EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology 2023, 24(9), 347–357
https://doi.org/10.12912/27197050/174254
ISSN 2719-7050, License CC-BY 4.0

Received: 2023.09.06
Accepted: 2023.10.17
Published: 2023.11.15

Integrated Geomatics and Remote Sensing Analysis of Forest Fire Propagation and Land Cover Change in Berkane, Morocco

Badr Ben Hichou[1,2*], Nadia Mhammdi[1] , Mohamed Dakki[3]

[1] Geophysics and Natural Hazards Laboratory, GEOPAC Research Center, Scientific Institute, Mohammed V University in Rabat, Rabat, Morocco

[2] Majal Berkane., N 2, Siége Social de la SDL Majal Berkane, Route Oujda, Berkane, 63300, Morocco

[3] GREPOM/BirdLife Morocco, Salé, 11160, Morocco

* Corresponding author's e-mail: badrbenhichou@gmail.com

ABSTRACT

By combining geomatics techniques and remote sensing data, this paper gives a thorough investigation of the forest fires that occurred close to Berkane, Morocco, from July 16 to July 18, 2023. The goals of the study included spatiotemporally tracking the propagation of active forest fires during the fire season, and to accurately map the burned area and detect changes in vegetation cover caused by the fire. A detailed fire severity mapping of the impact of the fire on the forest was made by this integrated approach. We used remote sensing data from various sources, including NASA FIRMS data for the fire period and Sentinel-2 satellite imagery acquired two days before and one day after the fire, to accomplish these goals. In terms of estimating the burned area, our study produced important findings. We were able to estimate 3508.12 hectares, 3517.98 hectares, and 3113.63 hectares using satellite imagery with dNBR, dNDVI, and supervised classification, respectively. These results offer considerable potential for directing post-fire management plans and preserving this critically important forest area. The integration of FIRMS data, Sentinel-2 images, and GIS in our research highlights the need of using this coordinated strategy to conduct an accurate and thorough evaluation of forest fires in the area. In addition to improving our understanding of forest fire dynamics, this study emphasizes the value of using cutting-edge geospatial and remote sensing techniques in attempts to manage wildfires and save the environment. The findings of this study will contribute significantly to guiding post-fire management strategies, thus promoting the conservation of the vital forest area.

Keywords: forest fires, remote sensing, GIS, Sentinel 2, NASA FIRMS.

INTRODUCTION

Forest fires pose a formidable challenge to both the environment and society, as they jeopardize biodiversity, local communities, and ecosystems (Kala, 2023). To tackle this pressing issue, remote sensing technologies have become indispensable tools for monitoring and managing forest fires on a global scale (Payra et al., 2023). Numerous studies have underscored the significance of remote sensing in providing vital information for understanding fire dynamics and assessing the environmental impact of forest fires (Arjasakusuma et al., 2022; Nolè et al., 2022; Payra et al., 2023). One such case study conducted in a Mediterranean region by Viana-Soto et al. (2020) demonstrated the effectiveness of remote sensing in evaluating post-fire vegetation recovery and mapping burned areas. By utilizing Sentinel-2 imagery, the researchers tracked the evolution of vegetation cover after a forest fire event. Their study highlighted the importance of integrating multispectral data with GIS techniques to accurately delineate burned areas and assess the regrowth of vegetation in the affected region.

Recently, Berkane, a province in Morocco (Figure 1), faced a forest fire from July 16 to 18, 2023, necessitating swift intervention from multiple teams. In the aftermath of this catastrophic event, it is essential to conduct comprehensive analyses to understand the fire's dynamics and its impact on the landscape. In response to this urgent need, our study focused on two primary objectives. Firstly, we aimed to gain insights into the spatiotemporal propagation of the active forest fires during the incident, providing valuable support to the on-ground teams. Secondly, we sought to detect changes in the vegetation cover resulting from the fire and create an accurate mapping of the burned area. To achieve these objectives, we employed an integrated approach that combined advanced geomatics methods and remote sensing data. The utilization of GIS and remote sensing technologies has proven to be a powerful tool in assessing and managing forest fires (Duncan, 2009). By integrating data from various sources, including NASA Fire Information for Resource Management System (FIRMS) data and Sentinel-2 satellite imagery, we conducted a comprehensive analysis of the fire's behavior and its consequences on the surrounding environment. The Sentinel-2 imagery, acquired before and after the wildfire, provided critical information on the extent of the affected area, enabling us to understand the spatial distribution and severity of the burned region.

Our study aims to significantly contribute to post-fire management strategies, which are pivotal in safeguarding the invaluable forest resources in the Province of Berkane. The accurate mapping of the burned area and the identification of vegetation changes will aid in formulating effective conservation and restoration plans (Perkl, 2016), minimizing the ecological impact, and promoting sustainable recovery efforts (Jenkins, 2022).

Throughout the subsequent sections of this article, we present the methodology employed to achieve our objectives, delving into the geomatics techniques and remote sensing analyses used. Additionally, we discuss the key findings and implications of our study, shedding light on the critical role of an integrated geomatics approach in understanding and mitigating the impact of forest fires. Ultimately, we hope this research will serve as a valuable resource for the scientific community, policymakers, and local authorities in their endeavor to address the challenges posed by forest fires and ensure the long-term resilience of affected ecosystems.

