SpatialAnalysis of Road Traffic Accidents Between Tunisian Regions

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Abstract

This study's goal is to identify the geographic hotspots of traffic accidents in Tunisia's coastal and inland areas using the spatial autocorrelation approach, with particular emphasis on the Moran and Getis-Ord indices. The approach used also allows adapting to the spatial structure observed locally, through local measures of spatial autocorrelation. The results show a fairly significant disparity in the concentration of these points between regions, types of road, geographic locations, and environments (urban, rural). In coastal areas, the black spotsare, also distributed in the governorate of Nabeul, Sfax and Sousse along the national and regional roads. However, in the inland areas, the black spotsare, distributed and found in a more abundant way in the governorates of Kef, Beja and Kairouan all along the rural roads. The precision brought by our results could help the public decision-maker as on accident prevention, particularly given the significant growth in the number of cars in Tunisia.

Keywords
Traffic accidents, black spots, spatial autocorrelation, Moran's index and Getis-Ord index.

1. Introduction
The considerable increase of the road network worldwide is a direct consequence of the significant growth of the world's car fleet. In fact, the world car fleet has increased in 2007 from 1,031,284,909 vehicles to 1,789,251,397 vehicles in May 2011 (French Automotive Industry 2012). The Tunisian car fleet has registered a considerable increase between 1985 and 2017 from 1,807,447 vehicles, it has increased from 304,653 in 1985 to 2,112,100 vehicles in 2017.Road accidents have grown significantly in parallel with the advancement of mobility and traffic.Currently, research is concentrating on two featuresas a result of these factors: (i) correcting technological issues with vehicle models, and (ii) maintaining infrastructural defects by modifying roads to current safety precautions. To do this, authorities must require a large investment. It is necessary to identify and adapt dangerous

areas (road black spots) to the traffic pattern.Finding dangerous road areas is a crucial first step in the diagnostic of safe driving; it tries to maximise the investment made in specific areas of the highway system to address infrastructure and facility shortcomings. (Elvick 2007; Harizi et al. 2016).The identification of these black spots has developed considerably using spatial econometrics and GIS techniques. In recent years, researchers have been introduced into their analysis's local spatial autocorrelation indexes. By keeping in mind, the geographical aspect of the spatial occurrences'concentrations, these newer approaches have the benefit of allowing the establishment of a local index of dangerousness. (Hauer 1996; Thomas 1996; Flahaut 2002).Multiple important aspects of the data on road accidents are missed by Tunisian authorities' varied methodologies, including network component.With a focus on the Moran index and Getis-Ord index, this paper seeks to locate and compare the road's black spots in Tunisia's coastal and inland locations using the spatial autocorrelation technique. According to our study, GIS is a useful tool for spatial analysis that may help with management and decision-making in the field of road safety.

The work's main body is organised as follows. Section 2 offers a review of the literature, and Section 3 details of the data used in this investigation. The spatial autocorrelation approach has been established in Section 4; Section 5 presents the application of this method to the detection of traffic black spots. Section 6 is where we arrive at the conclusion.

1.1 Objectives

Our aims are to identify the spatial-temporal distribution of road users in Tunisian hotspots regions, to involve the development of planning rules of road environment and to propose a precise tool in the recommendations for improving the level of safety.

2. Literature Review

The problem of detecting road accident black spots is a topic major issue for both policymakers and road infrastructure managers. Although functional definitions of black spots exist in so many nations, the concept itself is still the topic of heated debate among specialists in the field. (Elvik 2008).According to the literature currently available, several durationis used to describe traffic black spots. For example, 100 metres is found in Belgium (Flahaut et al. 2003), 250 metres in Austria (Elvik 2007), 100 metres in Germany (Elvik 2008), 100 metres in Hong Kong (Lai and Chan, 2004), 100 metres from the segment location and 50 metres for an intersection in Flanders (Elvik 2007; Geurts, 2006), 100 metres in Norway (Elvik 2007), 100 metres in Hungary (Elvik 2007), 200 metres in Portugal (Gomez 2013), 300 to 1000 metres in Croatia (Zovak et al. 2014) and 1000 metres in Tunisia (Harizi et al. 2016, Ouni and Belloumi 2019).To identify these high-risk regions, in practice, authorities established a lot of several strategies. (Elvick 2008; Hauer 1996). The majority of the methodologies employed by scientists are complimentary, including risk coefficient, density estimation, priority ranking, crash rate per unit of space-time, and degree of severity. (Harizi et al. 2016). There are three widely used definitions for black spot identification, according to Cheng and Washington (2005) and Elvik (2006): (i) Numerical definitions are based on accident frequency, (ii)risk levels and (iii)accident severity score. Most global road safety authorities favour these definitions although the scientific community does not find them appealing (Elvik 2007; Loo 2009),mostly due to their practical benefits for governments to adopt and monitor.

