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Research Article

Assessment of post-fire vegetation recovery in a part of the Marivan forests using remote sensing

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Abstract

Fires affect the structure, composition, and functioning of ecosystems. Monitoring post-fire vegetation recovery is critical for evaluating the ecological impacts of wildfires effects on ecosystems, and supporting ecosystem restoration after fires. Each year, many low- to moderate-intensity surface fires occur in the Zagros forests. This study aimed to assess vegetation recovery in a burned area of the northern Zagros forests by analyzing the spectral behavior of vegetation post-fire. Temporal OLI-Landsat 8 images from 2013 to 2018 were used. In the first step, accurate atmospheric correction was applied to the images. Five vegetation indices (VIs), NBR, NDVI, NDII, EVI, and MSAVI1 were used to monitor the vegetation recovery from two years pre-fire to three years post-fire. Both qualitative (i.e. visual analysis) and a quantitative (i.e. M-statistic separability index) approaches were used to evaluate the performance of VIs in distinguishing between burned and unburned areas. Surveys were conducted simultaneously in the burned and control areas with similar physiographic conditions to minimize phenological differences and isolate the effects of meteorological variations such as rainfall and drought, on vegetation regeneration and spectral changes. Visual assessment showed that all VIs responded well in detecting post-fire recovery, highlighting their effectiveness. Among the VIs, NBR demonstrated the highest discrimination performance, while NDVI showed the lowest sensitivity. The results showed that all VIs nearly returned to their pre-fire values within one year post-fire. This rapid recovery is attributed to the low intensity of surface fires and the fast coppice regeneration of oak trees post-fire which leads to increased canopy cover. Therefore, identifying burned areas becomes challenging just one year after the fire in some parts of Zagros forests due to the rapid recovery of vegetation.

Keywords: multi-temporal, Landsat imagery, spectral indices, surface fire, vegetation recovery.

1. Introduction

Forests are among the most important renewable natural resources, playing a vital and fundamental role in the continuity of life and the preservation and sustainability of ecosystems. The role of forest vegetation in reducing general soil erosion has been well-documented in fire regions (Yoonmi Kim et al., 2020). Forest watersheds serve as sources of drinking water, and well-managed natural forests provide benefits to urban populations in terms of high-quality drinking water and help prevent flooding (Ekhuemelo, 2016). Extensive and high-intensity fires are critical environmental threats that endanger forests and their ecosystem services worldwide (Jones et al., 2022). Forest fire results in long-term environmental impacts such as biodiversity loss , decline in terrestrial ecosystem productivity, decrease in soil fertility, reduced future crop production and increased air pollution (Bae et al., 2019; Sannigrahi et al., 2020; Venkatesh et al., 2020). Fire changes the physiology, amount, and efficiency of photosynthesis of vegetation which in turn affects plant competitiveness and successional stages (Bär et al., 2019). These physiological changes in vegetation after fire may reduce the growth of some species,

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enhance the growth of others, and alter the development of upper deciduous trees. In addition to the fact that woody species regenerate directly after a fire, herbaceous species typically regrow in the first years following the fire (Keeley & Keeley, 1981). Fire is often considered a destructive factor in vegetation; nevertheless, many ecologists believe that fire should be considered one of the inherent components of ecosystems, playing a major role in their regeneration and evolution (White & Jentsch, 2001).

Iran is one of the countries at high risk for forest fires. According to the Food and Agriculture Organization (FAO) database on Iranian forest fires from 1982 to 1995, the average annual number of fires was 130, with the destruction of about 5,400 hectares per year (Allard, 2001). However, the number of fires increased dramatically after 2000. A report by the Natural Resources and Watershed Management Organization (NRWMO) of Iran indicates that from 2000 to 2010, 14960 fires occurred, affecting a total area of 157121 hectares of Iranian forests and rangelands areas (Ghanbari Motlagh et al., 2022). One of the most fire-prone areas is Kurdistan Province (Allard, 2001), located in the western part of Iran, also known as Northern Zagros Forests. There is a high dependency of rural people on forest resources in the Northern Zagros. In this region, pollarding is a traditional practice used for fodder production (Ghazanfari et al., 2004; Moradi et al., 2022). Through traditional silvopastoral practices, oak leaves are used to provide livestock feed for almost seven months per year by forest dwellers (Valipour et al., 2014).

Studying fires and wildfires can contribute to understanding post-fire recovery management and ecological thought. Comparing post-fire regeneration of plants in differing ecosystems allows for the observation of patterns and trends (Au Yeung & Li., 2018). Remote sensing provides an excellent opportunity to collect imagery and provide information on forest cover at fine spatial and temporal scales (Boyd et al., 2002). Remote sensing refers to the science of identifying Earth's surface features and estimating their geo-biophysical properties using electromagnetic radiation. Spectral, spatial, and temporal resolutions are major characteristics of sensors that enhance target distinction. Observations at different resolutions offer a better alternative for natural resource management than traditional methods. Time series satellite data have long been used for generating information on forest disturbance and recovery dynamics. Remote sensing data offer valuable insights into the evolution of vegetation post-fire in forest regions, enabling the development of effective strategies for sustainable forest management (Au Yeung & Li, 2018; Boyd et al., 2002; Roy, 1999; Viana-Soto et al., 2017). The application of remote sensing has developed over the years and has been shown to provide opportunities to study fire and post-fire vegetation regeneration (Hare, 2020; Kibler et al., 2019).

