Assessments of forest fire locations in Tartous governorate using remote sensing techniques and Geographic Information Systems (GIS)

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Abstract

Forest fires, by their sudden and destructive nature, pose significant threats to natural ecosystems and human communities in a changing climate. In this regard, assessing and monitoring burned areas is a critical step in developing sustainable forest management measures. Since traditional forest fire monitoring is time-consuming and inaccurate, this problem must be addressed using remote sensing. This study aims to assess the dynamics of burned forest locations and the severity of fire disturbances during 2016–2020 in Tartous, using Landsat satellite image archives and spectral indices data. The study results indicate that during the period under study, approximately 3244.93 ha of forest area were burned in Tartous, including 2461.78 ha of forest cover in 2020 alone. The data were verified using modern standards to test the accuracy of the resulting maps. This study can be used to develop effective preventive measures by identifying the sites most vulnerable to forest fires.

Keywords: Forest fires, Sentinel, Tartous Governorate, NBR index, NDVI index.

Introduction:

Fires are periodic disturbances that strongly affect the structure and distribution of global forest ecosystems (Lan et al., 2022; Liu et al., 2024), causing loss of biodiversity, habitat, production and productivity, endangering people's lives (FAO, 2020). In recent decades, rapid climate change has increased the frequency and severity of wildfires (Stephens et al., 2013). The proximity of forests in some areas to agricultural lands increases the likelihood of their disturbance as a result of anthropogenic activities, including fires (Ali et al., 2020).

Systematic monitoring of burned areas has been strongly supported by the use of advanced geospatial technologies and remote sensing sensors during the past decades (Katagis and Gitas,2021). Remote sensing methods have become an unprecedented alternative to costly, labor-intensive field activities for monitoring forest ecosystems over large and remote geographical areas (Santana et al., 2018). Field observations are generally very complex in terms of spatial and temporal scales, especially when identifying categories of forest disturbance after fires (Filipponi, 2018). Multispectral satellite images with high spatial resolution have been widely used to measure forest areas before and after fires for mapping at regional and global scales (Gupta et al., 2016; Campagnolo et al., 2019), as well as to assess fire intensity (Kurbanov et al., 2017).

In this regard, rapidly evolving satellite technologies are significantly contributing to the automation of real-time fire detection processes, as well as mapping burnt areas at different spatial and temporal scales to assess the area of forest fires (Kurbanov et al., 2022; Pereira et al., 2018; Long et al., 2019).

Many global wildfire mapping techniques have been developed using satellite data, with Landsat 8 and Sentinel-2 imagery being used frequently in recent years (Kashnitsky, 2022; García-Llamas et al., 2019; Roy et al., 2019). Most of the remote sensing algorithms in use to assess burned areas are mainly based on the use of vegetation indices (VI) obtained from multi-temporal Landsat satellite images (Liu et al., 2020). such as the normalized difference vegetation index (NDVI) is frequently used in these assessments, using multi-temporal images (before and after the fire) (Vorobev et al., 2021; Odintsov et al., 2022). Important information about the interrelationship between vegetation cover and fires can be obtained using remote sensing data (Yankovich et al., 2019). Enhanced vegetation index (EVI), soil adjusted vegetation index (SAVI) (Quintero et al., 2019; Bright et al., 2019), (dNBR) the delta Normalized Burn Ratio NBR calculated by subtracting the post-fire NBR from the pre-fire NBR, has been shown to be related to the degree of vegetation disturbance caused by fire (Soverel et al., 2010), and its relative version index RdNBR (Cai and Wang, 2022). Satellite data are widely used to assess the degree of forest fire damage (Chu et al., 2013). Estimates of the degree of disturbance and post-fire mortality of forest stands can be considered as important factors needed to better understand the impact of forest fires on forest ecosystems (Shvetsov, 2022). One study suggested dividing remote sensing methods for assessing the degree of forest damage in burned areas into physical and experimental groups. Physical methods involve obtaining information about a burned object based on recording a signal reflected from a damaged surface by a detector (Chuvieco et al., 2019), while empirical methods rely on statistical regression or machine learning to estimate burned areas, they are relatively easy to implement and interpret (Gholamrezaie et al., 2022; Hu, Hu, 2019). In recent years, artificial intelligence has become a central tool in environmental disaster monitoring, particularly in analyzing and assessing wildfire severity. Machine learning algorithms, such as Random Forest and Support Vector Machines, have helped improve the accuracy of burning area classification when combined with spectral indices from satellite data such as dNBR. Recent studies show that using Sentinel-2 imagery with artificial intelligence techniques can produce accurate fire severity maps with an accuracy level exceeding 85%, making them effective tools for environmental impact assessment and post-fire restoration planning (Gholamrezaie et al., 2022). For example, combining Sentinel-2 data with classification algorithms resulted in highly reliable results in determining fire severity, with a significant improvement in statistical accuracy indices such as the kappa coefficient (Giglio et al., 2018). Recent innovations have greatly improved the precision and interpretability of burned area and severity mapping. Deep learning methods using convolutional neural networks (CNNs) and Vision Transformers (ViT) have been successfully applied to Sentinel-2 and Landsat data for accurate burned area classification (Wang et al., 2023). Furthermore, synthetic aperture radar (SAR) imagery from Sentinel-1 or RADARSAT, combined with U-Net or Transformer-based architectures, has enhanced fire mapping in cloud-covered or smoke-affected regions (Lan et al., 2023). Time-series analysis using platforms like Google Earth Engine (GEE) enables near real-time fire tracking and historical pattern analysis across multiple years (Zhang et al., 2024). For fire severity, hybrid indices such as combinations of dNBR and delta NDVI have shown improved sensitivity in detecting vegetation damage (Kinoshita et al., 2023). Additionally, integrating LiDAR-derived canopy height data provides 3D insights into the vertical structure loss, helping quantify severity beyond 2D imagery (Silva et al., 2023). The use of explainable machine learning models like XGBoost with SHAP interpretation techniques has also enabled better transparency and accuracy in burn severity classification (Gholamrezaie et al., 2023). Many countries around the world that suffer from forest fires lack sufficient data on the extent, impact, spread, and severity of these fires, which is particularly true of the forest cover in Syria (Ali et al., 2020). In these countries with complex and fragmented landscapes, forest fires typically occur over small areas (Veraverbeke et al., 2011). European Sentinel 2A satellite images were used to map the 2019 Farzala fire in Lattakia Governorate and determine the fire's intensity by calculating the Difference in Normalized Fire Ratio (dNBR) (Marhej et al., 2020). Landsat satellite archive was used to assess the dynamics of forest burnt areas and the degree of disturbance of ecosystems as a result of fires in (2007, 2013, 2015-2020) on the territory of the Lattakia of Syria (Ali and Zeina, 2023). Thus, assessing the extent of forest damage caused by fires and the associated tree loss remains a pressing issue (Frazier et al., 2018).

