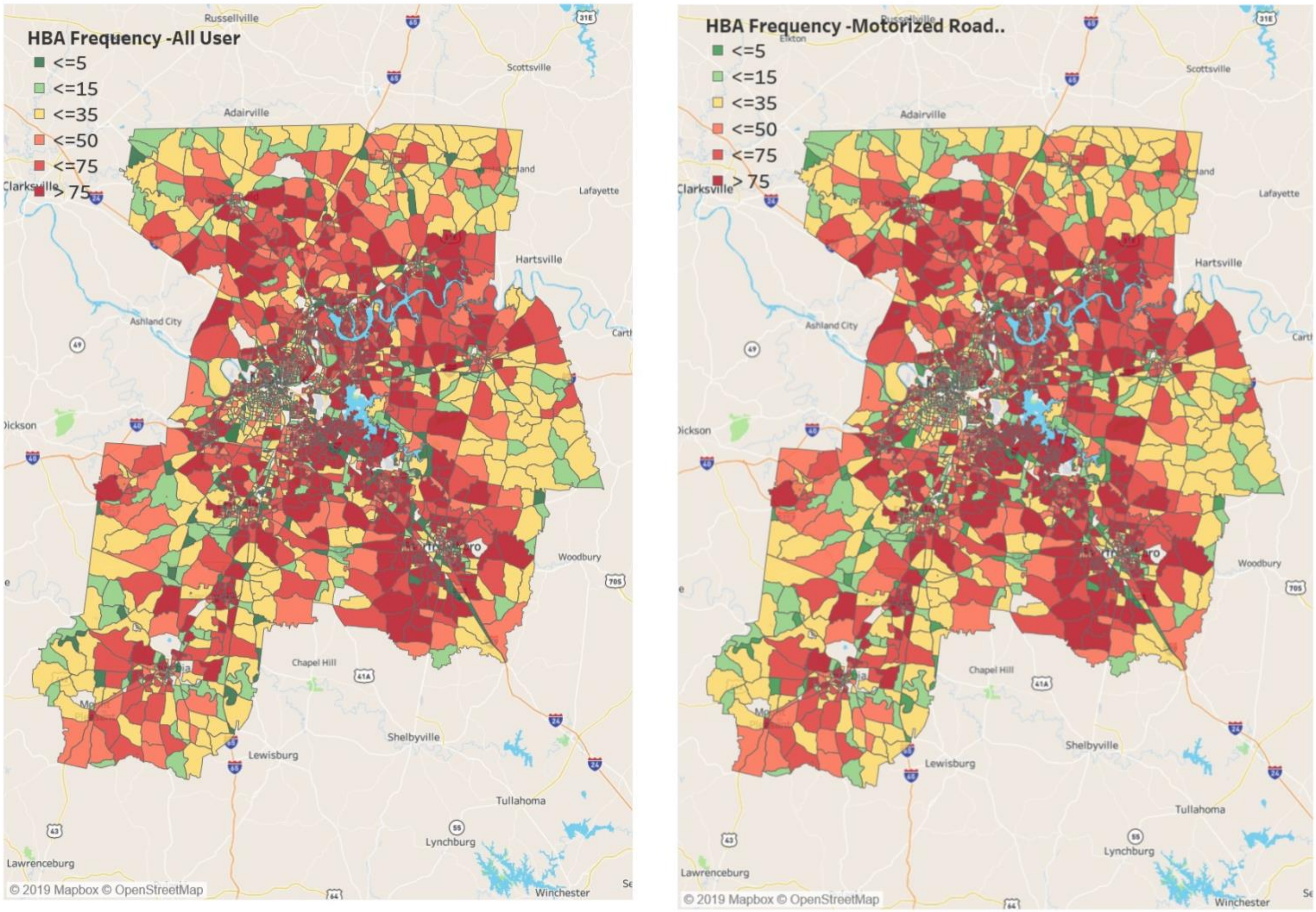


Figure 3 HBA Crash frequency of all road users (left) and motorized road users (right)

