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# An integrated spatio-temporal approach to examine the consequences of driving under the influence (DUI) in crashes

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ABSTRACT

Driving under the influence (DUI) is illegal in the United States because a driver's mental and motor skills can be seriously impaired by alcohol or drugs. Consequently, DUI violators' involvement in severe crashes is high. Motivated by the spatial and temporal nature of traffic crashes, this study introduces an integrated spatio-temporal approach to analyzing highway safety data. Specifically, this study estimates Geographically and Temporally Weighted Regression (GTWR) models to understand the consequences of DUI in crashes. GTWR can theoretically outperform traditional regression methods by accounting for unobserved heterogeneity that may be related to the location and time of a crash. Using Southeast Michigan crash data, this study finds that DUI is associated with a 25% higher likelihood of injury in a crash. The association between injury severity and DUI varies significantly across space and time. From the spatial aspect, DUI crashes in rural or small-town areas are more likely to cause injuries than urban crashes. From the temporal aspect, different times are associated with varying relationships between injury severity and DUI. If focusing on DUI crashes in late nights and early mornings, on Fridays, the entire northeast part from Clinton Charter Township to Port Huron is associated with severer injuries than other regions including Detroit's urban area and its south. On Mondays, the DUI crashes in the northwest are also more likely to cause severe injuries. The methodology introduced in this study takes advantage of modern computational tools and localized crash/inventory data. This method offers researchers and practitioners an opportunity to understand highway safety outcomes in great spatial and temporal details and customize safety countermeasures for specific locations and times such as saturation patrols.

## 1. Introduction

Driving under the influence (DUI) or driving while intoxicated (DWI) is illegal in the United States. (U.S. Government Publishing Office (GPO, 2003; FindLaw, 2017). DUI refers to the driver's behavior of operating a motor vehicle while under the influence of alcohol or drugs to a degree that mental and motor skills are seriously impaired. All 50 states use blood alcohol concentration (BAC) as a metric to measure the degree of alcohol intoxication; and 0.08% BAC is the national legal limit for a charge with DUI for adults aged 21 or older (National Highway Traffic Safety Administration (NHTSA, 2000). There is a zero-tolerance limit of 0.02% BAC for teen drivers under the age of 21 (DMV.ORG, 2017; Burch et al., 2019). The zero-tolerance limit varies from state to state. In some states, the zero-tolerance limit means a teen driver will be arrested for drunk driving if any measurable amount of alcohol is found in their body. In other states, the zero-tolerance limit refers to 0.02% BAC. For drugged driving, some states have established specific limits for the presence of intoxicating drugs. For example, the Virginia Code of Virginia Section 18.2-266 (Virginia's Legislative Information System (VLIS, 2005), the limit for cocaine is 0.02 milligrams per liter of blood and for methamphetamine, it is 0.1 milligrams per liter of blood. Some states (i. e., Arizona, Delaware, Georgia, and Indiana) have a zero-tolerance limit for drugged driving (Walsh, 2009). A driver who is charged with DUI often faces punishments and penalties including fines, license suspension, and imprisonment. DUI is a major threat to traffic safety. In 2015, there were nationwide 1,089,171 drivers arrested for DUI (Department of Justice (US) and Federal Bureau of Investigation (FBI, 2016), and 10, 265 people were killed in crashes that involve alcohol-impaired driving (National Highway Traffic Safety Administration (NHTSA, 2016). The number accounted for 29% of the total traffic-related fatalities on U.S.

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roadways in 2015.

Researchers have extensively discussed the correlates and consequences of DUI. Collectively, DUI drivers are likely to be young, male, not married, unemployed, and/or low-income persons (Kelly et al., 2004; Caetano and McGrath, 2005; Gruenewald and Johnson, 2010; Meesmann et al., 2015). The direct effect of drinking or drug use on drivers is impaired driving abilities, i.e., reduced ability to track moving objects, reduced ability to maintain lane position and brake appropriately, reduced information processing capability, and slow response to objects on road (National Highway Traffic Safety Administration (NHTSA, 2005). Impaired driving often leads to a significantly increased likelihood of crashes (World Health Organization (WHO, 2017), which is the most concerned consequence of DUI and is also the reason why there are strict laws against DUI. It is also found that DUI is significantly associated with increased injury severities in crashes (Kockelman and Kweon, 2002; Qi et al., 2013; Damsere-Derry et al., 2014; Pour-Rouholamin and Zhou, 2016; Liu et al., 2016a, 2016b).

To examine the roles of DUI and other factors in crashes, researchers analyzed archived traffic crash data through building regression models (Kockelman and Kweon, 2002; Alver et al., 2014; Chen et al., 2016; Pour-Rouholamin and Zhou, 2016; Liu et al., 2016a, 2016b; Maistros et al., 2016; Liu and Khattak, 2018; Zhang et al., 2018). Most of these models were used to estimate stationary relationships between injury severity and associated factors (Alver et al., 2014; Damsere-Derry et al., 2014; Chen et al., 2016). In other words, these relationships do not vary across either space or time. Since most achieved crash data provide a limited number of factors for modeling and analysis, unobserved heterogeneity may exist across observations. Researchers apply random-effects or mixed models to account for the unobserved heterogeneity (Maistros et al., 2016). Further, given that traffic crashes are distributed in space, they are likely to interact with the spatially diverse environments (from cultural, socio-economic, to geographic). Unobserved factors (such as driving culture and road conditions) that are associated with the space could be captured in geo-spatial modeling (Meliker et al., 2004; Noland and Quddus, 2005; Castro et al., 2013; Liu et al., 2016a, 2016b, 2016c; Wang et al., 2016; Liu et al., 2017; Liu et al., 2020). The geo-spatial modeling is featured by relaxing the relationships between crashes and factors, allowing the relationships to vary across space and to reflect the local correlates of crashes. The outcome of the geo-spatial approach can be used to differentiate safety improvement recommendations from location to location, rather than a uniform or overall solution based on the stationary correlates (Alver et al., 2014; Damsere-Derry et al., 2014; Chen et al., 2016). DUI is a social concern that is related to the socioeconomics of both the community and drivers themselves. It is a reasonable motivation to employ the geo-spatial modeling approach to examine the roles of DUI in crashes.

In addition, traffic crashes involve human behaviors which bear a time-of-day variation. Experiments showed that early morning, early afternoon, and late evening are associated with a longer reaction time and a reduced driving ability than other times in a day (Lenné et al., 1997). Besides, the time-of-day variation of traffic (National Cooperative Highway Research Program (NCHRP, 2012) and lighting conditions on road also present temporally varying environments to drivers. Therefore, the driving performance is likely to vary from time to time in a day. Previous crash studies have included the temporal aspect into discussion; and severe injuries are more likely to occur in early mornings or late nights (Kockelman and Kweon, 2002; Martin, 2002; Chang and Wang, 2006; Eluru et al., 2008), perhaps because of the light traffic and relatively high driving speeds. Furthermore, DUI is a behavior related to social activities, such as meeting friends at bars or restaurants. DUI crashes appear to pose temporally varying characteristics. It is important to include temporal factors into the analysis of DUI crashes.

Given the spatial and temporal characteristics of traffic crashes, it is valuable to explore these two characteristics in an integrated manner. Previous studies have developed the integrated spatial and temporal approaches to examine both two characteristics of traffic crashes (Wang and Abdel-Aty, 2006; Li et al., 2007; Castro et al., 2012; Blazquez and Celis, 2013). The most commonly used method is to include the factors related to temporal and spatial characteristics into analysis, such as including the land use variables in modeling and segmenting the crashes by time-of-day, day-of-week, month or year. These studies revealed the locations and times with high likelihoods of having a crash. This study applies an approach that integrates the spatial and temporal methods of modeling to analyze the injury severity with respect to DUI. This approach is Geographically and Temporally Weighted Regression (GTWR). Compared to approaches in previous studies, the advances of GTWR include:

1) It assumes that relationships between crash severities and factors are non-stationary from location to location and time to time and the non-stationary relationships help account for the unobserved factors related to space and time;
2) It takes the space and time between crashes into account and crashes that occurred in nearby locations and similar times are assumed to bear similar correlates with factors; and
3) It generates a local estimate regarding the influence of a factor on crash severity to represent the local influence during a short-time period which may be used to develop traffic safety improvement strategies/recommendations for particular locations and times, such as scheduling saturation patrols.

GTWR has been employed in many other areas, such as geographic (Huang et al., 2010) and environmental science (Bai et al., 2016a, 2016b). To the best of authors' knowledge, GTWR has not been widely applied to explore traffic crashes. This study contributes by introducing GTWR to untangle the spatially and temporally varying relationships between crash severity and associated factors and offering new insights into the correlates of crash severity with DUI.

