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SPATIAL DISTRIBUTION PATTERNS OF WILD-FIRES INCIDENTS IN SERBIA BASED ON VIIRS 375 M DATA FOR THE PERIOD 2013-2023

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Abstract. *This research investigates the spatial distribution and clustering patterns of wildland fires in Serbia from January 2013 to December 2023 using data obtained from NASA's Fire Information for Resource Management System (FIRMS). A total of 69,179 fires are mapped using the Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m thermal anomalies/active fire product, which offers improved spatial resolution and mapping capabilities. Spatial autocorrelation analysis, particularly Moran's I and Local Moran's I, is applied to assess the degree of clustering in the wildland fire incident dataset. Results indicate significant spatial patterns, highlighting critical areas for fire management and prevention. Municipalities such as Požarevac, Bogatić, Kikinda, Žitište, Sečanj, Šid, Irig, Ruma, and Stara Pazova, identified as HH clusters, should be prioritized for resource allocation. LH clusters, including Grocka, Beočin, and Velika Plana, need integration into regional strategies. Additionally, the persistent HL cluster in Kosjerić indicates an anomaly requiring focused intervention. These insights provide valuable information for targeted fire management strategies and highlight the importance of spatial analysis in understanding wildfire dynamics.*

Key words: *wildfire, spatial analysis, clustering patterns, Moran's I, Local Moran's I, Serbia*

1. INTRODUCTION

Climate change is responsible for the increased severity and frequency of natural disasters, including wildland fires, which significantly impact the environment, economy, and development of affected areas. The occurrence of wildland fires results from a complex interaction among ignition sources, weather, topography, and land cover [1]. The changes

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in land use, and land management significantly influence the occurrence and severity of wildland fires globally. This is especially noticeable in Europe, where shifts in land use have substantially altered fire patterns in recent decades. While the European Forest Fire Information System's satellite data offers extensive wildland fire statistics across European countries, there remains a critical need for detailed local analysis and a deeper understanding of the wildland fire conditions and associated challenges throughout Europe [2].

Projections indicate an increase in fire danger and burnt areas in southern Europe, with varying estimates of the increase per decade under high greenhouse gas emission scenarios [3]. This paper reviews 23 projection studies focusing on future wildland fire danger and activity in southern Europe, highlighting the increasing research effort on this topic. The review discusses the limitations and uncertainties in current wildland fire projections, including challenges related to climate projections, climate-fire models, and the influence of fuels, fire-vegetation feedbacks, and human-related factors on climate-fire relationships.

Using the standalone fire model (SFM), Khabarov et al. (2016) estimate a potential 200% increase in burned areas in Europe by 2090 under a 'no adaptation' scenario compared to 2000-2008, highlighting the urgency for effective adaptation measures. Under the same scenario, Balkan and Eastern European countries are projected to experience an extreme increase of 150-560% in burned areas by 2090 compared to 2000 [4].

In an attempt to address these challenges plethora of approaches are developed. To create a fire danger index for wildland fires, it is necessary to consider a wide range of factors beyond the weather forecast, such as fuel, moisture content, and topography. Due to the unavailability of information on the amount of combustible vegetative material, moisture content, and similar factors, leading world institutions such as Natural Resources Canada (NRC), the US National Oceanic and Atmospheric Administration (NOAA), and the Global Fire Early Warning System have implemented regional fire hazard forecasting systems based on their operational meteorological data, such as temperature, humidity, and precipitation, gathered from weather stations [5].

In addition to the previously mentioned models, geographical information systems (GIS) coupled with various methods proved to be suitable tools for fire danger mapping, fuel management, and fire effects assessment. For better visualization, several hazard variables such as vegetation type, topography, soil, and fire history can be additionally implemented in GIS applications [6]. On this subject, various authors have demonstrated the capacity of GIS to enhance the spatial analysis of fire danger indices, which are used for fire prevention and pre-suppression planning.

Gheshlaghi (2019) employed Geographic Information System (GIS) and Multi-Criteria Decision Analysis (MCDA) methods to produce forest fire risk maps [7]. The study utilized the GIS-based Analytical Network Process (ANP) as an MCDA method to create a fire risk map incorporating factors such as slope, altitude, land cover, and climate data. The results of this study included developing decision-making structures, calculating weighted supermatrices, and determining final priorities for accurate forest fire risk mapping.

