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Multivariate random parameter Tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: Spatiotemporal variations

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ABSTRACT

The increase in 65 years and older population in the United States compels the investigation of the crashes involving all aging (65 +) roadway users (drivers, passengers, bicyclists, and pedestrians) in order to ensure their safety. As such, the objective of this research is to provide a spatiotemporal comparative investigation of the crashes involving these aging roadway users in Florida via concurrently using the same set of predictors in order to obtain comparable findings among them. First, a new metric, namely Crash Rate Difference (CRD) approach is developed, which enables one to capture potential spatial and temporal (e.g., weekend and weekday) variations in crash rates of aging user-involved crashes. Second, a multivariate random parameter Tobit model is utilized to determine the factors that drive both the crash occurrence probability and the crash rate of 65+ roadway users, accounting for the unobserved heterogeneity. Findings show that there are statistically significant heterogeneous effects of predictors on the crash rates of different roadway users, which evidences the unobserved heterogeneity across observations. Results also indicate that the presence of facilities such as hospitals, religious facilities, or supermarkets is very influential on crash rates of 65+ roadway users, advocating that roadways around these facilities should be particularly scrutinized by road safety stakeholders. Interestingly, the effect of these facilities on crashes also differs significantly between weekdays and weekends. Moreover, the roadway segments with high crash rates vary temporally depending on whether it is a weekday or a weekend. These findings regarding the spatiotemporal variations clearly indicate the need to develop and design better traffic safety measures and plans addressing these specific roadway segments, which can be tailored to alleviate traffic safety problems for 65+ roadway users.

1. Introduction

Safety of roadway users has been a significant point of interest for researchers in the transportation field due to the considerable burden crashes put on both the public and agencies. Therefore, traffic crash-focused studies are of critical importance to eradicate crashes' adverse consequences, and to ensure the well-being of public. However, this task is not easy due to the complex nature of crashes that are comprised of several environmental-, traffic-, roadway-, and human-related factors. Moreover, previous research has elucidated that crashes involving aging users of roadways are driven by different factors than crashes involving other age groups, which makes this safety problem even more challenging (Abdel-Aty et al., 1998; Bayam et al., 2005). Scientific findings imply that aging induces physical and cognitive decline, slower reflexes, deteriorated vision, and other health conditions (Hellinga and Macgregor, 1999; Sandler et al., 2015; Szlyk et al., 1995), which contribute to this differentiation in the nature of crashes involving aging drivers. Moreover, Chipman et al. (1993) showed that crash rates of aging drivers are substantially higher than crash rates of drivers aged between 25–59 years, when driving exposure is taken into account. The combination of this elevated crash rates with increased physical fragility makes crashes involving aging users of roadways even more critical in terms of health and safety. In this study, "crashes involving aging users of roadways" are defined as the crashes involving at least one roadway user 65 years and older (driver, passenger, bicyclist or pedestrian), regardless of being at fault or not.

Effects of aging on traffic safety and crashes have also grabbed attention previously. Researchers have shown that there are significant correlations between driver age and several other crash-related factors such as annual average daily traffic (AADT), speed limit, time of day,

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congestion, weather, and roadway condition (Abdel-Aty et al., 1998; Bayam et al., 2005; Collia et al., 2003; Haleem and Gan, 2013). That is, aging drivers have been found to be not willing to drive at night, on congested roads, during adverse weathers, and they also prefer the roadways with lower speed limits in Florida. This is partly because most of the aging residents of Florida are retirees who do not need to travel at certain times (e.g. AM peak, PM peak etc.) and can plan their trips at their convenience to avoid these adverse conditions. Nevertheless, literature also indicates that aging drivers tend to avoid these adverse conditions partly to compensate the effects of aging such as declining cognitive and physical abilities, reduced eye sight, and slower reflexes (Bayam et al., 2005; Collia et al., 2003; Horberry et al., 2006; Mårdh, 2016; McGwin and Brown, 1999). For example, not driving at night can be seen as a form of compensation for reduced eyesight or sensitivity to glare. Aging drivers are also found to be more prone to crash involvement than other drivers while approaching intersections, and when there are traffic control devices (e.g. stop signs, traffic lights etc.) (McGwin and Brown, 1999; Ulak et al., 2017b). Consequently, it can be stated that aging users of roadways have unique crash involvement characteristics, which compels developing studies specifically focusing on this age group (Bédard et al., 2002). While limited, there are studies that specifically focus on the traffic, roadway and environment-related factors influencing the crashes involving aging users of roadways (Abdel-Aty et al., 1999, 1998; Eby and Molnar, 2009; Mayhew et al., 2006; McGwin and Brown, 1999; Ryan et al., 1998; Ulak et al., 2017a, b; Vemulapalli et al., 2016).

In the literature, crash studies adopt several different methods including spatial and statistical approaches. Articles of Lord and Mannering (2010) and Mannering and Bhat (2014) provide an extensive review of the statistical methods used in crash-focused studies. Among the regression models used in the literature, Poisson and negative binomial regression techniques are those that have been applied the most to model crash frequencies. Recently, other approaches such as Tobit regression (for crash rates) as well as other advanced techniques such as neural networks and machine learning have become popular among traffic safety researchers (Anastasopoulos et al., 2012b, 2008; Effati et al., 2015; Jang et al., 2010; Kalyoncuoglu and Tigdemir, 2004; Zeng et al., 2017a). Furthermore, the issue of unobserved heterogeneity in crash modeling has gained popularity among recent safety studies due to the intrinsic heterogeneity across individual observations (Anastasopoulos et al., 2012a; Ma et al., 2015; Mannering et al., 2016). As such, the unavailability to observe all the factors affecting the crash occurrence likelihood compels to account for the unobserved heterogeneity in crash modeling. Moreover, the effect of a factor may not be homogeneous across several observations, which also brings about the heterogeneity issue. In this study, a multivariate random parameter Tobit approach is conducted to account for the potential heterogeneity across observations and to model censored data that is frequently seen in crash data sets utilizing the power of Tobit approach. There is usually a substantial number of roadway sections on which zero crash rates are observed during a given time span (which implies a censored information); however, one can find crashes at that section in a different time span. Tobit model has been applied more frequently in the literature over the last years. For instance, Traynor (2005) has adopted the Tobit regression to model crash severities with a focus on the driving under alcohol influence. Study of Anastasopoulos et al. (2008) on interstate highway crash rates is one of the pioneering studies adopting the Tobit model in crash rate modelling. Other researchers have followed that study to model crash rates and injury severities by using the Tobit regression (Anastasopoulos et al., 2012b; Debnath et al., 2014; Islam and Hernandez, 2015; Xu et al., 2014) and also implemented random effects (Chen et al., 2014) and Bayesian extension of Tobit models (Zeng et al., 2017a) as well as multivariate random parameter Tobit models (Anastasopoulos, 2016; Zeng et al., 2017b).

In order to better understand the nature of crashes, several studies have investigated the factors that affect all types of roadway users (drivers, passengers, bicyclists, and pedestrians) (Anastasopoulos et al., 2012b; Eluru et al., 2008; Kim et al., 2008; Lee and Abdel-Aty, 2008; Siddiqui et al., 2012). However, most of the existing literature have focused on all crashes rather than only those that involve aging populations. Furthermore, crashes involving drivers, passengers, bicyclists, and pedestrians have generally been studied individually rather than together. To the authors' knowledge, a comparative investigation of crashes involving all types of aging users of roadways (i.e. drivers, passengers, bicyclists, and pedestrians) has not been done previously, which is the unique contribution of this paper. Moreover, the effect of aging people living near a roadway section on the crash rates is captured through the "Population Factor" metric previously introduced by Ulak et al. (2017b). Previous study of Yu and Abdel-Aty (2013) shows that there are substantial differences between weekend and weekday crashes on a mountainous freeway. Moreover, a recent study by Mannering (2018) discusses the presence and implications of temporal instability in the crash data and highlights that variations in the effect of explanatory variables (heterogeneity) might be due to this temporal instability. Inspired from these discussions, this paper also seeks to investigate weekday and weekend crashes separately to be able to capture potential spatiotemporal variations in aging user-involved crash rates.

As such, the objective of this research is to provide a spatiotemporal comparative investigation of the crashes involving these aging roadway users via a Tobit model-based approach. First, a new metric, namely Crash Rate Difference (CRD) approach is developed, which enables one to capture potential spatial and temporal (e.g., weekend and weekday) variations in crash rates of aging user-involved crashes. Second, the multivariate random parameter Tobit model determines the factors that drive both the crash occurrence probability and the crash rate of 65+ roadway users. The multivariate approach brings about the power to address the potential shared unobserved heterogeneities between drivers, passengers, bicyclists and pedestrians. Moreover, the population of aging people living in the study area is integrated into the analysis as a predictor to investigate the effect of population density on the crash occurrence probability and crash rate. The proposed methodology is applied to the whole State of Florida, one of the states that has the highest number of aging residents due to its particular attraction to retirees thanks to the moderate climate.

2. Methodology

2.1. Study area and data

This study considers all the major roadway sections (e.g. county roads, state roads, U.S. highways, etc.) excluding interstates in order to diminish heterogeneities imposed by different levels of roadways in the State of Florida, which consists of a total of 11,087 sections (Fig. 1). Roadway network and crash data for 2013 and 2014 were obtained from the Florida Department of Transportation (FDOT, 2015). In addition, the 2010 census data (U.S. Census Bureau, 2015) was also used to investigate the effect of population on the crash rate. Please see Fig. 2 for the spatial distribution of crashes involving 65+ roadway users and their population density in the Miami-Dade County.