In general, two different approaches, i.e., multi-temporal and time series analysis, are used to recognize fire patterns using remote sensing data. To analyze time series data, different approaches (e.g., Breaks for Additive Season and Trend [BFAST] or Continuous Change Detection and Classification [CCDC]) have been developed. In addition to the high complexity of these approaches, the crucial step in implementing them is establishing a threshold to identify fire-disturbed and undisturbed areas, which is often done based on expert knowledge (Solórzano & Gao, 2022). Therefore, a multi-temporal approach based on simple vegetation indices (VIs) can be a practical alternative for studying forest fire patterns. The Normalized Difference Vegetation Index (NDVI) is a widely used method for assessing fire recovery via time-series analysis, using calculations based on the red and near-infrared (NIR) Landsat bands. The Normalized Burn Ratio Index (NBR) uses the near-infrared and shortwave infrared Landsat bands to describe burn severity by comparing pre- and post-fire data (Hare, 2020; Idris et al., 2005). Many researchers have exploited multi-temporal images to investigate the spatial and temporal recovery processes (Au Yeung & Li, 2018). By analyzing indices such as the Enhanced Vegetation Index (EVI), NDVI, and Normalized Infrared Difference Index (NDII), a better understanding of the effectiveness of satellite observations in monitoring fire impacts on vegetation can be achieved (Caccamo et al., 2015). Studies monitoring vegetation recovery post-fires have shown that the rate of vegetation restoration varies depending on fire severity, habitat conditions, and forest type.

In Iran, the effects of fire on structure and natural regeneration of trees and shrubs were studied in the Guilan forests seven years post-fire (Nemati et al., 2019). Their results showed that tree density, diameter and basal area, and shrub species density decreased post-fire, while regeneration density increased. In another study, the process of natural vegetation regeneration in fire-affected areas of Golestan National Park was studied during the early years after the fire (Zare Maivan & Memariani, 2002). The results showed that herbaceous cover in the burned areas was more diverse than in surrounding areas. The potential for natural regeneration after fire damage is limited in many woody species, with only a few shrub species regenerating through shoots. Although the dynamics of post-fire vegetation recovery using remote sensing have been studied in various forest ecosystems, few studies have addressed the driving factors of recovery in Mediterranean ecosystems (Martín-Alcón & Coll, 2016) and fewer have concentrated on characterizing vegetation recovery levels in Iranian forests, particularly Zagros forests. Accurately evaluating vegetation recovery after a fire is essential for understanding the impacts of fire on important vegetation characteristics and for developing effective fire management strategies.

This study follows three main objectives:

- Assessing the rate of regeneration and recovery of vegetation in the months and years after fire in part of the Zagros forests using remote sensing data;
- Determining the suitability of multi-temporal Landsat 8-OLI imagery for monitoring post-fire vegetation recovery;
- Comparing different vegetation indices (NDVI ‹NDII, MSAVI1, EVI, and NBR) for monitoring post-fire vegetation recovery.

2. Materials and Methods

2.1. Study area

The study area is located in the Zagros forests of the western part of Iran, between the cities of Sarvabad and Marivan. The geographical coordinates of the study area range from 35˚ 19′ 41″ to 35˚ 24′ 49″ N, and 46˚ 13′ 6″ to 46′ 20′ 20″ E (Figure 1). A surface fire broke out in two patches, measuring 5 and 35 hectares, on August 8 and 9, 2015.

According to the Sarvabad meteorological station, the average annual rainfall in this area is 600 mm. In autumn and winter, the region is affected by Mediterranean streams, which carry high humidity. When these moist air masses collide with the highlands, they cause precipitation, a key factor contributing to the forested nature of the mountains in this region.The Zagros forests here are dominated by oak trees (*Quercus infectoria* Oliv., and *Quercus branti* Lindl.), and forest fires have occurred frequently in this area (Miri et al., 2024; Mohammadi et al., 2014). The study sites are characterized by medium to low-density forests with average canopy cover density ranging from 30% to 40%.

Higher precipitation in spring leads to increased herbaceous biomass growth, while dry weather and extreme summer heat cause severe dryness of herbaceous biomass, thereby increasing fire potential in the Zagros forests.

2.2. Datasets

Images from different periods of Landsat 8 - OLI (Path: 168, Row: 35), covering dates before and after the fire from 2013 to 2018 were used in this study (Table 1). A temporal resolution of one year was applied for the main analysis. Satellite imagery was selected on anniversary dates to minimize the effects of seasonal phenological variations (Sever et al., 2012). In addition to annual monitoring, images from three dates shortly after the fire, before the leaf fall of the trees, were also analyzed (18/08/2015, 18/09/2015 & 13/10/2015).

A digital topographic map at a scale of 1:25000 was used to extract linear features, i.e. roads and rivers, to assess the geometric accuracy of satellite images.

2.3. Field survey

Two burned areas, measuring 5 hectares and 35 hectares, located near the villages of Ahmadabad (date of fire occurrence 08/08/2015) and Khushkin (date of fire occurrence 09/08/2015), respectively, were reported by the Natural Resources Department of Sarvabad (Figure 2). A ground survey was conducted to map the burned area boundaries using a Global Positioning System (GPS; Garmin 78s) in September 2015.