The MODIS fire dataset, provided by The Fire Information for Resource Management System (FIRMS), offers access to satellite imagery, active fire/hotspots, and related products to identify the location, extent, and intensity of wildfire activity [8]. Levin and Heimowitz (2012) reviewed other databases, such as Landsat. However, they preferred to use the MODIS database because Landsat does not offer the temporal resolution and spatial coverage needed to monitor fires regularly and consistently. They quantified the spatial and temporal patterns of wildland fires in Israel since 2000 to analyze the physical and human factors leading to fire occurrence. By mapping wildland fire hotspots, it is possible to assess whether the fire risk is higher and to explain how land-cover and land-use patterns determine wildland fire risk [9].

Using data from the MODIS fire dataset and the receiver operating characteristic (ROC) method, Salma et al. (2023) validated the risk zones identified by the MCDA-AHP model and GIS [10]. They calculated the contribution of each factor, whether natural or anthropogenic, leading to fire initiation. The validation of the map confirmed the effectiveness of the employed model, providing a reliable tool for assessing wildfire risk zones.

Nikhil et al. (2021) highlight the importance of factors such as land cover types, slope angle, aspect, topographic wetness index, and distances from settlements, roads, tourist spots, and anti-poaching camp sheds are crucial for determining wildland fire risk zones. In the study, the application of GIS and the analytical hierarchy process (AHP) were employed to delineate forest fire susceptible zones, showcasing the utility of these approaches in fire risk assessment [11]. The research in [12] provides a comprehensive forest fire risk map using GIS-MCDA, AHP, and statistical analysis, aiding in proactive forest fire management.

By identifying and mapping Wildland-Urban Interface (WUI) areas based on building configuration and forest fragmentation, the study in [13] helps in understanding the spatial patterns of WUI and wildfire ignition points. The study highlights the vulnerability of peri-urban areas with dense clusters of buildings surrounded by forestland to fire ignition, emphasizing the need for targeted prevention strategies in such regions.

Nami et al. (2018) show the practical implications of integrating GIS-automated techniques with the quantitative data-driven evidential belief function (EBF) model for accurate estimation of wildfire probability. A wide range of predictor variables such as aspect, elevation, land use and land cover, soil type, and proximity to infrastructure were utilized, highlighting the importance of considering various factors in predicting fire occurrence. The study underscores the significance of human activities and infrastructure in influencing fire probability, suggesting the need for monitoring and managing these factors to mitigate wildfire risks effectively [154].

The research in [15] focused on predicting human-caused grassland fires using GIS spatial analysis and logistic regression, emphasizing the importance of assessing fire danger and weather conditions for fire management. The model developed in the study utilized topography, weather factors, and distances to human-built infrastructure to predict the probability of human-caused grassland fires. Correlations were found between ignition probabilities and various variables. The spatial distribution of ignition probabilities was higher in regions with greater human infrastructure density, such as villages and dirt roads, indicating a link between human activities and fire ignition.

Climate change in Serbia and the West Balkan region presents significant challenges, impacting various economic sectors and heightening the risk of natural disasters such as droughts, floods, and wildland fires. Notably, stubble burning poses a significant risk for wildland fires in Serbia, especially since these fires are more likely to spread from fields to forests.

A reliable network for monitoring wildland fires does not exist in Serbia, making it difficult to effectively manage and mitigate fire risk. The Emergency Management Sector of the Ministry of Internal Affairs of the Republic of Serbia maintains an internal database with general information on all fires where firefighter units operated. This database can provide the necessary input data for developing a unified network system for decision support to enable adequate forest fire risk management in wildland areas. By upgrading this database with diverse variables such as vegetation, topography, and distance from roads, rivers, and human settlements, this system would become a valuable tool for wildfire mitigation, offering real-time information, predictive analytics, and strategic guidance to improve preparedness and response efforts.

Due to inappropriate application and outdated legal directives regarding wildland fire protection, as well as a lack of appropriate infrastructure, insufficient human resources for fire prevention and suppression, and ineffective information distribution, there is a pressing need for a national decision-support system to effectively manage adaptation projects at both national and subnational levels [2,16].

In accordance with the Serbian Law on Fire Protection[1] the local self-government units (municipality), within the competence established by the Constitution and the law, organizes and ensures the conditions for the implementation of fire protection measures and the provision of assistance in eliminating or mitigating the consequences caused by fire and passes acts to improve the state of fire protection. The local self-government unit adopts the Fire Protection Plan, which includes, among other things, an assessment of the risk of fire.