METHODOLOGY

This study utilized an integrated approach (Figure 2) to analyze active forest fire propagation and map the burned area. NASA's FIRMS data provided near real-time information on active fire locations, while Sentinel-2 imagery captured before and after the fire (Figures 3 and 4) was processed to calculate the Normalized Burn Ratio (NBR) and the Normalized Difference

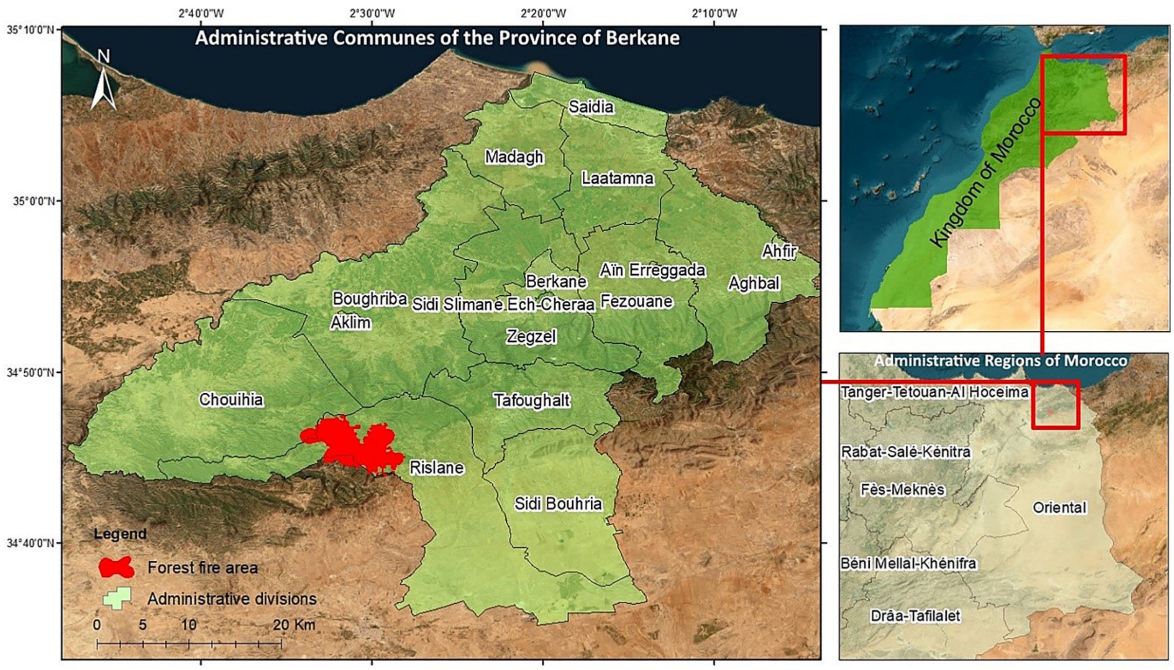

Figure 1. Geographic location map of the study area

Vegetation Index (NDVI). The differenced NBR (dNBR) and differenced NDVI (dNDVI) were computed to detect fire-induced changes in vegetation. Additionally, a supervised classification using the Maximum Likelihood algorithm was applied to map the burned area in detail.

Analysis of active forest fire propagation during the fire period

Acquisition of NASA FIRMS data

NASA's Fire Information for Resource Management System (FIRMS) provided active fire data used to map the areas of active fires near Berkane during the three-day forest fire. The fire-based maps offered through Web Feature Service (WFS) and shared on the ArcGIS Online Atlas was utilized. The used WFS information pertains to the detectable thermal activity observed by VIIRS satellites over the past 7 days. The data on VIIRS Thermal Hotspots and Fire Activity is generated through NASA's Land, Atmosphere Near real-time Capability for EOS (LANCE) Earth Observation Data, which forms a vital component of NASA's Earth Science Data.

Integration of the data to desktop GIS

The WFS was imported into GIS using ArcGIS Pro. This integration enabled us to create a map with filters on the basemap of the IGIS (Integrated Geographic Information System) of the

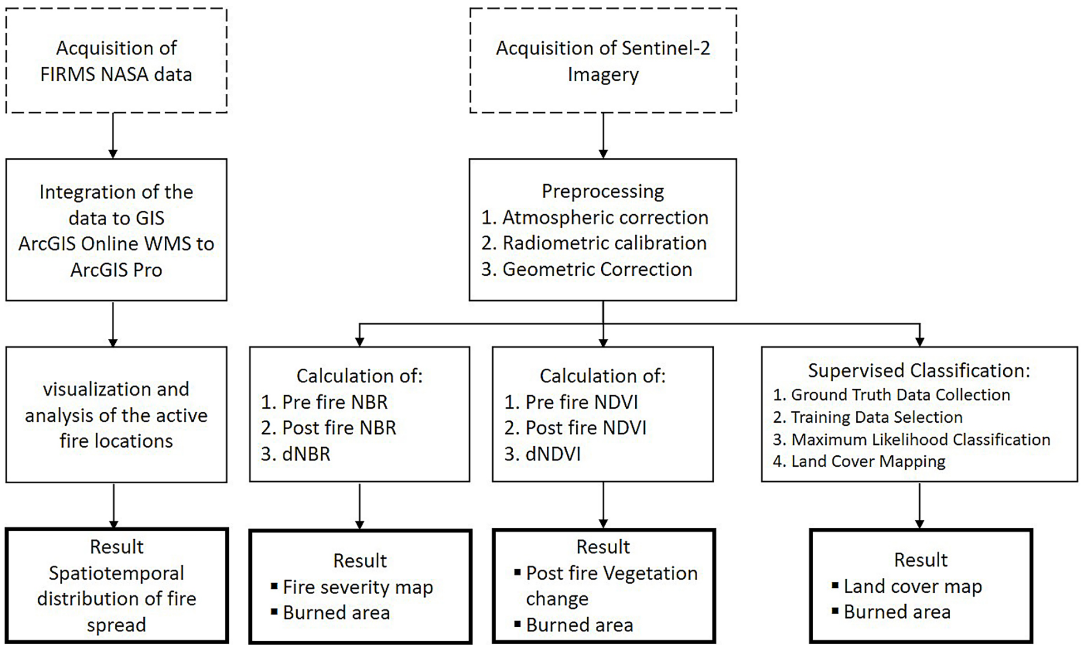

Figure 2. Diagram of the proposed methodology

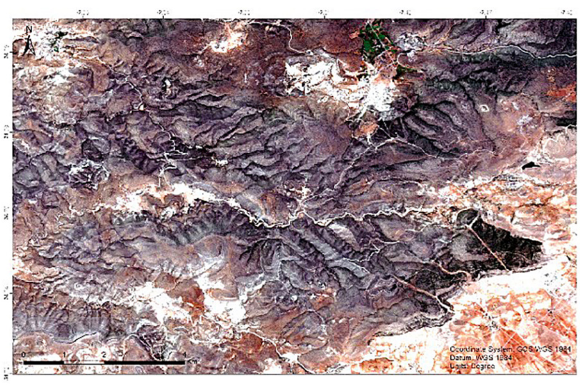

Figure 3. Sentinel-2 image before the fire (acquired on 14/07/2023)