Importance and justifications of the research

Forest fires are a serious problem for ecosystems, destroying vast areas of forests around the world every year. Therefore, estimating the extent of burned areas using remote sensing and classifying fire severity levels are essential tasks for developing sustainable forest management solutions, and creating a reference database of fires occurring over different years .

Tartous Governorate is exposed to catastrophic fires every year, and there are expectations that the number and area of these fires will increase in the future. This increase is primarily linked to changes in climate and land use (Gonçalves, Sousa, 2017; FAO, 2018).

Research objectives

The aim of the work is to assess the area of burnt areas in the Tartous governorate of the Syrian Arab Republic, formed after largescale forest fires in 2016-2020, using the NBR, dNBR, NDVI coefficients.

Materials and methods:

- Study area

The study area includes Tartous Governorate as shown in Figure (1), which constitutes the southern part of the western seafront of Syria, with a beach length of 90 km. Between two lines of longitude 35°52`54" and 36°19`34" East Greenwich, and two lines of width 34°38`36" and 35°16`40" North of the Equator. Its area is 189621 ha. It is bordered to the north by Lattakia Governorate, to the east by Hama and Homs Governorates, to the south by Lebanon, and to the west by the Mediterranean Sea.

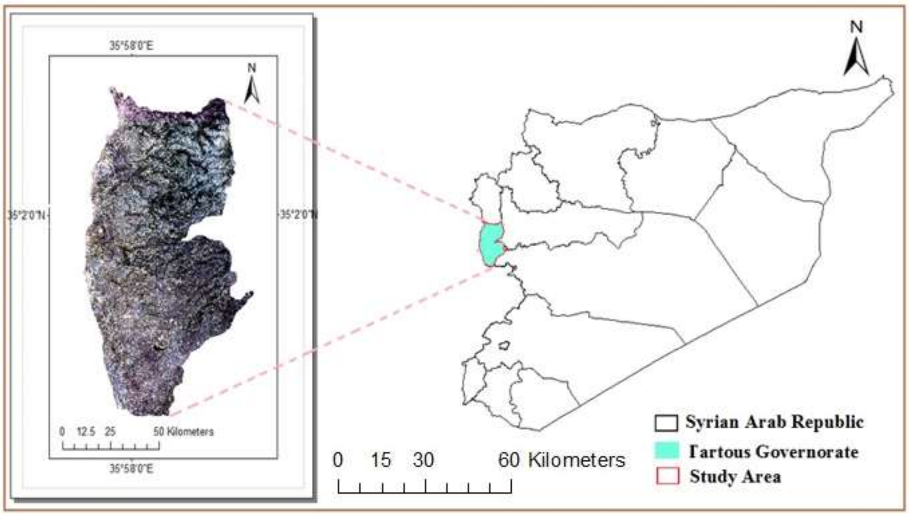

Figure (1): A map showing the administrative borders of the study area

Figure (2) present Topographic maps of Tartous Governorate derived from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (30 m resolution), showing elevation distribution (meters above sea level), slope gradients (degrees), and aspect directions. The inclusion of Slope and DEM layers improved the spatial accuracy of fire severity mapping, particularly in mountainous regions.

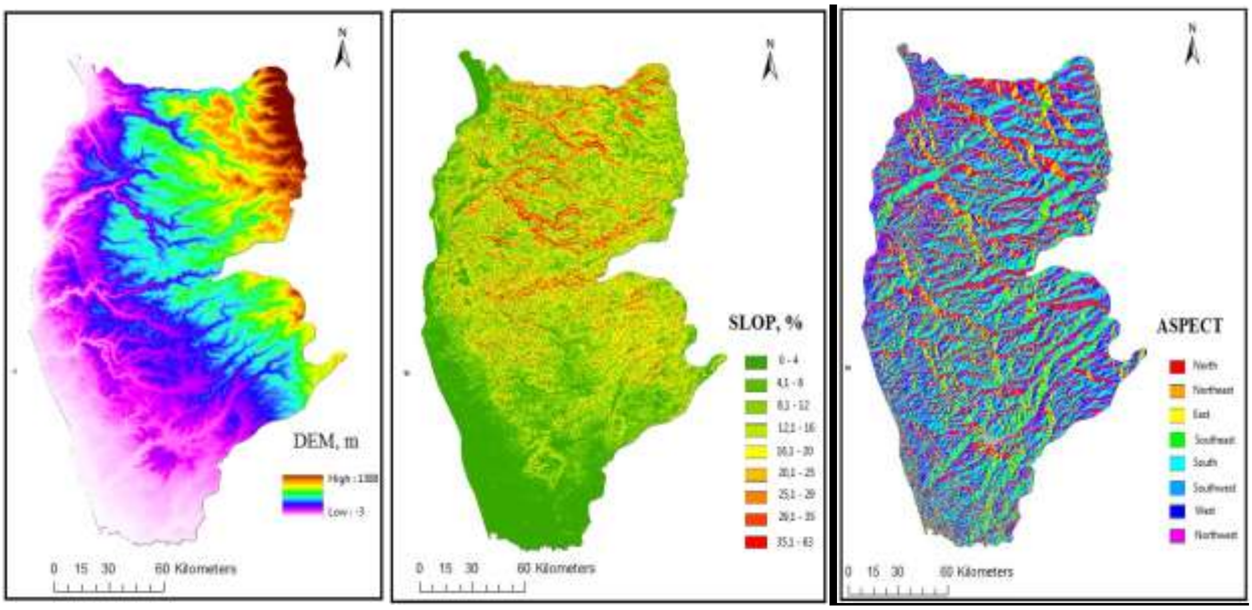

Figure (2): Elevation, Slope, and Aspect Maps of Tartous Governorate

- ***Research materials***

The research subject is the forest cover that has been exposed to fires in different years, which is mainly concentrated in the mountainous regions of Tartous Governorate.

- ***Satellite images***

In the study, Sentinel-2A imagery was used to monitor, assess, and map burn sites Table (1).

Table (1): Main characteristics of the used Sentinel-2A images.