Theoretically, a "black spot" is any place where there are greater accidents than other places identical to it through geographical factors associated (Elvik 2007). According to this definition, real accident hotspots on roads are places where geographical risk variables connected to highway engineering and/or mobility regulation involve a key role; therefore, engineering improvements can indeed reduce accidents. Black spot detection mistakes can result in both most false negatives (i.e.locations that are dangerous but appear safe) and a considerable number of false positives (i.e. securelocations misidentified as dangerous). These mistakes undermine the overall efficacy of the road safety management process and led to the wasteful use of resources intended for safety improvements.Traditional methods of identifying and analysing accident hotspots have some drawbacks, which include not considering the migration of crashes over time and not allowing for the identification of accurate positioning issues (Flahaut et al. 2003; Harizi et al. 2016). Spatial methods used to identify traffic accident clustering patterns often produce two types of results: (i) the first is the identification of the pattern of accidents in road sections, it incorporates quadrat techniques (Nicholson 1999), nearest neighbourapproaches (Levine et al. 1995; Nicholson 1999; Nunn and Newby 2015) and Ripley's K function (Yamada and Thill 2004; Yalcin and Duzgun 2015, Ouni and Belloumi 2018). (ii) The second fact is the local clustering tendency of accidents along the road segment, which is determined to use the kernel density estimation method (Loo et al. 2011; Prasannakumar et al. 2011; Mohaymany et al. 2013; Xie and Yan 2013; Bil et al. 2013; Yu et al. 2014; Erdogan et al. 2015; Thakali et al. 2015; Blazquez et al. 2013; Ouni and

Belloumi 2018) or the use of Moran and Getis-Ord field is applied in the spatial autocorrelation technique (Flahaut 2002; Flahaut et al. 2003; Steenberghen et al. 2004; Khan et al. 2008; Erdogan 2009; Moons et al. 2009; Gundogdu 2010; Songchitruksa and Zeng 2010; Truong and Somenahalli 2011; Prasannakumar et al 2011; Loo and Yao 2013; Xie and Yan 2013;Erdogan et al. 2015; Nunn and Newby 2015; Harizi et al. 2016; Ouni and Belloumi 2019). Fotheringham et al. (2000) contend that the average value of a spatial model in a dataset encompassing a research region, which characterises global clustering approaches, may not reflect the actual situation.

As a result, their involvement is less important. When employing the local spatial autocorrelation method, each geographic unitassigned a local spatial autocorrelation index (LISA)that spatially assesses the level of interdependence between accidents observed at neighbouring spatial units.The spatial density of crashes indicated by a high LISA value.This approach has the benefit of preserving natural resources and supplying a dangerousness index. (Flahaut, 2002). In our work, A collection of nearby spatial units with a LISA value greater than a threshold, called a "black spot".However, the presence of black spots is the result of spatial interaction between contiguous sites (Flahaut et al. 2003; Harizi et al. 2016; Ouni and Belloumi 2019). Black spots show concentrations and indicate spatial dependence between individual occurrences. Space models of accident can also be analysed by spatial autocorrelation. Statistics that simultaneously consider discrete event locations and their values (Pulugurtha et al. 2007). In general, the main objective is to identify black spots at the local scale.

3. Methods

Our approach is in stages. First, we need to research where accidents happen most frequently (identify accident spatial concentration zones or Black zones).No hypothesis proposed yet, in this exploratory investigation. The spatial autocorrelation approach, one of the most used statistical techniques, predicated on the idea that"what happens in a given geographical location depends on what happens in neighbouring locations" (Tobler 1970), this method is already used by Harizi et al. (2016) to show the inadequacies of the instruments of accident detection in Tunisia by public authorities. Places' relative positions between them, considered by spatial autocorrelation.Thus, two places near each other logically more similar than two distant locations. The foundation of this approach is an index assessing whether local or global spatial autocorrelation.

3.1. Global spatial autocorrelation

The first stage is to evaluate the spatial autocorrelation of the study area (the entire nation), which enables testing and estimation of whether the study area worldwide shows spatial autocorrelation.

