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Pedestrian injury severity in motor vehicle crashes: An integrated spatio-temporal modeling approach

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ABSTRACT

Traffic crashes are outcomes of human activities interacting with the diverse cultural, socio-economic and geographic contexts, presenting a spatial and temporal nature. This study employs an integrated spatio-temporal modeling approach to untangle the crashed injury correlates that may vary across the space and time domain. Specifically, this study employs Geographically and Temporally Weighted Ordinal Logistic Regression (GTWOLR) to examine the correlates of pedestrian injury severity in motor vehicle crashes. The method leverages the space- and time-referenced crash data and powerful computational tools. This study performed non-stationarity tests to verify whether the local correlates of pedestrian injury severity have a significant spatio-temporal variation. Results showed that some variables passed the tests, indicating they have a significantly varying spatio-temporal relationship with the pedestrian injury severity. These factors include the pedestrian age, pedestrian position, crash location, motorist age and gender, driving under the influence (DUI), motor vehicle type and crash time in a day. The spatio-temporally varying correlates of pedestrian injury severity are valuable for researchers and practitioners to localize pedestrian safety improvement solutions in North Carolina. For example, in near future, special attention may be paid to DUI crashes in the city of Charlotte and Asheville, because in such areas DUI-involved crashes are even more likely to cause severe pedestrian injuries that in other areas. More implications are discussed in the paper.

1. Introduction

A pedestrian could be any person on foot, walking or running for either short-distance traveling or recreational activities. Pedestrians are more vulnerable to severe injuries in traffic crashes than motorists. According to the Traffic Safety Facts released by National Highway Traffic Safety Administration (National Highway Safety Administration (NHTSA, 2018), over the past decade (2007 ˜ 2016), the portion of pedestrian fatalities in total motor vehicle fatalities has been constantly growing, from 11% to 16%. In 2016, there were 5,987 pedestrians killed in traffic crashes which were a 9% increase from the 2015 number of pedestrian fatalities and a 22% increase from the 2014 number in the United States. The report (National Highway Safety Administration (NHTSA, 2018) highlighted several characteristics of pedestrian fatalities which offer descriptive implications about contributing factors that are potentially related to pedestrian fatalities in motor vehicle crashes. For example, most crashes that caused pedestrian fatalities occurred after 6 pm and especially in the dark after sunset. Therefore, time of day and lighting condition may be important contributing factors to pedestrian fatalities. Other important characteristics of fatalities are related to pedestrian age and gender, land use, alcohol or drug involvement, vehicle type, and collision impact point.

To identify contributing factors and understand their complex relationships with pedestrian fatalities, many previous studies introduced rigorous modeling approaches to disentangle the correlates of pedestrian injuries in motor vehicle crashes (Davis, 2001; Siddiqui et al., 2006; Sze and Wong, 2007; Eluru et al., 2008; Kim et al., 2008, 2010; Forbes and Habib, 2015; Haleem et al., 2015; Niebuhr et al., 2016; Pour-Rouholamin and Zhou, 2016; Guo et al., 2017; Li et al., 2017; Zhang et al., 2018). The modeling results help researchers and practitioners develop effective countermeasures or safety guides to avoid severe pedestrian injuries in crashes or to reduce the extents of injuries that a pedestrian may suffer when struck by a motor vehicle. Some researchers recognized that one model often includes a limited number of factors or variables in the analysis due to either the research

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objectives (focusing on particular variables of interest) or data limitation. Therefore, some factors that may have significant influences on pedestrian injury severities are not able to be captured in traditional modeling approaches, such as regular logit or probit models (Davis, 2001; Siddiqui et al., 2006; Sze and Wong, 2007). To account for the uncaptured influences (due to unobserved variables in the model specification), researchers started looking for approaches to relax the fixed estimates about relationships between contributing factors and the pedestrian injury severity. Many recent studies employed a mixed/random-parameter modeling approach to allow estimates (i.e., coefficients of independent variables) to vary across individual observations or groups of observations (Eluru et al., 2008; Quddus, 2008; Chen and Chen, 2011; Kim et al., 2010, 2013; Behnood and Mannering, 2017; Forbes and Habib, 2015; Haleem et al., 2015; Xu and Huang, 2015; Rhee et al., 2016; Guo et al., 2017; Chen et al., 2018). In other words, one variable may have different estimated coefficients across observations or sample groups. This method has been successful in accounting for unobserved heterogeneity across observations and improving model predictive capabilities.

Traffic crashes that are distributed in the geographic space are outcomes of human activities interacting with the diverse cultural, socio-economic and geographic contexts. Some factors that have significant influences on pedestrian injuries are likely to be space-related, and these variables may also be unobserved in crash reports, causing unobserved heterogeneity mentioned above. Spatial modeling is a promising analytic approach that can capture the unobserved heterogeneity that relates to the space domain, namely unobserved spatial heterogeneity. This approach also relaxes the relationships between factors to account for the influences of unobserved factors on correlates of injury severity in crashes (Graham and Glaister, 2003; Meliker et al., 2004; Noland and Quddus, 2005; Castro et al., 2013; Wang et al., 2016; Liu and Khattak, 2017; Liu et al., 2016b, 2017a, 2018). Unlike mixed or random-parameter models, the spatial modeling approach allows model estimates to vary across space and to bear spatial patterns. The results help researchers and practitioners to identify locations where special attention are needed, e.g., in one area, speeding is associated with a particularly greater likelihood of fatality than in other areas.

In addition to the spatial nature, traffic crashes also have a nature related to the time. As mentioned above, traffic crashes are outcome of human activities in the transportation systems (Liu and Khattak, 2019). Both human behaviors (e.g., travel behavior and driving behavior) and transportation systems (e.g., vehicle design and road condition) change over time. Such temporal changes can also potentially influence the traffic safety on road and cause unobserved temporal heterogeneity if time-related factors are not well observed in analysis. Previous crash studies have included the temporal aspect into the discussion (Kockelman and Kweon, 2002; Martin, 2002; Chang and Wang, 2006; Eluru et al., 2008). Further, the temporal patterns of explanatory variables have been the focus of some previous studies (Dabbour, 2017; Behnood and Mannering, 2015, 2016). However, most of their discussions simply segmented the crashes by time periods and did not intend to simultaneously capture the temporal patterns of correlates of crashes. In addition, the panel data models have been applied in several traffic crash studies to reveal temporal information of the crashes. For example, the panel data Poisson regression model, random effect and random parameter (RP) negative binomial panel data models or tobit models are applied specifically to deal with temporal heterogeneity among factors associated with traffic crashes (Hu et al., 1998; Truong et al., 2016; Chen et al., 2014). However, outcomes based on those models may not clearly represent strong spatial or temporal patterns for the correlated factors.

Considering both the spatial and temporal aspects of traffic crashes, some studies have indeed developed methods to explain their influences on traffic crashes (e.g., Wang and Abdel-Aty, 2006; Li et al., 2007; Castro, 2012). The most commonly used method was to include the factors related to the time- and space-related characteristics into the modeling such as county, census tract, road type, or time of day, weekend or weekday. These studies revealed the locations and times with high likelihoods of having a crash. Such method has a different modeling mechanism compared to the geographically and temporally weighted regression model, which can capture the varying relationships between the crashes and many other potential correlated factors due to the diverse geographical and temporal contexts. Spatial-temporal models have also been utilized in many fields such as ecological, geoscience, land use etc. (Fotheringham et al., 2015; Chu et al., 2015; Liu et al., 2017b; Winarso et al., 2016; Li et al., 2016). But this approach is fairly under-utilized in traffic crash modeling, especially the pedestrian injury severity analysis. The objective of this study is to introduce an integrated spatiotemporal method to model the injury severity in crashes with a focus on pedestrian injuries. The method is called Geographically and Temporally Weighted Ordinal Logistic Regression (GTWOLR) that accounts for the ordinal nature of injury severity and the spatiotemporal features of traffic crashes. The GTWOLR assumes non-stationary relationships between pedestrian injuries and contributing factors. These relationships vary across both the space and time. The results are a group of local estimates for each factor, revealing spatial and temporal trends of the influences of a factor on the pedestrian injury severity in traffic crashes. The results are useful for developing proactive and localized pedestrian safety improvement strategies and recommendations, rather than stationary plans for the entire region. To the best of the authors' knowledge, this GTWOLR modeling approach has not been applied in the pedestrian safety.

