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ASSESSMENT AND MONITORING OF POST-FIRE RECOVERY USING SATELLITE IMAGERY AND THE STABILITY INDEX IN THE NORTH WEST OF ALGERIA

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Abstract: *Forest fire is phenomeno difficult to model because depend on many parameters, which vary in both time and space. It is therefore necessary to carry research and prevention actions as part of the improvement and management of this risk. The severity of wildfires due to hotter and drier global climate conditions affects ecological resilience and ecosystems at risk of deterioration following the failure of post-fire recovery. To properly prepare for wildfires, it is crucial to determine fire-sensitive areas, then locate fire suppression structures, and assess the spatial and temporal quantification of post-fire regeneration. The objectives of this study is fire detection using remote sensing and GIS, and make model to monitor the recovery of vegetation by using satellite imagery and the post-fire stability index. While undisturbed or recovered system states are characterized by rates of change close to zero. This reflects the typical pattern of decreasing change rates in post-fire recovery trajectories. For this, time series analyses of remote sensing images from Landsat between 2013 and 2020, both pre- and post-fire, were conducted in the Sidi Bel Abbés region, Algeria, and for the post-fire stability index, we used NBR and NBR2 as the base spectral indices to evaluate the post-fire stability index. therefore demonstrate the performance and relevance of the post-fire stability index compared to alternative approaches because this stability index provides a relatively simple and practical solution for consistent large-scale monitoring of post-fire recovery with satellite image. thus offers numerous opportunities for further research on fires, and forest recovery.*

KEYWORDS: *Post-Fire Recovery, Post-Fire Stability Index, Spatial Analysis and Multi-Temporal, Forest Fires.*

1 Introduction

Among the various factors that threaten forests in the Mediterranean region, and more particularly in Algeria, forest fires constitute the most devastating factor of degradation (FAO, 2025). Their intensity and brutality cause considerable losses, affecting vast areas of forest and pre-forest areas in relatively short periods of time (Montenegro et al. 2004; Türkan et al. 2023). Wildfires, or wildfires, are disasters that occur in vegetation formations dominated by forest trees and shrubs (Durlević et al. 2025). These fires can also occur in sub-forest formations, such as maquis (dense, closed vegetation growing on siliceous soil) and garrigue (more open vegetation, typical of calcareous soils). A forest fire is defined as a fire affecting an area of at least one hectare, in a single block, and with a minimum width of 25 meters. Algeria's already fragile forests require urgent protection as deforestation continues to increase, particularly due to recurring forest fires. Between 1990 and 2020, forest fires ravaged the equivalent of 779,872.11 hectares, with a total of 32,354 recorded outbreaks, resulting in significant ecological and economic consequences.

Most Mediterranean plant species exhibit effective regeneration mechanisms for overcoming the immediate effects of fire (Hundal et al. 2024). Plant species mechanisms can be passive or active, which may lead to a rapid process of vegetation cover (Perez-Cabello et al. 2009). However, the response of vegetation to fire is very complex and it is not easy to generalize because of the large number of factors that can affect the regeneration process (climatic influences, plant composition, topographic parameters, soil characteristics, etc.). Fire has become increasingly important in the Mediterranean and many other ecosystems, due to recent land-use and climatic changes (Pausas, 2004). Pinus halepensis

(Aleppo pine), together with the closely related Pinus brutia, are the most widespread trees in the Mediterranean Basin. Forest fires, when they are not frequent, promote the extension of conifers (Quezel, 1980). Note that the natural regeneration of the conifer forests in Mediterranean mountain, such as the cedar, is often consecutive to the emergence of fires, as shown locally the predominance of forest stands even-aged (Gonçalves & Sousa, 2017). Every year there are more than 1,000 forest fires in Algeria, affecting over 25,000 ha of forest and other woodland, the majority occur in the North. Although fire is a natural process of Mediterranean ecosystems (Chuvieco 1997,Trabaud et al. 1980). Spatial databases on forest fires are necessary to support fire Management programs and evaluate the manifold implications of fire occurrence (Koutsias et al. 1999).

Assessing the dynamics of natural regeneration and post-fire recovery, particularly in large areas, now increasingly requires data covering vast spatial extents over multiple time steps (Kirkland et al. 2024). Remote sensing therefore offers a viable and cost-effective solution for identifying and capturing observations of post-fire recovery dynamics. According to Aleksova et al. (2024), such approaches enable the monitoring of spatial and temporal patterns of vegetation regrowth, facilitating the assessment of ecosystem resilience and the effectiveness of post-fire management strategies.

Post-fire forest dynamics have been characterized by several satellite-derived spectral vegetation indices, which contrast short-wave infrared (SWIR) and near-infrared (NIR) wavelengths, such as the normalized burn rate (NBR). Hence, post-fire forest dynamics (e.g., fire severity and recovery) have strong correlations with field measurements (Gibson et al., 2020; Hislop et al., 2018; Kennedy et al., 2010; Shvetsov et al., 2019; White et al., 2017; Wulder et al., 2009). Comparing NBR changes with pre-fire NBR (RdNBR) improves accuracy, particularly for higher severity classes in heterogeneous landscapes (Miller et al., 2009; Miller and Thode, 2007). Several studies on the use of optical remote sensing for monitoring post-fire spectral forest regeneration have demonstrated that SWIR-based indices exhibit greater sensitivity to the impacts of fire on forest canopy and canopy structure regeneration, indicating their relevance for monitoring progressive canopy recovery (Cuevas-Gonzalez et al., 2009; Schroeder et al., 2011). A study from Southern California (Storey et al., 2016) showed that the modified version of the NBR, which compares two SWIR wavelengths (NBR2), has recently gained interest, with promising results for assessing post-fire vegetation regeneration.

This study builds upon the work of (Gibson et al.(2022), who utilized the Normalized Burn Ratio (NBR) and its variant NBR2 as foundational spectral indices to develop the Post-Fire Stability Index. The formulation of the Post-Fire Stability Index follows the structure and scaling of the widely applied Relativized Differenced Normalized Burn Ratio (RdNBR; Miller & Thode, 2007), which is typically employed on pre- and post-fire imagery to quantify immediate fire impacts.

2 Main objective and study area

The objective of this study is to monitor vegetation recovery after fire using remote sensing data and the stability index. Specifically, it analyzes post-fire vegetation recovery as a temporal and spatial process through a series of satellite images from 2013, 2014, 2016, and 2020.

The study area is a state-owned forest located in the wilaya of Sidi Bel Abbès in northwestern Algeria, which experienced a wildfire during the summer of 2014 (Fig. 1). The forest composition in this province is dominated by Aleppo pine, covering 63,432 hectares (97%). Other species are present in smaller proportions: eucalyptus (1,025 hectares, 2%), and a combination of holm oak and thuja (816 hectares, 1%).
The Matorral species present in the area include kermes oak, oxycedar juniper, mastic, calicotome, thuja, holm oak, rosemary, doum, cistus, and esparto (Larabi, 2016).

