Modeling the Influence of Hazardous Road Sections: Features of Road Traffic Accident Occurrence in Tunisia

Attig Ines
Department of Economics
Faculty of Economic Sciences and Management of Sousse
University of Sousse, Tunisia
attigines2@gmail.com

Ouni Fedy
Department of Transportation and Logistics
Higher Institute of Transport and Logistics of Sousse.
University of Sousse, Tunisia
fedy.ouni@gmail.com

Harizi Riadh
Department of Business Administration.
University of Bisha, Bisha, Saudi Arabia
College of Business, PO. Box 1113, BISHA, 61922, Saudi Arabia
rharizi@ub.edu.sa

Abstract

Road safety is a broad topic that includes many aspects, such as road conditions, vehicles, the environment, and driving characteristics. Understanding how every factor contributes to the frequency of accidents is therefore not a simple task. Modeling the frequencies of traffic injuries in dangerous road segments may therefore give detailed insights into the safety consequences of explanatory factors for the frequency of accidents. Thus, based on the variable of interest, many modelling approaches have been applied. The focus of this research is to explore the relationship between dangerous crashes on certain road sections and a variety of geometric, road, traffic flow, and spatial characteristics in the region of Monastir in Tunisia. Accident statistics for 70 accident-prone road sections were obtained for this purpose between 2013 and 2018. A negative binomial model was used in the analysis, and the empirical results are of great interest. The presence of national highways, high speed limits, and the existence of drainage systems and crash barriers can increase the number of crashes on unsafe road sections. Nevertheless, the presence of a correct alignment, roads with two-way lanes, the presence of vertical and horizontal signs, and roads without parking help reduce the frequency of accidents. This study therefore provides some useful insights into Tunisia's dangerous road segments, and these may help Tunisia's public authorities to develop effective interventions.

Keywords
Tunisia, road safety, accident frequency, hazardous road sections, negative binomial model.

1. Introduction
In the field of transport engineering, road traffic safety is considered to be the most studied subject. Indeed, Road accidents cause more than 1.2 million fatalities and over 50 million wounds per year (WHO, 2013). In the eastern Mediterranean and in the African region, the death rate is highest. In low- and middle-income nations, over 90 per cent of road accidents occurred (WHO, 2013). In recent years, many researchers have been heading out to predict road accidents on transport infrastructure such as the identification of hazardous road sections. The construction of models linking the number of accidents at road with the volume of traffic and the technical characteristics of the infrastructure, and its environment provides useful insights when carrying out the safety diagnosis for the preparation of the

prevention decision. We present these models here, and then illustrate them by applying them to the modeling of the links between the number of accidents over a given period and the technical characteristics of the section and its environment and the volume of traffic. It is important to define the variables that contribute to an accident by applying a successful corrective measure at dangerous places. However, how to differentiate between almost safe intersections with low accident risk and those where there is no incidence of collisions attributable to a spontaneous mechanism is a basic challenge often found in accident studies.

1.1. Objectives

The objective of this research is to examine the relationship between the number of crashes on dangerous road sections and a variety of geometric, road, traffic, and spatial characteristics in the region of Monastir, Tunisia.

2. Literature Review

Considerable research effort has focused on modeling accident frequency on different scales, such as for road segments (Lao et al., 2011; Venkataraman et al., 2011; Meng and Qu, 2012; Park et al., 2012; Usman et al., 2012; Geedipally et al., 2012; Ye et al., 2013; Li et al., 2013; Yu and Abdel-Aty, 2013; Aguero-Valverde, 2013; Cheng et al., 2013; Yu and Abdel-Aty, 2013; Harizi et al., 2016), intersections (Kim and Washington, 2006; Kim et al., 2007; Depaire et al., 2008; Lord et al., 2010; Castro et al., 2012), and counties (Ye et al., 2009; Geedipally and Lord, 2010; Lao et al., 2011). Our literature review in this section focuses mainly on frequency models on the micro level, such as for road segments, junctions, and intersections. Road traffic accidents result from the interaction between several factors related to drivers, vehicles, road infrastructure, and environmental characteristics. As the number of traffic collisions is a non-negative integer, accident frequency analysis commonly involves count data modeling.

Several studies have been undertaken to develop count data models for predicting road crashes (Harizi et al., 2016). These include Poisson regression models (Kumara and Chin, 2005; Ye et al., 2013; Li et al., 2013), negative binomial models (Lord and Kuo, 2012; Meng and Qu, 2012; Gomes et al., 2012; Pirdavani et al., 2013; Ye et al., 2013), zero-inflated models (Lee and Mannering, 2002; Kumara and Chin, 2003; Qin et al., 2004; Malyshkina and Mannering, 2010), bivariate/multivariate models (Wang et al., 2011; Caliendo et al., 2013; Narayanamoorthy et al., 2013), hierarchical/multilevel models (Usman et al., 2012; Deublein et al., 2013), the Conway–Maxwell–Poisson model (Francis et al., 2012), random parameter count models (Bullough et al., 2013; Park et al., 2016; Naznin et al., 2016), random effects models (Ouni and Belloumi, 2020), spatial and temporal correlation models (Castro et al., 2012; Mitra and Washington, 2012), generalized additive models (Li et al.,2009), and finite-mixture/latent-class and Markov switching models (Zou et al., 2013; Zou et al., 2014).

Among these models, the Poisson model is frequently used in the road-accident literature, often based on Lord's study (2006) or the various alternatives, such as the negative binomial and zero-inflated models (Anastasopoulos and Mannering, 2009). In previous research efforts, many studies have found that some common factors increase the frequency of collisions, such as section length (Qin et al., 2004; Anastasopoulos and Mannering, 2009), the presence of a work zone (Chen and Tarko, 2014), the winter season (Malyshkina et al., 2010), the number of ramps in the driving direction (Anastasopoulos and Mannering, 2009), the greatest degree of curvature (Venkataraman et al., 2013), and a depressed median configuration (Bullough et al., 2013). Other factors are associated with a decreased frequency of collision, such as the angle of the intersection (Dong et al., 2016; Hzami et al., 2020), the presence of ice on the road surface (Agbelie, 2016a), and the presence of a shoulder on minor roads (Dong et al., 2016; Harizi and Ben Hchaichi, 2018).