The main objective of this research is to provide an in-depth understanding of the spatial distribution patterns of wildland fire incidents in Serbia over the period 2013-2023, specifically at the municipal level. By applying spatial autocorrelation (Moran's I and Local Moran's I), the research seeks to highlight critical areas for fire management and prevention, thereby offering valuable insights for targeted resource allocation and strategic interventions.

2. Methods and Data

2.1. Data

In this research data regarding fire incidents were obtained from NASA's Fire Information for Resource Management System (FIRMS). Specifically, the Visible Infrared Imaging Radiometer Suite (VIIRS) 375[2] m thermal anomalies / active fire product is used. This product complements Moderate Resolution Imaging Spectroradiometer (MODIS) fire detection, with the improved spatial resolution of the 375 m data that provides a greater response over fires of relatively small areas and provides improved mapping of large fire perimeters. The product uses a multi-spectral contextual algorithm to identify sub-pixel fire activity and other thermal anomalies.

For the period from January 2013 to December 2023, 69179 fires are mapped. For the analysis only fire pixels with nominal and high confidence are considered, 95% of a total number of fire pixels mapped. Nominal confidence pixels are those free of potential sun glint contamination during the day and marked by strong (>15K) temperature anomaly in either day or night-time data. High confidence fire pixels are associated with day or night-time saturated pixels.

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[1] "Official Gazette of RS", no. 111/2009, 20/2015, 87/2018 and 87/2018 - other laws

[2] VIIRS 375m NRT (Suomi NPP) NRT VIIRS 375 m Active Fire product VNP14IMGT distributed from NASA FIRMS. Available on-line https://earthdata.nasa.gov/firms. doi:10.5067/FIRMS/VIIRS/VNP14IMGT_NRT.002

2.2. Spatial analysis

In this research, spatial-autocorrelation is applied for the analysis of the wildland fire patterns. The spatial autocorrelation of wildland fire refers to the degree to which the occurrence or intensity of fires in one area is correlated with that of neighbouring areas. This analysis can provide valuable insights into the underlying processes driving wildland fire dynamics. In brief, spatial auto-correlation is related to the degree to what extent objects or activities in space approximate to others in their vicinity [17]. In spatial statistics, there are many possible ways of measuring spatial auto-correlation by various methods. In this study, Moran's I, arguably the most used method in practice for the analysis of global spatial autocorrelation, is applied for the indication of clustering in the given dataset [18]. Moran's I values range from -1 to 1, where: a Moran's I value close to 1 indicates positive spatial autocorrelation, meaning that similar values tend to cluster together in space, a Moran's I value close to -1 indicates negative spatial autocorrelation, meaning that dissimilar values tend to be located near each other in space, and a Moran's I value close to 0 suggests no spatial autocorrelation, indicating a random spatial pattern where values are not related to their spatial proximity.

Local Indicators of Spatial Association (LISA), Local Moran I, is used to identify spatial clusters [19]. Local Moran's I is important for finding local clusters of high values (high-high clusters) or low values (low-low clusters), as well as geographical outliers (high-low or low-high clusters). This information is useful for understanding geographical patterns and processes that may not be apparent from global assessments of spatial autocorrelation alone.

For the purpose of this study spatial database is created in free and open access and open source Geographic Information System software QGIS3.4[3]. The fire data, presented as point vectors are overlapped with NUT2 administrative vector polygons representing municipalities. Using function count points by polygon all the registered fire pixels belonging to a certain territory are collected and the total number of fires is assigned as an attribute to the relevant municipality. Moran's I and Local Moran's I are computed in GeoDa[4], a free software package for spatial data analysis, geo-visualization, spatial autocorrelation and spatial modelling.

3. Results and Discussion

3.1. Moran's I analysis results

For conducting Moran's I statistical test, first order queen contiguity is applied for defining the spatial weights (i.e. relationships). In order to achieve robust estimates of statistical significance 9999 permutations are conducted. Permutations are used in spatial analysis to construct a test statistic distribution based on the null hypothesis of no spatial autocorrelation. Permutations generate a reference distribution by randomly shuffling the variable's values across geographic locations, and assist in determining if the observed spatial pattern in the data is statistically significant or merely the result of random chance.