Besides determining whether the model is aggregated, dispersed, or random, the global Moran index analyses the spatial autocorrelation based on the locations of the zones and the values of their attributes.

$$\mathrm{I_m} = \frac{n}{s_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad (1)$$

And,

$\mathbf{w_{i,j}}$represents the proportions reflecting the proximity relationships,$\mathbf{s_0} - \sum_{\mathbf{i=1}}^{\mathbf{n}}\sum_{\mathbf{j=1}}^{\mathbf{n}}\mathbf{w_{i,j}}$, $\boldsymbol{z_i = x_i \text{-} \bar{x}}$, $\boldsymbol{z_j = x_j \text{-} \bar{x}}$, $\boldsymbol{x_i}$indicates the amount of the variable *x* at location *i*, $\boldsymbol{x_j}$indicates the amount of the variable *x* at location *j*, $\bar{\mathbf{x}}$indicates the average value of $\boldsymbol{x_i}$, **n** means the number of places and (i, j) represents the localities. The global Moran index values varied between – 1 et + 1 (Ouni and Belloumi 2019).

The level of accumulation of high or low values is measured by the overall Getis-Ord (G) index. Rather, it measures the concentration of high or low values for a particular research region, and its application enables the verification of the model's aggregate, dispersed, or random nature.

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j} \qquad \mathbf{(2)}$$

With,

$\mathbf{w_{i,j}}$Represents the shadows of strong relations in the weighting,$\boldsymbol{x_i}$Indicate the value of the variable x instead of i.

, $\boldsymbol{x_j}$ Indicate the value of the variable x instead of i*j*, **n** refers to the number of places and (i, j) indicates the locations. Specifically, G enables the examination of the spatial dimension and locations of many occurrences and the position in space where a phenomenon occurs.

As long as they are comparable, this indicator compares the various characteristics of the study locations.

3.2. Local Spatial Autocorrelation

Scientists discovered the local indicators of spatial autocorrelation across many investigations. (Getis and Ord, 1992; Anselin, 1995). Each geographical unit I (1 km in our case) is identified by a value of the local index of spatial autocorrelation, or LISA (Local Indicator of Spatial Association).LISA is one of the indexes that have been developed following the decomposition of the global index.

These local indexes allow the detection of local pockets of spatial autocorrelation (Flahaut, 2002). In this case, the local Moran index (L_i) is defined as follows:

$$L_i = \frac{(n-1)(x_i-\overline{x})\sum_{i=1}^{n} w_{ij}(x_j-\overline{x})}{\sum_{j=1}^{n} w_{ij}(x_j-\overline{x})^2} \quad \textbf{(3)}$$

The Getis-Ord local index (G *) is a statistical tool for identifying statistically significant geographical aggregates of high values (in our context, black spots, or unsafe parts) and low values (non-hazardous sections).With each highway kilometre, it generates a new feature class with a score (z) and a surplus value (p).

$$G^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{X}\sum_{j=1}^{n} w_{ij}}{s\sqrt{\frac{(n\sum_{j=1}^{N} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})^2)}{n-1}}} \quad \textbf{(4)}$$

With,

$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$, $s = \sqrt{\sum_{j=1}^{n} x_j^2}$, x_j Indicatesthe variable x at a place j , w_{ij} is the weight matrix between the zones i and zones j . Finally, n represent the full numberof locations considered.

4. Data Collection

Every accident has an exact geographic location that is identified as a point on a map. Figure 1 gives a clear and precise picture of the spatial distribution of traffic accidents in Tunisia. One of the key characteristics of road accidents in Tunisia is their disproportionate distribution across geographical areas. The analysis of Figure 1 shows a fairly significant disparity, according to the road network, between the number of deaths and injuries occurring on national roads and in an area compared with the rest of the roads.