The scene	Satellite	The condition	Image number	History of photography
1	Sentinel-2A	Before the fire	S2A_MSIL2A_20160620T083601	20 June 2016
2	Sentinel-2A	After the fire	S2A_MSIL2A_20160917T083601	17 September 2016
3	Sentinel-2A	Before the fire	S2A_MSIL2A_20170611T08301	11 June 2017
4	Sentinel-2A	After the fire	S2A_MSIL2A_20171019T083601	19 October 2017
5	Sentinel-2A	Before the fire	S2A_MSIL2A_20180616T083601	16 June 2018
6	Sentinel-2A	After the fire	S2A_MSIL2A_20181106T083601	6 November 2018
7	Sentinel-2A	Before the fire	S2A_MSIL2A_20190628T083601	28 June 2019
8	Sentinel-2A	After the fire	S2A_MSIL2A_20191123T083601	23 November 2019
9	Sentinel-2A	Before the fire	S2A_MSIL2A_20200618T083601	18 June 2020
10	Sentinel-2A	After the fire	S2A_MSIL2A_20201030T083601	30 October 2020

A series of multispectral images from the Sentinel-2A satellite were selected over the lands of Tartous Governorate over the years: (2016 ,2017 ,2018 ,2019 ,2020). As a result, 10 scenes (images) were selected for all study periods with a spatial resolution of 10 meters. Images have undergone standard geometric and radiometric calibration G1. To form homogeneous images in Tartous, atmospheric correction was performed for all Sentinel-2A images in the FLAASH unit, Linear spectral alignment of the images was performed in the software ENVI-5.1.

The Sentinel-2B satellite was used in this research, using a clear image from the Sentinel-2B satellite, taken on 3 September 2016 over Tartous Governorate. The Sentinel-2B image underwent initial geometric and radiometric correction for radiation and atmospheric conditions. 4 of the 13 spectral channels of Sentinel-2B were used, namely 2, 3, 4 (RGB) and 8 (NIR), were used to prepare a forest cover map at a high spatial resolution of 10 meters as shown in Table (2).

Table (2): Characteristics of the four Sentinel-2A spectral channels.

№	Channels Sentinel-2B	Spectral range (mkm)	Spatial accuracy, m
1	Band 2- Blue	0.490	10
2	Band 3 - Green	0.560	10
3	Band 4 - Red	0.665	10
4	Band 8 - NIR	0.842	10

- ***Research methods***

1. Conducting analysis of multi-temporal Sentinel-2 satellite images.
2. Using Supervised classification with reliable training data based on NDVI index to obtain fire locations.
3. Based on the mathematical relationship of the dNBR index applied within the ArcGIS10.3 and ENVI 5.1 programs, the area of burned sites was determined during the years: 2016-2020.
4. Determine the severity of fires in 2020 and their geographical distribution.
5. Calculating the NDVI index to obtain a forest cover map in Tartous Governorate in 2016.
6. The methodology was adopted and the accuracy of the results obtained within the ENVI program was evaluated using the Confusion Matrix and reliable training data.

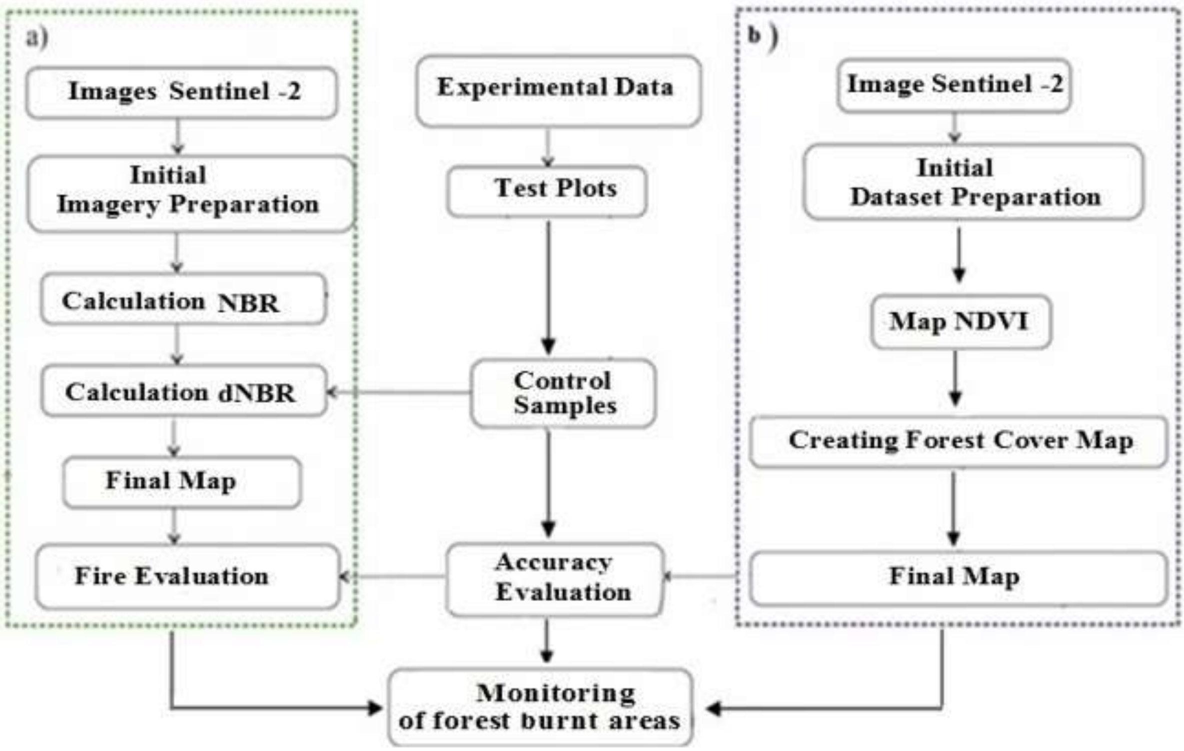

Figure (3): Methodology for monitoring forest fire sites: a) Preparing fire maps based on Sentinel 2 satellite data. B) Preparing a forest cover map according to the Sentinel 2 satellite data.

Figure (3) shows the stages of assessing and monitoring forest fire sites using Sentinel. These stages were divided into two stages: Phase 1: Preparing fire maps in Tartous Governorate based on Sentinel-2A satellite images over different years with an average spatial resolution of 10m. The second phase is to prepare a forest cover map based on the Sentinel-2B image with a high spatial resolution of 10 m.

To assess the location and area of fires in the forest areas of Tartous during the years 2016-2020, as shown in field work was conducted in the burned areas to identify test plots in the period 2022-2024 work was carried out by georeferencing fires on the ground using (Field visits, Google Maps, satellite maps, and Yandex high-resolution).