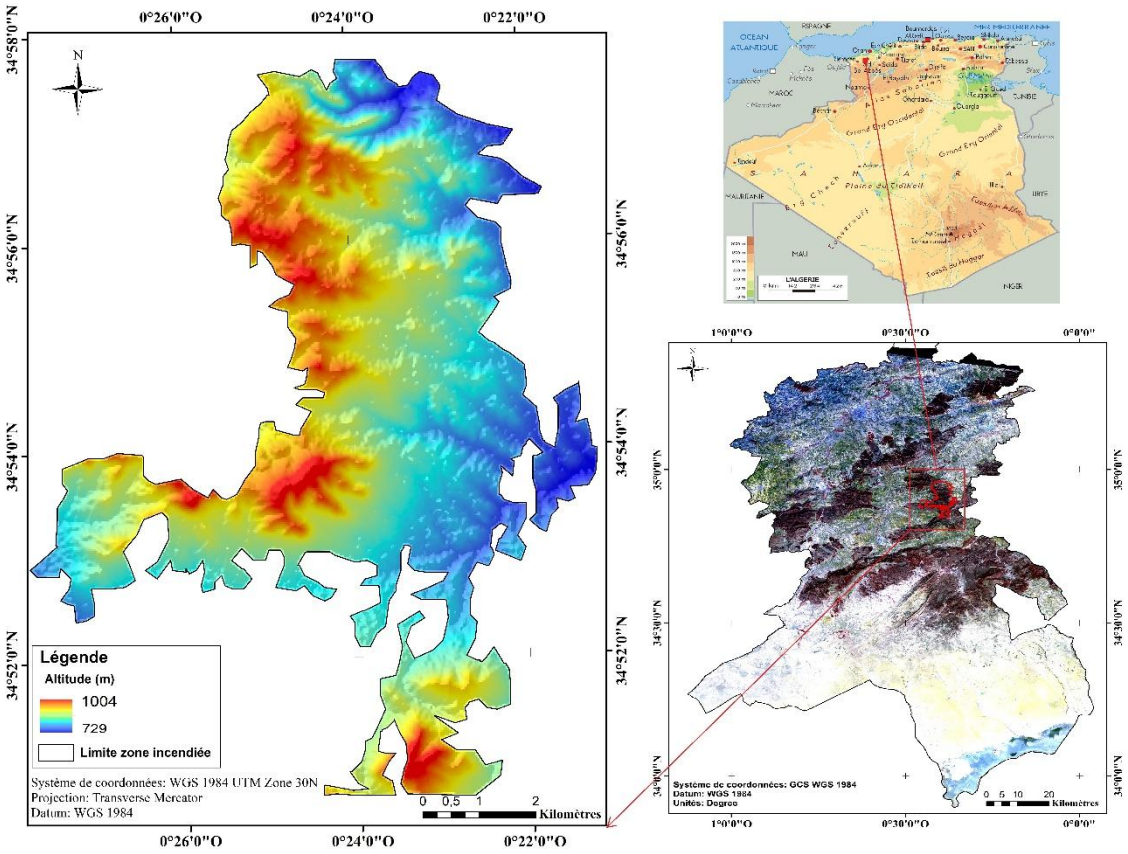


Fig.1: Geographical location of the area of the Sid Bel Abbés forest massif (Northwest Algeria)

3 Materials and Methods

The primary objective of this study is to rigorously assess and quantify the spatio-temporal dynamics of vegetation recovery within a burned area through a diachronic analysis of remote sensing data, employing a derived post-fire index and integrating field-based observations. This investigation focuses on characterizing the regrowth trajectories of different plant species and analyzing the spatial heterogeneity of post-fire regeneration patterns. Although several remote sensing approaches were evaluated for monitoring vegetation recovery, the present study specifically presents results derived from the NDVI, NBR, and NBR2 post-fire stability index, selected for their sensitivity to vegetation structure and fire-induced disturbances.

The Sidi Bel Abbes forest massif occupies an area of 205,672 ha, comprising 25 state-owned forests and giving a coverage rate of (23%) compared to the overall area of the Wilaya. In terms of the area of forest massifs, the Daïra of Merine (study area) presents the first position, of which it alone occupies (33.63%) of the total forest area (C.F.SBA, 2017). The main species that characterize the forest massif of this area are the Aleppo pine (Pinus halepensis) and the thuja (Tetraclunis articulata), which are species endemic to North Africa. The Aleppo pine is undoubtedly the species that has the highest expansion power in the region. There are also other stands of smaller extension, such as the Holm oak. Because the holm oak occupied a larger area in the region, it covered large areas that were reduced following the expansion of agricultural activities. Generally, the stands are often mixed with Aleppo pine. The Thuja occupies small areas, a plant group generally at an advanced stage of degradation due to overgrazing. After fire, the regeneration of the Thuja is mainly ensured by stump shoots which give rise to very dense coppices, showing a high risk of flammability due to the resin with which the plant is impregnated (Boudy, 1950).

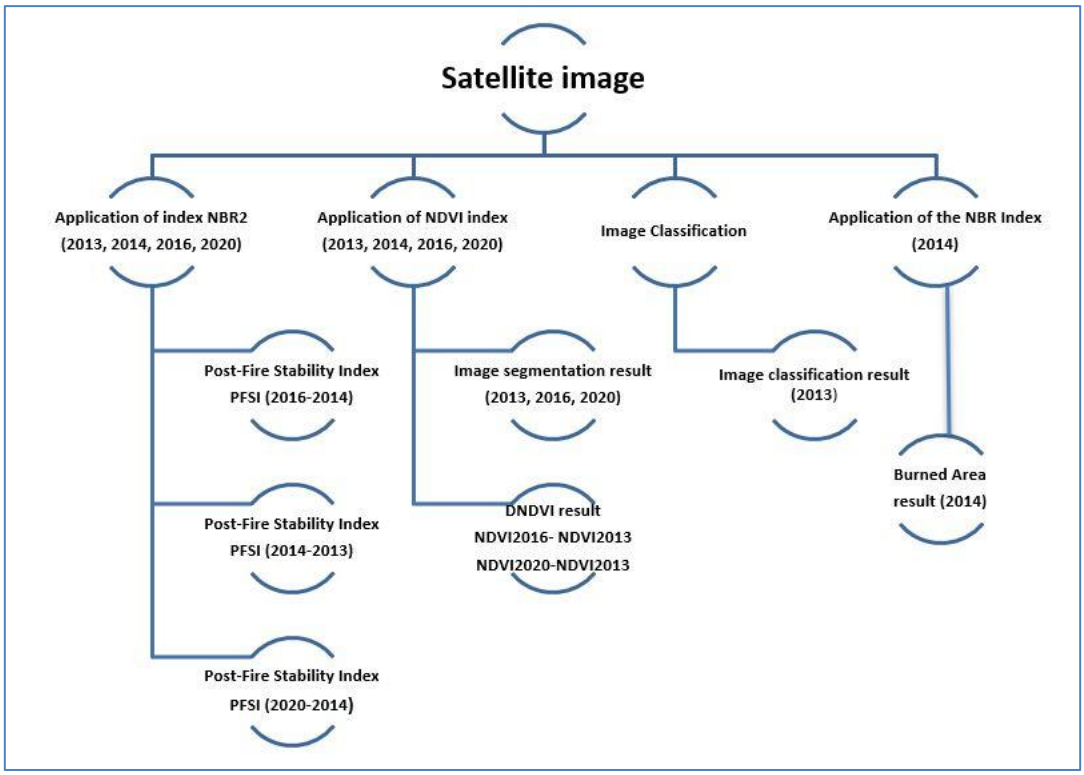


Fig. 2: Flowchart of the methodology

Therefore, this work is divided into three methods to determine the regeneration rate and validate the importance of the new stability index method.
To do this, we evaluated various indices that would allow us to assess post-fire regeneration namely:

3.1 Applicable model

3.1.1 Normalized Difference Vegetation Index (NDVI):

The NDVI, developed by Rouse et al. (1974) is, without doubt, the index most widely used in various applications of remote sensing, including evaluation of the process of regeneration post-fire (Henry and Hope, 1998; Viedma et al., 1997). This index allows for the visualization within a single band of the dynamics of responses related to the density and type of vegetation cover, by optimizing the contrast between the visible and near-infrared ranges. It is correlated with the chlorophyll activity of the surfaces:

$$\mathbf{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}} \qquad (1)$$

where, for satellite remote-sensing data, RED and NIR represent reflectance values of PlanetScope's B6 and B8 bands. In ground cameras, RED and NIR indicate DN values of narrowband red and NIR bands calculated from narrowband images obtained using dual-band filters.