First, 2013 and 2014 crash data were integrated with the roadway network data in order to find the crash frequencies at each individual roadway section. A total of 161,322 aging (65+) crash occupants (drivers: 122,129; passengers: 36,924; bicyclists: 868; and pedestrians: 1401) is identified in the 2013 and 2014 crash databases. In addition, a total of 127,845 crashes was identified to involve these 161,322 crash occupants. Aging passengers (36,924 individuals) were found to be involved in 32,310 different crashes whereas there were 113,444 crashes recorded that involve aging drivers (122,129 individuals). Among those 127,845 crashes: 93,177 crashes only involved aging drivers, 12,449 crashes only involved aging passengers (drivers in these crashes belong to 64 years or younger age group), 651 crashes only involved

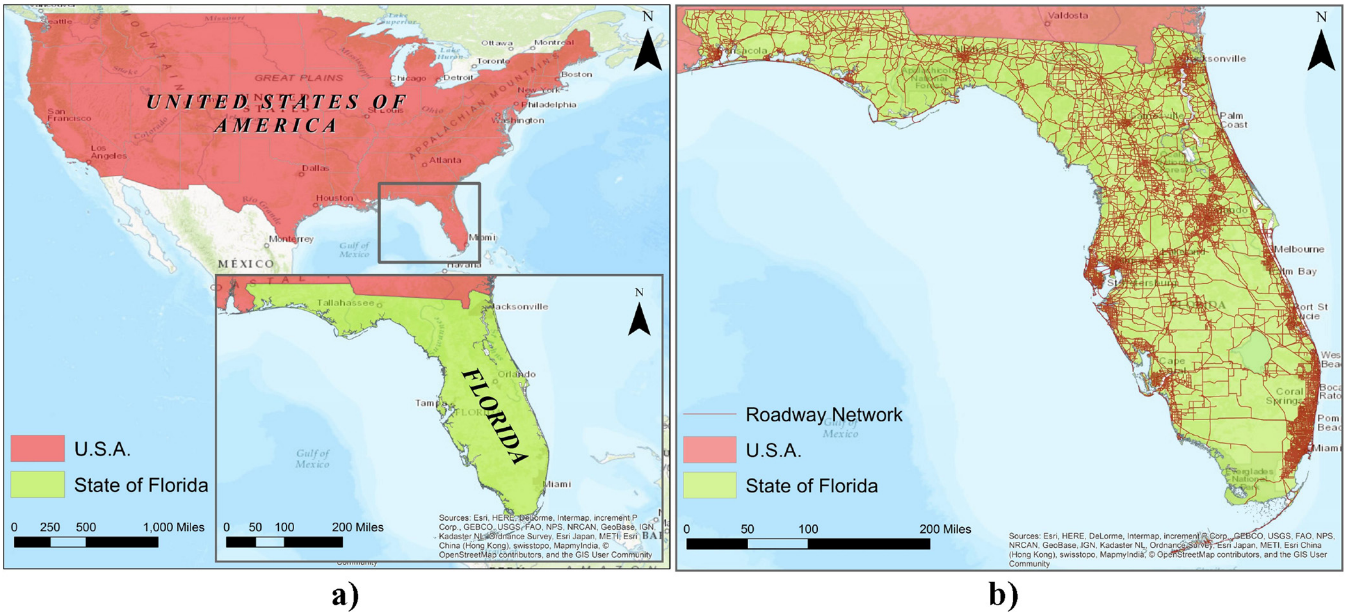


Fig. 1. (a) study area; (b) Florida roadway network.

aging bicyclists, and 1075 crashes only involved aging pedestrians. 19,787 out of 127,845 crashes were identified to involve both aging drivers and aging passengers, while 433 crashes were found to involve both an aging driver and an aging non-motorist (pedestrian or bicyclist).

The roadway sections correspond to the individual roadways with specific identification numbers (IDs) given by FDOT. The roadway data includes several traffic- and geometry-related variables (see Table 1), which were used to model the crash rate of aging roadway users. Note that the data set contains some roadway sections that stretch for long

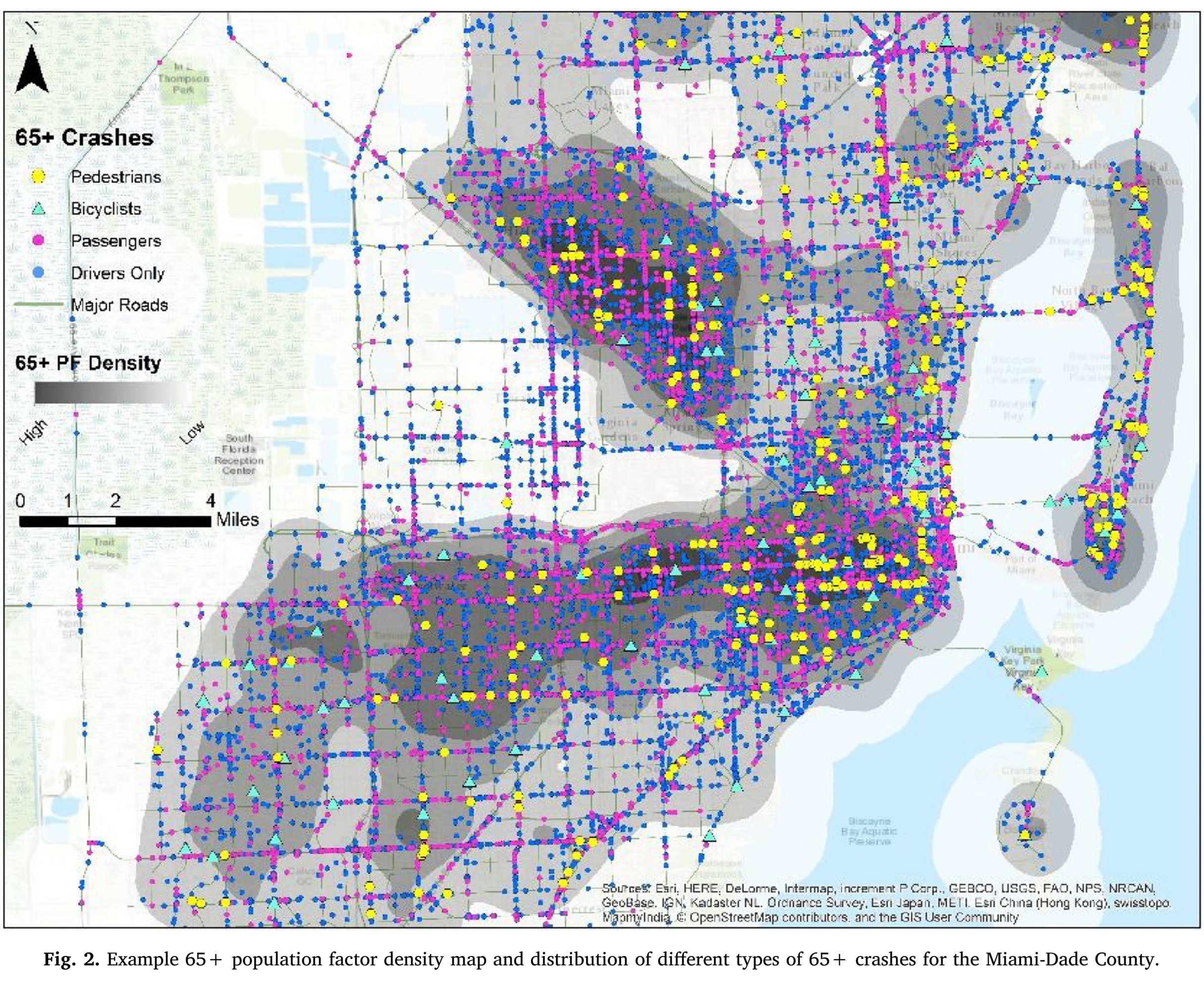


Fig. 2. Example 65 + population factor density map and distribution of different types of 65 + crashes for the Miami-Dade County.

Table 1
Descriptive statistics and definitions of predictor variables used in the Tobit model.

Predictor Variables	Min	Max	Mean	Med	St.D.	DT	Definition
65 + PF Density	0	9.29	0.53	0.14	0.91	C	Population Factor density for aging (65+) population (Section 2.2.).
AADT	1e-3	15.99	0.86	0.56	0.96	C	Annual Average Daily Traffic, indicator of traffic volume, normalized by 10,000.
Truck AADT	0	1.26	0.06	0.03	0.07	C	AADT for trucks, normalized by 10,000.
Speed Limit	1.5	7	3.66	3.5	0.58	C	Speed limit of the roadway (e.g. 1.5 = 15 mph, 3.5 = 35 mph, 7 = 70 mph, etc.)
Bike Lane	0	1	0.09	0	0.28	B	Indicator of presence of bike lane on the roadway; 0: no, 1: presents.
Arterial Rd	0	1	0.07	0	0.25	B	Indicator whether roadway is a primary arterial; 0: no, 1: yes.
County Rd	0	1	0.16	0	0.36	B	Indicator whether roadway is a county road; 0: no, 1: yes.
Median Width	0	4.08	0.09	0	0.15	C	Average median width of the roadway (feet), normalized by 100.
Shoulder Type	0	1	0.11	0	0.31	B	Shoulder type; 0: no shoulder or no pavement, 1: paved shoulder.
Shoulder Width	0	3.48	0.41	0.4	0.36	C	Average shoulder width of the roadway (feet), normalized by 10.
Sidewalk Width	0	3.58	0.19	0	0.29	C	Average sidewalk width of the roadway (feet), normalized by 10.
Intersection #	0	41.88	0.71	0.50	0.96	C	Number of intersections per mile of roadway.
Health Facility	0	1	0.30	0	0.46	B	Indicator whether there is a health facility within 0.1 mile of roadway; 0: no, 1: yes.
Hospital	0	1	0.02	0	0.15	B	Indicator whether there is a hospital within 0.1 mile of roadway; 0: no, 1: yes.
School	0	1	0.30	0	0.46	B	Indicator whether there is a school within 0.1 mile of roadway; 0: no, 1: yes.
Religious Facility	0	1	0.45	0	0.50	B	Indicator whether there is a religious facility within 0.1 mile of roadway; 0: no, 1: yes.
Supermarket	0	1	0.24	0	0.43	B	Indicator whether there is a supermarket within 0.1 mile of roadway; 0: no, 1: yes.