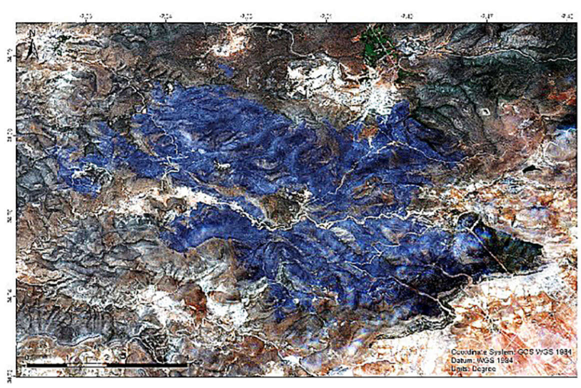

Figure 4. Sentinel-2 image after the fire (acquired on 19/07/2023)

Province of Berkane, enhancing the visualization and analysis of the active fire locations.

Change detection and mapping of the burned area after the fire period

Acquisition and preprocessing of Sentinel-2 imagery

Sentinel-2 satellite images were acquired before the fire on July 14, 2023, and after the fire on July 19, 2023. These images have a spatial resolution of 10 meters, which is ideal for accurately mapping the burned area. Sentinel-2 satellite has various spectral bands (Figure 5), capturing visible, near-infrared, and shortwave infrared wavelengths. These bands provide key data for diverse applications, including land cover analysis and environmental monitoring. The acquired images underwent a series of preprocessing steps, which included atmospheric correction, radiometric calibration, and geometric correction. These essential preparatory measures ensured that the imagery was optimized and ready for accurate calculations of NBR, NDVI, and supervised classification.

Calculation of pre fire NBR, post fire NBR and dNBR

Normalized burn ratio

The NBR is an essential index used to detect burnt areas in large fire zones. It employs both near-infrared (NIR) and shortwave infrared (SWIR) wavelengths to highlight changes in vegetation caused by fire (Key and Benson, 2005). Healthy vegetation typically exhibits high reflectance in the NIR and low reflectance in the SWIR region, while burnt areas show the opposite behavior with low reflectance in the NIR and high reflectance in the SWIR. To leverage the spectral differences, NBR utilizes the ratio between NIR and SWIR bands, as shown in the Equation 1 below:

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

A higher NBR value indicates healthy vegetation, while a lower value indicates bare ground or recently burnt areas. Non-burnt areas typically have values close to zero.

Burn severity (dNBR)

To estimate the severity of the burn, the difference between the pre-fire and post-fire NBR values is computed, leading to the calculation of differenced Normalized Burn Ratio (dNBR). Higher dNBR values correspond to more severe damage, whereas negative dNBR values may indicate regrowth of vegetation following a fire. The Equation 2 used to calculate dNBR is illustrated below:

$$dNBR = NBR\ prefire - NBR\ postfire \quad (2)$$

The resulting dNBR image was binarized using the natural break method to identify pixels

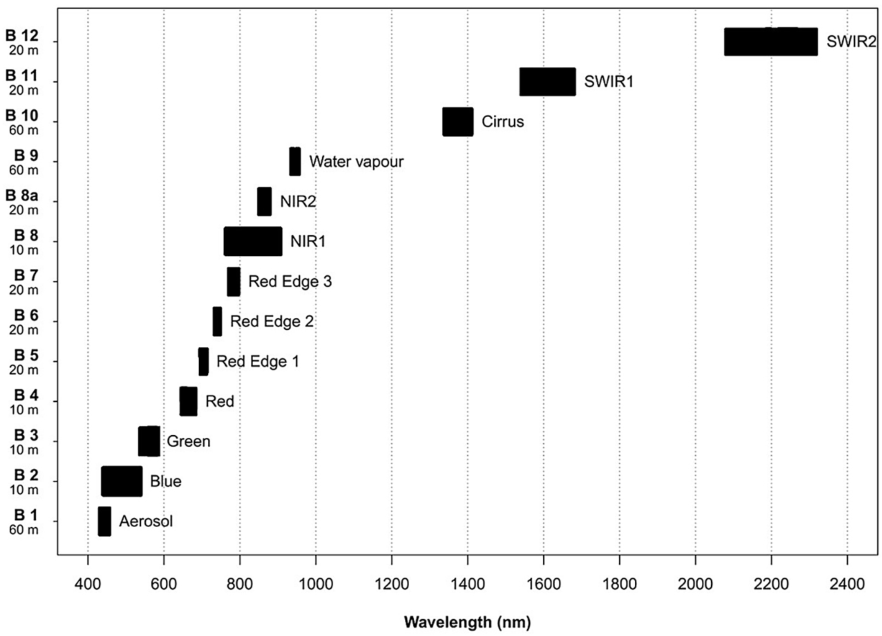

Figure 5. Characteristics of the Sentinel-2 multispectral instrument

corresponding to the burned area. These pixels were then converted from raster format to vector format in the form of polygons, facilitating the creation of an accurate burned area map.

The burn severity is estimated using dNBR image. The United States Geological Survey (USGS) has presented a classification table for interpreting burn severity based on dNBR calculations, provided in Table 1 below.

Table 1. Classification of burn severity using dNBR calculation (Proposed by USGS)

Severity level	dNBR range
Unburned	-0.100 to 0.99
Low severity	0.100 to 0.269
Moderate-low severity	0.270 to 0.439
Moderate-high severity	0.440 to 0.659
High severity	0.660 to 1.300

Calculation of pre fire NDVI, post fire NDVI and dNDVI

The Normalized Difference Vegetation Index is a standardized index allowing you to generate an image displaying greenness (relative biomass). This index takes advantage of the contrast of the characteristics of two bands from a multispectral raster dataset - the chlorophyll pigment absorptions in the red band and the high reflectivity of plant materials in the near-infrared band (Rouse et al., 1973).

The Normalized Difference Vegetation Index is calculated using the Equation 3:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (3)$$

where: NIR – represents the Near Infrared band and R represents the Red band. Similar to the NBR method, the NDVI was calculated for images before and after the fire.