3.1.2 NDVI differencing (DNDVI)

To measure changes in biomass, the Difference NDVI (DNDVI) method was used, as this technique compares and calculates NDVI values from images acquired on two different dates. Applying this method requires NDVI images corresponding to pre- and post-fire dates, with each image initially having a value range of -1 to +1. Histogram equalization was employed to adjust these values, distributing them with equal probability across a 0 –255 range for both

images. This step was followed by the creation of a Difference NDVI (DNDVI) image by subtracting the NDVI image of one date from that of another. In this study, the 2013 NDVI image was subtracted from the 2016 NDVI image for the first period, and the 2013 NDVI image was subtracted from the 2020 NDVI image for the second period, as shown in the following equations:

$$\boldsymbol{DNDVI} = NDVI\ (2016) - NDVI\ (2013) \qquad (2)$$

$$\boldsymbol{DNDVI} = NDVI\ (2020) - NDVI\ (2013) \qquad (3)$$

3.1.3 Normalized Burn Ratio (NBR)

Landsat Normalized Burn Ratio (NBR) are available for Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8-9 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) Collection 1 and Collection 2 scenes that have been processed to Landsat Level-2 Surface Reflectance products. *Landsat 9 = Collection 2 only.*
So, NBR is used to identify burned areas and provide a measure of burn severity. It is calculated as a ratio between the NIR and SWIR values in traditional fashion as:

$$\boldsymbol{NBR} = \frac{NIR - SWIR}{NIR + SWIR} \qquad (4)$$

In Landsat 4-7, NBR = (Band 4 – Band 7) / (Band 4 + Band 7).
In Landsat 8-9, NBR = (Band 5 – Band 7) / (Band 5 + Band 7).
NBR is delivered as a single band product.

3.1.4 Normalized Burn Ratio 2

Normalized Burn Ratio 2 (NBR2) modifies the Normalized Burn Ratio (NBR) to highlight water sensitivity in vegetation and may be useful in post-fire recovery studies.

As the same of NBR, Landsat Normalized Burn Ration 2 (NBR2) are acquired from Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8-9 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) Collection 1 and Collection 2 scenes that have been processed to Landsat Level-2 Surface Reflectance products. *Landsat 9 = Collection 2 only.*

NBR2 is calculated as a ratio between the SWIR values, substituting the SWIR1 band for the NIR band used in NBR.

$$\boldsymbol{NBR2} = \frac{SWIR1 - SWIR2}{SWIR1 + SWIR2} \qquad (5)$$

In Landsat 4-7, NBR2 = (Band 5 – Band 7) / (Band 5 + Band 7)
In Landsat 8-9, NBR2 = (Band 6 – Band 7) / (Band 6 + Band 7)
NBR2 is delivered as a single band product.

3.1.5 Image segmentation:

Image segmentation is an image processing technique that allows for the identification of homogeneous areas within an image. These homogeneous areas are called segments. This technique enables the classification of an image by placing each pixel within its immediate context.

3.1.6 Post-fire stability index

*According to R.K. Gibson et al., (2022), they used NBR and NBR2 as the base spectral indices to develop the post-fire stability index. The formula for this index mirrors the structure and scale of the *Relativised Differenced Normalised Burn Ratio* (RdNBR; Miller and Thode, 2007), an index widely used on pre- and post-fire imagery to assess immediate fire impact. They also adapted this concept to evaluate longer-term effects by performing a rolling annual comparison of images within the post-fire time series. In our case, the post-fire stability index was compared against reference methods based on the pre-fire period (2013), in which initial spectral values corresponded to a multi-year average.*
So in the present study, we adapted this framework to evaluate ongoing post-fire effects by employing a continuous sequence of multi-temporal imagery, reflecting the slow pace of forest regeneration in Mediterranean ecosystems.

The post-fire stability index was evaluated using the following equations:

$$\textbf{NBR\% of prefire value} = \left(\frac{Postfire\ NBR}{Prefire\ NBR}\right) * 100 \qquad (6)$$

$$\textbf{NBR2 \% of prefire value} = \left(\frac{Postfire\ NBR2}{Prefire\ NBR2}\right) * 100 \qquad (7)$$

$$\textbf{NBR Postfire Stability Index} = \frac{(NBR\ at\ Time\ t - NBR\ at\ Time\ t-1)}{(sqrt\left(ABS\left(\frac{NBR\ at\ Time\ t-1}{1000}\right)\right))} \qquad (8)$$

So We calcultate PFSI with the formula:

$$\textbf{PFSI: NBR2 Postfire Stability Index} = \frac{(NBR2\ at\ Time\ t - NBR2\ at\ Time\ t-1)}{(sqrt\left(ABS\left(\frac{NBR2\ at\ Time\ t-1}{1000}\right)\right))} \qquad (9)$$

3.2 Datasets

The study was carried out on images Landsat acquired in 2013, 2014, 2016 and 2020 to evaluate forest regeneration (Table 1).

Table 1. Characteristics of satellite images used in the study

Image	*Dates Acquisition*	*Band Number*	*Spectral Wave*	*Spatial Resolution*
Landsat 8 Oli	*30-09-2013* *31-07-2014* *01-09-2014* *06-09-2016* *01-09-2020*	*Band 2*	*0,45 - 0,51*	*30 m*
		Band 4	*0,64 - 0,67*	
		Band 5	*0,85 - 0,88*	
		Bande 6 (SWIR 1)	*1,57 - 1,65*	
		Band 7 (SWIR 2)	*2,11 - 2,29*	