However, other studies have yielded contradictory results. For example, Abdel-Aty and Radwan (2000) and Kumara and Chin (2005) found that the degree of the horizontal curve increases the frequency of collisions, while Chang (2005) reported the opposite. Moreover, Dong et al. (2016) reported that average daily traffic volume on a road is associated with an increased risk of accidents, while (Malyshkina et al., 2009) showed that it diminished the frequency of accidents. Next, Carson and Mannering (2001) determined that the posted speed limit was associated with a reduced frequency of accidents, while Dong et al. (2016) reported the opposite. In addition, Caliendo et al. (2016) found that the number of lanes correlated with increased accident risk, while Abdel-Aty and Radwan (2000) recorded a decreased risk of accidents in such urban sections.

Urban environments have been shown to experience a greater number of crashes (Chen and Tarko, 2014), but other researchers have asserted the opposite (Bullough et al., 2013; Agbelie, 2016a; Agbelie, 2016b). Gomes et al. (2012) showed that a right turn increases the frequency of collisions, while Kumara and Chin (2005) reported the opposite. Venkataraman et al. (2013), meanwhile, reported that lighting on segments is related to increased frequency, while Wang et al. (2011) reported the opposite. Furthermore, Dong et al., (2016) showed that lane width was associated with an increased probability of accidents, while Park et al. (2016) found that lane width diminishes the risk of accidents.

Finally, Chin and Quddus (2003) concluded that increased frequency correlated with the median width, but Anastasopoulos and Mannering (2009) reached a contrary finding.

3. Methods

3.1 The Poisson regression model

Poisson regression is a method for regression analysis in statistics, and it is often used with count model data. The Poisson regression takes the response parameter *Y* using a Poisson distribution and assumes that a linear combination of unknown parameters will model the logarithm of the predicted value. A Poisson regression pattern is often defined as a log-linear model (Li et al., 2013). The Poisson (log-linear) regression model is the most elementary model that explicitly considers the non-negative aspect of the value of the number of dependent variables. In this model, the probability of a few events y_i, where y is the total number of victims divided by the number of kilometers, and $(y_i = 0,1,2, \dots)$ given the vector of covariant x_i, is given by the Poisson distribution (Kumara and Chin, 2005):

$$P(y_i) = \frac{\exp(-\lambda i\ )\,\lambda_i^{(y_i)}}{y_i!} \quad \textbf{(1)}$$

Where $P(y_i)$ is the probability of y_i crashes happening on section *i* of the road, thus giving the estimated number of accidents in a set time period is the road segment *i*, and λ_i is the Poisson parameter. By using a log-linear function, Poisson regression defines the Poisson parameter λ_i as a function of the explanatory variables as follows:

$$\lambda_i = exp(\beta\ X_I) \quad \textbf{(2)}$$

Where β is a vector of approximate parameters that can be calculated using traditional maximum likelihood methods, X_i is a vector of explanatory variables that define geographical features, properties of the road, and other associated details for the road section that may influence the probability of accidents occurring.

$$V\left({}^{\gamma_i}/_{X_i}\right) = E\left({}^{\gamma_i}/_{X_i}\right) = \mu_i = e^{X_i\beta} \quad \textbf{(3)}$$

On building the probability function, the maximum likelihood procedure is then used to quantify correlations.
The "log likelihood" function using the "maximum likelihood" method, is shown in:

$$L = \sum_{i=1}^{n} \ln\left[\frac{e^{\mu_i}\,\mu_i^{\gamma_i}}{\gamma_i!}\right] = \sum_{i=1}^{n}[-\mu_i\ +\ \gamma_i\ \ln\mu_i\ -\ \ln\gamma_i\ ] \quad \textbf{(4)}$$

The prediction of regression coefficients in the Poisson regression model is obtained using the Newton–Raphson iteration method. The corresponding iteration algorithm is executed using the STATA 15 statistical software to obtain the calculated coefficients (Ye et al., 2013).

3.2 The Negative Binomial Model

Another type of regression analysis that is used for count model data is the negative binomial model, which is based on a gamma-distributed error term. The observation of the i-th dependent variable takes the following probability distribution function: (Kim and Washington, 2006; Cafiso et al., 2010)

$$P\ (\gamma_i) = \left[\frac{\tau(\gamma_i + r)}{\gamma_i\,!\,\tau(r)}\right]\left[\frac{\mu_i}{\mu_i\ + r}\right]^{\gamma_i}\left[\frac{r}{\mu_i\ + r}\right]^{\gamma} \quad \textbf{(5)}$$

The mean of the negative binomial distribution is:

$$E\left[{}^{\gamma_i}/_{X_i}\right] = \mu_i\ =\ e^{X_i\,\beta} \quad \textbf{(6)}$$

The variance of the negative binomial distribution is always above the mean.

$\boldsymbol{\alpha} = \frac{\mathbf{1}}{\boldsymbol{r}}$ is the dispersion parameter.

In the negative binomial regression model, and in relation with regression coefficients, the dispersion parameter α= 1/r must be calculated (Qin et al., 2004; Malyshkina and Mannering, 2010). The negative binomial log-likelihood equations can be defined as:

$$L\ =\ \sum_{i=1}^{n}\left[\sum_{j=0}^{\gamma_i - 1}\ln\left(e^{r^*} + j\right) -\ \ln\gamma_i\,!\ + \gamma_i\ \ln(\mu_i) - \left(e^{r^*}\ +\ \gamma_i\right)\ln\left(\mu_i\ +\ e^{r^*}\right)\right]\ + ne^{r^*}\ln e^{r^*} \quad \textbf{(7)}$$

This section is devoted to performing a descriptive statistical study of the temporal and specific characteristics of accidents, as well as the distribution of accidents on dangerous road sections according to factors related to road characteristics and the road's environment that may influence accident frequency (Table 1).