## 2. Methodology

### 2.1. Data acquisition

The crash data used in this study are from the Southeast Michigan Council of Governments (SEMCOG, 2017). The data cover all types of motor vehicle crashes (N = 138,529) that occurred in Southeast Michigan in 2015. Road inventory data were also obtained from the Southeast Michigan Council of Governments (SEMCOG, 2017). Key variables include the number of lanes, highway class, speed limit, traffic volume, bike lane type, etc. The road facility data are linked with crash data by matching their spatial extents. There are 26 crashes that are away from a road link (outside of the right-of-way of the closest road link) and thus are removed from the analysis. This study performed error-checking and removed observations with erroneous or incomplete information. The final dataset has 138,499 crashes for modeling. Note that, the variable "driving under the influence" or "DUI" is defined by two variables ("ALCOHOL" and "DRUG") in the original dataset. If a driver is either impaired by alcohol or drug in a crash, this crash is coded as "driving under the influence" or "DUI". Among the 138,499 crashes, 4706 crashes involved with DUI.

### 2.2. Modeling framework

This study introduces an integrated spatio-temporal modeling approach, namely Geographically and Temporally Weighted Regression (GTWR), to reveal the potentially spatially and temporally varying correlates of crash severity with associated factors. It is possible that the variations of such correlates are not substantial, indicating that correlates are relatively stationary across space and time. To verify whether the variations are substantial, a traditional regression model was estimated for comparison. A traditional ordered logistic model was estimated for the ordered severity responses (StataCorp, 2013; Liu et al., 2016).

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

where $y_j$ is the $j$th crash; $i$ is the level of injury severity, $i = 1 \sim k$ levels; $x_j$ are independent variables, summarized in Table 1; $\beta$ are estimated coefficients representing the relationships between crash severity and independent variable; $\alpha_i$ is the model constant term at $i$th level of injury severity, $\alpha_0 = -\infty$ and $\alpha_k = +\infty$.

Traditional models (i.e., Eq. (1)) take all observations in model estimation at the same time. The output of such models is one coefficient for each variable, representing the global relationship between crash severity and a factor, regardless of the influences of space and time. However, for data that are spatially and temporally distributed in nature, it might be worthy to further examine local relationships that may vary across space and time. The spatially and temporally varying relationships can be used to specify traffic safety improvement strategies for different regions and times, instead of applying the same strategy for all.

GTWR has been designed to simultaneously tackle the spatial and temporal variations of model estimates (Liu et al., 2019). GTWR is extended from the Geographically Weighted Regression (GWR). In GWR, the spatial distribution of observations is important. Rather than taking all observations in model estimation at the same time, GWR takes a sub-group of observations for estimating a local model for a particular location, termed target location. The target location is often the location of an observation and moves from one observation to another. Each target location is corresponding to a sub-group of observations which are centered at the target location. For each target location, the corresponding sub-group observations come from nearby observations that are geographically within a certain distance to the target location. The distance is termed bandwidth in GWR. It requires multiple times of run to determine the optimal bandwidth, in order to reach the best model performance, often measured by Akaike Information Criterion-AIC (Fotheringham et al., 2002; Kemp, 2008). Models with smaller AICs and smaller bandwidth are preferred which produces a greater effective number of parameters (Kemp, 2008). Estimation of a local model for a target location is only based on the observations in the corresponding sub-group, but the observations in a sub-group do not equally contribute to the model estimation. GWR assumes that observations that are closer to the target location have more influences on the model estimation than those further away; thus, observations are weighted according to their geographic distance to the target location. Some observations may be sampled multiple times in different local models (corresponding to different target locations), but these observations are weighted differently across local models as their relative geographic distance to the target location changes. Given the feature of the GWR, the data sample size needs to be large enough to ensure that each stratum of the data represents the population is considered as sufficient (Kemp, 2008). In this study, a sample size of 138,499 crashes is sufficient for modeling. With respect to GTWR, the temporal characteristic of observations is added upon the framework of GWR. The process of estimating GTWR can be summarized in four steps:

**Table 1**
Descriptive statistics of variables (total N = 138,499).

| Variable | Percent | Valid N |
|---|---|---|
| Crash severity (in KABCO scale)* | | |
| K = Fatal Injury | 0.26% | 362 |
| A = Incapacitating Injury | 1.13% | 1,562 |
| B = Non-incapacitating Evident Injury | 4.79% | 6,637 |
| C = Possible Injury | 14.49% | 20,065 |
| O = No Injury | 79.33% | 109,873 |
| Driving under influence - DUI (1 = yes; 0 = otherwise) | 3.40% | 4,706 |
| Crash type | | |
| 1 = Single | 17.46% | 24,187 |
| 2 = Head on | 3.78% | 5,232 |
| 3 = Angle | 17.51% | 24,250 |
| 4 = Rear-end | 37.15% | 51,459 |
| 5 = Sideswipe | 16.83% | 23,309 |
| 6 = Other | 7.27% | 10,062 |
| Young drivers involved (< 25 years old. 1 = yes; 0 = otherwise) | 34.33% | 47,548 |
| Senior drivers involved (> 64 years old. 1 = yes; 0 = otherwise) | 15.46% | 21,407 |
| Pedestrian/bike involved (1 = yes; 0 = otherwise) | 1.61% | 2,236 |
| Lighting condition | | |
| 1 = Daylight | 69.05% | 95,637 |
| 2 = Dawn | 2.17% | 3,005 |
| 3 = Dusk | 2.24% | 3,107 |
| 4 = Dark - with street lights on | 15.01% | 20,792 |
| 5 = Dark- without street lights on | 10.27% | 14,229 |
| 6 = Unknown | 1.25% | 1,729 |
| Weather | | |
| 1 = Clear or cloudy | 83.79% | 116,049 |
| 2 = Other (fog, smoke, rain, snow, severe wind, etc.) | 16.21% | 22,450 |
| Speed limit | | |
| 1 = "< = 30 mph" | 22.95% | 31,780 |
| 2 = "35 ~ 45 mph" | 47.10% | 65,229 |
| 3 = "50 ~ 60 mph" | 17.88% | 24,757 |
| 4 = "> 65 mph" | 12.08% | 16,733 |

*Note*: * is defined in MI Traffic Crash Report Manual (Michigan Department of State Police, 2014).

1) Weighting observations

First, for a target location (i.e., a particular observation), all observations are weighted based on their geographical distance to the target location, giving a spatial weight for each observation. Bi-square Kernel Weighting (BKW) function is often used: (Fotheringham et al., 1998):

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

where, $w_t^S(u_j, v_j)$ is the spatial weight for $t$th observation in the sub-group which is centered at $j$th observation in the entire sample; $d_{jt}$ is the geographical distance of $t$th observation from the center; $d_{max}$ is the distance from the target observation to its furthest observation in the entire sample.

Then all observations are weighted based on their temporal distance to the target observation, generating a temporal weight for each observation. This study considers three temporal aspects including time of day (TOD), day of week (DOW), and month of year (MOY). A similar BKW function can be developed for each temporal aspect:

$$w_t^{TOD}\left(t_j^{TOD}\right) = \left(1 - \left(\frac{t_{jt}^{TOD}}{t_{max}^{TOD}}\right)^2\right)^2 \tag{3}$$

$$w_t^{DOW}\left(t_j^{DOW}\right) = \left(1 - \left(\frac{t_{jt}^{DOW}}{t_{max}^{DOW}}\right)^2\right)^2 \tag{4}$$

$$w_t^{MOY}\left(t_j^{MOY}\right) = \left(1 - \left(\frac{t_{jt}^{MOY}}{t_{max}^{MOY}}\right)^2\right)^2 \tag{5}$$

where $w_t^{TOD}\left(t_j^{TOD}\right)$, $w_t^{DOW}\left(t_j^{DOW}\right)$ and $w_t^{MOY}\left(t_j^{MOY}\right)$ are weights from three temporal aspects for $t^{h}$ observation in the sub-group; $t_{jt}^{TOD}$, $t_{jt}^{DOW}$ and $t_{jt}^{MOY}$ are the temporal distances from tth observation to the target observation; $t_{max}^{TOD}$, $t_{max}^{DOW}$ and $t_{max}^{MOY}$ is the maximum time difference between the target observation and other observations in the entire sample. The temporal distances are relative time differences that consider the periodical feature of TOD, DOW, and MOY. For example, the temporal distance between 1:00 and 23:00 is 2 h rather than 22 h. Last, the spatial and temporal weights are combined (by multiplying) to lead to a spatio-temporal weight for all observation with respect to the target location (Huang et al., 2010; Bai et al., 2016a, 2016b).

$$w_t^{ST}(u_j,\ v_j,\ t_j) = w_t^{S}(u_j,\ v_j)\ \times\ w_t^{TOD}\left(t_j^{TOD}\right) \times w_t^{DOW}\left(t_j^{DOW}\right) \times w_t^{MOY}\left(t_j^{MOY}\right) \tag{6}$$

where $t_j$ represents $t_j^{TOD}$, $t_j^{DOW}$ and $t_j^{MOY}$. The observation at the target location has a spatial weight, temporal weight, and spatio-temporal weight that are all equal to 1.