The differenced NDVI (dNDVI) was obtained by subtracting the NDVI Post Fire from the NDVI Pre Fire, enabling the detection of fire-induced changes in vegetation (Equation 4).

$$dNDVI = NDVI\,prefire - NDVI\,postfire \quad (4)$$

The resulting dNDVI image was binarized using the natural break method to detect burned areas.

Supervised classification using maximum likelihood

A supervised classification was conducted using the Maximum Likelihood algorithm to map land cover, with a specific focus on delineating burned areas. Regions of interest identified during field surveys were used as training samples for the classification (Fisher, 1922). The burned areas were then converted from raster to vector format, represented as polygons, enabling accurate calculation of their total surface area.

For supervised classification to generate a land cover map using Sentinel-2 imagery, optical and infrared bands are commonly employed. Sentinel-2 has multiple spectral bands, including B2 (Blue), B3 (Green), B4 (Red), B8 (Near Infrared), B11 (Mid-Infrared), and B12 (Mid-Infrared). These bands cover wavelengths from visible to infrared, providing valuable information to differentiate and classify various land surfaces such as urban areas, forests, crops, water bodies, etc. The choice of bands depends on the classification type and specific characteristics of the study area. To create a comprehensive multi-band image, the selected bands are stacked in a specific order based on their respective spectral wavelengths (Table 2). The bands are arranged as follows: B2 (Blue), B3 (Green), B4 (Red), B8 (Near Infrared), B11 (Mid-Infrared), and B12 (Mid-Infrared). Each band is assigned as a separate layer in the new stacked image.

By combining the bands in this manner, the resulting stacked image becomes a valuable resource for land cover analysis and classification. The different layers in the image capture distinct information about the Earth's surface, such as vegetation health, water bodies, urban areas, and soil characteristics. This multi-band approach enables a more detailed and accurate land cover classification, aiding in applications related to environmental monitoring, land use planning, and natural resource management.

Table 2. Corresponding bands between Sentinel-2 and the stacked image

Stucked bands	New order the final stacked image
B2 (Blue)	Band 1
B3 (Green)	Band 2
B4 (Red)	Band 3
B8 (Near Infrared)	Band 4
B11 (Mid-Infrared)	Band 5
B12 (Mid-Infrared)	Band 6

RESULTS AND DISCUSSION

Spatiotemporal analysis of the active forest fire

On July 16, 2023, FIRMS (NASA) released information on its near-real-time data portal regarding the start of the propagation of an active forest fire near Douar Dghabcha. During July 17, 2023, the fire rapidly spread to the surrounding areas in the north, northwest, and west of Douar. In response to this critical situation, emergency intervention teams were quickly duplicated on the second day and deployed to the field. Their coordinated efforts helped limit the spread of active fires, mainly concentrated to the north of Douar Beni Oual. Thanks to the relentless efforts of the teams on the ground and the use of aerial resources such as Canadair aircraft, the active forest fires were brought under control by the end of the third day, July 18, 2023. The teams managed to contain and completely extinguish the flames, thus preventing further spread and protecting the surrounding areas.

This spatiotemporal monitoring map (Figure 6) illustrates the progression of the active forest fire from its origin near Douar Dghabcha to its extinction through the joint efforts of the intervention teams. During the entire course of the forest fire, it should be noted that no settlements were affected and there were no injuries or casualties.

Normalized burn ratio

In our analysis, we employed the Normalized Burn Ratio to classify the NBR images into 5 distinct classes using natural breaks (figures 7 and 8). This classification method effectively highlighted the burned area, evident through the presence of specific NBR values between -0.33 and -0.42. These values were indicative of the fire's impact, aiding in the identification of the affected regions.

Differenced normalized burn ratio

Subsequently, we generated the burned area map using the dNBR (Figure 9), which facilitated a binary classification of the area into burned and unburned regions. The geoprocessing results yielded essential information, indicating that the extent of the burned area covers an approximate total of 3508.12 hectares. Our analysis involved examining the histogram of the dNBR image, where pixel values ranging from 0.131 to 0.568 were attributed to the burned area (figure 10). Conversely, pixel values falling below 0.131 represented the unburned areas. This approach allowed for a clear delineation of the extent of the fire-affected zone, providing valuable insights into the distribution and severity of the burn. Our classification and geoprocessing techniques