4. Data Collection

The region of Monastir, Tunisia is the focus of this study. Monastir is located in the east of the country and covers an area of 1,024 square kilometers, which is about 0.6% of the country's total area. Monastir is bordered by the region of

Sousse to the north and Mahdia to the south (**Fig. 1**). It has a population of 548,828 people with a density of 539 inhabitants per square kilometer, according to the latest 2014 data. Monastir hosts approximately 1,200 industrial enterprises, mainly producers of textiles for export to European countries. The road network comprises 361 km of roads, including 15 km of national highways, 272 km of regional highways, and 74 km of local highways (**Fig. 2**).
Two data sets were used, namely crash reports and highways data. Crash reports were obtained from the national observatory on road safety (NORS) in Tunisia, the National Guard, and the traffic police in Tunisia. Data about road features were obtained from the Ministry of Equipment, Housing and Territorial Development in Tunisia (MEHTD). In our study, in order to propose a predictive modelling approach, all non-severe and serious crashes were mutually analyzed. The data covered a six-year period from January 1, 2013 to December 31, 2018. The accident frequency of each dangerous road section for each year was considered as an observation for the 70 considered dangerous road sections, based on 1499 recorded crashes. Table 1 shows the descriptive statistics with reference to the important elements used in the modelling process.

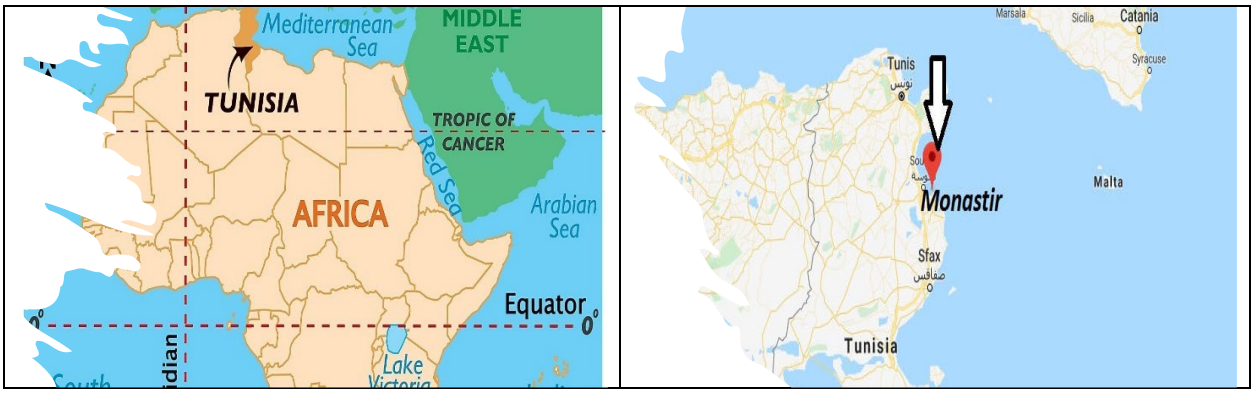

Figure 1. Geographical location of the Monastir region

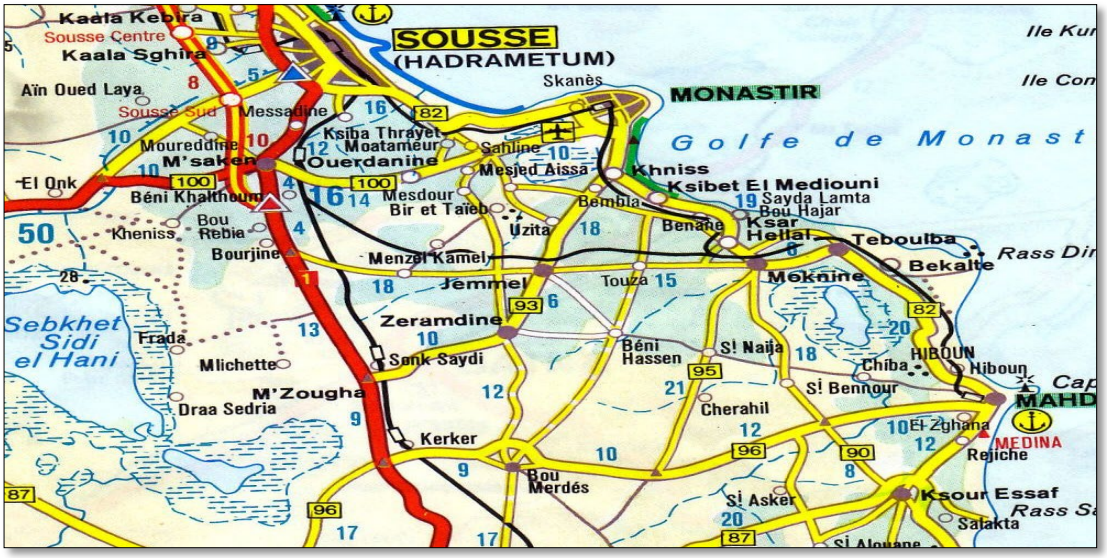

Figure 2. Road network sections in the Monastir region

5. Results and Discussion

Table 2 shows the estimated effects using the negative binomial model for crash occurrences in the hazardous road sections. Twelve parameters had statistically significant coefficients for calculating accident risk, as can be seen in Table 2. It is noteworthy that some of the selected variables were found to be insignificant, such as the presence of a straight alignment, luminosity, and visibility. Their insignificance may be explained through the uniqueness of the

data obtained from the police reports, the methodology employed, and the dependent variable in the model (Ouni and Belloumi, 2020). It is notable that the dispersion parameter α, as calculated from the negative binomial model, tended to vary slightly from zero (0.589), confirming the suitability of the negative binomial model when compared to the Poisson model. The model has a reasonable overall statistical fit, as indicated by the ρ^2 statistic.