Figure (4) illustrates the spatial distribution of the reference samples used for the accuracy assessment. A total of 40 reference points were selected, consisting of 23 burned samples and 17 unburned samples. The burned areas are represented by the designated markers, while the unburned areas are displayed with distinct symbols. The reference points were distributed across the study area to ensure proper coverage of both fire-affected and unaffected forest sites. This spatial representation highlights the reliability of the sampling design, which enhances the accuracy and credibility of the classification results.

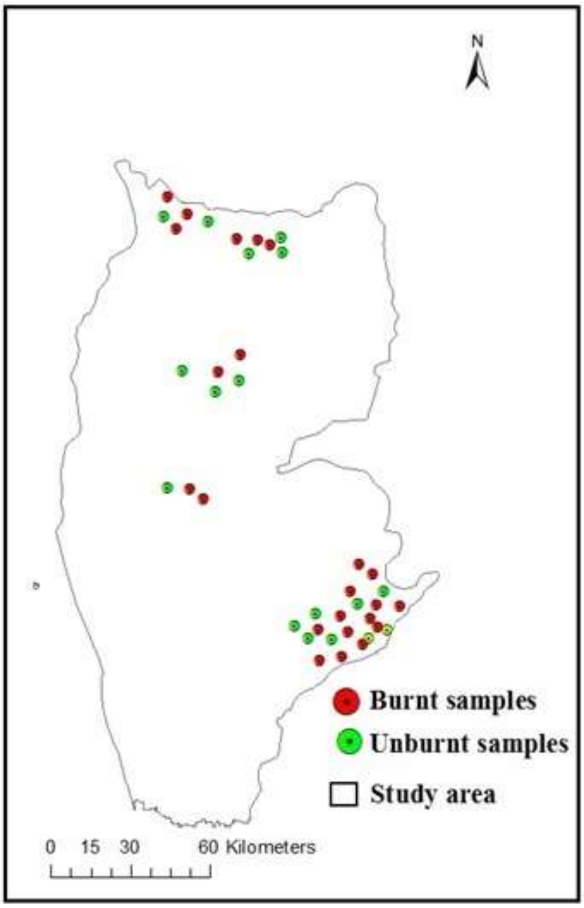

Figure (4): Spatial distribution of burned and unburned Forest samples within the study area

- Analysis Sentinel-2 satellite images.

1. **Analysis of Sentinel-2A images:**

- **Burn Severity Classification Method:**

The classification of burn severity was derived using the Differenced Normalized Burn Ratio (dNBR), which is a widely applied spectral index for post-fire assessment. The NBR index was calculated for both pre-fire and post-fire satellite images using the near-infrared (NIR) and shortwave infrared (SWIR) bands. The NBR index uses two specific spectral bands from Sentinel-2A imagery:

- NIR (Near Infrared) band: Band 8 (~842 nm), which reflects healthy vegetation.
- SWIR (Shortwave Infrared) band: Band 12 (~2190 nm), sensitive to burned vegetation and soil.
- The formula for calculating the Normalized Burn Ratio (NBR) is:

NBR = (B8 - B12) / (B8 + B12)

- The NBR index has a range of values from -1 to +1.
- Low NBR values (e.g., below 0.1 or negative) indicate burned or severely damaged areas.
- High NBR values indicate healthy vegetation.
- You can calculate the difference in NBR before and after fire (dNBR) to assess burn severity:

dNBR = NBR (befor) – NBR (after)

Based on the computed dNBR values, burn severity was classified into three levels:

- Low/Unburned (dNBR < 0.1): Areas with no fire impact or minimal vegetation disturbance.
- Moderate (0.1 – 0.44): Areas with noticeable vegetation damage and partial canopy loss.
- High (dNBR > 0.44): Areas with severe fire effects, including significant canopy consumption and vegetation mortality.

This simplified classification enhances the interpretability of the results and provides a reliable representation of fire severity across the study area.
The degree of damage in the burned areas was divided from Low to High (burned areas of categories 1, 2, and 3), and their area in the study area was clarified using the Based on the computed dNBR values. To do this, based on data from field studies and existing terrain maps, and, a final point layer was formed for the burned forest areas in the Tartous lands, consisting of three vegetation cover categories with varying degrees of damage caused by the 2020 forest fires, figure (5). A separation of fire degree categories was also performed in the ENVI-5.1 program, were converted to vector format (Shap) in ENVI-5.0.and the area of each category was calculated in the ArcGIS-10.3 program.

To obtain thematic maps of forest fires from NDVI images in ENVI-5 software, classification was performed using the supervised classification method, depending on the index dNBR, which made it possible to locate the fires and determine their intensity and area. As a result of this classification, a thematic map of Tartous was obtained, divided into 5 land cover categories, and fires were highlighted in red, as shown in Figure (6).

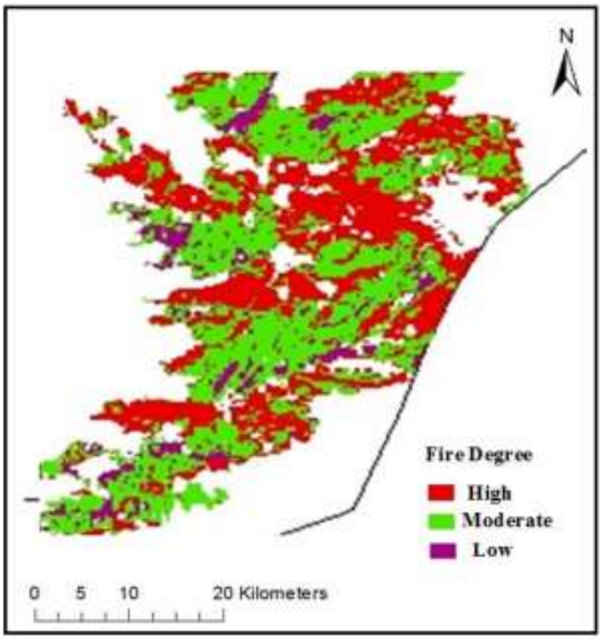

Figure (5): Part of the thematic layer of the 2020 fire in Tartous lands, containing three categories of vegetation cover according to the degree of damage caused by the fires.

