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Monitoring Changes In The Spatio-Temporal Characteristics And Dynamics Of Vulnerable Versus Protected Road User's Collisions Hot Spots

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Abstract

This study analyses the changes in the spatio-temporal distribution of vulnerable (VRUs) versus protected road user's (PRUs) collisions hot spots in coastal regions in Tunisia over the period 2006-2018. It suggests an innovative multi-stage spatial crash hot spot analysis approach that combines the spatial analysis and spatio-temporal pattern analysis. First, optimized PRUs and VRUs hot spots Versus optimized PRUs and VRUs probable hot spots were used to determine settings that will produce optimal hot spot analysis results. Second, kernel density estimation will be used under six temporal scales (a.m. rush hours, p.m. rush hours, working days, non-working days, daytime and nighttime PRUs and VRUs collisions). The findings indicate that the majority of optimized PRUs and VRUs hot spots were portrayed in the northern part of the study area particularly in road junctions between national and regional highways. The detected PRUs and VRUs hot spots locations for non-working days are not concentrated in comparison with working days. Less PRUs and VRUs hot spots were identified during daytime in comparison with nighttime. Finally, the detected PRUs and VRUs hot spots locations for a.m. peak hours are not concentrated in comparison with p.m. peak hours. From a policy view point, the results could assist public authorities to delineate less hazardous road locations.

Keywords: Vulnerable Road user's; Protected Road user's; Optimized hot spot; Probable hot spot; Kernel density estimation.

1. Introduction

The transportation system is regarded as one of the most complicated and hazardous systems people have to deal with on a daily basis. This complexity is also clearly apparent in road traffic collisions (RTCs) analysis as they simply cross the areas of engineering, geography and human behavior (Sabel et al. 2005). RTCs are rapidly becoming a threat to community health and national growth in many developing regions since they lead to poverty by causing fatalities, injuries, and disabilities. It is estimated that 1.2 million persons are killed and not less than 50 million injured each year in the world in RTCs. It has been forecast that RTCs will become the fifth leading cause of mortality by 2030 (WHO, 2013). While improvement has been reported in high income countries, the same cannot be said about low income countries with particular focus on the African continent which is a signatory to numerous developmental programs yet lack the financial resources needed to reduce RTCs (Moyer et al. 2017). All types of road users such as protected road user "PRUs" and vulnerable road users "VRUs" are likely to be injured or dead in RTCs, but there are significant differences in death rates among different groups of road users. PRUs are those road users who generally have protective shells, restraints and higher collision masses compared to other road users (Damsere-Derry et al., 2017). Such road users are predominantly in enclosed cars and with road crashes, enjoy greater safety. Vehicle occupants including drivers and passengers are classified as PRUs. VRUs is a term used to describe individuals who are the most vulnerable in traffic, i.e. those unprotected by an outside shield (Damsere-Derry et al., 2017). Pedestrians and two-wheeler including cyclists and motorcyclists are accordingly considered as VRUs. For the enhancement of traffic safety, it is essential to understand several properties of VRUs and PRUs collisions both temporally and spatially. Considerable studies efforts have been made on applying various geostatistical techniques to RTCs hot spot identification such as K-means clustering (De Silva et al., 2018., Waldon et al., 2018), Bernoulli spatial model (Dai, 2012), Kernel Density Estimation “KDE” approach (Blaskez and Celis 2013 ; Takhali et al., 2015 ; Shafabakhsh et al., 2017 ; Toran Pour et al.,2018 ; Ouni and Belloumi, 2018 ; Colak et al., 2018 ; Chen et al., 2018 ; Achu et al., 2019 ; Le et al., 2020 ; Nazneen et al., 2020 ; Özcan and Küçükönder, 2020 ; Islam and Dinar, 2021 ; Bajada and Attard, 2021), Network-based KDE (Loo and Yao , 2013 ; Xie and Yan, 2013 ; Mohaymany et al., 2013 ; Benedek et al., 2016 ; Chen et al., 2018 ; Lee and Khattak, 2019 ; Harirforoush and Bellalite, 2019), and spatial autocorrelation indicators (Songchitruksa and Zeng, 2010 ; Gundogdu, 2010 ; Blaskez and Celis 2013 ; Xie and Yan, 2013 ; Erdogan et al., 2015 ; Colak et al., 2018 ; Lee and Khattak, 2019 ; Ouni and Belloumi, 2019, Le et al., 2020). Chen et al, (2018) applied a mixture of spatial statistical approach to identify hot spots of road traffic crashes in a redeveloping area of Shanghai. They found that more hot spots occurred in urban area at road intersections than on road segments. De Silva et al., (2018) applied an epidemiological and built environment analysis of RTCs in Sri Lanka. They found that all hot spots were in urban areas, and most were at intersections. Ouni and Belloumi (2019) examined the methodological issues of identifying RTCs hot zones and probable hot zones in Tunisia. They concluded that hot zones and probable hot zones are located along highways with a prominent rural character.