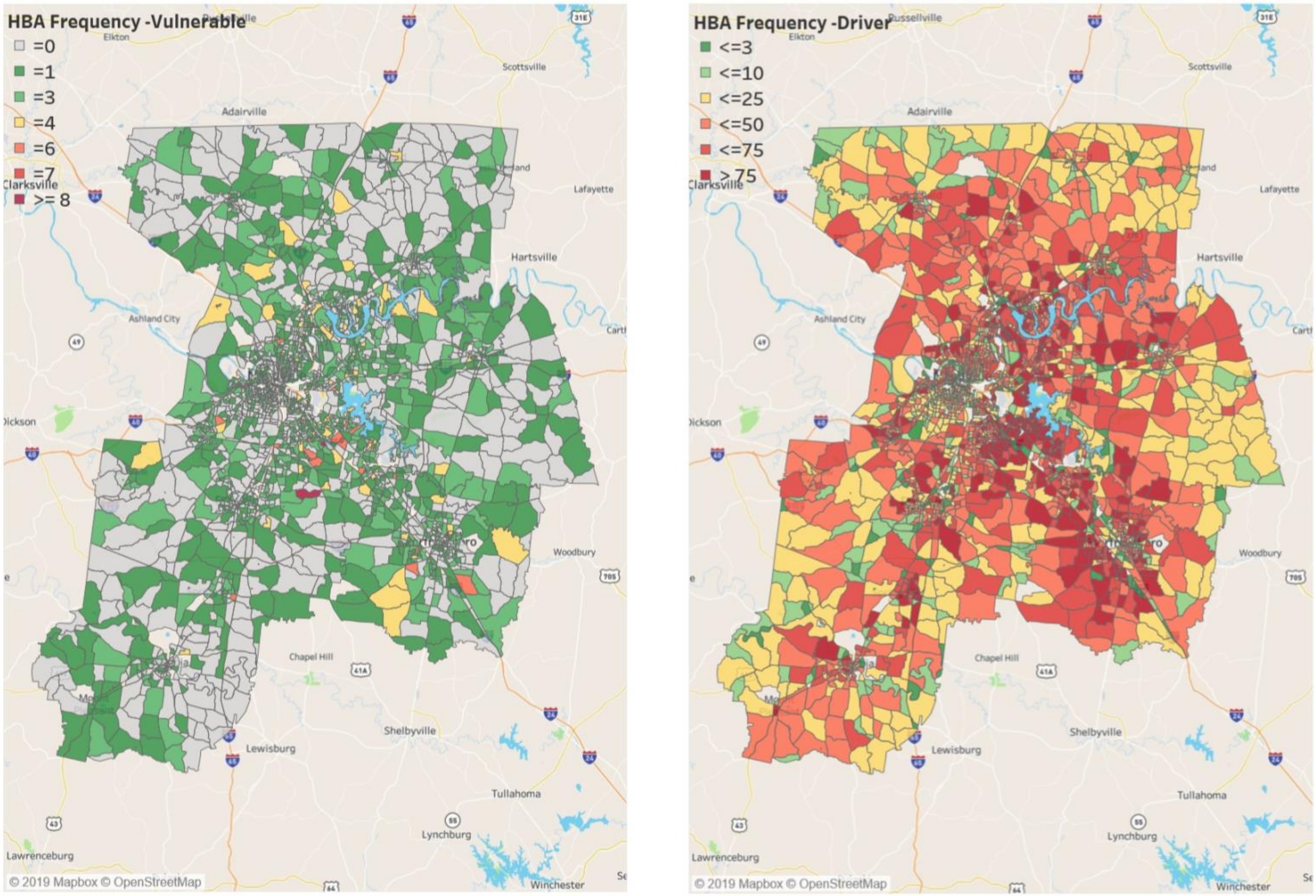


Figure 4 HBA Crash frequency of the vulnerable road users (left) and driver (right)

Table 4 presents the results of the estimated HSPF models. We used TAZ's population as the exposure variable in Negative Binomial models. The significant value of the overdispersion parameters indicates that the NB model is statistically better than the Poisson model.

All the AMT variables also have a significant correlation with the HBA crash frequency. Overall, the finding indicates that miles traveled by road users in the transportation network by different modes of transportation have significant associations with their corresponding HBA crash frequency. The positive sign indicates that as average miles traveled increases, road users' crash frequency increases. A comparison of the elasticity of the coefficients indicates that AMT by drivers has the highest elasticity compared to all other modes followed closely by motorized road users. Alternatively, AMT of Walk and Bike has the lowest elasticity.

Table 4 Estimated HBA safety performance functions

		Road User Types				
	Variables	All Users	Drivers	Motorized Road Users	Vulnerable	Elasticities at Mean
Average Miles Traveled by:	All users	.00304*** (.0001)	-	-	-	.381
	Drivers only	-	.00413*** (.0001)	-	-	.377
	Motorized Road Users	-	-	.00319*** (.0001)	-	.381
	Transit	-	-	-	.0318*** (.0045)	.122
	Walk & Bike	-	-	-	.0211** (.0074)	.050
	Population (as exposure)	1.000	1.000	1.000	1.000	-
	Constant	-1.11*** (.0261)	-1.38*** (.0260)	-1.1*** (.0264)	-6.48*** (.0371)	-
	Dispersion Parameter	.154***	.147***	.171***	.325***	-
	Model Statistics					
	χ^2	3054	3040	2996	387	-
	Number of Observations	2524	2524	2524	2524	-
	Akaike information criterion	30947	29564	30977	6528	-

Legend: * p<.05; ** p<.01; *** p<.001

Scenario Evaluation

The population of the study area is modeled to increase from 1.52 million in 2018 to 2.33 million in 2033. As a result, we expect to see a higher number of crashes in both scenarios compared to the base. As presented in Table 5, daily miles traveled by all road users increased by 52% in the EC-2033 scenario. This increase in the Transit-2033 scenario was 48%. Alternatively, in the Transit-2033 scenario combined miles traveled by walk, bike, and transit modes increased by 76% which is 28% higher than the equivalent value in the EC-2033 scenario.