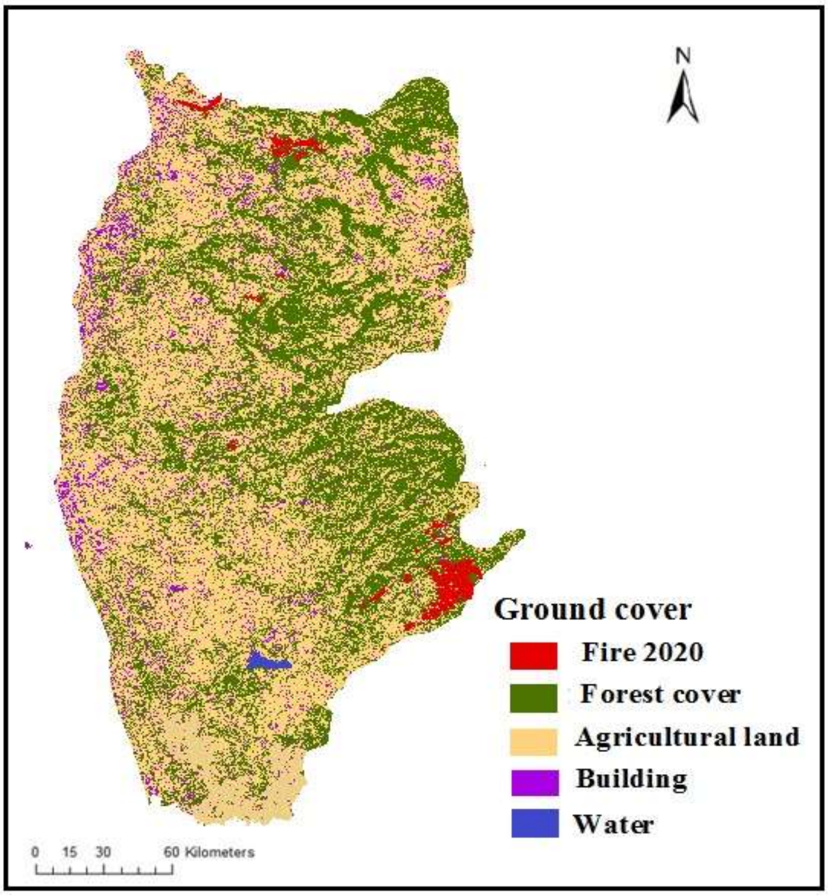

Figure (6): Thematic map in Tartous for 5 land cover categories, obtained by supervised classification method the area of large fire sites for the year 2020 can be seen on the map (in red).

2. Sentinel-2B satellite image analysis to prepare a forest cover map.

The NDVI map of Tartous Governorate as shown in the figure (6), was obtained by applying the mathematical relationship widely used by researchers in recent years:

$$NDVI= (NIR - RED) / (NIR + RED),$$

Where: NIR - near-infrared band of the spectrum. RED - red band of the spectrum.
The range of index values is from -1 to +1.

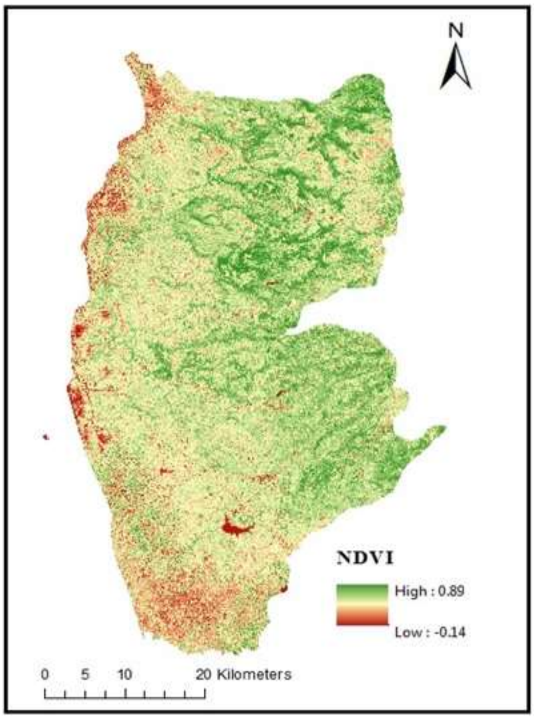

Figure (7): Thematic map resulting from the NDVI index

For vegetation, the index value starts at 0.2 and above. As for the forest cover, the index value starts from 0.65 and above, which made it possible to obtain a map of the “forest cover” category in the form of vector Figure (8), After excluding other land cover categories "cropland" and "fruit trees" in ArcMap 10.3.

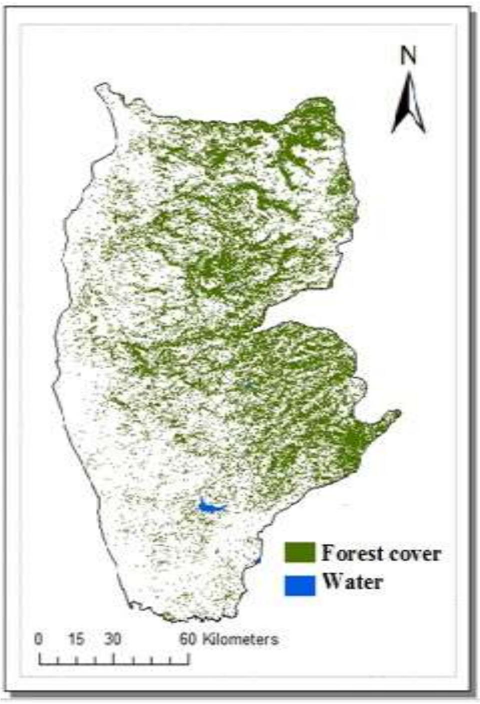

Figure (8): Vector layer of forest cover based on the Sentinel-2 image in Tartous.

− Statistically analyze the trend of burned areas in Tartous Governorate (2016–2020)

A temporal trend analysis of fire areas in Tartous Governorate was conducted during the period from 2016 to 2020 using data on the recorded burned areas (in hectares) for each year.

The analysis relied on applying simple linear regression to determine whether there was an upward or downward trend in burned area across years. Year was used as the independent variable (X) and burned area as the dependent variable (Y).

$$Y = a + bX$$

where:

−Y = Burned Area (hectares(

−X = Year

−a = Intercept (value of Y when X=0(

- b = Slope (rate of change of burned area per year)
- $\bar{Y}$ = mean of Y values

The parameters a (intercept) and b (slope) are estimated using the Ordinary Least Squares (OLS) method, which minimizes the sum of squared residuals between observed and predicted values. Given data points (X_i, Y_i) for i=1,2,...,n:

$$b = (n \Sigma X_iY_i - \Sigma X_i \Sigma Y_i) / (n \Sigma X_i^2 - (\Sigma X_i)^2)$$
$$a = \bar{Y} - b \bar{X}$$

where:
- n = number of observations
- $\bar{X}$ = mean of X values
- $\bar{Y}$ = mean of Y values

−Coefficient of Determination (R^2): Measures the proportion of variance in Y explained by X. Calculated as:

$$R^2 = 1 - (SS_{res} / SS_{tot})$$

Where: SS_{res} is the sum of squared residuals and SS_{tot} is the total sum of squares.

