

GEOSTATISTICAL SPATIAL DECISION-MAKING FOR IDENTIFYING ROAD HAZARDOUS ROAD SEGMENTS IN RURAL AREAS

Abstract. Road safety has now become a major concern in many countries. In Algeria, as elsewhere, many factors are involved in the phenomena of road accidents. In this field of research, our study aims to spatial identification along a road network the hazardous road segments which present a dangerousness index. We proceeded the use of geostatistical approach, in particular global $G(d)$ statistic and local $G_i^*(d)$ statistic of Getis-Ord. However, in an operational framework, this approach is highly dependent on hypothesis on the process of the measurement of the spatial proximity based on the distances between the BSUs. Thus, the interpretation of empirical results based on the optimal choice of the weighting structure and the critical distance. Methodologically, this work allowed to test an approach for assess the safety levels experimented in the case of road network specifically higher accidents risk in the Wilaya of Mascara (north west of Algeria). The first results confirm the validity of the method and allow a recoverable mapping by managers in the choice of measures of preventive management.

Key words: Road safety, Autocorrelation, GIS, Rural roads, Algeria

Miloud Driss¹

¹ *Laboratory of Sciences and Technology of Water, University Mustapha Stambouli of Mascara, Mascara - 29000, Algeria.*

Mohamed Amine Hamadouche²

² *Laboratory of Geomatic, Ecology and Environment, University Mustapha Stambouli of Mascara, Mascara - 29000, Algeria.*

Brahim Safi^{3,*}

³ *Processes Engineering Department, Faculty of Technology, M'hamed Bougara University of Boumerdes, Boumerdes - 35000, Algeria, Phone: +213 774 375 336, e-mail: *safi_b73@univ-boumerdes.dz*

Mohsen Mhadhbi⁴

⁴ *Laboratory of Useful Materials, National Institute of Research and Physical-chemical Analysis, Technopole, SidiThabet 2020 Ariana, Tunisia*

Mostefa Lallam¹

¹ *Laboratory of Sciences and Technology of Water, University Mustapha Stambouli of Mascara, Mascara - 29000, Algeria.*

Introduction

The phenomenon of spatial distribution of data that occur in space is a challenge to explain the central issues in many areas of knowledge, whether for health, accident, geology, agronomy, among many others. These studies are increasingly common due to the availability of GIS with convivial interfaces. The fast development and adoption of GIS technology as a tool to manage, explore, analyze and visualize spatial data, and growth of spatial analysis methods of data that are included in the modules of GIS software, received an increasing attention (Booth, 2004). The Exploratory Spatial Data Analysis (ESDA) is a set of techniques to describe and visualize spatial distributions, identify similar or dissimilar spatial locations, to detect spatial association models, clustering, and provide other forms spatial heterogeneity (Bailey and Gatrell, 2004).

There are a variety of spatial tools developed to assist in understanding the spatial concentrations of road accidents.

However, according to Khan *et al.* (2008) the most important problems that traffic officials are considering is: where and how to implement precautionary measures and provisions so that they can have the most significant impact on road safety. Moreover, the existence of black zones of

road accidents is the consciousness of the obvious spatial interaction between locations contiguous accidents (Flahaut *et al.*, 2003). Also, it is appropriate to take precautions to prevent accidents, can only be set after the correct determination of hazardous sections (Savas Durduran, 2010).

The works of Anselin in 1995 and Ord and Getis in 1995 have enabled to ESDA to shifting its a global spatial analysis of the study area to a local analysis likely to identify the main interests in the study area (Wu and Mielniczuk, 2002). Thus, the local spatial autocorrelation measures decompose the global index in order to identify the individual contribution of each location and all locations taken in its vicinity to the spatial structure observed locally. So, there is a fundamental development to facilitate the use of spatial statistics in applied research. These indices are tools for decision support for the interpretation of maps and images in search of critical locations that can inform both basic research and applied research (Zaninetti, 2007).

The main objective of this paper is to present the potential of GIS and technical representation for defining spatial concentrations of road accidents. However, the most promising of these tools is the global and local statistic of Getis and Ord that reveals spatial abilities to identify the locations of accidents (Khan *et al.*, 2008). In the Algerian literature, there are no studies on the spatial distribution of accidents, except a study that has been established by Mendas *et al.* (2006) on a road segment of 63 kilometers. Mendas *et al.* (2006) have used an approach to the ESDA, similar to that developed in this paper presented only by global and local spatial autocorrelation measures of Moran. This study is the first national-level work focuses on the spatial identification of road accidents on a road network.

