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Spatio-temporal pattern of vulnerable road user's collisions hot spots and related risk factors for injury severity in Tunisia

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ABSTRACT

High risk of vulnerable road users (VRUs) injuries and fatalities have received higher interest nowadays in Tunisia. By using VRUs crash record (from January 1, 2001 to December 31, 2013), we describe the spatial pattern of VRUs collisions according to different temporal scales such as *(a.m. vs p.m. rush hours VRUs collisions, working days vs non-working days VRUs collisions, daytime vs nighttime VRUs collisions)* and investigate the influence of personal and environmental factors for VRUs injuries severity within the Center-East region in Tunisia. The empirical results are of great variety: spatial clustering pattern of each subtype of VRUs collisions according to temporal scale were clearly observed with the exception of daytime VRUs collisions, which shows a random tendency. All time-based subtypes of VRUs collisions also were found to be clustered along the national highways and regional highways especially in the regions of Sousse and Sfax. Results from VRUs severity model suggest that the degree of injury severity is higher for male than for female victim. The Tunisian VRUs are more likely to be involved in severe collision than non-Tunisian VRUs. Among driver contributory factors, the change of direction and hazardous overtaking increase the probability of sustaining fatal accidents compared to other driver contributory factors. The season factor shows that accident severity during the summer season is higher. From a policy view point, this kind of analysis can certainly help Tunisian public authorities to develop appropriate safety measures that can possibly reduce the number of VRUs injuries and fatalities.

1. Introduction

Road traffic accidents are actually a serious health problem contributing each year to over 4.5 million deaths all over the world (Naghavi et al., 2014). The road accident deaths have regularly increased from 1990 to 2013 with the majority of deaths occurring in low and middle-income countries. The highest road traffic death rates take place in African countries (Naghavi et al., 2014). Peden, Scurfield, Sleet, Mohan, and Hyder (2004) reported that about 85% of fatalities resulting from traffic accidents occur in Low and Middle Income Countries. According to Patel et al. (2016), vulnerable road users such as pedestrians, motorcyclists, and bicyclists carry a disproportionate share of the injury burden. All types of road users are likely to be injured or killed in traffic accidents, but there are significant differences in mortality rates between different groups of road users. Practically 50% of all deaths on the world's highways are among VRUs: pedestrians (22%), motorcyclists (23%),

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and bicyclists (4%) (WHO, 2015). Regarding VRUs collisions on a worldwide scale, yearly, more than 400,000 pedestrians die with large proportion of these fatalities taking place in low income countries (Naci, Chisholm, & Baker, 2009). Zaloshnja and Miller (2006) reported that the economic cost of accidents involving pedestrians and cyclists is estimated at approximately 40 billion dollars.

Thus, VRUs such as pedestrians and two-wheeler users have more risk than others vehicle occupants and sustain most of the burden trauma. African countries, including Tunisia are actually confronting a major public health problem regarding VRUs injuries... In Tunisia, passenger cars accounted for the highest share in total road accidents (33.39%) followed by motorcyclist (19.35%), pedestrians (17.63%), trucks (14.13) and taxi (6.32%) (NOITDSRS, 2016).

High risk of VRUs injuries and fatalities in Tunisia have received higher interest nowadays and considerable efforts have been devoted to further improve VRUs safety in several components.

In order to address the safety issues of VRUs, appropriate actions should be undertaken. They consist of development and implementation of more targeted design of pedestrian facilities (Papadimitriou, Lassarre, & Yannis, 2016), improvement of communication in regards to traffic priorities, convince of VRUs to not violate this rule (Castanier, Paran, & Delhomme, 2012); concentration on the use of helmets for cyclists and motorcyclists (Juhra et al., 2012; Šraml, Tollazzi, & Renčelj, 2012) and education of pedestrians about the specific rules in traffic (Papadimitriou et al., 2016). VRUs injury prevention programs vary from global programs centered on educating VRUs about personal safety to updates of local VRUs collisions hot spots intended to correct an engineering defect that was judged responsible for a high frequency of collisions at a specific location, including adoption of a reduction in speed limits in residential areas with a large number of VRUs and area-wide traffic calming. The scale and type of VRUs prevention programs vary according to the main cause of VRUs collisions as well as the availability of financial resources for prevention. A large scale injury interventions are often to be advantageous prevention tools (Cinnamon et al., 2011), nevertheless, they are often less effective in certain situations, such as for addressing vulnerability areas or vulnerability groups (Nilsen & Yorkston, 2007). Nilsen (2004) concluded that the effectiveness of community based injury prevention programs varies over time and space. Quite simply, what has worked in one location at a specific time will not necessarily prove effective in another location or at another time (Cinnamon, Schuurman, & Hameed, 2011).

However, researches discussing spatial and temporal pattern involving VRUs are very limited. Two common key points for improving VRUs safety consist of (1) decreasing the occurrence of VRUs collisions and (2) minimizing the level of injury severity when VRUs are exposed to traffic crashes. The aim of this study is to describe the spatio-temporal pattern of VRUs collisions according to temporal scale such as (a.m. *vs* p.m. rush hours VRUS collisions, working days *vs* non-working days VRUs collisions, daytime *vs* nighttime VRUs collisions) and to develop a multinomial logit model in order to study the contribution of several variables to VRUs collisions severity. Our study contributes to the literature from empirical and modeling methodological standpoints since it is the first study conducted in examining the spatio-temporal clusters and multiple factors on injury and fatality in motor vehicle crashes involving VRUs in Tunisia. Thus, the paper provides the primary results for VRUs collisions in Tunisia using KDE and Ripley's K-function within a GIS environment during a specific period. In this regard, our contributions are twofold. Firstly, we detect dangerous areas where there is an increased risk of accidents. Secondly, we determine the explanatory factors that significantly contribute to the VRUs injury risk from personal, temporal and environmental aspects.

The rest of the paper is organized as follows. Section 2 presents a literature review. In Section 3, we present the study area and data. Section 4 gives an overview about the methodology empsloyed in the study, whereas Section 5 presents the empirical results and their discussion. Finally, Section 6 concludes the paper.

2. Literature review

A primary step to enhance traffic safety is to identify locations where safety problems exist. One of the major problems that public authorities oriented towards is exactly where and how to implement preventive measures to have the most significant impact on road safety. Given the large number of fatalities caused by road traffic accidents, GIS has appeared as an essential instrument for identifying locations associated with high accident risk and presenting graphical confirmation of accident clusters on maps. VRUs collisions tend to form clusters in space and over time through the fact that their occurrence is linked to traffic volumes, which reveal different spatial and temporal patterns due to their relationship to natural environmental factors such as climatic conditions, the configuration of the road network such as the positions of access and egress points, and insufficient maintenance of highways (Yamada & Thill, 2004). There exist wide varieties of studies associated with time-related crashes. Such kind of analysis highlights the temporal hot spots, and presents a better visualization and understanding of crash variation from a non-spatial perspective (Li, Zhu, & Sui, 2007; Plug, Xia, & Caulfield, 2011).

2.1. Kernel density estimation

One of the most commonly employed methods to determine road traffic accident hot spots is the Kernel density estimation (KDE) approach (Benedek, Ciobanu, & Man, 2016). By computing the number of incidents in a defined region or network, the density of each subgroup accidents involved in our research for each pixel is calculated. As result, a discrete density surface is continuous by interpolation (Plug et al., 2011). According to Benedek et al. (2016), KDE is considered in two forms:

(1) planar Kernel density estimation (PKDE) and (2) network Kernel density estimation (NKDE). NKDE is an extension of the standard KDE.

The standard KDE employs Euclidian distance measure in a continuous planar space by analyzing hot spots locations. For instance, Anderson (2009) used KDE and K-means clustering to identify hot spots locations in London. The results show that the majority of hot spots locations involving pedestrians and cyclists occur in central London, at or near pedestrian crossings and bus stop. Shalini and Geetam (2013) investigated pedestrian accident hot spots in Delhi using Getis-ord Gi and KDE. Their results show that fatal crash density is higher at some regions when population density is higher. Also high percentage of accident occurring during nighttime between 8 pm and 10 pm. Truong and Somenahalli (2011) used a KDE and spatial autocorrelation approach to identify and ranking pedestrian vehicle crash hot spots and unsafe bus stops in Adelaide metropolitan area, Australia. As a result, 3 and 10 pedestrian vehicle crash hot spots are identified at intersections and at mid-block location respectively. In addition, the majority of pedestrian vehicle crash hot spots were located near the intersections of Main North road.

NKDE employs network distance measure along roadway while analyzing hot spots locations. For instance, Loo, Yao, and Wu (2011) applied NKDE to identify vehicle and pedestrian crashes hot spots locations in Shanghai, China. As a result, hot spots were more likely to be detected at road junctions. In addition, crashes involving pedestrians happened more frequently at city center mainly due to the higher exposure of pedestrians and a great number of vehicle-vehicle crash hot spots were found on expressways. Dai, Taquechel, Steward, and Strasser (2010) applied NKDE and K-function to identify crash clusters on an urban university campus in USA. The results show that among the 119 pedestrian crashes, nearly 70% occurred at intersections and over 30% occurred in mid-blocks locations. More recently, Benedek et al. (2016) applied NKDE to identify road traffic crashes vulnerability areas in Cluj-Napoca, Romania. The results show that majority of crashes vulnerability areas were located at the city entrances-exits and the city center. None of KDE and NKDE can be tested for statistical significance (Truong & Somenahalli, 2011). This is a major drawback of these methods. Researchers however complement KDE approach with statistical solutions to identify statistically significant clusters such as Monte Carlo simulation solution (Bíl, Andrášik, & Janoška, 2013; Sabel, Kingham, Nicholson, & Bartie, 2005) or Poisson distribution test (Erdogan, Yilmaz, Baybura, & Gullu, 2008). While there are a variety of KDE features to choose from, several researches (O'Sullivan & Unwin, 2002; O' Sullivan and Wong, 2007; Silverman, 1986) suggest that Kernel function has no significant impact on results. However, density pattern will certainly be influenced by the choice of bandwidth (Plug et al., 2011). Several researches identified a variation interval for the optimal bandwidth such as 100 m (Bíl et al., 2013; Dai et al., 2010; Loo & Yao, 2013); 200 m (Anderson, 2006, 2009), 800 m (Thakali et al., 2015); 1 Km (Mohaymany, Shahri, & Mirbagheri, 2013). Consequently, appropriate bandwidth should be determined according to the aim of study. In urban areas for example, a bandwidth between 100 and 300 m is recommended (Bíl et al., 2013).

