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Case Study

# Intensity evaluation of fire and restoration process of the forest using remote sensing techniques (Case Study: North Ukraine)

**Moslem Dehnavi Eelagh[a,*], Ali Taheri[b]**

[a]*Ph.D. student of Geospatial Information Systems, School of Surveying Engineering and Geospatial Information, College of Engineering, University of Tehran, Tehran, Iran*

[b]*Master's student of Geospatial Information Systems, School of Surveying Engineering and Geospatial Information, College of Engineering, University of Tehran, Tehran, Iran*

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ABSTRACT

**Background and objective:** In recent years, we have witnessed the growth of forest fires due to severe climate changes and increased human activities. These fires impose many destructive effects on the environment and human health. Therefore, it is necessary to identify and measure the intensity of forest fires and plan for the revitalization of vegetation.
**Materials and methods:** This study aims to investigate the intensity of the fire in the forest areas of northern Ukraine using Sentinel-2 satellite images and using the indicators of different normalized burn ratios (dNBR), relatively different normalized burn ratios (RdNBR), and relativized burn ratio ( RBR) in the Google Earth Engine (GEE) cloud platform and comparing the results of the extent of the fire area extracted from the indicators with the data available by the European Forest Fire Information System (EFFIS). Also, the Normalized Difference Vegetation Index (NDVI) was used to investigate the process of forest cover restoration.
**Results and conclusion:** The results showed that the RBR and RdNBR indices in study areas A and B have been able to estimate the fire extent with 1.43% and 5.96% differences compared to EFFIS data. Also, the results of the NDVI index showed that after two years of the fire, in study areas A and B, 76.06% and 58.86% of the damaged forest cover improved, respectively.

## 1. Introduction

Forests are essential for human life and play an important role in climate regulation, soil protection, and economic issues. Forests influence regional and global climate by using biological, chemical, and physical processes that affect the atmospheric composition, hydrological cycle, and planetary energy (Abdikan et al., 2022). In addition to the positive effects that forests have on the planet's climate, they help all living beings, especially humans, by preventing soil erosion, increasing water quality, and purifying the air (Teodoro Carlón Allende et al., 2021; Li, 2018). In addition, forests are the habitat of many plants and animals and provide essential natural resources, from wood and food to medicinal

* *Corresponding author.* Tel.: +98-933-858-3145
E-mail address: moslem.dehnavi@ut.ac.ir , ORCID: 0000-0002-3180-9537

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plants.

For this reason, innovative knowledge and technology should be used to achieve sustainable management of forest resources and the best use of economic, social, and environmental aspects for the present and future generations (Gülci et al., 2021). In recent years, due to climate warming and frequent human activities, forest fires have caused severe short-term and long-term environmental damage and affected people's lives worldwide. The leading causes of forest fires can be divided into two categories: environmental factors and intentional and unintentional human activities (Bar et al., 2020; Cai & Wang, 2022).

Environmental factors affecting fire include the following:

1. Vegetation type: Vegetation in forest areas is one of the influencing factors in fire intensity. For example, in forests with broad-leaved trees, due to the kind of wood, the power of ignition is higher than in forests with coniferous trees (Alkhatib, 2014). Also, dried branches on trees and mosses attached to tree trunks influence the fire's severity. Also, the company of trees in the forest that have dried up due to pests and diseases can be an influential factor in the severity of the fire.

2. Weather conditions: Weather conditions are also one of the influencing factors in fire and increasing fire intensity. Lack of precipitation, increase in temperature followed by drought in forest areas, and solid lightning striking the forest are some of the influencing factors in forest fires. Also, moderate to strong winds during a forest fire cause the fire to spread (Abdikan et al., 2022; Stankova, 2023; Widodo et al., 2019).

3. Topography of the land: The height of the fireplace from the sea level, the slope, the slope's direction, and the land's surface condition are very influential in the intensity and spread of the fire (Ghermandi et al., 2019; Ghorbanzadeh et al., 2019). Fire spreads more orderly and uniformly than in flat lands. For example, rock is a factor in forest fire prevention in forests located in a landslide. Another reason for the fire caused by the slope in coniferous forests is the presence of fruit cones, which gather at the bottom of the forest due to the slope, and in case of fire, it causes a more intense fire at the bottom of the forest.

Another factor in forest fires is intentional and unintentional human activities, which can be called changing the land use cover (LULC) for industrial and agricultural purposes. The lack of agricultural land in forest areas has reduced farmers' income, and the lack of pastures for cattle grazing has forced the forest-dwelling villagers to burn their farming lands and fields yearly. Also, the development and growth of industry have caused humans to destroy forests every year with different methods, one of which is forest fires (Guk et al., 2023; Wu et al., 2021).

According to the official report of the United Nations, from 1998 to 2017, severe forest fires accounted for 3.5% of natural disasters, during which 6.2 million people were injured and 2398 people lost their lives, and damage the cost of these fires amounted to 68 billion dollars. Forest fire causes soil erosion, destruction of habitats of rare species, and change in water flow. On the other hand, the fire of vegetation in the forest is known as a source of release of suspended particles and carbon dioxide ($CO_2$), and rare gases in the atmosphere and causes atmospheric pollution and climate changes at the global level (Zarei et al., 2021; Delcourt et al., 2021).

However, fire has many benefits, such as regulation of fuel accumulation, revitalization of vegetation by removing fungi and microorganisms, control of diseases and insects, obtaining more energy through exposure to sunlight, exposure to minerals soil, and release of nutrients. Still, generally, forest fires are recognized as threats (Chowdhury & Hassan, 2015). After the fire, determining the total damaged area, the degree of damage, and appropriate methods to restore vegetation are the primary goals of forest management.

Forest fire damage assessment generally includes field surveys effectively conducted for small areas (Xulu et al., 2021). However, assessing forest damage in larger areas is difficult and expensive. Due to the increase in wildfires globally, innovative computational approaches using remote sensing are needed to provide faster and more cost-effective assessments of larger affected areas and have been successfully used to assess burn severity worldwide. Even with its help, the causes of fire can be identified, and its recurrence can be prevented (Näsi et al., 2015). Since the late 1970s, the availability of remote sensing products with their multi-scale and multi-temporal capabilities has been a valuable and cost-effective tool for spatial monitoring of land cover change, especially in detecting forest fires, obtaining fire intensity, determining the amount of potentially combustible materials and the monitoring of the forest regeneration process before and after the fire has created (Boucher et al., 2016; Gülci et al., 2021).