2. Data

The study focuses on pedestrian injuries and their correlates in traffic crashes. This study makes use of a unique crash database provided by the North Carolina Department of Transportation (North Carolina Department of Transportation (NCDOT), 2018). The database contains pedestrian-motor vehicle collisions that occurred in North Carolina between 2007 and 2014. The Division of Bicycle and Pedestrian Transportation at NCDOT pre-processed the data and the pedestrian injuries have already been coded in KABCO Injury Classification Scale (American Association of State Highway and Transportation Officials (AASHTO, 2010). With that said, this study still performed error-checking and removed observations with missing or clearly wrong information (for variables of interest) from the database. Finally, a total of 13,854 pedestrian-motor vehicle crashes are used for GTWOLR modeling and discussion.

Table 1 shows the variable descriptive statistics. Several variables are intentionally categorized, including pedestrian age, motorist age, motor vehicle speed, and annual average daily traffic (AADT) to examine whether a non-linear relationship exists between them and the pedestrian injury severity. Further, the variable categorization helps to highlight the sample groups of interest, such as the senior pedestrians. The KBACO injury scale distribution shows that only 5.1% of crashes did not result in any pedestrian injuries, and more than 55% of these crashes caused involved pedestrians to suffer from evident or severer injuries. Of sampled crashes, 8.8% resulted in a pedestrian fatality. The injuries that pedestrians may sustain in a motor vehicle crash seem to be much severer than motorist injuries (Liu et al., 2016a). According to the same pedestrian-motor vehicle crashes, less than 2% of crashes caused evident or severer injuries to motorists. Of sampled crashes, 20% are labeled "Pedestrian Failed to Yield" in the database. However, the authors did not find the information to identify whether a motorist failed to yield prior to the event of a crash. More statistics are shown in Table 1. Noticeably, pedestrians were found to be intoxicated by alcohol or drug in 13.8% of sampled crashes, while intoxicated motorists were found in only 3.1% of these crashes. Pedestrian intoxication may be a reason causing the occurrence of some crashes.

Space- and time-referenced data allow researchers to examine the spatial and temporal data patterns. Fig. 1 presents the spatial and

Table 1
Variable Descriptive Statistics.

Variable (Total N = 13,854)		Frequency	Percent
Injury severity	O: No injury	708	5.1%
	C: Possible injury	5285	38.1%
	B: Evident injury	5495	39.7%
	A: Disabling injury	1147	8.3%
	K: Killed	1219	8.8%
Pedestrian failed to yield (1 = Yes, 0 = Otherwise)		2785	20.1%
Pedestrian age	< = 18 yrs old	2893	20.9%
	19 ˜ 24 yrs old	2167	15.6%
	25 ˜ 40 yrs old	3363	24.3%
	41 ˜ 55 yrs old	3197	23.1%
	56 ˜ 70 yrs old	1432	10.3%
	> 70 yrs old	802	5.8%
Pedestrian gender	Female	4919	35.5%
	Male	8935	64.5%
Pedestrian intoxicated (by alcohol or drug)	No	9919	71.6%
	Yes	1912	13.8%
	Missing	2023	14.6%
Pedestrian position	Paved shoulder	1115	8.0%
	Sidewalk	585	4.2%
	Travel lane	9123	65.9%
	Other	1158	8.4%
	Crosswalk	1873	13.5%
Crash location	Non-intersection	8258	59.6%
	Intersection with signals	2442	17.6%
	Intersection with traffic signs	1198	8.6%
	Other intersection	1956	14.1%
Land use	Other	2330	16.8%
	Commercial	5876	42.4%
	Residential	5648	40.8%
Motorist age	< = 20 yrs old	1195	8.6%
	21 ˜ 30 yrs old	2694	19.4%
	31 ˜ 45 yrs old	3079	22.2%
	> 45	4472	32.3%
	Unknown	2414	17.4%
Motorist gender	Female	4880	35.2%
	Male	6593	47.6%
	Unknown	2381	17.2%
Motorist intoxicated (by alcohol or drug)	No	9801	70.7%
	Yes	426	3.1%
	Missing	3627	26.2%
Motor vehicle speed	< = 10 mph	3476	25.1%
	11 ˜ 20 mph	1764	12.7%
	21 ˜ 30 mph	1828	13.2%
	31 ˜ 45 mph	4366	31.5%
	> 45 mph	1599	11.5%
	Unknown	821	5.9%
Motor vehicle type	Auto	6891	49.7%
	Pickup	1735	12.5%
	SUV	2163	15.6%
	Van	783	5.7%
	Truck or Bus	481	3.5%
	Other or unknown motorized vehicle	1801	13.0%
Visibility and lighting	Daylight	6797	49.1%
	Dark with streetlights	3094	22.3%
	Dark without streetlights	3234	23.3%
	Other	729	5.3%
Land use	Rural (< 30% developed)	2377	17.2%
	Mixed (30% to 70% developed)	1996	14.4%
	Urban (> 70% developed)	9481	68.4%
Traffic volume (AADT)	< 4600	2113	15.3%
	4601 ˜ 9600	2130	15.4%
	9601 ˜ 16000	1969	14.2%
	16001 ˜ 26000	2254	16.3%
	> 26000	2146	15.5%
	Unknown	3242	23.4%
Lane number	< = 2 lanes	7916	57.1%
	3 ˜ 4 lanes	3386	24.4%
	> 4 lanes	2258	16.3%
	Unknown	294	2.1%
Road alignment - Curve (1 = yes, 0 = otherwise)		886	6.4%
Level terrain surface (1 = yes, 0 = otherwise)		10867	78.4%
Weather (1 = clear or cloudy, 0 = otherwise)		12585	90.8%

Table 1 (*continued*)

Variable (Total N = 13,854)		Frequency	Percent
Time of day	Early morning	1931	13.9%
	Morning peak	1395	10.1%
	Mid-day	3296	23.8%
	Afternoon peak	3941	28.4%
	Night	3291	23.8%
Weekend (1 = yes, 0 = otherwise)		3392	24.5%
Time of year	Spring (Mar, Apr, May)	3222	23.3%
	Summer (June, July, Aug)	3022	21.8%
	Fall (Sep, Oct, Nov)	4257	30.7%
	Winter (Dec, Jan, Feb,)	3353	24.2%

temporal distributions of pedestrian-motor vehicle crashes that occurred in North Carolina from 2007 to 2014. As expected, crashes are more likely to occur at locations with more human activities (especially walking activities) and greater population sizes. Clear spatial clusters are found in urbanized areas including Charlotte, Greensboro, and the Triangle Area of North Carolina. Fig. 1(c) presents the temporal trends of pedestrian-motor vehicle crashes in North Carolina. Regardless of the seasonal variations, there is a growing trend in the monthly counts of pedestrian-motor vehicle crashes statewide, partially due to the constantly growing vehicle miles traveled in the state (North Carolina Department of Transportation (NCDOT), 2018). In terms of injury severity, the percentages of crashes that resulted in evident or severe pedestrian injuries vary across time but slowly decreasing from 2007 to 2014.

3. Modeling Framework

3.1. Geographically and Temporally Weighted Ordinal Logistic Regression (GTWOLR)

This study makes use of time- and space-referenced crash data and explores the spatio-temporal patterns of pedestrian injury severity correlates in traffic crashes. The key approach is called Geographically and Temporally Weighted Ordinal Logistic Regression (GTWOLR), which is an advanced modeling method that is extended from the regular Ordinal Logistic Regression (OLR) by adding time and space perspectives into modeling.

The regular OLR is often used to estimate the relationships between factors and injury severity that has an ordered nature (Liu et al., 2015; Liu and Khattak, 2018) and the OLR model can be used to predict the probability of a crash causing certain levels of injury severity (StataCorp, 2013):

$$p_{ij} = \Pr(y_j = i) = Pr(\alpha_{i-1} < \beta x_j + \mu < \alpha_i) = \frac{1}{1 + \exp(-\alpha_i + \beta x_j + \mu)} - \frac{1}{1 + \exp(-\alpha_{i-1} + \beta x_j + \mu)} \quad (1)$$

where, y_j is the j^{th} crash; i is the level of pedestrian injury severity, $i = 1$ ˜ k levels, and $k = 5$ for KABCO scale injuries; x_j are potential contributing factors, also called explanatory variables as shown in Table 1; β are model coefficients representing the relationships between pedestrian injury severity and explanatory variables; α_i is the model intercept term at i^{th} level of injury severity, $\alpha_0 = -\infty$ and $\alpha_5 = +\infty$; μ is the error term.