The estimated results can be interpreted through the marginal effect, the variable modality coefficients, the elasticity, or the Incidence Rate Ratio (IRR). Indeed, it should be noted that the IRR reflects the influences of variables on the frequency of traffic accidents. If a specific IRR is greater than 1 (IRR> 1), it confirms that this factor increases the frequency of crashes. However, if the IRR of a particular variable is less than 1 (IRR <1), it confirms that this factor decreases the frequency of accidents. If (IRR = 1), it indicates this factor makes no difference. The average daily traffic variable (10,000 vehicles < ADT < 20,000 vehicles) contributes to increasing the frequency of accidents on hazardous road sections (IRR = 1.161, 95% CI [1.053 -1.279]) compared to the reference case (ADT < 10,000 vehicles). Indeed, this result is compatible with many previous studies (Gomes, 2012; Caliendo et al., 2016; Anastasopoulos, 2016; Park et al., 2016; Dong et al., 2016; Ma et al., 2017; Hzami et al., 2020).

A growth in the amount of traffic, the level of congestion, and irregular driving habits generally increases the frequency of serious accidents (Ouni and Belloumi, 2020). The speed limitation variable is divided into four categories according to the maximum permitted speed displayed for a road: 50 km/h, 70 km/h, 90 km/h, and 110 km/h.

As shown in Table 2, the 110 km/h speed limit increases the frequency of accidents (IRR = 1.541, 95% CI [1.001-2.372]) compared to the reference case of a 70 km/h speed limit. This outcome reflects the findings of past analyses, such as those of Daniels et al. (2010) and Aguero et al. (2010), particularly for roads outside the urban agglomeration with speed limits in excess of 90 km/h. Some other limited studies (Yu and Abdel-Aty, 2013; Mitra and Washington, 2012) have found that limiting speed to less than 50 km/h increases the risk of accidents, however.

The variable for parking is divided over two categories, namely a road with parking and a road without parking. As shown in Table 2, roads with parking have a greater accident frequency (IRR = 1.157, 95% CI [1.004 - 1.334]) than roads without parking, which is our reference case. This finding agrees with earlier studies, such as those of Wang et al. (2011) and Elliott et al. (2003), which have demonstrated that parking increases the risk of accidents. For example, roads with heavy traffic flows and high-speed limits may be affected by parking spaces in terms of unexpectedly slowing down vehicles and increasing the unpredictability in the environment for drivers. In addition, the presence of horizontal signs decreases the frequency of accidents (IRR = 0.789, 95% CI [0.633 - 0.983]).

This result is consistent with those of previous studies (Lord et al., 2010; Castro et al., 2012; Mitra and Washington, 2012) that have shown that the existence of horizontal signs reduces the risk of accidents, while their absence increases the risk. Likewise, Castro et al. (2012) found that road markings reduce the risk of accidents by making more visual information available to drivers about road boundaries and helping drivers to judge their own speed, especially at night. In addition, drivers can better judge their performance by being able to maintain a position relative to the lane axis at a particular speed. A road equipped with a drainage system also has a lower frequency of accidents (IRR = 0.872, 95% CI [0.793 -0.959] compared to the reference case when a drainage system is absent. Indeed, road surface conditions increase the risk of accidents. It has been suggested that road surface conditions may be a cause of sudden decisions to reduce speed. A bad road surface condition in combination with human error and vehicle defects will therefore increase the frequency and severity of road accidents.

Elliot et al. (2003) showed that bad road surfaces can also make controlling a vehicle more difficult and lead to accidents. The accident day variable refers to the day of the week in which an accident occurred. In our case, Wednesday, Friday, and Sunday seem to have the greatest risk of accidents at dangerous road sections. This concurs with prior studies (Sze and Wong, 2007; Rifaat et al., 2011) that indicated that the day of the week can have an effect on accident occurrence. The causes of accidents can also derive from the driver's behavior, vehicle defects, and environmental characteristics. In our case, driving in a prohibited manner, driver inattention, vehicle defects, unsuitable road conditions, not respecting priority, dangerous overtaking, alcohol use, and speeding all increased the chances of a road traffic accident at hazardous road sections (IRR= 1.69, 95% CI [1.004, 2.84] /IRR=1. 45, 95% CI [1.07, 2.21] / IRR= 1.72, 95% CI [1.17, 2.52] / IRR= 1.66, 95% CI [0.19, 3.02] / IRR= 1.57, 95% CI [1.21, 2.20] / IRR= 1.49, 95% CI [1.05, 2.11] / IRR= 2.03, 95% CI [1.30, 3.15] and IRR= 1.39, 95% CI [0.98, 1.97], respectively). This again reflects the results of previous studies. Speed is a contributing factor in 75% of South Africa's fatal traffic accidents, for example, according to Satchwell (2002). Drivers were also more likely to experience road crashes when under the influence of alcohol, with the risk of accidents rising rapidly with the blood alcohol content.

The impact of alcohol was also identified in 50% of police accident reports in a study in Nigeria by Bekibele (2007). Vehicle defects such as bursting tires, technical faults, and defective lights can also contribute to an increased frequency of accidents on hazardous road sections by limiting drivers' capacity to control their vehicles. Due to the current economic conditions and the shortage of domestic vehicle factories, several African countries, including Tunisia, lack regulations and checks at border entry points to stop the import of old, unsafe vehicles. This is

exacerbated by lack of attention to vehicle maintenance, especially for safety-critical components like tires and brakes, and some replacement parts may be poor quality. Currently in Tunisia, there is a large market for all types of secondhand vehicles and spare parts due to the poor economic performance in recent decades.