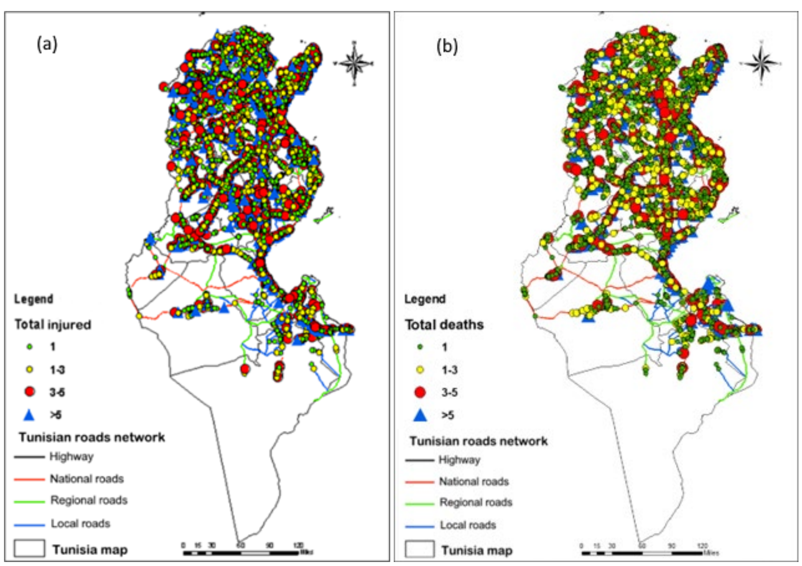

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Figure 1. Distribution of roads traffic injuries (a) and deaths (b) in Tunisia

The various tools used by the Tunisian authorities neglect several important dimensions of road accident data, specifically, the aspect of the network from which they come, the stochastic aspect of the accidents, the possible errors in their location and make it impossible to define the black areas of road accidentology (Harizi et al.2016), The purpose of this paper is to locate and compare road traffic black spots in coastal locations, including the governorates of Nabeul, Sousse, Monastir, Mahdia and Sfax and inland Tunisia including the governorates of Kairouan, Sidi bouzid, Kasserine, Kef, Jendouba, Siliana and Beja. We limit ourselves here only to data concerning accidents with bodily injuries that took place on the network of numbered roads in the coastal and inland areas, because this accident is in principle always listed since it requires the intervention of the gendarmerie or police services. At the national level, all road traffic accidents involving injuries must be reported to the National Traffic Guard or the National Security. Figure 2 illustrates the spatial pattern of accidents along the coastal and inland areas.

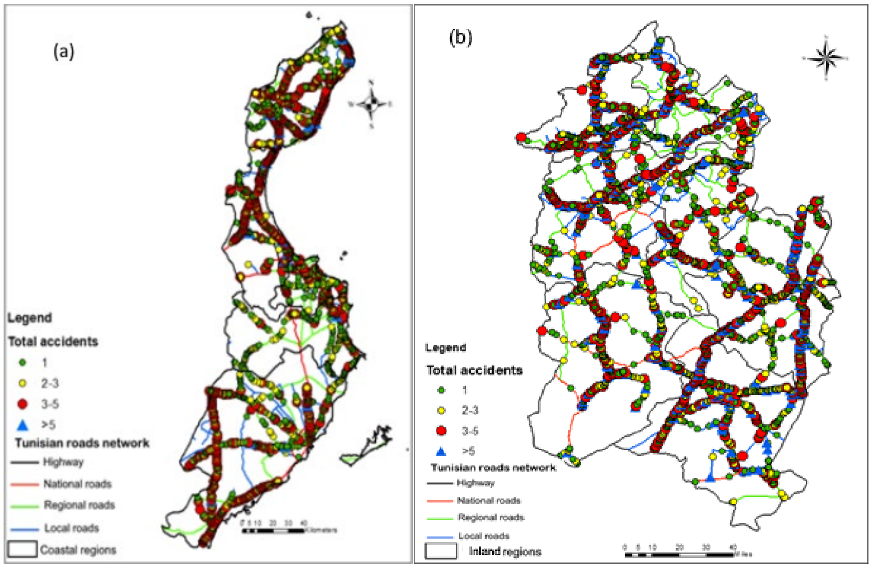

Figure 2. Spatial distribution of accidents in coastal (a) and inland (b) areas

Approximately, 7690 crashes in coastal areas and 8775 crashes in inland areas are between 2010 and 2018. Most spatial techniques for identifying dangerous road segments require segmentation of the road. A highway organised into a collection of pieces of constant length or divided into homogeneous sections of different length Highway divisionshas several problems, one of which is that it depends on the researchers' subjective evaluation of the segments' lengths and homogeneity. Because there is a stone marker per kilometre in Tunisia, the site of accidents on numbered highways may be pinpointed to within one thousand metres.The statistical analysis of the number of accidents is heavily impacted by the decision of the length of the road sections. (Thomas. 1996). For the length of the road segments that would be analysed in this study, 1 km was used as the spatial reference measure.