2.2. Vrus injuries severity

We restrict our review here to pedestrian, cyclist and motorcyclist injury severity. Understanding the factors, which influence the severity and the frequency of roads traffic accidents, is crucial to preventing serious injuries. Clifton, Burnier, and Akar (2009) explored the impact of personal and environmental characteristics on the severity of injuries sustained by pedestrians involved in vehicle crashes using generalized ordered probit model. They took into account three severity classes, which are no injury, injury and fatal injury. Results of the modeling process show that women pedestrians involved in accidents are injured less frequently than male. However, children have a serious likelihood of sustaining severe injuries while elderly pedestrian are more likely to be fatally injured. Kim, Ulfarsson, Shankar, and Mannering (2010) investigated pedestrian injury and severity in North Carolina between 1997 and 2000. Among their important findings, the injury severity of pedestrians rises with male pedestrian, dark lighted/unlighted, freeway route, straight grade, speed involved both pedestrian and motorist at fault. On the other hand, traffic signal, inclement weather condition, curved road and pedestrian walking along roadway proven to lower risk of sustaining severe injury. Tay, Choi, Kattan, and Khan (2011) identified the factors determining the severity of pedestrian–vehicle crashes in South Korea. Results of modeling process showed that male driver, drunk driver, elderly pedestrian, country road, freeway road, national road, provincial road, road width 20 m or less, fog/snow, morning peak, afternoon peak and nighttime variables increased the likelihood of severe injury. Aziz, Ukkusuri, and Hasan (2013) explored the determinants of pedestrian–vehicle crash severity in New York City between 2002 and 2006. Their results suggested that elderly pedestrian, male pedestrian, dark lighted road and pedestrian crossing intersection increased the likelihood of severe injury. Eluru, Bhat, and Hensher (2008) examined pedestrian and bicyclist injury severity level in traffic crashes. The results suggested that male gender, older non-motorist including pedestrian and bicyclist, non-motorist under the influence of alcohol, 6 pm–12am, 12a.m–6a.m, and frontal impact are found to frequently increase the severity of accidents. Kim, Kim, Ulfarsson, and Porrello (2007) explored bicyclist injury severities in bicycle–motor vehicle accidents. A sample of 2934 over the period 1997–2002 was used. Results of modeling process showed that speeding, bicyclist age 55 and over, bicyclist is intoxicated, driver is intoxicated, curved road, a.m. peak hour, and darkness with no streetlight increased the likelihood of severe injury. On the other hand, helmet use, driver at fault, the presence of two lanes decreased the likelihood of severe injury. Schneider and Savolainen (2011) compared the severity of motorcyclist injury by crash types in Ohio, USA using multinomial logit model. A sample of 14,317 over the period of 2006 to 2010 was used. Results of modeling process showed that female, presence of alcohol, horizontal curvature, curve on grade and driveway related increased the likelihood of severe injury, while speeding related accident and adverse weather condition decreased the likelihood of severe injury.

Comparing previous studies, there are notable agreements of significant contributing factors and some exceptions, particularly when it comes to factors such as gender, intersections type, lighting condition, road surface conditions, roadway alignment and time of accident. For example (Aziz et al., 2013; Clifton et al., 2009; Eluru et al., 2008; Kim et al., 2010; Rifaat, Tay, & de Barros, 2011) indicated that males pedestrians are associated with higher severity levels, while (Moudon, Lin, Jiao, Hurvitz, & Reeves, 2011; Tay et al., 2011) reported the opposite. Earlier researches of (Clifton et al., 2009; Eluru et al., 2008; Moudon et al., 2011; Pai, 2009; Quddus, Noland, & Chin, 2002; Rifaat et al., 2011; Sze & Wong, 2007; Tay et al., 2011) indicated that the time of accident has an effect on VRUs collisions occurrence. Tay et al. (2011) and Rifaat et al. (2011) indicated that more severe injuries occur in the nighttime periods as compared the daytime periods. Clifton et al. (2009) reported that daylight conditions increase severity, while (Rifaat et al., 2011) reported the opposite. Quddus et al. (2002) and Sze and Wong (2007) indicated an increased risk of severe injury when accident occur at intersections. Nevertheless, Eluru et al. (2008) showed that intersection related accidents appeared to present a diminished risk of severe injury and fatality. Previous researchers found that roadway alignment have an effect on accident occurrence. As the study of Ulfarsson, Kim, and Booth (2010) and Kim et al. (2010) reported that curved road are associated with less severe injuries, while Quddus et al. (2002) reported the opposite.

2.3. Gaps in the literature

A variety of spatial integrated approaches was used to identify hot spot locations such as NKDE with K-function (Dai et al., 2010), KDE with Getis-Ord Gi (Shalini & Geetam, 2013), KDE with K-means clustering (Anderson, 2009), KDE with Ripley's K-function and nearest neighbor distance analysis (Shafabakhsh, Famili, & Bahadori, 2017). However, no previous studies have discussed spatial and temporal pattern involving VRUs collisions.

3. Study area and data

Three sets of data were used in this study as follow: (1) collisions data obtained from the National Observatory for Information, Training, Documentation and Studies on Road Safety (NOITDSRS) in Tunisia, (2) Highways data obtained from the Ministry of Equipment, Housing and Territorial Development in Tunisia (MEHTD) and (3) administrative map was obtained from DIVA-GIS.[1]

3.1. Study area

The study area covers the Center-East region of Tunisia. This region coveres the governorates of Sousse, Monastir, Mahdia and Sfax. Contributing with a large part in the development of the country, the Center-East region has a strategic role that goes beyond regional and even national framework as evidenced by large projects. It covers 14213 km^2, which represents 9.2% of total area of the country.

Census results related to the demographic, educational and economic characteristics of the population show that the Central-East region is among the most densely populated regions of Tunisia since it has a population of 2,418,200 inhabitants in 2009 that represents 23.1% of the total population with a density of 168 inhabitants / km^2 against 64 inhabitants/km^2 at national scale (National Statistics Institute, 2009)... The particular geographical position of the Center-East region has significantly contributed to make it an important link of interconnection with its national and international environment by a developed basic infrastructure in terms of road, maritime and air transport (the NH1 National road, the Tunis-Msaken freeway, the railway network, the Monastir and Sfax airports and the Sousse and Sfax commercial ports.

3.2. Road network

The road network of Center-East region consists of roughly 3000 km of public roads, split into about 2000 roads sections with varying length (min: 0.13 m; max: 10,596 m with a mean of 310 m). The coverage highways include freeways (A1), national highways (NH), regional highways (RH) and local highways (LH) as line features and excludes municipal highways and railways. The geocode procedure in ArcGIS 10.2 is used to locate highways and VRUs accidents on a GIS base map. This procedure requires a reference dataset that contains address attributes for the geographic features in the area of interest. The categorization of highways is an essential component used in transportation planning. Highway data should contain basic information to create highway dataset (Zhang, Thiemann, & Sester, 2010). In this road system, stone markers are placed every 1 km along each road so that a route ID and a measure, which specifies a reference marker on the specified road (Yamada & Thill, 2007), identify any location in the system. Highways were labeled with a distinctive name in order to best differentiate the roads. For example, for the road name NH2/Km150, NH designates the type of roadway as a National

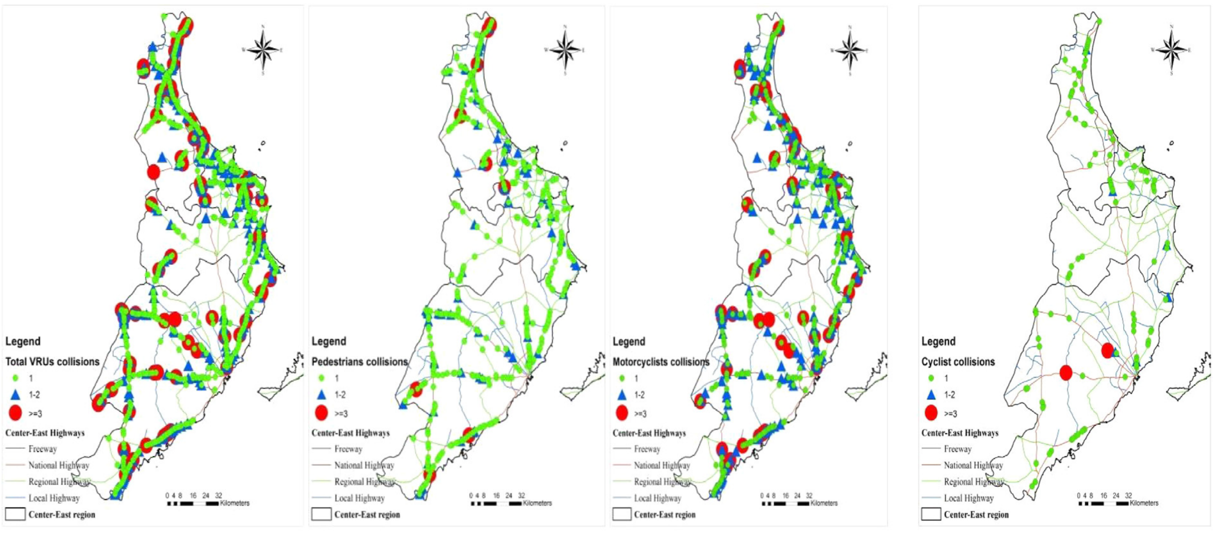
[1] http://www.diva-gis.org.

Highway and the last character "Km150" designates the stone markers information. The highway network in this study encompasses 3000 stone markers. In Tunisia, the stone markers are the only possible locations of crashes.