Table 1. Descriptive statistics

Explanotary Variables	Frequency (%)	Mean	Std. Dev
Average daily traffic (ADT)			
ADT < 10000 vehicles	528 (35.22 %)	0.352	0.477
10000 vehicles < ADT <20000 vehicles	747 (49.83 %)	0.498	0.500
20000 vehicles <ADT	224 (14.94 %)	0.149	0.356
Roadway alignement			
Right turn	104 (6.94 %)	0.069	0.254
Left turn	275 (18.35 %)	0.183	0.387
Right Alignment	1,120 (74.72 %)	0.747	0.434
Speed limit			
70 Km/h	18 (1.20 %)	0.012	0.108
50 km/h	774 (51.63 %)	0.516	0.499
90 km/h	649 (43.30 %)	0.432	0.495
110 km/h	58 (3.87 %)	0.038	0.192
Road surface condition			
Bad condition	547 (36.49 %)	0.364	0.481
Medium condition	96 (6.40 %)	0.064	0.244
Good condition	856 (57.10 %)	0.571	0.495
Number of lanes			
2x2 lanes	470 (31.35 %)	0.313	0.464
2 lanes	1,029 (68.65 %)	0.686	0.464
Urban/Rural			
Urban	379 (%)	0.252	0.434
Rural	1120 (%)	0.747	0.434
Presence of Drainage system			
Road not equipped with a drainage system	500 (33.36 %)	0.333	0.471
Road equipped with a drainage system	999 (66.64 %)	0.666	0.471
Public lighting			
Road equipped with public lighting	467 (31.15 %)	0.311	0.463
Road not equipped with public lighting	1,032 (68.85 %)	0.688	0.463
Visibility			
Unclear visibility	159 (10.61 %)	0.106	0.308
Clear visibility	1,340 (89.39 %)	0.893	0.308
Parking road			
Road with parking area	144 (9.61%)	0.096	0.294
Road without parking area	1,355 (90.39 %)	0.903	0.294
Vertical signs			
Section not equipped with vertical signs	84 (5.60%)	0.056	0.23
Section equipped with vertical signs	1,415 (94.40%)	0.943	0.23
Horizontal Signs			
Section not equipped with horizontal signs	75 (5.00%)	0.050	0.218

Section equipped with horizontal signs	1,424 (95.00 %)	0.949	0.218
Luminosity			
Section equipped with night luminosity	776 (51.77 %)	0.517	0.499
Section not equipped with night luminosity	723 (48.23 %)	0.482	0.499
Day of accident			
Monday	231 (15.41 %)	0.154	0.361
Tuesday	195 (13.01 %)	0.130	0.336
Wednesday	209 (13.94 %)	0.139	0.346
Thursday	226 (15.08%)	0.150	0.357
Friday	184 (12.27 %)	0.122	0.328
Saturday	255 (17.01 %)	0.170	0.375
Sunday	199 (13.28 %)	0.132	0.339
Time of accident			
00:00 – 01:59	77 (5.14 %)	0.051	0.220
02:00 – 03:59	52 (3.47 %)	0.034	0.183
04:00 – 05:59	63 (4.20 %)	0.042	0.200
06:00 – 07:59	153 (10.21 %)	0.102	0.302
08:00 – 09:59	132 (8.81%)	0.088	0.283
10:00 – 11:59	111 (7.40 %)	0.074	0.261
12:00 – 13:59	163 (10.87 %)	0.108	0.311
14:00 – 15:59	164 (10.94 %)	0.109	0.312
16:00 – 17:59	207 (13.81%)	0.138	0.345
18:00 – 19:59	156 (10.41 %)	0.104	0.305
20:00 – 21:59	124 (8.27 %)	0.082	0.275
22:00 – 23:59	97 (6.47 %)	0.064	0.246
Cause of accident			
Lighting problem	35 (2.34 %)	0.023	0.151
Driving in the wrong direction	15 (1.00 %)	.0100134	.0995
Driving without a driver's license	8 (0.53 %)	0.0053	0.072
Driver inattention	128 (8.54 %)	0.0854	0.279
Vehicle defects	67 (4.47 %)	0.044	0.206
Inadapted road condition	10 (0.67 %)	0.006	0.081
Passenger / pedestrian inattention	148 (9.88 %)	0.098	0.298
Non-respecting priority, lights, stop	462 (30.84 %)	0.308	0.461
Dangerous overtaking	214 (14.29 %)	0.142	0.350
Alcohol	25 (1.67 %)	0.016	0.128
Speeding	386 (25.77 %)	0.257	0.437
Type of accident			
Other types	46 (3.07 %)	0.030	0.172
Two-wheel collision	3 (0.20 %)	0.002	0.044
Passengers drop	1 (0.07 %)	0.000	0.025
Two wheels - barrier /animal	2 (0.13%)	0.001	0.036
Vehicle collision(s) - barrier/animal	88 (5.87 %)	0.058	0.235
Two-wheeler(s) - Vehicle(s)	195(13.01%)	0.130	0.336
Pedestrian (s) - Two wheels (s)	11 (0.73 %)	0.007	0.085
Multiples collisions	47 (3.14 %)	0.031	0.174
Skidding	333 (22.21 %)	0.222	0.415
Two-vehicle collision	597 (39.83 %)	0.398	0.489
Pedestrian (s) - Vehicle (s)	176 (11.74%)	0.117	0.322