Nowadays, satellites such as MODIS and VIIRS can be used for daily monitoring and determining the intensity of large-scale forest fires, but due to their low spatial resolution (250 to 375 meters), they are not suitable for detecting small-scale fires. Therefore, Landsat satellite images with a high spatial resolution (30 meters) can be used (Williamson et al., 2022), but due to the low temporal resolution (every 15 days), they can be used more to determine the intensity of the fire (Goodwin & Collett, 2014). Several times (after the fire) and two-time (before and after the fire), spectral indices have been used to map the severity of the fire and burn through remote sensing images.

One of the indicators used to determine the severity of the fire is the normalized burn ratio (NBR), Different relative (RdNBR) and relative burn ratios (RBR) are obtained (Mallinis et al., 2018). Amroussia et al. (2023) conducted a study in Tunisia and investigated the dNBR, RdNBR, and RBR indices extracted using Sentinel-2 satellite images, and the results show the adequacy of the RBR index followed by the RdNBR derived from Sentinel-2 for Assessing and mapping the severity of forest fires. In order to determine the accuracy of fire intensity in northeastern Siberian forests using the dNBR index obtained from Sentinel-2 satellite images, after calculating the fire intensity using this index by Delcourt et al., field observations of the burned area were carried out and the results it showed that the dNBR index has a good correlation with the field data of fire intensity above the ground surface (Delcourt et al., 2021).

Cai and Wang (2022) also compared dNBR and RdNBR indexes in research, and the results showed better performance of the dNBR index than the RdNBR index. They also concluded that the RdNBR index should be used cautiously to estimate burn severity in a specific location. Dindaroglu et al. (2021) in research to determine the intensity of the fire in Andırın, Kahramanmaras, and Cinarpınar forests, from the Normalized Difference Vegetation Index (NDVI), Difference Normalized Difference Vegetation Index (dNDVI), Normalized Difference Water Index (NDWI), NBR, dNBR, RBR, Soil Bare Index (SBI) and Stream Power Index (SPI) were used. The results showed that dNDVI, dNBR, RBR, and SBI indices have provided better results regarding fire severity. Also, according to the dNBR index, 75% of the studied area has been affected by fire.

In many studies, NBR, dNBR, RdNBR and RBR indices have been used to determine the intensity of fire in forest areas (Fassnacht et al., 2021; Pacheco et al., 2023; Santos et al., 2020; Ye et al., 2023). One of the most common indices for evaluating green plant biomass is the NDVI. One of the applications of this index is the remote evaluation of vegetation recovery processes after the fire (Stankova, 2023).

A study by Maillard was conducted to investigate the improvement process of forest fires in Bolivia from 2001 to 2021 using the NDVI index. The results showed that 53.6 areas affected by forest fires are recovering, which can be concluded that there is a continuous process of reconstruction throughout the country in areas affected by forest fires (Maillard, 2023). Based on the studies that were reviewed, a study that uses and compares all NBR, dNBR, RdNBR, and RBR indicators to detect the intensity of forest fire was not observed. Also, considering the importance of geographical location in the results of the indicators, a study that It was not found that there has been a study on the area.

As mentioned, there are several indicators for identifying burned forest areas using satellite images, each of which shows different results depending on the geographical conditions and the intensity of the fire. One of the goals of this study is to compare the dNBR, RdNBR, and RBR indices to determine the severity of fire in northern Ukraine, which was calculated using Sentinel-2 satellite images and in the cloud space of the Google Earth Engine (GEE). Its results were compared with the data available in the

European Forest Fire Information System (EFFIS). Also, to evaluate the improvement process of forest cover after the fire, the NDVI index was used in the intervals before, after, and one and two years after the fire.

## 2. Material and Methods

### 2.1. Study area

Kyiv and Zhitomir are two critical provinces in the north of Ukraine. Kyiv province is bounded on the east by Chernigov province, on the west by Vinnytsia, and south by Cherkasy province, and Zhitomir province is bounded on the east by Kyiv province, on the south by Vinnytsia province and on the west with Khmelnytskyi and Rovno province. The two sections also have a common border with the southern part of Belarus. The two regions, with 28131 square kilometers and 29832 square kilometers, respectively, have essential tourist attractions and industrial and commercial centers in Ukraine.

The climate of Kyiv province is very variable and varies from cold and snowy winter to warm and humid summer. The average annual temperature in the area is about 2 degrees Celsius. The summers are hot and humid, and in the winters, the temperature is significantly reduced, and snow and cold.

Zhitomir province also has hot and dry climates. The average temperature in summer is about 2-5 ° C and is about -5 ° C in winter. The province experiences more rainfall in spring and summer while less rain in the fall and winter. The two provinces are very diverse in terms of vegetation and forest. The southern parts of the two provinces usually have agricultural use, but the northern parts of the two provinces have high and high forests that include trees such as pine, oak, and almonds. Our study area, northwestern and northeast parts of Kyiv and Zhitomir provinces, are between $51^{\circ}08'49''$ to $51^{\circ}34'19''$ north latitude and longitude $28^{\circ}55'27''$ to $29^{\circ}55'28''$ east, shown in Figure 1.

