Discussing the Role of Traffic Safety in Sustainable Urban Mobility Plans Using Spatial Analysis Techniques

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Abstract. In recent years, EU has placed great importance on the safety of road users (real and perceived). In this context today in Greece, around 180 municipalities are implementing SUMPs for first time and therefore a primary identification of the hazardous points is made through the mapping of traffic incidents. This article presents the results of the mapping of traffic accidents in five metropolitan municipalities of Attica (Athens, Piraeus, Marousi, Kifisia, Chalandri), and their analysis using GIS tools. Network kernel density analysis was performed to determine the spots where a high concentration of severe accidents appeared, as well as spatial autocorrelation using Moran index and Hot-Spot Analysis in terms of time, driver's age and type of vehicle involved. The results indicate the hazardous points in the study areas and their particular characteristics. Finally, it is noted that the aforementioned analysis can contribute to the design of feasible solutions in order to improve road safety and at the same time, create a safe and sustainable transport system in each of the study cities.

Keywords: Traffic safety · Spatial analysis · SUMPs

1 Introduction

Contemporary cities face several serious challenges questioning their sustainability and efficiency [1]. The car-oriented approach that influenced transport planning process in cities mainly after 1950s [2], resulted in urban systems with intense traffic congestion, urban sprawl, environmental pollution, inaccessible and unattractive public spaces, movement barriers (e.g. arterials passing through central areas) and especially road accidents [3–5]. Focusing on road accidents and crashes, we should strongly mention that in recent years European Union (EU) has placed great importance on road users' safety (real and perceived), as it has considerable influence both in the operation of transport systems and in citizens' quality of life [6]. Tellingly, according to the European Commission [7], more than 35.000 people were killed and more than 1.5 Mio. Were injured in the year 2009 in European countries. Focusing on Greece, in the year 2017, Hellenic Statistical Authority (ELSTAT) recorded approximately 750 deaths, 700 serious and 12.200 minor injuries in approximately 10.800 incidents [8].

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Under these circumstances, a new perspective regarding cities and their future has emerged during recent years; this concept is no other than Sustainable Mobility [9]. Sustainable mobility describes a system that meets transport needs through promoting public transport, walking and cycling and, at the same time, enhances environmental integrity, social equity and economic efficiency. A new type of strategic plan, proposed by EU, that integrates all possible measures pointing towards an alternative mobility level, is the Sustainable Urban Mobility Plan (SUMP) [10]. It is worth mentioning that road safety is an integral part of sustainable mobility [11, 12] and SUMPs in particular. Today in Greece, around 180 municipalities are implementing SUMPs; by mapping the traffic incidents, the hazardous points are identified for the first time.

In this context this research outlines the results of the mapping procedure of traffic accidents in five metropolitan municipalities of Attica (Athens, Piraeus, Marousi, Kifisia and Chalandri) and their analysis using GIS tools. Network kernel density analysis was performed to determine the spots where a high concentration of severe accidents appeared, as well as spatial autocorrelation using Moran index in terms of time, driver's age and type of vehicle involved. The data of the research were derived from Hellenic Statistical Authority (ELSTAT) and concern the years 2012–2017.

2 Literature Review: Spatial Analysis of Traffic Accidents

A plethora of researchers have invested great efforts in studying the impacts of various risk factors [e.g. 13, 14] and road safety measures [15] and have developed or adopted several mathematical methodologies to approach crash prediction problems [e.g. 16] or road-road safety site prioritization problems [e.g. 17]. In the aforementioned context, in order to decrease traffic accidents and improve road safety levels, it is vital to understand how, where and when traffic accidents occurred, as these accidents are subject to both spatial and temporal variations [18]. A thorough understanding of spatial patterns can contribute significantly to tackle accidents effectively [19, 20]. Spatial analyses in road safety usually include the examination of crashes through taking into consideration their absolute or relative locations [5]. The way in which researchers select and define the spatial units of analysis influences directly the aim of the study, the interpretability of results and the data preparation as well [21].

