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THE EXAMINATION OF SPATIAL CLUSTERS IN THE ANALYSIS OF ACCIDENTS IN THE AREA OF REPUBLIKA SRPSKA

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Abstract: Spatial analysis of traffic accidents is the first step in the process of traffic safety management. Consideration of spatial distribution leads to the identification and ranging of potential hazards locations at different spatial levels. In this research, it has been considered an aggregate number of traffic accidents occurred in the territory of Republika Srpska. The analysis of traffic accidents included all traffic accidents that occurred during 2015., where the accidents with fatalities, injuries and material damage were considered. All types of accidents are aggregated to the level of municipalities which observed units in this research. The models and methods applied refer to spatial coefficients that used to identify spatial clusters for visualization purposes. The results showed different spatial clusters depending on the type of traffic accident. The most significant spatial clusters have been identified in municipalities with large population and high density of street network. Further directions of research should be directed to micro-locations, which would be used to analyze intersections and specific segments in order to identify the locations where the highest number of traffic accidents occured.

Keywords: Spatial analysis, Accidents, Macro-level, Spatial clusters

1. INTRODUCTION

Understanding the spatial distribution of data from phenomena occurring in space, today is a great challenge for interpreting central problems in many fields of knowledge and even in traffic. The analysis of spatial patterns was becoming more common in science, and this justifies the existence of many geographic-information tools with user-friendly interfaces. These systems allow the spatial visualization of observed entities that contain specific characteristics such as population, quality of life indices or certain economic indicators. For the purpose of considering and conducting spatial analysis, it is necessary to create and maintain spatial databases, depending on the research problem.

On the other hand, spatial analyzes are increasingly used in traffic safety because to the nature of data. One of the leading traffic safety problems is traffic accidents. The detailed and continuous monitoring of the spatial distribution of traffic accidents at specific spatial units is of key importance for the effective planning and implementation of appropriate activities in order to improve traffic safety. Spatial analysis of traffic accidents can be presented based on two approaches that are consistent with its implementation. The first approach refers to the visualization of locations where a large number of traffic accidents occur and the second approach to the consideration of spatial effect in mathematical models through a different framework of spatial research. In recent years, many researchers have examined the link between road accidents on the one hand and different spatial factors on the other (Levine et al., 1995; Abdel-Aty et al., 2013; Lee et al., 2014a, b; Saha et al., 2018).

Determination of causal factors can be systematized based on different spatial levels. The largest relationships at the spatial level relate to macroscopic studies that look at a wider area in order to identify the problems themselves. Macroscopic analyzes in traffic safety has aim to find a link between accidents and the features of spatial units that contained different spatial area. Analyze at this level often including spatial units such as the state (Aguero-Valverde and Jovanis, 2006), regions and district (Amoros et al. 2003; Noland and Oh, 2004; Huang et al., 2010), as well as smaller spatial units units (Abdel-Ati et al., 2013; Cai et al., 2017). Different spatial units often lead to diverse results on the observed locations. This requires the application of

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certain methods and models to new data sets and the identification and ranking of entities at which a significant risk of traffic accidents occurs.

In this process of thorough analysis traffic accident may found some specifics that are present in the observed data. One of the key disadvantages is the presence of spatial autocorrelation between the observed units, i. municipality, and others, relating to spatial heterogeneity that occurs when modeling traffic accidents. Analysis of spatial autocorrelation is of great importance in assessing the impact of different spatial entities. In this case, it is possible to determine that one feature of a municipality affects the values of other features at neighboring locations (Black and Thomas, 1998). Assessment of this impact involves analyzing the degree of correlation between features for each observed unit with features on neighboring units. The first step of assessing the degree of connectivity is to create a file that contains information about the neighbor structure for each location. This paper will apply different procedures for creating a spatial distance and spatial clusters in order to represent the spatial data interaction as accurately as possible.