Most conventional modeling approaches, including the regular OLR, take all observations simultaneously for model estimation and all observations in models are treated equally except weighted samples. The results from the regular OLR modeling are stationary relationships between pedestrian injury severity and explanatory variables. These relationships represent overall or global relationships. However, traffic crashes bear spatial and temporal natures. It is possible that local relationships (relative to global) in traffic crashes may vary across space

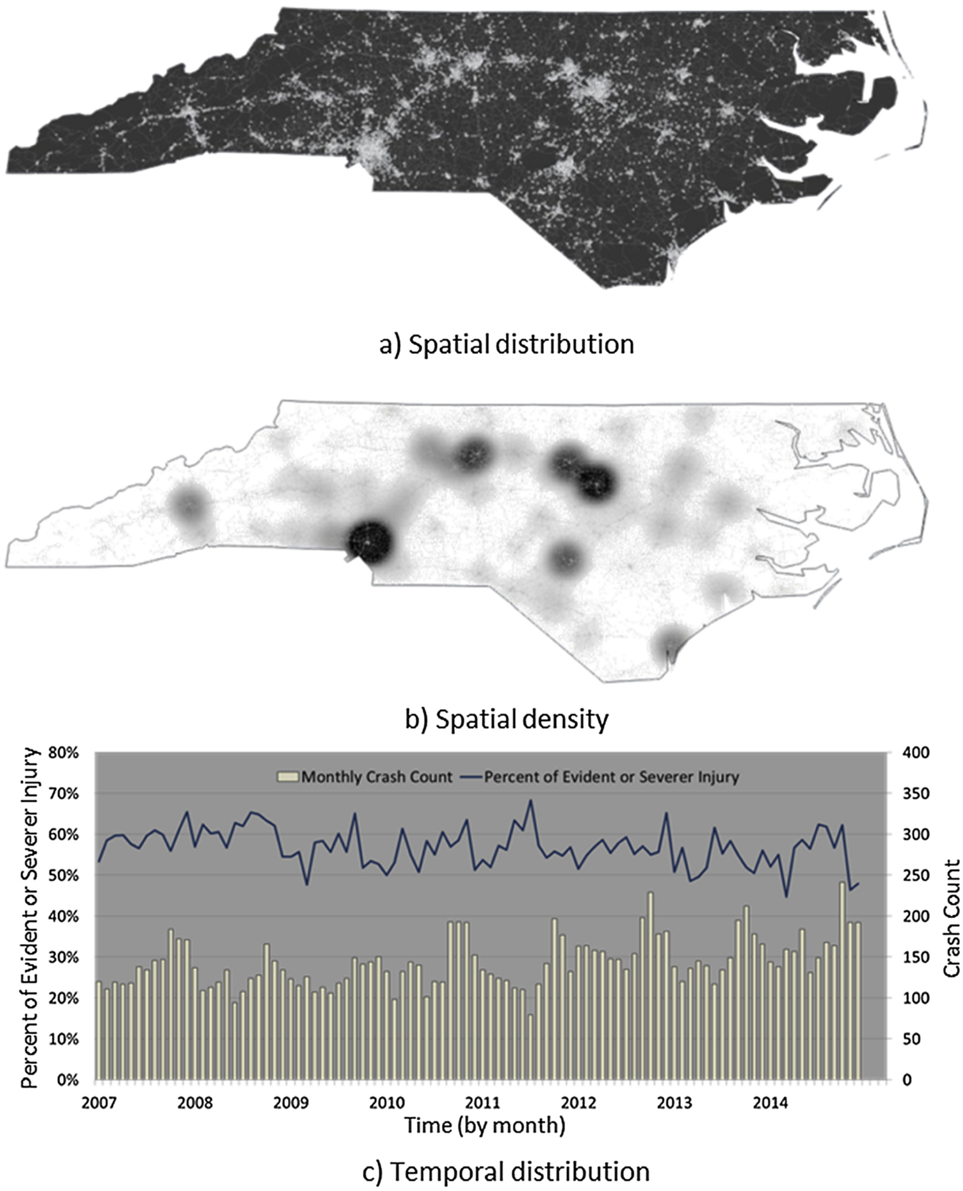

Fig. 1. Spatial and temporal distributions of pedestrian-motor vehicle crashes in North Carolina from 2007 to 2014.

and over time. This study introduces the GTWOLR to examine the local relationships. The fundamental GTWR can be expressed as: (Ma et al., 2018)

$$Y_j = \beta_0(u_j, v_j, t_j) + \sum_k \beta_k(u_j, v_j, t_j)X_{jk} + \varepsilon_j \tag{2}$$

where t_j could be any time-related information such as hour, day, week, month or year. (u_i, v_i) represents the coordinates of the crash location i. β are model coefficients, X_{jk} denotes the k th selected variables, and ε_j is the error term for observation j.

Unlike conventional modeling approaches, GTWOLR takes only a local sample of observations for the estimation of local relationships. The local sample has a spatio-temporal center where a target observation is located. The target observation moves from one observation to another in the entire sample. The local sample also has a temporal center which is the time when the target observation occurred. Together, a local sample has a spatiotemporal center which is determined by the target observation. For each observation, GTWOLR estimates a local relationship between a factor and the response variable. Further, observations in a local sample are not treated equally but reversely weighted according to the extents of their spatial and temporal separations from the target observation. Therefore, the target observation in a local sample has the greatest weight. Details of estimating GTWOLR are shown below, and the process is repeated for each observation as the spatiotemporal center once.

1) Weighting all observations Relative to a target observation (the spatiotemporal center), all observations are first assigned with a spatial weight according to their geographical distance to the center. Bi-square Kernel Weighting (BKW) function is often used (Fotheringham et al., 1998):

$$w_t^S(u_j, v_j) = \left(1 - \left(\frac{d_{jt}}{d_{max}}\right)^2\right)^2 \tag{3}$$

where, $w_t^S(u_j, v_j)$ is the spatial weight for t^{th} observation which is centered at j^{th} observation (as the target observation) in the entire sample; (u_j, v_j) denotes the location of j^{th} observation; d_{jt} is the geographical distance of t^{th} observation from the center; d_{max} is distance from the target observation to its furthest observation in the entire sample. Then all observations are weighted according to their temporal separations (i.e., time difference) to the target observation, generating a temporal weight for each observation. Similarly, a BKW function is used:

$$w_j^T(t_i) = \left(1 - \left(\frac{t_{ij}}{t_{max}}\right)^2\right)^2 \quad (4)$$

where, $w_j^T(t_i)$ is the temporal weight for j^{th} observation in the local sample; t_{ij} is the temporal distance from j^{th} observation to the target observation; t_{max} is maximum time difference relative to the target observation in the entire sample. Last, the spatial and temporal weights are combined (by multiplying) to generate a spatiotemporal weight for all observation with respect to the target observation (Huang et al., 2010; Bai et al., 2016).

$$w_j^{ST}(u_i, v_i, t_i) = w_j^S(u_i, v_i) \times w_j^T(t_i) \quad (5)$$

The target observation at the spatiotemporal center has a spatial weight, temporal weight and spatiotemporal weight that are all equal to 1. Note, this study assumes two aspects (i.e., space and time) of weighting have equivalent influences on model estimation. But the spatiotemporal weight is chosen as the final weighting mechanism.