Spatial analysis of point events, known as point pattern analysis (PPA), has been broadly examined by spatial scientists and a notable variety of methods have been developed for detecting high-risk sites (i.e. "hot spots"). The PPA methods can be classified into two broad categories [22, 23]. The first category includes methods which examine the first-order effects of a spatial process and the second category contains methods that examine the second-order effects of a spatial process [19]. Precisely, the first group focuses on the underlying properties of point events and measures the variation in the mean value of the process. It involves methods such as Kernel Density Estimation, Quadrat Count Analysis, etc. The second group mainly refers to the spatial interaction (dependency) structure of point events for spatial patterns, and includes methods such as Spatial Autocorrelation, Nearest Neighbor Statistics, G function, F function, K function, etc. In this research we focus on Kernel Density Estimation and Spatial Autocorrelation methods:

Kernel Density Estimation (KDE) is one of the most popular methods for analyzing the first order properties of points' distribution [22, 24]. It should be noted that this method is not a direct analytical method; on the contrary it constitutes an interpolation technique [25]. The KDE estimates the density within a range (bandwidth) of each observation to represent the value at the center of the window. Within the bandwidth, the KDE weighs nearby objects more than far ones based on a kernel function. The KDE generates a density of the events (discrete points) as a continuous field (e.g., raster). By using the density (or average attributes) of nearby objects to represent the property at the middle location, the KDE captures the very essence of location: it is not the place itself but rather its surroundings that make it special and explains its setting [26]. Delmelle et al. [27] mentioned that the KDE is an approach that leads to intuitive visualization and exploration of data.

The planar KDE has been used widely for traffic accidents "hot spots" analysis and detection. Some examples include: study of urban cyclists' traffic hazard intensity [28] wildlife-vehicle accident analysis [29, 30], pedestrian crash zones detection [31] highway accident "hot spot" analysis [32], etc. However, Kernels are projected over 2-D spaces, while road crashes occur in the road network which is a 1-D linear area [19]. Hence, in order to overcome this discrepancy, KDE has been expanded to network KDE approach [33] in which the network is now represented as fundamental units of equal network length (termed pixels). The studies utilized this method [e.g. 19, 34–36] concluded to results regarding each segment of the network, thus achieving greater accuracy.

In simple terms, spatial dependence essentially refers to events at a location (e.g. road crashes) being highly influenced by events at neighboring locations. It is typically measured via spatial autocorrelation metrics [5]. According to Griffith [37] spatial autocorrelation is the correlation between the values of a variable, which derives strictly from the proximity of these values in the geographic space. This approach is contradicting the general assumption of independent observation in the domain of classic statistics. Another similar definition proposed by Legendre and Legendre [38] mentions: "Spatial features have the tendency to be dependent. A phenomenon known as spatial autocorrelation can be defined as the property of random variables to take values over distance that are more similar or less similar than expected for randomly associated pairs of observations, due to geographic proximity".

Spatial autocorrelation can be used to describe and compare the spatial structure of a variable [39]. Specifically, this method contributes to [40]: a) test on model mis-specification, b) measure of the strength of the spatial effects on any variable, c) test on assumptions of spatial stationarity and spatial heterogeneity, d) identification of spatial clusters, e) understand the influence that the geometry of spatial units has on a variable, f) test on hypotheses about spatial relationships, g) identify the outliers, both spatial and non-spatial.

3 Methodology

This study adopts a quantitative approach in order to illustrate and analyze the spatial dimension of traffic accidents comprehensively. For this purpose, we used two different methods in order to obtain more efficient and representative results of the existing situation. The methods were Kernel Density Estimation (KDE) and Spatial Autocorrelation. It should be mentioned that this approach ensures a wide view of different aspects concerning the spatial dimension of accidents (e.g. clustering, interactions, etc.). After the application of the aforementioned methods, the paper presents these findings in the form of diagrams, and maps, thus evolving the understanding of the current usage patterns. The secondary data used were derived from Hellenic Statistical Authority (ELSTAT) and refer to traffic accidents concerning the years 2012–2017 in 5 municipalities in the metropolitan area of Athens. The database obtained included attributes regarding the location and the time of the accident, as well as the identity of street users involved. We should note that a pre-process was essential, in order to organize, and validate the accuracy of the data.