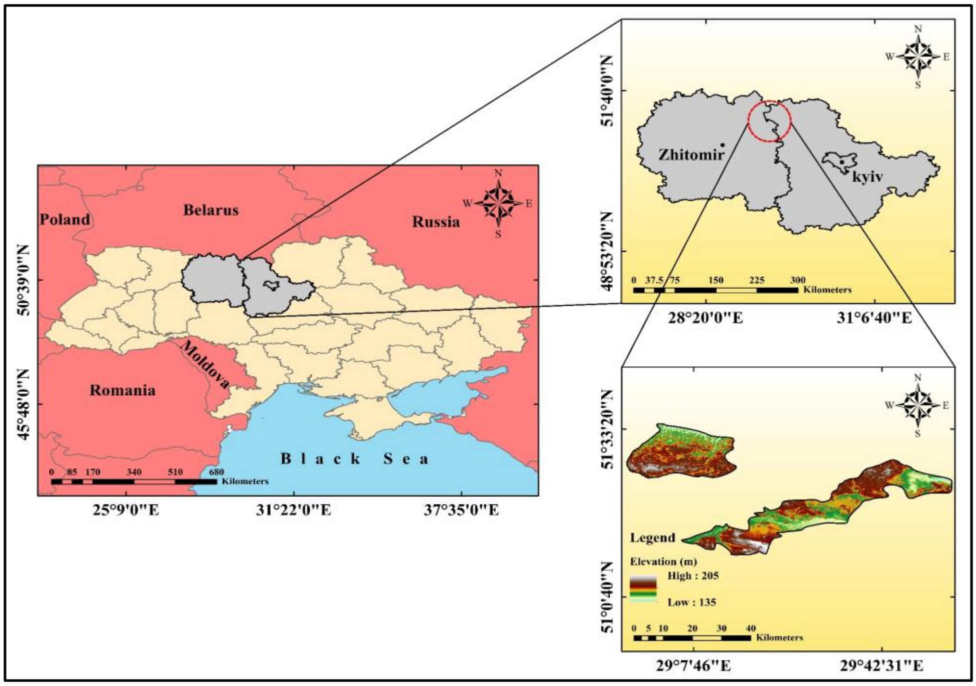


**Figure 1 - Location map of the study area**

## *2.2. Data collection*

The images used in this research were Sentinel-2 satellite images in the Google Earth Engine system. This satellite has provided multispectral images with different temporal and spatial resolutions and helps investigate the severity of burns and how vegetation changes. Sentinel-2 consists of two satellites named S2A and S2B. S2A was launched in 2015, and S2B in 2017. These satellites are placed at an altitude of 786 km above the earth and in a simultaneous solar orbit, and they rotate at an angle of 180 degrees to each other, and their rotation is inclined at 98.5 degrees. Sentinel-2 satellite is used for various applications such as geology, geotechnical engineering, agriculture, water resources management, forest management, and environmental monitoring.

This satellite is equipped with 13 multispectral bands with a resolution of 10 meters, 20 meters, and 06 meters. After selecting the study area and automatically removing the images with cloud cover above 5% in the GEE system, we reached the images with minimal cloud cover and they were used in the required processing. The specifications of the remote sensing satellite bands used in this research and the data collection date are according to Tables 1 and 2.

**Table 1 - Characteristics of Sentinel-2 remote sensing satellite**

| Satellite Mission | Bands | Spatial Resolution (m) | Spectral Resolution (nm) | Description |
|---|---|---|---|---|
| Sentinel-2 | B2 | 10 | 490 | Blue |
| | B3 | 10 | 560 | Green |
| | B4 | 10 | 665 | Red |
| | B8 | 10 | 842 | NIR |
| | B11 | 20 | 1610 | SWIR1 |
| | B12 | 20 | 2190 | SWIR 2 |

**Table 2 - Date of acquisition of remote sensing images**

| Data Type | Satellite Mission | Acquisition Data |
|---|---|---|
| Thermal | Sentinel-2 | 26 April 2019 |
| | | 02 May 2020 |
| | | 10 April 2021 |
| | | 12 May 2022 |

## 2.3. Research methods

In this research, different indicators are used in remote sensing to determine the intensity of fire in the forest, and then these results are compared. Also, the change process in forest vegetation before and after the fire is calculated and the amount of vegetation improvement is also calculated.

The following indicators have been used to determine the intensity of forest fires:

A different normalized burn ratio (dNBR) technique creates burn severity maps. dNBR is a quantitative measure of environmental changes caused by fire. Burn severity is assessed by the difference between the normalized burn ratio (NBR) for pre-fire and post-fire (Veraverbeke et al., 2010). NBR and dNBR were calculated using Sentinel-2 data before and after the fire to calculate the burn severity of the selected area. Bands 8 (NIR) and 12 bands (SWIR) were used for fire maps based on Sentinel-2 (Table 3) (Chambel et al., 2013).

**Table 3 - Burn spectral severity indices**

| Spectral Index | Sentinel-2 MSI Equation |
|---|---|
| NBR | $(B8A - B12) / (B8A + B12)$ |
| dNBR | $(NBR_{pre-fire} - NBR_{post-fire})$ |

Relative Different Normalized Burn Ratio (RdNBR) is another commonly used remote sensing index to assess burn severity in vegetation, which is relative to dNBR. Like dNBR, RdNBR relies on the normalized burn ratio (NBR) (Miller et al., 2009). RdNBR is a continuous index ranging from negative to positive, with higher positive values indicating more severe burn severity.

The RdNBR value using dNBR and NBR pre-fire values is according to Table 4 (Soverel et al., 2010):

**Table 4 - Burn severity spectral indices**

| Spectral Index | Sentinel-2 MSI Equation |
|---|---|
| Relative Differenced Normalized Burn Ratio (RdNBR) | $dNBR/sqrt(abs(NBR_{pre-fire}))$ |

The index used is the relativized burn ratio (RBR), which is conceptually very similar to the RdNBR and relative dNBR index and is used to assess the severity of forest fires. The resulting RBR values range from 0 to 1, with higher values indicating more severe burns. RBR value is obtained using dNBR and NBR pre-fire values according to Table 5 (Soverel et al., 2010):

**Table 5 - Burn severity spectral indices**

| Spectral Index | Sentinel-2 MSI Equation |
|---|---|
| Relativized Burn Ratio (RBR) | $dNBR/(NBR_{pre-fire} + 1.001)$ |

Based on the classification proposed by the European Forest Fire Information System (EFFIS), the unitless numbers obtained from the said indicators are divided into 4 categories according to Table 6 (Key & Benson, 1999).

**Table 6- Fire severity levels**

| Severity Level | dNBR | RdNBR | RBR |
|---|---|---|---|
| Unburned | < 0.100 | < -0.10 | < 0 |
| Low Severity | 0.100 – 0.255 | -0.10 – 0.10 | 0 – 0.2 |
| Moderate-low Severity | 0.256 – 0.660 | 0.10 – 0.27 | 0.2 – 0.4 |
| High Severity | > 0.660 | > 0.27 | > 0.4 |

Also, the Normalized Difference Vegetation Index (NDVI) has been used to check vegetation changes. It is a widely used vegetation index in remote sensing applications that measures the difference between near-infrared (NIR) reflectance and red visible light wavelengths. NDVI values range from -1 to 1, with negative values indicating areas without vegetation or dead vegetation and positive values indicating areas with greenery (Huete & Jackson, 1987). NDVI is commonly used for vegetation monitoring, land use/cover classification, and drought assessment. It is also used to study the effects of climate change, ecosystem function, and biodiversity protection. Table 7 shows bands 8 (NIR) and 4 (RED) prepare vegetation maps based on Sentinel-2. Vegetation classification is done based on the NDVI index, according to Table 8 (Jiang et al., 2008).

**Table 7 - Burn severity spectral indices**

| Spectral Index | Sentinel-2 MSI Equation |
|---|---|
| Normalized Difference Vegetation Index (NDVI) | $(NIR - RED)/(NIR + RED)$ |

**Table 8 - NDVI levels**

| NDVI Level | Range |
|---|---|
| Dead Plant | < 0.1 |
| Unhealthy Plant | 0.1 – 0.3 |
| Moderately Healthy Plant | 0.3 – 0.6 |
| Very Healthy Plant | > 0.6 |

The method followed in this study is shown in the flowchart presented in Figure 2.