3.3. Collisions data

This research is limited to VRUs collisions, which resulted in casualties; VRUs collisions with only material damage are excluded. Accidents with casualties are reported by the police and national guard and collated at NOITDSRS in Tunisia. The NOITDSRS is the only national source that offers complete information on accident circumstances, vehicles implicated and resulted consequences. It is also the most exhaustive and reliable single database concerning roadaccidents that can be used for longitudinal research in Tunisia. The statistics relate only to personal injury accidents that occur on public roads and that are reported to the police and national guard. These pieces of information are subsequently recorded using the official report of the accident. An official report of the accident is a document prepared by the national guard forces or the police with information about the unfolding of the accident. In Tunisia, a quality evaluation of accidents reports can potentially produce more information in determining inconsistencies in data. The data used here cover 13 years from January 1, 2001 to December 31, 2013, a period that is long enough to reduce random fluctuation. The reporting unit for the VRUs collisions examined here is the 1 Km long road segment. The collected crashes data include the route name and the stone markers information identical as GIS layer of highways for locating the crashes on highway map using linear referencing tool is available in ArcGIS 10.2. Accurate location of accidents at national level is a problem that often goes through a very complicated geocoding step. The locations of accidents were mapped with World Geodetic System 1984 (WGS84) projection, a similar projection to highways data. . Consequently, 1922 VRUs collisions, 1886 injured casualties and 547 fatality records within the 13-year period were used for this study. Fig. 1 shows the above-mentioned collisions within the study area that are represented as geocoded x and y coordinates. Red circles symbolize locations where more accidents happened. At first glance, it is not noticeable where there are significant clustering of VRUs collisions. It is required to apply appropriate analysis before conducting the hot spots analysis (Shafabakhsh et al., 2017).

As shown in Fig. 2, Sfax recorded the highest number of VRUs collisions among Center-Est region. The number was 860 representing 44.74% of total VRUs collisions. This is followed by Sousse with 464 VRUs collisions representing 24.14%. Knowledge of how accidents vary geographically by different highways provides indices to understand their determinants. Fig. 2b highlights the distribution of VRUs collisions in center-east region according to the hierarchy of road network. VRUs collisions seem to appear uniformly over the network. The comparison of the number of VRUs collisions by type of highways network reveals a rather significant disparity between the numbers of accidents that occur on NH with the rest of roads. In the governorate of Sfax, out of the 860 total VRUs collisions recorded in the 13-year period, 765 were on NH, 69 on RH and 26 on LH. In governorate of Sousse, NH recorded the highest number of accidents (380 accidents) against 62 at RH and 22 at LH. A detailed knowledge of the accident rate is essential to the definition of a road safety policy, at both the national and local levels. Accidents between several users are significant to conflicts of road use. Light vehicles and trucks are mostly involved in accidents with pedestrians and motorcyclists.



(a) (b) (c) (d)

Fig. 1. Distribution of VRUs collisions within study area (a: total VRUs, b: pedestrians, c: motorcyclists, d: cyclists).

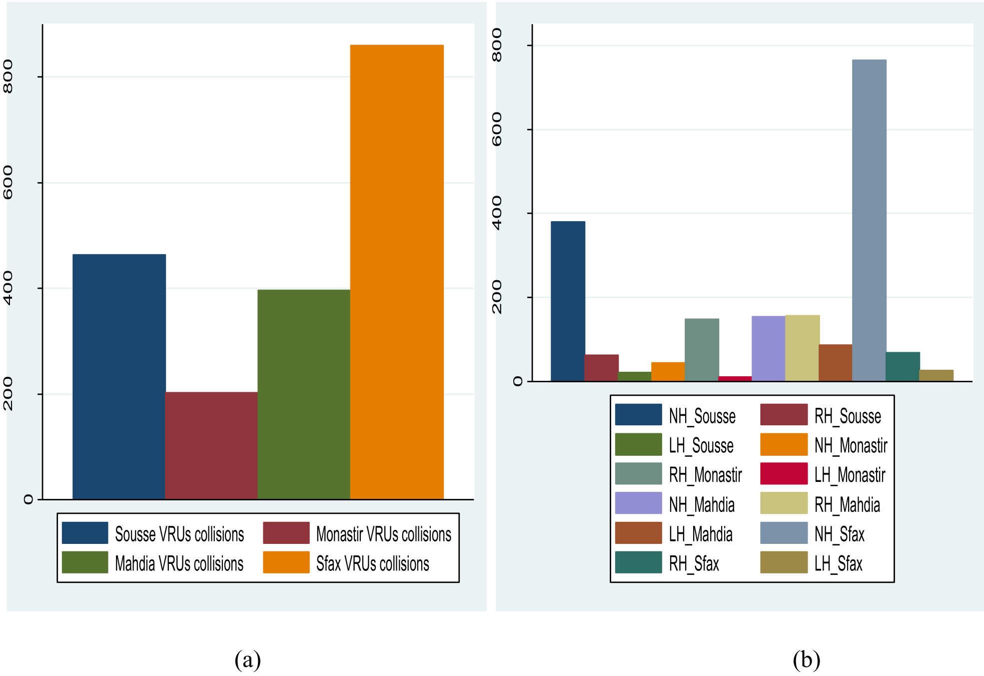


Fig. 2. The distribution of VRUs collisions in center east region: (a) according to gouvernorate; (b) according to the hierarchy of road network.

For the purpose of analysis, VRUs collisions were categorized into (1) a.m. rush hours VRUs collisions (n = 183); (2) p.m. rush hours VRUs collisions (n = 323); (3) working days VRUs collisions (n = 1396); (4) non-working days VRUs collisions (n = 526); (5) daytime VRUs collisions (n = 942) and (6) nighttime VRUs collisions (n = 980). Under reporting of crashes data was an issue throughout African countries and other low and middle income countries (Periyasamy et al., 2013; Abegaz, Berhane, Worku, Assrat, & Assefa, 2014). Therefore, exactness and the exhaustiveness of traffic accidents reports are very crucial for data entry and analysis. Implementing an effective and sustainable road accident information system should be a top priority in Tunisia. However, many records have missing values for various variables, such as VRUs age, junction details and weather conditions. After excluding records with missing values, a sample of 1500 VRUs collisions was obtained for modeling process.

Three different levels of VRUs severity were considered in the multinomial logit model: slight injuries, serious injuries and fatal injury. The advantage of the multinomial logit model is that it can consider more than two outcomes. In this case, three levels were selected based on the distribution of crash severity. Specifically, 33.87% of the observed crashes were slight injuries, 36.37% were serious injuries and the 29.40% were fatal injuries. The use of NOITDSRS and MEHTD data for hot spots identification and accident severity has certain shortcomings. In terms of NOITDSRS data, some attributes are not usually recorded. In addition, the under-reporting of property damage collisions may also be an issue.

4. Methodology

There are various spatial statistical techniques for analysis of spatial patterns to identify concentration of high or low road traffic accidents. The primary reason behind employing these techniques for detection of accidents hot spots rather than classical statistical techniques is the fact that accidents are a spatial phenomenon. Classical statistical techniques neglect the existing of geographical relationship between the different locations. Yet, it appears reasonable that the structure of road network can play crucial role in determining dangerous locations (Moons, Brijs, & Wets, 2009). This research aims to fill a gap in traffic safety studies by analyzing the differences in the spatial distribution of VRUs collisions according to three temporal scales. These scales are a.m. *vs* p.m. rush hours VRUs collisions, working days *vs* non-working days VRUs collisions, and daytime *vs* nighttime VRUs collisions. In addition, we investigated the influence of personal and environmental factors for VRUs injuries severity within the Center-East region in Tunisia. Firstly, Ripley's K-function coupled with KDE approach was used to detect the highways segments, where VRUs collisions were significantly clustered, dispersed or random. Secondly, a multinomial logit model was applied in order to study the contribution of several variables to VRUs injury severity. As a result, VRUs surveillance approach at local level over space and time focused for these locations. Therefore, predicting dangerous areas where there is an increased risk of accidents that requires intervention will assist public authorities to delineate less risky areas, which in turn can be appropriately used as models in the development of safer roads (Shafabakhsh et al., 2017).

4.1. Ripley's K-function

Ripley (1976) first introduced Ripley's K-function. Successfully applied in a number of other spatial accidents analysis (Jones, Langford, & Bentham, 1996; Kazemi, Jafari, & Yavari, 2016; Loo & Yao, 2013; Morelle, Lehaire, & Lejeune, 2013; Shafabakhsh et al., 2017; Yamada & Thill, 2004, 2007), Ripley's K-function has confirmed to be a powerful measure of the spatial relationship between point data. We employ Ripley's K function instead of other global spatial clustering methods because it summarizes spatial dependence over multiple different scales, handles all event distances, and does not aggregate points into areas (Yamada & Thill, 2004). Several variations of Ripley's original K-function have been suggested. Here we apply a standard transformation of the K-Function, also known as L(d):

$$\mathrm{L(d)} = \sqrt{\frac{\mathrm{A}\sum_{\mathrm{i=1}}^{\mathrm{n}}\sum_{\mathrm{j=1}}^{\mathrm{n}}\mathrm{K(i,j)}}{\pi \mathrm{n(n-1)}}} \tag{1}$$

where L(d) represents the difference between the observed K-function value and the expected K-function value under the complete spatial randomness hypothesis (CSRH), d is the distance, A refers to the total area containing the features, $K(i,j)$ is a weight, and n refers to the total number of features.

In this study, the Ripley's K-function was conducted by using ArcGIS 10.2 Spatial Statistics Tool of Multi-Distance Spatial Cluster Analysis. This tool combines a commonly used transformation $L(d)$ of Ripley's K-function with Monte-Carlo simulation (Thacher, Milne, & Park, 2017). In order to guarantee high performance of the Ripley's K-function, a statistical assessment based on Monte Carlo Simulation Process (MCSP) is often used to create confidence envelopes along the CSRH line for each K function result to test the statistical significance (Wu, Borland, & Nelson, 2011). At a given distance or scales of analysis, if the observed values are above the expected values and the upper confidence envelope created from the MCSP, the data are clustered in a statistically significant way. When the observed values are under the expected values and the low confidence envelope created from the MCSP, the data are dispersed in a statistically significant way (Thacher et al., 2017). On the other hand, if observed values are within the lower and upper boundaries created by the confidence envelopes, then the distribution does not differ in a statistically significant manner from random (Thacher et al., 2017)... Therefore, the results can have a 99% confidence level and the simulate outer boundary values edge correction were used for the calculation of all K functions in order to diminish the effect of boundary on the test results. All units of the Ripley's K-function outcomes are expressed in meters.