RTCs are rarely random in space and time due to the underlying environment on which RTCs are based, such as highways networks, traffic volumes and, essentially, human activities, often exhibits discernible spatial and temporal patterns (Xie and Yan, 2013). There were several past studies carried out associated with time-related crashes. However, their findings were mainly displayed by simple graphs, which do not enable us to visualize accident clusters varied over space and time (Dozza et al., 2016). It is crucial to have a deep understanding of both the spatial and temporal dimensions simultaneously of RTCs (Le et al., 2020). Previous spatio-temporal analysis studies solved the constraint of the time dimension as it can summarize both the spatial and temporal patterns (Plug et al.,2011; Kaygisiz et al., 2015; Vemulapalli et al., 2017; Ouni and Belloumi, 2018; Toran Pour et al., 2018; Cheng et al., 2019; Bil et al., 2019 ; Achu et al., 2019; Wang et al., 2019; Le et al., 2020; Ouni et al., 2020). Plug et al. (2011) investigated the spatio-temporal pattern of single and multiple vehicle collisions in Western Australia. They found that in non-metropolitan areas, collisions occur most frequently between 3 and 7 p.m. and between 8 to 11 p.m. in metropolitan areas. Kaygisiz et al. (2015) developed a spatio-temporal approach for collision prevention in relation to behavioral factors in driving in Turkey. Their results revealed that hot spots vary in both time and space according to vehicle type and the direction of traffic flow. Vemulapalli et al. (2017) applied GIS-based spatial and temporal analysis of aging-involved collisions in Florida. They found that aging-involved collisions tend to occur during mid-day rather than the peak hours. Toran Pour et al. (2018) explored the influence of pedestrians’ age and gender on the spatio-tempral distribution of pedestrian-vehicle collisions (PVC) in Australia. Results revealed that most PVC occur in the central of business district during the daytime, and occur mostly around hotels, clubs and bars during night time. Recently, Bil et al. (2019) applied a detailed spatio-temporal approach of traffic crash hot spots to the rural parts of primary roads in the Czech Republic between 2010 and 2018. Three temporal behavior types of hot spots were identified such as emergence, stability and disappearance hot spots. They found that the majority of hot spots remained stable over time and some hot spots emerge due to safety-related negative factors. Wang et al., (2019) developed a spatio-temporal workflow to assess bicycle-motorized vehicle collisions (BMVC) on high-risk locations in Taipei, Taiwan. They found that BMVC are more likely to aggregate in the winter, on weekdays, and during peak hours. Le et al. (2020) applied a GIS-based statistical analytic technique to explore the temporal-spatial patterns of RTCs hot spots in Hanoi varied according the specific time intervals of day and seasons. They found that collisions with the high severity indices often happen in winter. In contrast, collisions with the low severity indices often happen in spring and fall. Also, the majority of hot spots are mainly located at the intersections in the center of Hanoi and near the illegal crossroads.

Develop and implementation of reliable countermeasures to promote the safety of road users will require not only a better understanding of the main crash contributing factors but the spatio-temporal patterns of VRUs and PRUs as well. Since 1990, Tunisia has experienced exponential growth of motorization. Its open economic policies mixed with underdeveloped road system have resulted a massive burden of RTCs. One of the main issues facing the Tunisian public authorities is exactly where and how to implement preventives measures that will have significant impact on road safety. Achieving decreasing in the number of RTCs is generally a national concern. With this motivation, the objective of this research is to investigate the spatio-temporal distribution of RTCs affecting the VRUs and PRUs in Tunisia using several methods to help create protective countermeasures

at local level over space and time that can reduce such traffic collisions. To do so, this research suggests an innovative multi-stage spatio-temporal crash hot spot analysis approach that combines the spatial analysis and spatio-temporal pattern analysis. While this study identifies findings for specific areas within the coastal regions in Tunisia, the potential of the methodologies developed within this study extends beyond those study areas and may be applied to a wide variety of regions.

2. Data and methodology

2.1. The study area and data collection

The study area centers on the coastal regions of Tunisia including the governorates of Nabeul, Sousse, Monastir, Mahdia, and Sfax. The geographic location of the coastal regions extended from the North to the East is one of the comparative advantages that offers a variety of services through several sectors. The coastal zone plays a significant role in Tunisian cultural, social, and economic progress. On the other hand, the coastal zone is a space of extroversion at which Tunisia opens to the outside by to the concentration of infrastructure, including 9 ports, an oil terminal, and over 6 international airports (Ouni and Belloumi, 2019). These activities trigger a need for more intense mobility on the coast compared to inland areas which explain the increase in the motorization of coastal populations compared to inland areas.