2) Sampling local observations This step is done according to the spatiotemporal weights obtained from the first step. Observations with higher weights are more likely to be sampled, as they are both spatially and temporally close to the target observation. The local sample size needs to be determined by multiple runs, in order to obtain the optimal model estimation measured by Akaike Information Criterion-AIC (Bozdogan, 1987; Fotheringham et al., 2002). Varying sample sizes were tested to get the optimal size of the local sample, called optimal bandwidth. For this study, the optimal bandwidth is 3500 observations. The optimal bandwidth varies based on the total number of observations as well as the model specifications (e.g., variable selection and model form).
3) Re-weighting observations in the local sample This step is similar to the first step, calculating weights for observations only in the local sample rather than the entire sample.
4) Weighted regression The last step estimates a local model by incorporating the spatiotemporal weights from the previous step. To link to a conventional OLR model, GTWOLR can be written as (Fotheringham et al., 1998):

$$p_{ij} = \Pr(y_j = i) = \frac{1}{1 + \exp(-\alpha_i(u_j, v_j, t_j) + \beta(u_j, v_j, t_j)x_j)} - \frac{1}{1 + \exp(-\alpha_{i-1}(u_j, v_j, t_j) + \beta(u_j, v_j, t_j)x_j)} \quad (6)$$

where, $\alpha(u_j, v_j, t_j)$ and $\beta(u_j, v_j, t_j)$ are the local coefficients for j^{th} crash that occurred at time t_j and at the location (u_j, v_j).

Estimation results of GTWOLR have one local set of coefficients for each observation, representing the local relationships between contributing factors and pedestrian injury severity. The relationships may vary across space and time. This study created original source codes for GTWOLR in an R environment. The codes can be used for other studies focusing on traffic crash-related injury severity modeling.

It is known that random-parameter models or mixed models are often applied to address the unobserved heterogeneity by allowing model estimations vary across observations (Chen and Chen, 2011; Kim et al., 2013; Quddus, 2008; Rhee et al., 2016; Xu and Huang, 2015; Behnood and Mannering, 2015; Chen et al., 2018). Compared to this modeling approach, the GTWOLR allows researchers to examine whether the unobserved heterogeneity is related to the space and time. Traffic crashes bear the nature of space and time (Ma et al., 2017), and it is reasonable to assume that the correlates of crashes are embedded in some spatiotemporal patterns. Mixed models show random relationships between factors which are independent of the space and time, and GTWOLR assumes pedestrian injury severity is potentially related to the geography and time. Even though mixed- models may outperform our models in terms of model prediction, the GTWOLR can be used to reveal the spatial and temporal patterns of relationships between pedestrian injury severity and factors. Therefore, this study uses the GTWOLR to reveal such patterns and examine whether the spatial-temporal variations of model estimates are significant. Modeling results from GTWOLR are useful to localize traffic safety improvement solutions for specific locations and times, instead of the same strategies for all.

Further, the marginal effects are also estimated according to the modeling outputs. Marginal effects indicate the change of probability from a lower level of injury severity to a higher level with a unit change in the explanatory variable. The marginal effects can be estimated by the following equations (StataCorp, 2013):

$$\frac{\partial \Pr(y_{ij} \le c|\beta X_{ij})}{\partial X} = \frac{\exp(-\gamma_c + X_{ij}\beta + Z_{ij}v_i + \varepsilon_{ij})}{[1 + \exp(-\gamma_c + X_{ij}\beta + Z_{ij}v_i + \varepsilon_{ij})]^2}\beta' \quad (7)$$

where, y_{ij}= injury severity of pedestrian i involved in crash i ; c= injury severity level, $c = 1, 2, 3, 4, or\ 5$; $X_{ij} = (1 \times p)$ vector of covariates corresponding to fixed effects; β= fixed effects parameter for covariates X_{ij}; $Z_{ij} = (1 \times q)$ vector of covariates corresponding to random effects; v_i= random effects parameter for covariates Z_{ij}; γ_c= threshold value for injury severity level c; $\gamma_0 = -\infty$ and $\gamma_5 = +\infty$; ε_{ij}= model residuals $\varepsilon_{ij}\tilde{}N(0, \delta^2)$.

3.2. Non-stationarity test

The GTWOLR can reveal local correlates of pedestrian injury severity in traffic crashes. However, these local correlates may not necessarily vary significantly across space and over time, due to little influences of unobserved space- and time-related factors. If no significant variation is found, the local coefficients from GTWOLR estimation are relatively stationary and are generally close to the estimates from conventional OLR. To verify whether the local correlates of pedestrian injury severity vary significantly across the spatiotemporal domain, this study performed a non-stationarity test for GTWOLR estimates. The test is to compare ranges of local coefficients from GTWOLR estimation with the estimates from conventional OLR (which typically has only one coefficient for a variable along with a standard error). Since the ranges from the minimum and maximum coefficients may be too extreme, the interquartile range Delta from the lower quartile (25th percentile) to upper quartile (75th percentile) is calculated for comparison (Liu and Khattak, 2017; Liu et al., 2017a). The non-stationarity test is performed for each variable:

$$Delta = \beta^{upper} - \beta^{lower} \begin{cases} >1.96\,(S.E.)\ and\ max\ |z| > 1.96, & Non-stationarity\ Test\ PASSED \\ otherwise, & Non-stationarity\ Test\ FAILED \end{cases} \quad (8)$$

where, $S.E.$ is the corresponding coefficient's standard error from the conventional OLR model, and $|z_j|$ is the z-value of a local GTWOLR coefficient $\beta(u_j, v_j, t_j)$, equal to $|\frac{\beta(uj, vj, tj)}{SE(uj, vj, tj)}|$. If $Delta$ is greater than $1.96\,(S.E.)$ and the maximum $|z|$ is greater than 1.96, the non-stationarity test is passed, indicating a variable has significantly spatio-temporally varying local relationships with pedestrian injury severity.

3.3. Model comparison

Through incorporating the spatial and temporal aspects in model estimation, the GTWOLR models can theoretically outperform conventional OLR models, in terms of explaining the correlations between contributing factors and the response variable. To confirm whether this is true in this study focusing on correlates of pedestrian injury severity in traffic crashes, this study calculated the model log likelihood, Pseudo-R^2, and Akaike Information Criterion (AIC) to compare the GTWORL models and OLR models. The log likelihood for a regression model is equal to (StataCorp, 2013):

$$\ln L = \sum_{j=1}^{n} \sum_{i=1}^{k} I_i(y_j) \ln p_{ij} \tag{9}$$

where, $I_i(y_j) = \begin{cases} 1, & if\ y_j = i \\ 0, & otherwise \end{cases}$. The log likelihood is often negative, and a smaller magnitude implies a better model goodness-of-fit.

Pseudo-R^2 value represents the extent of model estimates explaining information in the data. It relates to the changes in log likelihood from a null model to a regressed model. For logistic models, Pseudo-R^2 is equal to:

$$Pseudo\ R^2 = 1 - \frac{\ln L}{\ln L_{null}} \tag{10}$$

where, $\ln L_{null} = \sum_{j=1}^{n} \sum_{i=1}^{k} I_i(y_j) \ln P_{ij}$, and P_{ij} is the overall probabilities of all levels of pedestrian injury severity. A greater Pseudo-R^2 value implies a potentially better model goodness-of-fit.

AIC values are also often calculated for model comparison. AIC relates to the model log likelihood and the number of parameters in a model. A smaller AIC value indicates a better model goodness-of-fit (Bozdogan, 1987). A three-point decrease in AIC values indicates a significantly better goodness-of-fit (Fotheringham et al., 2002). The AIC is equal to:

$$AIC = 2k - 2\ln L \tag{11}$$

where, k is the number of parameters in the model.

4. Results

4.1. Modeling outputs

Table 2 presents the model estimates from the regular OLR and marginal effects for each variable with respect to five levels of pedestrian injury severity. The OLR model estimates represent the overall or global relationships between contributing factors and pedestrian injury severity in traffic crashes. Only variables with statistically significant estimates (p-value < 0.05) are kept in the final model as shown in Table 2. Marginal effects were calculated based on the model estimates and can be used to interpret modeling results in a more intuitive way than using the odds ratios, i.e., the coefficients of an OLR model. A marginal effect indicates the percentage point change in the probability of a pedestrian suffering from a certain level of injury with one unit change in the explanatory variable, i.e., moving from the base level to target level (e.g., from pedestrian female to male).