The spatial autocorrelation of the observed units can be measured by global and local measures, for which exist many indicators (Getis and Ord, 1992; Anselin and Hudak, 1992). Accordingly, the aim of this paper is to analyze and visualize the spatial autocorrelation of municipalities in Republika Srpska. In addition, the paper discusses the identification of municipalities with an increased number of traffic accidents, which is of exceptional benefit to all subjects road safety in Republika Srpska.

2. METHODOLOGY

2.1. Preparation data

In this research, 56 municipalities in the Republika Srpska were observed. All municipality analyzes were created in the ArcGIS software package, where they are presented in the further analysis as linear surfaces. The traffic accidents analyzed in this paper are collected for the period of 2015, where each accident is considered as a point in space. The aggregation process was carried out with spatial tools, where each municipality has assigned a number of accidents that occur within it. The broader appearance of the prepared input data is shown in Figure 1. The variables included in this study relate to the different types of accidents observed to identify spatial clusters. The variables were:

- accidents with fatalities
- accidents with injuries
- accidents with property damage

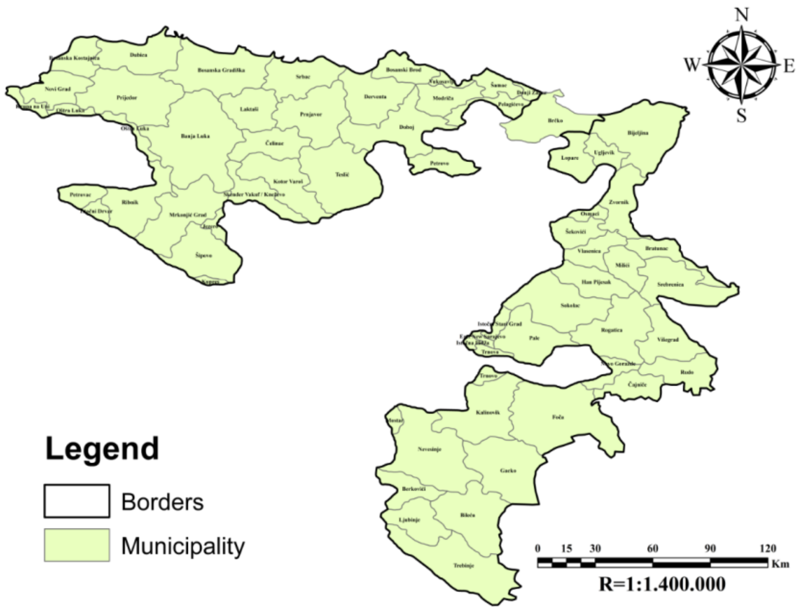


Figure 1. *Municipalities analyzed in Republika Srpska*

2.2. Model and method

In the process of analysis the models and methods were used in this paper to examine the interdependence between the observed units. In addition, methods have been applied to estimate the level to which the frequency of traffic accidents at a given location influences the values of the frequency of traffic accidents at an adjacent location. This process is examined by methods of spatial autocorrelation carried out by the introduction of spatial matrices (Moran, 1948; Cliff and Ord, 1973).

The space matrix represents all the negative matrices $W = (w_{ij} : i, j = 1, \dots, n)$ which represent the relationship between the n observed spatial units. The members of the spatial matrix w_{ij}, represent the spatial impact of unit j on unit i.

$$W = \begin{bmatrix} 0 & w_{ij} & w_{ik} \\ w_{ji} & 0 & w_{jk} \\ w_{ki} & w_{kj} & 0 \end{bmatrix}; \tag{1}$$

$$w_{ij} = \frac{1}{w_{max}} > 0$$

Matrices based on sharing a common boundary play a large role in examining spatial impact and examination spatial clusters. The indicator of this matrix was reflected in its members that represent the spatial integration of whether a traffic zone shares a boundary (l_{ij}) with another traffic zone. This matrix is defined as:

$$w_{ij} = \begin{Bmatrix} 1, & l_{ij} > 0 \\ 0, & l_{ij} = 0 \end{Bmatrix} \tag{2}$$

Autocorrelation of spatial data most often occurs when evaluating dependencies in a data matrix that is connected in space, so it may be that the effect of random error from a single observation unit, e.g. i = 1, manifest in the next spatial unit, i = 2. The presence of spatial autocorrelation is most easily observed using the Moran I index.