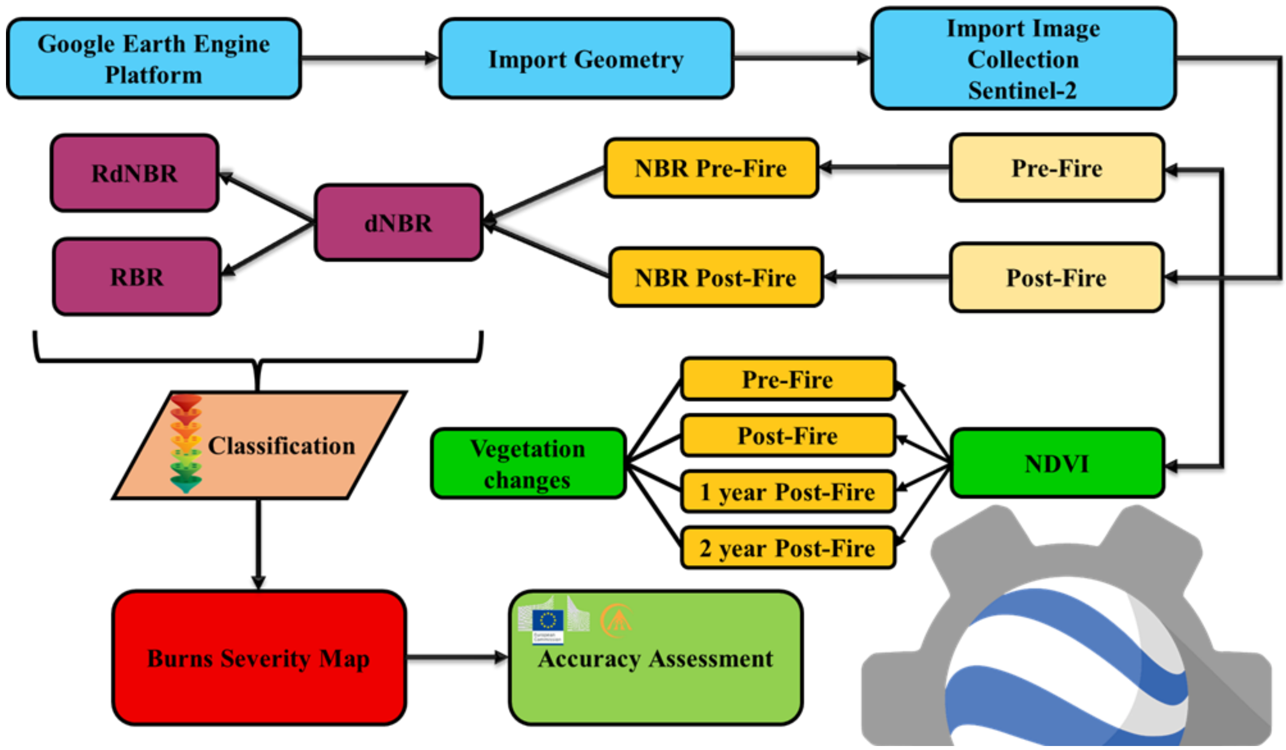


**Figure 2 - Flowchart of the method presented in this research**

## 3. Result and Discussion

### *3.1 Burned Areas Mapping*

Fire intensity maps using GEE were produced within seconds, showing that GEE has a very high advantage compared to other non-cloud computing options regarding data processing and storage cost.

Then, the fire maps without units were divided into 4 categories based on the classification proposed by the European Forest Fire Information System (EFFIS). results obtained from the classification of dNBR maps show that in study area A, 22356.81 hectares, equivalent to 70.25% of the area, have been affected by the fire. The highest fire intensity was medium intensity. In study area B, out of the total area of the site, 22,757.97 hectares, equivalent to 42.66% of the site, have been affected by fire, and the highest intensity of the fire was medium intensity. dNBR classified maps are according to Figure 3.

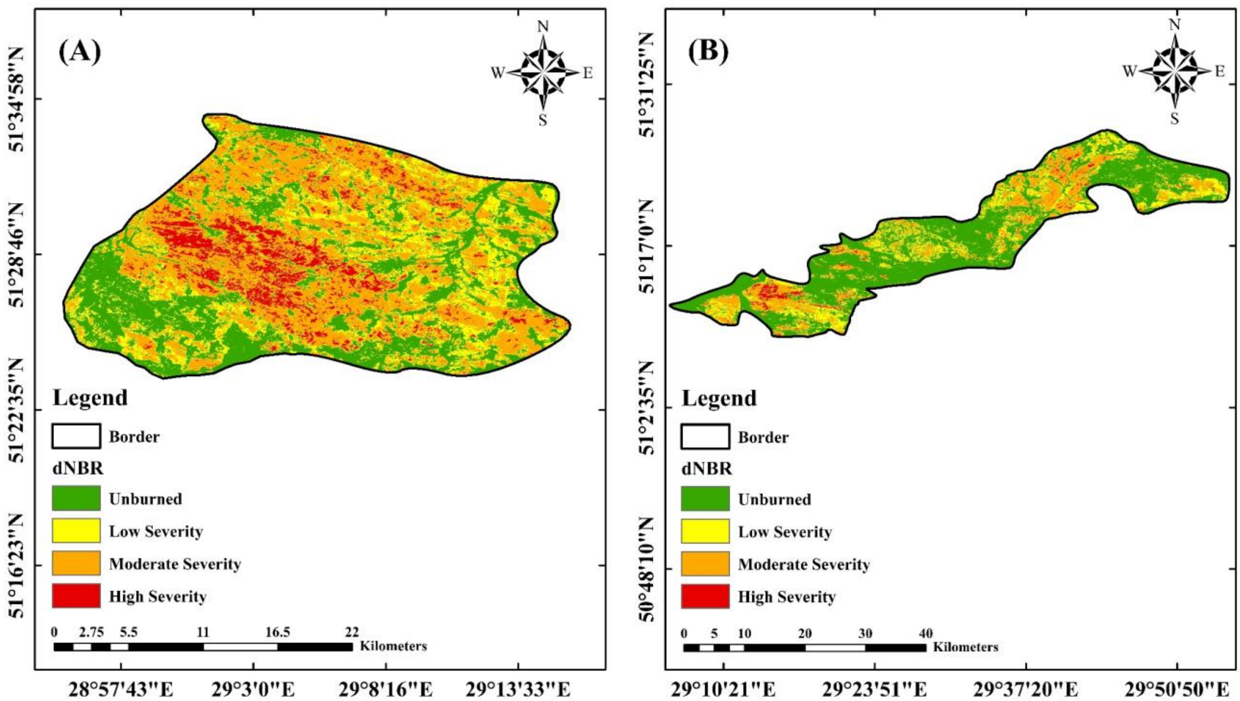


**Figure 3 - Burn severity maps based on the dNBR index**

Tables 9 and 10 also show the statistical analysis of dNBR for the entire region.