Table 2. Estimation results for the negative binomial model

Variables (Xi)	**Negative binomial model**				**IRR 95% CI**
	Coef	Std Error	P value	IRR	95% CI
Average daily traffic (ADT)					
ADT < 10000 vehicles [Ref]					
10000 vehicles < ADT <20000 vehicles	0.149	0.049	0.003***	1.161	[1.053 - 1.279]
Speed limit					
70 Km/h [Ref]					
110 km/h	0.432	0.219	0.049**	1.541	[1.001 - 2.372]
Roadway condition					
Bad condition [Ref]					
Good condition	-0.163	0.089	0.068*	0.849	[0.713 - 1.012]
Urban/Rural					
Rural [Ref]					
Urban	-0.130	0.052	0.014**	0 .877	[0.790 - 0.973]
Presence of Drainage system					
Road not equipped with a drainage system [Ref]					
Road equipped with a drainage system	-0.136	0.048	0.005***	0.872	[0.793 - 0.959]
Public lighting					
Road not equipped with public lighting [Ref]					
Road equipped with public lighting	-0.094	0.049	0.055*	0.909	[0.826 - 1.001]
Parking road					
Road without parking area [Ref]					
Road with parking area	0.146	0.072	0.043**	1.157	[1.004 - 1.334]
Horizontal Signs					
Section not equipped with horizontal signs					
Section equipped with horizontal signs	-0.236	0.112	0.035**	0.789	[0.633 - 0.983]
Day of accident					
Tuesday [Ref]					
Wednesday	0.351	0.086	0.000***	1.421	[1.2 - 1.684]
Friday	0.156	0.092	0.089*	1.169	[0.976 - 1.400]
Sunday	0.244	.0888808	0.006***	1.276	[1.072 - 1.519]
Time of accident					
16:00 – 17:59[Ref]					
06:00 – 07:59	-0.227	0.091	0.013**	0.796	[0.665 - 0.953]
08:00 – 09:59	-0.213	0.095	0.026**	0.807	[0.669 - 0.974]
10:00 – 11:59	-0.217	0.101	0.033**	0.804	[0.659 - 0.982]
14:00 – 15:59	-0.238	0.090	0.008***	0.788	[0.660 - 0.940]
18:00 – 19:59	-0.221	0.091	0.015**	0.801	[0.670 - 0.958]
Cause of accident					
Lighting problem [Ref]					
Driving in the wrong direction	0.525	0.265	0.048**	1.691	[1.004 - 2.848]
Driver inattention	0.434	0.183	0.018**	1.544	[1.077 - 2.214]
Vehicle defects	0.544	0.194	0.005***	1.723	[1.178 - 2.522]
Inadapted road condition	0.508	0.304	0.095*	1.662	[0.915 - 3.020]
Non-respecting priority, lights, stop	0.453	0.172	0.009***	1.573	[1.121 - 2.207]
Dangerous overtaking	0.400	0.177	0.024**	1.492	[1.052 - 2.115]
Alcohol	0.708	0.224	0.002***	2.03	[1.307 - 3.151]
Speeding	0.330	0.174	0.058*	1.391	[0.989 - 1.957]
Type of accident					
others type of [Ref]					

Two-wheeler(s) - Vehicle(s)	-0.627	0.136	0.000***	0.534	[0.409 - 0.697]
Skidding	-0.204	0.123	0.098*	0.815	[0.639 - 1.038]
Pedestrian (s) - Vehicle (s)	-0.740	0.140	0.000***	0.476	[0.362 -0 .627]
α (Negative binomial dispersion parameter)	0.11				
Number of observations	1499				
Log-likelihood at zero $LL(0)$	-2302.7				
Log-likelihood at convergence $LL(\beta)$	-1798.68				
$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)}$	0.21				

Statistical significance of the parameters is indicated as follows: ***. Significant at 1% ; -**.Significant at 5% ; * Significant at 10%

6. Conclusion

We tried to analyze the link between the number of dangerous accidents on road segments and a variety of relevant factors, such as geometric, road, traffic, and spatial characteristics. We estimated a negative binomial model and a Poison regression model using data for the road network of the Monastir region in Tunisia and accident data collected for 70 unsafe road sections between 2013 and 2018.

The results suggest that the negative binomial model is empirically superior to the Poisson model, but they are both of great interest, especially for understanding the causes of accidents from a spatiotemporal viewpoint, which may in turn help inform the decision-making of public authorities. It seems that the average daily traffic volume, a high-speed limit, the presence of on-street parking, the day of the week, and other common causes can increase the frequency of accidents on dangerous sections of road. The results provide an important information basis to guide public authorities in taking preventive actions to achieve greater road safety.

In addition, public decision-makers can increase drivers' perceptions of road hazards through a campaign to educate them about the risks of speeding, driving without due concentration, or not wearing a seat belt, because this may help to reduce the number of traffic accidents and their frequency.

References

Abdel-Aty, M. A., & Radwan, A. E. (2000). Modeling traffic accident occurrence and involvement. *Accident Analysis & Prevention*, *32*(5), 633-642.

Agbelie, B. R. (2016). A comparative empirical analysis of statistical models for evaluating highway segment crash frequency. *Journal of traffic and transportation engineering (English edition)*, *3*(4), 374-379.

Agbelie, B. R. (2016). Random-parameters analysis of highway characteristics on crash frequency and injury severity. *Journal of traffic and transportation engineering (English edition)*, *3*(3), 236-242.

Aguero-Valverde, J., & Jovanis, P. P. (2010). Spatial correlation in multilevel crash frequency models: Effects of different neighboring structures. *Transportation Research Record*, *2165*(1), 21-32.

Aguero-Valverde, J. (2013). Multivariate spatial models of excess crash frequency at area level: Case of Costa Rica. *Accident Analysis & Prevention*, *59*, 365-373.

Anastasopoulos, P. C., & Mannering, F. L. (2009). A note on modeling vehicle accident frequencies with random parameters count models. *Accident Analysis & Prevention*, *41*(1), 153-159.

Anastasopoulos, P. C. (2016). Random parameters multivariate tobit and zero-inflated count data models: addressing unobserved and zero-state heterogeneity in accident injury-severity rate and frequency analysis. *Analytic methods in accident research*, *11*, 17-32.

Bekibele, C.O. (2007). Risk factors for road traffic accident among drivers of public institutions in Ibadan, Nigeria. African Journal of Health Science, 14, 137– 142.

Bullough, J. D., Donnell, E. T., & Rea, M. S. (2013). To illuminate or not to illuminate: Roadway lighting as it affects traffic safety at intersections. *Accident Analysis & Prevention*, *53*, 65-77.

Cafiso, S., Di Graziano, A., Di Silvestro, G., La Cava, G., & Persaud, B. (2010). Development of comprehensive accident models for two-lane rural highways using exposure, geometry, consistency, and context variables. *Accident Analysis & Prevention*, *42*(4), 1072-1079.