Abbreviations and symbols Min: minimum, Max: maximum, Med: median (statistics), St. D.: standard deviation, PF: population factor, Rd: road, #: number. DT: Data Type; C: continuous, B: binary.

distances while others are much shorter. To account for this variation in length, some variables were normalized by the length of that roadway section. In the literature, it is customary to evaluate the crash rate by dividing number of crashes on a roadway section by the length and AADT on that section (Anastasopoulos et al., 2008). Similarly, the crash rates were found by dividing crash numbers to AADTs and the lengths in this paper. Furthermore, a maxima normalized crash rate (NCR) is defined (Eq. (1)) in order to have the same scale for the dependent variable of different groups (e.g., driver, pedestrians, etc.).

$$Crash\ Rate_r^k = \frac{\sum_{t=1}^{n} Crashes_{t,r}^k * 100{,}000{,}000}{\sum_{t=1}^{n} AADT_t * L_r * 365} \quad \text{and} \quad NCR_r^k = \frac{Crash\ Rate_r^k}{max(Crash\ Rate^k)} x100 \tag{1}$$

where r is the roadway ID (r = 1,2, ...11,087), k is the type of roadway user (total of 4 types: driver, passenger, bicyclist, and pedestrian), t is the year for which the crash data is available (t = 1,2), n is the number of years (n = 2), and L_r is the length of roadway r in miles. Here, NCR is the maxima-normalized crash rate used in statistical modeling and identification of significant independent variables.

2.2. Population factor density approach

In order to model the effects of aging population on the crash rates, a specific parameter, namely the "population factor" (PF) developed by Ulak et al. (2017b), is included as a predictor in the regression model. Population factor incorporates the effect and spatial relationship of both the number of households as well as counts and percentages of specific population groups living in the study region. The PF density approach is composed of two parts: 1) calculation of PF values based on census data, and 2) kernel density estimation (KDE) (Brunsdon, 1995) analysis to obtain a population density surface. Please refer to Ulak et al. (2017b) for further information on this approach. Average PF value was calculated for each roadway by using the resultant PF density map. Consequently, these PF values were also used in the Tobit model, rather than using actual counts or percentages, which was shown to be an effective approach for incorporating census information in the transportation safety studies (Ulak et al., 2017b). An example of the resultant PF density map for aging populations living in the Miami metropolitan area of Florida is illustrated in Fig. 2.

2.3. Spatiotemporal crash rate difference analysis

A comparative crash rate difference (CRD) analysis was conducted complementary to the multivariate random parameter Tobit model in order to investigate the spatiotemporal nature of the aging user-involved crashes. This approach can aid to observe the spatial differences between weekdays and weekends of different aging groups, and it can help to address an important concern in the traffic safety field: revealing the spatiotemporal differences in crash rates of different aging roadway users. In order to achieve this, two types of crash rates were calculated: 1) crash rates based on weekday crashes, and 2) those on weekends. Next, CRD metrics disclosed the inter-group (i.e. weekday vs. weekend) spatial differences and identified those locations where weekday and weekend crash rates were relatively higher or lower than each other. Note that, 22 weekdays were identified as official holidays, and these days might present different crash characteristics than a regular weekday does. However, a careful investigation of holiday weekday crashes indicated that regular weekdays and holiday weekdays had similar crash involvement numbers for aging crash occupants. Following formula was used to calculate the CRD values:

$$CRD_r^k = NCR_{r,wd}^k - NCR_{r,we}^k \tag{2}$$

where CRD_r^k is the "Crash Rate Difference" of the roadway user type k (i.e. driver, passenger, bicyclist, and pedestrian) for roadway segment r (r = 1,2, ...11,087), whereas $NCR_{r,wd}^k$ and $NCR_{r,we}^k$ are corresponding normalized crash rates of user type k for roadway segment r at weekdays and weekends, respectively.

2.4. Multivariate random parameter tobit model

The Tobit model is a type of censored regression model, which adopts a fixed common censoring threshold (Amemiya, 1985; Maddala, 1986). The model specifically considers lack of observation as censored. For instance, a data set for the occurrence rate of a specific incident may include zeros, which indicates that the incident does not necessarily occur at certain circumstances. A conventional model, such as the linear regression, would assume those zeros as observations even though they imply a censoring value (i.e., lack of incident by the end of a specific observation period). This assumption results in biased estimates while modeling the factors which drive the rate of that incident. Tobit model incorporates two components: 1) a binary case which investigates whether a crash occurred on a roadway or not, and 2) a second case that evaluates the rate of those crashes given it is not zero. The multivariate random parameter Tobit model, which regards zeros

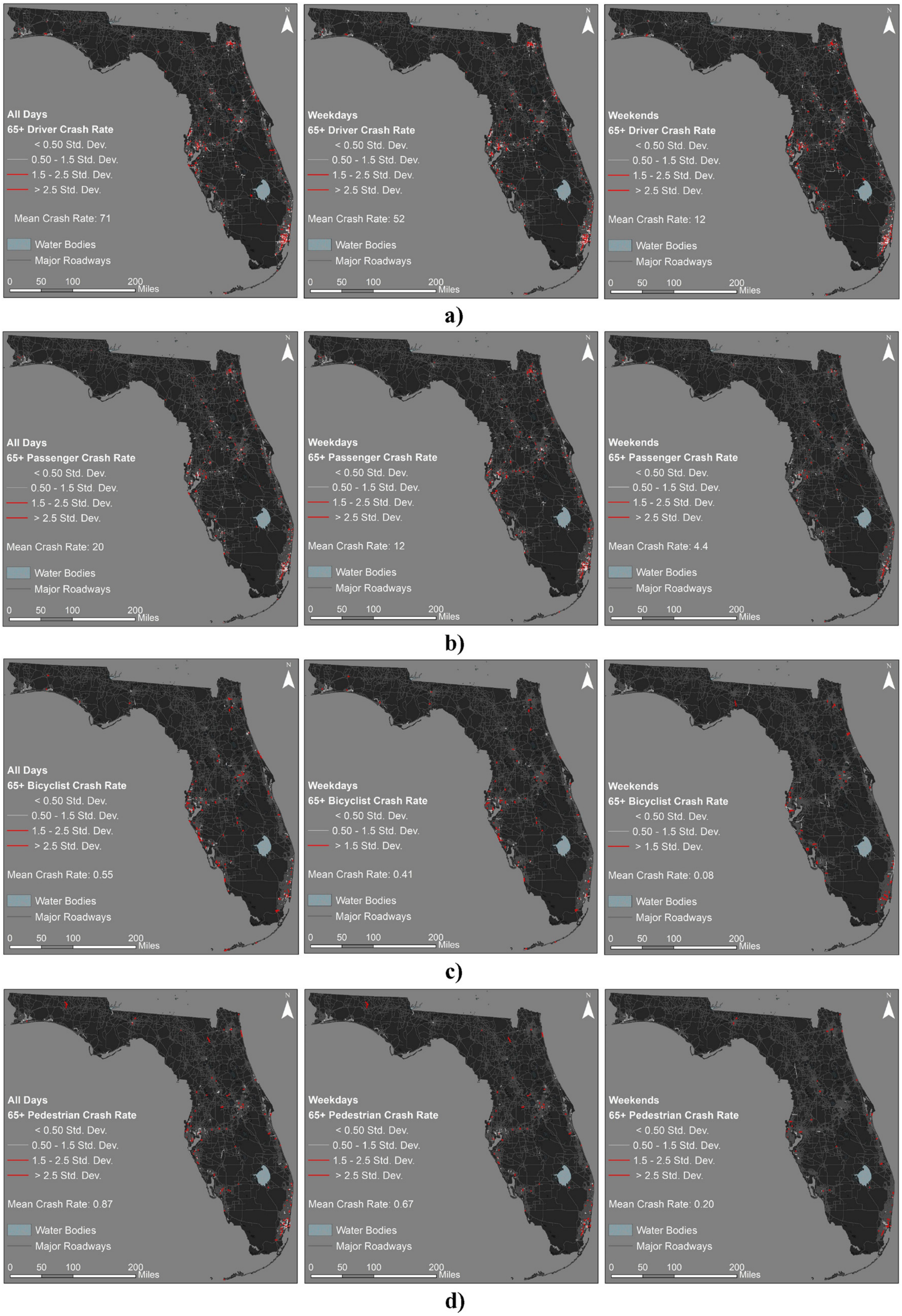


Fig. 3. Crash rates for all days, weekdays, and weekends; (a) 65+ Drivers; (b) 65+ Passengers; (c) 65+ Bicyclists; (d) 65+ Pedestrians.