**Table 9 - Statistical analysis of dNBR for the studied areas**

| dNBR | Study area (A) | Study area (B) |
|---|---|---|
| Maximum | 1.27 | 1.22 |
| Minimum | -0.64 | -0.71 |
| Mean | 0.27 | 0.06 |

**Table 10 - Classification of burned areas based on the dNBR index**

| Burn severity classification | Area of burned areas (hectares) | |
|---|---|---|
| | Area (A) | Area (B) |
| Unburned | 9467.78 | 30587.72 |
| Low Severity | 6816.66 | 10724.82 |
| Moderate Severity | 12899.38 | 10943.08 |
| High Severity | 2640.77 | 1090.07 |

Regarding the RdNBR index, the results obtained from the map classification show that in study area A, 29,079.12 hectares, equivalent to 91.37% of the area, were affected by fire and the most intense fire was of severe type. Study area B of the total area of 35,596.17 hectares, equivalent to 66.73% of the area, has been affected by fire, and the highest intensity of the fire was severe. The RdNBR classification maps are shown in Figure 4.

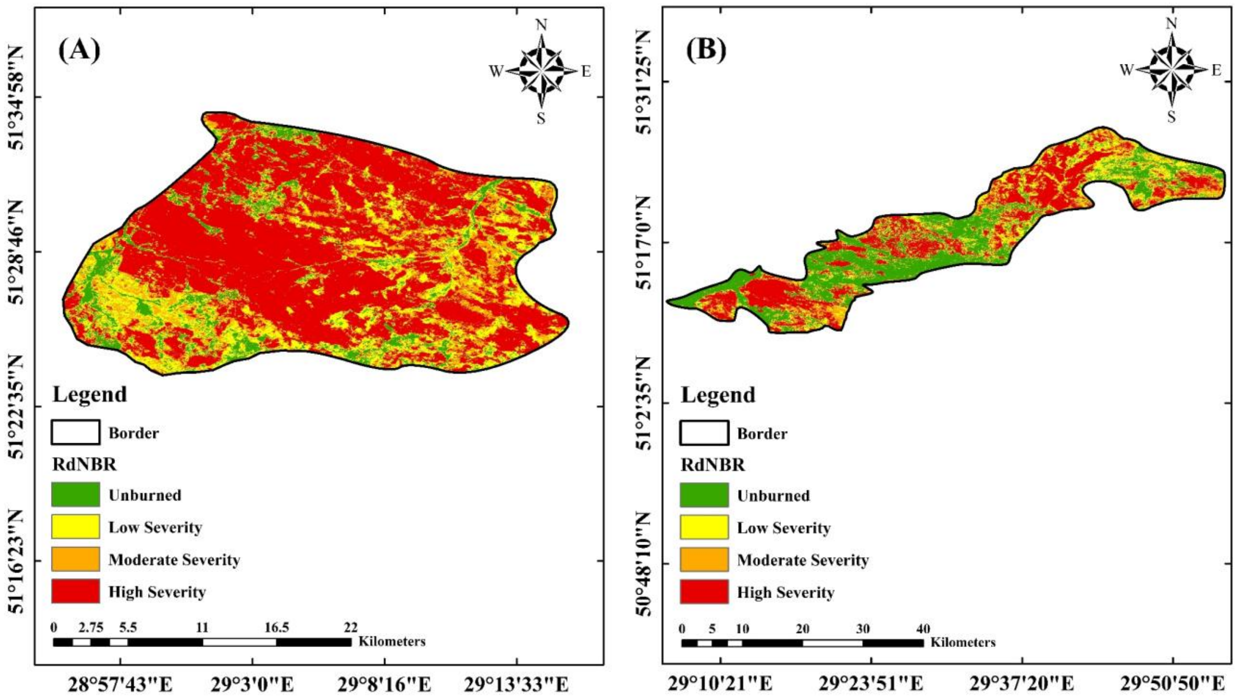


**Figure 4 - Burn severity maps based on the RdNBR index**

Tables 11 and 12 also show the statistical analysis of RdNBR for the entire region.

**Table 11 - Statistical analysis of RdNBR for the studied areas**

| dNBR | Study area (A) | Study area (B) |
|---|---|---|
| Maximum | 1.27 | 1.15 |
| Minimum | -0.86 | -0.91 |
| Mean | 0.23 | 0.08 |

**Table 12 - Classification of burned areas based on the RdNBR index**

| Burn severity classification | Area of burned areas (hectares) | |
|---|---|---|
| | Area (A) | Area (B) |
| Unburned | 2745.56 | 17749.51 |
| Low Severity | 5386.49 | 10438.59 |
| Moderate Severity | 5181.85 | 8099.98 |
| High Severity | 18510.78 | 17057.6 |

Regarding the RBR index, the results obtained from the classification of the maps show in the study area A, 26586.46 hectares, equivalent to 91.37% of the area, were affected by fire, and the most intense fire was of low intensity. In study area B, out of the total area of 29873.36 hectares, equivalent to 56% of the region, has caught fire and the most intense fire was of low intensity. The RdNBR classification maps are shown in Figure 5.