1. Road safety situation in Algeria

The road safety situation in Algeria has deteriorated with the number of deaths due to road accidents increasing, largely as a direct consequence of the rapid growth of the population, urbanization, lack of permanent investment in road safety and notably the number of vehicles fleet that caused substantial increase in recent years, more than 8 million vehicles (Driss *et al.*, 2014).

By shedding light on road deaths in Algeria, through an exploratory analysis of road accident data covering from 1990 to 2020 (Figure1):

- The period from 1990 to 1994: There is a decrease in the number of deaths. This is due to the security situation at the time and that travel during the night was almost non-existent. This number exceeded the mark of 4000 deaths annually, and it was precisely in 1994 that a peak was recorded with, 4022 killed on the country's various roads (Hebbar *et al.*, 2020; ONS, 2020).
- From 1995 to 2004: the evolution of the number of deaths fluctuated with an upward trend due to the strong growth in the automobile fleet and improvement in the security situation, and with the corollary of the gradual return of mobility.
- From 2001 to 2006: There was a slight decrease in 2005 in accidents due to the effect of law 16-04 of November 10, 2004 modifying and supplementing law no. 01-14 of August 19, 2001 relating to the organization, security and road traffic police.
- Indeed, the number of deaths experienced a remarkable increase from the year 2005 until 2015 except for the year 2010, there was a drop of 26% in deaths compared to 2009. This drop is explained by the adoption of law 09-03 of 2009 applied at the beginning of 2010, relating to the organization, security and police of road traffic which introduced more coercive regulations and the establishment of the new Highway Code.
- The period extending from 2015 to 2020 saw a negative evolution in the number of deaths, and in a remarkable way. This negative development is mainly due to the reforms carried out on the Highway Code, regarding fines and withdrawal of driving licenses, the organization of various awareness campaigns in order to mitigate this phenomenon and also to the tightening of the new law 17-05 of February 16, 2017. This action program consists of

reviewing the structural organization of road safety, implementing the points license and training professional drivers (Ouramdane *et al.*, 2020).

Likewise, road mortality recorded a significant drop in 2020 compared to 2019. That is, 2844 people lost their lives on our roads during 2020, compared to 3275 during the same period of the year 2019, which is equivalent to a decrease of 13.16%. An encouraging decline to which we can all contribute to progress. This exceptional drop must be put into perspective due to the context of the health crisis, which led to travel restriction measures which had massive effects on road traffic. Indeed, during periods of confinement the number of accidents fell sharply, particularly due to the confinement imposed by the authorities to curb the Covid-9 pandemic (Ouramdane *et al.*, 2020).

Finally, even if the established observation of statistical accident data up to the year 2020 revealed a significant decline, more efforts still need to be made in favor of road safety. Although these figures seem encouraging, but in terms of human lives, this makes a daily average of no less than 8 deaths.

Furthermore, the marked proportions between the rural and urban areas can be explained by the geographical characteristics and the length of the rural area, which constitutes a major cause of overspeed, leading to the risk of traffic accidents and the recording of more injuries and deaths (Hebbar *et al.*, 2020).

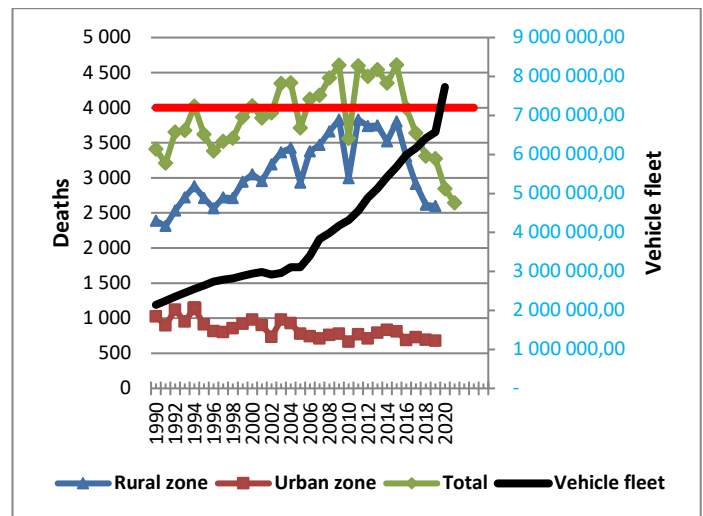


Fig. 1. Annual evolution of the number of deaths and the national vehicles fleet in urban and rural areas.