The use of unburned control plots adjacent to the study area helps minimize phenological variations, and the direct influence of meteorological events, such as rainfall and drought, on regeneration, thus reducing associated errors when comparing burned and unburned areas (Sever, Leach & Bren 2012). Therefore, a reference area and control plots were necessary to properly assess vegetation recovery. Thirty randomly selected points in unburned forests (i.e., as control plots), each with a minimum distance of 60 m (i.e., two Landsat pixel widths) from both one another and the burned areas, were selected and recorded using GPS (Figure 2). Care was taken to ensure similar conditions in terms of topography (elevation, slope, and aspect) and vegetation composition between the burned and unburned areas.

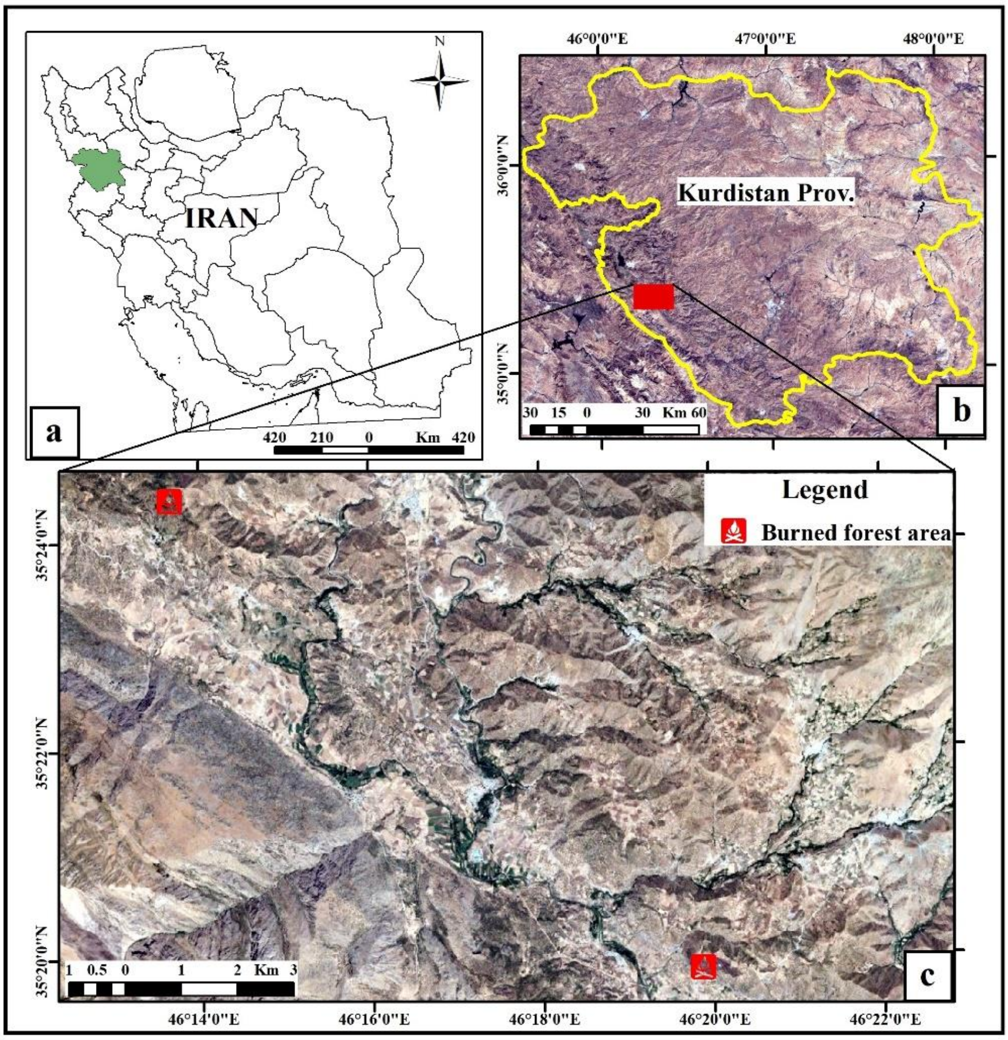

Figure 1. Location of the study area in Iran (a), Kurdistan Province (b), and the burned forest area (c) (Image from Google Earth)

Table 1. Landsat 8-OLI images used in this study

imagery date	Explanation	imagery date	explanation
11/08/2013	pre-fire	13/10/2015	2-months post-fire
14/08/2014	pre-fire	03/08/2016	1 yr. post-fire
16/07/2015	pre-fire	06/08/2017	2 yrs. post-Fire
18/08/2015	10-days post-fire	09/08/2018	3 yrs. post-Fire
18/09/2015	1-month post-fire		