Table 3 summarizes the local coefficients from the GTWOLR model and non-stationarity test results. For model comparison, the same explanatory variables were included in the GTWOLR model. As expected, the ranges of local coefficients cover the stationary coefficients from the OLR model. Model summary statistics including log likelihood, Pseudo-R^2 and AIC consistently show that the GTWOLR model outperformed the regular OLR model. Non-stationarity tests revealed that not all variables passed the test, indicating that some variables have a relatively stationary relationship with pedestrian injuries across the spatiotemporal domain. Noticeably, modeling results showed that increased pedestrian injury severities are associated with crashes that involved pedestrian intoxication, SUV, heavy-duty vehicle (bus or truck), or that occurred after sunset without streetlights. These results are consistent with previous findings (Liu et al., 2016a; Ouni and Belloumi, 2018; Martin, 2002; Zhang et al., 2018; Li et al., 2007; Eluru et al., 2008; Kim et al., 2010; Castro et al., 2013; Kim et al., 2008; Chang and Wang, 2006; Haleem et al., 2015; Siddiqui et al., 2006; Kockelman and Kweon, 2002; Pour-Rouholamin and Zhou, 2016; Guo et al., 2017). These relationships did not pass the test; therefore, these factors have similar relationships with pedestrian injury severity across the entire state, according to this study. Next section presents in-depth discussions on key variables, with a focus on variables that passed the test. Correlates of pedestrian injury severity related to these variables were found to have a significant spatiotemporal variation.

In general, the signs and magnitudes of coefficients are as expected. For example, relative to young or mid-aged pedestrians (25 ˜ 40 years old), senior pedestrians (70 years old or older) are likely to associate with severer injuries. The marginal effects show in a pedestrian-motor vehicle crash, for an involved senior pedestrian, the chance of suffering from evident or severer injury is 11.07 percent point more than for an involved young adult. The motor vehicle speed is also positively related to pedestrian injury severity. Findings are consistent with previous studies (Davis, 2001; Eluru et al., 2008; Kim et al., 2010, 2008; Haleem et al., 2015; Sze and Wong, 2007; Guo et al., 2017; Liu et al., 2016a)

4.2. Discussion of key variables

This section offers detailed model interrelation and discussion on key variables that passed the non-stationarity test according to GTWOLR model estimates. Relationships between these variables and pedestrian injury severity were found to have significant spatial and temporal variations. Fig. 2 maps spatially variations of pedestrian injury correlates. The bluer color indicates increased pedestrian injury severity and the greener color shows decreased injury severity, with respect to the change of a specific variable from its base level to a level of interest.

Pedestrian age has a strong but non-linear relationship with pedestrian injury severity. Non-adult (18 years or younger) and seniors (55 years or older) are more likely to be severely injured in traffic crashes than young or mid-aged adults (25 ˜ 40 years old). Such a finding is similar to what others found (Davis, 2001; Kim et al., 2010, 2008; Haleem et al., 2015; Sze and Wong, 2007; Pour-Rouholamin and Zhou, 2016; Guo et al., 2017; Davis, 2001). Marginal effects show the increased chance for sustaining evidence or severer injuries is around 3% more for non-adult and 7–11% for seniors. Fig. 2(a) shows that seniors (56˜70 years old) in the west of North Carolina (especially the City of Charlotte and Asheville) are even more likely to be severely injured than those in the east.

Paved shoulder and sidewalk seem to be protective for pedestrians when involved in a traffic crash. The results show that, as relative to crashes on travel lanes, those on a paved shoulder and sidewalk are associated with decreased injury severity for involved pedestrians. The results are consistent with findings in previous studies (Haleem et al., 2015; Siddiqui et al., 2006; Pour-Rouholamin and Zhou, 2016). The marginal effects show that if a pedestrian is standing on a paved shoulder before a traffic crash occurs, he or she is 13% less likely to suffer evident or severer injuries in this crash. Fig. 2(b) shows that a pedestrian standing on a paved shoulder is associated with an even smaller chance of suffering severe injuries in the region from east Charlotte to Greensboro–Winston-Salem–High Point areas. The sidewalk is associated with a smaller marginal effect (8.37%) than the paved shoulder. However, the marginal effect difference between paved shoulder and sidewalk does not imply that paved shoulders are more protective than sidewalks. This study reveals that given a pedestrian crash a paved shoulder is associated with a decreased injury severity as relative to a sidewalk. Sidewalks provide dedicated space for pedestrians and are often present in residential, recreational and business areas where pedestrian traffic is generally high. A paved shoulder is part of the highway and can be used by pedestrians and cyclists. Without knowing the pedestrian traffic volumes on these two types of facilities, it is unreasonable to compare their pedestrian safety performance. In this study, the number of crashes on paved shoulders is greater than the number on sidewalks. The results do not discourage the implementation of sidewalks. Relative to travel lanes, crosswalks also seem to be associated with a decreased pedestrian injury severity, give the negative coefficients as well as the marginal effects (3.3% smaller likelihood for evident or severer injuries). However, compared with other facility types such as paved shoulders and sidewalks, crosswalks are associated with an increased injury severity. The reasons may be

Table 2
Regular Ordered Logit Model Estimates and Marginal Effects.

Y = Pedestrian injury severity		Model			Marginal Effects				
Variable		β	Std. Error	p-value	O	C	B	A	K
Pedestrian failed to yield (1 = yes, 0 = otherwise)		0.320	0.043	0.000	−1.35%	−5.14%	2.25%	1.72%	2.51%
Pedestrian age (base: 25 ˜ 40 yrs old)	< = 18 yrs old	0.154	0.050	0.002	−0.74%	−2.40%	1.22%	0.80%	1.12%
	19 ˜ 24 yrs old	−0.111	0.052	0.035	0.59%	1.69%	−0.99%	−0.55%	−0.73%
	41 ˜ 55 yrs old	0.138	0.047	0.003	−0.67%	−2.16%	1.11%	0.72%	1.00%
	56 ˜ 70 yrs old	0.341	0.061	0.000	−1.51%	−5.37%	2.43%	1.81%	2.65%
	> 70 yrs old	0.554	0.076	0.000	−2.25%	−8.74%	3.40%	2.98%	4.61%
Pedestrian intoxicated (base: no)	Yes	0.318	0.052	0.000	−1.33%	−5.08%	2.17%	1.72%	2.52%
Pedestrian position (base: Travel lane)	Paved shoulder	−0.620	0.064	0.000	3.37%	9.46%	−5.77%	−3.08%	−3.98%
	Sidewalk	−0.406	0.088	0.000	2.01%	6.36%	−3.48%	−2.09%	−2.81%
	Other	−0.238	0.061	0.000	1.09%	3.78%	−1.88%	−1.25%	−1.74%
	Crosswalk	−0.164	0.061	0.007	0.73%	2.61%	−1.24%	−0.87%	−1.23%
Crash location (base: non-intersection)	Intersection with signals	−0.180	0.058	0.002	0.86%	2.83%	−1.45%	−0.94%	−1.30%
	Intersection with traffic signs	−0.042	0.062	0.504	0.19%	0.66%	−0.31%	−0.22%	−0.31%
	Other intersection	−0.104	0.049	0.035	0.48%	1.64%	−0.80%	−0.55%	−0.77%
Motorist age (base: 31 ˜ 45 yrs old)	< = 20 yrs old	0.151	0.065	0.020	−0.69%	−2.37%	1.12%	0.79%	1.15%
	21 ˜ 30 yrs old	0.147	0.050	0.004	−0.67%	−2.30%	1.09%	0.77%	1.11%
	> 45 yrs old	−0.034	0.045	0.447	0.17%	0.53%	−0.28%	−0.18%	−0.24%
Motorist gender (base: female)	Male	0.072	0.037	0.053	−0.31%	−1.15%	0.51%	0.39%	0.56%
Motorist intoxicated (base: no)	Yes	0.632	0.095	0.000	−2.26%	−10.00%	3.01%	3.49%	5.76%
Motor vehicle speed (base: < = 10 mph)	11 ˜ 20 mph	0.537	0.056	0.000	−3.43%	−8.90%	7.86%	2.32%	2.15%
	21 ˜ 30 mph	0.758	0.058	0.000	−4.45%	−12.99%	10.56%	3.52%	3.37%
	31 ˜ 45 mph	1.270	0.051	0.000	−6.15%	−22.44%	14.65%	6.76%	7.18%
	> 45 mph	2.079	0.069	0.000	−7.63%	−34.97%	13.31%	12.39%	16.89%
Motor vehicle type (base: auto)	Pickup	0.184	0.053	0.001	−0.86%	−2.88%	1.41%	0.96%	1.36%
	SUV	0.190	0.047	0.000	−0.88%	−2.97%	1.45%	1.00%	1.41%
	Van	0.112	0.065	0.086	−0.54%	−1.75%	0.89%	0.58%	0.81%
	Truck or Bus	0.645	0.095	0.000	−2.50%	−10.15%	3.55%	3.50%	5.60%
Visibility and lighting (base: daylight)	Dark with streetlights	0.217	0.060	0.000	−1.00%	−3.50%	1.81%	1.16%	1.53%
	Dark without streetlights	0.428	0.063	0.000	−1.82%	−6.96%	3.16%	2.35%	3.27%
	Other	−0.004	0.079	0.960	0.02%	0.06%	−0.04%	−0.02%	−0.03%
Lane number (base: < = 2 lanes)	3 ˜ 4 lanes	0.211	0.042	0.000	−0.99%	−3.32%	1.68%	1.11%	1.53%
	> 4 lanes	0.493	0.049	0.000	−2.07%	−7.83%	3.30%	2.66%	3.94%
Curve road	Yes	0.215	0.068	0.001	−0.92%	−3.41%	1.47%	1.15%	1.71%
Level road	Yes	−0.196	0.040	0.000	0.87%	3.10%	−1.41%	−1.04%	−1.52%
Time of day (base: night)	Early morning	0.451	0.055	0.000	−1.87%	−7.20%	2.97%	2.45%	3.64%
	Morning peak	0.242	0.077	0.002	−1.09%	−3.85%	1.83%	1.29%	1.82%
	Mid-day	−0.005	0.069	0.939	0.03%	0.08%	−0.05%	−0.03%	−0.04%
	Afternoon peak	0.057	0.055	0.301	−0.28%	−0.89%	0.47%	0.29%	0.40%
Weekend (1 = yes, 0 = otherwise)			0.091	0.039	0.019	−0.42%	−1.44%	0.68%	0.48%
Time of year (base: spring)	Summer	0.034	0.043	0.429	−0.15%	−0.53%	0.25%	0.18%	0.26%
	Fall	−0.052	0.049	0.291	0.24%	0.81%	−0.40%	−0.27%	−0.39%
	Winter	−0.134	0.053	0.011	0.65%	2.09%	−1.07%	−0.69%	−0.97%
K_1		−2.015	0.103	0.000					
K_2		0.889	0.099	0.000					
K_3		3.099	0.102	0.000					
K_4		3.988	0.105	0.000					
Summary Statistics	Number of observations	13854							
	Log likelihood at zero LL(0)	−18100.6							
	Log-likelihood at convergence LL(β)	−16493.3							
	Pseudo-R^2	0.089							
	AIC	33094.52							