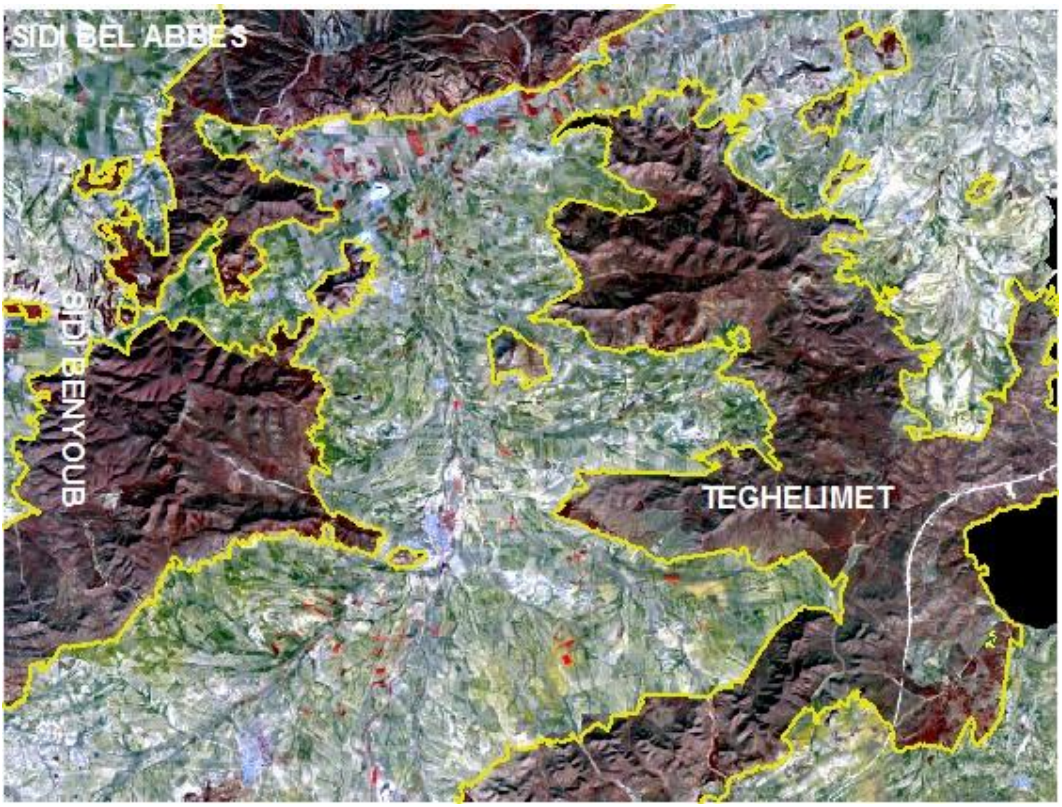


Fig. 3: Image 2014 Landsat 8Oli used in the study with forest boundary

3.3 Application of the NBR Index for Burned Area Delineation

In this study, the NBR index was applied to the 2014 Landsat imagery to delineate the extent of the burned area. The Normalized Burn Ratio (NBR) is used to map burned areas and to characterize fire severity. It is calculated as the normalized difference ratio in reflectance between the near-infrared (~0.76-0.9 µm) and shortwave infrared (~2.08-2.35 µm) portions of the electromagnetic spectrum, typically measured by satellite or other aerial platforms (Roy et al, 2006). Values of NBR are bounded between -1 and 1, with values close to 1 indicating healthy/productive vegetation and values near or below 0 often being burned or unproductive vegetation. A thresholding approach was implemented to isolate recently burned regions, resulting in the identification of approximately 5,000 hectares affected by the 2014 forest fire in the province of Sidi Bel Abbés.

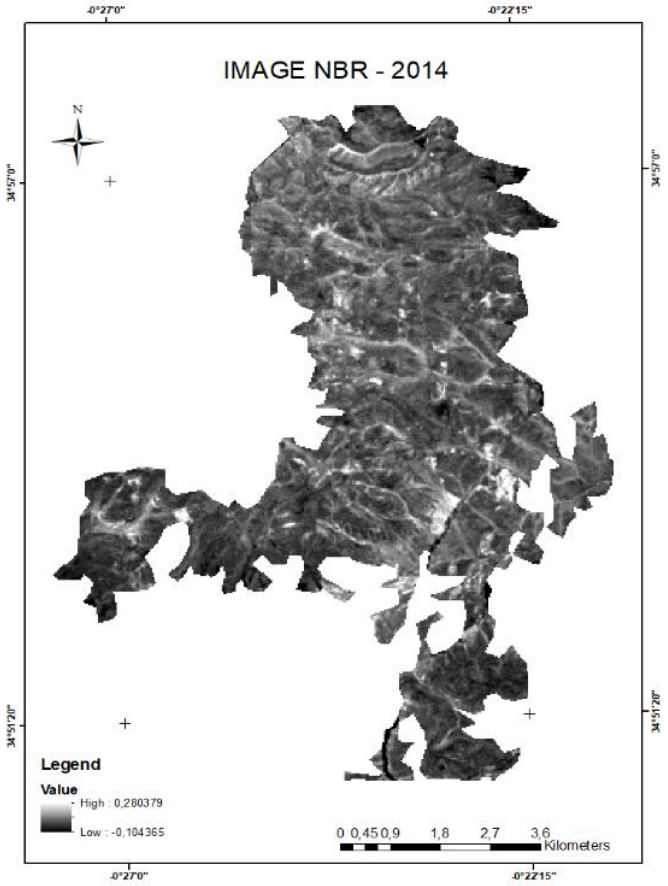


Fig. 4: Image NBR - 2014

The computation of the Post-Fire Stability Index requires the calculation of both NBR and NBR2, with NBR2 derived from the SWIR1 and SWIR2 spectral channels of the Landsat OLI 8 sensor. The resulting NBR2 values, which form an integral component of the index, are illustrated in the subsequent figures (Fig 5) and are used to quantify post-fire vegetation stability.

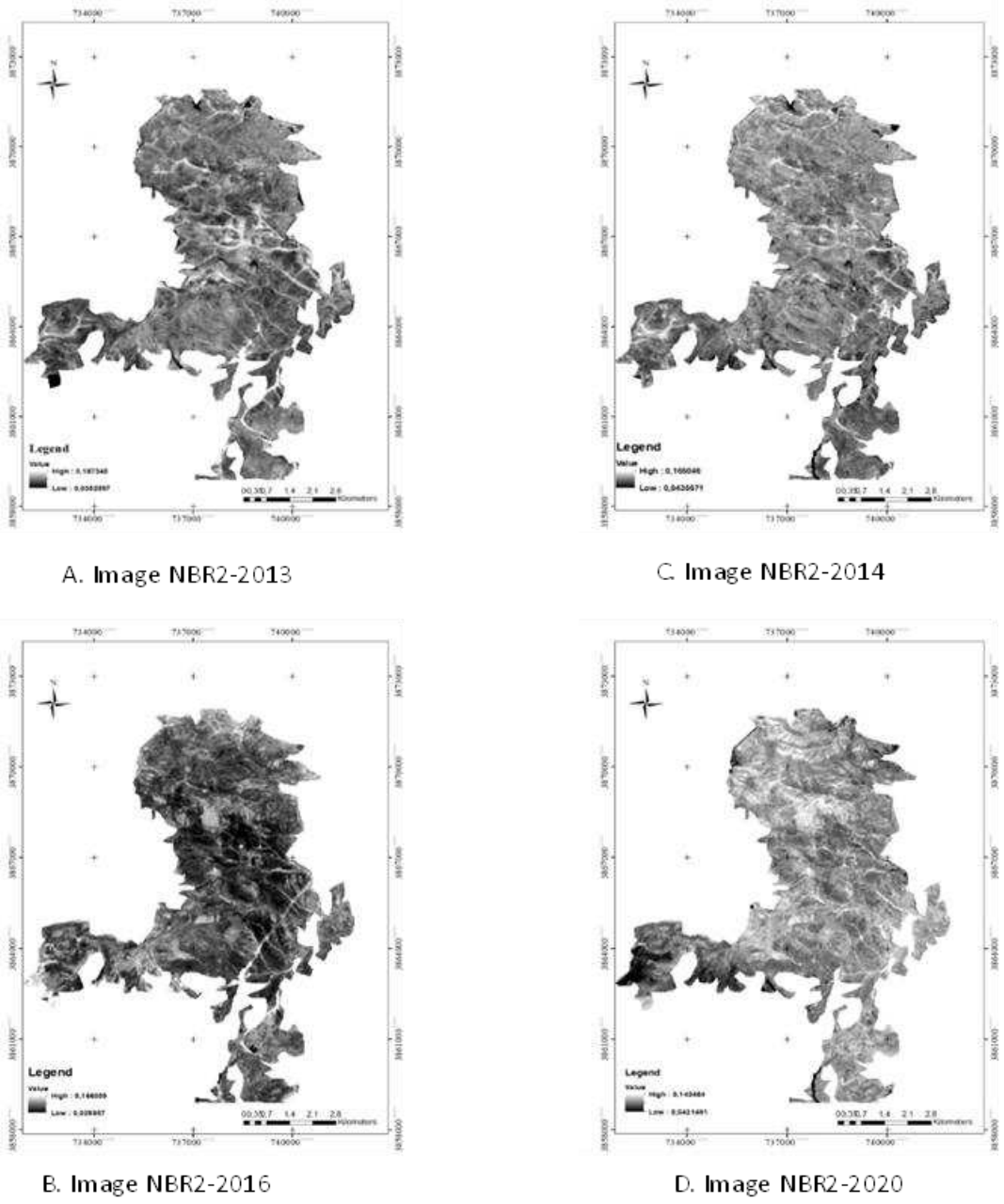


Fig. 5: Image NBR2 (2013, 2014, 2016, 2020)

This index are NBR and NBR2 are the base spectral indices to develop the post-fire stability index. The post-fire stability index formula follows the structure and scaling of the widely applied relativised differenced normalised burn ratio (RdNBR; Miller and Thode, 2007). These indices are generally widely used, since they are applied to pre- and post-fire images. In our study, we applied the NBR2 index to images from the years 2013, 2014, 2016, and 2020. This succession of years allows us to evaluate the rate of vegetation recovery per year interval following the use of the stability index.