The analysis is conducted for the cumulative period from 2013-2023, but also it looks at changes over the five-year period, in order to understand spatial-temporal changes, i.e., considering 2013, 2018 and 2023. Results of the global autocorrelation show a statistically

[3] https://www.qgis.org/en/site/
[4] https://spatial.uchicago.edu/geoda

significant spatial autocorrelation for all periods observed, i.e., the null hypothesis of no spatial autocorrelation, is rejected (Table 1). Therefore, the LISA method is used to identify spatial clusters.

Table 1 Results of the global autocorrelation (Moran's I)

Year	Moran's I	p-value	Z-value
2013	0.290	0.0001	6.679
2018	0.507	0.0001	11.628
2023	0.162	0.0045	4.0993
2013-2023	0.281	0.0001	6.894

3.2. Anselin Local Moran's I Cluster (LISA) and Outlier analysis results

Geographically, wildland fires are unequally distributed in Serbia. Most of them, over 60%, are detected in the province of Vojvodina, about 10 % in the province of Kosovo and Metohija, and the rest in Central Serbia. Cluster and Outlier analysis (Anselin Local Morans) reveals clusters of High (HH), and Low (LL) values, as well as outliers where municipalities with high values are surrounded by municipalities with low values (HL) and vice versa (LH).

The concentration of HH clusters is predominantly in the northern and central regions of Serbia. This suggests a regional pattern where certain municipalities are more prone to wildland fire incidents. Some municipalities, shift over time, such as Negotin and Smederevo, since they show up in individual years (2013 and 2018, respectively) but do not appear consistently in the long-term analysis.

As it can be seen from the Fig. 1, the spatial distribution of the identified clusters, as well as the number of municipalities that form them, differs over the observed periods. For instance comparing 2013 and 2018, with 2023, we can observe significantly more prominent HH clusters in 2013 and 2018, with 22, and 27 municipalities clustered, than in 2023, with only 12 municipalities forming two spatial clusters. This can point to similar spatial-temporal underlying causes like climate conditions in the clustered municipalities (for instance drought events).

However, considering the entire period (2013-2023) trend points to HH clusters concentrated largely in the eastern part of Vojvodina province, containing 19 municipalities forming one large cluster. Požarevac, Bogatić, Kikinda, Žitište, Sečanj, Šid, Irig, Ruma, and Stara Pazova appear consistently across all observed periods, indicating persistent high wildland fire incidents in these municipalities. On the other hand, Titel, Alibunar, Kovačica, Kovin, Opovo, Pančevo, Plandište, Nova Crnja, Zrenjanin, and Inđija are also consistently present in the long-term analysis (2013-2023).

LH clusters are municipalities with low numbers of fire incidents surrounded by neighbouring municipalities with high numbers of fire incidents. This spatial relationship is indicative of areas that may benefit from regional fire management practices despite having fewer incidents themselves. For instance, Grocka, Beočin, and Velika Plana appear consistently across multiple periods, suggesting a persistent pattern where these municipalities experience fewer fires relative to their neighbours. Other municipalities, such as Majdanpek, Temerin, Vladimirci, Despotovac, Boljevac, Zaječar, Palilula, Mladenovac, Kovin, and Pančevo, show up in specific years but not consistently across all periods. LH clusters highlight municipalities that, despite having low incident rates, are situated in high-risk regions. For instance, Bela Crkva with 330 wildland fire incidents in the 2013-2023 period, borders Kovin with 1274 wildland fire incidents. These areas are critical for understanding the broader regional dynamics of fire incidents. The presence of high incident rates in neighbouring municipalities suggests potential spillover effects or shared risk factors that could influence the wildland fire risk in LH municipalities.