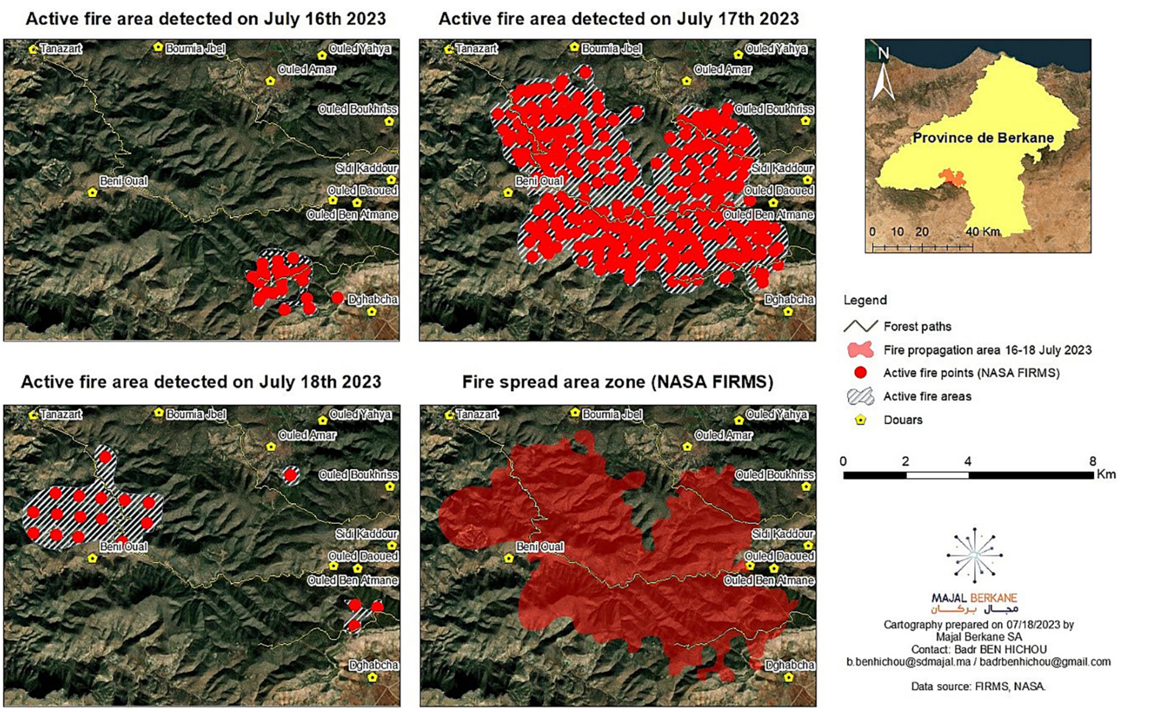

Figure 6. Spatio-temporal monitoring of the spread of the forest fire southwest of the city of Berkane, Morocco

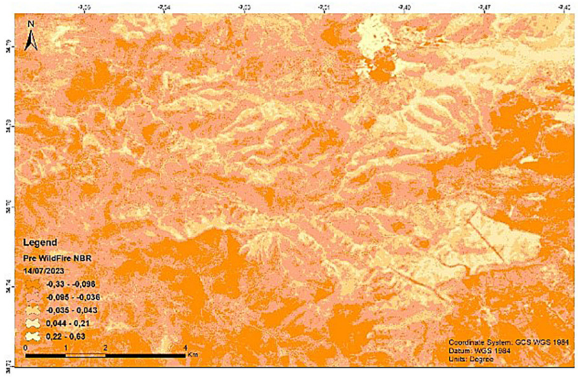

Figure 7. Pre-fire NBR map

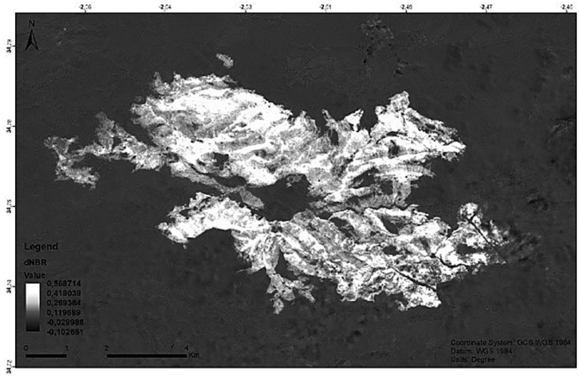

Figure 9. dNBR map in grayscale

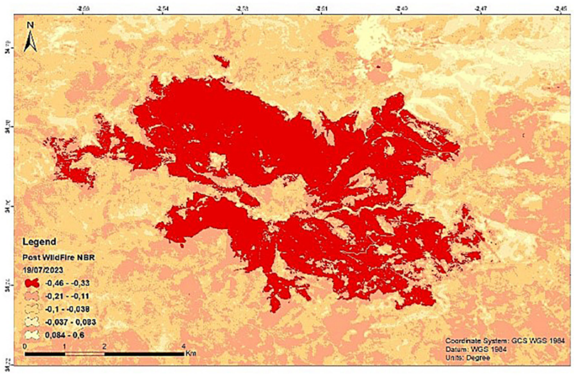

Figure 8. Post-fire NBR map

utilizing NBR and dNBR proved to be effective in accurately identifying and mapping the burned area. These findings are significant for understanding the impact of the wildfire and will aid in developing targeted strategies for post-fire recovery and conservation efforts.

Burn severity map

The burn severity map (Figure 11) was generated by classifying the pixels based on their corresponding dNBR values, resulting in the following categorization:

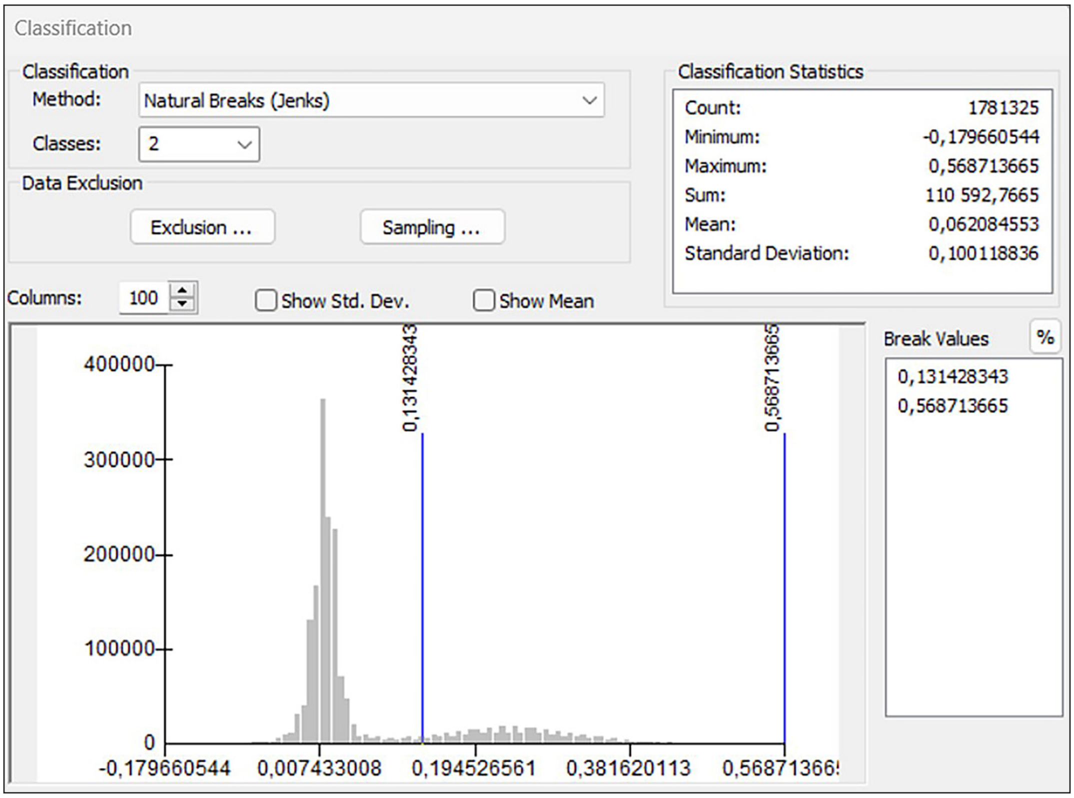

Figure 10. Binary classification of dNBR pixels using natural break

- low severity: This category encompasses dNBR values ranging from 0.100 to 0.269. It represents approximately 65% of the total burned area. Areas falling within this range indicate relatively lower levels of burn severity.
- moderate-low severity: Falling between 0.270 and 0.439 on the dNBR scale, this category covers about 35% of the burned area. It denotes regions with a slightly higher level of burn severity compared to the "Low Severity" category but still represents a moderate impact.