- p-value: Tests the null hypothesis that the slope b=0 (no trend). A small p-value (typically < 0.05) indicates the slope is statistically significant.

Results and discussion:

As a result of Mask classification of forest fires in the ENVI-5.0 program, followed by generalization and merging of classes with similar spectral values in the ArcGIS 10.3 software package, a thematic map of the distribution of fire locations during the time period under study was obtained Figure (9).

The graph, as shown in Figure (10) illustrates the annual burned area (in hectares) in Tartous Governorate between 2016 and 2020. A general fluctuation is observed over the years, with a dramatic spike in 2020, where the burned area reached approximately 2461.78 hectares, significantly higher than in previous years.

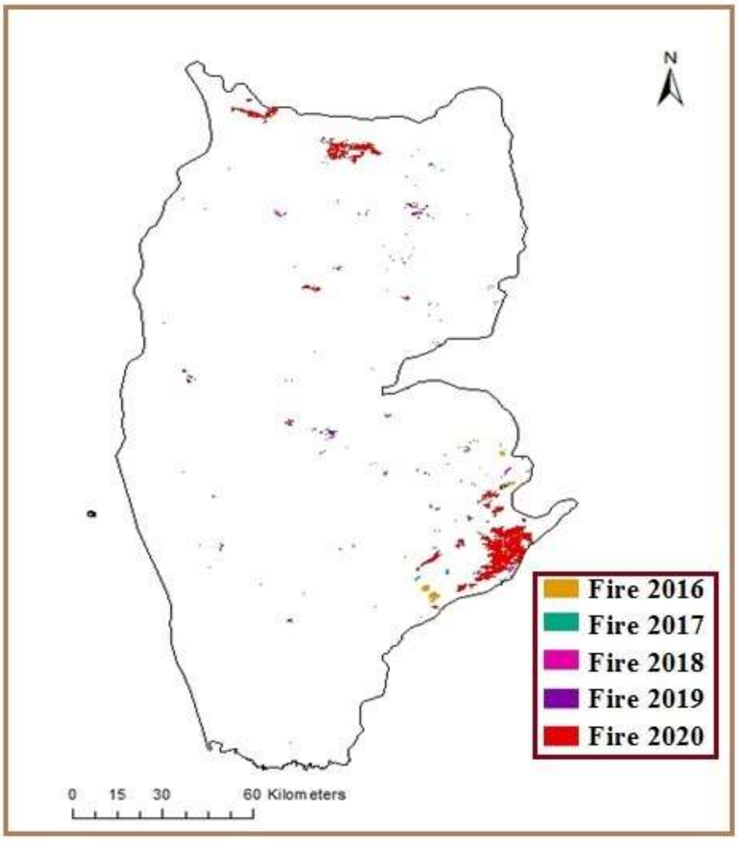

Figure (9): Distribution of fire sites during the years 2016-2020 in Tartous Governorate.

The exceptionally high fire extent in 2020 can be attributed to a combination of climatic, ecological, and anthropogenic factors. That year, extreme weather conditions, such as prolonged droughts, higher-than-average temperatures, and low relative humidity, created favorable conditions for the ignition and rapid spread of wildfires. In addition, strong winds during the fire season likely exacerbated fire behavior, making suppression efforts more difficult.

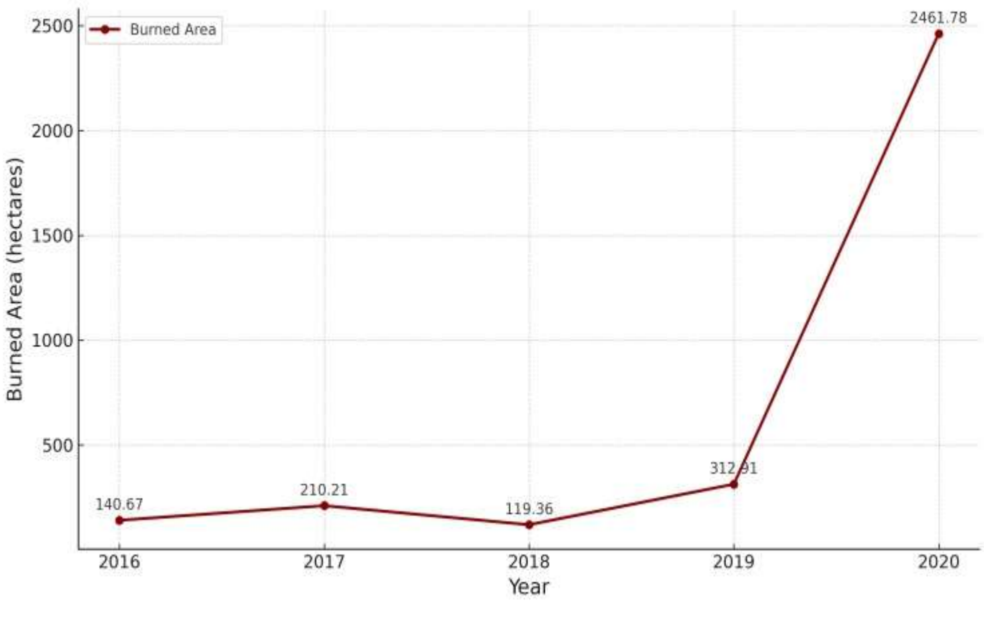

Figure (10): Annual burned area (in hectares) in Tartous Governorate between 2016 and 2020

From an ecological perspective, fuel accumulation (dry vegetation and dead biomass) due to inadequate forest management may have increased fire severity. Moreover, socio-political instability and reduced resources for fire prevention and suppression during that period may have contributed to the scale and persistence of the fires. In summary, the 2020 fire season represents an extreme event likely driven by compound stressors, emphasizing the need for integrated fire management strategies that combine remote sensing monitoring, climate risk assessment, and community-based preparedness.

The map as shown in the figure (11) illustrates the spatial distribution of wildfires in relation to forest cover within the study area. A clear concentration of fire events is observed in regions with dense forest cover. This spatial overlap suggests the vulnerability of forested landscapes to both climatic and anthropogenic stressors, especially in the absence of effective fire prevention and forest management strategies.