The Moran I index of spatial autocorrelation is a global indicator and one of the basic measures of spatial autocorrelation in spatial data (Moran, 1948). This index basically contains a space matrix and can be expressed by the formula:

$$I = \frac{n}{\sum\sum_{ij} W_{ij}} \cdot \frac{\sum\sum_{ij} W_{ij} (x_i - \bar{x})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{3}$$

Where is:

x_i= value of variable x on the observed unit i;
$\bar{x}$ = mean of variable x;
n = number of units observed;
W_{ij}= represents the distance matrix;

The Moran index of spatial autocorrelation is a method that is used to test the spatial relationships between different observed x_i spatial entities that appear in space. The Moran index value ranges from -1 to 1 and indicates the correlation of spatial entities, otherwise the negative index value indicates different values at locations.

The local Moran index for spatial notation x, observed at location i, is expressed as the L_i statistic:

$$L_i = f(x_i, x_i^n) \tag{4}$$

where, f represents the accident frequency function in the observed zone $x_i$and the adjacent zone x_i^n, this function can be expressed via the matrix and the eigenvalue z:

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} \begin{bmatrix} z_1 & z_2 & \cdots & z_n \end{bmatrix} \begin{bmatrix} w_{11} w_{12} \dots w_{1p} \\ w_{21} w_{22} \dots w_{2p} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ w_{p1} w_{p2} \dots w_{pp} \end{bmatrix} = \begin{bmatrix} z_1 \sum_{j=1}^{n} w_{1j}\, z_j\, z_1 \sum_{j=1}^{n} w_{2j}\, z_j \cdots z_1 \sum_{j=1}^{n} w_{nj}\, z_j \\ z_2 \sum_{j=1}^{n} w_{1j}\, z_j\, z_2 \sum_{j=1}^{n} w_{2j}\, z_j \dots z_2 \sum_{j=1}^{n} w_{2j}\, z_j \\ \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ z_n \sum_{j=1}^{n} w_{1j}\, z_j z_n \sum_{j=1}^{n} w_{2j}\, z_j \dots z_n \sum_{j=1}^{n} w_{nj}\, z_j \end{bmatrix} \tag{5}$$

This matrix describes the final form of creating spatial clusters in the analyzed area. The application of this methodology was observed by observing municipalities in order to identify clusters.

3. RESULTS

In this research, traffic accidents that occurred during 2015 in the area of Republika Srpska were analyzed. Traffic accidents presented as points in space, so their aggregation to the level of municipalities is enabled in order to compare their indicators. In the process of aggregation, 8922 traffic accidents were observed in 56 municipalities. Figure 2 presents the structure of traffic accidents by consequences, which is analyzed next in paper.