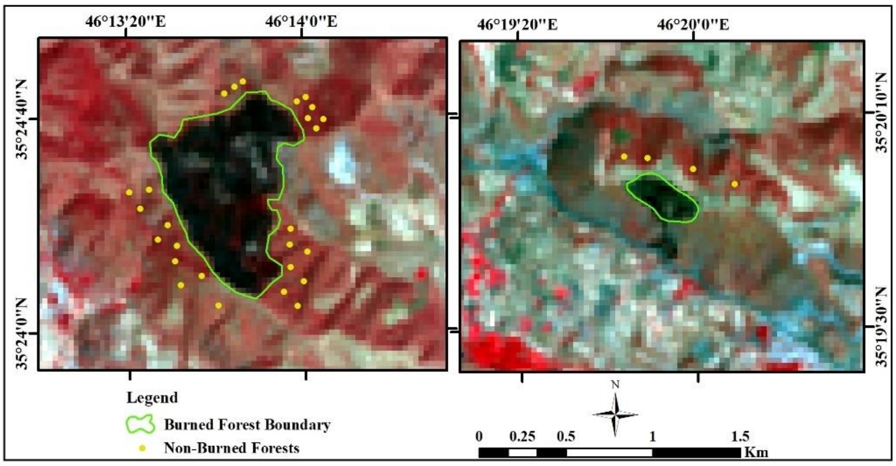

Figure 2. Burned forest maps and control points (in unburned forests) in Landat8-OLI imagery (RGB543) related to 18/08/2015 (10 days post-fire)

2.4. Pre-processing

Due to the use of multi-temporal images, appropriate atmospheric correction is necessary to eliminate atmospheric effects. To do so, a two-step atmospheric correction method was applied:

- Cosine of the Sun Zenith Angle (COST) method: The COST method is an image-based correction technique performed using TerrSet software. This method uses the Sun Zenith Angle as a parameter to approximate the effects of atmospheric gas absorption and Rayleigh scattering (López-Serrano et al., 2016).
- Regression method: An empirical regression-based method was developed to normalize the multi-temporal images. First, one image was selected as the base image, and then the spectral signatures of all other images were normalized to it using a linear regression mode (Heo & Fitz Hugh, 2000). In this study, the satellite image from one month pre-fire, i.e., 16/07/2015, was selected as the base image. A series of common points were selected from the darkest areas in the image. The spectral reflectance values at those points were extracted from the base image and other images, and a regression relationship was developed between each image and the base image. The coefficient of determination (R^2) for each regression was greater than 95%. Based on these methods, all satellite images were adjusted relative to the base image.

2.5. Vegetation indices

For post-fire recovery analysis, the use of spectral VIs provides a foundational tool, as they support temporal assessments of vegetation dynamics (Evangelides & Nobajas, 2020). Some VIs also have the potential to minimize the effects of extraneous factors such as atmospheric conditions, background substrate, and illumination variability (Evangelides & Nobajas, 2020; Verrelst et al., 2008). To assess the impact of fire on vegetation recovery and regeneration in the year of the fire occurrence and the surrounding years before and post the fire, i.e., from 2013 to 2018, five vegetation indices, NDVI, NDII, MSAVI1, EVI and NBR, were derived from Landsat8-OLI imagery. In addition to their sensitivity to vegetation changes, these indices—particularly those using the NIR band, which has the highest reflectance for vegetation in the infrared domain, are effective for monitoring post-disturbance vegetation dynamics.

Normalized Difference Vegetation Index (NDVI)

NDVI is one of the oldest, most widely used vegetation indices in the study of spatio-temporal changes in vegetation (Eq. 1).

$$NDVI = \frac{NR - RED}{NR + RED} \qquad \text{Eq.1}$$

NDVI is based on the principle that healthy vegetation reflects strongly in the NIR spectrum, whereas most non-vegetated surfaces do not. On the contrary, the dehydrated or unhealthy vegetation reflects less in the NIR band while maintaining similar reflectance in the visible wavelengths. Therefore, by combining these two spectral bands, NDVI can be used to distinguish healthy vegetation from stressed or unhealthy vegetation, making it an effective tool for monitoring vegetation recovery (Evangelides & Nobajas, 2020; Jahdi & Sefidi, 2024).

Normalized Difference Infrared Index (NDII)

NDII is obtained from the difference in the spectral reflectance of shortwave infrared and NIR reflectance bands (Eq. 2).

$$NDII = \frac{NIR - SWIR1}{NIR + SWIR1} \qquad \text{Eq.2}$$

This index was developed by Hardisky et al. (1983) and is sensitive to the water content in vegetation and the overall canopy moisture (Wilson & Norman, 2018). The value of this index decreases significantly at the end of the dry season and increases with the onset of the rainy season. This index is commonly used to assess plant water status and detect dehydration stress in vegetation. Similar to NDVI, the index values range between -1 and 1, where negative values indicate either the absence of vegetation or severely dry vegetation (Sriwongsitanon et al. 2016).

Enhanced Vegetation Index (EVI)

It is similar to the NDVI index but is more sensitive to changes in canopy structure, plant appearance, and physiological conditions. In this spectral index, the blue band is used to minimize the effects of background soil reflectance and atmospheric interference (Huete et al., 2002; Yunhee Kim et al., 2021) (Eq. 3).

$$EVI = 2.5 * \frac{NIR - RED}{NIR + 6RED - 7.5Blue + 1} \qquad \text{Eq. 3}$$

Modified Soil Adjusted Vegetation Index One (MSAVI1)

This index is similar to the SAVI index, but further minimizes the influence of soil background variability (Qi et al., 1994) (Eq. 4). The soil adjustment factor (L) in the SAVI index depends on the amount of vegetation cover. In MSAVI1, L is determined as an empirical function that decreases with lower vegetation density, which is typical in semi-arid regions. The L factor can be derived using a combination of NDVI and the Weighted Difference Vegetation Index (WDVI).