4.2. Kernel density estimation (KDE) analysis

Road traffic accidents are generally shown in space as dot denatures. It is extremely difficult to distinguish areas that contain multiple crashes. Density map helps to identify areas that have higher accidents concentrations using KDE method. KDE is recognized as a nonparametric approach (Silverman, 1986) has widely been applied to characterize the pattern in terms of the first-order properties of spatial data (Mohaymany et al., 2013). Taking that approach is the fact that point pattern has a density at any location within the study area not only at the location where the event happens or is displayed (Mohaymany et al., 2013; O'Sullivan & Unwin, 2002). KDE is used to calculate the number of collisions per kilometer of roads in order to identify locations where more VRUs collisions occurred By computing the number of incidents in a defined region or network, the density of each subgroup accidents involved in our research for each pixel is calculated. As result, a discrete density surface is continuous by interpolation (Plug et al., 2011).

In this regard, the density estimation function $\hat{f}(x)$ is given by:

$$\hat{f}(x) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \tag{2}$$

where n is the number of VRUs collisions, h is the smoothing parameter or bandwidth, which is always larger than 0, K is the kernel function, and d_i represents the distance between the location (x; y) and the location of the i^{th} collision (i = 1, 2, 3, ..., n). While there are a variety of KDEfeatures to choose from, several researches (O' Sullivan and Wong, 2007; O'Sullivan and Unwin, 2002; Silverman, 1986) suggest that kernel function has no significant impact on final results. However, density pattern will certainly be influenced by the choice of bandwidth (Plug et al., 2011). The bandwidth is a free parameter that exhibits a strong influence on the resulting estimate. According to O'Sullivan and Unwin (2002), a very small bandwidth will produce insufficient smoothing. On the other hand, a large bandwidth will over smooth the density estimation. Generally, it takes trial and error to produce a suitable KDE (Plug et al., 2011). Another fundamental parameter in the KDE method is the selection of the grid cell size. The effect of bandwidth choice in our study is illustrated in Fig. 3. It is shown that the density pattern becomes smoother with increasing bandwidth. As the bandwidth has increased from 1 Km to 20 Km, the local hot spots gradually combined with their neighbors, resulting in crash clusters at larger spatial scales (Loo et al., 2011). The 1 Km or 20 Km were found to be either too small or too large to make any meaningful interpretation for this scale analysis. Hence, in our case, a bandwidth of 3 Km and a cell size of 400 m based on Quartic Kernel function (Eqs. (3) and (4)) with ArcGIS 10.2 were used for all VRUs collisions as well as for the subsets.

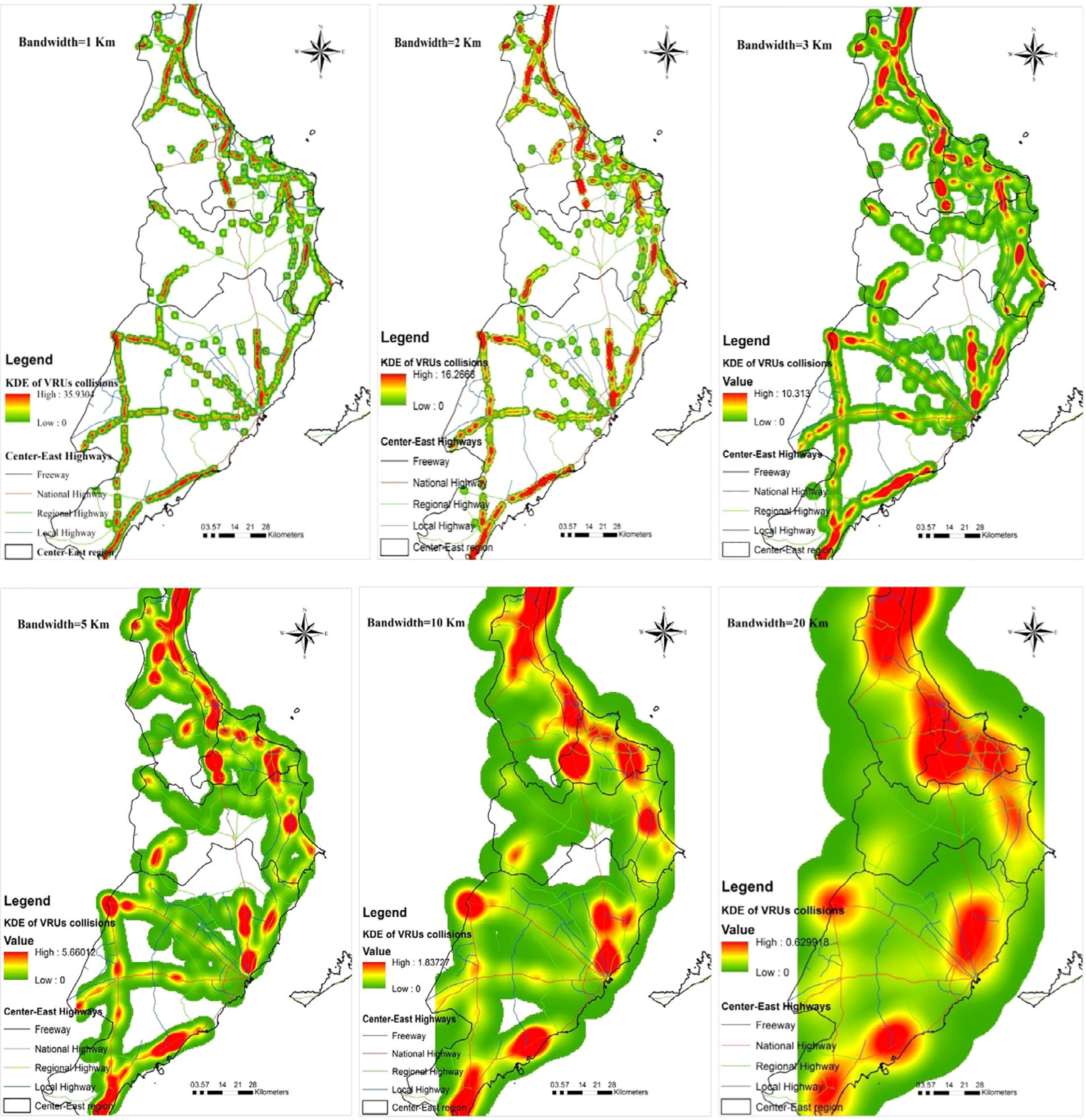


Fig. 3. Effect of bandwidth choice within study area.

$$k\left(\frac{d_i}{h}\right) = K\left(1 - \frac{d_i^2}{h^2}\right) \quad \text{when } 0 < d_i \leqslant h \tag{3}$$

$$k\left(\frac{d_i}{h}\right) = 0 \quad \text{when } d_i > h \tag{4}$$

where h is the smoothing parameter or bandwidth which is always larger than 0, K is the Kernel function, and d_i represents the distance between the location (x; y) and the location of the ith collision (i = 1, 2, 3, ..., n). In Eq. (4), K is often a scaling factor and its main function is to ensure the total volume under Quartic curve is one. The common values used for K are $\frac{3}{\pi}$ and 3/4.

The resulting density is expressed as the number of VRUs collisions per kilometer of roads. The resulting visual map exhibits hot spots where VRUs collisions occurrence is higher than other areas. In our work, the categorization was done by colors: Red color highlights locations with high collisions intensity, yellow color highlights locations with medium collisions intensity and green color highlights locations with low collisions intensity.

4.3. Vrus injury severity model

The crash injury severity used in this study is categorized into three levels in increasing severity; coded as 1 = Slight injuries, 2 = Serious injuries, and 3 = Fatalities (death within 30 days of the accident). To address this type of discrete outcome data, a multinomial logit model was used. In this model, we describe the relationship between the injury severity as a dependent variable and a set of explanatory variables.[2] The advantage of this model is that it allows calculating the likelihood that a victim will be involved in a severe accident. This calculation will allow us to know what are the major factors that determine the individual risk perception. The factors that aggravate the risk of individual injuries can also be determined. The multinomial logit model also satisfies the hypothesis of independence of irrelevant alternatives. This hypothesis reflects the fact that the ratio of two probabilities associated with particular two events is independent of other events. The multinomial logit model is used for a dependent variable with unordered categories. One category is chosen as the reference category. In this study, the slight injury will be the reference modality.

Let P_{ni} the probability of accident n will result in VRUs injury severity level i, such that:

$$P_{ni} = P(S_{ni} \geqslant S'_{ni}) \tag{5}$$

where S_{ni} representing a function determining the severity of VRUs collision.

$\forall i, i' \in$ I, $i \neq i'$, I represents a set of all possible severity categories. It's assumed that VRUs victim will experience the injury severity with the largest S_{ni}. In this context, a linear function was defined to determine VRUs injury severity outcome i as follows (Rifaat et al., 2011; Tay et al., 2011; Ulfarsson et al., 2010):

$$S_{ni} = \beta_i X_n + \varepsilon_{ni} \tag{6}$$

where S_{ni} is a severity function determining the injury severity category i for VRUs n, X_n is a vector of exogenous explanatory variables characterizing the nature of driver characteristics, vehicle characteristics, infrastructure and the environment for crashes n, β_i is a vector of coefficients to be estimated, which present the marginal variation of the explanatory variables effect on the probability of exposure of individual i to an accident, and ε_{ni} is an error term accounting for unobserved effects affecting the VRUs injury severity (Savolainen & Ghosh, 2008; Washington, Karlaftis, & Mannering, 2003). In this regard, the standard multinomial logit model is given by (McFadden, 1981):

$$\mathrm{P_{ni}} = \frac{\exp(\beta_i \mathrm{X_{in}})}{\sum_{\forall_{i \in I}} \exp(\beta_i \mathrm{X_{in}})} \tag{7}$$

We have previously noted that the coefficients from multinomial logit model can be difficult to interpret since they are relative to the base outcome. A positive coefficient does not necessarily indicate an increase in the likelihood of that particular injury severity level (Schneider, Savolainen, & Zimmerman, 2009). Accordingly, the odds ratio (OR), which is computed to estimate the rate of probability change of accident severity occurrence when a unit changes, is given by:

$$\mathrm{OR} = \exp(\beta_j) \tag{8}$$

Goodness of fit measures can be carried out to test how well VRUs severity model fits the data. To assess the overall fit of the model, it is possible to compare the model's Log-likelihood at convergence *LL(β)* with the model's Log-likelihood at zero *LL(0)*, which is the model with the constant as the only explanatory variable. This is done by calculating the McFadden ρ^2 goodness of fit index, which is defined as:

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{9}$$

The ρ^2 ranges from 0 (indicating that the model has no predictive power) to 1 for a perfect goodness-of-fit.