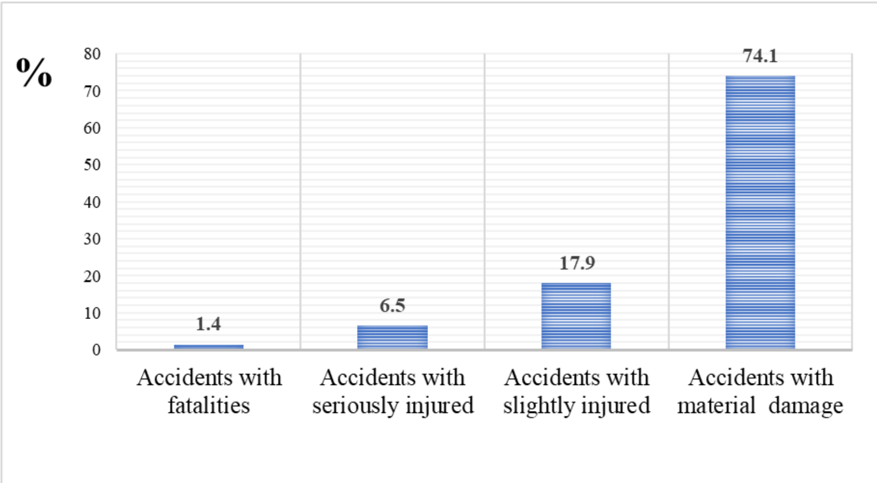


Figure 2. *Percentage of road accidents by consequences in the Republika Srpska during 2015.*

The first step in realization spatial analysis in macro-areas is to visualize the ranking of municipalities according to the number of traffic accidents. In this process, the total number of accidents was observed, where it was divided by a uniform distribution at seven one intervals. Figure 3 shows a map showing the total number of traffic accidents aggregated by municipalities.

The second step of spatial analysis in this paper concerns the calculation of spatial autocorrelation measures to identify spatial clusters. Local methods for obtaining spatial autocorrelation are calculated using the Moran index.

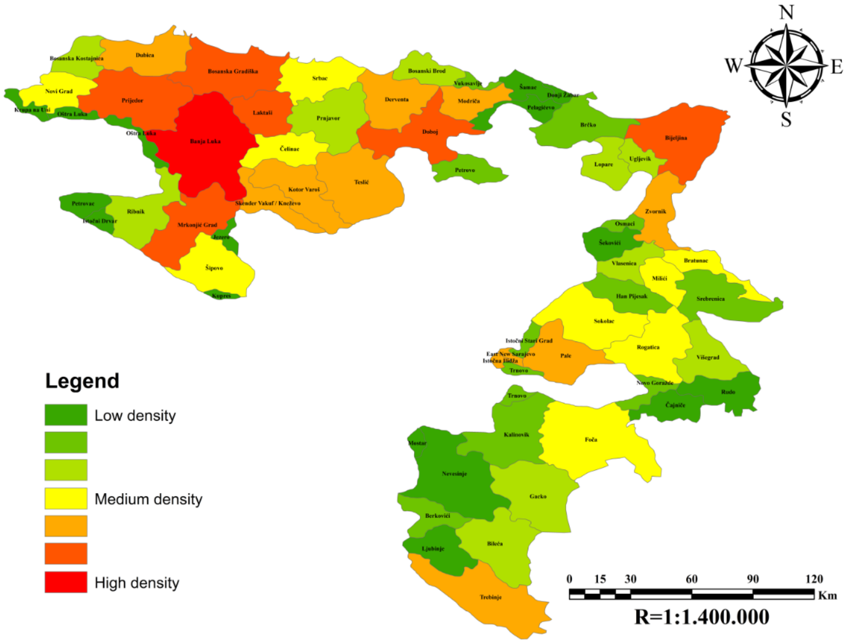
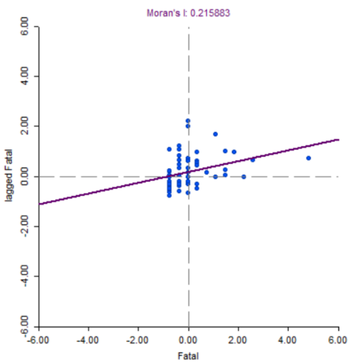
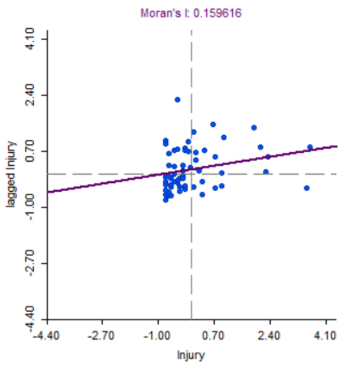


Figure 3. *Density of total number of traffic accidents in the observed area during 2015.*