$$MSAVI1 = \frac{\left(NIR - RED\right)}{\left(NIR + RED + L\right)}\left(1 + L\right) \qquad \text{Eq. 4}$$

Normalized Burn Ratio Index (NBR)

The NBR index is used to identify areas affected by fire and also to estimate the severity of vegetation burns. It is similar to the NDVI, but it uses the shortwave infrared band instead of red band. The numerical values of the NBR index, like NDVI, range between -1 and 1. In vegetated areas, positive values indicate healthy vegetation, while in burned areas, negative values correspond to higher burn severity (Escuin et al., 2008) (Eq. 5).

$$NBR = \frac{NIR - SWIR2}{NIR + SWIR2} \qquad \text{Eq.5}$$

2.6. Visual Analysis and Separability Index (SI)

In this study, the capability of the previously described VIs to detect burned areas at several dates post-fire was evaluated using visual analysis and the M-statistic separability index. Visual analysis of temporal plots of the NIR band and VIs was used to assess the spectral response of vegetation after the fire event, compared to unburned reference samples. Therefore, the status of vegetation in the year of fire occurrence, as well as the pre- and post-fire years, i.e., from 2013 to 2018, was analyzed. A graphical representation of VI behavior and forest recovery allows for a quick preliminary assessment. In addition to annual monitoring, vegetation recovery during the three months following the fire was also examined through the spectral behavior of vegetation in August, September, and October imagery (18/08/2015, 18/09/2015 & 13/10/2015).

The effectiveness of each vegetation index in separating burned from unburned classes can be measured using a separability index, which quantifies the spectral distance between two classes. The separability index was defined as:

$$M_b = \frac{\mu b - \mu ub}{\sigma b + \sigma ub} \qquad \text{Eq.6}$$

The M-statistic is a metric of class separability defined by Kaufman and Remer (1994) as the difference between the means (μ) of pixel values for two classes, burned (b) and unburned (ub), normalized by the sum of their standard deviations (σ). The M-statistic can be expressed as a signal-to-noise ratio, where the distance between the class means represents the signal strength, and the sum of the standard deviations represents the noise (Van Dijk et al., 2021). This metric has been widely used for burned area discrimination (Fornacca et al., 2018; Lasaponara, 2006; Roteta et al., 2019;

Van Dijk et al., 2021). Previous studies have indicated that M values typically range from approximately 0.2 to 2.0 for burned-unburned comparisons. Values less than one demonstrate poor separability, whereas values equal to or greater than one demonstrate good spectral separability. Higher M values generally result in better discrimination between classes (Roteta et al., 2019; Van Dijk et al., 2021).

3. Results and Discussion

3.1. Visual Analysis of spectral bands and vegetation indices

The NIR spectral band and various VIs are commonly used as indicators of vegetation recovery (Bright et al., 2019). A comprehensive illustration of the spectral behavior of the NIR and VIs is presented in Figure 3. Most VIs exhibited a consistent pattern following the fire, a noticeable decline immediately post-fire, relatively rapid recovery during the first year, and then a gradual recovery over subsequent years.

Visually, all VIs showed an appropriate response in post-fire assessment supporting their widespread efficiency for post-fire monitoring vegetation recovery. Among them, the NBR performed best, showing a substantial decrease immediately after the fire. In contrast, NDVI appeared to be the least effective. The NIR spectral graph also indicates that the spectral differences between burned and unburned regions diminished one year post-fire compared to other VIs. Table 2 shows the differences in spectral values of VIs before and after the fire. Previous studies (e.g., Bright et al., 2019; Evangelides & Nobajas, 2020) have similarly shown that NBR is highly effective in assessing burn severity and vegetation recovery, particularly in forested ecosystems (Frazier et al., 2018; Key & Benson, 2006; Van Wagtendonk et al., 2004; Warner et al., 2017). This effectiveness stems from the sensitivity of SWIR vegetation water content and NIR to leaf structure, making their combination in NBR particularly suitable for detecting changes in green vegetation and moisture content post-fire (Evangelides & Nobajas, 2020; Miller & Thode, 2007). NDII, like NBR, is calculated based on almost similar bands and demonstrated similar performance. According to Table 2 and Figure 3, NDII was the second-best performer in evaluating post-fire vegetation changes.

Due to its simplicity and relatively good performance and its suitability to a wide variety of sensors, including sensors that lack the SWIR bands; NDVI has been widely used for mapping burned areas and vegetation recovery monitoring (Escuin et al., 2008; Fornacca et al., 2018; Kennedy et al., 2010). Although NDVI is a valuable and reliable index for detecting vegetation presence, the effect of burning can be confused with other vegetation losses; therefore, many studies that have evaluated the use of NDVI in fire severity assessment have found them to be less effective than NBR (Warner et al., 2017). In our study, NDVI showed the lowest performance among the VIs for post-fire vegetation recovery assessment (Figure 3 & Table 2).