Normalized difference vegetation index

The results of the NDVI Pre Fire analysis revealed a minimum value greater than 0.0052 (Figure 12), while the NDVI Post Fire showed a minimum value of -0.1097 (Figure 13). These differences in values between the two NDVI images highlight the vegetation changes resulting from the fire. Significantly, the area impacted by the forest fires, as determined by the NDVI Post Fire, visibly coincides with the area highlighted by the NBR Post Fire.

Differenced normalized difference vegetation index

The dNDVI accurately delineated the pixels of the burned vegetation by classifying the image pixels into two classes using the natural break of its histogram, and allowed us to identify its surface area, which is 3517.98 hectares. This convergence in identifying the burned area strengthens

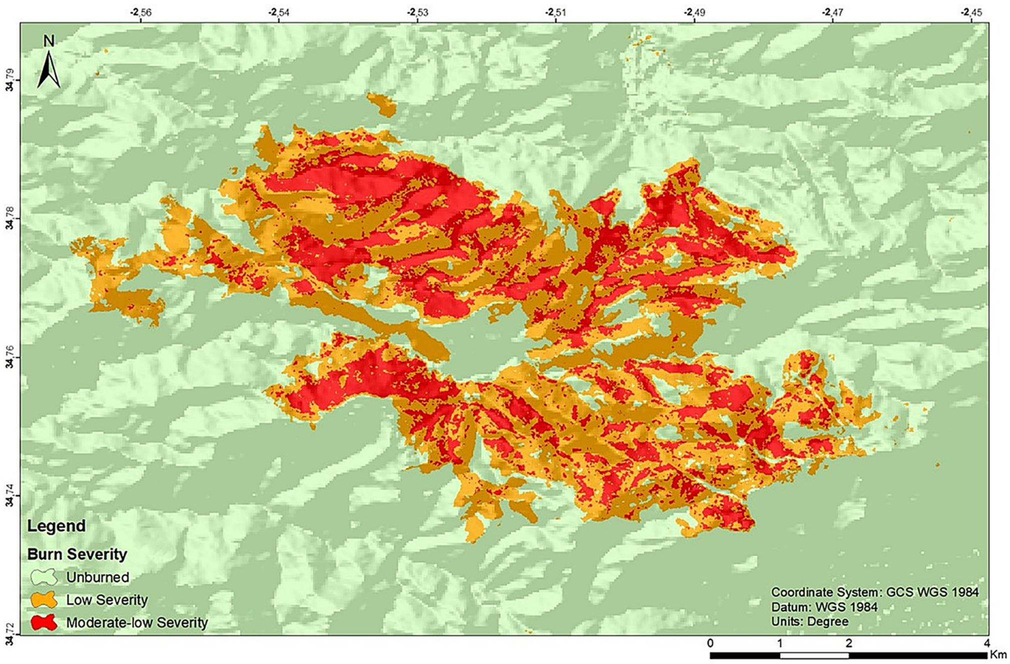

Figure 11. Burn severity map

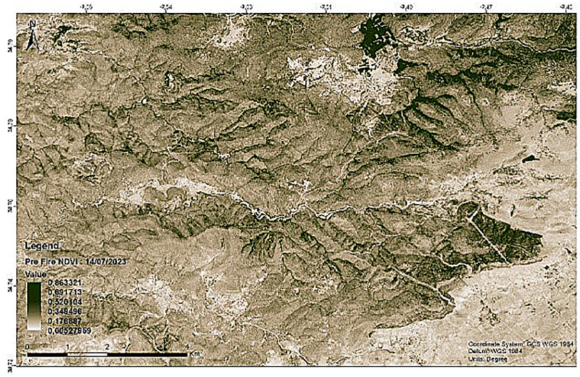

Figure 12. Pre-Fire NDVI Map

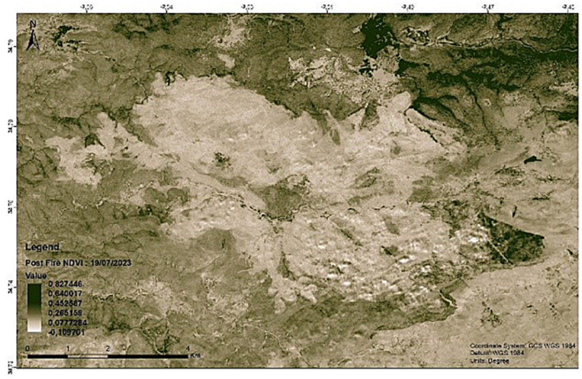

Figure 13. Post-Fire NDVI Map

the reliability of our results and enhances our confidence in the effectiveness of the change detection method used (Figure 14).

Supervised classification

Thanks to our in-depth understanding of the study area and the field visits conducted during the forest fire event, we were able to accurately determine five distinct land cover classes. These classes were utilized as regions of interest in the supervised classification of the Post Fire satellite imagery. The identified land cover classes included the burned area, unburned area (forest), areas covered with alfa vegetation, cultivated areas, and built-up areas. The scatterplot analysis was performed using relevant spectral bands to highlight the variations between land cover types. In the scatterplot, distinct clusters are evident for each class (region of interest), with the burned area prominently marked within a black circle, showcasing excellent separation of spectral characteristics among different land cover types. This effective capture of unique spectral signatures by the classifier led to a successful classification. Additionally, the analysis revealed minimal overlap between clusters representing different classes, providing further validation of the classification accuracy.