related to the impact direction angles between pedestrian and the involved vehicle, and the collisions on crosswalks are likely to be a zero-degree impact angle which often leads to higher injury severities than other angles (Chen et al., 2015).

Crashes that occurred at intersections seem to associate with a smaller likelihood of severe pedestrian injury than those occurring at non-intersection locations, which is also found in Eluru et al. (2008). Reasons may be related to the behaviors of both motorist and pedestrian when approaching an intersection. Vehicles when approaching an intersection are likely to slow down, and pedestrians may become more cautious when walking across an intersection than walking along a road segment. Modeling results showed that signalized intersections are associated with the smallest likelihoods of severe pedestrian injuries. Fig. 2(c) shows that signalized intersection crashes in the west of North Carolina (the City of Asheville) and southeast coast area are linked with even smaller severe injury likelihoods.

The age and gender of involved motorists are two important factors that relate to pedestrian injury severity in traffic crashes. Modeling results revealed that teenager drivers (20 years old or younger) and young adults (20 ˜ 30 years old) are associated with increased pedestrian injury severity, about 3% point increase for evident or severe injury according to marginal effects. However, older adults (over 45 years old) are estimated with associate with 0.7% lower likelihood of possible or no pedestrian injury. Male drivers are also correlated with severe pedestrian injuries. Fig. 2(d) highlights the metropolitan area of Charlotte where teenager drivers are likely associated with an even greater chance of causing severe pedestrian injuries in traffic crashes. Fig. 2(e) shows that male drivers in the east coast region may be one of the reasons, resulting in severe pedestrian injuries.

Driving under the influence (DUI) or driving while intoxicated

Table 3
Estimates from Geographically and Temporally Weighted Ordinal Logistic Regression and Non-Stationarity Test.

Y = Pedestrian injury severity		GTWOLR Model Estimates						Non-stationarity	
Variable		Mean β	Min β	Lower β	Upper β	Max β	Max |Z|	Delta	Test
Pedestrian failed to yield (1 = yes, 0 = otherwise)		0.302	0.216	0.199	0.401	0.402	3.993	0.202	Yes
Pedestrian age (base: 25 ˜ 40 yrs old)	< = 18 yrs old	0.132	0.013	0.004	0.278	0.279	2.249	0.274	Yes
	19 ˜ 24 yrs old	−0.107	−0.244	−0.279	−0.004	0.006	2.079	0.275	Yes
	41 ˜ 55 yrs old	0.107	−0.022	−0.028	0.228	0.230	2.178	0.256	Yes
	56 ˜ 70 yrs old	0.327	0.119	0.110	0.551	0.553	4.094	0.441	Yes
	> 70 yrs old	0.559	0.442	0.427	0.667	0.671	4.064	0.240	Yes
Pedestrian intoxicated (base: no)	Yes	0.335	0.187	0.161	0.443	0.446	3.999	0.282	Yes
Pedestrian position (base: Travel lane)	Paved shoulder	−0.652	−0.883	−0.891	−0.424	−0.423	6.596	0.467	Yes
	Sidewalk	−0.424	−0.764	−0.792	−0.107	−0.104	4.518	0.685	Yes
	Other	−0.180	−0.531	−0.541	0.012	0.015	4.104	0.553	Yes
	Crosswalk	−0.148	−0.298	−0.306	0.003	0.004	2.400	0.309	Yes
Crash location (base: non-intersection)	Intersection with signals	−0.177	−0.262	−0.268	−0.074	−0.074	2.189	0.194	Yes
	Intersection with traffic signs	−0.051	−0.205	−0.220	0.105	0.108	1.545	0.325	No
	Other intersection	−0.096	−0.191	−0.197	−0.006	0.001	1.848	0.191	No
Motorist age (base: 31 ˜ 45 yrs old)	< = 20 yrs old	0.180	0.048	0.017	0.351	0.353	2.436	0.334	Yes
	21 ˜ 30 yrs old	0.129	−0.005	−0.020	0.283	0.284	2.449	0.303	Yes
	> 45 yrs old	−0.027	−0.170	−0.192	0.057	0.058	1.772	0.249	No
Motorist gender (base: female)	Male	0.080	0.017	0.011	0.203	0.203	2.348	0.192	Yes
Motorist intoxicated (base: no)	Yes	0.742	0.315	0.261	1.119	1.120	5.206	0.857	Yes
Motor vehicle speed (base: < = 10 mph)	11 ˜ 20 mph	0.571	0.440	0.427	0.714	0.720	6.145	0.287	Yes
	21 ˜ 30 mph	0.839	0.677	0.656	1.009	1.009	8.113	0.353	Yes
	31 ˜ 45 mph	1.329	1.199	1.162	1.420	1.420	14.140	0.258	Yes
	> 45 mph	2.165	1.903	1.882	2.406	2.413	15.973	0.524	Yes
Motor vehicle type (base: auto)	Pickup	0.194	0.091	0.075	0.286	0.287	2.396	0.211	Yes
	SUV	0.228	0.159	0.151	0.318	0.319	2.935	0.167	Yes
	Van	0.075	−0.115	−0.131	0.240	0.242	1.661	0.370	No
	Truck or Bus	0.637	0.506	0.474	0.821	0.825	3.730	0.348	Yes
Visibility and lighting (base: daylight)	Dark with streetlights	0.243	0.038	0.016	0.384	0.386	3.134	0.369	Yes
	Dark without streetlights	0.426	0.306	0.283	0.536	0.538	3.883	0.253	Yes
	Other	0.045	−0.157	−0.182	0.256	0.259	1.473	0.438	No
Lane number (base: < = 2 lanes)	3 ˜ 4 lanes	0.198	0.095	0.086	0.307	0.308	3.107	0.221	Yes
	> 4 lanes	0.488	0.361	0.355	0.613	0.618	5.605	0.258	Yes
Curve road	Yes	0.211	0.132	0.121	0.383	0.385	2.051	0.263	Yes
Level road	Yes	−0.188	−0.304	−0.316	−0.050	−0.049	3.697	0.266	Yes
Time of day (base: night)	Early morning	0.420	0.345	0.328	0.579	0.582	4.686	0.251	Yes
	Morning peak	0.263	−0.004	−0.023	0.499	0.501	2.841	0.522	Yes
	Mid-day	−0.003	−0.094	−0.111	0.135	0.138	0.891	0.246	No
	Afternoon peak	0.054	−0.006	−0.018	0.114	0.120	0.905	0.133	No
Weekend (1 = yes, 0 = otherwise)		0.082	0.086	0.011	0.007	0.159	0.159	1.893	0.152
Time of year (base: spring)	Summer	0.012	−0.122	−0.133	0.153	0.154	1.455	0.286	No
	Fall	−0.052	−0.134	−0.146	0.029	0.030	1.338	0.175	No
	Winter	−0.160	−0.252	−0.276	−0.012	−0.010	2.187	0.265	Yes
K_1		−2.022	−2.461	−2.499	−1.687	−1.677	11.310	0.812	Yes
K_2		0.932	0.455	0.411	1.252	1.253	5.943	0.841	Yes
K_3		3.192	2.670	2.620	3.558	3.561	16.892	0.938	Yes
K_4		4.087	3.692	3.658	4.489	4.490	20.717	0.831	Yes
Summary Statistics	Number of observations	13854							
	Log likelihood at zero L(0)	−18100.59							
	Log-likelihood at convergence L(β)	−16293.14							
	Pseudo-R2	0.100							
	AIC	32694.28							