5. Empirical results and discussion

5.1. Ripley K-function results

Spatial pattern of all VRUs collisions as well as the subtypes of VRUs collisions according to temporal scale such as (a.m. *vs* p.m. rush hours VRUs collisions; working days *vs* non-working days VRUs collisions; daytime *vs* nighttime VRUs collisions) from January 1, 2001 to December 31, 2013 were identified by Ripley K-function coupled with KDE... The global clustering tendency of VRUs collisions are identified by interpreting the output chart of Ripley's K-function when comparing the observed K values (red line) with expected K values (Blue line) under CSRH. Fig. 4 highlights the results of Ripley K-function of each subtype of VRUs collisions.

[2] We use the STATA 12.0 statistical software package to estimate the multinomial logit model.

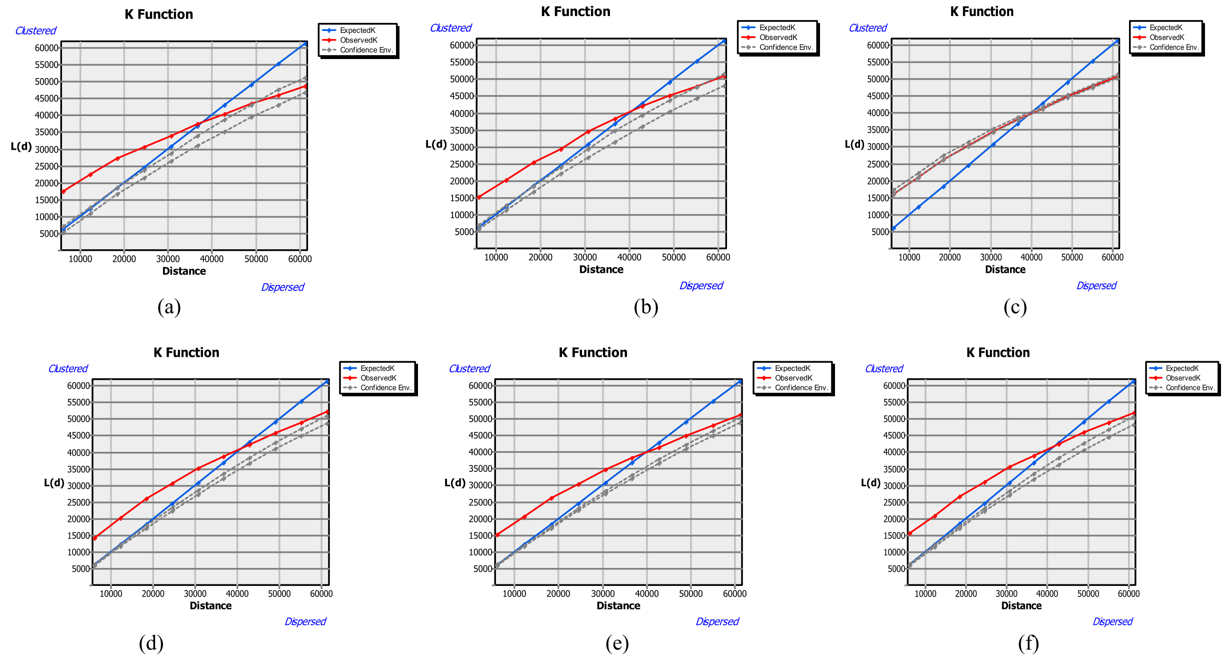


Fig. 4. Results of Ripley K-function (a: a.m. rush hours; b: p.m. rush hours; c: daytime; d: nighttime, e: working days, f: non-working days). Note: All VRUs collisions were found to be clustered below 40.000 m. The a.m. rush hours, p.p. rush hours, nighttime, working days, and non-working days VRUs collisions were found to be clustered below 38.000, 40.000, 41.000, 40.000 and 41.000 m respectively. Daytime VRUs collisions exhibit a random pattern.

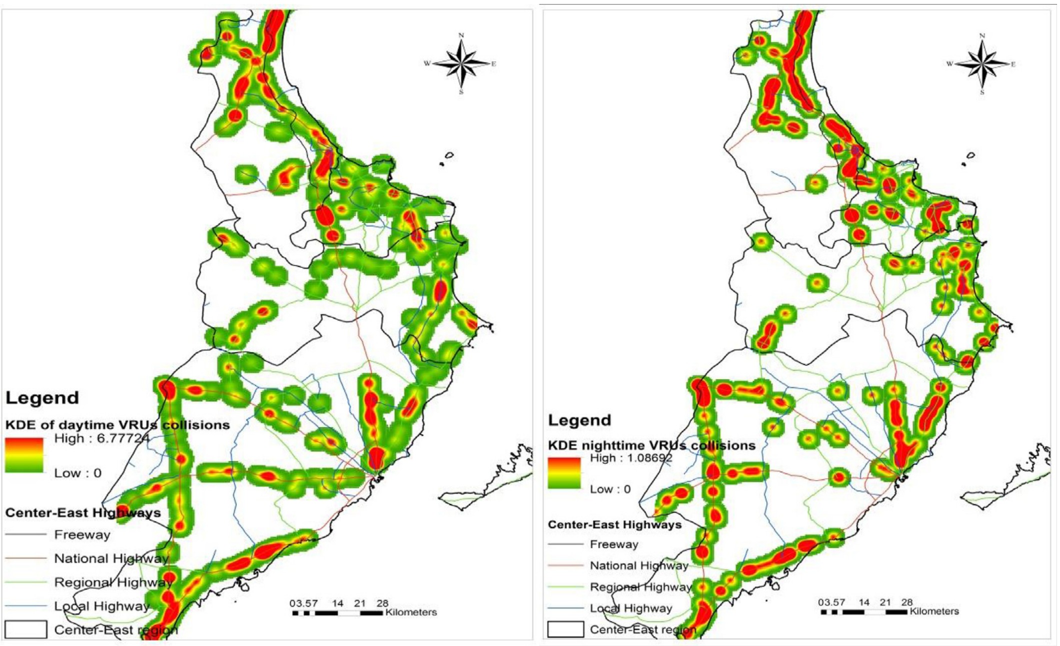
The permutation used in MCSP was set to 99 iterations to derive the statistical significance of the observed distribution, yield a significance level of 1% to create the confidence envelope. Spatial clustering pattern of each subtype of VRUs collisions according to temporal scale were clearly observed with the exception of daytime VRUs collisions, which show a random tendency (the observed K values are within the upper and lower confidence envelopes). All VRUs collisions as well as all subtypes of VRUs collisions were found to be clustered under approximately 38,000 to 41,000 m.

5.2. KDE results

While Ripley's K-function is useful to test the global clustering tendency of VRUs collisions, it cannot detect where exactly the VRUs collisions aggregates across the study Area. To overcome this shortcoming, a KDE was applied. This can assess VRUs collisions especially when only their approximate positions are available, and creating a more realistic picture of VRUs distributions.

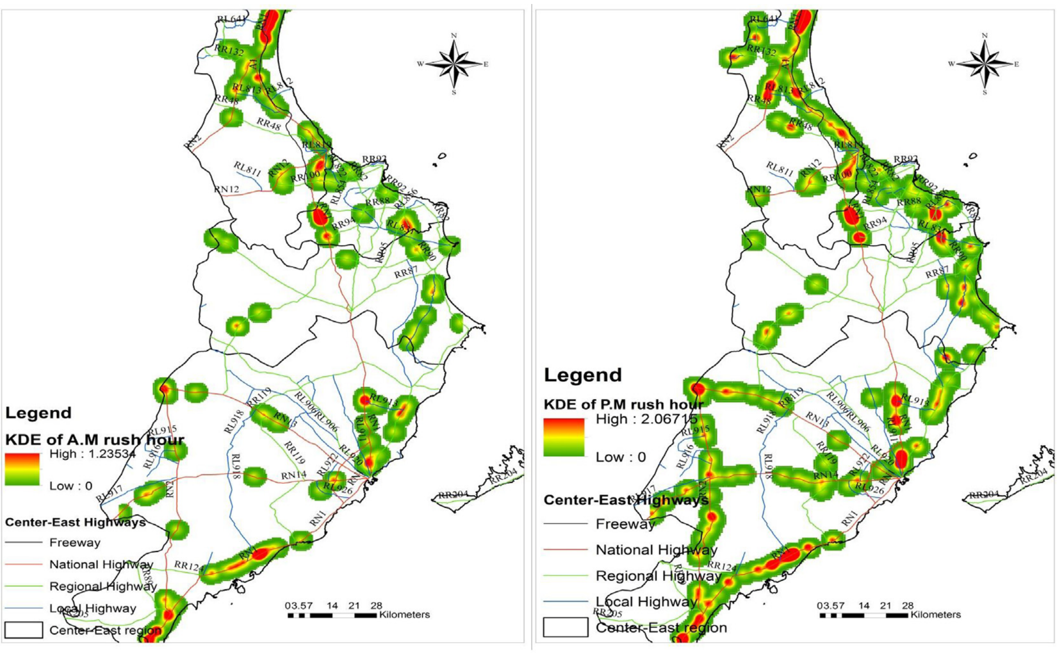
The bandwidth of 3 km creates a surface that presents various peaks and thus appears perfect to illustrate local interaction phenomena. It is clear that varied details are displayed at different temporal scales. As shown, KDE was performed for each subtype of VRUs collisions according to temporal scales (Figs. 5–7).

Performing KDE on the entire of Center-East region in Tunisia roughly, mirrors the overall crash density and is advantageous for identifying primary accidents Hot spots. Fig. 5 exhibits the visual spatial patterns of daytime VRUs collisions from 6 a.m. to 6p.m. (Fig. 5a) (n = 942) and nighttime VRUs collisions from 6p.m. to 6 a.m. (Fig. 5b) (n = 980). Within a broader geographic area, the daytime hot spots are centered in Sousse and Sfax counties and only a few hot spots are located in Mahdia and Monastir counties as indicated by Fig. 5a. All these hot spots were found along national highways and regional highways especially in NH1, NH2 and RH48. These highways encompass the majority of traffic volume. Likewise, the nighttime hot spots are centered especially in Sousse and Sfax and only a few are located in Mahdia and Monastir. All these hot spots were found along national highways and regional highways except of Mahdia and Monastir where hot spot were found along local highways. As compared to daytime, more hot spots were observed in both urban and rural areas of Monastir in nighttime. Given that there is approximately the same number of daytime and nighttime VRUs collisions, substantial differences can be observed between daytime and nighttime. Less hot spots were identified during daytime. Wood et al. (2012) noted that the risk of pedestrian accident is higher during night than in the daytime due to the lower visibility of pedestrians and the degraded ability of drivers in recognizing pedestrian crossing the road. . In addition, we found that hot spots were more found in rural areas for nighttime than daytime VRUs collisions. This is probably due to the effect of higher speed limits, aggressive driving behaviors during night, lower rate of seat belt use, and reduced visibility of VRUs during night and bad road surface conditions in rural areas as compared to urban areas.