2. Case Study and methods - Study Area and Data

The annual number of accidents on a road segment varies from one year to another and this is an important factor in analysing accidents. It can be explained by the accident risk inherent to a road segment. It is therefore of utmost importance that the study period be sufficiently long to ensure that samples are representative of the accident trend. Generally, a period of three to five years is sufficient to ensure the reliability of results (Moons *et al.*, 2009;

based on the distance d_{ij} . Each matrix of spatial weights w_{ij} is associated with a critical distance d_c .

The $Z(G)$ -scores for the statistic is computed as (2):

$$Z(G) = \frac{G - E(G)}{\sqrt{V(G)}} \quad (2)$$

where: The expectation and the variance are written below successively by Equations (3) and (4).

$$E(G) = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j}}{n(n-1)}, \forall_j \neq i \quad (3)$$

$$V(G) = E[G^2] - E[G]^2 \quad (4)$$

The first analysis applied concern the influence of the weights: w_{ij} on the determination of hazardous road segments of road accidents, by varying the exponent d_{ij} between 0, -1 and -2 (Fixed Distance, Inverse Distance and Inverse Distance Squared) between BSU i and j . The Figure 4 illustrated for each weighting function, the Getis-Ord global $G(d)$ statistic is calculated successively up to 10 neighbour of odd distances fixed at 300, 500, 1900 and 2100 meters. In this application, the number of neighbours varies from 2 to 20 with a step of an even numbers that are symmetrically distributed on both sides of each hectometer i studied, and corresponding to hazardous road segments varies from 2 to 20 hectometers.

The influence of a change in the weights function for a maximum distance of neighbourhood is set at 2100 meters. This distance is the largest used in all analyzes because it is intolerable in the context of specific rearrangements to the hazardous road segments of lengths equal or over 2000 meters. Also, according to the Public Works Department in charge of follow-up and maintenance of the Wilaya of Mascara road network, the hazardous road segments of 2000 meters' length are considered maximum in framework of a local approach. Moreover, this finding was demonstrated by Flahaut and Thomas (2002), in their work that consists to identifying the hazardous road segments by local spatial autocorrelation indices of Moran in road network of province Walloon Brabant in Belgium.

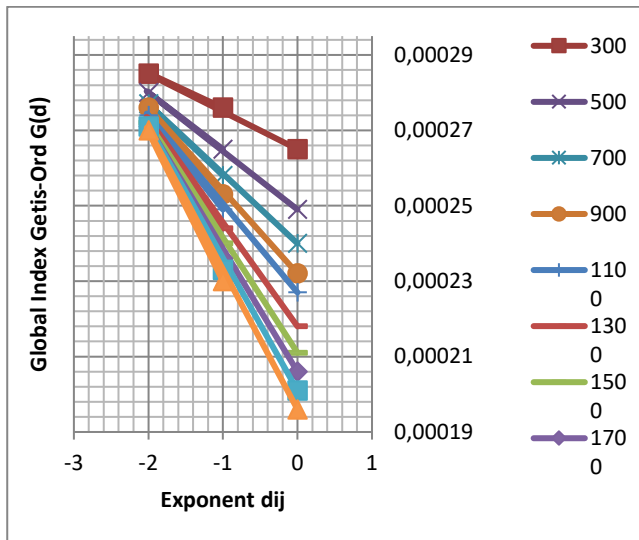


Fig. 4. The variation of the global Getis-Ord Statistic $G(d)$ with neighbourhood distances for different weighting functions.

The analysis of Figure 4 shows a decrease in the global $G(d)$ statistic for each function d when the neighbours number of BSUs increases: the association of a number of accidents between BSU i and its neighbours is in most cases is more intense with its immediate neighbours, or at least nearest neighbours BSUs. It may also be noted that this decrease in the global $G(d)$ statistic is more pronounced with two functions weights w_{ij} (proportional to d_{ij}^0 and d_{ij}^{-1}). This may explain that more distant BSUs included in larger zones are neglected in the calculation of the statistic.

3.2. Local Spatial Autocorrelation

The single measures of the global spatial autocorrelation have limited applications because individual locations of study area may not represent their real situation (Anselin, 1995; Getis and Ord, 1996; Fotheringham *et al*, 2000). Thus, the local spatial autocorrelation can be used to detect local clusters around an individual situation and spatial non stationary, especially in cases where the global spatial autocorrelation cannot manage to detect these patterns.

Also, Moons *et al.* (2009) and Haijin and Lianjun (2003) suggest that the local spatial autocorrelation must satisfy at least two requirements:

- The local statistic for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation,
- The sum of local indices for all observations is proportional to a global statistic of spatial association.

