



www.gi.sanu.ac.rs, www.doiserbia.nb.rs,
J. Geogr. Inst. Cvijic. 67(3) (249–264)



Original scientific paper

UDC: 911.2:502.7“2007/2017”(497.11)
DOI: <https://doi.org/10.2298/IJGI1703249P>

REMOTE SENSING ROLE IN ENVIRONMENTAL STRESS ANALYSIS: EAST SERBIA WILDFIRES CASE STUDY (2007–2017)

Ivan M. Potić^{*1}, Nina B. Ćurčić^{**}, Milica M. Potić^{***}, Milan M. Radovanović^{**/****}, Tatiana N. Tretiakova^{****}

* University of Belgrade, Faculty of Geography, Belgrade, Serbia

** Geographical Institute “Jovan Cvijić” SASA, Belgrade, Serbia

*** Independent researcher, Belgrade, Serbia

****South Ural State University, Institute of Sports, Tourism and Service, Chelyabinsk, Russia

Received: October 31, 2017; Reviewed: November 12, 2017; Accepted: November 30, 2017

Abstract: Wildfire has been one of the most dangerous environmental stressors nowadays. It is an important disturbance where ecosystem biomass is burned and where organisms are damaged or killed by fire. Therefore, the detecting and monitoring of this stressor are of great importance. During last decades, extensive forest fires have spread in Southern Europe, and they are registered in Serbia as well. During year 2007, several significant fires were registered in Stara Planina and Svrljiške Planine Mountains. The aims of this study were to detect land cover changes for the studied site from 2007–2017, to focus on monitoring the area affected by the wildfire, and to analyse the environment response to stressor. The study area is situated in East Serbia, partially covering the Mountains Stara Planina (western part) and Svrljiške planine (eastern part). The remote sensing techniques were used in the analysis and main satellite data were obtained via USGS Earth Explorer application. Six different classes were selected: Water, Forest, Pastures, Artificial area, Agriculture, and Bare soil. Results showed significant changes in two classes, Forest, and Pastures — the forest spread for more than 20% at the expense of pasture, which decreased more than 23%.

Keywords: machine learning, random forest, change detection, normalized burn ratio (NBR) index

Introduction

The productivity of species and ecosystem development can be constrained by physical, chemical and biological factors, and this perturbation is called environmental stress. Different types of environmental stressors can be defined in its origin: *natural* or *anthropogenic* (Cairns, 2013); *extrinsic* or *abiotic* (Lindgren & Laurila, 2005; Sørensen, Norry, Scannapieco & Loeschcke, 2005) or *biotic*. Natural abiotic stressors can be recognized as natural disasters

¹ Correspondence to: ipotic@gmail.com

(droughts, floods, wildfires, landslides), climate impact (winter season, high winds, intense sunlight, extreme temperatures, intense rainfall, acid rain) and others. Anthropogenic abiotic stressors can be recognized as fires, wood harvesting, agriculture (Cairns, 2013), and many others. Biotic stressors can be recognized as competitors, predators, parasites, and others (Bijlsma & Loeschcke, 2005).

Wildfire has been one of the most dangerous environmental stressors nowadays. It is a significant disturbance where much of the ecosystem biomass is combusted and burned, and organisms may be killed and damaged by intense heat and toxic exposure. Wildfires are considered to be caused by lightning or by human activities if their occurrence is registered near human settlements (Freedman, 2015). Also, some research results showed the relation between fire occurrence and solar activity (Radovanović & Gomes, 2009; Radovanović, Gomes, Yamashkin, Milenković, & Stevančević, 2017). During last decades, extensive forest fires have spread in Southern Europe, and they are registered in Serbia as well (Marković et al., 2016). Whether of natural or anthropogenic origin, forest fires are a potential risk both for ecosystems and human settlements and this risk can be decreased and managed by tracking the weather, controlling fires to limit available fuel and creating firebreaks (Petrasova, Harmon, Petras, & Mitasova, 2015).

During the year 2007, in Serbia a total of 22,161 ha of forests were damaged by fire, which is significantly higher than in previous years (2004 — 202 ha, 2005 — 52 ha, 2006 — 494 ha) (Statistical Office of the Republic of Serbia, 2010). In the same year, a total of five indicative fires were registered in Stara Planina Mountains, when forest and other wooded lands were burned in the total area of 1,390 ha (GFMC, 2008). Also, significant fires were recorded in the areas of Svrljiške Planine Mountains, Niš, Aleksinac, Merošin and Doljevac. This paper aims to detect the land cover change for the studied site from 2007–2017. The focus is on monitoring the area affected by the wildfire which is an environmental stressor and analyzing the environment response to the consequences that stressor caused. The characterisation of wildfire as a stressor can be featured through its spatial distribution which may be local, regional or global (Cairns, 2013), depending on its extent. Regarding spatial distribution, the role of remote sensing is substantial. The remote sensing as an environmental monitoring tool allows us to observe the nature before, during, and after the wildfire occurred. Pre-fire satellite imagery provides us the fuel types (Arroyo, Pascual, & Manzanera, 2008; Jia, Burke, Kaufmann, Goetz, Kindel, & Pu, 2006), occurrence of wildfire and burnt areas are also detectable (Fraser, Fernandes, & Latifovic, 2003; Stroppiana, Bordogna, Carrara, Boschetti & Brivio, 2012; Quintano, Fernández-Manso, Stein, & Bijker, 2011), and further,

fire management can be accomplished using remote sensing techniques (Duncan, Shao & Adrian, 2009).