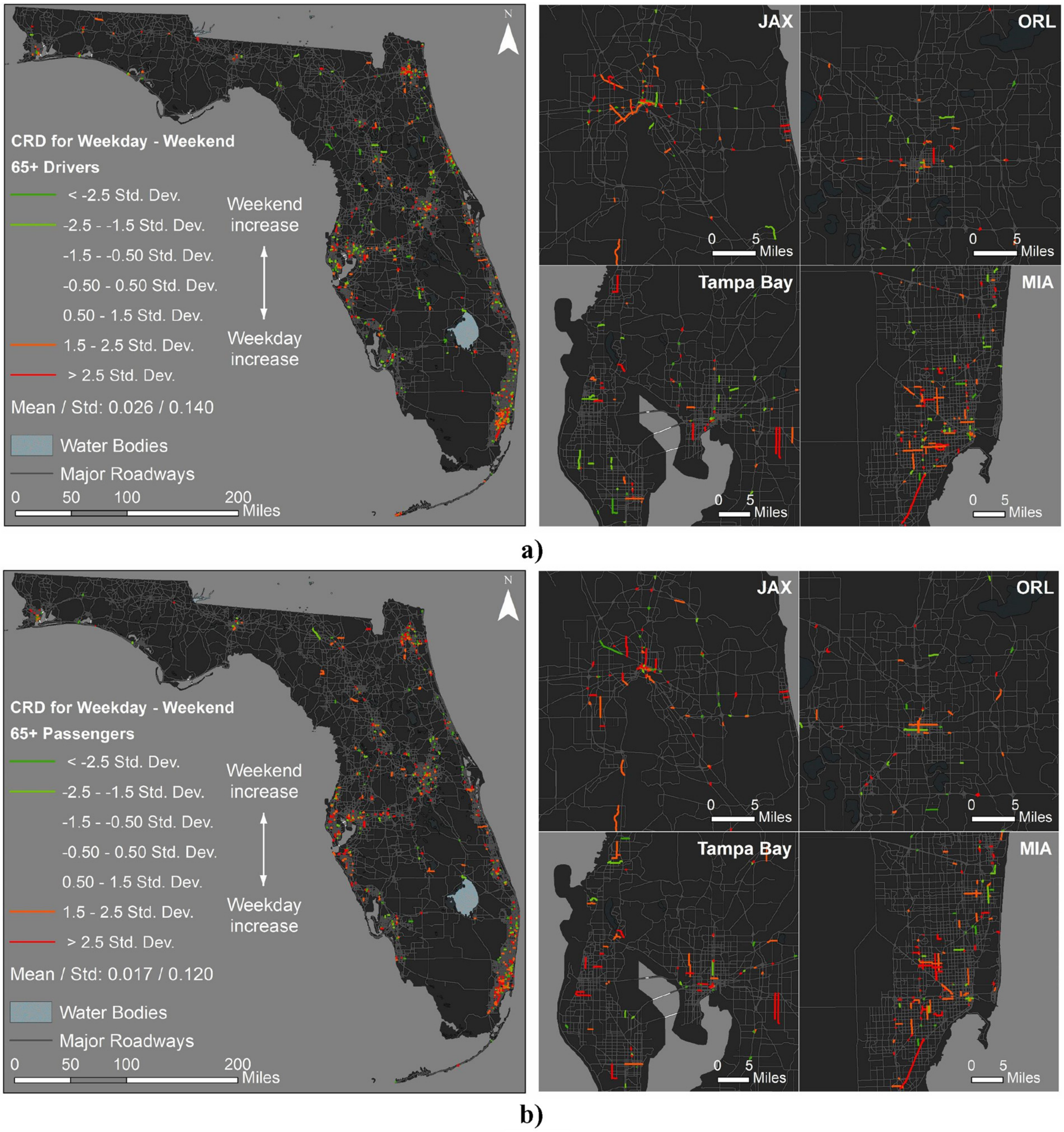


Fig. 4. CRD maps for crash rates – weekday crashes vs. weekend crashes; (a) 65+ Drivers; (b) 65+ Passengers; (c) 65+ Bicyclists; (d) 65+ Pedestrians, JAX: Jacksonville, ORL: Orlando, MIA: Miami.

in the data as censored circumstances, can be defined as follows (Amemiya, 1985; Maddala, 1986):

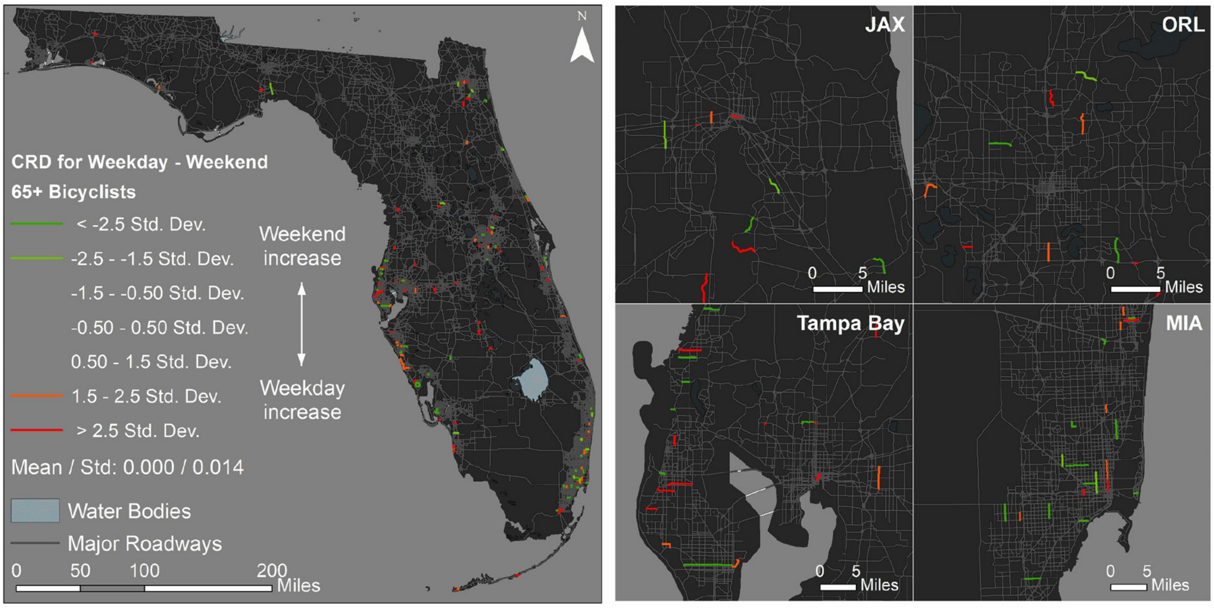
$$Q_{rk} = X_r\beta_{km}^r + \in_{rk} \quad \text{where } r = 1, \ \ldots, 11,087, \ \ m \text{ is predictors, and } k = 1, \ 2, \ 3, \ 4 \tag{3}$$

$$J_{rk} = 1 \text{ if } Q_{rk} > \lambda \text{ and } J_{rk} = 0 \text{ if } Q_{rk} \le \lambda$$
$$Q_{rk} = \begin{cases} Y_{rk}, & J_{rk} = 1 \\ missing, & J_{rk} = 0 \end{cases} \tag{4}$$

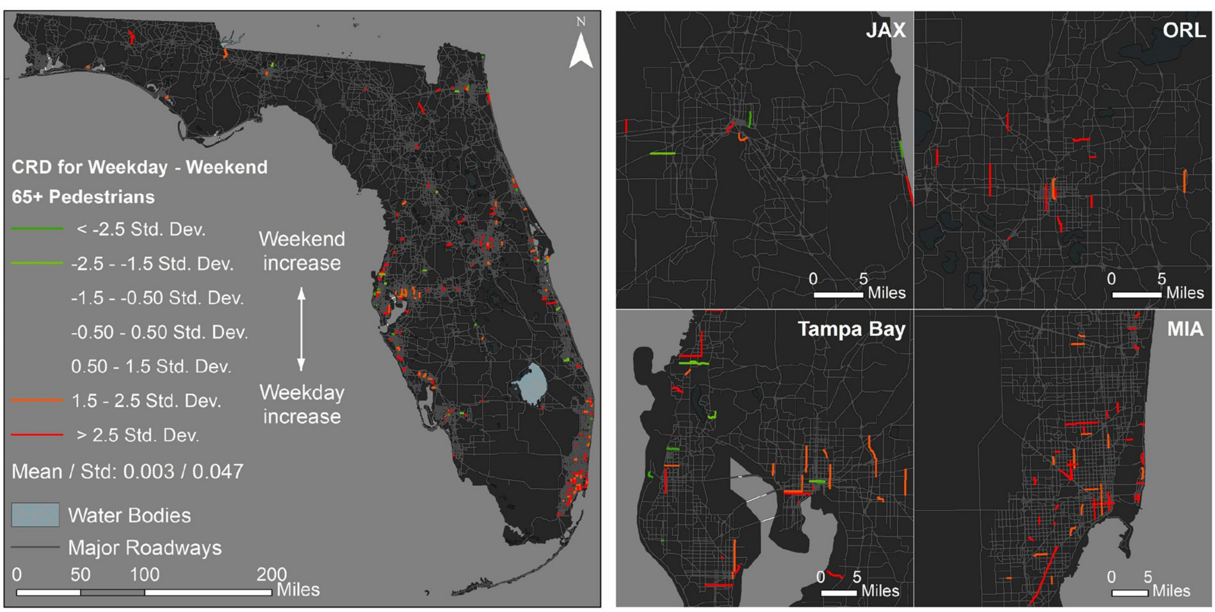
where Q_{rk} is crash rate (response variable) for the k^{th} roadway user type (i.e. 1: driver, 2: passenger, 3: bicyclist, 4: pedestrian) at the r^{th} roadway segment, X_r is vector of predictor variables, and β_{km}^r is vector of random parameters for different roadway user types and roadway segments ($\beta_{km}^r \sim N(\theta_{\beta_{km}}, \ \xi_{\beta_{km}}^2)$). In the Tobit model, Q_{rk} is unobserved; however, a censoring indicator, J_{rk} is observed (Eq. (4)). The observed dependent variable denoted by Y_{rk}, is equal to Q_{rk} if $J_{rk} = 1$. The value of Q_{rk} is missing if $J_{rk} = 0$. The common censoring threshold is denoted by the parameter λ. In this study, censoring threshold is set as $\lambda = 0$ since the crash rate on a roadway cannot be less than 0. $\in_{rk}$ is multivariate normally and independently distributed error terms with zero mean, variance σ^2, and correlation ρ ($\in_{rk} \sim MVN(0, \ \boldsymbol{\Sigma})$):