Firstly, the purpose of using KDE is to identify the hazardous locations (i.e. clusters) in the road network. It is essential to note that for the estimation of the planar Kernel density in each point of the grid two basic parameters are required, namely: kernel function (k-function) and bandwidth (i.e. search radius). The purpose of the k-function is to measure the so called "distance decay effect" [41]. In this study, the Bitweight function, which resembles better the Gaussian distribution function, is used in all the kernel density estimations. Regarding the estimation of kernel densities in the network space, we used the same general function. In our approach, the network kernel function is defined for two cases: (1) the location s does not coincide with a node and (2) the location coincides with a node [33, 42]. The selection of the right bandwidth is surely not an easy process. The range of the commonly used bandwidths starts at 50 m for urban areas and goes up to 500 m for highways [36]. In this study, we tested 6 different values, i.e. 50, 100, 200, 300, 400 and 500; by observing visualized output maps, the bandwidth of 200 m is selected and recommended for the identification of hazardous locations in the road network. Another important parameter for the network KDE is the maximum segment length (or pixel size). In the SANET tools manual, a rule of thumb is mentioned and recommended to the users; according to it, the pixel size has to be 10 times smaller than the selected bandwidth. In this study, this rule was respected; therefore, the maximum segment length is equal to 20 m.

Finally, another important issue that has puzzled researchers is related with the selection of the right density threshold(s) [35]. Initially, all the accidents and the road networks from all the municipalities were imported in QGiS and kernel densities were computed using v.kernel tool from GRASS GIS. At next, descriptive statistics, of kernel densities were estimated; by performing a X^2 test; it was observed that for a confidence interval of almost 95%, the density observations are gamma distributed. Using the cumulative probability function of Gamma distribution, we approached and finally determined the values of four thresholds. If the density at location s is higher than the first, second, third and fourth threshold, then this density value is also higher than the 85%, 90%, 95% and 99% of all density values, respectively. In the second stage, a dataset of densities was created for each municipality and for each road hierarchy level. Following the aforementioned approach, for each municipality and for each hierarchy level, four thresholds were determined.

Secondly in our analysis for spatial autocorrelation we use two different methods in order to produce better and more cohesive results. The first method calculates the index of Moran's I (Global and Local), which is a common statistical diagnostic tool that is defined as the division of the spatial variance with the total spatial variance of each variable [43, 44]. The main contribution of Moran's I is the evaluation whether a spatial pattern is clustered, random or dispersed. It works on both feature locations and features values simultaneously. The second method is the Hot-Spot Analysis which calculates the Getis-Ord Gi* statistics [40]. Specifically, this tool works by looking at each feature within the context of neighboring features. It identifies statistically significant hot spot as a location having high value and surrounded by high valued neighbors as well.

In both methods (applied in ArcGIS environment) we used the same parameters, thus ensuring the adoption of a common view between the results of each method. Precisely, for the conceptualization of spatial relationships, the inverse distance method was selected, as the closer two traffic accidents are in space, the more likely they are to interact with each other. Regarding the distance method; Manhattan distance method was chosen, since it is more appropriate for urban environment and when travel is restricted to a street network. Finally, the threshold distance was set to 3200m based on the size of the municipalities.

4 Results

The main results from the network kernel density estimation analysis could be concluded in the following: the highest mean and the maximum kernel density value were reported in the municipality of Athens. Furthermore, the median value is not equal to 0 as it happens in the other study municipalities; thus, there are not many segments in Athens with zero kernel density. The mean density value of Piraeus is approximately 4.5 times lower than Athens. The variance is also low compared to the municipality of Athens. Higher concentration of traffic accidents was reported in the municipality of Marousi compared to the other northern municipalities. In all study areas, the kernel densities in residential streets were lower than the ones in primary, secondary and collector roads. In addition, only in the residential streets, the median value is equal to zero; therefore, in the other road hierarchy levels, there are a few road segments, where no traffic accidents have been recorded in the examined period. Finally, no significant differences in the kernel densities can be observed between primary and secondary roads.

By applying the method described in the previous chapter, four thresholds per municipality were estimated (see Table 1). Road segments or spots with densities that are higher than the 99% of density values of each dataset were noticed using black color (black spots) (see Fig. 1-NW). As it can be seen, in order to characterize a spot as black in Athens, higher density values are required. In addition, it is observed that kernel densities are relatively high in the central areas of each municipality.