Data and methods

Study area

The location of the study area is East Serbia and includes the area of Suva Planina and Vlaška Planina Mountains, Belopalanačka and Pirotka Kotlina Basins, and the areas affected by wildfire: the western part of Stara Planina Mountains and the eastern part of Svrljiške Planine Mountains (Figure 1). Geographic coordinates of the area of interest are 42°58'48.0316" S, 22°11'29.9744" W, 43°23'15.5617" N, 22°59'37.8267" E, and the total area covers 1,951.6 km².

The Stara Planina Mountains are part of the Balkan Mountain system (Milovanović, 2010) and are an extension of the Carpathian Mountains. They run 560 km from Eastern Serbia through central Bulgaria to the Black Sea, and their western part (around one fifth of the whole massif) is situated in Serbia (Stojanović, Tsekova, Pešić, Milanović, & Milutinović, 2013).

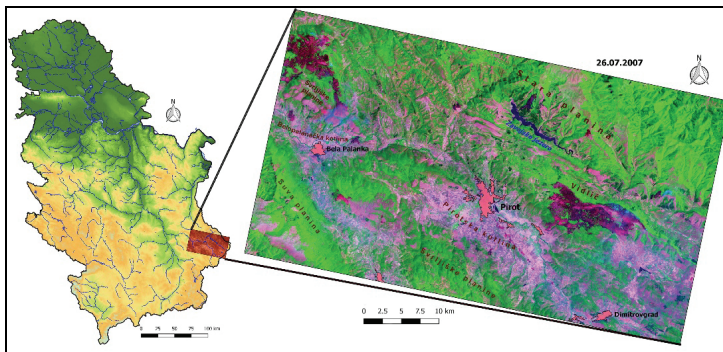


Figure 1. The area of interest: Landsat 5 false-color composite (SWIR, NIR, and Blue band) presenting wildfire occurrence (Source: SRTM 1 Arc-Second Global, USGS Earth Explorer, 2017 & Landsat 5, USGS EarthExplorer, 2017)

The Stara Planina mountains are characterized by natural values of great significance; therefore, the western part was established as a Nature Park in 1997 on the proposal of the Institute for Nature Conservation of Serbia (www.jpstaraplanina.rs; www.zzps.rs). The highest point in Serbia is situated at Midžor Peak (2,169 m) located on the Serbian-Bulgarian boundary, while the lowest is at the exit from the valley of Prlitski Potok Stream at 132 m (Milovanović, 2010). This is an area of sedimentary rocks and sediments of

different geological age, from the Palaeozoic to Cenozoic ages with the unique morpho-hydrologically dissected landscape. There are 1,195 taxons of vascular flora established with endemic and relic species (Amidžić; Krasulja & Belij, 2007), such as endemite *Campanula calycialata* V. Randelović & Zlatković growing in a single locality on Babin Zub peak (Randelović & Zlatković, 1998). Vegetation includes 24 forest and bush, and 28 grass communities, which are ranged from the lowest belt of thermophilic deciduous forests to the highest zone of subalpine and alpine meadows and pastures. The Stara Planina Mountains represent one of the six biodiversity hotspots in Europe (Jakšić, 2008; Papp & Erzberger, 2007; Stojanović et al., 2013), and one of the centers of Arctic-Alpine flora in the Balkan Peninsula (Stevanović et al., 2009).

The Svrljiške Planine Mountains are situated between the Svrljiška Kotlina Basin in the north, Niška Kotlina Basin in the west, and Belopalanačka Kotlina, Sićevačka and Gradištanska Kotlina Basins in the south (Zeremski, 2008). The highest point is situated at 1,334 m (Zeleni Vrh Peak). Due to complex geological history, climate and pedological cover, the Svrljiške Planine Mts. became a refugium of Tertiary flora and vegetation and are home to many endemic and relic species, such as *Ramonda serbica* Pančić, *Salvia officinalis* L., *Scabiosa fumarioides* Vis. & Pančić, *Centaurea chrysolepis* Vis., *Lilium jankae* A. Kern, *Satureja kitaibelii* Wierzb. ex Heuff., *Crocus hybridus* Petrović and *Corylus colurna* L. (Randelović, Đorđević, Zlatković & Avramović, 2004). Dominant forests are oak and beech forests, and the most widespread is the association *Carpino orientalis-Quercetum mixtum*. Forests of southern and western parts of the Svrljiške planine mountains are mainly destroyed and xerophytic pastures of submediterranean and steppe character were developed (Randelović et al., 2004).

Methodology

Main satellite data used in this study are obtained via *USGS Earth Explorer* application. Downloaded images were acquired on 10th July 2007 (pre-fire), 26th July (forest fire occurrence) and two images dating 12th and 21st July 2017. The data belong to *Landsat Surface Reflectance Higher-Level Data Products*, where atmospheric correction routines were applied to the Level 1 Landsat data to generate top of atmosphere reflectance, surface reflectance, brightness temperature, and masks for clouds, cloud shadows, adjacent clouds, land, and water (Landsat Surface Reflectance Higher-Level Data Products, 2017).

Software used to process the images is QGIS with Remote Sensing plugins *dzetsaka* and *SCP* QGIS (QGIS Python Plugins Repository, 2017). Since the study area was partially covered with clouds for the images acquired in 2017, mosaicking was performed to create a clean image. The mosaic that is created from the images acquired in July 2017 will be marked with a label 21st July 2017

in paper. Further, all of the images were clipped using Area of Interest (AOI) vector which presents the study area to complete the pre-processing steps. Next step is the creation of Land Cover maps. Pixel-based classification as supervised learning task is performed employing the machine learning *Random Forest* (RF) (Pedregosa et al., 2011) algorithm.