2) Sampling sub-group observations

In GWR, the step is done according to the geographic distance (or spatial weight) respect to the target location. In GTWR, this step is done according to the spatio-temporal weight 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.

3) Re-weighting observation in sub-group

The weights imply the relative contributions as compared to all other observations in a model. The weights generated in first step are according to all observations. Therefore, after sampling observation for a sub-group, these sampled observations needed to be re-weighted by repeating the first step.

4) Weighted regression

The last step estimates a local model by incorporating the spatio-temporal weights from the previous step. To link to traditional ordered logit regression, GTWR can be written as (Fotheringham et al., 1998):

$$\begin{aligned} p_{ij} = &\ \Pr(y_j = i) \\ = &\ \frac{1}{1+\exp(-\alpha_i(u_j,\ v_j,\ t_j) + \beta(u_j,\ v_j,\ t_j)x_j)} \\ & - \frac{1}{1+\exp(-\alpha_{i-1}(u_j,\ v_j,\ t_j) + \beta(u_j,\ v_j,\ t_j)x_j)} \end{aligned} \tag{7}$$

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 $t_j$ at the location $(u_j,\ v_j,\ t_j)$.

GTWR outputs a local set of coefficients for each observation, representing the local relationships of crash severity and factors. Compared to traditional regression approaches, GTWR can theoretically explain more about correlates of crash severity by incorporating spatial and temporal characteristics of data. However, the crash severity may have little relationships with space and time and thus the spatial variations revealed by GTWR are not significant. The coefficients of local models in GTWR may be relatively stationary andven close to the results from traditional regression. In this case, it is hard to say GTWR outperforms a traditional regression, and the simple modeling framework (i.e., ordered logit) is enough and should be preferred.

To answer whether the spatio-temporal variations are substantial, results from GTWR and traditional ordered logit models were comparatively examined through a non-stationarity test. The coefficients pose a distribution with a minimum, lower quartile, median, upper quartile, and maximum. Considering that the minimum and maximum coefficients may be too extreme, the non-stationarity test takes a conservation range *Delta* from the lower quartile and upper quartile. Then the test compares this range to the corresponding coefficient's standard error in the traditional ordered logit model. The non-stationarity test was individually performed for each variable:

$$Delta = \beta^{upper} - \beta^{lower} \begin{cases} > 1.96\ (S.E.)\ and\ Upper\ Quantile|z| > 1.96,\ Pass\ the\ Non-stationarity\ Test \\ otherwise,\ Fail\ the\ Non-stationarity\ Test \end{cases} \tag{8}$$

where $S.E.$ is the corresponding coefficient's standard error in the traditional model, and $|z_j|$ is the z-value of a local GTWR coefficient $\beta(u_j,\ v_j,\ t_j)$, equal to $\left|\frac{\beta(u_j,\ v_j,\ t_j)}{SE(u_j,\ v_j,\ t_j)}\right|$. If *Delta* is greater than $1.96\ (S.E.)$ and the upper quantile $|z|$ is greater than 1.96, the non-stationarity test is passed, indicating significant spatio-temporal variations of GTWR estimates; otherwise, GTWR estimates are relatively stationary. The upper quantile $|z|$ is used to require at least 25% of observations to have statistically significant estimates ($z > 1.96$), in order to pass the test. This study produced original source codes for GTWR in an R environment. By applying the GTWR model, we expect to better understand the spatial and temporal trends of the correlations with crash injury severity, especially for DUI crashes. However, due to the limited power to randomize the coefficients based on the space and time instead of fitted distributions (i.e., normal, Gamma, or Weibull), the GTWR model can only output localized estimated that are highly relevant to space and time.

Note that, this study chooses the GTWR to model the data owing to the research purpose and the capability of GTWR, not because this modeling approach outperforms all other alternative models. Researchers often employ random-parameter (RP) models to capture the unobserved heterogeneity resulting from unobserved factors in the data (Anastasopoulos and Mannering, 2009; El-Basyouny and Sayed, 2009; Venkataraman et al., 2011). Both the GTWR and RP models can account for the influence of unserved factors on the model estimates, allowing the model estimates to vary across observations. Further, advanced machine learning models are also frequently used to achieve improved model performance in terms of prediction accuracy (Iranitalab and Khattak, 2017). One of the key features for GTWR (as compared with RP models and machine learning models) is that GTWR models can uncover whether there are clear spatial and/or temporal patterns in the model estimates which fulfill the purpose of this study – to show whether there are significant variations in relationships between the crash injury severity and DUI involvement along with other contributing factors. If there are significant spatial and/or temporal variations in these relationships, localized safety countermeasures may be developed for specific locations and times instead of countermeasures for an entire area or region.

### 2.3. Model comparison

The overall model's goodness-of-fit was compared by calculating the log likelihood and Akaike Information Criterion (AIC). The log likelihood at a regressed model can be calculated by (StataCorp, 2013):

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

where, $I_i(y_j) = \begin{cases} 1, & \text{if } y_j = i \\ 0, & \text{otherwise} \end{cases}$. A better goodness-of-fit is associated with a greater log likelihood. The extent of information explained by the model can be reflected by the changed log likelihood from a null model to a regressed model with variables. Pseudo-$R^2$ for logistic models can be calculated by:

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

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 probability of having a level of injury severity.

AIC has been often used for model comparison. A smaller AIC value often points to a better goodness-of-fit (Bozdogan, 1987). When comparing GTWR and traditional modeling, a three-point decrease of AIC indicates a significantly better goodness-of-fit (Fotheringham et al., 2002). The AIC can be calculated by:

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

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

## 3. Results

### 3.1. Descriptive statistics

Table 1 summarizes the variables of interest after error-check (N = 138,499 crashes). There were more than 20% of crashes involving injuries including fatalities. The DUI crashes accounted for 3.4% of all crashes. Rear-end appeared to be the most frequent crash type, accounting for 37.15% of all crashes. There were 34.33% of crashes that involved young drivers ages 24 and younger, and 15.46% that involved seniors ages 65 and older. Pedestrians or bikers were involved in 1.61% of crashes. Regarding the crash contexts, more than 25% of crashes occurred in darkness, and 10.27% occurred in streets without lights on. More than 16% occurred in adverse weather including raining, snow, and fog. Road facility features are also of interest in this study such as speed limit.