Table 1. Presentation of threshold values.

	k shape	θ scale	thre1 (85%)	thre2 (90%)	thre3 (95%)	thre4 (99%)
Athens	0.3	43.7	28.6	40.1	61.7	117.6
Piraeus	0.1	22.0	5.0	8.7	16.7	40.5
Kifisia	0.1	21.2	0.6	1.9	6.2	24.0
Marousi	0.1	22.6	2.5	5.2	12.0	34.2
Chalandri	0.1	17.5	1.7	3.6	8.6	25.5
Primary roads	0.4	49.2	37.6	51.3	76.7	141.4
Secondary roads	0.3	50.7	35.9	49.6	75.3	141.0
Collector roads	0.3	32.7	20.8	29.3	45.3	86.8
Residential streets	0.1	26.6	4.8	8.9	18.0	45.9
All municipalities	0.1	45.0	11.3	19.1	36.0	85.3

Specifically, high concentrations have been reported around the center of Athens, in primary roads in Piraeus, in the central part of Kifisia and in primary arterial roads in Chalandri. The spatial pattern is almost similar for all the study areas.

An alternative approach is to use different thresholds for each different road hierarchy level. In Fig. 1-NE, the black spots seem to spread out of the main arteries of the metropolitan area of Athens. In residential streets, the thresholds values are lower. Hence, a comparatively high concentration of traffic accidents in a spot is not an obligatory condition for calling it black. Problematic junctions mainly in the road network of Athens can be identified clearly now; again, many of the black spots are concentrated around central Athens and particularly in some secondary and collector roads. In addition, according to this analysis some junctions (primary roads intersecting) in the central part of Piraeus are quite problematic. In the road networks of the rest municipalities, a few "dangerous" junctions can be observed.

Regarding the findings of the Spatial Autocorrelation Analysis, we should highlight the following: The results of the "Global Moran's I" analysis show significant spatial autocorrelation for severity (Moran's $I = 0.0232$, $p < 0.01$), season (Moran's $I = 0.02986$, $p < 0.01$) and time (Moran's $I = 0.02298$, $p < 0.01$) of the accidents, revealing the existence of potential patterns in their spatial distribution. On the other hand, the patterns of the age of victim and the vehicle type involved do not appear to be significantly different than random. Furthermore, when it comes to the calculation of the "Local Moran's" Index, we should mention that in total, 14 high-high clusters were detected concerning the severity of accidents. They were observed on the primary road network of the metropolitan area, which includes roads that carry high traffic volume. Also, most of the high-low outliers were close to low-low clusters, while low-high outliers were mainly located near the high-high clusters (see Fig. 1-SW).

Finally, when using the Getis-Ord Gi* statistic for the severity of accidents, 141 hot spots (99% confidence) were detected. As it can be observed from Fig. 1-SE, most of the hot spots are located on the primary and secondary network, showing that high traffic volume and high speed (especially at night) may cause severe accidents.