The map reveals a spatial pattern where fires tend to spread across contiguous forest patches lacking natural or artificial firebreaks, facilitating the expansion of fire fronts over large areas. This distribution provides a critical indicator for identifying priority zones for rehabilitation, fuel load reduction, and strategic fire risk planning. Overall, according to the study results, the total area burned in the years 2016-2020 amounted to approximately 3244.93 ha.

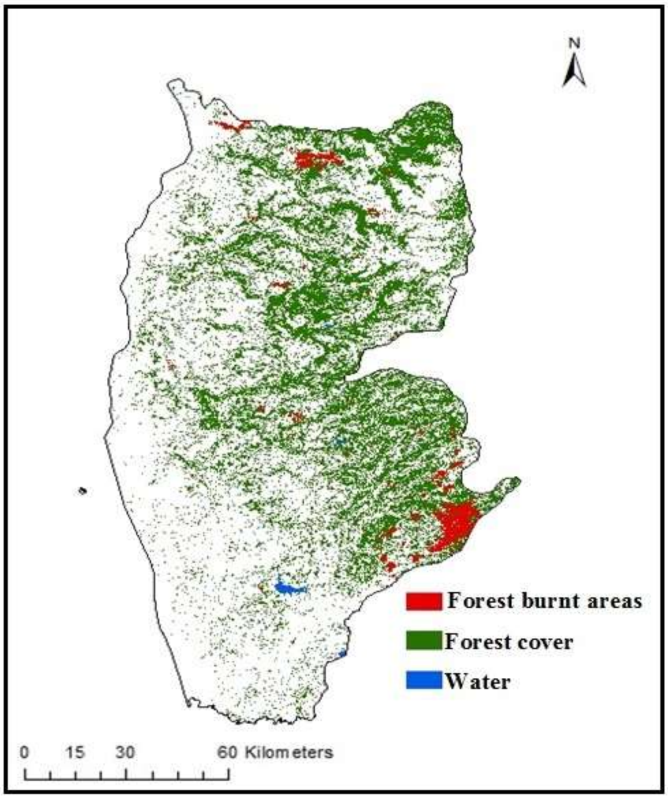

Figure (11): Distribution of forest burnt areas during the years 2016-2020 in in Tartous Governorate.

Using the annual burned area data, the following regression equation was obtained:

$$Y = -1,135,026.57 + 565.37 \times X$$

Table (3) showsThe regression results indicate a statistically significant increasing trend in the burned area over the study period. The slope was approximately 565 hectares per year, indicating that the burned area increased on average by 565 hectares annually from 2016 to 2020. The coefficient of determination (R^2) was 0.84, meaning that 84% of the variance in burned area can be explained by the passage of time. The p-value was 0.01, which is less than the significance level of 0.05, confirming that the upward trend is statistically significant.

This increase was especially notable in 2020, where a sharp peak in burned area was observed, suggesting possible changes in environmental conditions or increased fire susceptibility

Table (3). Statistical Parameters of the Linear Regression Model (2016–2020).

Parameter	Value
Slope (b)	565.37 hectares/year
Intercept (a)	-1,135,026.57
R-squared (R^2)	0.84
p-value	0.01

Figure (12) illustrates the spatial distribution of forest fire severity across a targeted region using satellite-derived classifications.

The map categorizes fire impact into 3 distinct classes based on remote sensing indices (likely using NBR or dNBR thresholds derived from pre- and post-fire satellite imagery:

- High Severity (Red): First-degree: 799.11ha.

Indicates areas where vegetation suffered complete or near-complete canopy loss.

Reflects intense fires, often resulting in soil exposure, high tree mortality, and disruption of ecological processes. These zones are often the hardest to regenerate and may require active reforestation interventions.

- Moderate Severity (Green): 1083.15ha.

Represents moderate to severe damage. Some vegetation remains, but significant thermal stress or crown scorch occurred. Natural recovery is possible but may be slow depending on species composition and post-fire conditions.

- Low Severity (Purple): Third-degree: 579.52 ha.

Marks areas with minimal canopy damage, often due to surface fires. Understory vegetation may have burned, but overstory trees are likely to survive. These areas are more resilient and may recover quickly without major management input.

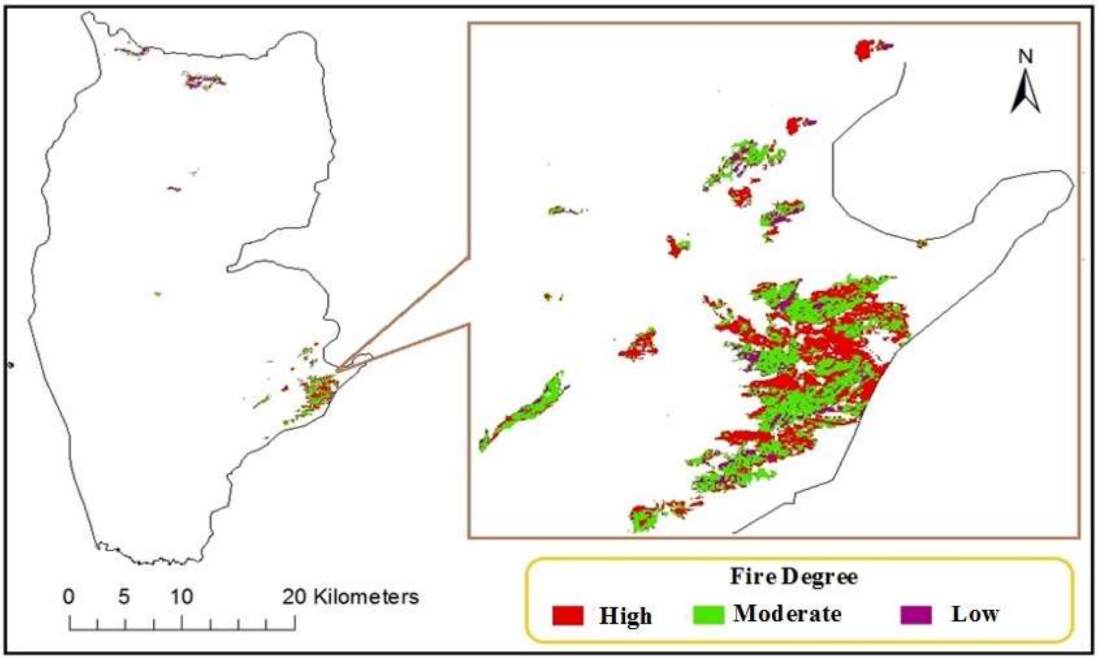

Figure (12): Fire intensity levels and geographical distribution in 2020 in Tartous Governorate

The following table (4) presents the confusion matrix for burned and unburned forest samples, including Producer's Accuracy, User's Accuracy, and their corresponding commission and omission errors. This evaluation ensures a reliable accuracy assessment of the classification results.