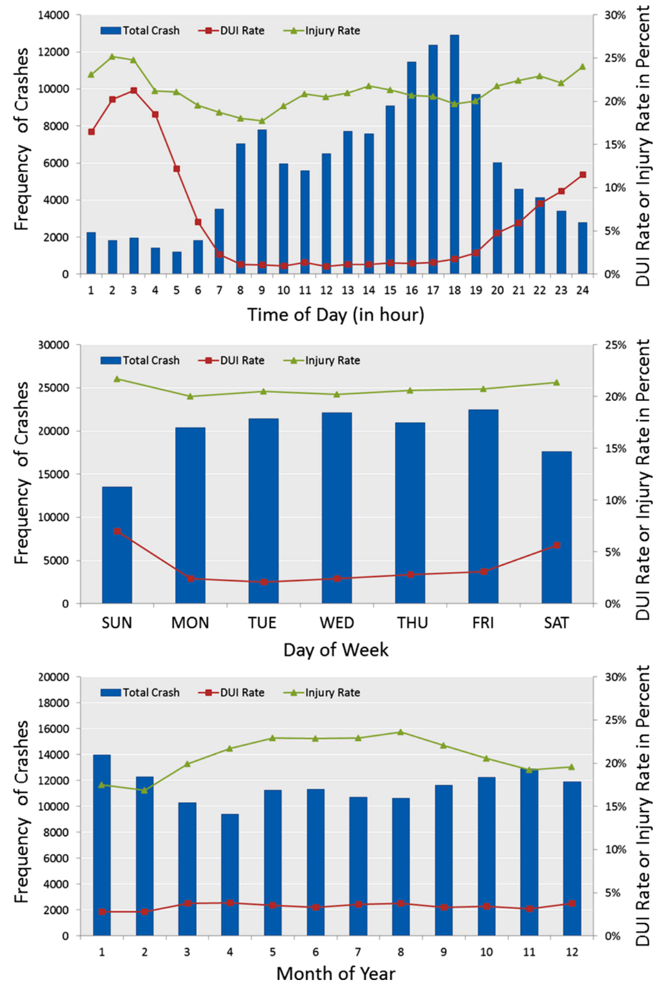


**Fig. 1.** Temporal distributions by time-of-day, day-of-week, and month-of-year.

### 3.2. Spatial and temporal distributions

Fig. 1 presents temporal variations of crash frequency and percentages of crashes that involved DUI and caused injuries, by time-of-day, day-of-week, and month-of-year, respectively. The crash frequency, in general, follows the temporal distribution of traffic volumes throughout a day, with AM and PM peaks (National Cooperative Highway Research Program (NCHRP, 2012). Weekends had smaller volumes than weekdays. January had the most traffic volume and April had the least. Crashes that involved DUI offenses seem to be more likely to occur at late nights (after 10 pm) or early mornings (before 6 am), and on weekends. There is no significant variation across months regarding the DUI rate, the percent of crashes that involve DUI over all crashes. In terms of the injury rate (percent of crashes that caused injuries), early morning (before 4 am) crashes were more likely to lead to injuries. The chance of injury in crashes appears to be stabilized across day-of-week, around 20%, but with slightly greater rates on weekends. The month-of-year variation shows that the injury rates were higher in the middle of year, between May and August.

Further, this study examines the time-of-day variations on some specific days of a week, including Wednesday, Friday, Saturday, and Sunday, as shown in Fig. 2. Wednesday represents a normal weekday, and it shows similar patterns with Friday, in terms of the peak hour crash frequency, rates of DUI and injuries. Weekends including Saturday and Sunday have different patterns from weekdays, and there are more crashes in the afternoon. DUI rates are higher in the early morning than

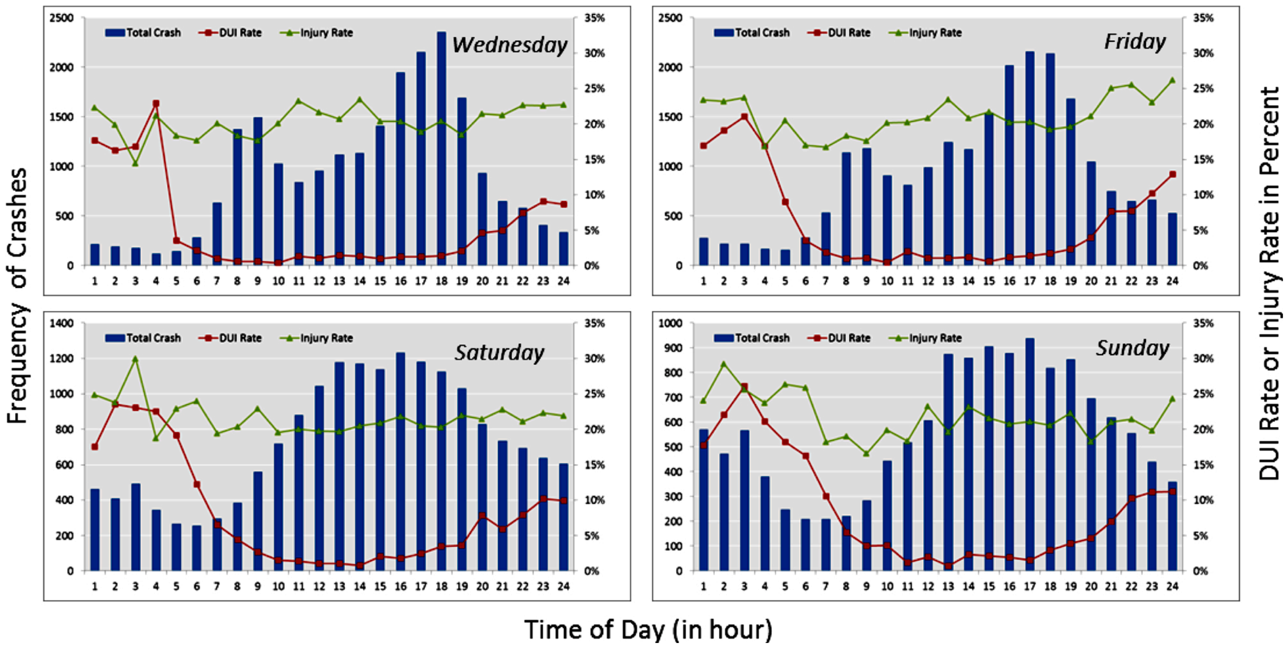


**Fig. 2.** Time of day distributions on Wednesdays, Fridays, Saturdays, and Sundays.

daytime across all days of a week (Fig. 2).

Fig. 3 shows the spatial distributions of crashes. The colors in each sub-figure represent the levels of crash density. Colors are comparable only within a sub-figure and not between sub-figures. General crashes were clustered in populous areas, i.e., Detroit and Ann Arbor, see Fig. 3 (a); and injury crashes had similar spatial distributions, see Fig. 3(c). DUI crashes had a different spatial distribution which highlights some areas with higher likelihoods of DUI, see Fig. 3(b). In addition, given that DUI crashes are more likely to occur at late nights and early mornings, the distributions for crashes that occurred before 6 am or after 10 pm are also presented in Fig. 3. Different spatial patterns are found for late night or early morning crashes. For example, Fig. 3(d) shows that in Ann Arbor, much less crashes occurred at late nights or early mornings, relative to other regions; however, there is a noticeable cluster of DUI crashes during these periods, see Fig. 3(e). The rough visual inspection indicates that Ann Arbor's late-night or early morning crashes were more likely to be associated with DUI than other regions, which requires further examination to verify.

### 3.3. Overview of modeling results

Table 2 presents results from traditional ordered logit regression, showing the global correlates of injury severity with respect to factors including whether an involved driver was driving under influence (DUI). Marginal effects were calculated to show the change of the injury severity (in percent) with a one-unit change of an independent variable (or change from the base to the corresponding level of attribute) when all other variables are held constant at their means. Table 3 presents the GTWR results. As GTWR results have a set of coefficients for each observation (as target location), the ranges of coefficient of corresponding variables are shown in Table 3. If both traditional ordered logit regression and GTWR are performed appropriately, the estimates from the former are supposed to be within the ranges of coefficients from the latter. Based on the summary statistics (i.e., Pseudo $R^2$ and AIC), GTWR outperformed the traditional ordered logit model. Further, each variable's estimates in GTWR were checked through the non-stationarity test, to see whether the estimates pose substantial variations. The test results show that half of the estimates in GTWR vary significantly from observation to observation. It indicates that spatio-temporal variations do exist and are substantial.

### 3.4. Discussion of modeling results

It is confirmed that a crash involving DUI driver(s) is more likely to cause injury (Kockelman and Kweon, 2002; Qi et al., 2013; Damser-e-Derry et al., 2014; Pour-Rouholamin and Zhou, 2016; Liu et al., 2016a, 2016b). The likelihood of being injured in a crash could be increased on average by 25.1% if DUI was involved, as indicated by marginal effects in the traditional logit model. GTWR results reveal the ranges of coefficients. The minimum coefficient for DUI is 0.056, implying that in the entire study region and time DUI is associated with an increased chance of injury. Noticeably, for other variables except the involvement of pedestrian or biker, GTWR coefficients ranged from negative to positive. This means that in some regions, given certain conditions (i.e., variables at certain values), the injury likelihood increased; while in other regions, the likelihood may decrease. Therefore, developing uniform safety countermeasures based on the traditional model may cause unexpected outcomes. Different locations or times may require localized solutions.

Table 4 shows the coefficients of DUI temporally varying across time-of-day, day-of-week, and the month-of-year. The coefficients are average values across space. It seems that DUI-involved crashes were more likely to cause injuries in the late morning and noon (9 am–12 pm) relative to other times. There was a greater likelihood of injury in DUI crashes on Mondays and Fridays. On Fridays, DUI crashes in the late morning and noon (9 am–12 pm) were even more likely to lead to injuries. The variation of DUI coefficients was not substantial across different months.