Table 2. The difference between pre- and post-fire (2014-2015) of vegetation indices (VIs) and their ranks

VIs	**NBR**	**NDII**	**MSAVI1**	**EVI**	**NDVI**
Difference	0.31	0.18	0.14	0.099	0.057
Rank	1	2	3	4	5

Although many studies have utilized a combination of NBR and NDVI to assess post-fire vegetation recovery, these VIs are susceptible spectral mixing effects caused by atmospheric conditions and soil brightness. To address these limitations, the present study also employed the EVI and MSAVI to more accurately evaluate spectral reflectance recovery after fire. The results, as presented in Table 2, indicate that EVI and MSAVI outperformed NDVI in monitoring post-fire vegetation recovery.

Spectral behavior pattern of burned forest in the two months post-fire

Given the superior performance of the NBR index in detecting post-fire changes across pre- and post-fire years (Figure 3), it was further analyzed at a finer temporal scale in the month immediately following the fire. Specifically, NBR values for July, August, September, and October of 2015, representing pre-fire and up to two months post-fire were analyzed in both burned and unburned forests. As shown in Figure 3, a significant decline in NBR value was visually detectable in burned areas beginning in August, and two months following the fire (September and October 2015) (Figure 4). Therefore, in this short period (2 months), no remarkable vegetation recovery was observed.

The spectral behavior of reference points had an almost steady trend in these months (Figure 4).

3.2. Separability Index

Table 3 shows separability index calculated for the burned area plots between pre- and post-fire periods. As shown, separability index values exceed one only between the year immediately before the fire (2014) and the year of fire occurrence (2015), indicating a strong spectral separability, and after that, it seems that with the fast vegetation recovery due to surface-fire, the separability index indicates poor separation.

In addition, the temporal trajectory of the burned areas (i.e. mean of burned area) was compared with that of the unburned reference plots to provide a more realistic picture of the ecological conditions of the disturbed vegetation. Using solely burned samples, such as pre-and post-fire, does not account for potential variations in vegetation phenology or unusual weather events (Fornacca et al., 2018). Table 4 presents the separability index values calculated between the burned and control area (Unburned) for each year. Separability index values equal to or greater than one denote good spectral separability. The highest separability index values were observed immediately post-fire (2015), suggesting strong class separation, likely a result of substantial differences in mean reflectance and/or reduced standard deviations. The grey rows indicated immediately post-fire vegetation index values.

Table 3. Separability index values between burned area plots and control area plots in each year. Highlighted cells indicate the three best performers in the following rank/color order: 1st, 2nd, 3rd. The grey row indicates immediate post-fire values.

Time/VIs	NIR	NDVI	NBR	NDII	EVI	MSAVI1
2013 (Pre-Fire)	0.04	0.09	0.09	0.02	0.36	0.12
2014 (Pre-Fire)	0.20	0.23	0.16	0.03	0.12	0.11
2015 (Post-Fire)	3.16	1.07	2.45	2.16	1.51	1.86
2016 (1 yr. Post-Fire)	0.02	0.70	0.37	0.43	0.66	0.42
2017 (2 yrs. Post-Fire)	0.05	0.65	0.47	0.50	0.49	0.35
2018 (3 yrs. Post-Fire)	0.14	0.13	0.41	0.03	0.35	0.20

Table 4. Separability index values calculated between burned area plots and unburned control plots across pre- and post-fire occurrence. Highlighted cells indicate the three best performers in the following rank/color order: 1st, 2nd, 3rd. The grey row indicates immediate post-fire values.

Time/VIs	NIR	NDVI	NBR	NDII	EVI	MSAVI1
2013 (Pre fire)- 2014 (Pre fire)	0.53	0.27	0.11	0.13	0.06	0.32
2014 (Pre fire)-2015 (Post fire)	4.97	0.63	2.12	1.77	1.69	4.15
2014 (Pre fire) - 2016 (1 yr. Post fire)	0.18	0.35	0.28	0.46	0.60	0.44
2014 (Pre fire) - 2017 (2 yr. Post fire)	0.58	0.35	0.35	0.53	0.60	0.43
2014 (Pre fire) - 2018 (3 yr. Post fire)	0.35	0.40	0.05	0.17	0.21	0.15

Results obtained from the separability index analyses showed that among the VIs considered in this study, NBR showed better discrimination performance than other VIs, while NDVI exhibited the lowest sensitivity (Tables 3 and 4). Chen et al. (2014) in a study of post-fire forest recovery in the Greater Hinggan Mountain area, concluded that NDVI, one of the most widely used VIs, was not suitable for monitoring post-fire recovery. The NBR represents the vegetation-to-soil ratio (Bright et al., 2019). A high NBR value indicates healthy green vegetation, while a low value indicates recently burned areas or bare land.