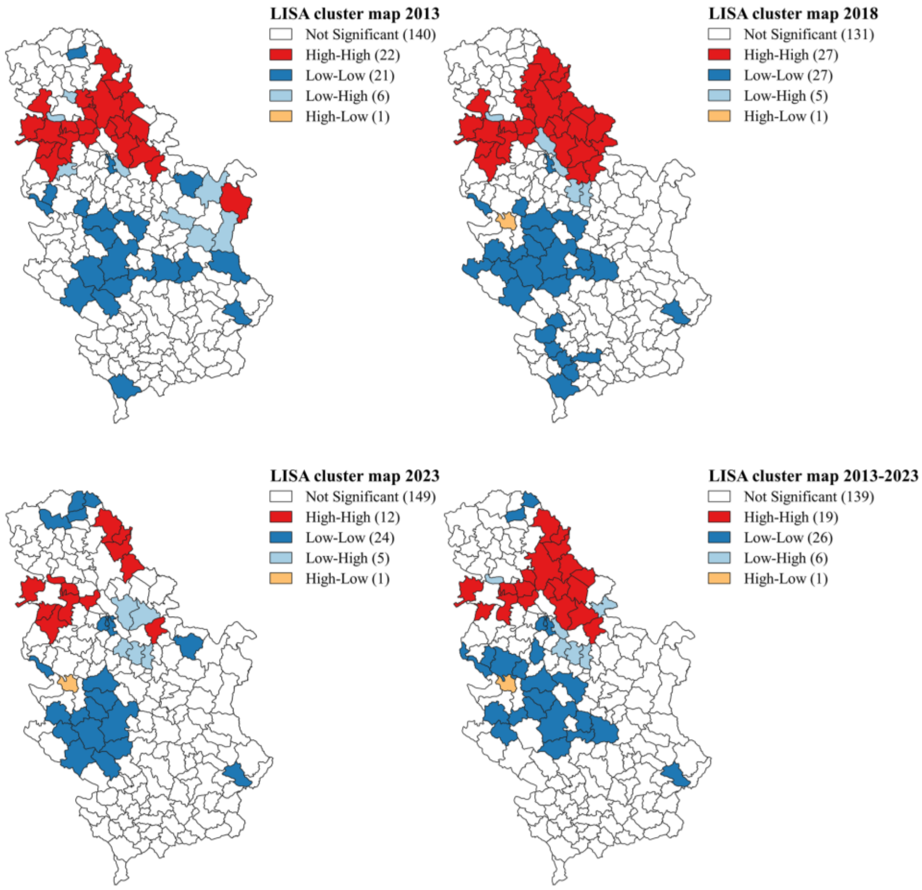

Fig. 1 Cluster and Outlier analysis (Anselin Local Moran's I)

HL clusters represent municipalities with high numbers of wildland fire incidents surrounded by neighbouring municipalities with low numbers of fire incidents. This pattern suggests that the municipality is an outlier in its region, experiencing significantly more wildland fire incidents compared to its neighbours.

Kosjerić is the only municipality identified as a High-Low cluster in both 2018 and 2023, and consistently across the entire period from 2013 to 2023. This suggests a persistent anomaly where Kosjerić consistently experiences a high number of fire incidents despite its neighbouring areas having low incidents. The persistent HL clustering of Kosjerić indicates that it has unique risk factors or conditions leading to higher wildland fire incidents compared to its surroundings. This isolation requires a focused investigation into local conditions. The absence of other HL clusters underscores the distinctiveness of Kosjerić's situation. Understanding why Kosjerić deviates from regional norms can provide insights into specific local vulnerabilities.

3.3. High Incident vs. High-High Clusters

High wildland fire incident counts do not automatically translate to HH clusters. Factors like geographical spread, neighbouring municipality fire incidents, and local conditions play significant roles in forming clusters. Some municipalities, such as Smederevo and S. Mitrovica (Table 2), consistently report high numbers of fire incidents but do not always form HH clusters. This suggests that while these areas experience many fires, they may not have the same spatial clustering as other areas. The presence of HH clusters indicates areas where wildland fire incidents are not only frequent but also geographically concentrated. This spatial concentration can be critical for identifying regions that may benefit from targeted fire prevention and management strategies. HH clusters show spatial dependence, meaning that fire incidents in these areas are likely influenced by incidents in neighbouring municipalities. This dependence is crucial for understanding and addressing the underlying causes of fire incidents.