Regarding other factors, head-on crashes were severer than other types of crashes. Results show that head-on crashes were associated with a 23.4% increased likelihood of causing an injury. Crashes that involved young drivers (i.e., less than 25 years old) were 1.9% more likely to have an injury. Senior drivers (i.e., over 64 years old) were found to associate with a 3% increased likelihood of sustaining an injury. If a pedestrian or biker was involved in a crash, this crash had a 67.6% more chance to lead to an injury. Compared to crashes with daylight, crashes under the dark with street lights were found 3.3% more likely to associate with injuries. The DUI crash rate under this lighting condition was about 8.94%, which was much higher than those during daytime (1.51%). Interestingly, crashes under dark with no street lights were associated with decreased likelihoods of injury (see Table 2), even though the DUI

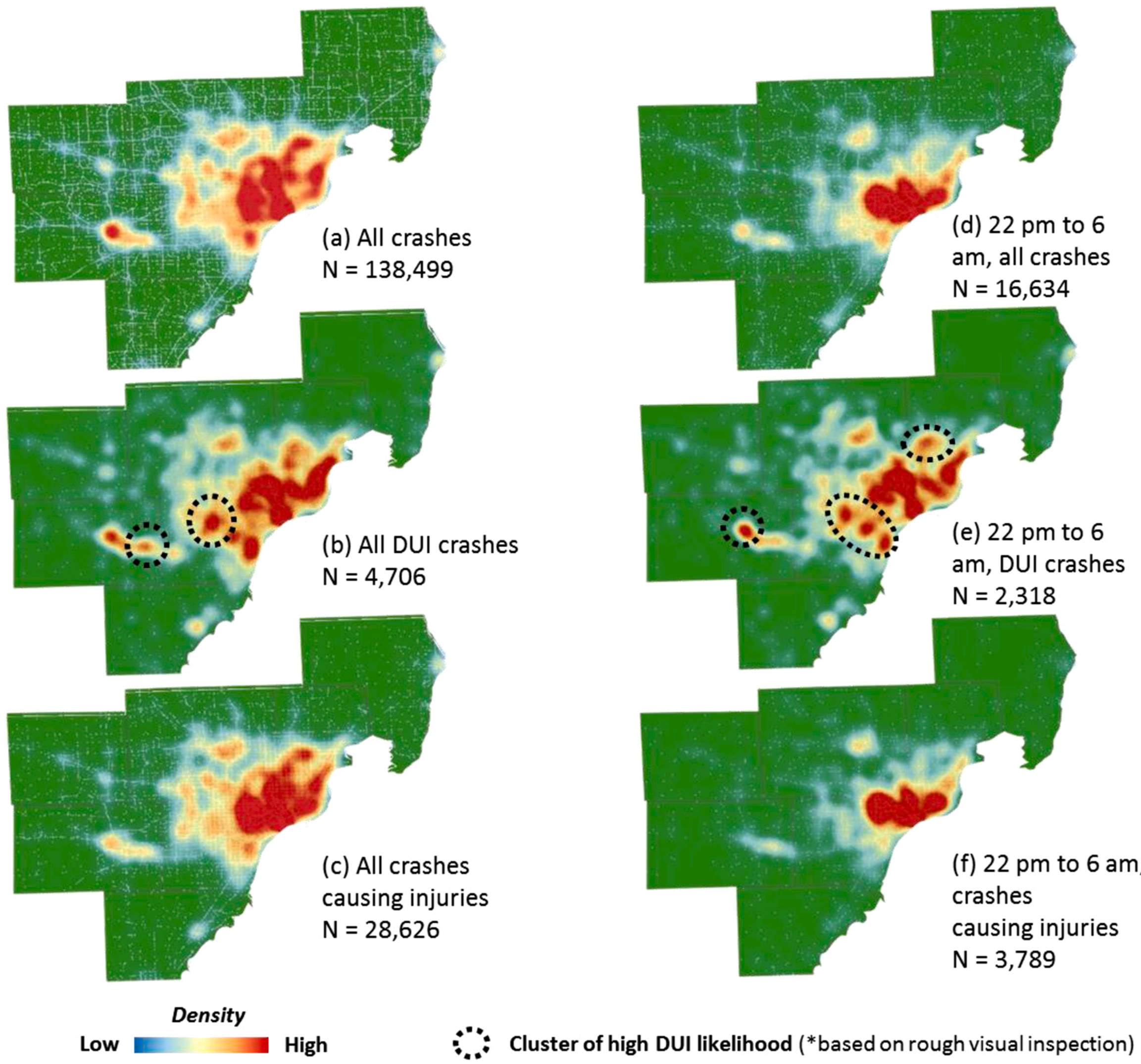


**Fig. 3.** Spatial distributions of crashes.

crash rate under no lighting condition was 8.63% similar to that under dark with lighting condition. This might be due to unobserved heterogeneity that could be captured by the unobserved data (i.e., real travel speed which is not available to us). However, we found that higher likelihoods of injury were associated with higher road classes (i.e., higher speed limits). The results show that speed limits greater than 65 mph were associated with a 10% increased likelihood of sustaining an injury. Similar to dark without lighting, adverse weather conditions (i.e., fog, smoke, rain, snow, severe wind) were found to associate with decreased injury likelihoods. Again, this seemingly counterintuitive result may be related to unobserved heterogeneity that was not quite relevant to space and time.

GTWR results can be mapped in space across time. GTWR results have a set of local coefficients for each target location (i.e., observation); thus, each variable has N = 138,499 estimates/coefficients (β). If ignoring the temporal aspect, one variable may just need one map to show all local estimates that vary in space. If including the temporal aspect, one map may only show the spatially varying estimates within a specific period, i.e., one or two hours. Fig. 4 maps coefficients (β) of DUI: the center figure shows the local coefficients averaged across all times; the 12 smaller figures show the local coefficients within 2 -h periods throughout a day. Note that, the minimum of coefficients is positive, indicating that DUI was likely to cause severer injuries in crashes relative to non-DUI. The local coefficients mapped in Fig. 4 show in which part of the modeling region DUI was even more likely to associate with severe injuries in crashes, than the behavior of DUI in other parts.

According to the map in the center, DUI crashes outside of Detroit's urban area in the northeast region were more likely to cause injuries than crashes within the urban area. Noticeably, there are some clusters of great likelihoods of getting injuries in DUI crashes. These clusters include crashes in the City of Ann Arbor, the corridor of I-96 from Brinton to Fowlerville, the roads in/around Clinton Charter Township, and Port Huron (northeast comer of the modeling region). From the temporal aspect, crashes that occurred between 10 pm and 6 am presented similar spatial patterns of local coefficients of DUI. The patterns imply that DUI was more likely to cause injuries in crashes in rural areas/small towns than in crashes in Detroit's urban region. One of the reasons may be related to the driving speed. For the same roads (function and classification), rural areas are likely to have higher driving speeds than urban areas (due to either the traffic volume, law enforcement or roadside environment) and the driving speed is positively related to the injury severity (if other factors are held constant). Therefore, crashes in rural areas tend to be more severe than those in urban areas. It would be valuable to have the information of driving speed prior to the event of a crash (or collision) in modeling. However, such information is not commonly available in the crash database. The GTWR modeling approach can account for unobserved heterogeneity due to the influences of unobserved factors (e.g., driving speed) on the

**Table 2**
Results from Traditional Ordered Logit Model.

| Variable | | Model Estimates | | | Marginal Effects | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | β | S. E. | Pr(>\|z\|) | O | C | B | A | K |
| Driving under influence - DUI (1 = yes; 0 = otherwise) | | 1.233 | 0.032 | 0.000 | −25.1% | 15.3% | 7.6% | 1.8% | 0.4% |
| | Head on | 1.163 | 0.034 | 0.000 | −23.4% | 14.4% | 6.9% | 1.7% | 0.4% |
| | Angle | 0.544 | 0.025 | 0.000 | −9.2% | 6.2% | 2.4% | 0.5% | 0.1% |
| Crash type (base = Single) | Rear-end | 0.079 | 0.022 | 0.000 | −1.2% | 0.8% | 0.3% | 0.1% | 0.0% |
| | Sideswipe | −0.765 | 0.029 | 0.000 | 9.9% | −7.0% | −2.3% | −0.5% | −0.1% |
| | Other | −0.315 | 0.034 | 0.000 | 4.4% | −3.1% | −1.0% | −0.2% | 0.0% |
| Young drivers involved (< 25 years old. 1 = yes; 0 = otherwise) | | 0.126 | 0.014 | 0.000 | −1.9% | 1.3% | 0.5% | 0.1% | 0.0% |
| Senior drivers involved (> 64 years old. 1 = yes; 0 = otherwise) | | 0.191 | 0.019 | 0.000 | −3.0% | 2.1% | 0.7% | 0.2% | 0.0% |
| Pedestrian/bike involved (1 = yes; 0 = otherwise) | | 3.299 | 0.043 | 0.000 | −67.6% | 15.3% | 32.8% | 15.3% | 4.2% |
| | Dawn | −0.204 | 0.050 | 0.000 | 2.9% | −2.1% | −0.7% | −0.1% | 0.0% |
| | Dusk | −0.124 | 0.047 | 0.009 | 1.8% | −1.3% | −0.4% | −0.1% | 0.0% |
| Lighting condition (base = Daylight) | Dark - with street lights on | 0.147 | 0.019 | 0.000 | −2.3% | 1.6% | 0.6% | 0.1% | 0.0% |
| | Dark- without street lights on | −0.218 | 0.026 | 0.000 | 3.1% | −2.2% | −0.7% | −0.2% | 0.0% |
| | Unknown | −1.062 | 0.119 | 0.000 | 11.5% | −8.3% | −2.5% | −0.5% | −0.1% |
| Adverse weather (fog, smoke, rain, snow, severe wind, etc.) | | −0.386 | 0.024 | 0.000 | 5.4% | −3.8% | −1.3% | −0.3% | −0.1% |
| | 35–45 mph | 0.425 | 0.019 | 0.000 | −6.6% | 4.5% | 1.6% | 0.3% | 0.1% |
| Speed limit (base = "< = 30 mph) | 50–60 mph | 0.550 | 0.023 | 0.000 | −9.3% | 6.3% | 2.4% | 0.5% | 0.1% |
| | > 65 mph | 0.582 | 0.027 | 0.000 | −10.1% | 6.8% | 2.6% | 0.6% | 0.0% |
| Constant/Intercept 1 | | 1.947 | 0.027 | 0.000 | | | | | |
| Constant/Intercept 2 | | 3.450 | 0.029 | 0.000 | | | | | |
| Constant/Intercept 3 | | 5.089 | 0.035 | 0.000 | | | | | |
| Constant/Intercept 4 | | 6.820 | 0.059 | 0.000 | | | | | |
| | Number of Observations | 138,499 | | | | | | | |
| | Log Likelihood at Null Model | −93,525.83 | | | | | | | |
| SUMMARY STATISTICS | Log Likelihood at Regression Model | −87,315.80 | | | | | | | |
| | Pseudo $R^2$ | 0.066 | | | | | | | |
| | AIC | 174,675.6 | | | | | | | |