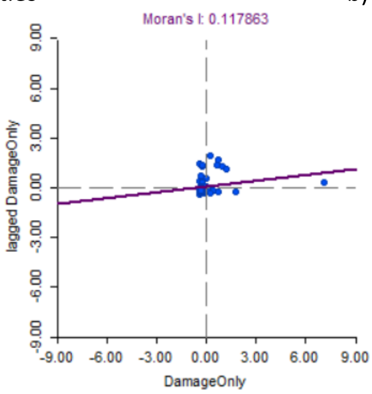
Moran index testing was performed using 999 simulations, which is sufficient for biased results. When analyzing the Moran coefficient, the presence of spatial autocorrelation between municipalities was observed. The coefficient values differ with respect to the type of accident observed. The highest coefficient was recorded in traffic accidents with fatalities (0,215883), while the smallest was obtained in traffic accidents with material damage (0,117863). These results indicate the presence of spatial autocorrelation (Figure 4).



a) accidents with fatalities



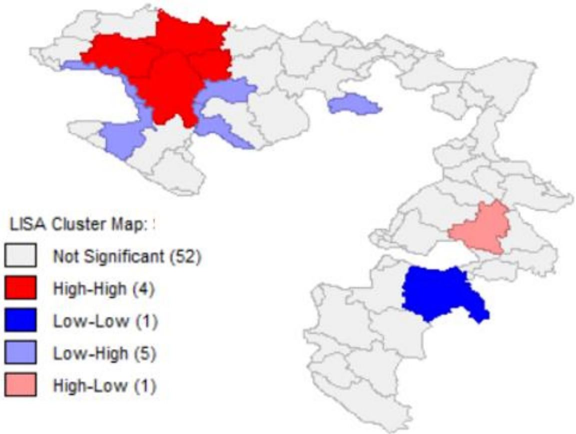
b) accidents with injuries



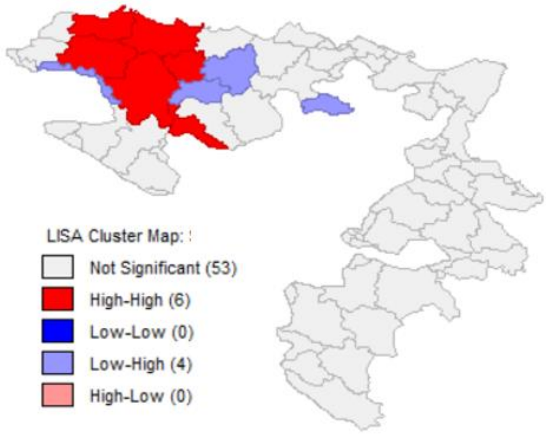
c) accidents with property damage

Figure 4. *Values of the Moran Index based on 999 simulations of accidents with fatalities, injuries and property damage.*

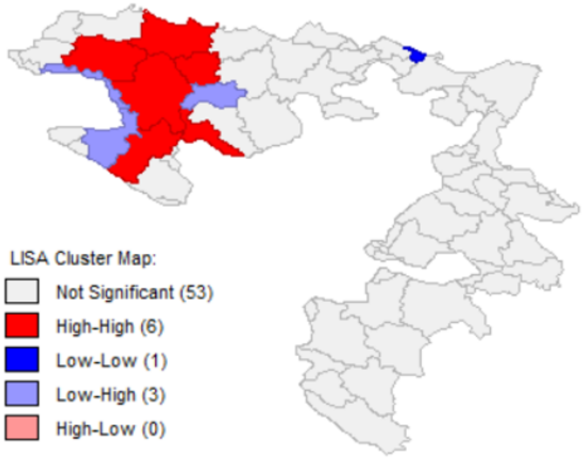
After spatial autocorrelation with a significance threshold of less than 5% (p <0.05) was identified, spatial variations as well as spatial clusters were examined. In order to determine spatial variation, local GI * statistics were conducted for the entire analyzed area. This analysis can be interpreted as an indicator of local areas or as hotspot entities. Therefore, local Moran's I (LISA, Anselin, 1995) and GI * statistics of Getis and Ord (1992) are used to examine where the areas with the highest number of traffic accidents are grouped. In this case, accidents involving the dead, injured and material damage were observed. LISA identifies 4 situations, namely clusters with high-high rates, high-low rates, low-high rates, and low-low rates. A high GI * statistic indicates the spatial clustering of a large accident frequency value and a small value indicates a low accident frequency. Figure 5 shows the spatial clusters with increased number of accidents for different types of accidents.