Training zones are vectorized using high-resolution Google maps imagery, Bing maps imagery, and Landsat 5 & 8 color composites in QGIS. Landsat 5 Land Cover (LC) map from 10th July 2007 (Figure 2a) is going to show the wildfire fuel, while the Landsat 8 LC map (Figure 2b) will present the recent condition of the environment. Both LC maps are going to be used to perform the change detection. Six different classes are classified: Water, Forest, Pastures, Artificial area, Agriculture, and Bare soil.

To ensure the quality of the classification, the accuracy assessment is accomplished calculating the error matrix, which is presented as a table that compares reference data (i.e., ground truth data) with map information for a number of sample areas (Congalton & Green, 2009). For the completion of accuracy assessment, at least 17 randomly selected points for each class are collected. Two types of the accuracy assessment are calculated: overall accuracy, which is a presentation of the ratio between the number of correctly classified samples and the total number of sample units (Congalton & Green, 2009) and Kappa analysis, which is presented as a discrete multivariate technique to statistically determine if there are significant differences between two error matrixes (Bishop, Fienberg, & Holland, 1975, Congalton & Green, 2009). To assure the quality of the accuracy assessment points, high-resolution Google and Bing imagery employed with Landsat 5 & 8 color composites.

For the wildfire detection, there are two groups of Landsat 5 Thematic Mapper (TM) input bands for the precise detection of burned areas: a) visible and Near Infra-Red (NIR), b) Visible and NIR and Short Wave Infra-Red (SWIR) (Bastarrika, Chuvieco & Martin, 2011). There are several different spectral indices and techniques available and used by authors, and Landsat TM/ETM+ data have been used by tradition to map burned areas and fire severity (Barbosa, Grégoire & Pereira, 1999; Bastarrika, Chuvieco & Martin, 2011; Chuvieco, Englefield, Trishchenko & Luo, 2008; Díaz-Delgado, Lloret, & Pons, 2003; García & Chuvieco, 2004; Howard & Lacasse, 2004; Key & Benson, 1999, 2004; Miller & Yool, 2002; Patterson & Yool, 1998; Roy, Boschetti & Trigg, 2006; Salvador, Valeriano, Pons, & Díaz-Delgado, 2000; Santos, Caetano, Barbosa & Paúl, 1999; Smith et al., 2007; White, Ryan, Key. & Running, 1996) where NBR (Eq. 1) and Δ NBR (Eq. 2) indices are engaged.

$$\text{NBR} = (\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR}) \quad (1)$$

where: NIR = Landsat 5 Band 4 (0.76–0.90 μm) and Landsat 8 Band 5 (0.85–0.88 μm), SWIR = Landsat 5 Band 7 (2.08–2.35 μm) and Landsat 8 Band 7 (2.11–2.29 μm);

$$\Delta\text{NBR} = \text{pre-fireNBR} - \text{post-fireNBR} \quad (2).$$

Loópez García & Caselles (1991) developed the NBR algorithm in a mild-warm/subtropical climate study area using Landsat 5 imagery. SWIR band values increase most after the fire, and the NIR band values decrease most after the fire as these bands correspond best with vegetation change due to fire in the forested ecosystem in which it was developed. The NBR index highlights the areas that have been burned.

The ΔNBR , which uses the NBR pre-fire and post-fire calculated index, highlights the burn extents and severity ruled on the difference between these two index layers (Table 1). ΔNBR offers a quantitative measure of environmental change caused by the fire, or temporal difference (Key & Benson, 1999; Key & Benson, 2004) and ΔNBR symbolizes a scaled index of the extent of change triggered by fire (van Wagtendonk, Root & Key, 2004).

Table 1. Burn severity categories (Key & Benson, 1999)

ΔNBR	Burn Severity
< -0.25	High post-fire regrowth
-0.25 to -0.1	Low post-fire regrowth
-0.1 to +0.1	Unburned
0.1 to 0.27	Low-severity burn
0.27 to 0.44	Moderate-low severity burn
0.44 to 0.66	Moderate-high severity burn
> 0.66	High-severity burn

Output values of NBR equation are constrained to +/-1 while ΔNBR values are not constrained to the range, although most output values will be between -1 and +1.

NBR index is calculated for the pre-fire period (10th July) and fire period (26th July 2007). Since the NBR index values have some misinterpretations, mostly in water and artificial area LC classes, these NBR values need to be filtered. All of the overlapping pixels from both NBR raster's with water and artificial area LC classes from 10th July 2007 were removed to create clean NBR map (Figure 3).

In the final stage of the research, ΔNBR map area is used to mask the areas on the pre-fire map to extract the land cover and to examine the fire fuel. Also, the 10-year post-fire land cover is masked with a same ΔNBR map to present the

recent condition of the burned area and to be able to perform change detection of the environment.

Results and discussion

Results of the full extent of study area are presented in Figure 2 and Table 2. The pre-fire Land Cover map, created using Landsat 5 satellite imagery acquired on 10th July 2007 (Figure 2a), is the presentation of the environment state approximately ten days before the wildfire started. The current state of the environment is presented in the Land Cover map (Figure 2b), and it is created using Landsat 8 satellite imagery acquired on 21st July 2017.

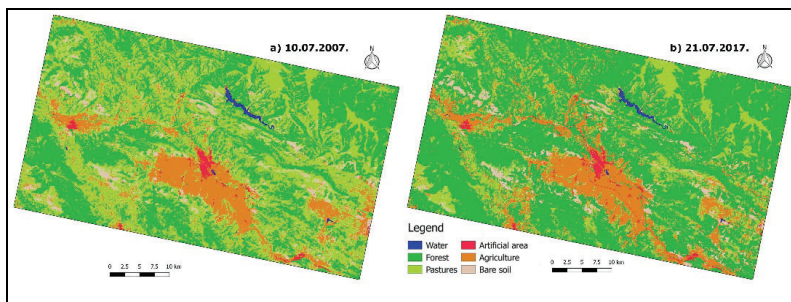


Figure 2. Land Cover map for the pre-fire period (a) and post-fire period (b).