5. Results and Discussion

Only statistics on injury accidents that happened on the numbered road network in coastal and inland areas are included here.The nearby rock marking facilitates government officials in determining the precise location of an accident. These markers are located at the roadside and are 1 km apart. As a spatial reference for the length of the road segments we are analysing in this example, we will use a distance of 1 km.We employed the Euclidean distance (as the crow flies), which is the distance in a direct line separating two geographic places, to quantify the spatial autocorrelation.The variance decreases as the analysis's scale is reduced, whereas the correlation increases monotonically.(Thomas 1996).The distinctive contribution of each site to the total autocorrelation measurements is thus shown by local measures of spatial autocorrelation. A positive z-score denotes the presence of adjacent road segments with comparable values (high or low values).The geographical aggregation of high values indicated by a high z score and a low (p) value.A low (p) value with a low and negative z score show a geographical clustering of low values. As a result, the aggregation is more intense the higher (or lower) the z score. No geographic aggregation may exist if the z score is close to zero. Unsafe Road segments are more likely to cluster together when the z score is statistically significant positive and higher than 1.96, whereas black spots are less likely to cluster together when the z score is negative and lower than 1.96. (Harizi et al. 2016). With a positive z-score value and a positive global Moran index value that is near to one in all zones, our data demonstrate a trend towards clustering. The global Getis-Ord index follows the same pattern.(Figures 3 and 4).

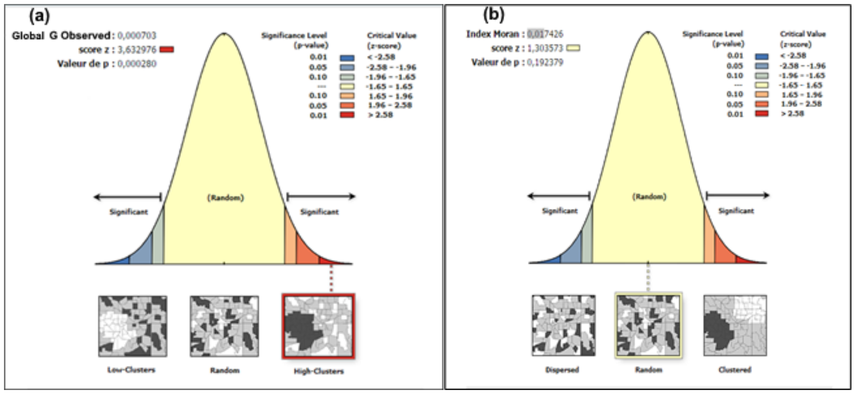

Figure 3. Result of the global spatial autocorrelation in coastal areaswith Global Getis G. (a) and Index of MoranI_m (b)

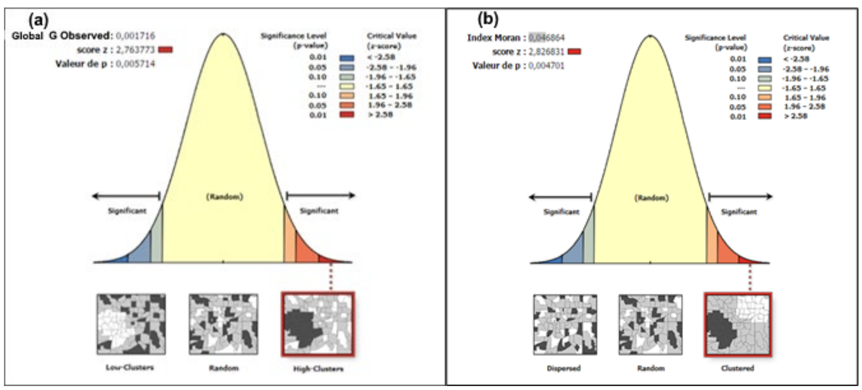

Figure 4.The result of the global spatial autocorrelation in the interior areas with Global Getis G. (a) and Index of MoranI_m (b)

Figures 5 and 6 allow exploring the spatial autocorrelation. They demonstrate that the average number of crashes per kilometre of road at the identified black spots has a positive connection with Li* and Gi*, and that the relationship between these two variables is exponential rather than linear.