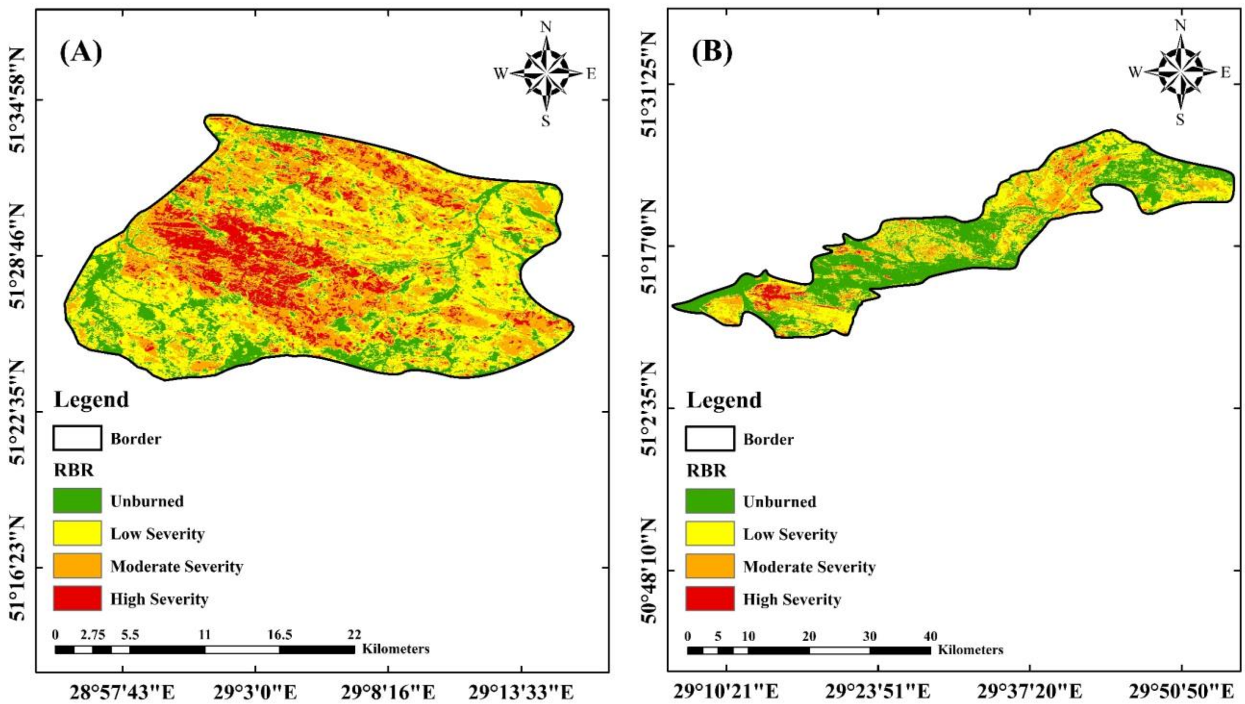


**Figure 5 - Burn severity maps based on the RBR index**

Tables 13 and 14 also show the statistical analysis of RdNBR for the entire region.

**Table 13 - Statistical analysis of RBR for the studied areas**

| dNBR | Study area (A) | Study area (B) |
|---|---|---|
| Maximum | 0.75 | 0.73 |
| Minimum | -0.59 | -0.81 |
| Mean | 0.18 | 0.04 |

**Table 14 - Classification of burned areas based on the RBR index**

| Burn severity classification | Area of burned areas (hectares) | |
|---|---|---|
| | Area (A) | Area (B) |
| Unburned | 5238.14 | 23472.33 |
| Low Severity | 12553.52 | 18930.88 |
| Moderate Severity | 10097.38 | 9382.69 |
| High Severity | 3935.56 | 1559.79 |

## *3.2. Accuracy assessment*

To evaluate the accuracy of the burned area estimation by sentinel-2 satellite data, the data recorded by the European Forest Fire Information System (EFFIS) was used. In study areas A and B, the European Forest Fire Information System registered fires with 26,210 and 33,595 hectares, respectively, on April 16, 2020, and April 3, 2020. By comparing the EFFIS statistics with the results mentioned in the previous section, we conclude that in study area A, the RBR index is 1.43%. In study area B, the RdNBR index is 5.96% different from the EFFIS statistics identify the fire. Also, according to EFFIS statistics, out of the total fire area in study area A, the most damage, with 61.9%, is related to coniferous trees, followed by mixed trees at 29.5%, scrubland at 4.3%, and agricultural areas with 3.2% and broadleaf trees have suffered the most damage, with 1.2%. In study area B, the most damage, with 35%, is related to agricultural regions, followed by conifers at 25.5%, mixed trees at 17.2%, bushes at 11.9%, and broad-leaved trees at 10.4% have seen.

## *3.3. Reforestation after fire*

We need vegetation maps of the study areas before and after the fire to investigate the forest vegetation restoration process after the fire. For this, using the NDVI index, vegetation maps for 2019 (the year before the fire), 2020 (after the fire), 2021, and 2022 (one and two years after the fire), according to Figures 6 Up to 9, are obtained.