The Getis-Ord $G_i^*(d)$ statistic indicates spatial aptitudes to identify traffic accidents related to weather conditions that are grouped in different locations depending on weather conditions (Bailey and Gatrell, 2004), to describe the inter-province differences in traffic accidents and mortality on roads of Turkey (Erdogan, 2009) and to identify the hot pieces and the probable hot spots that seeks to anticipate the dangers and prevent the frequency of accidents (Gundogdu, 2011; Colak *et al.*, 2018).

Anderson (2009) has proposed an original method which uses GIS and Kernel Density Estimation (KDE) to create a basic spatial unit of a hotspot and statistical analysis to cluster the hotspots according to attribute data of the accident including the surrounding area. Also, Ge *et al.* (2022) describes a traffic accident black spot recognition model based on the adaptive kernel density estimation method combined with the road risk index. The KDE is one of the most popular methods for analyzing the first order properties of a point event distribution (Bailey and Gatrell, 2004). This study focuses on identifying the spatial distribution of traffic accidents covering the geographical area of London.

Steenberghen *et al.* (2010) have proposed a new methodology for identifying clusters of point-based events on a network-based on a moving-segment approach and

network distances. This method has some major advantages. The use of network distances instead of Euclidean distances gives a more realistic measure of spatial correlation for events that are the result of movements along a network. The methodology is applied to traffic accidents to detect dangerous locations on the road network of the city of Brussels in Belgium. The statistical significance of clusters of accidents is tested using a Monte Carlo simulation.

Generally, the Local Indicators of Spatial Association (LISA) have been successfully used in various research areas; to characterize remote sensing (Abed and Kaysi, 2003), to detect the spatial clustering of contamination in epidemiological studies (Tsai *et al.*, 2009), to study changes in population and employment in the city of Dijon, France (Baumont *et al.*, 2004) and for estimation of individual tree growth as an explanatory variable in a forest (Haijin and Lianjun, 2003). Similarly, Torun and Düzgün, (2006) suggests vulnerability model to overlap of hazard zone by using the local measures of Getis-Ord $G_i^*(d)$ statistic and the KDE to reveal vulnerability of people and places due to oil transportation and accidents in Istanbul strait. Moreover, Boots (2002), Getis and Aldstadt (2004) and Flahaut (2004) have defined a detailed description on the ESDA and the LISA. However, the local indicator of spatial association may be an appropriate indicator of local spatial heterogeneity and useful to study the effects of neighbouring zones of different phenomena.

However, the local spatial autocorrelation statistics Getis-Ord $G_i^*(d)$ is calculated for each feature in a dataset. The results $Z(G_i^*)$ -scores show where feature with either high or low values cluster spatially. For statistically significant positive $Z(G_i^*)$ -scores, the larger the $Z(G_i^*)$ -scores is, the more intense the clustering of high values. For statistically significant negative $Z(G_i^*)$ -scores, the smaller the $Z(G_i^*)$ -scores, the more intense the clustering of low values (Mitchell, 2005). The $G_i^*(d)$ statistic works by looking at each feature within the context of neighboring features.

The local Getis-Ord $G_i^*(d)$ statistic is given by Equation (5):

$$G_i^* = \frac{\sum_{j=1}^n w_{i,j} x_j - \bar{X} \sum_{j=1}^n w_{i,j}}{s \sqrt{\left[n \sum_{j=1}^n w_{i,j}^2 - \left(\sum_{j=1}^n w_{i,j} \right)^2 \right]}} \quad (5)$$

where the symbols are such that defined above except, for the average number of accidents on the entire road network (Equation. (6)) and S is the variance of accidents from BSU $_i$ to BSU $_j$ at a distance d_{ij} , it is defined by Equation (7).

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (6)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (7)$$

The local spatial autocorrelation Getis-Ord $G_i^*(d)$ statistic is calculated and replaced by their standardized form and interpreted according to the quintiles of the normal Laplace-Gauss (Zaninetti, 2007). The $Z(G_i^*)$ -scores for the statistic is computed with Equation (8), and that is associated with a statistical significance for each BSU $_i$.

$$Z(G_i^*) = \frac{\sum_{j=1}^n w_{i,j} x_j - \bar{X} \sum_{j=1}^n w_{i,j}}{s \sqrt{\frac{n \sum_{j=1}^n w_{i,j}^2 - \left(\sum_{j=1}^n w_{i,j} \right)^2}{n-1}}} \quad (8)$$

However, for our case, the values of the local spatial autocorrelation statistics Getis-Ord $G_i^*(d)$ can be interpreted as representative of the spatial autocorrelation degree of the Getis-Ord global $G(d)$ and therefore these statistics reflects a stronger association between the observed number accidents in the BSUs. While, the results above show that the hazardous zones of road accidents can be identified with a weight proportional to d_{ij}^{-2} . Thus, each BSU is characterized by a statistic (index) value that represents the individual contribution of the situation (spatial proximity) in the local spatial autocorrelation measure, but we must determine a critical distance (d_c) appropriate to the spatial distribution of road accidents observed between BSUs which ensures that each BSU has at least one neighbour (Flahaut, 2004).