VRUs and PRUs collisions records in coastal regions in Tunisia over the recent 13 years from 2006 to 2018 collected from National Observatory for Road Safety (NORS) in Tunisia were used in this study. The study is limited to PRUs and VRUs collisions which resulted in casualties. The collected collisions data include the route name identical as GIS layer of highways for locating both PRUs and VRUs collisions on highway map using linear referencing tool available in ArcGIS 10.6. The locations of PRUs and VRUs collisions were mapped with World Geodetic System 1984 (WGS84) projection, a similar projection to the highways data. Consequently, 4090 PRUs and 3600 VRUs collisions records within the survey period were used for this study. Figure 1 shows that PRUs and VRUs collisions, injuries and fatalities were oriented in a Northwesterly-Southwesterly trend and stretch longest side of the study area. The majority of previous scientific studies are based on hypothetical or selected highways rather than the entire road network (Ouni and Belloumi, 2019). This study differs completely from those studies by using a detailed geocoded road network consists of approximately 3720 km of numbered road, divided in about 130 km of a Freeway, 834 Km of National highways (NH), 1800 Km of Regional highways (RH), and 956 Km of Local highways (LH).

2.2. Methodology

Optimized hot spots analysis

The optimized hot spot analysis tool distinguishes statistically significant spatial clusters of high values (hot spots) and low values (cold spots) from the given incident point or weighted data to determine settings that will produce optimal hot spot analysis results. It automatically aggregates incident data, identifies an appropriate scale of analysis, and corrects for both multiple testing and spatial dependence using the False Discovery Rate (FDR) correction method (ESRI – ArcGIS Pro, 2021). The tool uses the aggregation method to count the collisions within fishnet grids. The optimized hot spot analysis tool uses the Getis-Ord G_i* statistics. Successfully applied in several other spatial RTCs analysis (Gundogdu, 2010; Songchitruksa and Zeng, 2010; Erdogan et al., 2015; Ouni and Belloumi, 2019), the Getis-Ord G_i* first introduced by Getis and Ord (1992) is estimated as follow:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}{}^2 - (\sum_{j=1}^{n} w_{ij})^2}{n-1}}}, \forall\ i \neq j \quad (1)$$

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j{}^2}{n} - (\bar{X}^2)} \quad (3)$$

Where x_j is the attribute value for feature j, w_{ij} is the spatial weight between feature i and j, and n is to the total number of features. G_i* returns z-score and p-value which are used to estimate the statistical significance of spatial autocorrelation. The resulting map provides the z-scores and p-values for each PRUs and VRUs collisions dataset aggregated in a fishnet grid. A z-score of ± 1.65, ± 1.96 and ± 2.58 represent the optimized hot spot with 90%, 95% and 99% confidence levels respectively. A feature's high z-scores associated with small p-values indicate spatial clustering of high values. A low (negative) z-scores associated with small p-values indicate a spatial aggregation of low values. When more z-scores are high (or low), the aggregation is more intense. A z-score near zero indicates the absence of spatial aggregation (Ouni and Belloumi, 2019). The probability value of a being a hot spot must be greater than the threshold z-score value of 1.645 obtained from a normal distribution at 95% confidence level (Gundogdu, 2010; Ouni and Belloumi, 2019). Therefore, the threshold z-score value between 1.002 and 1.645 is chosen to highlight the optimized probable hot spots (Ouni and Belloumi, 2019).

KDE analysis

KDE is one of the most popular and well-established non-parametric approach which has been widely used 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 collision occurs or is displayed (Ouni and Belloumi, 2018). This approach can provide researchers with a continuous and smooth surface of spatial density estimations by weighting nearby points more than far ones based on a particular kernel function. One common mathematical function used is given below:

$$\hat{f}(x,y) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \tag{4}$$

Where $\hat{f}(x,y)$ is the density estimation at location (x,y) , n is the number of collisions, h is the smoothing parameter or bandwidth which is always larger than 0 (only points within bandwidth h are used to estimate $\hat{f}(x,y)$), K is the kernel function, and d_i represents the distance between the location (x; y) and the location of the i^{th} collision. There are a wide variety of kernel functions, such as Gaussian, Quartic, Negative exponential, Triangular and Epanichnekov functions (Ouni et al, 2020). In this study, the Quartic kernel function available in ArcGIS 10.6 is applied. The specific form of the Quartic kernel function is:

$$k\left(\frac{d_i}{h}\right) = K\left(1 - \frac{d_i^2}{h^2}\right) \quad \text{when} \quad 0 < d_i \le h \tag{5}$$

$$k\left(\frac{d_i}{h}\right) = 0 \quad \text{when} \quad d_i > h \tag{6}$$

in equation (5), K is the kernel function, h is the bandwidth and d_i represent the distance between the location (x; y) and the location of the ith collision. in equation (6), K is often a scaling factor and its main function is to ensure the total volume under Quartic curve is 1. The common values used for K are 3/π and 3/4.