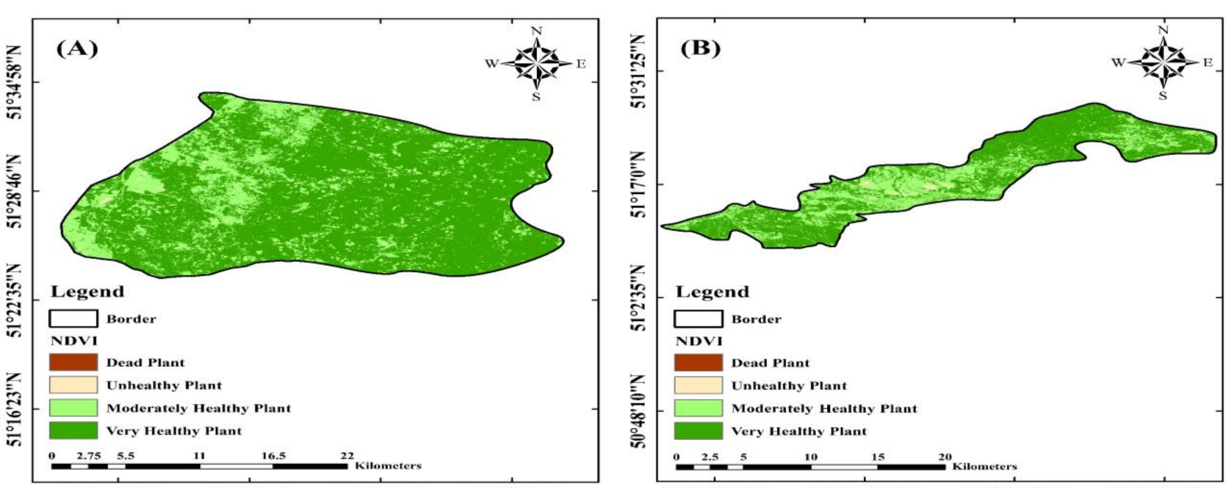


**Figure 6 - Vegetation maps based on the NDVI index for 2019**

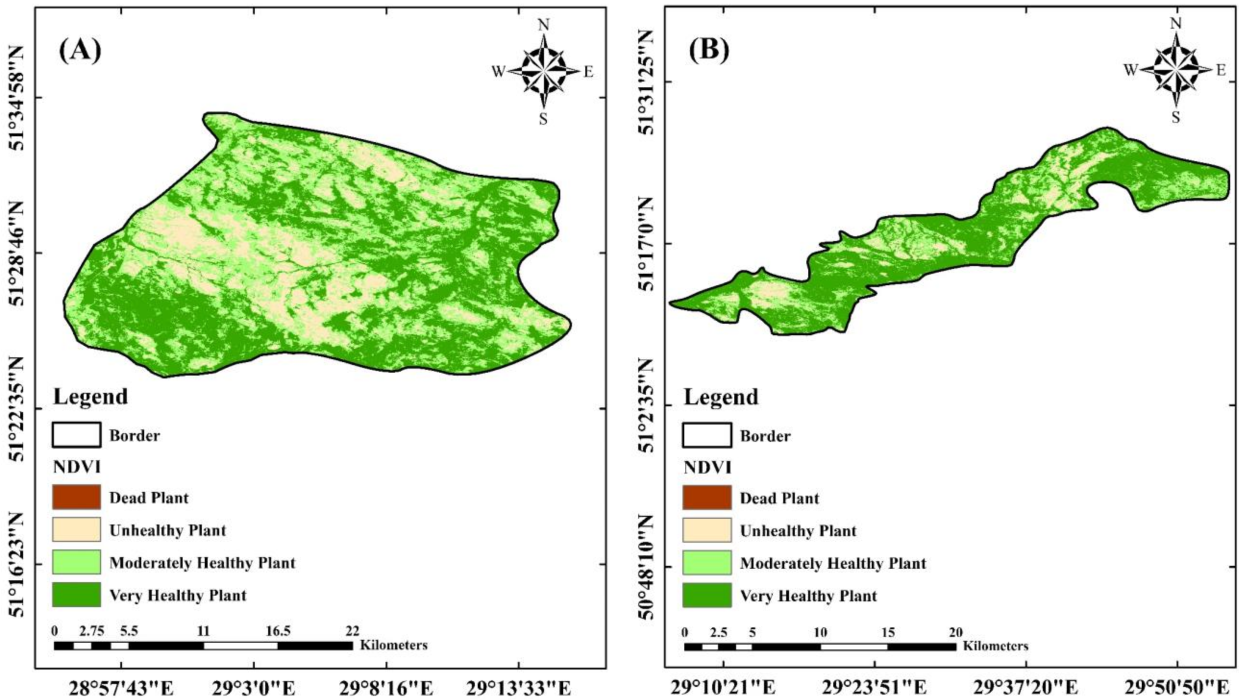


**Figure 7 - Vegetation maps based on the NDVI index for 2020**

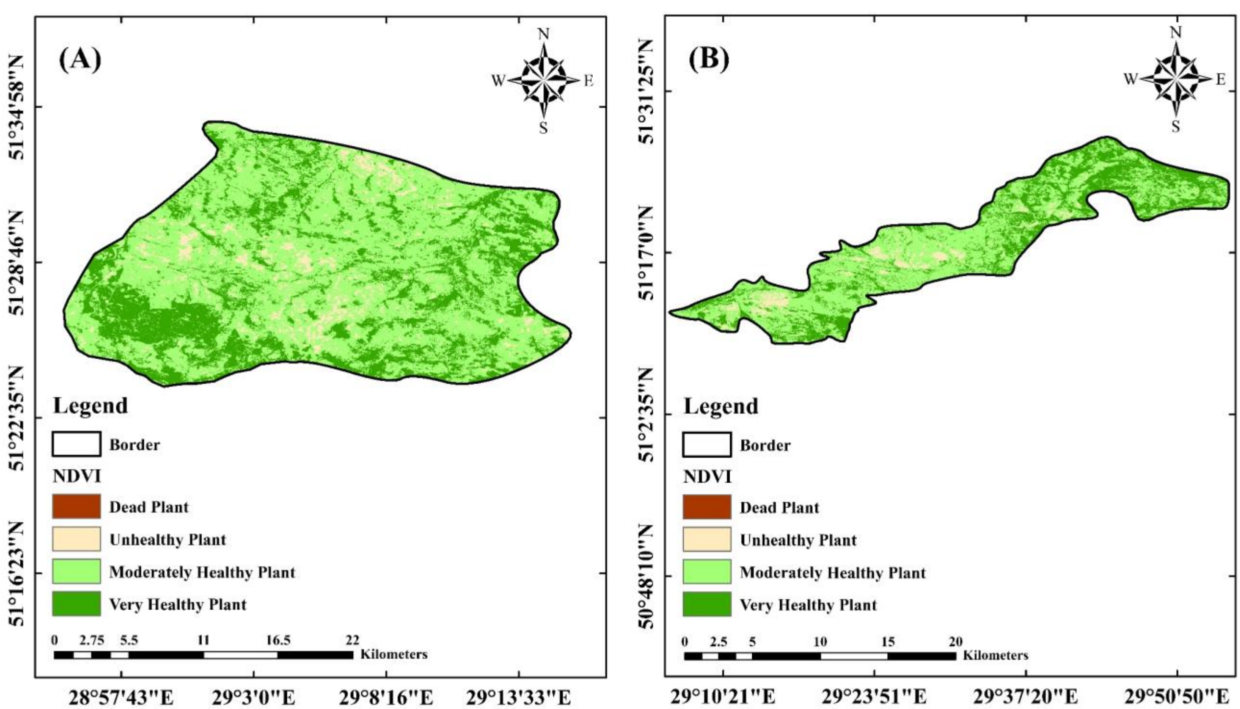


**Figure 8 - Vegetation maps based on the NDVI index for 2021**

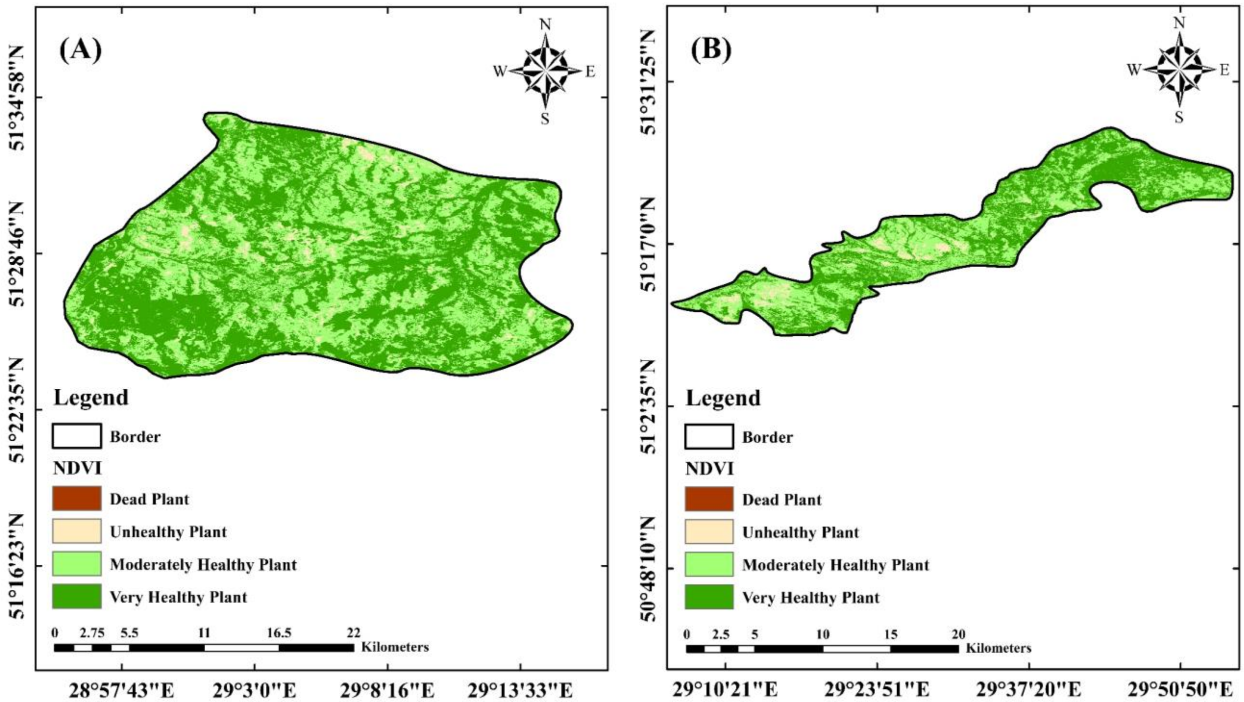


**Figure 9 - Vegetation maps based on the NDVI index for 2022**

Tables 15 and 16 also show the statistical analysis of NDVI for the entire region.

**Table 15 - Statistical analysis of NDVI for the study areas**

| NDVI | Study area (A) | | | | Study area (B) | | | |
|---|---|---|---|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 | 2019 | 2020 | 2021 | 2022 |
| Maximum | 0.90 | 0.94 | 0.92 | 0.94 | 0.89 | 0.95 | 0.92 | 0.94 |
| Minimum | 0.03 | -0.24 | -0.18 | -0.17 | 0.17 | -0.23 | -0.10 | -0.01 |
| Mean | 0.71 | 0.57 | 0.61 | 0.66 | 0.67 | 0.67 | 0.67 | 0.69 |

**Table 16 - Statistical analysis of NDVI for the study areas**

| NDVI | Study area (A) | | | | Study area (B) | | | |
|---|---|---|---|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 | 2019 | 2020 | 2021 | 2022 |
| Dead Plant | 0.02 | 0.14 | 0.45 | 0.1 | 0.13 | 1.14 | 0.59 | 0 |
| Unhealthy Plant | 306.43 | 6065.97 | 2327.12 | 1452.56 | 287.9 | 5591.85 | 2527.08 | 2300.15 |
| Moderately Healthy Plant | 4019.63 | 11663.95 | 14505.02 | 12826.87 | 8736.1 | 13769.65 | 17092.85 | 16730.55 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Very Healthy Plant | 27498.55 | 14094.59 | 14992.11 | 17545.11 | 44321.5 | 33983.05 | 33725.16 | 34314.99 |

According to Table 15, it can be seen that the minimum NDVI value in 2020 in both study areas has become negative, which indicates that the vegetation has been damaged. It can also be seen that this amount has completely decreased in 2021 and 2022, which suggests the restoration of part of the damaged forest vegetation. Also, according to Table 16, it can be seen that after the fire of 2020, in area A, 13,403 hectares of very healthy vegetation in 2019 changed to relatively healthy, unhealthy, and dead vegetation .In study area B, 10,338 hectares of vegetation Very healthy vegetation in 2019 turned into relatively healthy, unhealthy, and dead vegetation in 2020.

One year after the fire and in 2021, about 3739.28 hectares of dead and unhealthy vegetation was covered with relatively healthy and very healthy vegetation in area A. In study area B, about 2065 hectares of dead and unhealthy vegetation cover has become relatively healthy and very healthy vegetation. One year after 2021 and in 2022, area A has about 874.68 hectares of dead and unhealthy vegetation to relatively healthy and very healthy vegetation; in study area B, about 227 hectares of dead and unhealthy vegetation has become relatively healthy and very healthy vegetation. The results show that the highest forest vegetation improvement occurred in the first year after the fire. Also, after two years in areas A and B, 76.06% and 58.86% of the damaged vegetation in the fire effect has been improved.