Caliendo, C., De Guglielmo, M. L., & Guida, M. (2013). A crash-prediction model for road tunnels. *Accident Analysis & Prevention*, *55*, 107-115.

Caliendo, C., De Guglielmo, M. L., & Guida, M. (2016). Comparison and analysis of road tunnel traffic accident frequencies and rates using random-parameter models. *Journal of Transportation Safety & Security*, *8*(2), 177-195.

Carson, J., & Mannering, F. (2001). The effect of ice warning signs on ice-accident frequencies and severities. *Accident Analysis & Prevention*, *33*(1), 99-109.

Castro, M., Paleti, R., & Bhat, C. R. (2012). A latent variable representation of count data models to accommodate spatial and temporal dependence: Application to predicting crash frequency at intersections. *Transportation research part B: methodological*, *46*(1), 253-272.

Chang, L. Y., & Chen, W. C. (2005). Data mining of tree-based models to analyze freeway accident frequency. *Journal of safety research*, *36*(4), 365-375.

Chen, E., & Tarko, A. P. (2014). Modeling safety of highway work zones with random parameters and random effects models. *Analytic methods in accident research*, *1*, 86-95.

Cheng, L, Geedipally, S., Lord,D., 2013. The Poisson–Weibull generalized linea rmodel for analyzing motor vehicle crash data. Safety Science 54, pp 38–42.

Chin, H. C., & Quddus, M. A. (2003). Applying the random effect negative binomial model to examine traffic accident occurrence at signalized intersections. *Accident Analysis & Prevention*, *35*(2), 253-259.

Daniels, S., Brijs, T., Nuyts, E., & Wets, G. (2010). Externality of risk and crash severity at roundabouts. *Accident Analysis & Prevention*, *42*(6), 1966-1973.

Depaire, B., Wets, G., & Vanhoof, K. (2008). Traffic accident segmentation by means of latent class clustering. *Accident Analysis & Prevention*, *40*(4), 1257-1266.

Dong, N., Huang, H., Lee, J., Gao, M., & Abdel-Aty, M. (2016). Macroscopic hotspots identification: a Bayesian spatio-temporal interaction approach. *Accident Analysis & Prevention*, *92*, 256-264.

Deublein, M., Schubert, M., Adey, B. T., Köhler, J., & Faber, M. H. (2013). Prediction of road accidents: A Bayesian hierarchical approach. *Accident Analysis & Prevention*, *51*, 274-291.

Elliott, M. A., McColl, V. A., & Kennedy, J. V. (2003). *Road design measures to reduce drivers' speed via'psychological'processes: a literature review*. TRL.

Francis, R. A., Geedipally, S. R., Guikema, S. D., Dhavala, S. S., Lord, D., & LaRocca, S. (2012). Characterizing the performance of the conway-maxwell poisson generalized linear model. *Risk Analysis: An International Journal*, *32*(1), 167-183.

Geedipally, S. R., & Lord, D. (2010). Investigating the effect of modeling single-vehicle and multi-vehicle crashes separately on confidence intervals of Poisson–gamma models. *Accident Analysis & Prevention*, *42*(4), 1273-1282.

Geedipally, S. R., Lord, D., & Dhavala, S. S. (2012). The negative binomial-Lindley generalized linear model: Characteristics and application using crash data. *Accident Analysis & Prevention*, *45*, 258-265.

Gomes, S. V., Geedipally, S. R., & Lord, D. (2012). Estimating the safety performance of urban intersections in Lisbon, Portugal. *Safety science*, *50*(9), 1732-1739.

Harizi, R., Ouni, F., M'raihi, R. (2016). Detection and classification of road accident black zones using exploratory spatial data techniques. *International Journal of Trend in Research and Development,* 3(1), 173-180.

Harizi, R., & Ben Hchaichi, T. (2018). The traffic of school buses in the urban area of Tunis: modelling and simulating with meta-heuristic means. *International Journal of Knowledge Management in Tourism and Hospitality*, *2*(1), 12-33.

Hzami, M., Ouni, F., & Harizi, R. (2020). Spatio-temporal hotspots analysis of pedestrian-vehicle collisions in tunisian coastal regions. *2020 IEEE 13th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA),* Fez, Morocco, 2020, pp. 1-6.

Kim, D. G., & Washington, S. (2006). The significance of endogeneity problems in crash models: An examination of left-turn lanes in intersection crash models. *Accident Analysis & Prevention*, *38*(6), 1094-1100.

Kim, D. G., Lee, Y., Washington, S., & Choi, K. (2007). Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models. *Accident Analysis & Prevention*, *39*(1), 125-134.

Kumara, S. S. P., & Chin, H. C. (2003). Modeling accident occurrence at signalized tee intersections with special emphasis on excess zeros. *Traffic injury prevention*, *4*(1), 53-57.

Kumara, S. S. P., & Chin, H. C. (2005). Application of Poisson underreporting model to examine crash frequencies at signalized three-legged intersections. *Transportation Research Record*, *1908*(1), 46-50.

Lao, Y., Wu, Y. J., Corey, J., & Wang, Y. (2011). Modeling animal-vehicle collisions using diagonal inflated bivariate Poisson regression. *Accident Analysis & Prevention*, *43*(1), 220-227.

Lee, J., & Mannering, F. (2002). Impact of roadside features on the frequency and severity of run-off-roadway accidents: an empirical analysis. *Accident Analysis & Prevention*, *34*(2), 149-161.

Li, Y., & Bai, Y. (2009). Highway work zone risk factors and their impact on crash severity. *Journal of Transportation engineering*, *135*(10), 694-701.

Li, Z., Wang, W., Liu, P., Bigham, J. M., & Ragland, D. R. (2013). Using geographically weighted Poisson regression for county-level crash modeling in California. *Safety science*, *58*, 89-97.

Lord, D. (2006). Modeling motor vehicle crashes using Poisson-gamma models: Examining the effects of low sample mean values and small sample size on the estimation of the fixed dispersion parameter. *Accident Analysis & Prevention*, *38*(4), 751-766.