Several studies suggest that the accuracy of kernel function k is less important than the impact of bandwidth h. However, the density pattern well certainly be affected by the choice of bandwidth. A very small bandwidth will produce under-smoothed density map. On the other hand, a large bandwidth will over smooth the density estimation, so we risk losing information, which will exhibit less variability between areas. Therefore, after several tests, a bandwidth of 3000 meters and cell size of 400 meters was selected for the density analysis for the studied period. In this paper, the 13-years from 2006 to 2018 PRUs and VRUs collisions data were divided according to six temporal scales (daytime (5 a.m. to 5 p.m.), nighttime (5 p.m. to 5 a.m.), a.m. rush hours (7 a.m. to 9 a.m.), p.m. rush hours (5p.m. to 7 p.m.), working days (Monday to Friday) and non-working days (Saturday and Sunday)). Then the density of each subset is analyzed using KDE approach. The hot spots for all these points patterns could be easily defined via visual KDE surfaces.

3. Results and discussion

3.1. Optimized PRUs and VRUs hot spots analysis

Figure 1 delineates the optimized PRUs and VRUs hot spots and probables hot spots. The resulting map creates a new output feature class with a z-score and p-value for each PRUs and VRUs collisions dataset aggregated in a fishnet grid. The author can notice that 144 and 91 optimized PRUs and VRUs statistically significant hot spots respectively were detected with 90%, 95% and 99% confidence levels. It is obvious that optimized PRUs and VRUs hot spots are not randomly distributed. The majority of optimized PRUs and VRUs hot spots were portrayed in the northern part of the study area especially in the governorates of Nabeul and Sousse. Absolutely no optimized PRUs and VRUs hot spots were found in the governorate of Monastir, and Mahdia. Since G_i* z-score can be measured for each fishnet grid, it can be used as a dangerousness index. The riskiest grid would be the grid with the largest z-score value, and the least risky grid would be the grid with the smallest z-score value. This approach actually zooms into locations which demand further investigation. The outputs showed that there were 62 grids and 85 grids with G_i* z-score > 2.58 and G_i* p-values < 0.01 for PRUs and VRUs respectively. It indicates that these grids were the riskiest locations with the statistical meaning at the confidence level of 99%. These locations were ranked in ascending order according to a dangerousness index and displayed visually on the map (figure 2.b and 2.d). Closer examination of the riskiest PRUs and VRUs hot spots reveals some outstanding spatial clusters of crashes covering specific locations. Since each map has identified distinct and similar clustering patterns. Several important spatial features are discernible. The majority of these hot spots were portrayed in the governorates of Nabeul. All these hot spots are located along national and regional highways, more precisely in NH1, RH28, RH29, RH42, RH43, RH44 where more rural activities are taking place. These findings have been assigned to several explanations, such as higher speed limits, aggressive driving behaviors, lower rate of seat belt use and bad road surface conditions in rural area as compared to urban area, which suggests that a priority for traffic safety enhancement should be put along these rural hot spots. A rather significant disparity was observed between the hot spots that occur on regional highways with the rest of roads. Not surprisingly, the highlighted governorate overlaps the more densely regional highways in Tunisia. The highest numbers of PRUs and VRUs hot spots are observed at the central part of the region of Nabeul particularly in road junctions between NH1 and RH28 and between NH1 and RH42 which link many of the residential areas to these highways. A finding consistent with (Truong and Somenahalli, 2011; De Silva et al., 2018) which reported that hot spots are mainly located at intersections between the major roads. In our case, the threshold z-score value between 1.002 and 1.645 at 95% confidence level is chosen to highlight the optimized probable hot spots. A probable hot spot refers to a location that that are not a hotspot yet but have high potential for being hotspot in near future. Thus, PRUs and VRUs collisions can be anticipated easily. By running optimized hot spot analysis, a more distinctive pattern of optimized PRUs and VRUs probables hot spots could be detected. PRUs probable hot spots are identified everywhere in the region, mainly in the north and southwestern part of the region. Some VRUs probable hot spots were also portrayed in the central part of the region in the vicinity of the governorate of Sousse.