(a) (b)

Fig. 5. Results of KDE (a: daytime; b: nighttime).



(a) (b)

Fig. 6. Results of KDE (a: a.m. rush hours; b: p.m. rush hours).

In addition, the glaring headlights of other vehicles belonging to the opposite direction may possibly impair drivers' driving capabilities at night. Almost no hot spots were found in daytime in the southeastern part of study area as compared to nighttime. In daytime, no hot spots were found in Monastir and Mahdia. According to the hierarchy of road network, few hot spots were found in local highways as compared to national and regional highways. This is not surprising, given that these

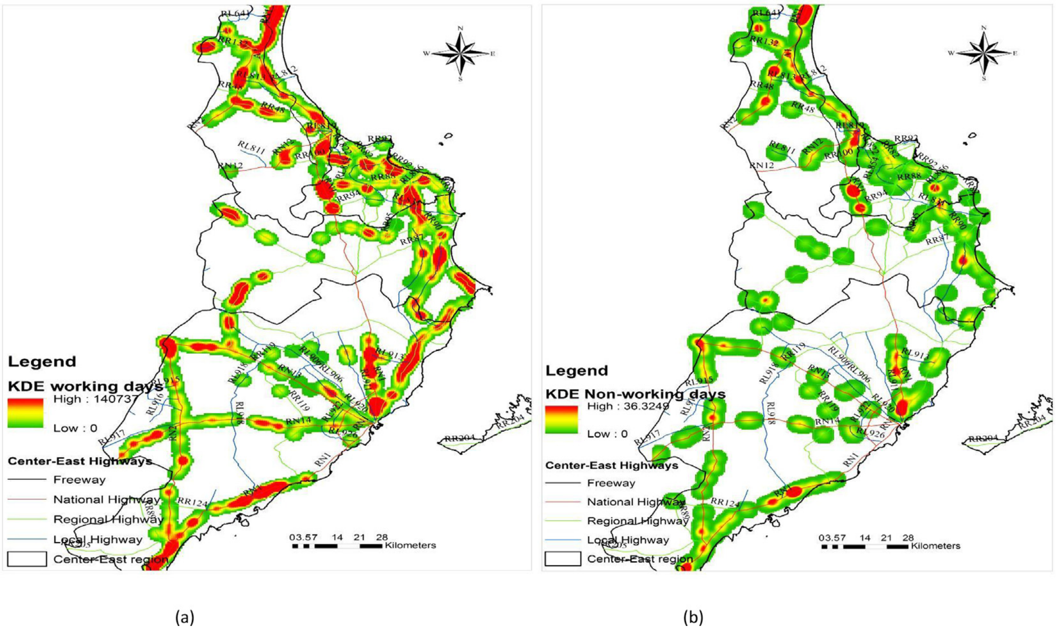


Fig. 7. Results of KDE (a: working days; b: non-working days).

roads are characterized by old design, without paved shoulder and absence of road signs. In relation to highway engineering, posted speed limits and road bump sign reduce the risk of accidents, given the increase in the amount of visual information available to drivers especially during the night. For most of the VRUs collisions hot spots, increasing the number of road signs decreases crash frequency, as drivers likely compensate for the increased number of stop signs on the highway segment by reducing speed and increasing alert as they approach an intersection with a stop sign (Agbelie, 2016). In addition, the presence of paved shoulder on the road offers a safer zone for VRUs. Further efforts should be focused on improving the safety on national highways.

Fig. 6a and b provide insight into the visual spatial pattern of a.m. and p.m. rush hours VRUs collisions respectively. A total of 183 and 323 VRUs collisions were reported during a.m. rush hours (7 a.m. to 9 a.m.) and p.m. rush hours (5p.m. to 7p.m.), respectively. With a lower number of collisions, the detected hot spots locations for a.m. and p.m. are not as concentrated in comparison with daytime and nighttime VRUs collisions. During a.m. rush hour, remarkable hot spots locations can also be found in the region of Sousse and Sfax. The majority of these hot spots tend to be located along major highway entrance especially NH1, RH100 in the region of Sousse and NH1 located in the southern part of the region of Sfax. As for p.m. rush hour, Notable Hot spots locations can also be found in the region of Sousse and Sfax and only a few are located in Mahdia and Monastir. All these hot spots were found along national highways and regional highways. Assessing the a.m. with the p.m. rush hour VRUs collisions, both similarities and discrepancies were observed. The most important distinction between them is that there were fewer hot spots identified during a.m. than during p.m. rush hour. These findings were consistent with previous studies (Park, Lee, & Jeon, 2016), which reported an increased risk of collision on weekday evening peak periods. Further, this result may be attributed to stress and aggression when driving in congested road during p.m. peak hours. During this time, the majority of individuals return at home after work or school. This finding is probably linked to the fact that people are tired due to the time spent on working. Overall, both of these two subtypes of VRUs collisions tend to cluster along the national highways and regional highways, especially in the governorates of Sousse and Sfax.

Fig. 7a and b provide insight into the visual spatial pattern of working days and non-working days VRUs collisions respectively. There were 1396 and 526 VRUs collisions for working days (Monday, Tuesday, Wednesday, Thursday and Friday) and non-working days (Saturday and Sunday), respectively. As show in Fig. 7a, the spatial pattern of working days VRUs collisions tend to be more conforming to daily patterning of activities (Levine, Kim, & Nitz, 1995). They are centered within urban and rural areas of both Sousse and Sfax governorates as well as along the major roads. Besides Sousse and Sfax, working days hot spots were also identified in rural areas of Mahdia. Several notable hot spots within Sousse and Sfax include those at the NH1. As for non-working days VRUs collisions, most of the hot spots were located in the rural areas of Sousse, Monastir and Sfax (Fig. 7b). Almost no hot spots were found in Mahdia. When comparing working days and non-working days VRUs collisions, they all tend to cluster in the rural areas of the Center-East region with the exception of Sousse and along major roads such as NH1. The most important distinction between them is that there were fewer hot spots identified during non-working days than during working days. This is not surprising, considering that there are more VRUs collisions during working days than non-working days. This result shows particular preferences regarding individuals who do not drive in weekend days.

After visual assessment of each subtype maps of VRUs collisions, it can be observed that the nighttime map contains the largest amount of locations with a high number of VRUs collisions. In reverse the a.m. rush hours map has the least amount of high-density locations. The lower density during a.m. rush hours could possibly be due to the overall lower number of VRUs collisions happening during this time. A random tendency point pattern such as daytime VRUs collisions even contains some clustering pattern in visualization by the KDE. It is noteworthy that some VRUs collisions hot spots appear repeatedly in the same location for different subsets. This indicates that these locations actually have a steady high density of VRUs collisions and not just a temporary hot spot that may have been appeared by chance. These kinds of results are important since they may suggest that it is possible to predict some temporal trend to the VRUs collisions distribution, which may help to improve the road safety situation in Tunisia. There are clearly relationships between land use and behavior for different temporal scale and both the exposure as well as the frequency of certain kinds of activities. This is not surprising, given that the majority of the identified hot spots are located at rural areas with two lanes, bad road surface condition, straight alignment, absence of public lighting, absence of guardrail and speed bump. These hot spots are characterized by total disorganization: pedestrian crossing anyhow, anarchic businesses located throughout these areas, schools built without taking into account the safety of children, which probably contribute to heavy traffic volume during rush hours increasing thus the risk of VRUs collisions. Generally, the increase in traffic volume and the level of congestion with irregular driving behavior increase the increased frequency of VRUs collisions. Obviously, the surrounding land uses are important as well as these will certainly specify the nature, magnitude and intensity of conflict between VRUs and motorized traffic. Generally, the spatial patterns of VRUs collisions are highly influenced by daily individual activities. Tunisia's public authorities could use these findings to evaluate if some land-use practices in the Center-East region help to reduce the overall regional traffic demand.

5.3. Vrus injury severity results

In order to give a more detailed picture of the distribution of the variables, a descriptive statistics and cross tabulations between explanatory variables and VRUs collisions severity were presented in Table 1. In this table, the injury severity columns contain percentages calculated across columns within one row. In this case, three levels were selected based on the distribution of crash severity. Specifically, 33.87% of the observed crashes were slight injuries, 36.37% were serious injuries and the 29.40% were fatal injuries.

The corresponding VRUs injury severity model estimation results are presented in Table 2. The results are consequently reported in two categories: one for the likelihood of serious injury and one for the likelihood of fatalities. Results of the odds ratio and their corresponding 95% confidence intervals are presented in Table 2. It should be noted that the OR reflects the influences of variables at a certain level of accident severity. For example if an OR of specific factor at an accident severity is superior to 1 (OR > 1), it confirms that this factor increases the likelihood of sustaining a severe injury. On the contrary, if OR of a specific variable at a certain level of accident severity is less than one (OR < 1) it confirms that this factor decreases the likelihood of sustaining a severe injury. If it is equal to the unity (OR = 1), it indicates no difference between comparison groups. We consider in the model only the explanatory variables that are significant... It is noteworthy that some of variables selected were found to be insignificant such as VRUs age, pedestrian at fault, and roadway alignment. Their insignificance may be explained by the uniqueness of data obtained from the police reported data, the methodology employed, and the dependent variable in the model.

It is also noteworthy that an ordered logit model on the same data resulted in a log-likelihood at convergence of −1584.56 and that an ordered probit model on the same data improved this only to −1576.04. On the basis of estimation results presented in Table 2, the Log Likelihood at convergence LL(β) = −1361.37 and Log likelihood at zero, LL(0) = −1633.59 give the McFadden ρ^2 goodness of fit of 0.16, which is quite good given the amount of variance in injury severity data. Thus, the −1361.37 of the multinomial logit model presented in this work is a statistically significant improvement in model fit. Therefore, the detailed results of ordered logit and ordered probit models are not given. Here the McFadden ρ^2 measures the improvement in model log-likelihood over a model with only alternative specific constants. The results show that the parameters are of plausible sign and that overall model fit is good.