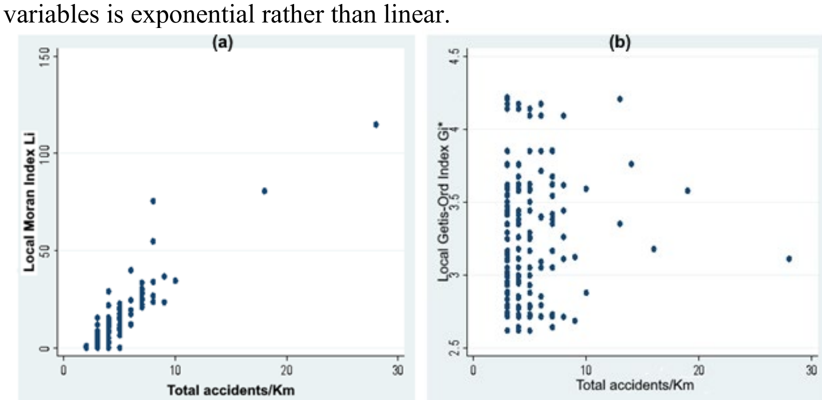

Figure 5.The relationship between the number of accidents/km at black spots as a function of Li* (a)and Gi*(b) in coastal areas

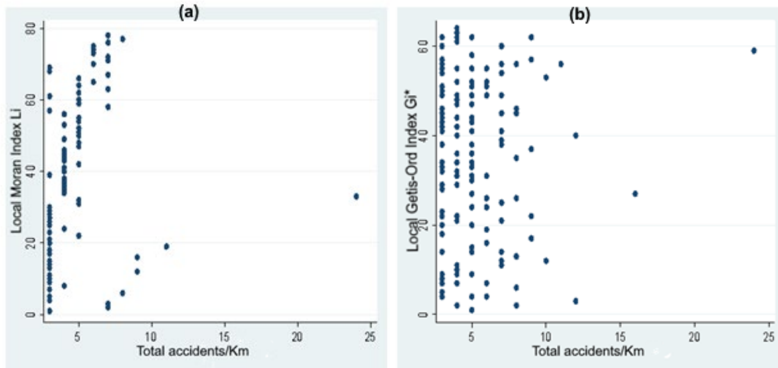

Figure 6. The relationship between the number of accidents/km at black spots as a function of L_i* (a) and G_i*(b) in the inland areas

Our concern is to be able to apply I_i and Gi* as two indicators of dangerousness, which will allow us to classify and identify areas with elevated risk of accidents, and thus to compare the results obtained according to the segregation that we have assumed from the beginning (coastal vs. inland).For the purpose of identifying traffic black spots, the computation of Li* and Gi* as dangerousness indicators are useful. When calculating Li *and Gi*, the number of neighbours considered, is correlated with the geographical distribution seen from every kilometre of the highway. It is necessary to aggregate nearby kilometres into geographical areas to distinguish hazardous and non-hazardous areas, since the kilometre is the smallest spatial unit in which incidents are located. Otherwise, it is a question of aggregating kilometres that are spatially adjacent and have a same number of accidents that characterise them into sufficiently homogeneous sections of road to identify the danger areas. An association of high accident values between neighbouringkilometres will be considered as forming a Black zone.
Figures 7 and 8 give a clear and precise picture on the geographical distribution of black spots of road traffic detected in coastal and inland areas of Tunisia using local indexes Li*and Gi*.

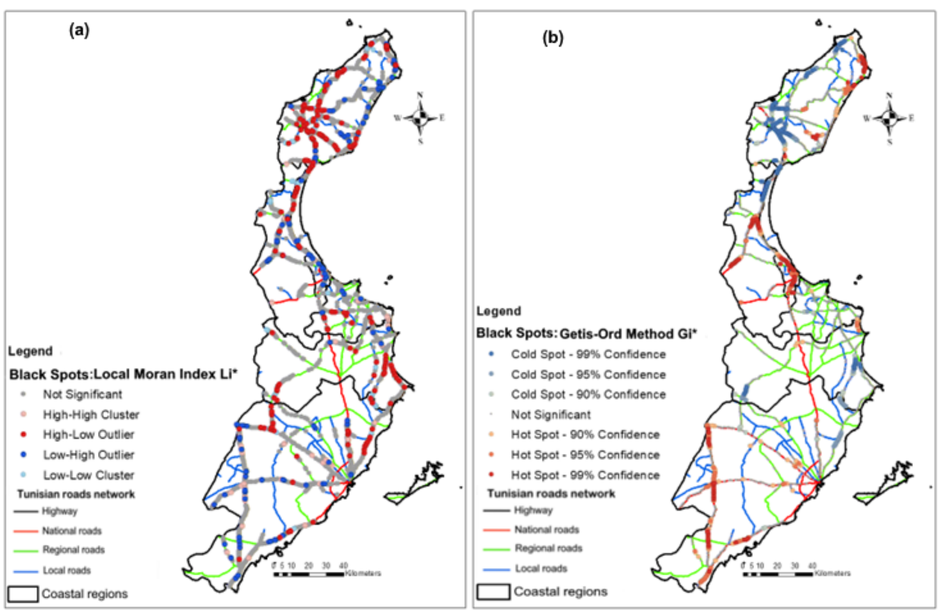

Figure 7.Black spots in the Tunisian coastal area's traffic, according to the local indexL_i* (a) and $\boldsymbol{G_i}$ *(b)