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{\varepsilon_1}^2 & \rho_{\varepsilon_2\varepsilon_1}\sigma_{\varepsilon_2}\sigma_{\varepsilon_1} & \rho_{\varepsilon_3\varepsilon_1}\sigma_{\varepsilon_3}\sigma_{\varepsilon_1} & \rho_{\varepsilon_4\varepsilon_1}\sigma_{\varepsilon_1}\sigma_{\varepsilon_4} \\ \rho_{\varepsilon_1\varepsilon_2}\sigma_{\varepsilon_1}\sigma_{\varepsilon_2} & \sigma_{\varepsilon_2}^2 & \rho_{\varepsilon_3\varepsilon_2}\sigma_{\varepsilon_2}\sigma_{\varepsilon_3} & \rho_{\varepsilon_4\varepsilon_2}\sigma_{\varepsilon_2}\sigma_{\varepsilon_4} \\ \rho_{\varepsilon_1\varepsilon_3}\sigma_{\varepsilon_3}\sigma_{\varepsilon_1} & \rho_{\varepsilon_2\varepsilon_3}\sigma_{\varepsilon_2}\sigma_{\varepsilon_3} & \sigma_{\varepsilon_3}^2 & \rho_{\varepsilon_4\varepsilon_3}\sigma_{\varepsilon_3}\sigma_{\varepsilon_4} \\ \rho_{\varepsilon_1\varepsilon_4}\sigma_{\varepsilon_4}\sigma_{\varepsilon_1} & \rho_{\varepsilon_2\varepsilon_4}\sigma_{\varepsilon_4}\sigma_{\varepsilon_2} & \rho_{\varepsilon_3\varepsilon_4}\sigma_{\varepsilon_3}\sigma_{\varepsilon_4} & \sigma_{\varepsilon_4}^2 \end{bmatrix} \tag{5}$$

The model parameters were estimated by the Bayesian inference.



c)



d)

Fig. 4. (*continued*)

Please refer to Chib (1992); Geweke (1993), and Zeng et al. (2017b) on details of the Bayesian estimation of multivariate random parameter Tobit model. Gibbs sampling Markov chain Monte Carlo (MCMC) simulation was used for the estimation (11,000 iterations, 1000 initial draws omitted for burn-in) and the number of required iterations was identified using the Raftery-Lewis diagnostic (Raftery and Lewis, 1992). Freeware JAGS (Just Another Gibbs Sampler) and R software were used for the estimation of the model (Plummer, 2003). Due to lack of prior information on the parameters and the hyper-parameters, diffuse (i.e. non-informative) priors were specified. To be specific, following priors were defined for Bayesian modeling:

$$\in_{rk} \sim MVN(0,\ \boldsymbol{\Sigma}) \quad \text{where} \quad \Sigma^{-1} \sim Wishart(R,\ r), \quad R = I_4, \quad r = 4$$

$$\beta_{km}^{r} \sim N(\theta_{\beta_{km}},\ \xi_{\beta_{km}}^{2}), \quad \text{where} \quad \theta_{\beta_{km}} \sim N(0,\ 10^4), \quad \xi_{\beta_{km}}^{2} = (\tau_{\beta_{km}})^{-1}, \quad \tau_{\beta_{km}} \sim \Gamma(10^{-3},\ 10^{-3})$$

Deviance information criterion was used to test model fitness (Gelman et al., 2003) (Eq. (6)). Following the estimation of parameters, marginal effects of variables on the positive observations were calculated as follows (Greene, 1999):

$$DIC = -2\log(p(y\theta)) + 2p_D \tag{6}$$

$$\frac{\partial E(y_i x,\ y_i > 0)}{\partial x_k} = \beta_k\{1 - \lambda(\delta)[\delta + \lambda(\delta)]\} \tag{7}$$

where $p(y\theta)$ is the likelihood function, p_D is effective number of

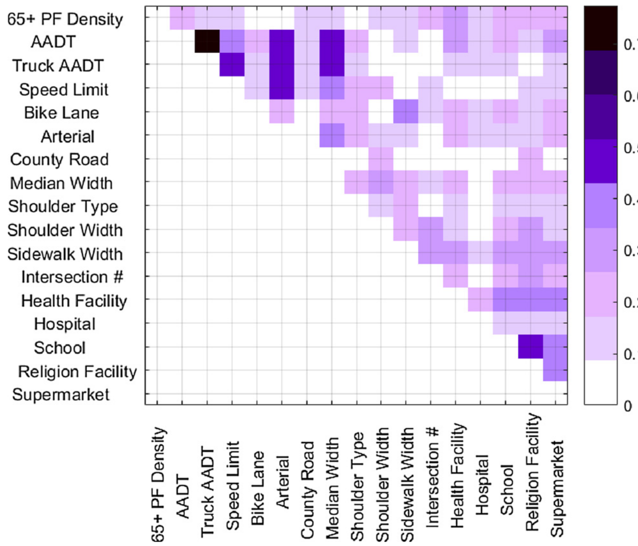


Fig. 5. Correlation graph for candidate variables.

parameters, $\delta = x\beta_{km}/\sigma_k$ and $\lambda(\delta) = \phi(\delta)/\Phi(\delta)$.

3. Results

3.1. Spatiotemporal analysis

Crash rate results for the study region and time period can be seen in Fig. 3 where there is a substantial difference between different aging groups (i.e. drivers, pedestrians etc.) as well as considerable spatio-temporal variations in crash rates of each group. Note that Fig. 3 can be examined both horizontally and vertically. Horizontal examination shows the temporal variation in crash rates of a particular aging roadway user group (e.g., pedestrians) for different time of the week: all days, week days and weekends. Vertical examination, on the other hand, is valuable to compare crash rates and the spatiotemporal variation in these rates for different aging roadway users (e.g., drivers vs. pedestrians). Large metropolitan areas such as Miami (Southeast), Tampa Bay (Midwest), Orlando (Central Region), and Jacksonville (Northeast) are the regions where highest numbers of 65+ motorist and non-motorists crash rates are observed. Yet, aging bicyclist and pedestrian (non-motorist) crash rates exhibit slightly different spatial patterns than the 65+ motorists' crash rates do. That is, roadway segments with high crash rates for motorists are observed both in rural areas and urban areas whereas non-motorists crash rates are substantially higher in urban areas, which is fairly intuitive. In addition, a considerable difference is observed between those crash rates calculated by accounting for weekday and weekend crashes separately. That is, the roadway segments with high crash rates vary temporally depending on whether it is a weekday or a weekend. This information is critical in showing that agencies should consider this temporal variation in developing new traffic safety measures and plans for those specific roadway sections. The proposed CRD approach presents a technique to help revealing those critical segments that vary temporally.

Fig. 4 shows the results of the CRD approach, and presents the differences between weekday and weekend crash rates. Moreover, both the whole Florida and a closer look to four major urban areas, namely Jacksonville, Orlando, Tampa Bay, and Miami, are provided in Fig. 4. Fig. 4 shows those roadway segments which have substantially higher crash rates either for weekdays or weekends. Therefore, these segments (colored in orange-red or light green-green) may guide agencies and officials in providing temporally tailored remedies in order to alleviate the associated traffic safety problems for 65+ roadway users.

3.2. Multivariate random parameter Tobit model

In order to avoid the multicollinearity in the regression model, highly correlated variables were identified by using Pearson correlation coefficients of the predictors as shown in Fig. 5. The following pairs were identified as highly correlated: "AADT and Truck AADT", "AADT and Arterial", "Speed Limit and Arterial", and "Religious Facility and School". Therefore, "Truck AADT", "Arterial", and "School" were not included in the final model. Furthermore, "County Road", "Shoulder Type", "Shoulder Width", and "Sidewalk Width" variables were found to be having very small variation (mostly the same value for different roadway segments), and were consistently insignificant in the model. Therefore, those variables were also dropped to focus on the variables deemed to be significant. Note that, in this study, a 95% confidence level was chosen for the statistical significance of predictors, and Deviance Information Criterion (DIC) (Gelman et al., 2003) was used to

Table 2
Multivariate random parameter Tobit model error parameters and goodness-of-fit.

All Days									
65+ Crashes	All Days			Weekdays			Weekends		
Regressor	Estimate	SE	95% CI	Estimate	SE	95% CI	Estimate	SE	95% CI
$\sigma_{Drivers}$	15.119	0.110	(14.9,15.34)	14.708	0.118	(14.48,14.94)	15.474	0.171	(15.115.76)
$\sigma_{Passengers}$	14.807	0.157	(14.44,15.08)	15.610	0.137	(15.31,15.86)	14.039	0.099	(13.85,14.23)
$\sigma_{Bicyclists}$	2.696	0.018	(2.66,2.73)	2.559	0.017	(2.53,2.59)	2.382	0.016	(2.35,2.41)
$\sigma_{Pedestrians}$	1.790	0.012	(1.77,1.81)	1.144	0.008	(1.13,1.16)	1.951	0.013	(1.93,1.98)
$\rho_{Drivers\ vs.\ Passengers}$	0.530	0.009	(0.51,0.55)	0.415	0.010	(0.39,0.43)	0.403	0.010	(0.38,0.42)
$\rho_{Drivers\ vs.\ Bicyclists}$	0.038	0.010	(0.02,0.06)	0.042	0.010	(0.02,0.06)	0.022	0.010	(0,0.04)
$\rho_{Drivers\ vs.\ Pedestrians}$	0.089	0.009	(0.07,0.11)	0.019	0.009	(0.000.04)	0.069	0.010	(0.05,0.09)
$\rho_{Passengers\ vs.\ Bicyclists}$	0.025	0.010	(0.01,0.04)	0.025	0.009	(0.01,0.04)	0.037	0.009	(0.02,0.06)
$\rho_{Passengers\ vs.\ Pedestrians}$	0.042	0.010	(0.02,0.06)	0.026	0.010	(0.01,0.05)	0.023	0.010	(0,0.04)
$\rho_{Bicyclists\ vs.\ Pedestrians}$	*0.011*	*0.010*	(-0.01,0.03)	*0.004*	*0.009*	(-0.01,0.02)	*0.003*	*0.009*	(-0.02,0.02)
# of total observations	11,087			11,087			11,087		
# of uncensored $_{Drivers}$	6,906			6,320			4,037		
# of uncensored $_{Passengers}$	4,486			3,687			2,242		
# of uncensored $_{Bicyclists}$	618			465			148		
# of uncensored $_{Pedestrians}$	803			639			212		
DIC(null) / DIC(β, σ)	75,985.3 / 57,717.7			70,705.9 / 53,911.8			60,725.3 / 51,690.4		

Abbreviations SE: standard error, 5% CI: 95% Confidence Interval, DIC: Deviance Information Criterion.
*Italic indicates that the estimate is not statistically significant at 95% confidence level.