3.4 Classification

In this study, a supervised classification was performed on 2013 Landsat imagery (fig 6), preceding the 2014 wildfire, to delineate the different forest vegetation classes present in the area affected by the fire. The Maximum Likelihood Classification (MLC) algorithm was applied due to its effectiveness in assigning pixels to classes based on the highest probability derived from spectral signatures, assuming normal distribution of the class statistics (Richards, 2013; Lillesand et al. 2015). Representative training samples were selected for each vegetation type to guide the classification

process. The classification yielded four primary vegetation classes: cedar (Tetraclunis articulata), Aleppo pine (Pinus halepensis), mixed forest, and shrubland.

The identification of these classes provides critical information regarding species composition, which is relevant for understanding combustibility and potential fire propagation dynamics, as different species exhibit varying flammability and fuel characteristics (Catry et al. 2010). The classification was validated by field observations and auxiliary data to confirm the spatial distribution of vegetation types and their representation in the classified map. This vegetation map served as a foundational dataset for subsequent post-fire analyses, including the assessment of fire impacts and post-fire recovery using NDVI, NBR, and NBR2 indices.

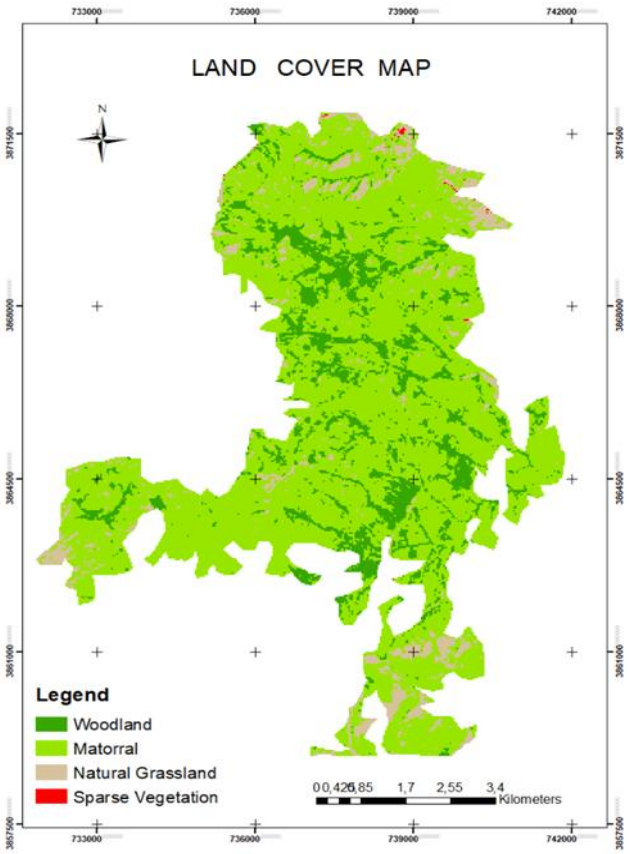


Fig. 6: Image classification 2013

The classification was performed using ArcGIS software, with the following Landsat image caracteristic:

- *LANDSAT_SCENE_ID = "LC81980362013177LGN02"*
- *SPACECRAFT_ID = "LANDSAT_8"*
- *MAP_PROJECTION = "UTM"*
- *DATUM = "WGS84"*
- *UTM_ZONE = 30*

Table 2. percentage of plant formation in the study area

Plant Formations	***Area (ha)***	***%***
Woodland	***770,22***	***14,93***
Matorral	***4006,71***	***77,69***
Natural Grassland	***375,93***	***7,29***
Sparce Vegetation	***4,23***	***0,08***

3.5 Atmospheric correction :

The objectif of atmospheric correction is to remove the impact of atmosphere in satellite measurements (TOA radiance LTOA) in order to get a parameter (reflectance) that characterize the observed Earth surface. The DN measured or registered by a sensor is composed of two components. One is the actual radiance of the pixel which we wish to record, another is the atmospheric component. The magnitude of radiance leaving ground is attenuated by atmospheric absorption and the directional properties are altered due to scattering. Other sources of errors are due to the varying illumination geometry dependent on sun's azimuth and elevation angles, ground terrain. As the atmosphere properties vary from time to time, it becomes highly essential to correct the radiance values for atmospheric effects. Once we have obtained the reflectance image, we transform the MIN and MAX values from 0 to 1.

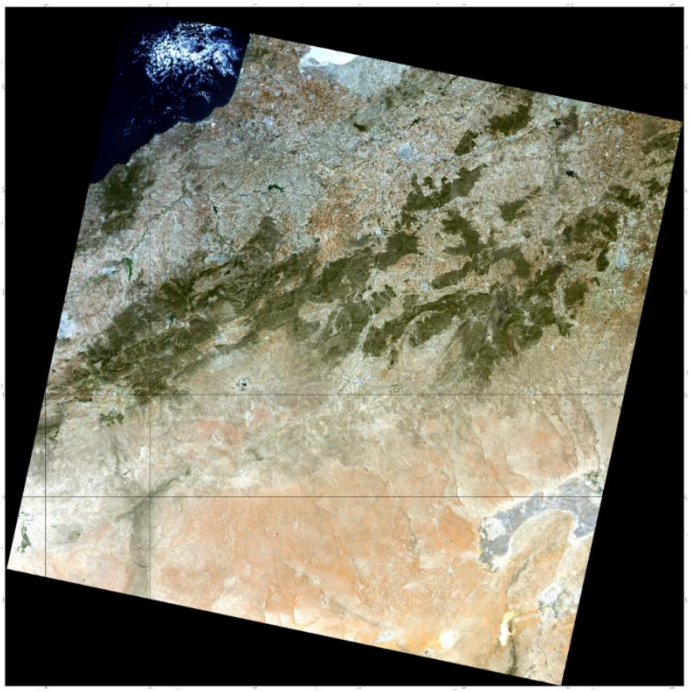


Fig. 7: Image Landsat8 Oli 2014 with atmospheric correction

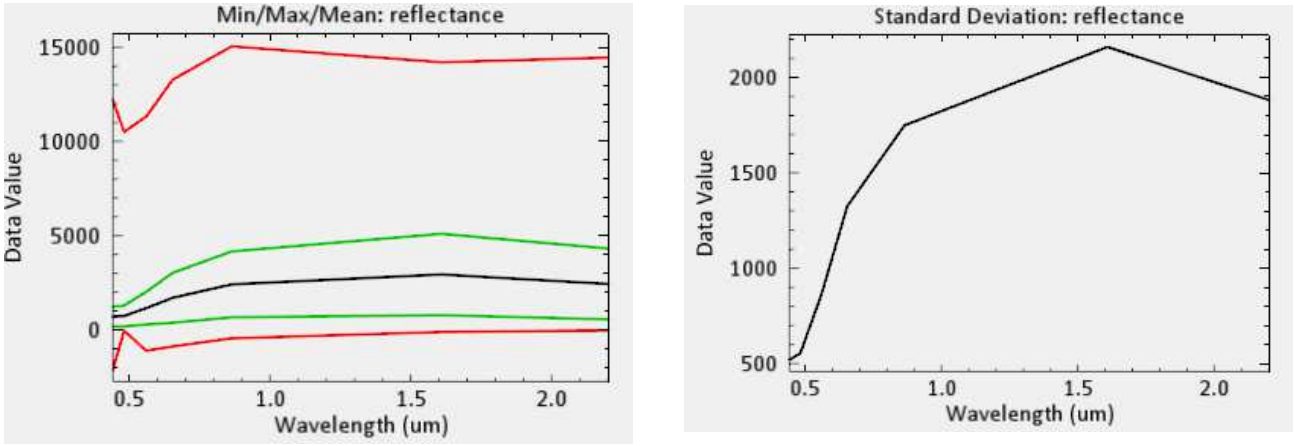


Fig. 8: Result of valeur transformation of Image Landsat8 Oli 2014 with atmospheric correction