Note: $|z| = |\frac{\beta(u_i, v_i, t_i)}{SE(u_i, v_i, t_i)}|$. *Delta* $= \beta^{upper\ quantile} - \beta^{lower\ quantile}$; Test = Non-Stationarity Test; Yes = Passed the Test; No = Failed the Test.

(DWI) is illegal in the United States (GPO, 2003; FindLaw, 2017). The use of alcohol or drugs (when exceed a certain amount) could seriously impair mental and vehicle driving skills (Kim et al., 2008, 2010; Kockelman and Kweon, 2002; Pour-Rouholamin and Zhou, 2016). Clearly, DUI threatens pedestrians on road with severe injuries. Modeling results showed that if a crash involved an intoxicated driver, the chance for a pedestrian suffering from evident or severer injuries increases by 12.3%. Fig. 2(f) highlights the west North Carolina including the city of Charlotte and Asheville. In these areas, DUI involved crashes are likely to cause even severer pedestrian injuries than DUI crashes in other areas in North Carolina.

The vehicle speed, especially over 45 mph, is significantly associated with a 42.6% increased likelihood of evident or severer pedestrian injuries compared to 10 mph or less. Fig. 2(i) shows that the effect of speeds on pedestrian injury severity can be even greater in the City of Charlotte. Motor vehicle type is also an important factor significantly correlated to pedestrian injuries in traffic crashes. Modeling results showed that the mass of a vehicle is positively related to pedestrian injury severity. Relative to a regular passenger car, pickup, SUV and trucks are associated with increased pedestrian injury severity. For truck or bus involvement in crashes, the increase in the chance of evident or severer injury is 12.6% point. Fig. 2(g) showed that crashes that involved a pickup may cause even severer injuries in areas from the Triangle Area to the City of Fayetteville and the coastal city, Wilmington.

Compared to daylight, darkness is associated with an increased

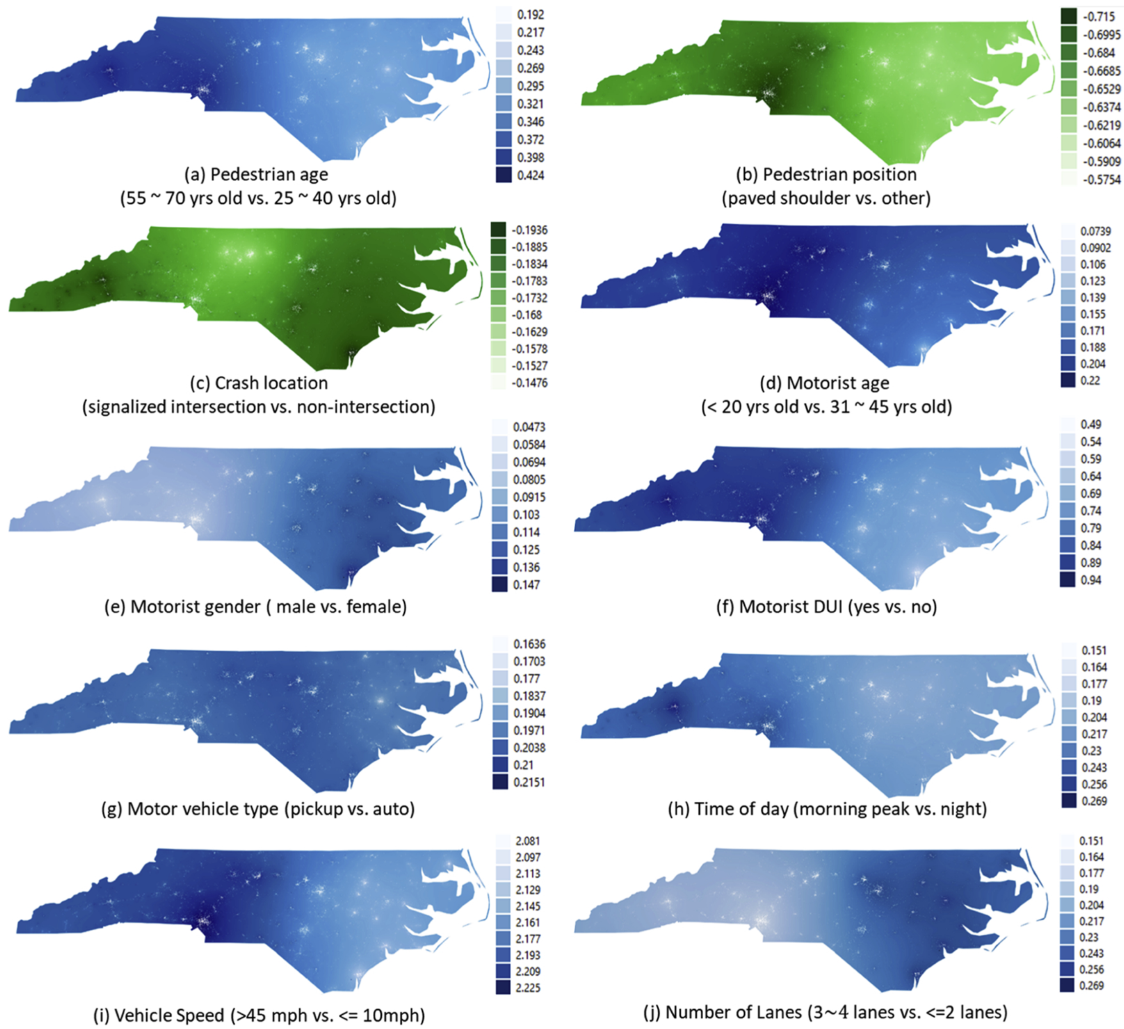

Fig. 2. Spatially varying relationships between pedestrian injury severity and selected variables.

likelihood for evident or severer injuries, especially when there is no lighting. The marginal effect for darkness without lighting is an 8.7% increase in the likelihood for evident or severer injuries. The lane number is also a significant factor for pedestrian injury severity. Wider roads with more lanes are associated with increased injury severity. For example, if walking on a road with more than 4 lanes, the likelihood of resulting an evident or severer injury in a crash is increased by nearly 10% as compared to walking on a road with 2 lanes or less. Wide roads with more than 4 lanes probably have the raised medians or refuge islands where pedestrians can stop before finishing crossing a multilane road. The raise medians and refuge islands are found to be effective in protecting pedestrians (Federal Highway Administration (FHWA, 2019). The presence of the raise medians and refuge islands remains unknown in this study. In addition, roads with more lanes have a higher speed limit than roads with less lanes, and vehicle speed is found to be positively related to pedestrian injury severity in the model. Again, without knowing the exposure information, especially the pedestrian traffic on two types of facilities, it is questionable to compare their safety performance. This study uncovers the risk of injury types. A road with more than 4 lanes is associated with a greater risk of evident or severer injuries than a road with 2 lanes or less. Gårder (2004) found that 4-lane streets are associated with a higher crash rate due to the higher traffic volumes as well as higher speeds than 2-lane streets. Fig. 3(j) show highlights the eastern region of North Carolina for an even greater association between the lane number and injury severity. In terms of roadway geometry, pedestrian crashes on a curve or slope are likely to be severer than those on a straight or flat road. At a curve or grade, drivers' sight distance may be limited and they could not react as promptly as they could on a straight or flat segment.