Table 3
Multivariate random parameter Tobit model results – all days.

All Days												
65+ Crashes	Drivers			Passengers			Bicyclists			Pedestrians		
Regressor	θ	SE	95% CI	θ	SE	95% CI	θ	SE	95% CI	θ	SE	95% CI
Intercept	−0.51	0.248	(-0.84,-0.10)	−0.59	0.404	(-1.28,0.10)	−0.87	0.281	(-1.27,-0.31)	−0.72	0.246	(-1.14,-0.23)
SD (ξ)	0.33	0.084	(0.19,0.52)	0.63	0.227	(0.32,1.04)	0.51	0.145	(0.23,0.72)	0.39	0.140	(0.17,0.65)
65 + PF Density	8.50	0.182	(8.09,8.82)	7.60	0.614	(6.12,8.36)	−2.23	0.167	(-2.51,-1.87)	−3.02	0.356	(-3.7,-2.49)
SD (ξ)	7.95	1.430	(5.58,10.17)	11.84	0.536	(10.97,12.8)	6.64	0.427	(5.84,7.45)	6.70	0.354	(6.13,7.33)
AADT	−2.53	0.320	(-2.96,-1.73)	−1.22	0.212	(-1.53,-0.77)	−0.59	0.201	(-0.98,-0.28)	*0.16*	*0.184*	*(-0.19,0.45)*
SD (ξ)	1.69	0.415	(0.91,2.50)	2.40	0.596	(1.25,3.33)	0.18	0.068	(0.10,0.31)	6.70	0.354	(0.13,0.33)
Speed Limit	0.63	0.065	(0.51,0.77)	−1.49	0.690	(-2.55,-0.20)	−2.84	0.514	(-3.57,-1.8)	−1.53	0.252	(-1.87,-1.03)
SD (ξ)	5.14	0.229	(4.63,5.48)	5.32	0.384	(4.48,5.84)	1.81	0.218	(1.36,2.14)	0.72	0.100	(0.53,0.86)
Bike Lane	−0.20	0.130	(-0.43,0.06)	0.18	0.035	(0.08,0.24)	0.91	0.306	(0.48,1.41)	1.01	0.273	(0.50,1.40)
SD (ξ)	0.31	0.089	(0.18,0.50)	0.16	0.048	(0.08,0.25)	0.29	0.074	(0.15,0.42)	0.29	0.086	(0.17,0.47)
Median Width	*−0.12*	*0.246*	*(-0.76,0.18)*	*0.63*	*0.548*	*(-0.16,1.36)*	0.59	0.369	(-0.05,1.15)	*0.07*	*0.069*	*(-0.08,0.17)*
SD (ξ)	0.46	0.114	(0.28,0.73)	0.86	0.314	(0.34,1.50)	0.53	0.238	(0.24,1.09)	0.32	0.119	(0.13,0.55)
Intersection #	2.01	0.358	(1.13,2.53)	0.77	0.348	(0.18,1.37)	0.28	0.078	(0.12,0.40)	−0.26	0.090	(-0.44,-0.09)
SD (ξ)	1.01	0.315	(0.55,1.47)	0.33	0.114	(0.19,0.59)	0.28	0.050	(0.18,0.36)	0.62	0.065	(0.51,0.75)
Health Fac.	0.32	0.300	(-0.02,0.81)	0.98	0.649	(0.20,2.09)	0.57	0.068	(0.43,0.69)	0.92	0.295	(0.28,1.21)
SD (ξ)	0.27	0.073	(0.14,0.41)	0.60	0.321	(0.11,1.09)	0.10	0.050	(0.040.21)	0.23	0.122	(0.07,0.47)
Hospital	0.71	0.221	(0.30,1.11)	−0.17	0.138	(-0.45,0.00)	0.78	0.371	(-0.02,1.4)	0.46	0.450	(-0.13,1.43)
SD (ξ)	0.33	0.066	(0.24,0.49)	0.37	0.225	(0.15,0.85)	0.87	0.184	(0.59,1.25)	0.50	0.131	(0.32,0.84)
Religious Fac.	*0.15*	*0.184*	*(-0.09,0.45)*	0.64	0.540	(-0.01,1.81)	0.59	0.147	(0.25,0.76)	0.74	0.235	(0.24,1.09)
SD (ξ)	0.43	0.195	(0.23,0.82)	0.52	0.266	(0.23,1.06)	0.19	0.111	(0.07,0.44)	0.31	0.072	(0.21,0.49)
Supermarket	−0.27	0.081	(-0.41,-0.11)	0.99	0.527	(0.11,1.74)	1.15	0.500	(0.34,1.90)	1.14	0.342	(0.49,1.60)
SD (ξ)	0.20	0.036	(0.15,0.30)	0.45	0.139	(0.25,0.73)	0.27	0.070	(0.16,0.39)	0.37	0.093	(0.20,0.52)

Abbreviations: β: estimated coefficient mean, SE: standard error, 95% CI: 95% Confidence Interval, SD: standard deviation.
* Italic indicates that the estimate is not statistically significant at 95% confidence level.

Table 4
Multivariate random parameter Tobit model results – weekdays.

Weekdays												
65+ Crashes	Drivers			Passengers			Bicyclists			Pedestrians		
Regressor	θ	SE	95% CI	θ	SE	95% CI	θ	SE	95% CI	θ	SE	95% CI
Intercept	−0.58	0.357	(-1.23,-0.02)	−1.19	0.542	(-2.16,-0.19)	−0.40	0.095	(-0.54,-0.27)	−1.02	0.280	(-1.30,-0.42)
SD (ξ)	0.58	0.093	(0.42,0.77)	0.53	0.094	(0.37,0.71)	0.19	0.067	(0.12,0.32)	0.21	0.102	(0.08,0.40)
65 + PF Density	7.96	0.274	(7.36,8.42)	7.93	0.591	(6.44,8.71)	−3.37	0.323	(-3.87,-2.69)	−2.82	0.234	(-3.15,-2.20)
SD (ξ)	9.81	0.958	(8.56,11.97)	16.60	0.501	(15.25,17.23)	6.63	0.524	(5.42,7.18)	4.60	0.227	(4.01,4.91)
AADT	−2.40	0.433	(-2.95,-1.26)	−2.10	0.173	(-2.30,-1.64)	−0.76	0.172	(-1.06,-0.53)	0.25	0.095	(0.02,0.36)
SD (ξ)	1.67	0.418	(1.17,2.57)	3.84	0.333	(3.30,4.46)	0.26	0.065	(0.17,0.41)	0.14	0.059	(0.07,0.28)
Speed Limit	0.37	0.096	(0.21,0.57)	−1.43	0.550	(-2.17,-0.18)	−2.62	0.468	(-3.16,-1.53)	−1.00	0.128	(-1.15,-0.70)
SD (ξ)	4.99	0.258	(4.27,5.28)	5.21	0.375	(4.29,5.69)	1.60	0.170	(1.23,1.84)	0.46	0.069	(0.33,0.53)
Bike Lane	*0.13*	*0.217*	*(-0.21,0.57)*	1.28	0.671	(-0.10,2.10)	1.01	0.290	(0.33,1.44)	0.89	0.254	(0.40,1.29)
SD (ξ)	0.69	0.129	(0.48,0.93)	0.71	0.231	(0.34,1.19)	0.29	0.121	(0.11,0.62)	0.39	0.124	(0.22,0.70)
Median Width	0.27	0.168	(-0.02,0.58)	*0.56*	*0.553*	*(-0.23,1.65)*	1.07	0.535	(0.39,2.22)	0.50	0.112	(0.23,0.64)
SD (ξ)	0.64	0.094	(0.49,0.82)	0.70	0.191	(0.38,1.12)	0.71	0.268	(0.33,1.39)	0.29	0.123	(0.15,0.60)
Intersection #	1.98	0.438	(1.06,2.52)	1.10	0.333	(0.36,1.62)	0.17	0.018	(0.13,0.20)	−0.17	0.117	(-0.36,-0.02)
SD (ξ)	0.75	0.159	(0.50,1.00)	0.46	0.080	(0.35,0.62)	0.09	0.044	(0.040.19)	0.21	0.106	(0.08,0.39)
Health Fac.	0.68	0.393	(-0.09,1.12)	2.17	0.972	(0.56,3.50)	1.00	0.190	(0.58,1.21)	0.60	0.111	(0.39,0.79)
SD (ξ)	0.41	0.077	(0.26,0.52)	0.46	0.119	(0.30,0.73)	0.15	0.043	(0.08,0.24)	0.41	0.146	(0.15,0.72)
Hospital	*0.25*	*0.203*	*(-0.05,0.81)*	*0.12*	*0.124*	*(-0.11,0.32)*	*−0.10*	*0.127*	*(-0.27,0.19)*	0.40	0.217	(-0.03,0.76)
SD (ξ)	0.67	0.260	(0.34,1.26)	0.34	0.104	(0.14,0.52)	0.54	0.198	(0.24,0.85)	0.47	0.131	(0.25,0.73)
Religious Fac.	*0.11*	*0.122*	*(-0.07,0.41)*	0.23	0.118	(0.07,0.46)	0.59	0.126	(0.27,0.73)	0.49	0.149	(0.09,0.72)
SD (ξ)	0.36	0.120	(0.16,0.54)	0.21	0.050	(0.14,0.32)	0.21	0.042	(0.13,0.30)	0.88	0.200	(0.41,1.14)
Supermarket	0.37	0.186	(0.08,0.71)	0.71	0.314	(0.11,1.18)	1.01	0.353	(0.43,1.47)	0.62	0.085	(0.38,0.70)
SD (ξ)	0.58	0.143	(0.27,0.81)	0.25	0.055	(0.17,0.37)	0.28	0.061	(0.18,0.40)	0.15	0.120	(0.040.44)

Abbreviations: β: estimated coefficient mean, SE: standard error, 95% CI: 95% Confidence Interval, SD: standard deviation.
*Italic indicates that the estimate is not statistically significant at 95% confidence level.

compare the constructed model with the null model (only intercept).