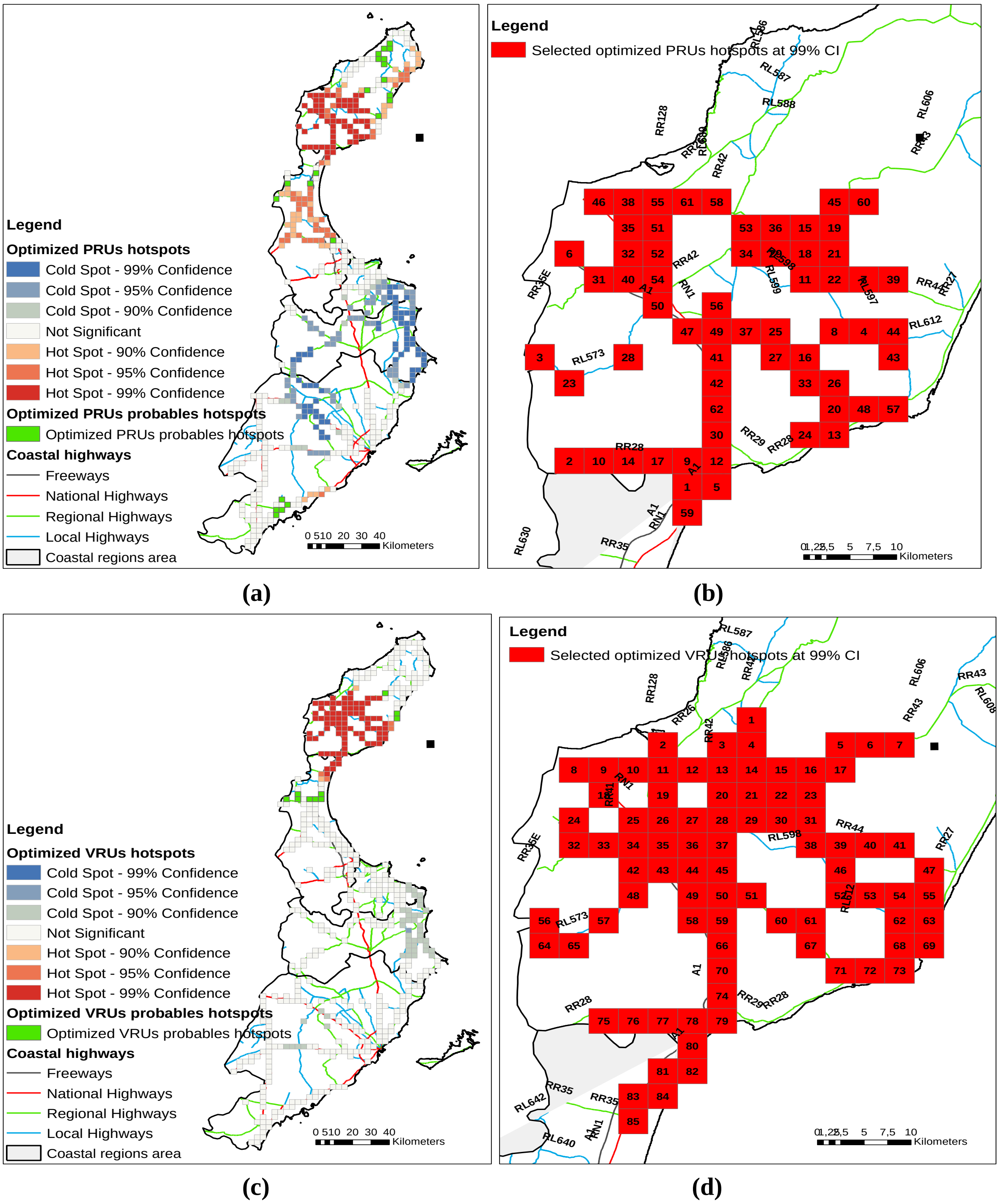

Figure 1 : (a) Optimized PRUs hot spots and probable hot spots, (b) Zoomed view of the riskiest PRUs hot spots, (c) Optimized VRUs hot spots and probable hot spots, (d) Zoomed view of the riskiest VRUs hotspots

3.2. Spatio-temporal pattern of PRUs and VRUs hot spots

For the purpose of analysis, PRUs collisions were categorized into: a.m. rush hours (n = 412); p.m. rush hours (n = 673); working days (n = 2823); non-working days (n = 1267); daytime (n = 2074) and nighttime PRUs collisions (n = 2016). VRUs collisions were categorized into: a.m. rush hours (n = 338); p.m. rush hours (n = 685); working days (n = 2590); non-working days (n = 1010); (5) daytime (n =

1772) and nighttime VRUs collisions (n = 1828).