Among VRUs gender, male VRUs are associated with an increased risk of fatal accident ((OR = 1.52; 95%CI [0.15–0.69])) compared to female VRUs. . This finding is consistent with some previous studies (Aloulou & Naouar, 2016; Aziz et al., 2013; Clifton et al., 2009; Eluru et al., 2008; Kim et al., 2010; Pai, 2009; Quddus et al., 2002; Rifaat et al., 2011). Aloulou and Naouar (2016) found that the risk of being victim of a fatal accident is 8.6 times higher for a male than for a female in Tunisia. This can be explained by the fact that in Tunisia, men move more at night and they are more involved in different activities than women are. There are several factors that explain the dangerous behavior of men: the role assigned to them in society, indifference about the usefulness of helmet, aggressive driving, lack of awareness of the consequences related to the excess of speed in urban areas or out of town and driving without concentration (under alcohol or drugs sometimes).

Among VRUs nationality, the Tunisian VRUs are more vulnerable compared to not Tunisians VRUs ((OR = 2.55; 95%CI [0.12–1.75])). . Roadway functional classification refers to the location of accidents according to the hierarchy of road network. Our results are consistent with previous VRUs studies (Kim et al., 2010; Moudon et al., 2011; Tay et al., 2011). We found that compared to other road functional class, crashes occurring in national highway have a higher proportion of serious injury ((OR = 2.94; 95%CI [0.34–1.78])). In Center-East region, national highways are characterized by old design, which does not comply with safety requirements imposed today. In addition, the high proportion of these roads is located outside the urban center that often did not have sidewalks, separate paths for VRUs. These placed the VRUs at higher risks. In these

Table 1
Descriptive statistics and cross tabulations between explanatory variables and VRUs crash severity.

Variables	VRUs Injury severity count			Mean	Std. Dev
	Slight injuries	Serious injuries	Fatal injuries		
VRUs injury severity	508(33.87%)	551 (36.37%)	441(29.40%)		
1. VRUs characteristics					
VRU Gender					
Male	360(35.50%)	383(37.77%)	271(26.73%)	0.67	0.46
Female	148(30.45%)	168(34.57%)	170(34.98%)	0.32	0.46
VRU nationality					
Tunisian	485(33.47%)	531(36.65%)	433(29.88%)	0.96	0.18
Not Tunisian	23(45.1%)	20(39.22%)	8(15.69%)	0.03	0.18
Causality victim	508(33.87%)	551(36.37%)	441(29.40%)		
Pedestrian	304(34.78%)	327(37.41%)	243(27.80%)	0.59	0.49
Cyclist	81(32.40%)	86(34.40%)	83(33.20%)	0.16	0.37
Motorcyclist	123(32.71%)	138(36.30%)	115(30.59%)	0.25	0.43
2. Roadway characteristics					
Road functional class					
Freeway	67(33.17%)	77(38.12%)	58(28.71%)	0.13	0.34
National highways	228(37.81%)	204(33.83%)	171(28.36%)	0.4	0.49
Regional highways	41(30.6%)	51(38.06%)	42(33.34%)	0.08	0.28
Local highways	13(16.05%)	44(54.32%)	24(29.63%)	0.05	0.22
Municipal highways	141(33.02%)	159(37.24%)	127(29.74%)	0.28	0.45
Highways not numbered	18(33.96%)	16(30.19%)	19(35.85%)	0.03	0.18
Roadway alignment					
Not reported	390(33.88%)	425(36.92%)	336(29.19%)	0.76	0.42
Straight	54(34.18%)	57(36.08%)	47(30.05%)	0.1	0.30
Curve right	60(32.79%)	68(37.16%)	55(34.18%)	0.12	0.32
Curve left	4(50%)	1(12.50%)	3(37.50%)	0.007	0.05
Junction detail	508(33.87%)	551(36.37%)	441(29.40%)		
Not at junction	115(32.03%)	147(40.95%)	87(27.02%)	0.23	0.42
Roundabout	38(43.18%)	28(31.82%)	22(25%)	0.05	0.23
T or straggled junction	241(33.71%)	248(34.69%)	226(31.61%)	0.47	0.49
cross roads	114(33.73%)	128(37.78%)	96(28.40%)	0.22	0.41
Road surface condition					
Wet or dump	81(29.14%)	119(42.81%)	78(28.06%)	0.18	0.38
Dry	427(34.94%)	432(33.73%)	363(35.35%)	0.81	0.38
3. Accident characteristics					
Driver at fault					
Not Driver at fault	212(34.87%)	231(37.99%)	165(27.14%)	0.40	0.49
Change of direction	20(28.17%)	21(29.58%)	30(42.25%)	0.04	0.21
Driving without a license	3(20%)	6(40%)	6(40%)	0.05	0.22
Alcohol/drugs	9(37.50%)	10(41.67%)	5(20.83%)	0.05	0.23
Hazardous overtaking	41(30.83%)	57(42.86%)	35(26.32%)	0.008	0.09
Distraction/inattention	60(32.61%)	63(34.24%)	61(33.15%)	0.01	0.09
Driver fatigue	0	3(42.86%)	4(57.14%)	0.01	0.12
Speeding	85(33.83%)	89(35.46%)	77(30.68%)	0.08	0.28
Walking back	16(61.54%)	7(26.92%)	3(11.54%)	0.12	0.32
Not right alignment	33(39.76%)	29(34.94%)	21(25.30%)	0.004	0.06
Disrespecting priority	28(32.94%)	29(34.12%)	28(32.94%)	0.16	0.37
Omission of traffic signs	1(7.69%)	6(46.15%)	6(46.15%)	0.01	0.13
Pedestrian at fault					
Not Pedestrian at fault	336(33.50%)	366(36.49%)	301(30.01%)	0.66	0.47
careless / reckless crossed	151(33.86%)	171(38.34%)	124(27.80%)	0.29	0.45
pedestrian walking / staying the road	21(41.18%)	14(27.45%)	16(31.37%)	0.03	0.18
Type of vehicle implicated					
Passenger car	410(34.08%)	436(36.24%)	357(29.68%)	0.8	0.39
Truck/Heavy Truck	34(35.79%)	34(35.79%)	27(28.42%)	0.06	0.24
Taxi	18(51.43%)	9(25.71%)	8(22.86%)	0.02	0.15
Shared-taxi	32(26.23%)	53(43.44%)	37(30.33%)	0.08	0.27
Motorcycle	14(31.11%)	19(42.22%)	12(26.67%)	0.03	0.17
Visibility					
Clear visibility	173(37.37%)	156(33.69%)	134(28.94%)	0.3	0.46
Average visibility	277(32.02%)	334(38.61%)	254(29.36%)	0.57	0.49
Unclear visibility	58(33.72%)	61(35.47%)	53(30.81%)	0.11	0.31
4. Environment characteristics					
Day of accidents	508(33.07%)	551(36.73%)	441(29.40%)		
Sunday	55(28.80%)	86(45.03%)	50(26.18%)	0.12	0.33
Monday	67(31.90%)	60(28.57%)	83(39.52%)	0.14	0.34
Tuesday	85(33.46%)	80(31.50%)	89(35.04%)	0.16	0.37
Wednesday	71(34.80%)	62(30.39%)	71(34.80%)	0.13	0.34

Table 1 (*continued*)

Variables	VRUs Injury severity count			Mean	Std. Dev
	Slight injuries	Serious injuries	Fatal injuries		
Thursday	71(39.44%)	68(37.78%)	41(22.78%)	0.12	0.32
Friday	57(27.80%)	94(45.85%)	54(26.34%)	0.13	0.34
Saturday	102(39.84%)	101(39.45%)	53(20.70%)	0.17	0.37
Time of accidents	508(33.87%)	551(36.73%)	441(29.40%)		
00.00–03.59	27(29.35%)	36(33.13%)	29(31.52%)	0.06	0.24
04.00–07.59	92(41.07%)	79(35.27%)	53(23.66%)	0.14	0.35
08.00–11.59	101(32.06%)	120(38.10%)	94(29.84%)	0.21	0.40
12.00–15.59	115(33.27%)	121(35.48%)	205(30.79%)	0.22	0.41
16.00–19.59	133(32.44%)	148(36.10%)	129(31.46%)	0.27	0.44
20.00–23.59	40(33.90%)	47(39.83%)	31(26.27%)	0.07	0.26
Season of accident					
Winter	178(38.44%)	169(36.50%)	116(25.05%)	0.3	0.46
Spring	65(31.86%)	85(41.67%)	54(26.47%)	0.13	0.34
Summer	180(29.51%)	216(35.41%)	214(35.08%)	0.4	0.49
Autumn	85(38.12%)	81(36.32%)	57(25.56%)	0.14	0.35
Weather condition					
Fine	371(32.32%)	430(37.46%)	347(30.23%)	0.76	0.42
Raining	122(39.23%)	106(34.08%)	83(26.69%)	0.2	0.4
Fog	1(50%)	1(50%)	0(0%)	0.001	0.03
Cloud	14(37.84%)	12(32.43%)	11(29.73%)	0.02	0.15

roads, drivers or motorcyclist did not respect the posted speed limit. Some previous studies that examined the relationship between VRUs severity and vehicle speeds found the same results (Yasmin and Eluru, 2013; Savolainen & Ghosh, 2008; Schneider et al., 2009; Sze & Wong, 2007). Generally, there are apparently some considerable differences in behavior in rural areas versus urban areas. Further studies exploring the linkage between VRUs collisions severity and a variety of geometric characteristics, roadway characteristics, traffic flow characteristics along national highways in Tunisia could shed further light on this issue.

Accident characteristics include driver at fault, type of vehicle implicated and visibility. Driver at fault can be identified as a major accident factor derived from the driver's behavior. The change of direction and hazardous overtaking increase the probability of sustaining fatal accidents ((OR = 1.91; 95%CI [0.05–1.25])) and ((OR = 1.33; 95%CI [−0.08 to 4.16])) respectively compared to other driver contributory factors. This can be explained by reducing the driver's capacity to keep mastery of his vehicle at change of direction or hazardous overtaking. With VRUs collisions, drivers are more frequently at fault as compared with VRUs.