In this study, a multivariate random parameter Tobit analysis was conducted. Table 2 presents the error parameters (σ and ρ), number of observations in each case, and DIC results of implemented models. Tables 3–5 present estimation results for drivers, passengers, bicyclists, and pedestrians on all days, weekdays, and weekends, respectively. Table 6, on the other hand, shows the marginal effect of (statistically significant) predictors on the (maxima-normalized) crash rates of 65+ roadway users for all days, weekdays, and weekends. Moreover, Fig. 6 illustrates the marginal effects on spider charts. Findings indicate that

Table 5
Multivariate random parameter Tobit model results – weekends.

Weekends												
65+ Crashes	Drivers			Passengers			Bicyclists			Pedestrians		
Regressor	θ	SE	95% CI	θ	SE	95% CI	θ	SE	95% CI	θ	SE	95% CI
Intercept	**−1.16**	**0.506**	**(-1.91,-0.25)**	**−0.78**	**0.263**	**(-1.12,-0.19)**	**−0.30**	**0.074**	**(-0.42,-0.14)**	**0.05**	**0.135**	**(-0.17,0.23)**
SD (ξ)	0.37	0.104	(0.23,0.62)	0.40	0.106	(0.25,0.60)	0.35	0.046	(0.26,0.44)	0.17	0.033	(0.11,0.24)
65 + PF Density	**6.16**	**0.565**	**(5.09,6.94)**	**4.88**	**0.782**	**(3.29,5.87)**	**−4.93**	**0.642**	**(-5.68,-3.43)**	**−3.10**	**0.386**	**(-3.57,-2.28)**
SD (ξ)	15.58	0.418	(14.42,16.12)	16.95	1.145	(14.51,18.41)	7.13	0.585	(5.607.82)	3.57	0.331	(2.86,3.94)
AADT	**−2.93**	**0.577**	**(-3.54,-1.73)**	**−3.85**	**0.629**	**(-4.53,-2.25)**	**−1.24**	**0.048**	**(-1.31,-1.14)**	**−0.41**	**0.060**	**(-0.52,-0.31)**
SD (ξ)	3.00	0.230	(2.72,3.62)	5.17	0.271	(4.80,5.71)	0.23	0.041	(0.17,0.31)	0.60	0.084	(0.38,0.73)
Speed Limit	***−0.36***	***0.364***	***(-0.84,0.34)***	**−1.69**	**0.600**	**(-2.42,-0.43)**	**−1.81**	**0.291**	**(-2.16,-1.20)**	**−1.01**	**0.132**	**(-1.15,-0.7)**
SD (ξ)	4.98	0.379	(4.10,5.39)	4.58	0.433	(3.58,5.04)	0.92	0.100	(0.74,1.03)	0.20	0.026	(0.15,0.25)
Bike Lane	**0.34**	**0.055**	**(0.24,0.45)**	**0.25**	**0.054**	**(0.16,0.36)**	***0.27***	***0.361***	***(-0.27,1.10)***	**0.37**	**0.162**	**(0.18,0.68)**
SD (ξ)	0.25	0.048	(0.18,0.37)	0.12	0.046	(0.06,0.24)	6.58	0.959	(3.88,7.59)	0.21	0.075	(0.12,0.43)
Median Width	**0.31**	**0.276**	**(-0.03,0.93)**	**0.39**	**0.175**	**(0.07,0.65)**	**0.77**	**0.163**	**(0.51,1.13)**	***0.03***	***0.404***	***(-0.63,0.78)***
SD (ξ)	0.42	0.112	(0.25,0.66)	0.35	0.090	(0.23,0.55)	0.40	0.091	(0.26,0.59)	1.08	0.190	(0.71,1.48)
Intersection #	**1.74**	**0.450**	**(0.74,2.3)**	**0.90**	**0.215**	**(0.43,1.21)**	**0.17**	**0.052**	**(0.06,0.26)**	**−2.99**	**0.920**	**(-4.07,-1.18)**
SD (ξ)	0.82	0.133	(0.55,1.09)	0.39	0.103	(0.24,0.57)	0.35	0.074	(0.24,0.46)	3.75	0.462	(2.80,4.33)
Health Fac.	**1.07**	**0.313**	**(0.38,1.44)**	**0.85**	**0.472**	**(0.13,1.61)**	**0.68**	**0.139**	**(0.46,0.92)**	**0.65**	**0.054**	**(0.56,0.75)**
SD (ξ)	0.23	0.124	(0.11,0.54)	0.40	0.129	(0.20,0.63)	0.29	0.109	(0.11,0.47)	0.25	0.047	(0.17,0.34)
Hospital	**0.20**	**0.088**	**(0.01,0.36)**	**0.67**	**0.333**	**(0.15,1.19)**	**0.43**	**0.183**	**(0.00,0.69)**	**0.59**	**0.270**	**(0.19,1.27)**
SD (ξ)	0.47	0.093	(0.31,0.63)	0.44	0.124	(0.27,0.76)	0.28	0.088	(0.11,0.41)	0.40	0.069	(0.30,0.62)
Religious Fac.	**0.34**	**0.239**	**(0.03,0.79)**	**0.42**	**0.143**	**(0.07,0.63)**	**0.15**	**0.062**	**(0.03,0.26)**	**0.61**	**0.197**	**(0.18,0.89)**
SD (ξ)	0.40	0.163	(0.21,0.70)	0.40	0.090	(0.25,0.54)	0.33	0.174	(0.16,0.71)	0.45	0.172	(0.23,0.78)
Supermarket	***−0.01***	***0.023***	***(-0.05,0.07)***	**0.31**	**0.087**	**(0.07,0.43)**	**0.27**	**0.118**	**(0.06,0.50)**	**0.71**	**0.176**	**(0.35,0.90)**
SD (ξ)	0.07	0.031	(0.040.16)	0.15	0.042	(0.07,0.22)	0.40	0.116	(0.25,0.60)	0.22	0.064	(0.14,0.37)

Abbreviations: β: estimated coefficient mean, SE: standard error, 95% CI: 95% Confidence Interval, SD: standard deviation.
* Italic indicates that the estimate is not statistically significant at 95% confidence level.

Table 6
Marginal effects of significant variables on maxima-normalized crash rates.

	All days				Weekdays				Weekends				
Regressor	Drv	Pas	Bic	Ped	Drv	Pas	Bic	Ped	Drv	Pas	Bic	Ped	Incr
65 + PF Density	3.40	2.25	−0.10	−0.16	3.07	2.31	−0.15	−0.12	2.04	1.27	−0.30	−0.23	1
AADT	−1.01	−0.36	−0.03	~	−0.93	−0.61	−0.03	0.01	−0.97	−1.00	−0.08	−0.03	1
Speed Limit	0.25	−0.44	−0.12	−0.08	0.14	−0.42	−0.12	−0.04	~	−0.44	−0.11	−0.07	1
Bike Lane	−0.08	0.05	0.04	0.05	~	0.37	0.05	0.04	0.11	0.07	~	0.03	1
Median Width	~	~	0.03	~	0.10	~	0.05	0.02	0.10	0.10	0.05	~	1
Intersection #	0.80	0.23	0.01	−0.01	0.76	0.32	0.01	−0.01	0.58	0.23	0.01	−0.22	1
Health Facility	0.13	0.29	0.02	0.05	0.26	0.63	0.05	0.03	0.35	0.22	0.04	0.05	1
Hospital	0.28	−0.05	0.03	0.02	~	~	~	0.02	0.07	0.17	0.03	0.04	1
Religious Facility	~	0.19	0.03	0.04	~	0.07	0.03	0.02	0.11	0.11	0.01	0.05	1
Supermarket	−0.11	0.29	0.05	0.06	0.14	0.21	0.05	0.03	~	0.08	0.02	0.05	1

Abbreviations: Drv: Driver, Pas: Passenger, Bic: Bicyclist, Ped: Pedestrian; Incr: Incremental change in variable that creates marginal effect, ~: not significant.

standard deviations (ξ) of parameters are always statistically significant, which validates the use of random parameter model, and evidences the unobserved heterogeneity across observations. That is, the effects of predictors (e.g. AADT, Health Facility, etc.) on the crash rates of different roadway users are heterogonous and vary across observations (i.e. not homogeneous/fixed effect). The results also show that there are significant error correlation (ρ) between different roadway user types except between pedestrians and bicyclists.

Results show that "Speed Limit" is statistically significant for motorists and non-motorists except drivers in the weekend. "Hospital" is found statistically significant for all days and weekends for all 65+ occupants, while it is significant only for pedestrians during weekdays. An interesting result is that the facility variables (i.e. "Health Facility", "Religious Facility", and "Supermarket") appear to be statistically significant for 65+ roadway users and most of the times, (except "Supermarket" for 65+ Drivers during weekends and "Religious Facility" Drivers during weekdays), which is intriguing. Even though these facility variables are statistically significant in most cases, the magnitude of their effect changes for both between different 65+ roadway users and temporally (Table 6 and Fig. 6). Facility variables are observed to be far more effective on the non-motorists crash rates rather than the crash rate of motorists.

"65 + PF Density" increases the 65+ crash rate for motorist at all times, which shows the importance of investigating the effect of the population living in the vicinity of the roadway on the crash rate of that specific roadway. For non-motorists, on the other hand, it seems that 65+ non-motorists involve in less crashes close to the locations with high aging density. Similarly, "Intersection #" increases the crash rate for the 65+ motorists and bicyclists, but not pedestrians. This finding for motorists confirms with a well-known issue that roadway complexities such as intersections affect aging roadway users considerably (Bayam et al., 2005; McGwin and Brown, 1999; Stamatiadis et al., 1991). "Speed Limit", on the other hand, seems to have statistically significant increasing effect only for 65+ Driver crash rates (except during weekends), while it has decreasing effect on crash rates of passengers and non-motorists.