Figures 2 and 3 provides insight into the visual spatial pattern of daytime, nighttime, a.m. rush hours, p.m. rush hours, working days and non-working days PRUs and VRUs collisions in coastal regions in Tunisia. As shown in figures 4 and 5, PRUs and VRUs collisions appear to exhibit similar spatial patterns. It is clear that varied details are displayed at different temporal scales. Assessing daytime and nighttime hot spots, there were clearly some outstanding spatial clusters covering specific locations. Substantial differences can be noticed between daytime and nighttime hot spots. Less PRUs and VRUs hot spots were identified during daytime. This is likely a consequence of reduced visibility under dim lighting, higher vehicular speed under lighter traffic flows, and possible negligence or inattentiveness that occur during nighttime. Further, dark conditions may also lead to longer response times by emergency crews. These findings were consistent with (Wood et al.,2012) which found that pedestrian collisions are higher during nighttime than in the daytime due to the reduced visibility of pedestrians and the degraded ability of drivers in recognizing pedestrians crossing the road. During nighttime, PRUs and VRUs hot spots are identified everywhere in the region, mainly in the northern part and in lateral highways in the southern part especially in NH-1 and NH-2 which link the region of Sfax to the region of Gabes and Skhira respectively. The link Sfax-Skhira-Gabes host heavy traffic flow generated by the phospho-chemical activity between these areas.

Assessing a.m. and p.m. peak hours' hot spots within a broader geographic area, both similarities and discrepancies were observed. The most important distinction between them is that the detected hot spots locations for a.m. peak hours are not concentrated in comparison with p.m. peak hours. These findings followed (Ouni and Belloumi, 2018; Ouni et al.,2020) which reported an increased risk of collisions during evening peak hours. These results are reasonable. This is likely a consequence of stress caused by driving in congested road during p.m. peak hours. Several p.m. peak hours' hot spots are centered within urban and rural areas of both Nabeul, Sousse and Sfax governorates as well as along the major roads and only a few are located in Monastir. No hot spots were detected in the region of Mahdia.