Land Cover maps statistics are presented in Table 2. Significant change is present in two classes, Forest, and Pastures. The forest spread for more than 20% at the expense of pasture, which decreased more than 23%. It should be considered that class of Forest contains bushes and low vegetation. The analysis for the other classes does not show significant oscillations, beside the Agriculture class which has increased over the time.

Table 2. Classification reports for Land Cover maps for full extent of the study area

Classification report for 10 th July 2007				Classification report 21 th July 2017		
Class	Pixel Sum	Percentage %	Area [km ²]	Pixel Sum	Percentage %	Area [km ²]
Water	6,962	0.33	6.2658	6,369	0.29	5.7321
Forest	81,0521	37.4	729.4689	1,263,319	58.26	1,136.9871
Pastures	957,189	44.1	861.4701	441,430	20.36	397.287
Artificial area	18,048	0.88	16.2432	21,973	1.01	19.7757
Agriculture	261,193	12	235.0737	332,115	15.32	298.9035
Bare soil	114,599	5.29	103.1391	103,284	4.76	92.9556

Reliability of the classified data is tested calculating the confusion matrix with final *Overall accuracy* and *Kappa analysis* (Table 3a & b). Forest, Agriculture and Bare soil classes acquired from the 2007 imagery have been misclassified compared to ground truth points for 17.65%. The most misclassified data is within Bare soil class (33.3%) and Pastures (30%) for the data classified from the imagery acquired in 2017 (Table 3b). Final Overall accuracy and Kappa analysis present high accuracy for the classification.

Table 3. Accuracy assessment for the a) 10th July 2007 and b) 21st July 2017 Land Cover map

a) 10 th July 2007 Confusion matrix							Accuracy statistics	
Class	Water	Forest	Pastures	Artificial area	Agriculture	Bare soil	Overall Accuracy	Kappa
Water	19	0	0	0	0	0	89.17%	87.00%
Forest	1	17	1	0	0	0		
Pastures	0	3	19	1	3	1		
Artificial area	0	0	0	18	0	2		
Agriculture	0	0	0	1	17	0		
Bare soil	0	0	0	0	0	17		
b) 21 st July 2017 Confusion matrix							Accuracy statistics	
Class	Water	Forest	Pastures	Artificial area	Agriculture	Bare soil	Overall Accuracy	Kappa
Water	19	0	0	0	0	0	87.50%	85.01%
Forest	0	17	5	0	0	1		
Pastures	0	0	16	0	1	1		
Artificial area	0	0	0	19	0	1		
Agriculture	1	0	0	1	20	4		
Bare soil	0	0	0	0	0	14		

Masking of the burned area is performed using NBR index. The index misinterpretation which occurs within the Water and Artificial area (disadvantage of the index) is corrected by masking the areas with the Land Cover maps corresponding classes and excluding it from index results. The difference can be seen in Figures 3a and 3b, where variant a) is filtered NBR and variant b) is not filtered.

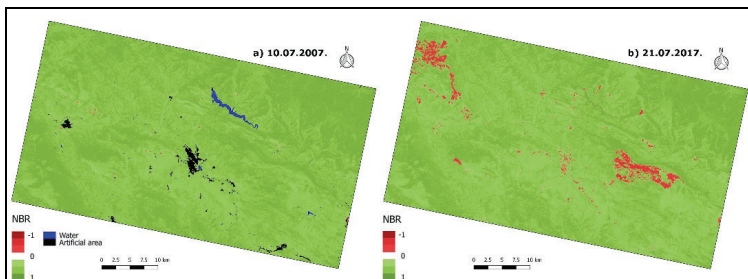


Figure 3. Pre-fire filtered NBR (a); Wildfire occurrence & post-fire NBR, non-filtered (b)

Δ NBR highlights the burn extents and severity, so the area under wildfires and fires in agriculture fields near the human settlements are marked with red polygons in Figure 4. The Δ NBR value threshold used for the extraction of the burned areas is 0.1. All positive values greater than the threshold are marked as burned area, as proposed in the Table 1.

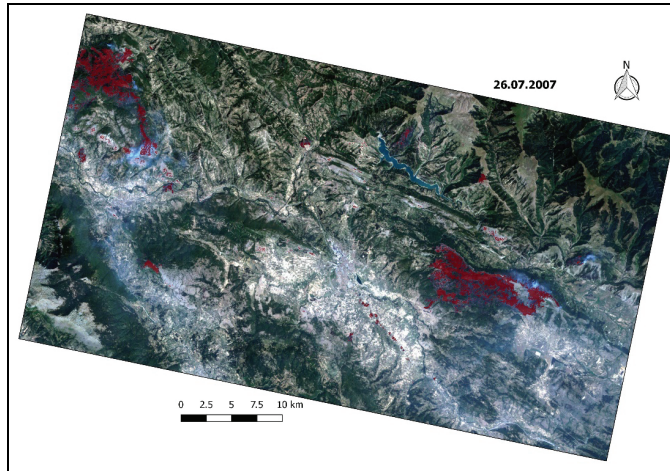


Figure 4. Δ NBR wildfire polygons overlaying Landsat 5 color composite (Source: Landsat 5, USGS EarthExplorer, 2017)

The aim of this paper, the change detection analysis for the burned areas is successfully performed by masking and extracting the land cover data from both years (2007 and 2017) using Δ NBR polygons (Figure 5). The burned areas presented with red polygons in the Figure 4 cover 41.52 km² in total. The Figure 5 presents the classes from the Land Cover maps affected by wildfires. Pre-fire and post-fire classification and change detection report for the burned area by class is presented in Table 4.