a) accidents with fatalities



b) accidents with injuries



c) accidents with property damage

Figure 5. *Spatial clusters of traffic accidents based on the LISA index*

Figure 5 showed the results of the LISA index for road accidents with fatalities, injuries and property damage. In traffic accidents with fatalities, 4 municipalities were identified with high-level spatial patterning. In the case of traffic accidents involving injuries and property damage, significant high-high spatial clusters were recorded in 6 municipalities.

4. DISCUSSION AND CONCLUSION

This study analyzed spatial autocorrelation between municipalities in the Republika Srpska, where traffic accidents that occurred during 2015 were observed. Methods for testing spatial autocorrelation were applied in the analysis, namely local Moran's I (LISA, Anselin, 1995) and GI * statistics of Getis and Ord (1992). For the purpose of this research, modern spatial tools were used in order to conduct spatial statistics as well as to visualize the results obtained.

The Geographic Information System (GIS) is a popular tool for visualizing traffic accidents as well as for their spatial analysis. Spatial analysis of traffic accidents is of great importance for understanding the conditions of occurrence of an accident in order to plan preventive activities at a specific location. Studies to date have found that traffic accident characteristics are different according to the characteristics of the area in which they occurred (Paulozzi et al., 2007; Traynor, 2008). After identifying the municipalities where a large number of traffic accidents occur, the relationship between the frequency of accidents and the municipalities using bivariate spatial autocorrelation showed.

In this study, the existence of spatial autocorrelation between one variable (traffic accidents) at the observed location and other characteristics at the adjacent location is proved. In addition, it has been shown that the determinants of disasters are different depending on urban areas, after grouping has been established, the relationship between the accident rate and the level of characteristics of municipalities is expressed by bivariate spatial autocorrelation. It is particularly important to point out the traffic accidents with the dead and the traffic accidents with the injured. These two variables showed a similar spatial autocorrelation coefficient, but different results were observed when conducting local Moran's I statistics and GI * statistics. Municipalities recorded using these two spatial statistics indicate easy determination of hotspot zones. What characterizes the total number of traffic accidents are the municipalities in which large cities are located, which are characterized by a high population density compared to other municipalities. In these municipalities, a large number of traffic accidents was observed, which is justified by the fact that in these unicipalities there was also a high exposure of all road users. All three types of traffic accidents showed similar results, however, the spatial autocorrelation coefficient differs significantly. This can be justified by the fact that the distribution of the aggregate number of accidents varies with the type observed.

The results of this research can be used as the first step in other scientific research as well as pointing to the very problem of traffic safety within the macroscopic analysis of municipalities in the Republika Srpska. Future research should focus on examining the factors that affect the frequency of traffic accidents within municipalities. This relationship can be examined by different regression models as conducted in many studies (Quddus, 2008; Abdel-Aty et al., 2013; Lee et al., 2014a, b; Saha et al., 2018). On the other hand, the results of this work can help decision-makers in the field of traffic safety as well as transport planning to take appropriate measures to reduce traffic accidents in the Republika Srpska. The decision-making of the traffic safety subjects should be considered from the aspect of allocation of funds that are crucial in the traffic safety at the municipal level. In addition, the study clearly identifies the municipalities within which micro-analyzes of traffic safety should be conducted in order to identify more detailed issues. These problems can be interpreted through the analysis of certain segments in which it occur a increased number of traffic accidents occur.

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