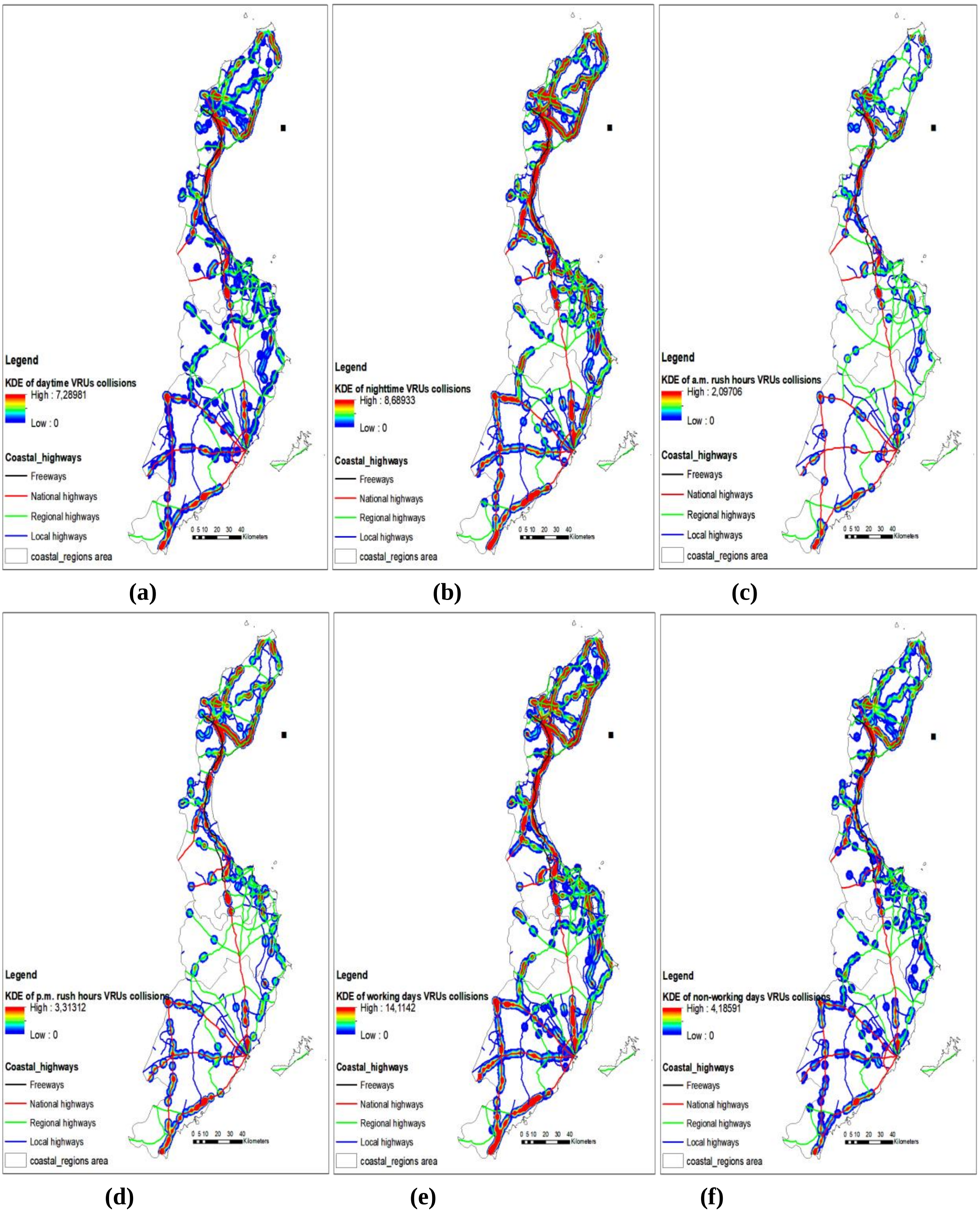

Figure 2 : KDE results of VRUs collisions : (**a)** Daytime, (**b)** Nightime, (**c)** a.m rush hours, (**d)** p.m rush hours, **(e)** Working days, **(f)** Non-working days