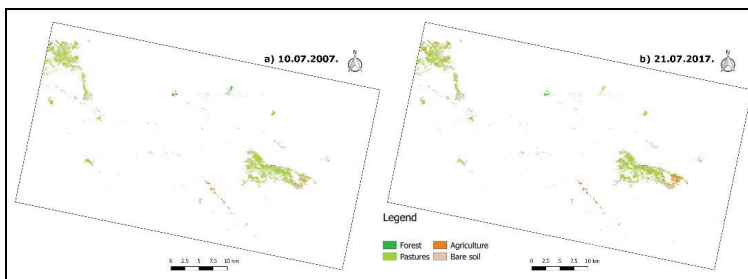


Figure 5. Land Cover map of the fire affected area with excluded Water and Artificial area classes

Land Cover maps and change detection results for the areas burned in 2007 wildfires show the domination of pastures (59% in 2007 and 51% in 2017) and bare soil (33% in 2007 and 2017). Depending on the climate condition, these two classes are very closely related, especially in 2007 dry season, when dry pastures are detected and classified as bare soil. The area covered by Agriculture class is increased due to the expansion of the agriculture production in the Nišava river basin. Pasture class has highest decrease percentage compared to 2007.

Table 4. Land Cover maps classification report for burned areas and change detection analysis

Classification report for 10 th July 2007				Classification report 21 th July 2017			Change detection % (2017–2007)
Class	Pixel Sum	Percentage %	Area [km ²]	Pixel Sum	Percent age %	Area [km ²]	
Forest	974	2.112	0.877	1,208	2.619	1.087	0.507
Pastures	2,7242	59.06	24.518	23,375	50.682	21.038	–8.378
Agriculture	2,881	6.246	2.593	6,515	14.126	5.864	7.88
Bare soil	15,029	32.582	13.526	15,023	32.573	13.521	–0.009

The change detection analysis is not performed on two initial classes, Water and Artificial area due to the NBR index misinterpretation. Land cover change detection is performed for the detected burn areas, and it reveals that the highest increase in percentage (7.88%) and area (5.864 km²) is for a land cover Agriculture class, while the Forest class has an increase of 0.507% compared to 2007. The other two classes record a decrease in percentage and area coverage (Table 4).

Nowadays, the detection of wildfires using space borne remote sensing data is widespread (Dwyer, Pinnock, Grégoire, & Pereira, 2000; Giglio, Csiszar, & Justice, 2006; Giglio et al., 2008; Schroeder et al., 2015). Contemporary remote sensing methods such as machine learning algorithms used in this research are appropriate in predicting the land cover, which high accuracy assessment ratio proves that. Since the wildfire fuel types were not the main objective, machine learning pixel-based algorithms meet the necessary need to present the land cover with high accuracy, and Land Cover map properly demonstrates the environment state at sensing period.

Prompt and evident way to detect fire using satellite imagery is to create a false color composite using SWIR, NIR and visible (blue and/or green) band (NASA, 2017, PDX, 2001). This band combination gives us quick insight into the state of the environment. The assessment of burned areas employing the NBR index is widespread among researchers. Δ NBR uses the pre-fire and post-fire NBR index and highlights the burn extents and severity. The area affected by the wildfire

and analyzed using the Δ NBR is easily and accurately masked (Figure 5). During the paper workflow, the problem that arose with the NBR (and Δ NBR) is that the index has false detection in the urban areas and areas covered by water.

Conclusions

The environment response to the wildfire as a stressor is the complete revitalization of the burned areas, especially in the inaccessible and remote natural areas. The RF classifier, despite its good accuracy assessment, cannot make the total difference between bare soil and pastures, which is noticeable in the Table 4 (and in accuracy assessment Table 3) where can be seen that 32.58% of Bare soil have been burnt. The percent value is so high because bare soil can consist of a very tiny layer of vegetation which cannot be accurately detected using optical spaceborne sensors.

Despite the Land Class map accuracy errors, remote sensing techniques can provide sufficient data for wildfires analysis and land cover classification and it is proven technology for more than 30 years, the on-going period for mapping burned areas using optical satellite systems. The remote sensing advantage is that it provides rapid information in natural disaster management, especially in inaccessible, isolated and remote areas. Further, monitoring the changes in the environment helps us to understand how the environment is struggling with stress such as wildfire. The data extracted from satellite imagery can be a good indicator for the environment management, so the global change detection using Landsat 8 satellite and other imagery is widely used (Roy et al., 2014). The advantages of remote sensing in the forest fire monitoring are that large areas can be covered, the areas under wildfire can be frequently and repetitively covered, the method can provide a quantitative measurement of ground features using radiometrically calibrated sensors, semiautomatic or automatic processing and analysis, and it allows to reduce the cost per unit area of coverage.

Acknowledgements

This research was supported by Ministry of Education, Science and Technological Development of the Republic of Serbia (Project No. III-47007) and by the Act 211 Government of the Russian Federation, Contract No. 02.A03.21.0011. Data used in this paper are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at USGS/EROS, Sioux Falls, SD. <http://lpdaac.usgs.gov> (link is external).

References

Amidžić, L., Krasulja, S., & Belij, S. (Eds.). (2007). *Protected Natural Resources in Serbia*. Belgrade: Ministry of Environmental protection, Institute for Nature Conservation.