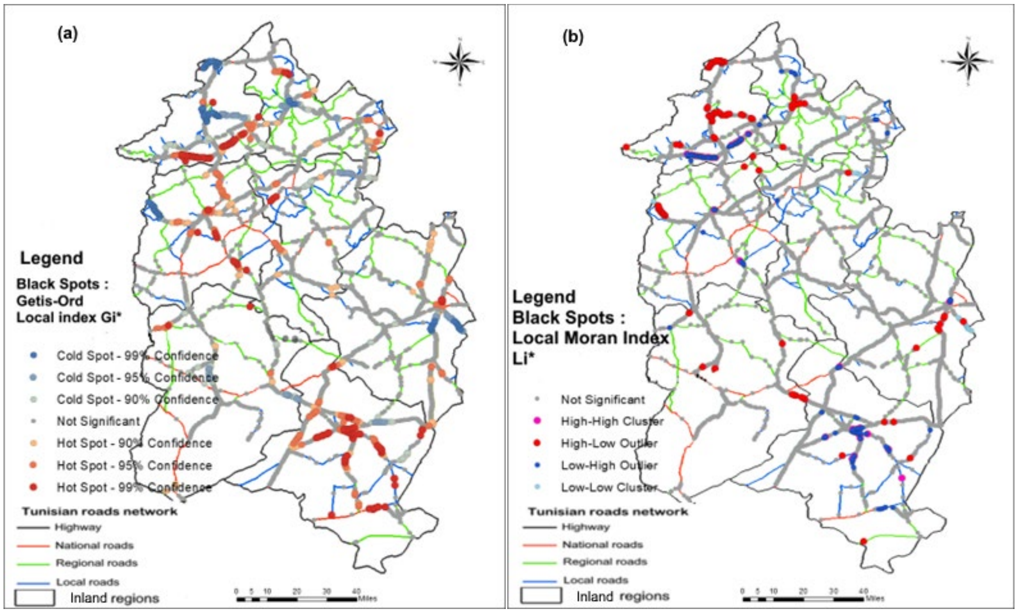

Figure 8. Black spots in the Tunisian inland area's traffic, according to the local indexG_i *(a) and L_i* (b)

The likelihood of becoming a black spot value for Li* and Gi* must be higher than the predefined threshold 1.65 generated from a normal distribution at 95% confidence level. First, we note that the black spots exist in specific areas and not on the entire network. Second, we note that a simple reading of the maps shows that there are differences in the concentration of these points between regions, types of roads, geographical locations, and environments (urban, rural). The results show that the black spots of road traffic exist on the Tunisianroad network, they are notdistributed equally over the whole network. They occur along certain sections of roads determined well, especially in residential areas. Even if we compare our results with the areas already detected by public authorities (NOITDSRS, 2016), we find that the same areas fixed by these authorities and which have undergone improvement interventions at later dates, remain (some of them) dangerous areas still requiring improvements (infrastructure, facilities, marking, etc.). It may be that the solutions were partial and did not affect the entire black spot problem. The two methods are used to give equivalent results (Figure 9).