**Table 3**
Results from Geographically and Temporally Weighted Regression.

| Variable | | Mean β | Min β | Lower β | Upper β | Max β | Upper \|Z\| | Delta | Test |
|---|---|---|---|---|---|---|---|---|---|
| Driving under influence - DUI (1 = yes; 0 = otherwise) | | 1.245 | 0.056 | 1.044 | 1.417 | 3.077 | 4.274 | 0.373 | YES |
| | Head on | 1.012 | 0.090 | 0.816 | 1.204 | 2.100 | 3.766 | 0.388 | YES |
| | Angle | 0.407 | −0.430 | 0.232 | 0.583 | 1.419 | 2.588 | 0.351 | YES |
| Crash type (base = Single) | Rear-end | −0.047 | −0.907 | −0.219 | 0.127 | 0.820 | 1.221 | 0.347 | NO |
| | Sideswipe | −0.938 | −1.935 | −1.147 | −0.732 | 0.096 | 3.787 | 0.415 | YES |
| | Other | −0.464 | −1.537 | −0.642 | −0.280 | 0.719 | 1.845 | 0.362 | NO |
| Young drivers involved (< 25 years old. 1 = yes; 0 = otherwise) | | 0.101 | −0.217 | 0.031 | 0.166 | 0.494 | 1.214 | 0.135 | NO |
| Senior drivers involved (> 64 years old. 1 = yes; 0 = otherwise) | | 0.187 | −0.361 | 0.116 | 0.264 | 0.653 | 1.593 | 0.148 | NO |
| Pedestrian/bike involved (1 = yes; 0 = otherwise) | | 3.232 | 1.898 | 3.011 | 3.445 | 4.707 | 9.095 | 0.435 | YES |
| | Dawn | −0.515 | −16.463 | −0.468 | 0.218 | 2.444 | 0.759 | 0.687 | NO |
| | Dusk | −0.344 | −15.921 | −0.387 | 0.108 | 4.150 | 0.728 | 0.495 | NO |
| Lighting condition (base = Daylight) | Dark - with street lights on | 0.124 | −2.104 | 0.028 | 0.264 | 1.793 | 1.267 | 0.236 | NO |
| | Dark- without street lights on | −0.305 | −15.151 | −0.363 | −0.012 | 1.858 | 0.804 | 0.351 | NO |
| | Unknown | −1.530 | −15.491 | −1.674 | −0.483 | 2.486 | 1.151 | 1.191 | NO |
| Adverse weather (fog, smoke, rain, snow, severe wind, etc.) | | −0.515 | −4.931 | −0.637 | −0.267 | 1.787 | 1.973 | 0.370 | YES |
| | 35~45 mph | 0.412 | −0.106 | 0.321 | 0.503 | 0.881 | 2.891 | 0.182 | YES |
| Speed limit (base = "< = 30 mph) | 50~60 mph | 0.547 | −0.035 | 0.422 | 0.677 | 1.268 | 3.092 | 0.255 | YES |
| | > 65 mph | 0.549 | −0.100 | 0.411 | 0.685 | 1.448 | 2.861 | 0.274 | YES |
| Constant/Intercept 1 | | 1.797 | 0.800 | 1.586 | 2.006 | 3.016 | 8.395 | 0.420 | YES |
| Constant/Intercept 2 | | 3.379 | 2.474 | 3.165 | 3.584 | 4.750 | 13.500 | 0.419 | YES |
| Constant/Intercept 3 | | 5.106 | 4.053 | 4.870 | 5.327 | 6.777 | 16.227 | 0.457 | YES |
| Constant/Intercept 4 | | 7.054 | 5.631 | 6.679 | 7.379 | 11.605 | 13.250 | 0.699 | YES |
| | Number of Observations | 138,499 | | | | | | | |
| | Log Likelihood at Null Model | −93,525.83 | | | | | | | |
| SUMMARY STATISTICS | Log Likelihood at Regression Model | −85,118.28 | | | | | | | |
| | Pseudo R2 | 0.090 | | | | | | | |
| | AIC | 170,280.56 | | | | | | | |

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

crash outcomes (e.g., injury severity), especially when the unobserved heterogeneity is related to the geographical areas (and also the time). The modeling results in this study to some extent reflect the capability of the GTWR of uncovering the space- and/or time-related unobserved heterogeneity.

Besides, the crashes that occurred between 6 and 8 am are found to have similar patterns with crashes before 6 am, while DUI was even more likely to cause injuries in rural areas. Between 8 am ~10 am, crashes in Port Huron and the west part of the modeling region are more likely to lead to injuries if involving DUI. Crashes that occurred between 10 am and 2 pm present in general similar patterns – the west region was found to have a greater likelihood of injury in DUI crashes. The patterns of DUI coefficients vary noticeably from before to after 2 pm. For the times between 2 pm and 6 pm, crashes in the northeast part of the modeling region seem to be more severe if DUI was involved. When a crash occurred between 6 pm and 10 pm, still, DUI was likely to cause