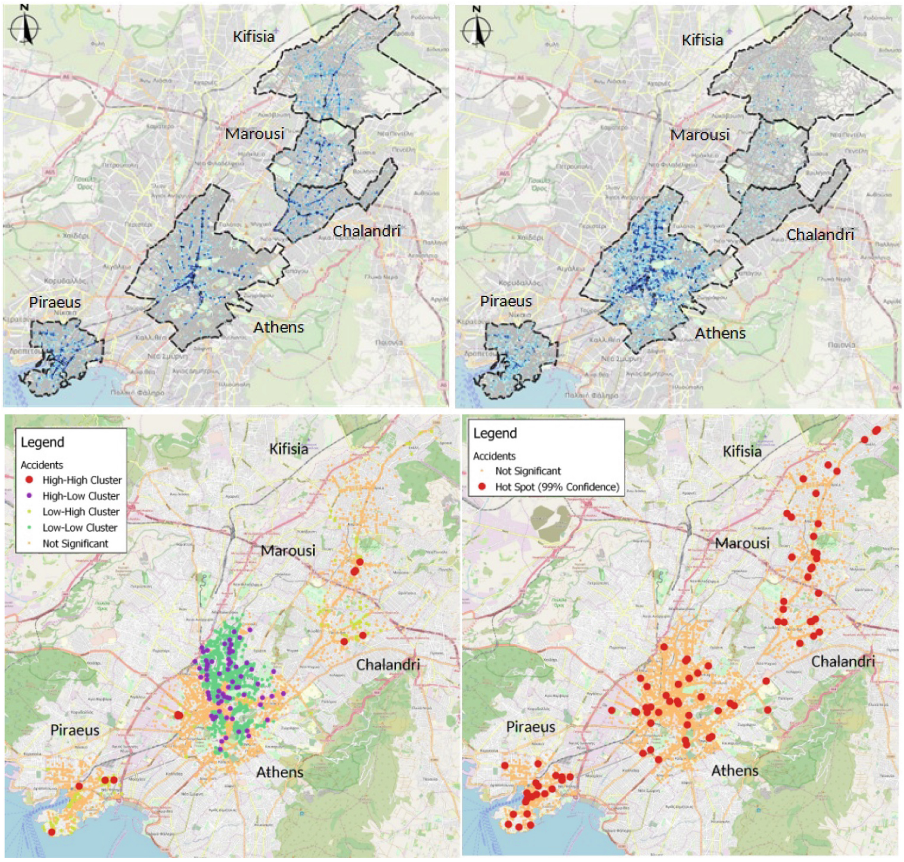

Fig. 1. Network KDE (NW-Municipality and NE-Hierarchy) and Spatial Autocorrelation (SW-Local Moran's I and SE- Hot Spot Analysis, both concerning severity).

5 Discussion and Conclusions

The current research deals with the spatial dimension of road accidents by using two different methods (KDE and spatial autocorrelation). These methods as applied in the five municipalities of Athens' Metropolitan Area indicate some valuable findings. The KDE method cannot produce absolute results, since its output depends highly enough on the initial parameters (i.e. bandwidth, distribution, etc.) and the selected thresholds. In this study, the bandwidth was chosen to be equal to 200 m and a methodology to define thresholds using Gamma distribution was presented. To identify hazardous spots in the road network of a municipality area efficiently, a planner should use different thresholds per road hierarchy level. By using "global" thresholds, a planner can make comparisons between similar municipalities or areas in terms of concentration of black spots in order to understand well enough the seriousness of traffic safety problems in the study area. Apart from KDE, the spatial autocorrelation methods unveiled that the spatial distribution of the accidents is correlated with severity, season, and time (e.g. peak hours). Hence, it would be substantial for SUMPs to formulate flexible measures adjusted to different seasons, and time periods, or to implement measures prioritized according to the severity of the accidents. As it seems the efficient analysis of existing road accidents provides valuable information about dangerous points or corridors.

In an attempt to bridge the gap between analysis and planning procedure of a SUMP, we suggest some example measures or interventions corresponding to the three dimensions of traffic safety (Risk, Severity and Exposure): The analysis revealed a noticeable spatial pattern where black spots are mainly concentrated in the central cores of the study area. Therefore, the creation of ring road zones will reduce through movements, thus decreasing the exposure in the city centers. Moreover, in arterial roads (mainly high risk linear clusters), planners should decide appropriate solutions including: a) construction of roundabouts in case of serious movement conflicts, b) widening of sidewalks or other pedestrian oriented interventions, c) construction of cycle tracks, when the coexistence with cars in cycle lanes seems dangerous and d) bus lanes. These interventions contribute significantly to reducing accidents' risk i.e. probability of traffic accident occurrence. Furthermore, planners should also pay attention to hazardous clusters by considering the enhancement of horizontal and vertical signing indicating lower speed limits. In central areas especially, where spatial analysis identified significant hotspots, they should propose the creation of traffic calming areas with a speed limit up to 20–30km/h. These measures will deal effectively with the severity of the accidents. Finally, municipalities which implement road safety measures, have to develop a traffic safety observatory in order to monitor and evaluate the progress of road accidents, and hence reconsider their further actions.

In general, it is explicit that road safety has undoubtedly a great role to play in SUMPs. Hence, the methods we applied can be fundamental tools, used both in analysis and monitoring process. Definitely, these tools add an extra dimension to traffic safety analysis and they are easy-to-use for transport and urban planners with basic GIS knowledge. For this reason, this research has notable value and could be considered as a small but at the same time important step towards a truly integration of road safety in SUMPs. At last, spatial analysis of road accidents and their connection with SUMPs cannot be fully argued in one single research. Another take could be the implementation of more spatial analysis techniques and afterwards the combination of the results in order to produce an integrated evaluation index. Moreover, further research can deal with the formulation of models aiming to predict the spatial distribution of accidents and factors affecting it (e.g. geographically weighted regression). Finally, new studies can use our findings, in order to propose planning solutions.

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