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. *Transportation research part A: policy and practice*, *44*(5), 291-305.

Lord, D., & Kuo, P. F. (2012). Examining the effects of site selection criteria for evaluating the effectiveness of traffic safety countermeasures. *Accident Analysis & Prevention*, *47*, 52-63.

Ma, X., Chen, S., & Chen, F. (2017). Multivariate space-time modeling of crash frequencies by injury severity levels. *Analytic Methods in Accident Research*, *15*, 29-40.

Malyshkina, N. V., & Mannering, F. L. (2010). Empirical assessment of the impact of highway design exceptions on the frequency and severity of vehicle accidents. *Accident Analysis & Prevention*, *42*(1), 131-139.

Meng, Q., & Qu, X. (2012). Estimation of rear-end vehicle crash frequencies in urban road tunnels. *Accident Analysis & Prevention*, *48*, 254-263.

Mitra, S., & Washington, S. (2012). On the significance of omitted variables in intersection crash modeling. *Accident Analysis & Prevention*, *49*, 439-448.

Narayanamoorthy, S., Paleti, R., & Bhat, C. R. (2013). On accommodating spatial dependence in bicycle and pedestrian injury counts by severity level. *Transportation research part B: methodological*, *55*, 245-264.

Naznin, F., Currie, G., Logan, D., & Sarvi, M. (2016). Application of a random effects negative binomial model to examine tram-involved crash frequency on route sections in Melbourne, Australia. *Accident Analysis & Prevention*, *92*, 15-21.

Ouni, F., & Belloumi, M. (2020). Analysis of Traffic Accident Occurrence at Hazardous Road Locations: A Case Study in Tunisia. *International Journal of Public Policy and Administration Research*, *7*(1), 1-15.

Park, E. S., Carlson, P. J., Porter, R. J., & Andersen, C. K. (2012). Safety effects of wider edge lines on rural, two-lane highways. *Accident Analysis & Prevention*, *48*, 317-325.

Park, J., Abdel-Aty, M., & Lee, J. (2016). Use of empirical and full Bayes before–after approaches to estimate the safety effects of roadside barriers with different crash conditions. *Journal of safety research*, *58*, 31-40.

Pirdavani, A., Brijs, T., Bellemans, T., Kochan, B., & Wets, G. (2013). Evaluating the road safety effects of a fuel cost increase measure by means of zonal crash prediction modeling. *Accident Analysis & Prevention*, *50*, 186-195.

Qin, X., Ivan, J. N., & Ravishanker, N. (2004). Selecting exposure measures in crash rate prediction for two-lane highway segments. *Accident Analysis & Prevention*, *36*(2), 183-191.

Satchwell, K.M., 2002. Report to His Excellency. The President of the Republic of South Afirca. Road Accident Fund Commission

Usman, T., Fu, L., & Miranda-Moreno, L. F. (2012). A disaggregate model for quantifying the safety effects of winter road maintenance activities at an operational level. *Accident Analysis & Prevention*, *48*, 368-378.

Venkataraman, N. S., Ulfarsson, G. F., Shankar, V., Oh, J., & Park, M. (2011). Model of relationship between interstate crash occurrence and geometrics: exploratory insights from random parameter negative binomial approach. *Transportation Research Record*, *2236*(1), 41-48.

Venkataraman, N., Ulfarsson, G. F., & Shankar, V. N. (2013). Random parameter models of interstate crash frequencies by severity, number of vehicles involved, collision and location type. *Accident Analysis & Prevention*, *59*, 309-318.

Wang, C., Quddus, M. A., & Ison, S. G. (2011). Predicting accident frequency at their severity levels and its application in site ranking using a two-stage mixed multivariate model. *Accident Analysis & Prevention*, *43*(6), 1979-1990.

World Health Organization, "Global Status Report on Road Safety 2013: Supporting a Decade of Action," Published March 2013.

Ye, X., Pendyala, R. M., Washington, S. P., Konduri, K., & Oh, J. (2009). A simultaneous equations model of crash frequency by collision type for rural intersections. *Safety science*, *47*(3), 443-452.

Ye, X., Pendyala, R. M., Shankar, V., & Konduri, K. C. (2013). A simultaneous equations model of crash frequency by severity level for freeway sections. *Accident Analysis & Prevention*, *57*, 140-149.

Yu, R., & Abdel-Aty, M. (2013). Utilizing support vector machine in real-time crash risk evaluation. *Accident Analysis & Prevention*, *51*, 252-259.

Zou, Y., Zhang, Y., & Lord, D. (2013). Application of finite mixture of negative binomial regression models with varying weight parameters for vehicle crash data analysis. *Accident Analysis & Prevention*, *50*, 1042-1051.

Zou, Y., Zhang, Y., & Lord, D. (2014). Analyzing different functional forms of the varying weight parameter for finite mixture of negative binomial regression models. *Analytic methods in accident research*, *1*, 39-52.

Biographies

Attig Ines is a PhD student in Economics from the Faculty of Economic Sciences and Management of Sousse (Tunisia). Ms Attig obtained a bachelor's in international trade from higher institute of management of Sousse and a Master of Transportation and Supply Chain Management from Higher Institute of Transport and Logistics of Sousse, Tunisia. Her research interests include transportation systems, traffic safety and transport geography.

Ouni Fedy is a PhD student in Economics from the Faculty of Economic Sciences and Management of Sousse (Tunisia). Mr. Ouni holds a Bachelor of Transportation and Supply Chain Management from Higher Institute of Transport and Logistics of Sousse and a Master of applied transportation and logistics from Institute of Industrial Management of Sfax, Tunisia. He has published journal and conference papers. His research interests include modelling and planning of transportation systems, traffic safety and transport geography.

Harizi Riadh, PhD in Economics from the University of Montpellier 1 (France), is professor at the University of Tunis (Tunisia) and the University of Bisha (Saudi Arabia). He has published journal and conference papers. Some of his main areas of research are that of modelling and planning of private and public systems, governance, and infrastructure logistics.