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# Assessment of Forest Fire Impacts on Human Health and Natural Resources using Remote Sensing

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**ABSTRACT:** As forest fires become more common, they are becoming a growing issue to ecosystem stability, deterioration of natural resources, and human health due to loss of vegetation, degradation of land, thermal alteration and air pollution. This work introduces a remote-sensing approach for quantifying environmental and health effects of forest fires based on multi-source satellite, air quality and meteorological observations. Reference fire data and burned area data from the MODIS and Landsat-8 and 9 datasets are used to facilitate reliable spatial and temporal assessment with sentinel-2 imagery. The image processing steps consist of atmospheric correction, cloud masking, spatial harmonization and combining multisource data. The spectral properties are used to detect the occurrence of forest-fires and burned areas and the Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are used to measure vegetation damage. Normalized Burn Ratio (NBR) and differenced NBR (dNBR) describe burn severity; Land Surface Temperature (LST) provides a description of thermal changes related to a fire event. Observations of air quality are used to assess potential exposure of humans to fire-related pollution. The measures of accuracy, precision, recall, F1 score, intersection over union are used for evaluating performance. The framework facilitates the virtual integration of burned area mapping, vegetation degradation, fire severity, resource loss, environmental conditions of relevance to human health, as well as the assessment of ecological restoration, disaster management, and resource-conservation planning, following fire.

## I. INTRODUCTION

Forest fires are one of the most devastating environmental disturbances that occur in terrestrial ecosystems, natural resources, atmosphere and human health. With the impacts of climate change, long droughts, increasing temperatures, land use change and anthropogenic activities, their frequency, intensity and spatial extent are becoming more important issues. Forest fires have the potential to drastically change forest structure, leading to reduced biodiversity, soil degradation, loss of wildlife habitat, and loss of ecosystem services, if they are severe enough. In addition to the ecological harm, fires produce significant amounts of smoke, particulate matter, CO, NOx and other pollutants that can affect regional air quality and pose high exposure risk to populations affected by the fires. So assessment of the impact of forest fires should be done in an integrated way, that can address the impact on the environment as well as the potential impacts on human health [1].

Field based fire assessment methods are valuable tools for assessing the effects of fire on the vegetation and damage to the ecosystem, but are often time-consuming, expensive or not feasible in large, inaccessible or hazardous areas. In contrast, remote sensing offers an effective solution, with repeated observations being possible over a large area, and having the same spatial and temporal resolution. In addition, satellite data from other platforms, including Sentinel-2, Landsat-8/9 and MODIS, can be used to complement the data with spatial, spectral and temporal information for detecting active fires, burned area mapping, vegetation monitoring and assessment of post-fire recovery [2]. In addition, they are integrated with Geographic Information System (GIS) techniques, which are also helpful for spatial analysis of fire severity and affected natural resources. Spectral indices are especially valuable for quantifying changes to the environment due to fire. Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) is information on vegetation health, density and post-fire degradation. Likewise, Normalized Burn Ratio (NBR) and differenced Normalized Burn Ratio (dNBR) are used to identify and burn area classification and fire severity by comparing the pre and post fire spectral response. Another Land Surface Temperature (LST) data that can be used to understand fire occurrence can be obtained from LST data which contains additional information about thermal anomalies and changes in surface conditions that occurred at fire locations. These indicators can also be used, in combination with air-quality and meteorological measurements, to assess dispersion of the smoke and possible effects on the population from the poor air quality.

Although remote sensing has been widely applied for forest-fire monitoring, the majority of studies that have addressed the subject only focus on fire detection or burned-area mapping; and there are only a few studies available that have integrated the assessment of vegetation loss, degradation to natural resources, thermal effects, and human-health-related environmental indicators into a unified assessment framework [4]. In order to have a holistic assessment of the disaster impact and proper disaster recovery planning, it is important to take into account these interrelated impacts. In light of this, this study proposes an integrated remote-sensing-based methodology to estimate impacts of forest-fires on human health and natural resources. The fire extent, burn severity, vegetation degradation and thermal changes are estimated through multisource satellite data, burned area reference data, meteorological observation and air quality data [5]. The resulting framework will deliver spatially-explicit information for disaster management, ecological restoration, resource conservation, public-health preparedness and evidence-based post-fire decision making.