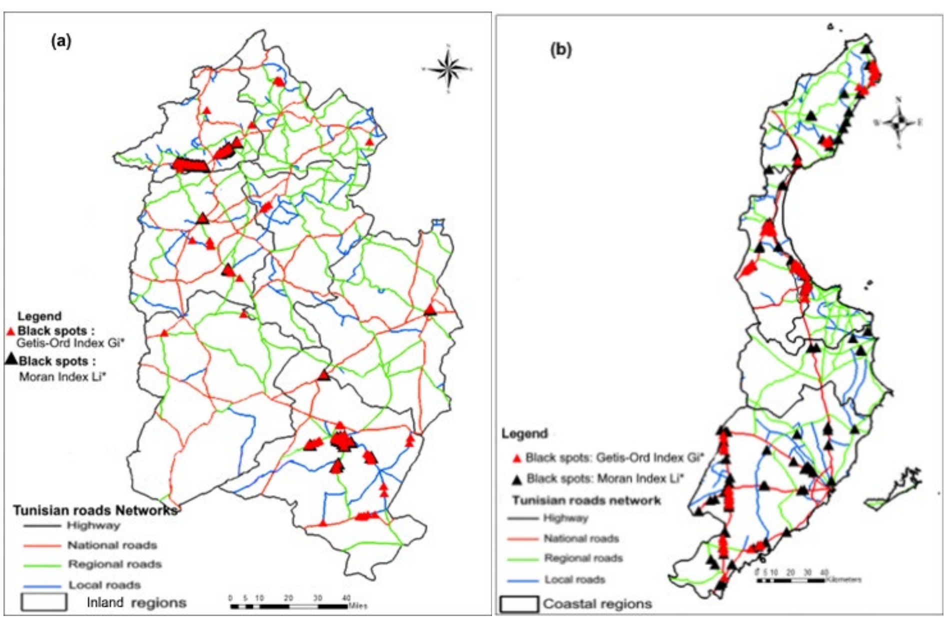

Figure 9. Correspondence and differences betweenL_i* and G_i * in Inland regions (a) and coastal regions(b)

In coastal areas, the black spots are also distributed in the governorate of Nabeul, Sax and Sousse along the national and regional roads. However, in inland areas, the black spots are distributed and more abundant in the governorates of Kef, Beja and Kairouan along the rural roads.

Once again, the use of Moran and Getis-Ord indexes shows that these techniques are complementary and inseparable (global and local autocorrelations). The representations that we produce using GIS constitute a decision support tool that facilitates the objective interpretation of the presence or absence of accident pockets on certain road sections.

The comparison of black spots in inland and coastal areas remains overly sensitive to several parameters specific to each zone, including physical geography, climate, number of inhabitants, population density (especially urban), distribution of traffic according to the networks, the volume of transit on their major routes, and the socio-economic context of each zone. The coastline is an area where the population is denser and is concentrated, where economic activities are becoming increasingly dense. The concentrationof cities further stimulates the intensification of trade through the creation of specifically urban activities such as trade andservices. On the otherhand, the Tunisian coastline is a space of extraversion of the country at which Tunisia opens up to the outside world through its port and airport infrastructure of international trade (Ouni and Belloumi, 2019). These activities trigger a need for mobility more intense on the coast than in inland areas, which explains the increase in motorisation of coastal populations compared to inland areas. It is for all these reasons that the accidentology, especially the black spots of road traffic, appear more intense in the Tunisian coast rather than in inland areas.

Certain of the design ideas we suggest including redoing the pavement, better lighting, making pedestrian refuges in the middle of the road, adding directional signs, and improving some dangerous road portions by adding signals or traffic circles. The improvements needed to make a whole network of dangerous roads secure are inexpensive but can provide significant benefits in terms of reducing the frequency of traffic accidents, injuries, and property damage.

6. Conclusion

A crucial prerequisite in the prevention of car crashes is the identification and investigation of areas that cause more accidents than average. This article's goal is to use the spatial autocorrelation technique to locate the geographic hotspots in Tunisian inland and coastal areas. The spatial autocorrelation method is an effective method and could also be the basis for the identification of dangerous road sections on maps. It is based not on the number of accidents or on the frequency of accidents but rather on local measures of spatial autocorrelation via the local Moran index (Ii) and the Getis-Ord index (Gi*) as two indicators of dangerousness that allow the identification of high-risk areas for accidents, and thus to compare the results obtained.In the coastal areas, the black spots are equally distributed in the governorate of Nabeul, Sax and Sousse along the national and regional roads. However, in interior areas, the black spots are distributed and found more abundantly in the governorates of Kef, Beja and Kairouan along the rural roads.

Traffic accident concentrations are mostly explained by the physical features of the road infrastructure and, the associated environmental factors. Under these conditions, GIS will contribute to reduce the frequency of traffic accidents. However, the accuracy, reliability, and completeness of the traffic accident records are crucial to the success of these studies. Last but not least, if planning, preventive, awareness-raising, and enforcement efforts had been prioritised in these regions, traffic accidents would have been prevented. Considering Tunisia's significant rise in the number of cars, we believe that the knowledge and specifics offered in this article will assist the public authorities in making decisions on road safety.

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