- Arroyo, L. A., Pascual, C., & Manzanera, J. A. (2008). Fire models and methods to map fuel types: The role of remote sensing. *Forest Ecology and Management*, 256(6), 1239–1252. doi: <https://doi.org/10.1016/j.foreco.2008.06.048>
- Barbosa, P. M., Grégoire, J. M., & Pereira, J. M. C. (1999). An algorithm for extracting burned areas from time series of AVHRR GAC data applied at a continental scale. *Remote Sensing of Environment*, 69(3), 253–263. doi: [https://doi.org/10.1016/S0034-4257\(99\)00026-7](https://doi.org/10.1016/S0034-4257(99)00026-7)
- Bastarrika, A., Chuvieco, E. & Martin, M. P. (2011). Mapping burned areas from Landsat TM/ETM+ data with two-phase algorithm: Balancing omission and commission errors. *Remote Sensing of Environment*, 115(4), 1003–1012. doi: <https://doi.org/10.1016/j.rse.2010.12.005>
- Bijlsma, R., & Loeschke, V. (2005). Environmental stress, adaptation and evolution: an overview. *Journal of Evolutionary Biology*, 18(4), 744–749. doi: <https://doi.org/10.1111/j.1420-9101.2005.00962.x>
- Bishop, Y., Fienberg, S., & Holland, P. (1975). *Discrete Multivariate Analysis: Theory and Practice*. Cambridge, MA: MIT Press.
- Cairns, J. Jr. (2013). Stress, Environmental. In *Encyclopedia of Biodiversity*, (2nd Ed.) (Vol. 7, pp. 39–44). Waltham, MA: Academic Press.
- Chuvieco, E., Englefield, P., Trishchenko, A.P., & Luo, Y. (2008). Generation of long time series of burn area maps of the boreal forest from NOAA-AVHRR composite data. *Remote Sensing of Environment*, 112(5), 2381–2396. doi: <https://doi.org/10.1016/j.rse.2007.11.007>
- Congalton, R. & Green, K., (2009). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton, FL: CRC Press. Retrieved from https://books.google.rs/books?hl=en&lr=&id=T4zj2bnG1dEC&oi=fnd&pg=PP1&dq=Assessing+the+Accuracy+of+Remotely+Sensed+Data:+Principles+and+Practices+2008+&ots=RSmA bpi-XB&sig=kpCmHw3_b5a6M4E8Uab2PoZOHwo&redir_esc=y#v=onepage&q=Assessing%20the%20Accuracy%20of%20Remotely%20Sensed%20Data%3A%20Principles%20and%20Practices%202008&f=false
- Díaz-Delgado, R., Lloret, F., & Pons, X. (2003). Influence of fire severity on plant regeneration by means of remote sensing imagery. *International Journal of Remote Sensing*, 24(8), 1751–1763. doi: <https://doi.org/10.1080/01431160210144732>
- Duncan, B. W., Shao, G. & Adrian, F. W. (2009). Delineating a managed fire regime and exploring its relationship to the natural fire regime in East Central Florida, USA: a remote sensing and GIS approach. *Forest Ecology and Management*, 258(2), 132–145. doi: <https://doi.org/10.1016/j.foreco.2009.03.053>
- Dwyer, J., Pinnock, S., Grégoire, J.-M., Pereira, J. M. C. (2000). Global spatial and temporal distribution of vegetation fire as determined from satellite observations. *International Journal of Remote Sensing*, 21(6–7), 1289–1302. doi: <https://doi.org/10.1080/014311600210182>
- Fraser, R. H., Fernandes, R. & Latifovic, R. (2003). Multi-temporal mapping of burned forest over Canada using satellite-based change metrics. *Geocarto International*, 18(2), 37–47. doi: <https://doi.org/10.1080/10106040308542271>

Potić, I. et al. — Remote sensing role in environmental stress analysis: East Serbia case study

- Freedman, B. (2015). Ecological Effects of Environmental Stressors. *Oxford Research Encyclopedia of Environmental Science*. doi: <https://doi.org/10.1093/acrefore/9780199389414.013.1>
- García, M. & Chuvieco, E. (2004). Assessment of the potential of SAC-C/MMRS imagery for mapping burned areas in Spain. *Remote Sensing of Environment*, 92(3), 414–423. doi: <https://doi.org/10.1016/j.rse.2004.04.011>
- GFMC (2008). Republic of Serbia — Forest Fires in 2007. *International Forest Fire News (IFFN)*, 37, 41–47. Retrieved from http://www.fire.uni-freiburg.de/iffn/iffn_37/09-IFFN-37-Serbia.pdf
- Giglio, L., Csiszar, I., & Justice, C.O. (2006). Global distribution and seasonality of fires as observed with the Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) sensors. *Journal of Geophysical Research*, 111(G2). doi: <https://doi.org/10.1029/2005JG000142>
- Giglio, L., Csiszar, I., Restás, Á., Morisete, J. T., Schroeder, W., Morton, D., & Justice, C. O. (2008). Active fire detection and characterization with the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). *Remote Sensing of Environment*, 112(6), 3055–3063. doi: <https://doi.org/10.1016/j.rse.2008.03.003>
- Howard, S. M. & Lacasse, J. M. (2004). An evaluation of gap-filled Landsat SLC-Off imagery for wildland fire burn severity mapping. *Photogrammetric Engineering and Remote Sensing*, 70(8), 877–880. Available from <https://pubs.er.usgs.gov/publication/70156729>
- Jakšić, P. (Ed.). (2008). *Prime Butterfly Areas: A Tool for Nature Conservation in Serbia*. Belgrade, Serbia: HabiProt.
- Jia, G. J., Burke, I. C., Kaufmann, M. R., Goetz, A. F. H., Kindel, B. C. & Pu, Y. (2006). Estimates of forest canopy fuel attributes using hyperspectral data. *Forest Ecology and Management*, 229(1–3), 27–38. doi: <https://doi.org/10.1016/j.foreco.2006.03.021>
- Key, C. H., & Benson, N. C. (1999). The Normalized Burn Ratio (NBR): A Landsat TM Radiometric Index of Burn Severity. Retrieved from: https://archive.usgs.gov/archive/sites/www.nrmisc.usgs.gov/files/norock/products/SEVER36_im_copy6.pdf
- Key, C. H. & Benson, N. C. (2004). *Remote Sensing Measure of Severity: The Normalized Burn Ratio. FIREMON Landscape Assessment (LA) V4 Sampling and Analysis Methods*. Collins, CO: USFS Rocky Mountain Research Station.
- Landsat 5, USGS EarthExplorer (2017). Retrieved from <https://earthexplorer.usgs.gov/>
- Landsat Surface Reflectance Higher-Level Data Products (2017). Retrieved from <https://landsat.usgs.gov/landsat-surface-reflectance-high-level-data-products>
- Lindgren, B. & Laurila, A. (2005). Proximate causes of adaptive growth rates: growth efficiency variation among latitudinal populations of *Rana temporaria*. *Journal of Evolutionary Biology*, 18(4), 820–828. doi: <https://doi.org/10.1111/j.1420-9101.2004.00875.x>
- López García, M. J., & Caselles, V. (1991). Mapping burns and natural reforestation using thematic mapper data. *Geocarto International*, 6(1), 31–37. doi: <https://doi.org/10.1080/10106049109354290>