Table 2 Top ten municipalities according to the number of wildland fire incidents

2013	2018	2023	2013-2023
Bor (338)	Smederevo (918)	Smederevo (460)	Smederevo (5780)
S. Mitrovica (321)	Zrenjanin (740)	S. Mitrovica (274)	S. Mitrovica (2553)
Smederevo (297)	S. Mitrovica (618)	Žitište (267)	Zrenjanin (2471)
Zrenjanin (279)	Pančevo (492)	Ruma (174)	Žitište (2318)
Ruma (246)	Kovačica (465)	Zrenjanin (143)	Vršac (1922)
Žitište (206)	Kovin (439)	Pećinci (134)	Ruma (1880)
Paraćin (184)	Žitište (435)	Cršac (98)	Pančevo (1574)
Pećinci (155)	Vršac (426)	Glogovac (98)	Paraćin (1531)
Kovin (152)	Ruma (425)	Bor (79)	Sečanj (1414)

5. Concluding Remarks

The spatial patterns identified through Anselin Local Moran's I analysis highlight the importance of considering spatial relationships and neighbouring influences in wildland fire incident management. By integrating these insights into fire management policies, authorities can allocate resources more effectively, tailor interventions to local conditions, and enhance overall fire prevention and response strategies.

The spatial autocorrelation analysis of fire incidents in Serbia from 2013 to 2023 reveals significant spatial patterns that provide valuable insights for policy and management interventions. By examining HH, LH, and HL clusters, several key conclusions and recommendations emerge for enhancing wildland fire management and prevention strategies: 1) Municipalities consistently forming HH clusters, such as Požarevac, Bogatić, Kikinda, Žitište, Sečanj, Šid, Irig, Ruma, and Stara Pazova, should be prioritized for fire management resources due to their spatial concentration of incidents. Investigating the underlying causes for persistent high fire incidents in these municipalities, including factors such as vegetation type, land use, climate conditions, and human activities, will aid in creating effective prevention measures; 2) Municipalities forming LH clusters, such as Grocka, Beočin, and Velika Plana, should be integrated into broader regional fire management strategies. Despite having fewer incidents themselves, they are situated in high-risk regions; 3) consistent identification of Kosjerić as a High-Low cluster indicates a persistent anomaly where this municipality experiences significantly higher fire incidents compared to its neighbours.

While the spatial autocorrelation analysis provides valuable insights into the spatial distribution of fire incidents in Serbia, several limitations should be acknowledged: 1) the analysis conducted at the municipal level may mask finer-scale variations in fire incident patterns within municipalities, leading to potential aggregation bias. Municipal boundaries may not accurately reflect the spatial extent of fire risk factors, such as wildland-urban interfaces or ecological boundaries, which could influence the observed spatial patterns; 2) While spatial autocorrelation identifies spatial associations, it does not establish causal relationships between fire incidents and underlying risk factors, requiring additional causal inference methods for deeper understanding; 3) While spatial autocorrelation analysis provides valuable descriptive insights, translating these findings into actionable policy recommendations requires careful interpretation and consideration of practical feasibility.

Therefore, several areas warrant further investigation to enhance understanding of this initial study: 1) Conduct in-depth research to identify the specific causal factors contributing to the spatial patterns observed in HH, LH, and HL clusters; 2) Investigate temporal trends in wildland fire incident patterns to identify any emerging hotspots or shifts in spatial dynamics over time; 3) Develop predictive models for identifying potential future wildland fire hotspots based on historical incident data and environmental variables.

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ANALIZA PROSTORNE DISTRIBUCIJE INCIDENTA POŽARA U SRBIJI NA OSNOVU PODATAKA VIIRS 375 M ZA PERIOD 2013-2023.

Ovo istraživanje analizira prostornu distribuciju i obrasce klastera požara u divljini u Srbiji od januara 2013. do decembra 2023. koristeći podatke dobijene iz NASA-inog Sistema informacija o požarima za upravljanje resursima (FIRMS). Ukupno 69179 požara je mapirano pomoću Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m. Analiza prostorne autokorelacije, posebno Moran I i Lokal Morans I, je primenjena da bi se procenio stepen grupisanja mapiranih požara. Rezultati ukazuju na značajne prostorne obrasce, ističući kritične oblasti za upravljanje i prevenciju požara. Opštine Požarevac, Bogatić, Kikinda, Žitište, Sečanj, Šid, Irig, Ruma i Stara Pazova, su identifikovane kao "High-High" klasteri. "Low-High" klaster, uključuje Grocku, Beočin i Veliku Planu. Pored toga, "High-Low" klaster u Kosjeriću ukazuje na anomaliju koja zahteva fokusiranu intervenciju. Ovi uvidi pružaju korisne informacije za fokusirane strategije upravljanja požarima i ističu važnost prostorne analize u razumevanju dinamike požara.

Ključne reči: *divlji požari, prostorna analiza, klasterovanje, Moran's I, Local Moran's I, Srbija*