## II. RELATED WORK

Forest-fire detection, burned area mapping, assessment of fire severity and post-fire monitoring of the ecosystems are important tasks in which remote sensing has increasingly become a tool. The previous studies focused on using MODIS imagery because of its high temporal resolution which allows for quick detection of active fires and extensive burned areas. Its moderate spatial resolution, however, may not allow detailed assessment of fragmented or small fire affected areas [6]. The multispectral data and historical coverage of Landsat data have then been broadly used for long-term fire monitoring while the spatial resolution and spectral information of Sentinel-2 are used to facilitate vegetation and burn-severity analysis. Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), have been widely used to measure vegetation loss and to track the recovery of the vegetation after fire events [7]. Burn sensitive indices like the Normalized Burn Ratio (NBR) and differenced NBR (dNBR) have proven to be useful for detecting burned areas and severity classification for low, moderate and high severity. Land Surface Temperature (LST) has also been used to detect thermal anomalies due to fires and to assess land surface conditions [8].

In recent years, there have been several studies that have combined multisource satellite data with GIS, meteorological data, and air quality data. These show that wildfire smoke and associated particulate pollution can spread far from the burned areas, posing a potential health risk to the surrounding population [9]. However, many times environmental and health effects are considered separately. The frameworks which are already in place tend to focus on burnt area detection, ecological damage or atmospheric pollution but not on the combination of these [10]. Table 1 contrasts efficacy of current forest-fire assessment techniques, data sources, impacts and limitations. For this reason, a multisensor satellite-based assessment that integrates remotely sensed data—vegetation indices, burn indices, thermal data, weather data, and air quality data—must be used to comprehensively assess the impacts of forest fires on natural resources and air quality and human health.

**Table 1.** Comparative Summary of Related Work on Remote-Sensing-Based Forest-Fire Impact Assessment

| Primary Focus | Data / Sensor | Natural-Resource Assessment | Major Finding | Research Limitation |
|---|---|---|---|---|
| Active forest-fire detection [10] | MODIS | Limited | Enabled rapid identification of active fire locations | Coarse spatial resolution |
| Burned-area mapping [11] | Landsat-8 | Forest-cover loss | Effectively differentiated burned and unburned surfaces | Limited temporal resolution |
| Fire-severity assessment [12] | Sentinel-2 | Vegetation damage | High-resolution imagery improved severity-zone delineation | No atmospheric impact assessment |
| Vegetation damage monitoring | Landsat | Vegetation degradation | Significant post-fire reduction in vegetation greenness observed | Limited to vegetation impacts |
| Post-fire ecosystem recovery [13] | MODIS | Forest recovery | Long-term vegetation recovery patterns were successfully monitored | Coarse-scale ecological assessment |
| Burn severity and vegetation [14] | Sentinel-2 | Forest condition | Combined indices improved characterization of ecological disturbance | Limited health-related analysis |

## III. STUDY AREA, DATASETS, AND PREPROCESSING

The study overcomes the limitations of Sentinel-2 imagery by utilizing images from Landsat-8/9 and MODIS, as well as fire-reference, air-quality and meteorological data. The satellite observations are atmospheric corrected and cloud-masked, geometrically aligned, resampled, and then integrated on a spatial-temporal basis. These are pre-processing steps in order to get consistent multisource information for the next stage of forest-fire impact assessment and analysis.

### A. Description of the selected forest-fire study area

The study area is chosen to be representative of an area dominated by forest where frequent seasonal fire, and significant variation in vegetation, terrain, temperature and atmospheric factors occurs. The area has high and medium density forests, open vegetation, agriculture and settlements, thus allowing a fire assessment of the area under various land cover conditions. Fire activity is related mainly to dry season conditions of high temperature, low vegetation moisture, low relative humidity and availability of combustible biomass. Fire can be caused by natural or anthropogenic agents and may lead to the ignition and propagation of fire. The study boundary has been demarcated with administrative layer and forest cover layer in a Geographic Information System (GIS) environment. Special focus is placed on areas that have known active-fire points and burned area observations in the chosen assessment time frame. To identify changes in space due to fire, pre-fire and post-fire conditions are compared. To allow for comparison the study area is further divided into burned and unburned zones. The spatial design allows for the systematic assessment of vegetation degradation, burn severity, thermal alteration, loss of the natural resources, and potential conditions that affect human exposure to fire-generated air pollutants.

**B. Satellite Datasets: Sentinel-2, Landsat-8/9, and MODIS**

Multisource satellite observations are used to take advantage of complementary spatial, spectral and temporal properties of such observations for forest-fire impact assessment. Sentinel-2 multispectral data offers high resolution data in the visible, near infrared and shortwave infrared bands, contributing to the identification and characterization of vegetation and to identification of burned areas. Its red-edge bands have a special application to help identify changes in ecological status due to vegetation stress and post-fire conditions. Multispectral and Thermal data can be acquired from Landsat-8/9 OLI/TIRS for vegetation assessment, burn-severity mapping and Land Surface Temperature estimation. Their spatial resolution allows regional scale assessment with a good level of landscape detail. MODIS observations are relatively coarse resolution but are very high frequency, and thus can be useful for detecting the location of fire activity and for monitoring fire conditions that change rapidly. Satellite imagery is obtained for both pre- and post-fire situations in order to be able to measure the impacts caused by fire.