- Marković, V., Nagy, I., Sik, A., Perge, K., Laszlo, P., Papatoma-Köhle, M., Promper, C. & Glade, T. (2016). Assessing drought and drought-related wildfire risk in Kanjiza, Serbia: the SEERISK methodology. *Natural Hazards*, 80(2), 709–726. doi: <https://doi.org/10.1007/s11069-015-1991-4>
- Miller, J. D. & Yool, S. R. (2002). Mapping forest post-fire canopy consumption in several overstory types using multi-temporal Landsat TM and ETM data. *Remote Sensing of Environment*, 82(2–3), 481–496. doi: [https://doi.org/10.1016/S0034-4257\(02\)00071-8](https://doi.org/10.1016/S0034-4257(02)00071-8)
- Milovanović, B. (2010). *Climate of the mountain Stara Planina (Klima Stare planine)*. Belgrade, Serbia: Geographical institute “Jovan Cvijić” SASA. Retrieved from http://www.gi.sanu.ac.rs/site/media/com_form2content/documents/c23/a113/f466/gijc_pi_075_bosko_milovanovic_srp.pdf
- NASA (2017). How to Interpret Common False Color Images. Retrieved from <https://earthobservatory.nasa.gov/Features/FalseColor/page6.php>
- Papp, B., & Erzberger, P. (2007). Contributions to the bryophyte flora of Western Stara Planina Mts (E Serbia). *Studia Botanica Hungarica*, 38, 95–123. Retrieved from http://publication.nhmus.hu/pdf/Studia/StudiaBotHung_2007_Vol_38_95.pdf
- Patterson, M. W., & Yool, S. R. (1998). Mapping fire-induced vegetation mortality using Landsat Thematic Mapper data: A comparison of linear transformation techniques. *Remote Sensing of Environment*, 65(2), 132–142. doi: [https://doi.org/10.1016/S0034-4257\(98\)00018-2](https://doi.org/10.1016/S0034-4257(98)00018-2)
- PDX (Portland State University) (2001) Band combinations. Retrieved from <http://web.pdx.edu/~emch/ip1/bandcombinations.html>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M. & Duchesnay, É. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830. <http://www.jmlr.org/papers/volume12/pedregosa11a/pedregosa11a.pdf>
- Petrasova, A., Harmon, B., Petras, V., & Mitasova, H. (2015). Tangible Modeling with Open Source GIS. *Springer International Publishing*. doi: <https://doi.org/10.1007/978-3-319-25775-4>
- QGIS Python Plugins Repository (2017). Retrieved from <https://plugins.qgis.org/plugins/>
- Quintano, C., Fernández-Manso, A., Stein, A., & Bijker, W. (2011). Estimation of area burned by forest fires in Mediterranean countries: A remote sensing data mining perspective. *Forest Ecology and Management*, 262(8), 1597–1607. <https://doi.org/10.1016/j.foreco.2011.07.010>
- Radovanović, M., & Gomes, J. F. P. (2009). *Solar Activity and Forest Fires*. New York, NY: Nova Science Publishers.
- Radovanović, M., Gomes, J. F. P., Yamashkin, A. A., Milenković, M., & Stevančević, M. (2017) Electrons or protons: what is the cause of forest fires in western Europe on June 18, 2017? *Journal of the Geographical Institute “Jovan Cvijić” SASA*, 67(2), 213–218. doi: <https://doi.org/10.2298/IJGI1702213R>
- Randelović, N., Đorđević, D., Zlatković, B., & Avramović, D. (2004). Svrlijske planine refugijum endemičnih biljnih vrsta i fitocenoza. *XII Naučno-stručni skup „EkoIst’04” sa međunarodnim*

Potić, I. et al. — Remote sensing role in environmental stress analysis: East Serbia case study

učešćem, Ekološka istina, Zbornik radova, Bor, 30.05–02.06.2004. Tehnički fakultet u Boru — Univerzitet u Beogradu. Retrieved from https://www.researchgate.net/publication/319905104_SVRLJISKE_PLANINE_REFUGIJUM_ENDEMICNIH_BILJNIH_VRSTA_I_FITOCENOZA_SVRLJISKE_PLANINE_MOUNTAINS_REFUGE_OF_ENDEMIC_PLANT_SPECIES_AND_PHYTOCENOSES

Randelović, V., & Zlatković, B. (1998). *Campanula calycialata* (series *Saxicolae* Witasek), a new species from Serbia (Yugoslavia). *Flora Mediterranea*, 8, 85–92.