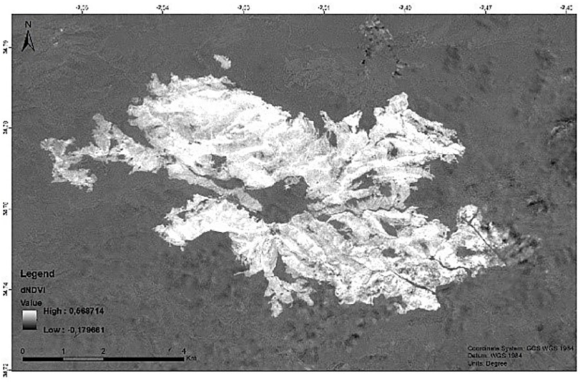

Figure 14. dNDVI map in grayscale

The maximum likelihood classification method was employed to generate a precise land cover map, as each class exhibited unique spectral signatures. This classification method allowed us to effectively differentiate between various land cover types, enhancing the accuracy of our mapping results (Figure 15). To validate the accuracy of the land cover map, we conducted extensive field visits and performed a rigorous comparison between real-world observations and the classified satellite image. Additionally, we calculated the confusion matrix, which provided us with the Kappa coefficient, a reliable measure of the classification accuracy. According to our findings, the "burned area" class covered an area of 3113.63 hectares. This information serves as a key component in assessing the extent of the forest fire's impact (Figure 16).

The spatiotemporal analysis of the active forest fire near Berkane, Morocco, offers valuable perspectives on the importance of early detection and rapid response, the significance of geospatial analysis in understanding wildfire patterns, and the implications for post-fire recovery and ecosystem management. These perspectives

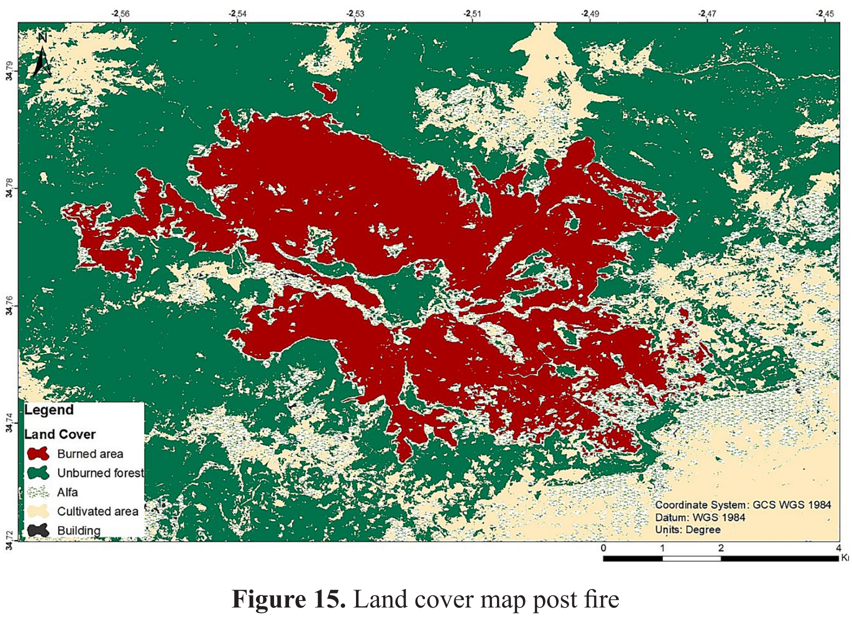

Figure 15. Land cover map post fire

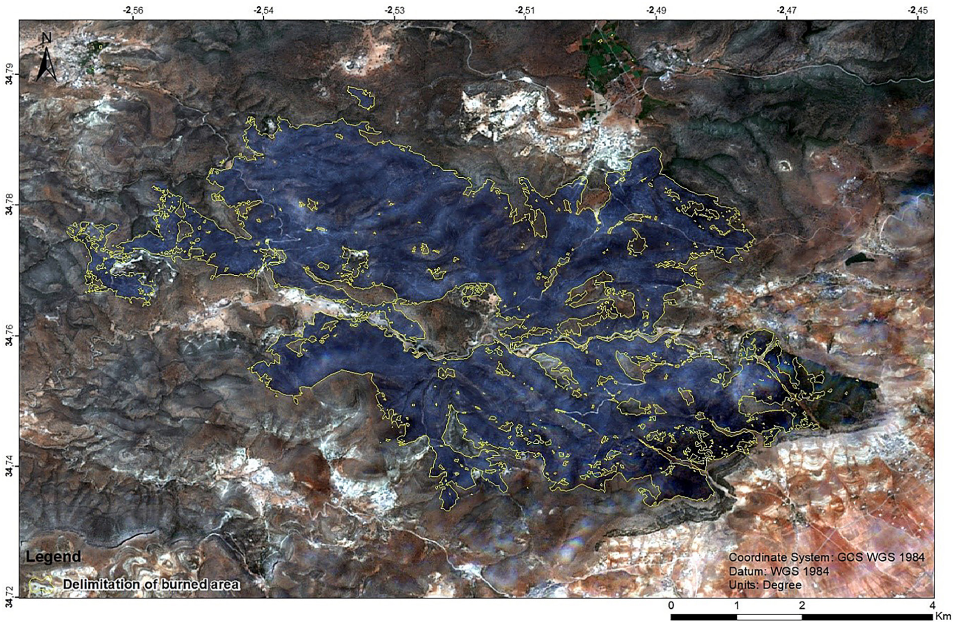

Figure 16. Post-fire burned area delimitation on true-color Sentinel 2 image

underscore the need for integrated approaches that combine advanced monitoring technologies, effective emergency response strategies, and comprehensive ecological assessments to address the challenges posed by wildfires and ensure the sustainable management of forest ecosystems. Further research and ongoing monitoring efforts are essential to deepen our understanding of the long-term ecological impacts and to guide informed decision-making for ecological restoration and conservation in fire-prone regions. The recent surge in research on forest fire analysis and mapping using remote sensing techniques has significantly advanced our understanding of how technology can be leveraged to better detect and manage forest fires. The studies mentioned in this article and many others have contributed valuable insights into various aspects of this field, each with its unique approach and focus. One common theme among these studies is the utilization of deep learning and machine learning algorithms to enhance the accuracy and efficiency of forest fire detection and mapping. This approach, as seen in by Ghali (2023), not only streamlines the identification process but also reduces the risk of false positives, ultimately aiding in early intervention and mitigation efforts. Another noteworthy trend is the integration of multiple data sources, including satellite imagery, aerial imagery, and UAV imagery. Maffei et al. (2021) have pioneered the use of multi-spectral and thermal imagery for forest fire prediction, showcasing the potential of combining different data types to provide a more comprehensive understanding of possible forest fires. This fusion of data sources offers a richer and more detailed perspective on the factors of forest fires.