**Table 4**
Coefficients of DUI at Different Times, Averaged across Space.

| | | Week | | | | | | | Month | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Sun | Mon | Tue | Wed | Thu | Fri | Sat | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| Hour | Avg. | 1.02 | 1.34 | 1.26 | 1.10 | 1.22 | 1.47 | 1.20 | 1.24 | 1.24 | 1.28 | 1.24 | 1.21 | 1.17 | 1.18 | 1.23 | 1.29 | 1.31 | 1.29 | 1.23 |
| 1 | 1.01 | 0.96 | 1.08 | 1.03 | 1.00 | 1.12 | 1.05 | 0.94 | 0.99 | 0.97 | 0.99 | 0.98 | 0.97 | 0.97 | 0.97 | 0.99 | 1.06 | 1.10 | 1.08 | 1.05 |
| 2 | 0.99 | 0.94 | 1.07 | 1.04 | 1.02 | 1.13 | 1.03 | 0.90 | 0.99 | 0.94 | 0.96 | 0.94 | 0.94 | 0.93 | 0.94 | 0.97 | 1.05 | 1.11 | 1.09 | 1.02 |
| 3 | 0.98 | 0.92 | 1.07 | 1.07 | 1.01 | 1.13 | 1.02 | 0.89 | 0.98 | 0.93 | 0.93 | 0.93 | 0.91 | 0.91 | 0.92 | 0.96 | 1.03 | 1.10 | 1.07 | 1.01 |
| 4 | 0.99 | 0.90 | 1.11 | 1.11 | 1.04 | 1.19 | 1.05 | 0.87 | 1.02 | 0.95 | 0.92 | 0.94 | 0.89 | 0.90 | 0.92 | 0.96 | 1.05 | 1.11 | 1.14 | 1.09 |
| 5 | 1.05 | 0.91 | 1.16 | 1.20 | 1.14 | 1.26 | 1.08 | 0.87 | 1.10 | 1.00 | 1.02 | 0.96 | 0.90 | 0.93 | 0.94 | 0.98 | 1.11 | 1.17 | 1.19 | 1.16 |
| 6 | 1.16 | 0.92 | 1.22 | 1.29 | 1.21 | 1.33 | 1.18 | 0.91 | 1.22 | 1.11 | 1.07 | 1.00 | 0.99 | 1.05 | 1.08 | 1.11 | 1.17 | 1.33 | 1.33 | 1.26 |
| 7 | 1.28 | 1.00 | 1.29 | 1.36 | 1.25 | 1.39 | 1.31 | 1.01 | 1.32 | 1.23 | 1.20 | 1.14 | 1.10 | 1.14 | 1.16 | 1.21 | 1.30 | 1.40 | 1.43 | 1.39 |
| 8 | 1.34 | 1.05 | 1.33 | 1.41 | 1.26 | 1.44 | 1.38 | 1.07 | 1.40 | 1.30 | 1.25 | 1.19 | 1.18 | 1.22 | 1.22 | 1.27 | 1.35 | 1.45 | 1.48 | 1.48 |
| 9 | 1.36 | 1.14 | 1.37 | 1.41 | 1.26 | 1.30 | 1.57 | 1.21 | 1.44 | 1.38 | 1.38 | 1.25 | 1.23 | 1.27 | 1.27 | 1.26 | 1.27 | 1.36 | 1.52 | 1.49 |
| 10 | 1.40 | 1.22 | 1.43 | 1.28 | 1.28 | 1.19 | 2.00 | 1.30 | 1.48 | 1.44 | 1.43 | 1.28 | 1.27 | 1.24 | 1.30 | 1.32 | 1.32 | 1.49 | 1.56 | 1.48 |
| 11 | 1.40 | 1.23 | 1.43 | 1.27 | 1.27 | 1.23 | 2.04 | 1.33 | 1.41 | 1.43 | 1.43 | 1.39 | 1.37 | 1.34 | 1.30 | 1.32 | 1.36 | 1.52 | 1.53 | 1.42 |
| 12 | 1.37 | 1.10 | 1.36 | 1.23 | 1.25 | 1.25 | 1.90 | 1.42 | 1.36 | 1.38 | 1.44 | 1.42 | 1.39 | 1.30 | 1.26 | 1.33 | 1.38 | 1.43 | 1.47 | 1.36 |
| 13 | 1.34 | 1.06 | 1.29 | 1.26 | 1.21 | 1.23 | 1.74 | 1.47 | 1.34 | 1.37 | 1.44 | 1.35 | 1.35 | 1.26 | 1.22 | 1.31 | 1.36 | 1.40 | 1.40 | 1.28 |
| 14 | 1.28 | 0.99 | 1.27 | 1.29 | 1.14 | 1.17 | 1.58 | 1.44 | 1.28 | 1.37 | 1.38 | 1.32 | 1.25 | 1.21 | 1.19 | 1.27 | 1.32 | 1.34 | 1.29 | 1.20 |
| 15 | 1.26 | 0.93 | 1.29 | 1.35 | 1.08 | 1.14 | 1.50 | 1.38 | 1.23 | 1.28 | 1.37 | 1.34 | 1.27 | 1.18 | 1.18 | 1.27 | 1.29 | 1.28 | 1.22 | 1.21 |
| 16 | 1.25 | 0.93 | 1.33 | 1.36 | 1.03 | 1.18 | 1.45 | 1.29 | 1.20 | 1.23 | 1.35 | 1.33 | 1.26 | 1.19 | 1.20 | 1.27 | 1.30 | 1.26 | 1.21 | 1.19 |
| 17 | 1.25 | 0.96 | 1.38 | 1.31 | 1.04 | 1.21 | 1.45 | 1.24 | 1.17 | 1.17 | 1.31 | 1.32 | 1.26 | 1.19 | 1.23 | 1.30 | 1.32 | 1.29 | 1.24 | 1.19 |
| 18 | 1.23 | 1.00 | 1.42 | 1.23 | 1.04 | 1.21 | 1.40 | 1.19 | 1.15 | 1.15 | 1.25 | 1.27 | 1.25 | 1.20 | 1.23 | 1.28 | 1.34 | 1.27 | 1.22 | 1.19 |
| 19 | 1.20 | 1.06 | 1.45 | 1.17 | 0.97 | 1.21 | 1.34 | 1.15 | 1.13 | 1.13 | 1.21 | 1.23 | 1.22 | 1.15 | 1.19 | 1.25 | 1.30 | 1.27 | 1.21 | 1.16 |
| 20 | 1.17 | 1.09 | 1.45 | 1.10 | 0.92 | 1.20 | 1.32 | 1.10 | 1.11 | 1.11 | 1.15 | 1.17 | 1.18 | 1.13 | 1.13 | 1.17 | 1.24 | 1.28 | 1.20 | 1.15 |
| 21 | 1.15 | 1.10 | 1.35 | 1.07 | 0.92 | 1.20 | 1.30 | 1.08 | 1.10 | 1.08 | 1.12 | 1.14 | 1.13 | 1.08 | 1.11 | 1.12 | 1.22 | 1.25 | 1.21 | 1.15 |
| 22 | 1.11 | 1.07 | 1.18 | 1.07 | 0.93 | 1.18 | 1.24 | 1.06 | 1.07 | 1.05 | 1.10 | 1.10 | 1.10 | 1.06 | 1.07 | 1.10 | 1.18 | 1.20 | 1.15 | 1.07 |
| 23 | 1.07 | 1.04 | 1.12 | 1.05 | 1.01 | 1.14 | 1.13 | 1.02 | 1.04 | 1.03 | 1.04 | 1.05 | 1.05 | 1.03 | 1.04 | 1.07 | 1.14 | 1.18 | 1.15 | 1.09 |
| 24 | 1.04 | 0.99 | 1.11 | 1.04 | 1.00 | 1.14 | 1.08 | 0.98 | 1.02 | 1.00 | 1.00 | 1.02 | 1.00 | 0.99 | 1.00 | 1.04 | 1.10 | 1.16 | 1.11 | 1.08 |

severe injuries in the northeast part of the region, but with a highlight that DUI crashes in Port Huron were much severer.

Further, given that most DUI crashes occurred in late nights and early mornings, Fig. 5 presents the local DUI coefficients between 10 pm to 6 am, across seven days of a week. In all days except Fridays, crashes that occurred in rural or small-town areas were more likely to cause injuries than crashes within Detroit's urban area. On Fridays, the entire northeast part from Clinton Charter Township to Port Huron was found to have severer injuries in DUI crashes than other regions including Detroit's urban area and its south. On Mondays, the DUI crashes in the northwest were also a concern, in terms of DUI associating increased injury severity.

This study is focused on the influence of DUI on crash severity. This paper presents mapped results only for the variable of DUI during selected time periods. Result maps for DUI during other times or other variables can also be developed in the same manner.

## 4. Limitations

Data accuracy may be a threat to the validity of results presented in the paper. Data used in this study were from two sources. The extent of inaccuracy is unknown and may be inconsistent between sources. The GTWR requires accurate information about where and when a crash occurred. The geo-reference was checked in the GIS platform, and erroneous observations (i.e., if a crash was not located within the right of way of highway facility) were removed from modeling and discussion. However, the time when a crash occurred remains unchecked, though the crash frequency distributions, in general, follow the time-of-day variations of traffic volumes. In addition, this study is focused on DUI. Since DUI is regarded as a serious criminal offense, it is possible that a DUI crash may be more likely to be filed than a small crash that caused minimal damage. In Michigan, it is required to report all crashes that caused injury or property damage of \$1000 or more (Michigan Department of State Police, 2014). It is also possible that the variable-DUI may contain inaccurate information, as some drivers can refuse to be tested for DUI.

Besides, the results presented in this paper may be limited by the model specification with a limited number of variables. Because of the data limitation, the models in this study may lack some important factors (such as vehicle types, law enforcement levels, media campaigns, traffic laws and regulations) that are likely to correlate with the crash outcomes. Though the GTWR can capture a certain degree of unobserved heterogeneity due to the influence of unobserved factors on model estimates, the modeling results may change with additional variables in the models.

Further, given the research purpose and the capability of GTWR, this study chooses the GTWR modeling approach to perform the analysis. It does not imply that the GTWR outperforms alternative models. This study does not offer a comprehensive comparison between the GTWR and other advanced modeling approaches such as random-parameter models and machine learning models.