## 4. Conclusion

Today, identifying and evaluating the severity of forest fires and planning for forest restoration and prevention of new fires has become an important issue all over the world. Every year, thousands of hectares of forests around the world are caught on fire, which has devastating effects on the environment and human health. Therefore, by identifying and managing it, it is possible to prevent more damage to the environment and also avoid spending large budgets to deal with fire.

Nowadays, camera measurement has become a valuable and cost-effective tool to identify and evaluate the intensity of the fire, and it can be used for forest management. In this research, three indices of different normalized burn ratios (dNBR), relative different normalized burn ratios (RdNBR), and relativized burn ratios (RBR) were used in the forest area in northern Ukraine to evaluate the intensity and extent of the fire. Considering that in the previous studies on the identification of burned forest areas, in each area, a particular index has better estimated the extent and intensity of the fire. Therefore, it was concluded that the geographical conditions and the type of vegetation in the area have a significant effect on the results of the indicators.

Also, the Normalized Difference Vegetation Index (NDVI) was used to assess the damage to the forest cover and the recovery process of the forest cover two years after the fire. Sentinel-2 satellite images were used to calculate the indices in the GEE cloud platform. Before the creation of the gee system, we had limitations in the field of cloud cover, which caused errors in identifying forest-burned areas, but in this system, we automatically applied cloud cover below 5% to reduce the error as much as possible.

The results showed that in study areas A and B, the RBR and RdNBR indices have been able to estimate the extent of the fire. Also, the results of the NDVI index showed that in the said areas, we had witnessed 76.06% and 58.86% improvement in the burnt forest cover, respectively.

The results of this study can be used as a tool for better decision-making by organizations such as the environment and forestry for the efficient management of critical situations.

For future studies, it is suggested to use more diverse indicators to identify forest-burned areas. Also, artificial intelligence methods such as Random Forest, SVM, and Logistic Regression can be used to identify burned forest areas based on field data. Geospatial Information System (GIS) can produce risk zoning maps by combining different layers of information involved in forest fires, the outputs of which, along with remote sensing outputs, can reduce uncertainty in the results.

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