4 Results and Discussion

To better assess post-fire regeneration and determine the contribution of the stability index, we proceed by:

4.1 Segmentation of NDVI

Segmenting NDVI images two years after fire (2016) and six years after fire (2020), allows us to limit the number of classes reflecting the regeneration dynamics and to interpret them more easily.
Furthermore, segmenting the NDVI images reflects the procedures followed to group pixels to form areas that can be interpreted as thematic classes. We obtained four classes based on vegetation density. This study uses the so-called pixel-by-pixel segmentation approach (Caloz and Collet, 2001). In this case, clustering is based solely on the criterion of spectral
similarity between pixels. Two pixels are said to be similar if their respective spectral luminance values are similar, and in this case, spatial zoning is simply the result of classifying the pixels into categories, the results are in the following figures:

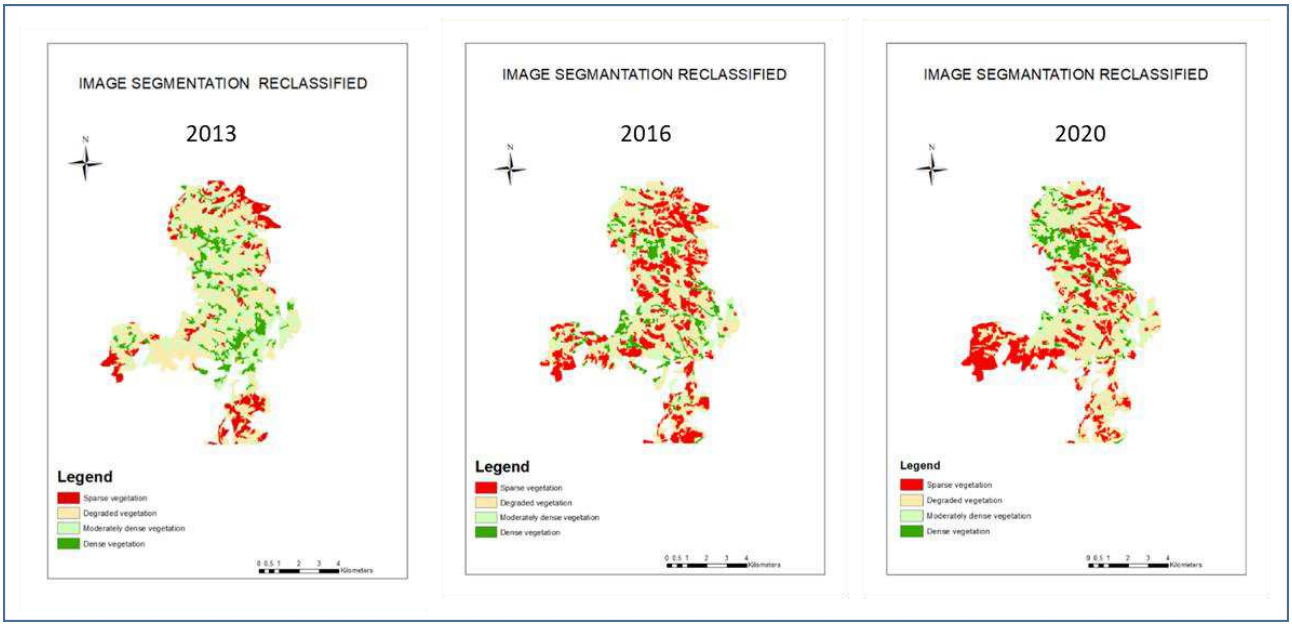


Fig. 9: Image segmentation : 2013, 2016, 2020

In the following table, we see the mutation and variation of vegetation density before and after fire.

Table 3. Vegetation density result by segmentation of NDVI

	Area		
Before and after fire 2014	*2013 (ha)*	*2016 (ha)*	*2020 (ha)*
Sparse vegetation	***635,49***	***1452,51***	***1494,99***
Degraded vegetation	***2202,03***	***1946,61***	***2068,65***
Moderately dense vegetation	***1736,73***	***1293,21***	***1232,19***
Dense vegetation	***582,84***	***464,76***	***361,26***

4.2 Change Detection: Normalized Difference Vegetation Index Differentiation (DNDVI)

The NDVI, which is a ratio between near-infrared and red, is designed to measure the greenness and density of vegetation captured in a satellite image. The graphical representation of this index shows that healthy vegetation exhibits a very characteristic spectral reflectance curve. The NDVI is this difference expressed as a number, ranging from -1 to 1.

The NDVI of plant species in general, calculated regularly over several periods, can reveal a wealth of information, particularly on plant health, vegetation density, and its mutations.

And so on, from 2013 to 2020, to observe vegetation changes over a long period. To identify changed areas in an image from different dates, we used a thresholding technique based on the histogram of the differenced image. The results show that significant changes are located in the tails of the histogram distribution, while pixels showing no significant changes tend to cluster around the averages. These results were transformed into representative maps according to four degrees : no vegetation recovery, slow vegetation recovery, average vegetation recovery, and fast vegetation recovery.

At this stage, the analysis focuses primarily on classification changes from the initial pre-fire state. Alternatively, for each class in the initial state, the analysis identifies the classes where pixels are transferred in the final image state. This is because the changes are reported as areas.

Comparing these two figures (Figures 10) shows that the average vegetation recovery and the fast vegetation recovery per class have increased in area, indicating that post-fire forest regeneration becomes significant after a few years.