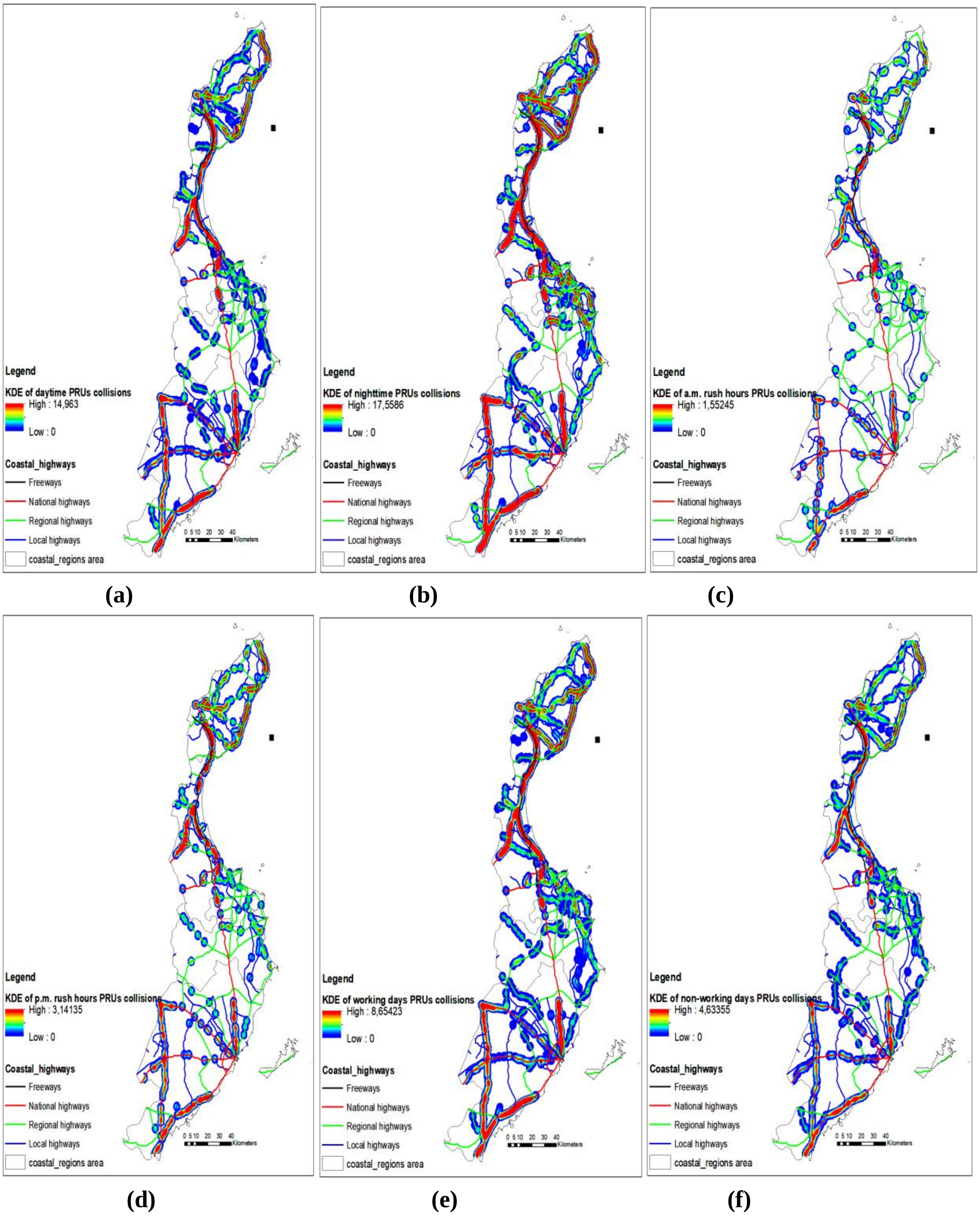

Figure 3 : KDE results of PRUs collisions : (**a)** Daytime, (**b)** Nighttime, (**c)** a.m. rush hours, (**d)** p.m. rush hours, **(e)** Working days, **(f)** Non-working days

This can be explained by the fact that Mahdia has remained isolated in relation to the bordering regions and the transit axes NH-1. Also, no freeways serve Mahdia directly. The detected hot spots locations for non-working days are not concentrated in comparison with working days. This result is more conforming to daily patterning of activities. This result could lead also to particular preferences regarding people who do not drive in non-working days. During working days, remarkable PRUs and VRUs hot spots locations were portrayed in the region of Nabeul especially in RH-26, RH-27 and RH-28, in the region of Sousse especially in NH-1, NH-6 and LH-819 and in the region of Sfax particularly in NH-2 and in road junctions between NH1 and RH-124 and between NH-1 and LH-918. These roads accommodate huge traffic volumes travelling at high speeds resulting in a high risk of PRUs collisions occurrence. The NH-1 is a very prominent road which other regional roads are connected to and links all the coastal regions of Tunisia.

After the visual assessment of maps of PRUs and VRUs hot spots, it can be noticed that some hot spots were portrayed repeatedly in the same location for each subtype period. Such kinds of results are significant as it may suggest that it is possible to predict some spatio-temporal trends to the PRUs and VRUs collisions distribution.

4. Conclusions and future research directions

This study investigates the changes in the spatio-temporal distribution of PRUs versus VRUs collisions hot spots in coastal regions in Tunisia over a recent 13 years from 2006 to 2018. The study findings not only highlight the risky collision areas and time periods, but can also promote to developing more reliable PRUs and VRUs transportation plans and policies. The main findings are as follow: (1) the majority of optimized PRUs and VRUs hot spots were portrayed in the northern part of the study area especially in the governorates of Nabeul and Sousse particularly in road junctions between national and regional highways which link many of the residential areas. (2) the detected PRUs and VRUs hot spots locations for non-working days are not concentrated in comparison with working days. (4) less PRUs and VRUs hot spots were identified during daytime in comparison with nighttime. (5) the detected PRUs and VRUs hot spots locations for a.m. peak hours are not concentrated in comparison with p.m. peak hours.

From a policy viewpoint, exploratory analyses such as the present effort provide key details that could be used by planners and decision-makers to build educational agendas aimed at promoting safety and well-being for PRUs and VRUs. Specifically, the type of data, maps, analyses, and insights presented in this study suggests recommendations in terms of enforcement, education, and engineering. Typically, PRUs and VRUs injury prevention programs range from global programs focused on developing education and awareness campaigns to reduce unsafe behavior on the roads, to updates of local programs intended to correct an engineering defect judged responsible for an increased frequency of collisions at a specific location. Other hazardous location-specific treatments include traffic calming, reducing and controlling the speed limits, roadside safety messaging, and traffic law enforcement (Balakrishnan et al., 2019). Undoubtedly, the surrounding land uses are important as well as these will certainly specify the nature, magnitude, and severity of conflict between VRUs and motorized traffic users. Decision-makers are striving to provide alternatives to ensure a better cohabitation between all road users.

It is important to bring to light some shortcomings in the study that could have an un-intended impact on the findings. Our research data were restricted to coastal regions in Tunisia. An obvious extension is always important to include a larger sized database including additional regions. This research could also gain by addressing a fine-grained spatial approach that looks into interactions between land use, VRUs, and PRUs. Despite the limitations mentioned above, this research represents a crucial contribution, as to the best of the author's knowledge, this reflects one of the first attempts to adopt a space-time analytical approach in investigating hot spots of VRUs and PRUs collisions in coastal regions in Tunisia. Such approach can raise awareness of the need for better monitoring and development of future road-safety-related interventions. This is likely to provide decision-makers with important insights on improving road safety situation for PRUs and VRUs.

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