As for temporal effects, the actual time of crash is used to generate the overall temporal effect. Besides that, pedestrian-motor vehicle crashes that occur at different times of a day appear to result in different levels of pedestrian injury severity. Early morning crashes are likely to cause the severest pedestrian injuries. Relative to crashes at night, early morning crashes are linked to a 9.1% increase in the chance of evident or severer injuries. Crashes that occurred during morning peak hours are also associated with increased pedestrian injury severity. Fig. 2(h) shows that morning peak hour crashes can be even more dangerous for pedestrians in the west North Carolina including the city of Charlotte and Asheville.

In addition to spatial variations, correlates of pedestrian injury severity also present temporal variations found in this study. Fig. 3 shows how these correlates, i.e., relationships between pedestrian injury severity and factors, vary over time. Overall, these correlates are relatively stationary for crashes that occurred between 2007 and 2009; they become un-stabilized from 2009 to 2012, and correlates found in crashes after 2013 return to a relatively stationary status. The reason may be related to the data reporting procedures which could be inconsistent over time, or it may be related to the impact of the economic improvement after the financial crisis in 2008 to 2009 Noticeably, from 2007 to 2014, crashes that involved DUI or a teenager driver, or crashes that occurred in morning peak hours are associated with a generally

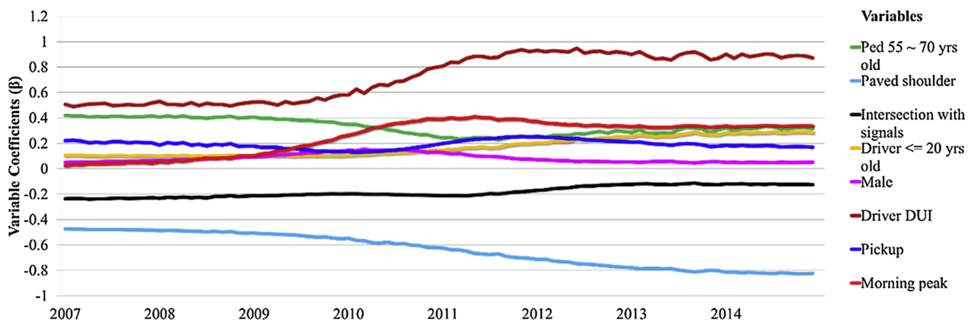

Fig. 3. Temporally varying relationships between pedestrian injury severity and selected variables.

(but not constantly) increasing likelihood of causing severe pedestrian injuries. These temporal trends imply a near-future focus for researchers and practitioners who are working on improving pedestrian safety. The focus may be on DUI, teenager driver and morning peak hour traffic. More implications can be drawn from the modeling results.

5. Limitations

The accuracy of the results presented in this study heavily depends on the accuracy of crash data used for modeling. For example, this study includes a variable about whether the involved pedestrian failed to yield prior to the event of a crash. Since the crash reporters were often not at the scene at the moment of collision, it is possible that they were given inaccurate information by witnesses, involved pedestrians or motorists. The data was pre-processed in a professional manner and generally provided by NCDOT. That being said, the extent of data inaccuracy remains unknown to authors.

The spatiotemporal modeling needs space- and time-referenced data. This study is focused on motor vehicle traffic crashes that involved pedestrians. The geo-reference information was checked for whether an observation is located within the right-of-way of highway facilities. However, the time-reference remains unchecked, though the crash counts, in general, follow the traffic volume variations (seasonal and trend).

It is possible that some minor crashes were not reported, partially because there was no damage or harm resulted. Therefore, the crash records included in the database used by this study may not represent the overall sample in the study area. Further, the models presented in this study included a limited number of variables that are available in the database. The results may vary if other factors are included in models, e.g., who was at fault during the crash.

6. Conclusions

Considering the spatial and temporal nature of traffic crashes, this study introduces an integrated spatiotemporal modeling approach to untangle the correlates of pedestrian injury severity in traffic crashes. These correlates may vary across space and over time, due to the unobserved heterogeneity that relates to space and time. The modeling approach is called Geographically and Temporally Weighted Ordinal Logistic Regression (GTWOLR) that leverages the space- and time-referenced crash data and powerful computational tools. The data are pedestrian-motor vehicle crashes that occurred in North Carolina from 2007 to 2014. The GTWOLR is an advanced modeling method extended from the regular Ordinal Logistic Regression (OLR) by incorporating time and space information in modeling. Theoretically, the GTWOLR approach outperforms OLR models as it accounts for influences of unobserved factors related to space and time, which has been confirmed in this study according to model summary statistics.

This study performed non-stationarity tests to verify whether the local correlates of pedestrian injury severity from GTWOLR have a significant spatiotemporal variation. Results showed that not all variables passed the tests, indicating some factors have a relatively stationary relationship with pedestrian injury severity. The results showed that increased pedestrian injury severities are associated with crashes that involved pedestrian intoxication, SUV, heavy-duty vehicle (bus or truck), or that occurred after sunset without streetlights. These relationships do not vary significantly across space and time domain. This study highlighted some factors that have significantly varying relationships with pedestrian injury severity. These factors include pedestrian age, pedestrian position, crash location, motorist age and gender, driver intoxication, motor vehicle type and the crash time in a day. These factors have an overall relationship with pedestrian injury severity, which can be seen from the regular OLR modeling results. The GTWOLR results showed that these relationships also vary significantly across space and time domain. For example, pedestrian age has a nonlinear relationship with pedestrian injury severity. Seniors are more likely to be severely injured in traffic crashes than young or mid-aged adults. Seniors in the west of North Carolina are even more likely to be severely injured than those in the east. If a crash involved an intoxicated driver, the chance for a pedestrian suffering from evident or severer injuries increases. The GTWOLR results highlighted the west North Carolina including the city of Charlotte and Asheville where DUI involved crashes are even more likely to cause severe pedestrian injuries than DUI crashes in other areas. Further, some correlates of pedestrian injury severity also vary over time. For example, from 2007 to 2014, crashes that involved DUI or a teenager driver, or crashes that occurred in morning peak hours are associated with a generally (but not constantly) increasing likelihood of causing severe pedestrian injuries.

The results from GTWORL modeling are valuable for practitioners to localize pedestrian safety countermeasures for specific locations and offer insights for near future focuses on pedestrian safety. For example, the spatial variations showed that DUI crashes in the city of Charlotte and Asheville are more likely to cause severe pedestrian injuries than the same crashes in other areas. In addition, the temporal variations imply a trend that DUI crashes are linked with an increased likelihood of causing severe pedestrian injuries. Therefore, DUI and teenage drivers' education may be a near-future focus for pedestrian safety improvements (e.g., re-education in driving, increase law enforcement, or development of shared driving modes for the drunk) in North Carolina, especially for the city of Charlotte and Asheville.

This study makes both methodological and empirical contributions. This study introduces an advanced modeling approach, namely GTWOLR, to explore the correlates of pedestrian injury severity in traffic crashes. This modeling approaches take advantage of powerful computation tools and make use of the space- and time-referenced data. This modeling approach can be applied by other studies that explore space- and time-referenced crash data. Besides, this study revealed spatiotemporally varying correlates of pedestrian injury severity, which are new empirical insights in this area of study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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