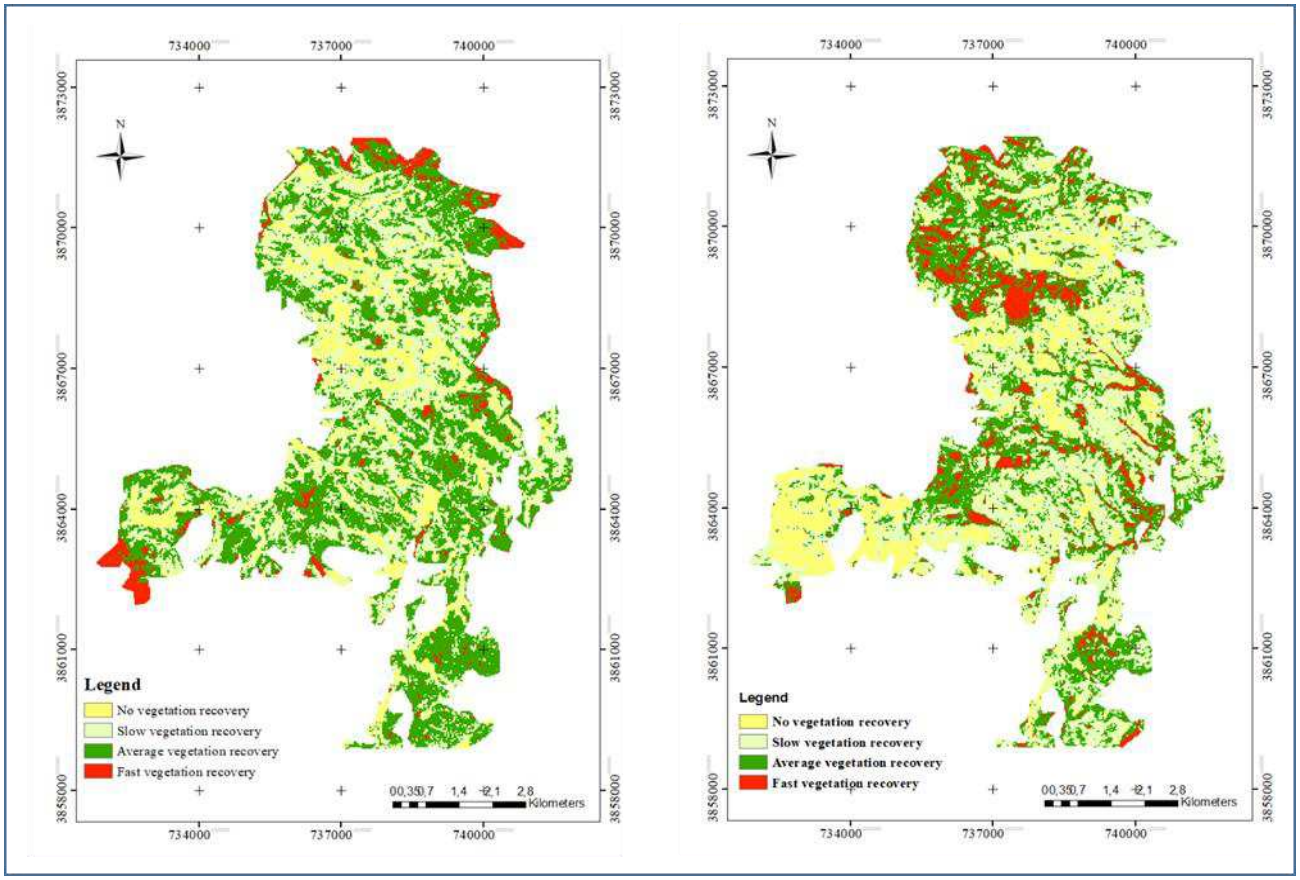


Fig. 10: DNDVI: [NDVI2016 - NDVI2013] , DNDVI: [NDVI2020 - NDVI2013]

4.3 The post-fire stability index (PFSI)

As we said before, we used NBR and NBR2 as the base spectral indices to develop the post-fire stability index. The post-fire stability index formula follows the structure and scaling of the widely applied relativised differenced normalised burn ratio (RdNBR; Miller and Thode, 2007), which is normally applied to pre and post-fire imagery to assess the immediate post-fire impact.

So the candidate methods used to calculate the "post fire stability index" were generated by the following equations as cited before:

$$\boldsymbol{NBR} = \frac{NIR - SWIR2}{NIR + SWIR2} \qquad (1)$$

$$\boldsymbol{NBR2} = \frac{SWIR1 - SWIR2}{SWIR1 + SWIR2} \qquad (2)$$

according to ***R.K. Gibson et al****.*

$$\boldsymbol{NBR\%\ of\ prefire\ value} = \left(\frac{Postfire\ NBR}{Prefire\ NBR}\right) * 100 \qquad (3)$$

$$\boldsymbol{NBR2\ \%\ of\ prefire\ value} = \left(\frac{Postfire\ NBR2}{Prefire\ NBR2}\right) * 100 \qquad (4)$$

$$\textbf{NBR Postfire Stability Index} = \frac{(NBR\ at\ Time\ t - NBR\ at\ Time\ t-1)}{(sqrt\left(ABS\left(\frac{NBR\ at\ Time\ t-1}{1000}\right)\right))} \quad (5)$$

So We calcultate PFSI with the formula:

$$\textbf{PFSI: NBR2 Postfire Stability Index} = \frac{(NBR2\ at\ Time\ t - NBR2\ at\ Time\ t-1)}{(sqrt\left(ABS\left(\frac{NBR2\ at\ Time\ t-1}{1000}\right)\right))} \quad (6)$$

So the Eqs. (3) and (4) are pre-fire baseline methods and Eqs. (5) and (6) are the post-fire stability indices based on NBR and NBR2.

This new approach to post-fire monitoring and recovery using satellite imagery, which we present here, is based on the concept that a disturbed state of a system results in increasing or decreasing rates of change.
While undisturbed, unchanged, or recovered states are characterized by rates of change close to zero.

To further determine the performance and relevance of the post-fire stability index, we used alternative vegetation recovery approaches through time-series image analysis, NDVI, and image segmentation, followed by independent validation using post-fire vegetation surveys conducted one year after the fire in 2013. This post-fire stability index has proven to be a powerful model for field measurements of post-fire vegetative response. Higher values of the post-fire stability index indicate higher levels of post-fire regrowth.
This post-fire stability index therefore offers a practical solution for consistent, large-scale monitoring of post-fire regeneration using satellite imagery.

Therefore, we can state that the post-fire stability index examines the rate of change in the years following the fire, for all severity classes, including unburned areas. Typically, after a fire, increases in NBR2 occur over several years due to the rapid increase in vegetative biomass.
Post-fire stability index values close to zero at a given time step are not sufficient, on their own, to diagnose a stable system state. Index values for all severity classes must also be synchronous with the surrounding unburned environment over several consecutive years. Interannual variations are expected in forest systems, even in the absence of fire-related changes, due to a variety of natural and anthropogenic processes occurring at various spatial and temporal scales (Kennedy et al., 2014). Using the Post-Fire Stability Index (PFSI) results, we can visually and statistically compare the spectral variations of burned areas with those of surrounding unburned areas on an annual basis. This allows for a better understanding of the spatial and temporal patterns of post-fire recovery across large landscapes. The figures below show the results of Post-Fire Stability Index calculated based on the years following the fire in our case (2014-2013, 2016-2014 and 2020-2014). A simple interpretation of these results clearly shows the areas where vegetation recovery is occurring at a fast rate.

The PFSI index takes on higher values when there is strong recovery. The PFSI image for the Sidi Bel Abbès site was calculated using the pre-fire NBR2 image from 2013 and the post-fire NBR2 image from 2014, 2016, and 2020.
The PFSI image obtained for the state of regeneration in 2014, a few months after the fire (Figure 11, A), shows that almost the entire burned area exhibits a very low index, represented by zero or low regeneration classes, indicating that the post-fire recovery rate is lower than the pre-fire recovery rate. The vegetation has not yet had the time necessary to reach a medium or high recovery rate.