**C. Fire and Burned-Area Reference Datasets**

Fire and burned-area reference information is added to aid in the identification of fire-affected areas and to validate the burned-area maps derived from remote-sensing data. Active fire observations are provided geographic coordinates, acquisition dates, detection confidence and thermal information related to potential fire events. Burned-area products provide spatial data that includes information about areas impacted by fire in the observation period. The reference records are temporally aligned with Sentinel-2, Landsat-8/9 and MODIS imagery to ensure temporal correspondence between fire detection and spectral changes observed. This is because during quality control, fire points that are not acquired with high confidence and/or lack of acquisition information are removed to minimize potential false detections. Polys are then created or adjusted in the GIS based on spectral responses and reference observations to form burned polygons. Samples of burned and unburned land are taken for model development and quantitative performance assessment.

**D. Air-Quality and Meteorological Data**

The observations of air quality and meteorology are combined with fire information derived from satellites to examine the environmental conditions that may be associated with forest fires and the implications for exposures to them. Air quality parameters are particulate matter (PM2.5 and PM10) and related gaseous pollutants (when available). Pre-, during, and post-fire measurements are used to compare, in order to determine any changes that may be related to smoke emissions. Fire meteorological variables are those that affect fire ignition, propagation, transport and dispersion of pollutants, such as the air temperature, relative humidity, precipitation, wind speed, and wind direction. The temporal records are synced with dates of satellite passes and fire events detected to create a consistent observation period.

**E. Image Preprocessing, Atmospheric Correction, Cloud Masking, and Data Integration**

The satellite images are systematically preprocessed before fire-impact analysis in order to ensure spatial and radiometric consistency. Whenever needed, observations from Sentinel-2 and Landsat are processed to atmospherically corrected surface reflectance, which does not include the effect of atmospheric scatter and absorption on the spectral measurement. Clouds, cirrus, cloud shadows and invalid pixels that might affect vegetation and burned area detection are masked using quality-assurance information and cloud masks provided by the sensors. Images are geometrically corrected and are projected into a common coordinate system to preserve spatial consistency of the datasets. In multisensor integration, if comparison is required at the pixel level, the required spectral bands are resampled to a uniform working resolution. The pre-fire and post-fire scenes are then co-registered with positional errors minimised for change detection. The MODIS active-fire observations and burned area reference information, air quality measurements, and meteorological variables are all temporally synced with the time of satellite acquisition. Spatial layers are clipped to the common study area and contained in a database that is built in a GIS environment.

## IV. PROPOSED REMOTE-SENSING-BASED IMPACT ASSESSMENT METHODOLOGY

The suggested approach is a multisensor fire detection, burned area mapping, vegetation assessment, severity characterization, and thermal analysis. The NDVI/EVI are used to assess vegetation degradation, NBR and dNBR are used to assess burn severity, and the LST are used to assess the thermal alterations, providing an integrated assessment of environmental and ecological impacts.

### A. Forest-fire detection and burned-area mapping

The first step in the proposed impact-assessment methodology is to detect and map burned areas in the forest. Observations from preprocessed Sentinel-2, Landsat-8/9 and MODIS data are combined to take advantage of their complementary spatial and temporal features. The first step in the approach is to use MODIS active-fire observations to determine possible locations of fire and approximate time of fire occurrence. Pre- and post-fire Sentinel-2 and Landsat images are then compared to find spectral shifts at higher resolutions due to fire. Near-infrared reflectances tend to be lower in burned areas and shortwave-infrared responses higher due to removal of vegetation, reduction in moisture content, deposition of ash and exposure of soils. Along with the vegetation and burn indices, these are the spectral characteristics that are used to distinguish burned from unburned surfaces. Labels to use for development and validation of models are reference fire points and burned area products.