From Figure 3, we found that there was little difference in VIs between the burned forest and unburned forest areas from one year post-fire. To illustrate this quantitatively, we calculated separability index analysis, and the results are shown in Tables 3 and 4. We concluded that the separability index of VIs between the burned and unburned forest areas indicated poor spectral separability. It can be concluded that the forest had recovered one year after the surface fire in the study area. All VIs clearly could not differentiate burned and unburned areas even one year post-fire, supporting the notion that these forests recover quickly and

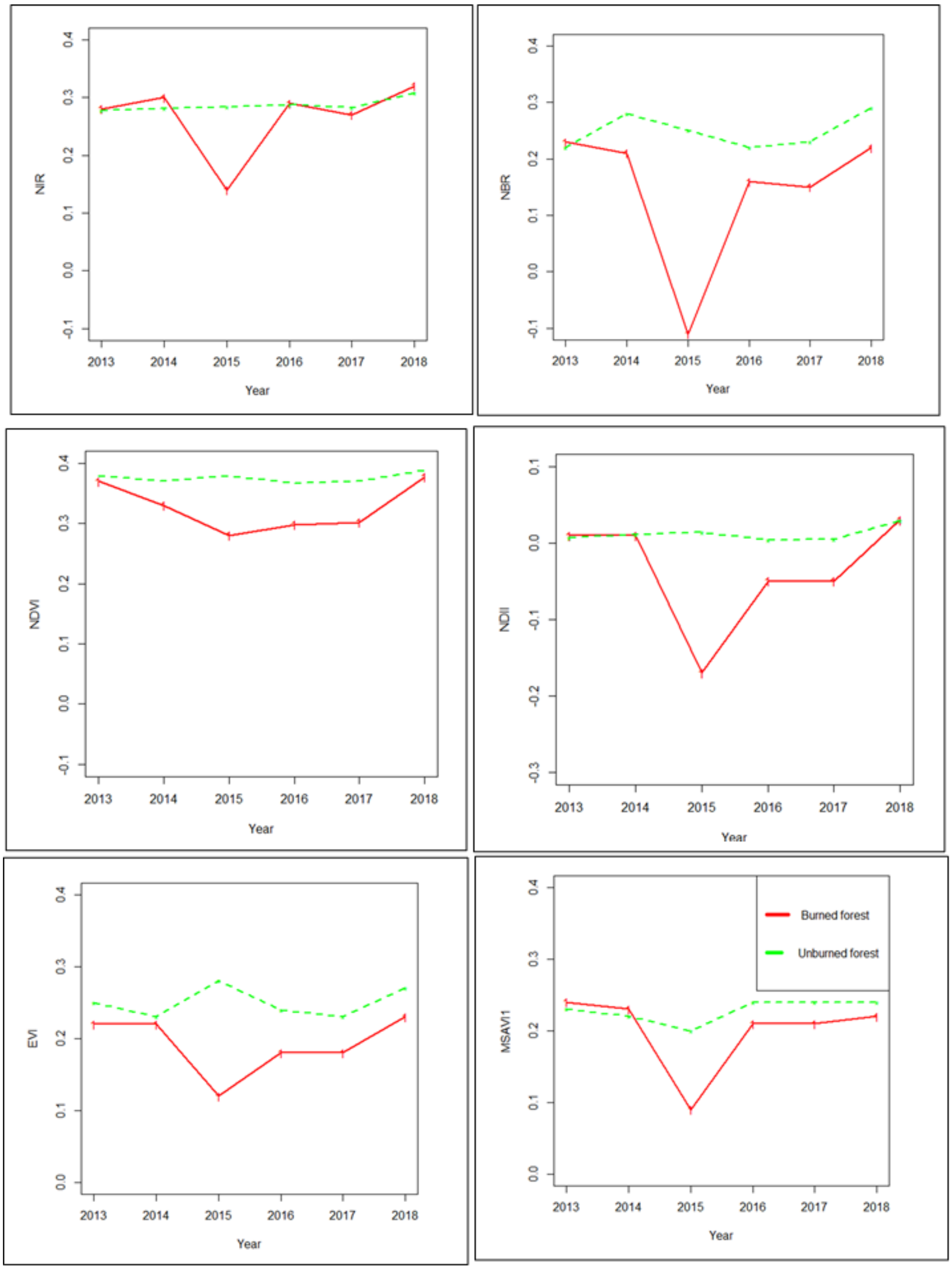

Figure 3. Mean spectral reflectance of NIR and vegetation indices (VIs) for the burned area (red line) and reference area (green dashed line) over time: from two years pre-fire (2013-2014) to post-fire (2015) and one, two and three years following the fire (2015 to 2018)

return to pre-fire greenness levels as measured by reflectance. Low-intensity surface fires and the rapid coppice regeneration of oak trees post-fire lead to an increase in canopy cover. Therefore, vegetation restoration occurs quickly, making it difficult to distinguish burned areas one year post-fire in some forest regions of the Zagros.

We decided to limit this research to VIs observations, as our aim was to describe overall vegetation recovery at the landscape level. In future studies, ground-based measurement of vegetation characteristics along with time series analysis of multispectral images, could better describe the trends of vegetation recovery post-fire and enhance the interpretability of satellite observations (Bright et al., 2019; Hudak et al., 2007).

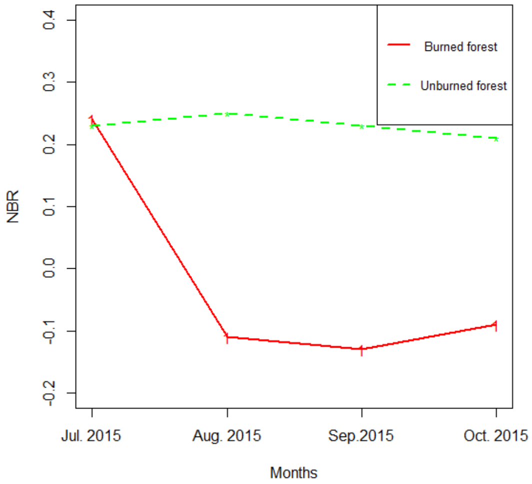

Figure 4. Mean NBR index for the burned area (red line) and reference area (green dashed line) over time: from July (16/07/2015) (Pre-fire) to October 2015 (up to 2 months post-fire)

4. Conclusions

The behavior of spectral indices is affected by the type of vegetation and the intensity of fire. This study investigated vegetation recovery using multispectral images after a surface fire in the northern Zagros forests, Iran.