Roy, D. P., Boschetti, L., & Trigg, S. N. (2006). Remote sensing of fire severity: Assessing the performance of the normalized burn ratio. *IEEE Geoscience and Remote Sensing Letters*, 3(1), 112–116. <https://doi.org/10.1109/LGRS.2005.858485>

Roy, D., Wulder, M. A., Loveland, T. R., Woodcock, C. E., Allen, R. G., Anderson, M. C., Helder, D., Irons, J. R., Johnson, D. M., Kennedy, R., Scambos, T. A., Schaaf, C. B., Schott, J. R., Sheng, Y., Vermote, E. F., Belward, A. S., Bindschadler, R., Cohen, W. B., Gao, F., Hipple, J. D., Hostert, P., Huntington, J., Justice, C. O., Kilic, A., Kovalskyy, V., Lee, Z. P., Lyburner, R., Masek, J. G., McCorkel, J., Shuai, Y., Trezza, R., Vogelmann, J., Wynne, R. H., & Zhu, Z. (2014). Landsat-8: Science and product vision for terrestrial global change research. *Remote Sensing of Environment*, 145, 154–172. doi: <https://doi.org/10.1016/j.rse.2014.02.001>

Salvador, R., Valeriano, J., Pons, X., & Díaz-Delgado, R. (2000). A semi-automatic methodology to detect fire scars in shrubs and evergreen forests with Landsat MSS time series. *International Journal of Remote Sensing*, 21(4), 655–671. doi: <https://doi.org/10.1080/014311600210498>

Santos, T. G., Caetano, M. R., Barbosa, P. M., & Paúl, J. U. (1999). A comparative study of vegetation indices to assess land cover change after forest fires. *Remote Sensing for Earth Science, Ocean, and Sea Ice Applications*, 3868. doi: <http://dx.doi.org/10.1117/12.373108>

Schroeder, W., Oliva, P., Giglio, L., Quayle, B., Lorenz, E., & Morelli, F. (2015). Active fire detection using Landsat-8/OLI data. *Remote Sensing of Environment*, 185, 210–220. doi: <https://doi.org/10.1016/j.rse.2015.08.032>

Smith, A. M., Drake, N. A., Wooster, M. J., Hudak, A. T., Holden, Z. A., & Gibbons, C. J. (2007). Production of Landsat ETM+ reference imagery of burned areas within Southern African savannahs: comparison of methods and application to MODIS. *International Journal of Remote Sensing*, 28(12), 2753–2775. doi: <https://doi.org/10.1080/01431160600954704>

Sørensen, J. G., Norry, F. M., Scannapieco, A. C. & Loeschke, V. (2005). Altitudinal variation for stress resistant traits and thermal adaptation in adult *Drosophila buzzatii* from the New World. *Journal of Evolutionary Biology*, 18(4), 829–837. doi: <https://doi.org/10.1111/j.1420-9101.2004.00876.x>

SRTM 1 Arc-Second Global, USGS Earth Explorer (2017). Retrieved from <https://earthexplorer.usgs.gov/>

Statistical Office of the Republic of Serbia (2010). *Statistical Pocketbook of Serbia 2010 (Statistički kalendar Srbije 2010)*. Belgrade: Statistical Office of the Republic of Serbia. Retrieved from <http://pod2.stat.gov.rs/ObjavljenePublikacije/G2010/pdf/G20102004.pdf>

Stevanović, V., Vukojičić, S., Šinžar-Sekulić, J., Lazarević, M., Tomović, G., & Tan, K. (2009). Distribution and diversity of Arctic-Alpine species in the Balkans. *Plant Systematics and Evolution*, 289, 219–235. doi: <https://doi.org/10.1007/s00606-009-0230-4>

- Stojanović, M., Tsekova, R., Pešić, S., Milanović, J., & Milutinović, T. (2013). Diversity and a biogeographical review of the earthworms (Oligochaeta: Lumbricidae) of the Balkan Mountains (Stara Planina Mountains) in Serbia and Bulgaria. *Turkish Journal Of Zoology*, 37, 635–642. doi: <https://doi.org/10.3906/zoo-1301-33>
- Stroppiana, D., Bordogna, G., Carrara, P., Boschetti, M., & Brivio, P. A. (2012). A method for extracting burned areas from Landsat TM/ETM+ images by soft aggregation of multiple Spectral Indices and a region growing algorithm. *ISPRS Journal of Photogrammetry and Remote Sensing*, 69, 88–102. doi: <https://doi.org/10.1016/j.isprsjprs.2012.03.001>
- van Wagtenonk, J. W., Root, R. R. & Key, C. H. (2004). Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. *Remote Sensing of Environment*, 92(3), 397–408. doi: <https://doi.org/10.1016/j.rse.2003.12.015>
- White, J. D., Ryan, K. C., Key, C. C. & Running, S. W. (1996). Remote sensing of forest fire severity and vegetation recovery. *International Journal of Wildland Fire*, 6(3), 125–136. doi: <https://doi.org/10.1071/WF9960125>
- Zeremski, M. (2008). Kras Svrljiških planina. *Zbornik radova Odbora za kras i speleologiju. Posebna izdanja, DCLXIII*, 2–22.

www.jpstaraplanina.rs

www.zzps.rs