In case of vehicle implicated, the shared taxi was also found to be significant in the serious injury function and estimated to be associated with higher VRUs injury severity ((OR = 1.55; 95% CI [−0.01 to 0.90])). This result can be explained by the dangerous behavior of drivers, which do not respect traffic lights and road signs. The average visibility was also found to be significant in the serious injury function and estimated to be associated with higher VRUs injury severity ((OR = 1.33; 95%CI [0.21–0.55])) relative to clear visibility as reference category. This finding is probably linked to the effect that poor visibility increases the VRUs collisions.

In terms of environment characteristics, the season factor shows that accident severity during the summer season is higher ((OR = 1.82; 95%CI [0.29–0.9])). These results are explained by the increase on the activity of people in good weather conditions and their reasons for travel and consequently their exposure to the risks of accidents and daylight in summer months lasts longer than in winter months. In Tunisia, summer is characterized by the growth of economic activity and social relations (return of migrants, and activities related to interior and international tourism), which generate in return increased traffic on the roads. This finding is consistent with those of Pai (2009) and Moore, Schneider, Savolainen, and Farzaneh (2011). Nevertheless, Kim et al. (2007) found that the risk of sustaining a severe accident is higher during spring. Day of accident refers to day accident in which the accident occurred. In our case, Monday, Tuesday, Wednesday, Thursday and Saturday are associated with lower injury severity involving VRUs. This finding is consistent with Pai (2009) and Quddus et al. (2002), which reported that weekend days are associated with severe injuries as compared to weekdays, while Sze and Wong (2007) reported the opposite. The fine weather condition is a significant factor in the injury severity model and estimated to be associated with higher VRUs injury severity relative to foggy weather as reference category ((OR = 1.36; 95%CI [0.003–0.63])). This result is consistent with previous findings (Kim et al., 2010; Moore et al., 2011; Tay et al., 2011; Zahabi, Strauss, Manaugh, & Miranda-Moreno, 2011), which showed a decreased risk of fatal accident under inclement weather conditions such as rainy. This finding is probably linked to the effect of reduced speed levels under inclement weather conditions, as drivers tend to drive carefully under hazardous conditions.

With respect to time of accident, a number of different periods were associated in the multinomial logit model. The best specification was based on the partitioning of the day into six dummy variables for 4 h time intervals. Compared with late night period (Midnight to 03.59) as reference time period, early morning time on the thresholds indicates a low likelihood of severe injuries. This result may capture the fact that in Tunisia, traffic flow during early morning is relatively low.

Table 2
Estimation result of VRUs injury severity model.

	Odds Ratio and 95% confidence interval [Lower-Upper];OR (95% CI)					
	Serious injuries			Fatal accidents		
	Odds Ratio	(95% CI)		Odds Ratio	(95% CI)	
		Lower	Upper		Lower	Upper
1. VRUs characteristics						
VRU Gender						
Female (ref)						
Male				1.52***	0.15	0.69
VRUs nationality						
Not Tunisian VRUs(ref)						
Tunisian VRUs				2.55**	0.12	1.75
Causality victim						
Cyclist (ref)						
Pedestrian	0.49**	−1.39	−0.08			
Motocyclist	0.38***	−1.59	−0.31	0.47**	−1.44	−0.06
2. Roadway characteristics						
Road functional class						
Freeways (ref)						
National Highways	2.94***	0.34	1.78	2.11**	−0.003	1.51
Junction detail						
Not at junction(ref)						
Roundabout	0.57**	−1.9	−0.005			
Road surface condition						
Wet or dump(ref)						
Dry	0.69**	−0.68	−0.06			
3. Accident characteristics						
Driver at fault						
Not driver at fault (ref)						
Change of direction				1.91**	0.05	1.25
Hazardous overtaking				7.69*	−0.08	4.16
Omission of traffic signs	0.40**	−1.82	−0.05	0.24**	−2.67	0.17
Type of vehicle implicated						
Passenger car(ref)						
Taxi	0.47*	−1.56	0.05			
Shared-taxi	1.55*	−0.01	0.90			
Visibility						
Clear visibility (ref)						
Average visibility	1.33**	0.21	0.55			
4. Environment characteristics						
Day of accident						
Sunday(ref)						
Monday	0.57**	−1.04	−0.07			
Tuesday	0.60**	−0.96	−0.05			
Wednesday	0.55**	−1.06	−0.10			
Thursday	0.61**	−0.96	−0.01			
Saturday	0.63**	−0.89	−0.02	0.57**	−1.06	−0.05
	Serious injuries			Fatal accidents		
	Odds Ratio	(95% CI)		Odds Ratio	(95% CI)	
		Lower	Upper		Lower	Upper
Time of accidents						
00.00–03.59(ref)						
04.00–07.59				0.53*	−1.24	0.00
Season of accident						
Winter(ref)						
Summer				1.82***	0.29	0.9
Weather condition						
Fog(ref)						
Fine	1.32*	−0.06	0.58	1.36**	0.003	0.63

Goodness-of-fit measures: Number of observations = 1500; Log likelihood at convergence LL(β) = −1361.37; Log likelihood at zero, LL(0) = −1633.59; The Mcfadden goodness of fit ρ^2 = 0.16 ref = Reference category. Slight injury is reference category with coefficients restricted at zero.
*** Significant at 1%; ** Significant at 5%; * Significant at 10%
Coefficients that were not significant at the 10% level were restricted to zero and omitted from the table.

6. Conclusions and future research directions

While many nations around the world have strategies to mitigate VRUs collisions, it is apparent that many countries such as Tunisia are lacking in VRUs basic safety amenities. A greater understanding of risk factors associated with VRUs injury is required in order to reduce this persistent public health problem. The spatial component of traffic accidents has usually interested scientists and GIS-users through identifying hot spots to target prevention efforts. Previous studies did not investigate VRU collisions both spatial and temporally, and that portrays the Tunisian reality. Firstly, this study presents an innovative approach to spatial analysis of traffic accidents. An integrated two-step approach was applied. Ripley's K-function was used to detect the highways segments, where VRUs collisions were significantly clustered, dispersed or random. While Ripley's K-function is useful to test the global clustering tendency of VRUs collisions within study Area, it cannot detect where exactly the VRUs collisions aggregates across the study Area. To overcome this, a KDE was applied. Taking that approach is the fact that point pattern has a density at any location within the study area not only at the location where the event happens or is displayed (Mohaymany et al., 2013). This can be a suitable property that fits KDE to assess VRUs collisions especially when only their approximate positions are available, creating a more realistic picture of VRUs distributions. As result spatial clustering pattern of each subtypes of VRUs collisions according to temporal scale were clearly observed under the distance of 38–40 km with the exception of daytime VRUs collisions which shows a random tendency. All time-based subtypes of VRUs collisions also were found to be clustered along the National Highways and Regional Highways especially in the region of Sousse and Sfax. After visual assessment of each subtypes maps of VRUs collisions, it can be observed that the nighttime map contains the largest amount of locations with a high number of VRUs collisions. In reverse the a.m. rush hours map has the least amount of high density locations. The lower density during a.m. rush hours could be due to the overall lower number of VRUs collisions happening during this time. These results are important since they may suggest that it is possible to predict some temporal trend to the VRUs collisions distribution, which may help to improve the road safety situation in Tunisia.

Secondly, we investigated the influence of personal and environmental factors for VRUs injuries severity within the Center-East region in Tunisia. Results from VRUs severity model suggest that the degree of injury severity is higher for male than female victim. The Tunisian VRUs are more likely to be involved in severe collision than non-Tunisian VRUs. Among driver contributory factors, the change of direction and hazardous overtaking increase the probability of sustaining fatal accidents compared to other driver contributory factors. The season factor shows that accident severity during the summer season is higher. The fine weather condition is a significant factor in the injury severity model and estimated to be associated with higher VRUs injury severity relative to foggy weather.

From a policy view point, this kind of analysis can certainly help public authorities in Tunisia to develop appropriate safety measures that can possibly reduce the number of VRUs injuries and fatalities. Once hot spots are identified, most appropriate interventions are required to reduce accidents. This will involve the development of planning rules of road environment, identify shortcomings in the regulation and make recommendations to identify solutions for the elimination of black areas and better management of the road environment. VRUs collisions are preventable. A better knowledge of the spatial distribution of VRUs collisions in Tunisia could help decision makers in developing effective measures to enhance road safety by developing a suitable land use practices, creating efficient transportation systems, and formulating proper traffic policies and laws. An effective national road safety policy is crucial to tackle the problem. In general, road safety policy should be developed according to a systemic approach that looks into interactions between land use, vehicle, motorized and non-motorized users. The attractiveness of this research is that it suggests recommendations in terms of enforcement, education, and engineering. One of the apparent messages of this study is that there is requirement to improving driver behavior. Driver at fault can be identified as a major accident factor derived from the driver's behavior. With VRUs collisions, drivers are more frequently at fault as compared with VRUs. It is fundamental that high-quality information on road traffic accidents is a precondition for VRUs safety diagnosis and the development of effective safety enhancement programs. Yet, Erdogan et al. (2008) proved that the achievements of good results was based on the success of spatial analysis, which depends essentially on the exactness, trustworthiness and the exhaustiveness of traffic accidents reports. Any kind of effort to tackle the issue of underreporting is very crucial for data entry and analysis to enhance spatial analysis of road safety.

The results of this study are subject to some limits. Firstly, our research data were restricted to Center-East regions in Tunisia. An obvious extension is always important to include a larger sized database including additional regions. Furthermore, data that are more detailed compared to NOITDSRS crash reports including a more in-depth diagnosis of the accident scene would certainly open up additional investigations opportunities and give more accurate model estimation. Secondly, many researches employed the KDE method to identify hazardous segments since this method calculates the density of crashes in a neighborhood around those crashes without statistical significance. Further location reference including the use of GPS can potentially enhance the current location approaches (Anderson, 2009; Bíl et al., 2013). Thirdly, while this work is limited to the evaluation of VRUs crash hot spots and related risk factors for injury severity, additional investigation is required based on the linkage between hot spots-based crash counts and a variety of geometric characteristics, roadway characteristics, traffic flow characteristics and spatial features along these sections.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.trf.2018.05.003.

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