Our study illustrated the potential of Landsat 8-OLI time series analysis for documenting post-fire vegetation recovery in Zagros forests. Landsat time series analysis can provide useful information on post-fire vegetation recovery across surface wildfire extents.

To better distinguish between fire disturbance and general changes in ecological conditions of the vegetation, such as climate variations, the spectral responses of burned pixels were compared to their unburned counterparts. According to the spectral behavior patterns of the NIR band and five spectral indices in burned and unburned (control points) areas, each of the implemented indices can identify vegetation regeneration and recovery one year post-fire. Based on the results, the spectral reflectance trend of the NIR band and the VIs is similar, showing a decrease after fire occurrence. Following the fire, the spectral reflectance of the vegetation increases and reaches its previous value one year after the fire due to forest regeneration and recovery. We found that for post-fire recovery analysis, the Landsat NIR band and the NBR vegetation index had the best performance. Following the fire, the NBR index drops sharply, then increases slightly in the following months, and by the following year due to vegetation regeneration and recovery, increases sharply and returns to its pre-fire level (Ryu et al., 2018).

Studies similar to ours are needed in other burned areas of the Zagros, where landscape-wide information on post-disturbance vegetation recovery is required. This information can be used to inform management decisions; for instance, patches that have not recovered could be included in the post-fire management plan (Fornacca et al., 2018).

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پایش بازیابی پوشش گیاهی پس از آتش‌سوزی در بخشی از جنگل‌های مریوان با استفاده از سنجش از دور

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چکیده

آتش‌سوزی ها بر ساختار، ترکیب و عملکرد بوم‌سازگان‌ها تاثیرگذار است. پایش احیا و بازسازی پوشش گیاهی پس از آتش‌سوزی به منظور ارزیابی اثرات آتش‌سوزی بر بوم‌سازگان‌های جنگلی ضروری است. هرساله، تعداد زیادی آتش‌سوزی سطحی با شدت کم تا متوسط در جنگل‌های زاگرس اتفاق می‌افتد. این پژوهش با هدف بررسی میزان بازیابی پوشش گیاهی پس از آتش‌سوزی در بخشی از جنگل‌های زاگرس شمالی از طریق بررسی تغییرات رفتار طیفی این جنگل‌ها انجام شد. برای این کار تصاویر سنجنده OLI ماهواره Landsat8 از سال ۲۰۱۳ تا ۲۰۱۸ مورد بررسی قرار گرفتند. در گام اول تصحیح اتمسفری دقیق بر روی داده‌ها انجام شد. از پنج شاخص طیفی NBR، NDVI، NDII ، EVI و MSAVI1 به منظور پایش بازیابی پوشش گیاهی منطقه سوخته از دو سال قبل از آتش‌سوزی تا سه سال پس از آتش‌سوزی استفاده شد. در این پژوهش از یک رویکرد کیفی (تفسیر بصری نمودارهای تغییرات طیفی شاخص‌ها) و یک رویکرد کمّی (شاخص تفکیک‌پذیری M-statistic) برای ارزیابی عملکرد شاخص‌ها در تفکیک طبقات سوخته و نسوخته استفاده شد. برای پایش و به حداقل رساندن اثر تغییرات فنولوژیکی و تأثیر مستقیم تغییرات آب و هوا، مانند بارندگی و خشکسالی، بر روند احیا و تغییرات طیفی پوشش گیاهی، بررسی‌ها همزمان در دو منطقه دچار حریق و شاهد با وضعیت فیزیوگرافی مشابه انجام شد. با توجه به ارزیابی کیفی، همه شاخص‌ها عملکرد خوبی در ارزیابی بازسازی پوشش گیاهی پس از آتش‌سوزی داشتند. تحلیل شاخص کمّی تفکیک‌پذیری نیز نشان داد که شاخص NBR نسبت به سایر شاخص‌های بررسی شده در این پژوهش عملکرد بهتری دارد. شاخص NDVI عملکرد ضعیف‌تری نسبت به سایر شاخص‌ها ارائه داد. نتایج نشان داد که ارزش همه شاخص‌ها تنها در یکسال پس از آتش‌سوزی به مقادیر قبل از آتش‌سوزی رسیده است. آتش‌سوزی سطحی با شدت کم و همچنین سرعت بالای زادآوری جست‌های بلوط منجر به این نتیجه شده است. بنابراین احیای پوشش گیاهی در منطقه مورد بررسی به سرعت اتفاق افتاده است. به همین دلیل در برخی از مناطق جنگل‌های زاگرس، تشخیص مناطق سوخته تنها یکسال پس از آتش‌سوزی دشوار است.

واژه‌های کلیدی: آتش‌سوزی سطحی، احیای پوشش گیاهی، شاخص‌های طیفی، چند زمانه، ماهواره لندست.

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