A comparison of the HBA crash frequency in both scenarios indicates the Transit-2033 scenario has fewer traffic crashes compared to the EC-2033 scenario. Overall, in the Transit-2033 scenario, crashes decreased by 0.7% compared to the EC-2033 scenario. HBA crash rate is also 10% lower in the Transit scenario compared to the EC-2033 scenario.

Table 5 Comparison of the EC-2033 and Transit scenario

	Daily Million Miles Traveled			HBA Crash Frequency			Annual Crash Rate × (HBA Crash Frequency per Million Miles Traveled)		
	Base	EC-2033	Transit-2033	Base	EC-2033	Transit-2033	Base	EC-2033	Transit-2033
All Road users	36.80	56.12 (53)	54.71 (49) *	122,048	173,208	171,970	9.09	8.46	8.61
Drivers only	26.30	41.29 (57)	40.31 (53) *	92,720	132,215	131,293	9.66	8.77	8.92
Motorized Road Users	35.30	53.65 (52)	52.06 (47) *	121,382	174,993	173,680	9.42	8.94	9.14
Transit, Walk & Bike (combined)	1.53	2.47 (61) *	2.65 (73) *	666**	761	759	1.19	0.84	0.78
Transit	1.05	1.68 (60) *	1.86 (76) *	666**	761	759	1.74	1.24	1.12
Walk & Bike	0.48	0.78 (64) *	0.79 (65) *	666**	761	759	3.80	2.67	2.63

× HBA crash frequency / (365* Daily Million miles traveled)
* % change compared to the based scenario
** Vulnerable road user crashes

Discussion

The HSPF has one major difference with the traditional SPFs or aggregate crash prediction models. HBA focuses on number of crashes that road users have, whereas the traditional SPFs and aggregate crash prediction models focus on safety of a road entity (e.g., number of crashes in one intersection or TAZ) (e.g., Mohammadi, Shafabakhsh, and Naderan 2018; Naderan and Shahi 2010; Highway Safety Manual 2010; Pirdavani et al. 2012a, 2012c). HSPF uses the average miles traveled by road users in the transportation system (regardless of the origin and destination of their trips) to predict the safety of road users under different scenarios. Therefore, HSPF can reflect the travel characteristics of road users by capturing travelers' average trip length, frequency, and modal share.

It is noteworthy that both HBA crash frequency and travel demand characteristics are both measured at the same location (i.e., TAZ corresponding to road users' home address). We hypothesized travel demand strongly correlated with HBA crash frequency. Results of the regression analysis failed to reject this study hypothesis. Negative binomial models' output indicated that as average miles traveled increases, road users' crash frequency increases. However, the rate of increase varies for different modes of transportation.

Fewer number of crashes and lower HBA crash rates for vulnerable road users in Transit-2033 scenario compared to the EC-2033 scenario support the safety in numbers phenomenon, in which a motorist is less likely to collide with a person walking and bicycling if more people walk or bicycle (Jacobsen 2015). Bicyclists and pedestrians have higher injury and fatality rates compared to other road users; nevertheless, increases in the number of bicyclists and pedestrians (through modal shift) would decrease the number of motorized road users that pose a risk to others (Schepers and Heinen 2013). An increase in the number of bicyclists and pedestrians in the transportation system will reduce VMT leading to fewer traffic crashes.

HSPF can be used as a complementary technique to evaluate the transportation system. This method can be used by safety planners for evaluating the safety impact of the transportation network design alternatives, changes in the transportation system management, as well as zoning and land use patterns within cities on road users' exposure to the traffic system and, eventually, their safety. These findings are based on the Nashville metropolitan area where travel is still highly car-oriented and more dependent on personal vehicles. Nevertheless, the methodology developed in this study could be applied to other geographical contexts, while those areas have travel demand models that simulate individuals' trips in transportation networks.

Future Direction

One of the problems with the crash frequency is that it does not account for the injury severity. This issue could raise concern, particularly when we are considering vulnerable road user crashes. These groups have a higher risk of injury compared to motorized road users. One direction for future studies is to consider the monetized value of the person-injury as a dependent variable in the analysis. This issue was addressed in the four HBA applications in the appendix.

Furthermore, the HBA method only considers traffic crashes of residents of the study area; nevertheless, road safety literature indicates that travelers (i.e., tourists) also have a noteworthy share in traffic crashes. HBA methodology could be developed in future studies to incorporate the role of travelers in the analysis.

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