Table (4). Confusion matrix for burned and unburned forest samples.

Class	Burned (Predicted)	Unburned (Predicted)	Total Reference	User's Accuracy	Producer's Accuracy	Commission Error	Omission Error
Burned	21	2	23	95.5%	91.3%	4.5%	8.7%
Unburned	1	16	17	88.9%	94.1%	11.1%	5.9%
Total	22	18	40	—	—	—	—

Producer's Accuracy (PA) indicates the probability that a reference sample has been correctly classified. It reflects the omission error, where omission occurs when samples of a class are left out. User's Accuracy (UA) represents the reliability of the classification for each category, i.e., the probability that a sample classified into a given category actually belongs to that category. It reflects the commission error, where commission occurs when a sample is wrongly assigned to a class. In this study, the burned class achieved a Producer's Accuracy of 91.3% and a User's Accuracy of 95.5%, while the unburned class achieved a Producer's Accuracy of 94.1% and a User's Accuracy of 88.9%. The overall results confirm the high accuracy of the classification, supported by a Kappa coefficient of 0.85.

The line chart as shown in the figure (13) compares the Producer's Accuracy and User's Accuracy for the burned and unburned classes. Producer's Accuracy reflects the likelihood that reference samples are correctly classified (omission error), while User's Accuracy reflects the reliability of the classification results for each class (commission error). The chart shows high accuracy values for both classes, confirming the robustness of the classification.

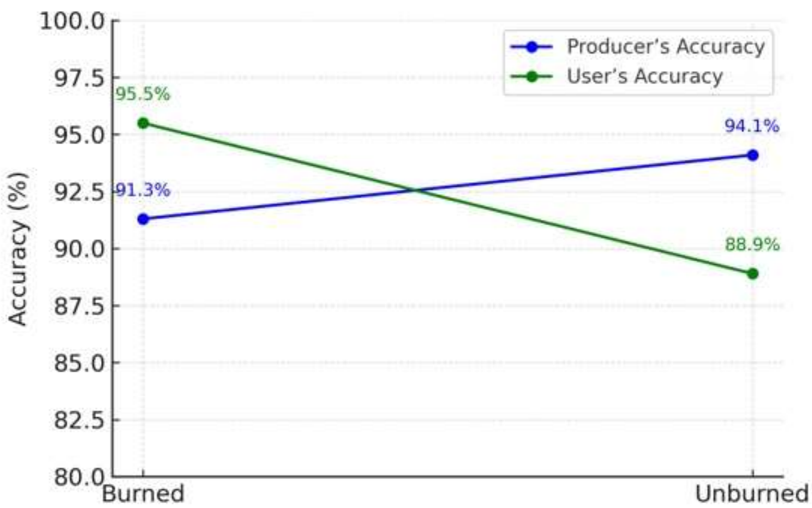

Figure (13): Comparison between Producer's Accuracy (PA) and User's Accuracy (UA)

Conclusions:

- ✓ The study results showed that it is possible to successfully detect burned areas and assess the degree of damage using remote sensing indicators and Landsat satellite imagery.
- ✓ The NBR and NDVI indicators used in this study yielded acceptable results, demonstrating their suitability.
- ✓ Some forest sites were exposed to fires multiple times, with the largest proportion of forest fire area in 2020 (2461.78 ha, or 75.87 %) being concentrated in the mountainous areas of Tartous Governorate.
- ✓ The second-degree Moderate Severity fire in 2020 occupied the largest area of the fire degrees.
- ✓ The study provides clear details on ground-truthing.The number, distribution, and collection methods for validation points are described.

Recommendations:

- ✓ Conduct further monitoring of burned forest areas in Syria using data from the Sentinel-2 satellite, which has higher spatial resolution.
- ✓ Create a database on the area and geographical distribution of fires on a regular basis, so that this data can be fed into a computer program that can provide the necessary information for forest fire management.
- ✓ incorporating topographic variables such as slope and elevation insignificantly enhances the accuracy of burn severity assessment.
- ✓ After forest fires occur, it is necessary to identify the burned areas and determine the type and severity of the fire in order to identify the areas that require intervention to remove completely or partially burned tree trunks, as well as to identify areas that may be at risk of soil erosion and sites that require artificial reforestation.

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تقييم مواقع حرائق الغابات في محافظة طرطوس باستخدام تقنيات الاستشعار عن بُعد ونظم المعلومات الجغرافية

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الملخّص

تشكل حرائق الغابات بطبيعتها المفاجئة والمدمرة تهديدات هائلة للنظم البيئية الطبيعية والمجتمعات البشرية في ظل مناخ متغير. وفي هذا الصدد، يعد تقييم المناطق المحروقة ورصدها خطوة حاسمة في تطوير تدابير للإدارة المستدامة للغابات. وبما أن مراقبة حرائق الغابات التقليدية تستغرق وقتاً طويلاً وهي غير دقيقة، فلا بدّ من معالجة هذه المشكلة باستخدام تقنيات الاستشعار عن بُعد ونظم المعلومات الجغرافية. تهدف هذه الدراسة إلى تقييم ديناميكيات مواقع الغابات المحروقة وخطورة الاضطرابات الناجمة عن الحرائق في 2016-2020 في محافظة طرطوس، باستخدام أرشيف صور الأقمار الصناعية لاندسات وبيانات المؤشرات الطيفية. تشير نتائج البحث إلى أنه خلال فترة الدراسة، تم احترق ما يقارب 3244.93 هكتاراً من مساحة الغابات في محافظة طرطوس، ومنها مساحة 5290.15 هكتاراً من الغطاء الحراجي في عام 2020 فقط. تم التحقق من دقة البيانات باستخدام المعايير الحديثة لاختبار دقة الخرائط الموضوعية الناتجة. يمكن استخدام هذه الدراسة في إعداد تدابير وقائية فعّالة من خلال تحديد المواقع الأكثر عرضة لحرائق الغابات.

الكلمات المفتاحية: حرائق الغابات، سينتينل، محافظة طرطوس، مؤشر NBR، مؤشر NDVI.