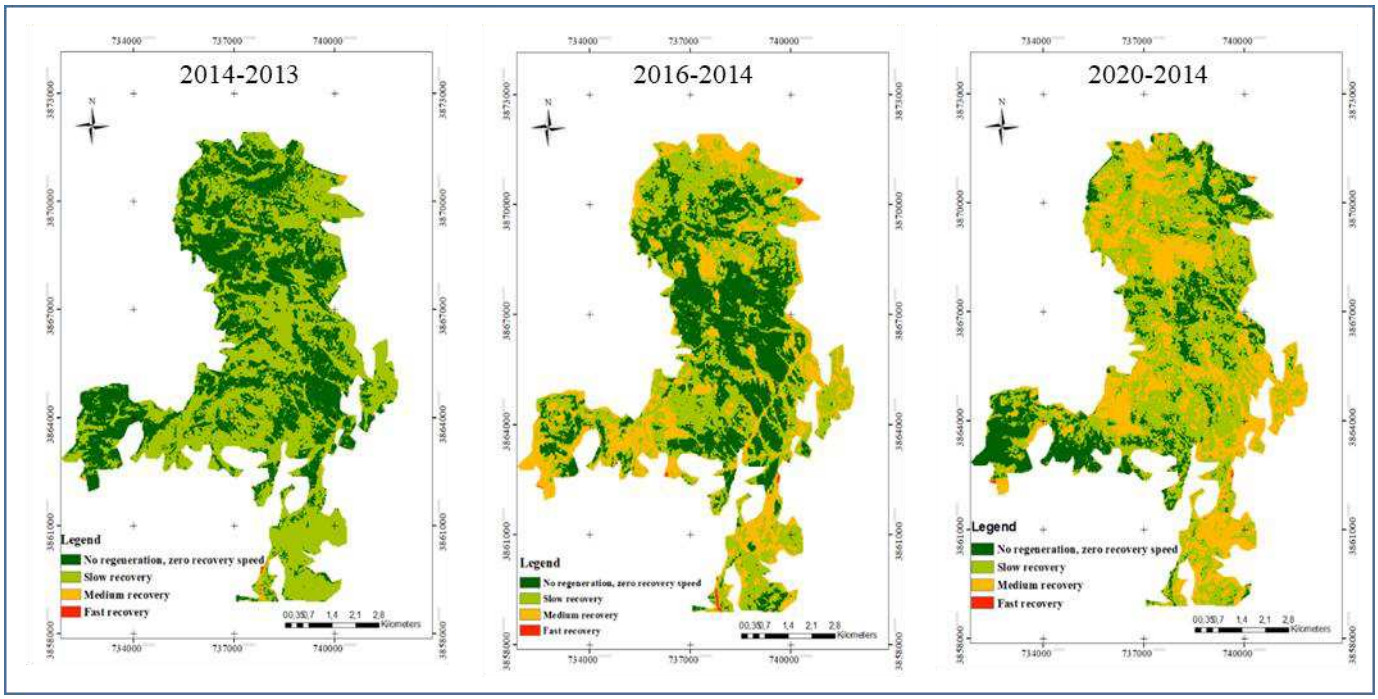


Fig. 11: PFSI : Post-Fire Stability Index (2014-2013), (2016-2014), (2020-2014)

For 2016 (Figure 11, B), we see moderate regeneration occurring in the burned area, where the area was covered with sparse vegetation, implying a less severe fire.
Comparing the results of PFSI with field data 2014, 2016 and 2020 we found that the forest species generally regenerate after three years and their rate of recovery become more important depending on topographic and climatic conditions.

Reading the histograms, we see that positive post fire stability index (PFSI) values increase in importance with the number of years after the fire. This information confirms that post-fire regeneration becomes more significant from the second year after the fire, hence the natural cycle of forests.

Table 4. PFSI : Post-Fire Stability Index statistic recovery

Period	*2020 - 2014*		*2016 - 2014*		*2013 - 2014*	
Temporels series	***Sup. (ha)***	***%***	***Sup. (ha)***	***%***	***Sup. (ha)***	***%***
No regeneration, zero recovery speed	***1009.44***	***19.6***	***1728.63***	***33.5***	***2229.39***	***43.22***
Slow recovery	***2533.59***	***49.11***	***2256.57***	***43.76***	***2913.39***	***56.47***
Medium recovery	***1611***	***31.21***	***1160.73***	***22.5***	***13.41***	***0.26***
Fast recovery	***4.5***	***0.08***	***12.6***	***0.24***	***2.43***	***0.05***

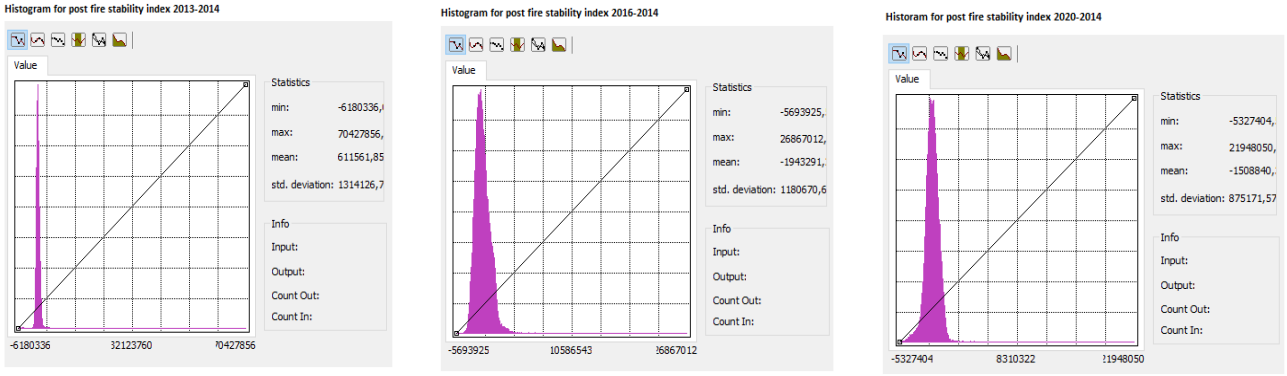


Fig. 12: Histogramme PFSI A(2014-2013), B (2016-2014), C(2020-2014)

5 Discussion

We found that analyzing Landsat time-series data specifically using the segmentation and differentiation DNDVI algorithm served as an effective tool for monitoring the gradual spectral recovery of trees across vast forest areas following fires. The results showed that forest regeneration in the Sidi Bel Abbès region between 2016 and 2020 was highly variable and depended on fire severity within the burned areas. As illustrated in Figures 9 and 10, NDVI values dropped below typical forest growth levels following the 2014 fires.
For the two vegetation degradation classes"sparse vegetation" and "degraded vegetation"large areas remained in these states two and four years post-fire, indicating poor regeneration; meanwhile, the segmentation algorithm revealed recovery trends across the burned zones, albeit at a slow pace.

Significant variability was observed in pre-fire baseline values (PSFI) depending on the number of years included in the baseline calculation. For instance, the choice of different pre-fire baselines altered the assessment of spectral recovery two years post-fire by an average of 22% across all severity classes.

The rate of change in spectral values from year to year throughout the post-fire recovery trajectory proved highly variable (Fig. 14); we found that, two years after the fire, recovery and regeneration of forest cover were very limited, whereas six years post-fire, vegetation recovery gained significant momentum.

6 Conclusions

Forest fires represent a natural disturbance and are among the primary drivers of landscape alteration and potential desertification in the semi-arid regions of the Mediterranean Basin. The severity of their impacts is particularly pronounced in dry and semi-arid areas, where climatic conditions and the presence of highly combustible fuels facilitate rapid fire propagation. Effective mitigation and restoration of fire-affected landscapes thus require the implementation of long-term strategies, including robust monitoring systems and predictive models capable of anticipating the evolution of burned areas.

This study demonstrates the utility of combining remote sensing data with the post-fire stability index to monitor and quantify post-fire forest regeneration. Unlike traditional approaches that rely heavily on pre-fire reference conditions, the post-fire stability index decouples the assessment of regeneration from pre-fire spectral variability, providing a more consistent and reliable metric for evaluating vegetation recovery over large spatial and temporal scales. Application of this index in northeastern Algeria revealed patterns of regeneration influenced by inter-annual climatic variability, as reflected in fluctuations of NBR2 values between 2016 and 2020, prior to the 2014 fire.

Field observations corroborated remote sensing analyses, emphasizing that post-fire regeneration is spatially heterogeneous across the Sidi Bel Abbès region. Variation in regeneration is likely driven by topographic factors, including altitude, slope, and terrain aspect, which modulate microclimatic and soil moisture conditions.

Despite these advances, it is important to acknowledge certain limitations. Remote sensing indices, including the post-fire stability index, provide indirect measures of vegetation recovery and may not fully capture species-specific regrowth dynamics or fine-scale ecological processes. Additionally, factors such as understory recovery, soil properties, and post-fire management interventions were not directly assessed in this study.

Future research should integrate high-resolution remote sensing, LiDAR-derived structural information, and comprehensive field surveys to refine post-fire recovery assessments. Further studies should also explore the influence of topography, species composition, and fuel characteristics on regeneration rates, thereby improving predictive modeling and informing targeted restoration strategies in fire-prone Mediterranean ecosystems. Additionally, AI-based analyses, integrating machine learning (Random Forest, XGBoost) and deep learning (Deep Neural Networks, Kolmogorov–Arnold Networks) with geospatial and remote sensing data, can enhance wildfire susceptibility mapping and post-fire impact assessments, as demonstrated by (Durlević et al 2026).

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