In particular, some factors provide useful insights. For example, the presence of a bike lane ("Bike Lane") increases the crash rates for

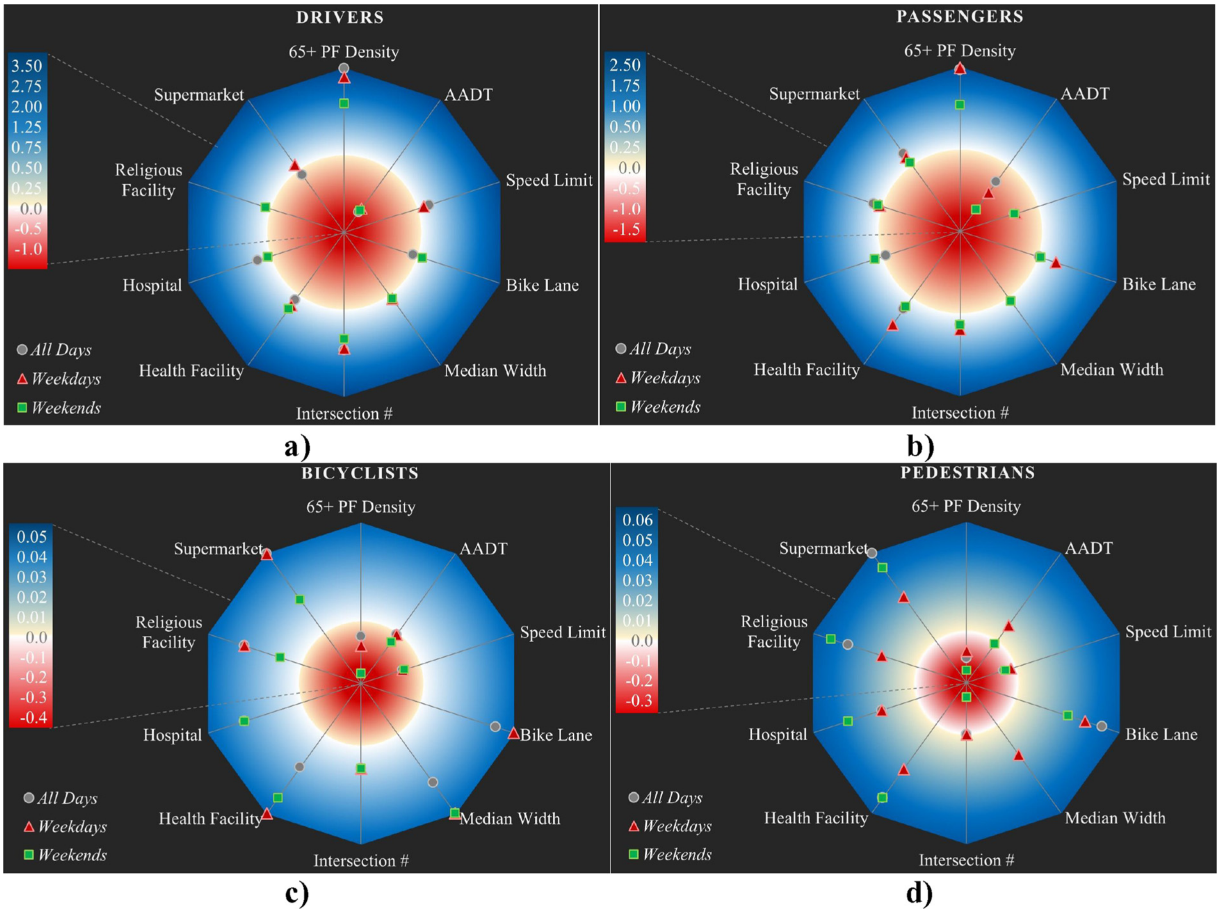


Fig. 6. Variations in marginal effects in different groups (a) 65+ drivers; (b) 65+ passengers; (c) 65+ bicyclists; (d) 65+ pedestrians.

bicyclists and pedestrians. Yet, the reason behind this phenomenon is more obscure in the case of the pedestrians. Increased crash rates for bicyclists are possibly due to the bicyclists' overrepresentation on roadways with bike lanes. Unfortunately, it is not possible to control the exposure of bicyclists on the roadways since the bicyclist traffic data is not available. If the bicyclist volume as well as the pedestrian volume data had been available, it would have improved the accuracy of the conducted analysis. Therefore, further examination is necessary to make more concrete conclusions, which is an interesting future research direction.

"Median Width" seems to increase crash rates of 65+ Bicyclists both at weekdays and weekends, and 65+ Pedestrians only at weekdays. It is possible that 65+ non-motorists might be more confident to cross the roadway when there is an available median. Due to this overconfidence, they might not be able to safely complete the crossing maneuver considering that aging people are usually less agile and slower than other age groups. This result is also unexpected because medians, which are supposed to provide safety for roadway users, may not be performing satisfactorily.

Facility variables (e.g. health facility, religious facility, etc.) are found to be eminently influential on the crash rates of all 65+ roadway users at most of the times (i.e. all days, weekdays, and weekends) (Table 6). Yet, interestingly, there are obvious differences between weekdays and weekends. For instance, at weekdays, "Health Facility" is very influential in crash rates of all groups while 65+ Passengers are affected the most, in particular. However, this influence of "Health Facility" is substantially consistent at weekends, as well. This is because, perhaps, health facilities operate during both during weekdays and weekends, and hence 65+ roadway users are exposed to traffic all times around these facilities. "Religious Facility" predictor, on the other hand, is far more influential at weekends than it is at weekdays. Moreover, this difference in the effect of "Religious Facility" between weekends and weekdays is more evident for pedestrians. Note that the effect of this predictor increases more than doubled in the case of 65+ Pedestrians (Table 6 and Fig. 6). Again, it is intuitive to think that religious facilities are more commonly visited during weekends. A similar trend is observed for the "Supermarket" variable as well, where the effect of this predictor on the crash rates of pedestrians mildly increases at weekends. However, it is more influential on weekdays than on weekends in the case of 65+ Drivers and Passengers. It is an interesting result that 65+ Drivers and Passengers perhaps prefer to go shopping during weekdays rather than weekends, which, in turn, increases the effect of "Supermarket" on the crash rate of 65+ occupants. In general, these findings inferred from the facility variables are reasonable and quite intuitive, yet it is important to highlight their substantial influence on the crash rates. These findings prove that roadways around these facilities are highly critical in terms of providing the safety for 65+ roadway users as well as the whole population.

4. Conclusions and future work

This study presents a spatial analysis and a multivariate investigation of the crashes involving aging (65+) drivers, passengers, bicyclists, and pedestrians by using the same set of predictors in order to obtain comparable findings among these different types of aging roadway users. For this purpose, we adopted a multivariate random parameter Tobit model that takes unobserved heterogeneity into account. Moreover, spatiotemporal variations in crash rates are investigated by separating weekday and weekend crashes. Such comparative investigation is a novel approach in order to understand the spatiotemporal nature of aging population-involved crashes. Findings reveal that the roadway segments with high crash rates vary spatially depending on whether it is a weekday or a weekend. This information is critical in showing that traffic safety measures and plans addressing specific roadway segments should be conducted considering this temporal variation. Moreover, the proposed CRD approach helps to pinpoint those critical segments that vary temporally.

The statistically significant standard deviations (ξ) of parameters indicate the heterogeneous effects of predictors on the crash rates of different roadway users, which validates the use of random parameter model, and evidences the unobserved heterogeneity across observations. Findings suggest that traffic safety measures and plans addressing specific roadway segments should be temporally tailored to alleviate traffic safety problems for 65+ roadway users. Furthermore, facility variables (healthcare, religious facility, and supermarkets) are found highly influential on the crash rates of all 65+ roadway users, advocating that roadways around these facilities should be particularly scrutinized by road safety stakeholders. For instance, the roadways around these facilities, especially roadways also closer to aging communities, can be identified in order to enhance the safety measures on these roadways. For example, yellow flashing lights can advise drivers to slow down during specific time periods around these roadways like the type of signalization used around schools. Moreover, police officers can be stationed on roadways close to a specific facility (e.g. religious facility) depending on time of week and time of day to ensure safety and proper driving.

In this study, 65+ population living around the studied roadways is also included to examine the effect of surrounding population on the crash rates by using a population factor – PF approach. Marginal effects show that 65 + PF increases driver crash rates while decreases crash rates of bicyclists and pedestrians. This result is rather peculiar since it is well-known that non-motorists involve in crashes much closer to their residencies than motorists do (Steinbach et al., 2013), and hence one would expect to see increasing effect of 65 + PF on the non-motorists. One explanation can be found in the calculation of the population factor. That is, PF does not account for senior centers or assisted living centers and it is rather designed to infuse the population number that has a travel potential, which may have considerable contribution in non-motorists crashes (please see Ulak et al (2017b) for details). The investigation of crashes involving aging non-motorists in the proximity of senior facilities is an intriguing future research direction. Nevertheless, 65 + PF is still highly influential on the motorist crash rates. It is also worth mentioning that facility variables such as health facility, religious facility, or supermarket are very important in modeling non-motorists' crash rates.

There are several limitations and caveats of the study. For example, roadway IDs are used in order to model the crash rates for homogenous sections. However, it is possible to conduct a further segmentation of roadways to increase the homogeneity, which would provide even finer estimations. This can be a promising future direction. Another issue is the overrepresentation of non-motorists on certain roadways such as those having bike lanes or ones in the urban areas. This may lead to erroneous estimations on the effects of predictors (e.g. bike lanes); however, it is not possible to control for this overrepresentation since the bicyclist and pedestrian traffic volumes are not available. Therefore, an effort to measure the bicyclist and pedestrian volumes possibly through bike-sharing or route tracking apps can be helpful in increasing the accuracy of the models. In terms of modeling, alternative approaches such as spatial autoregressive models, or machine learning techniques can be adopted to further analyze the data, which can be a promising future direction as well.

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