## 5. Conclusions

Given the spatial and temporal nature of traffic crashes, this study introduces the use of Geographically and Temporally Weighted Regression (GTWR) to explore the spatio-temporal patterns of crash severity. Theoretically, the GTWR outperforms traditional regression methods by accounting for influences of unobserved factors that may be related to space and time, which was confirmed in this study (in terms of *Pseudo* $R^2$ and AIC). The results of GTWR can be used to develop local safety countermeasures for specific times, instead of having a uniform solution regardless of time and space.

The finding regarding the correlates of crash severity with DUI is consistent with previous findings (Kockelman and Kweon, 2002; Qi

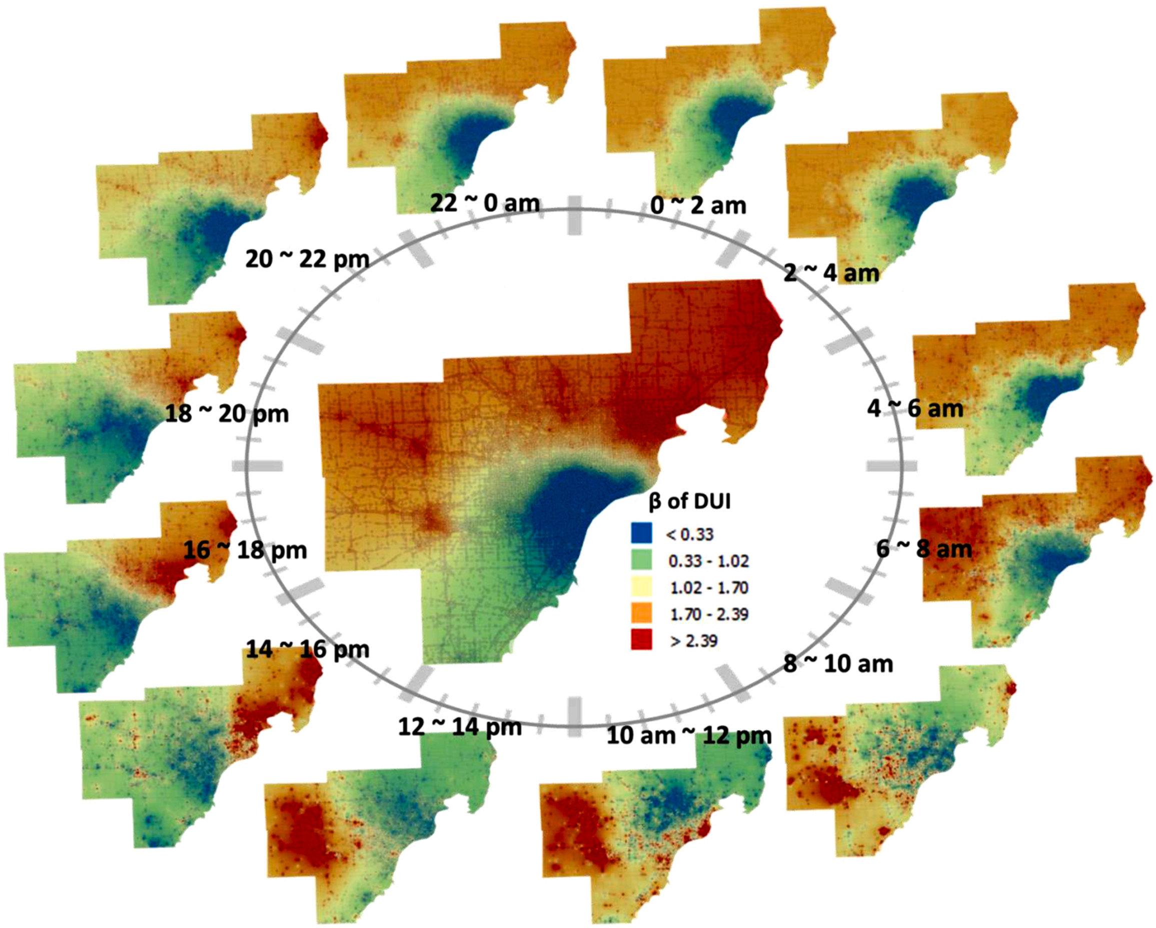


**Fig. 4.** Spatially and (time of day) temporally varying coefficients of DUI estimated by GTWR.

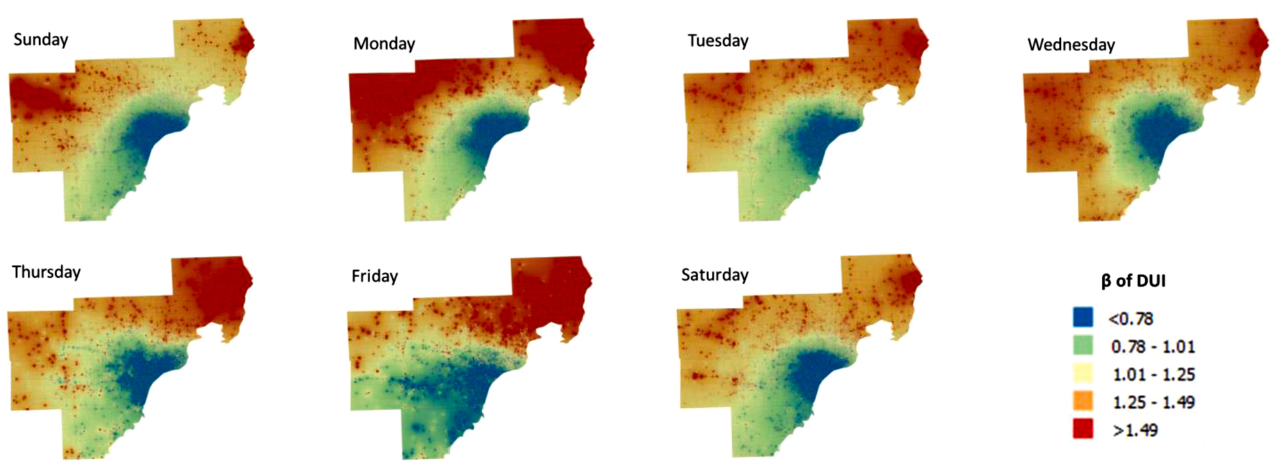


**Fig. 5.** Local coefficients of DUI between 10 pm to 6 a.m., across seven days of a week.

et al., 2013; Damsere-Derry et al., 2014; Pour-Rouholamin and Zhou, 2016; Liu et al., 2016a, 2016b); DUI is associated with an increased chance of injury given a crash. The average marginal effect showed that the injury likelihood was increased by 25% if a driver was DUI before a crash. Further, the GTWR revealed that the association between crash severity and DUI varies significantly across space and time. From the spatial aspect, DUI crashes in rural or small-town areas are more likely to cause injuries than crashes within Detroit's urban area. From the temporal aspect, different times may be associated with different spatial patterns of local relationships between injury severity and DUI. For example, between 10 am and 2 pm, crashes in the west part of the modeling region is found to have a greater likelihood of injury if DUI was identified. However, for the times between 2 pm and 6 pm, DUI crashes in the northeast part of the modeling region seem to be more. Further, the relationships between injury severity and DUI also vary from day to day. This study mapped results from crashes that occurred between 10 pm to 6 am. On Fridays, the entire northeast part from Clinton Charter Township to Port Huron is associated with severer injuries in DUI crashes than other regions including Detroit's urban area and its south. On Mondays, the DUI crashes in the northwest are also more likely to cause severe injuries. Results about other factors are generally consistent with the findings of previous studies. For example, crashes involving seniors were more severe. If a pedestrian or biker was involved, there was a 67% more chance to have an injury in the crash. Higher likelihoods of injury were also associated with higher classes of roadways (i.e., higher speed limits). Since this study is focused on the relationships between injury severity and DUI, the results for other variables are not mapped and discussed. The same visualization methodology can be sued to show their spatially and temporally varying relationships with the injury severity.

This study is focused on DUI crashes. Results from GTWR models convey important information about which areas and at what time interventions may be needed regarding the DUI crashes. The spatio-temporal variations of correlates of injury with other factors are not shown in this paper, but available from authors. The methodology introduced and demonstrated in this study has long-term values. GTWR takes advantage of modern computational tools and data with great spatial and temporal details. It allows researchers and practitioners to re-scrutinize the highway safety outcomes in greater depth and helps develop safety countermeasures customized to specific places or corridors and specified for particular periods, i.e., saturation patrols at night between 10 pm to 6 am near Port Huron).

## Author statement

The authors confirm contribution to the paper as follows: study conception and design: Jun Liu, Asad Khattak; data collection: Jun Liu; analysis and interpretation of results: Jun Liu, Xiaobing Li, Asad Khattak; draft manuscript preparation: Jun Liu, Xiaobing Li, Asad Khattak. All authors reviewed the results and approved the final version of the manuscript.

## 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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