The research conducted by Collins et al. (2020) introduces an essential dimension to the field by focusing on forest fire severity mapping. Their work highlights the importance of assessing the damage caused by fires, enabling better post-fire land cover change analysis. This contributes to a more holistic understanding of the ecological impact of forest fires. One of the standout features of our study is the incorporation of FIRMS data to pinpoint active fire locations. This addition is of significant value as it enables near real-time monitoring of forest fires, offering important insights for timely intervention and management. Additionally, our study adopts a supervised classification technique to map burned areas in detail. This method provides better results to understand the post fire change of land cover.

The articles reviewed here collectively highlight the ongoing advancements in forest fire analysis and mapping using remote sensing techniques. These studies demonstrate the importance of leveraging technology to enhance our ability to detect, monitor, and respond to forest fires. Our methodology, which integrates FIRMS data and utilizes supervised classification, represents a significant contribution to this field, enabling more effective forest fire management and ecological assessment.

CONCLUSIONS

The spatiotemporal analysis of the active forest fire highlights the successful efforts of emergency intervention teams in containing and extinguishing the flames, preventing harm to settlements and human lives. The utilization of advanced techniques such as NBR, dNBR, NDVI, and dNDVI proved instrumental in accurately identifying, quantifying, and assessing the extent of the burned area. The supervised classification method further aproaved these results, showcasing the potential of integrated approaches for comprehensive landscape assessment.

Looking ahead, these findings underscore the urgency of early detection and rapid response strategies in wildfire management. The study reinforces the importance of geospatial analysis as a valuable tool for understanding fire patterns and their ecological impacts. Moreover, the insights gained here will guide future strategies for post-fire recovery and ecosystem conservation, emphasizing the need for ongoing research and monitoring efforts in fire-prone regions. By combining technological advancements, effective emergency response, and ecological assessments, we can pave the way for more resilient and sustainable forest ecosystem management practices.

REFERENCES

1. Arjasakusuma, S., Kusuma, S.S., Vetrita, Y., Prasasti, I., Arief, R. 2022. Monthly Burned-Area Mapping using Multi-Sensor Integration of Sentinel-1 and Sentinel-2 and machine learning: Case Study of 2019's fire events in South Sumatra Province, Indonesia. Remote Sensing Applications: Society and Environment, 27, 100790.
2. Brean W. Duncan, Guofan Shao, Frederic W. Adrian. 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.
3. Collins, L., McCarthy, G., Mellor, A., Newell, G., Smith, L. 2020. Training data requirements for fire severity mapping using Landsat imagery and random forest. Remote Sensing of Environment, 245, 111839.
4. Fisher, R.A. 1922. On the mathematical foundations of theoretical statistics. Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character, 222, 309–368.
5. Ghali R., Akhloufi M.A. Deep Learning Approaches for Wildland Fires Remote Sensing: Classification, Detection, and Segmentation. Remote Sensing. 2023, 15(7), 1821.
6. Kala, C.P. (2023). Environmental and socioeconomic impacts of forest fires: A call for multilateral cooperation and management interventions. Natural Hazards Research.
7. Key, C.H., Benson, N.C. 2005. Landscape assessment (LA): Sampling and analysis methods. In Entwistle, P.G., DeBano, L.F., Neary, D.G. (Tech. Coords.), Proceedings: Restoration of American Southwest Ponderosa Pine Forests, General Technical Report. RMRS-GTR-150, 73–84. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.
8. Maffei, C., Lindenbergh, R., Menenti, M. 2021. Combining multi-spectral and thermal remote sensing to predict forest fire characteristics. ISPRS Journal of Photogrammetry and Remote Sensing, 181, 400–412.
9. Melissa B. Jenkins, Anna W. Schoettle, Jessica W. Wright, Karl A. Anderson, Joseph Fortier, Linh Hoang, Tony Incashola Jr., Robert E. Keane, Jodie Krakowski, Dawn M. LaFleur, Sabine Mellmann-Brown, Elliott D. Meyer, ShiNaasha Pete, Katherine Renwick, Robert A. 2022. Sissons, Restoring a forest keystone species: A plan for the restoration of whitebark pine (Pinus albicaulis Engelm.) in the Crown of the Continent Ecosystem, Forest Ecology and Management, 522, 120282.
10. Nolè, A., Rita, A., Spatola, M.F., Borghetti, M. 2022. Biogeographic variability in wildfire severity and post-fire vegetation recovery across the European forests via remote sensing-derived spectral metrics. Science of The Total Environment, 823, 153807.
11. Payra, S., Sharma, A., Verma, S. 2023. Application of remote sensing to study forest fires. In Atmospheric Remote Sensing, Elsevier, pp. 239-260.
12. Rouse Jr., J.W., Haas, R.H., Schell, J.A., Deering, D.W. 1973. Monitoring vegetation systems in the Great Plains with ERTS. In Third Earth Resources Technology Satellite-1 Symposium, 10–14 December 1973, Greenbelt, Maryland, NASA, 1, pp. 309-317.
13. Ryan M. Perkl. 2016. Geodesigning landscape linkages: Coupling GIS with wildlife corridor design in conservation planning, Landscape and Urban Planning, 156, 44-58.
14. Viana-Soto A., Aguado I., Salas J., García M. Identifying Post-Fire Recovery Trajectories and Driving Factors Using Landsat Time Series in Fire-Prone Mediterranean Pine Forests. Remote Sensing, 2020, 12(9), 1499.