Saiful Alam and Nusrat Jahan Tabassum (2023) demonstrated the use of a GIS to identify and measure regional patterns in connection to crash frequency and severity. Spatial autocorrelation of crashes and Getis Ord G_i^* were used in tandem to identify severity-based crash hotspots. This study's contribution is the incorporation of crash severity into hot spot analysis using GIS, which could lead to better-informed decision-making in the realm of highway safety.

Hinman *et al.* (2006) used the $G_i^*(d)$ statistic to identify local patterns of typhoid fever in Washington during the years 1906-1909. For better visualize the spatial concentrations of typhoid fever epidemics, several distance values were used in this study. The distances (d) were fixed at 150, 250, 500, 750 and 1000 meters. The shortest distance, 150 meters, was selected to capture localized infections, such as residences clustered around a single shared water source. The greater distance, 1000 meters, was selected to capture larger outbreaks more representative of a global infection source, such as the city-wide water supply.

However, the optimal choice of a critical distance (d_c) in order to determine local spatial autocorrelation indices Getis-Ord $G_i^*(d)$ on the geographic extent of our study area is the spatial process that promotes the aggregation phenomenon of spatial concentrations of road accidents. While, from a set of 10725 BSUs which constituted the

studied network, we have calculated the distances to the specified 20th nearest neighbour for a set of BSUs. Thus, adequate tool in the Spatial Statistics toolbox in ArcGis10.1 creates a list of distances between every BSU and its 20th nearest neighbour (2000 meters); from this list of distances, it then calculates the maximum, minimum, and average distance. The maximum value is the distance from each BSU to ensure that every BSU has at least 20 neighbours. The minimum value is the distance from each BSU to ensure that at least one BSU has 20 neighbours. The average value is the average distance to go from each BSU to find its 20 nearest neighbour distance. The results are illustrated in the Table 1 below.

Distances List (meters)	maximum	minimum	average
	1999.299	397.577	900.505
Approximate value	2000	400	1000

However, for each individual BSU i an index $Z(G_i^*)$ -scores is calculated and compared with the other BSUs. The length of the hazardous road segment is defined as $Z(G_i^*)$ -scores is maximized, this value corresponds to the maximum extent of spatial association of a large number of accidents between a hectometer and its neighbours, fostering a local index for each BSU i must be greater than the threshold value 1.645 obtained from a normal distribution at 95% confidence level (Gundogdu, 2011). This process allows choosing the level of contiguity that is best suited to the local spatial structure of road accidents observed: the length of a hazardous road segment is not fixed a priori, but differs for each hazardous road segment. Thus, the local index of spatial autocorrelation is used as an index of dangerousness. The intensity of the dangerous character depends on the value of the index, while the length of the hazardous road segments depends on the number of neighbouring BSU taken into account in calculating the index (Figure 5).

Fig. 5. Hazardous road segments for the local Getis-Ord $G_i^*(d)$ statistic.

Conclusions

to take effective policy action to improve road safety (Rygula *et al.*, 2023). The results are used to describe the spatial heterogeneity to detect locally hazardous segments of road accidents because the causes and consequences of traffic accidents are not limited to where road accidents occurred. However, the intensity, and the dangerous nature of these segments are highly dependent on the extent of spatial proximity based on the distances between BSUs (Flahaut *et al.*, 2003; Wu *et al.*, 2004). These neighbourhoods can be very different and govern the results. Thus, the interpretation of the empirical results, however, based on a good understanding of the meaning and the specific choice of the main parameters of global and local autocorrelation spatial measures. Also, it is important to ensure a degree of realism in the subjective choice of the weighting structure, thus a sensitive analysis was used. Accordingly, the validity of the modeling results is always critical to the availability and quality of road accidents data (Gundogdu, 2011; Brijs *et al.*, 2006). Furthermore, the results can serve as a quick guide for planners of the road network and local authorities of the wilaya of Mascara by mitigation of accidents.

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