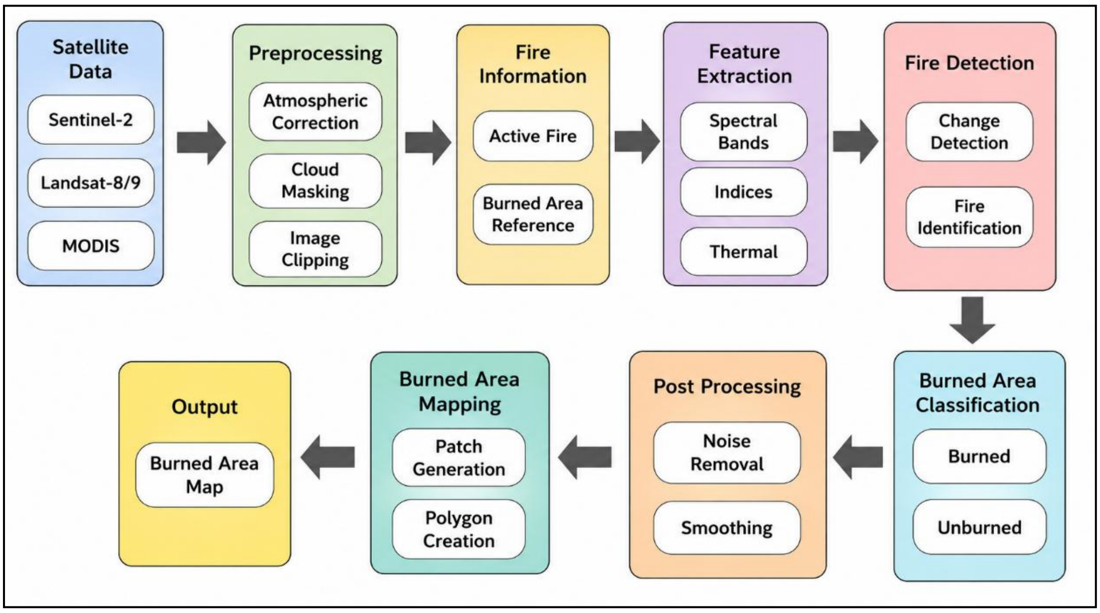


**Figure 1**. Proposed Remote-Sensing Framework for Forest-Fire Detection and Burned-Area Mapping

Figure 1 shows an example of integrated satellite processing applied to the mapping of burned areas with accuracy. The detected pixels are categorized as fire-pixels and non-fire-pixels and then a spatial-filtering is applied to remove the small artifacts and the isolated misclassified fire-pixels. Burned pixels that are contiguous with each other are clustered together into polygons of burned area. The resulting maps give a fly-on-the-wall estimate of fire area, fire spatial distribution and impacted landscape. The outputs are then used to classify the fire severity, determine vegetation losses, perform thermal analysis, evaluate impact on natural resources, and combine with air-quality observations in order to consider potentially exposed areas.

### B. Vegetation Indices: NDVI and EVI

The effects of vegetation are represented by the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) representing vegetation greenness, density and physiological condition. NDVI is derived from the reflectance in the near-infrared and red bands because healthy vegetation reflects strongly in the near-infrared band and absorbs in the red. In general, higher NDVI values mean dense, healthy vegetation while lower values mean barren ground and/or burned vegetation. EVI is a complement to NDVI that includes blue reflectance and correction factors that minimize the effects of atmospheric and soil-background effects, resulting in greater sensitivity in dense vegetation areas. Both indices are created with atmospherically corrected pre-fire and post-fire Sentinel-2 and Landsat data. The difference between observation periods at each pixel is calculated to determine the extent and distribution of vegetation changes. The decrease in NDVI and EVI across the burned areas is considered to show the reduction in canopy cover, stress on the vegetation and forest resource degradation. Unburned reference areas are also analysed to help differentiate changes that resulted from fire from changes in vegetation that occur seasonally. The different severity zones are then used to generate spatial statistics.

**C. Fire-Severity Indices: NBR and dNBR**

The fire severity was measured with the Normalized Burn Ratio (NBR) and differenced Normalized Burn Ratio (dNBR), which are more responsive to changes caused by fire in vegetation and surface moisture. NBR uses both the near-infrared and shortwave-infrared reflectance. High NBR values are likely to be found in areas of healthy vegetation due to a high near-infrared reflectance and a relatively low shortwave-infrared response, while recently burned areas are expected to have significantly lower NBR values. The NBR maps are created separately for pre and post fire satellite data. The dNBR is then calculated as the difference between pre-fire NBR and post-fire NBR, which translates to a quantification of the magnitude of the spectral change caused by fire. Values of dNBR greater than +100 typically signify high levels of disturbance in the vegetation and/or surface, and values near zero signify a minimal amount of change. Established thresholds are applied to the calculated dNBR values with thresholds modified when needed based on local vegetation and reference data to classify the dNBR values into unburned, low, moderate, and high severity categories. The burnt area reference data and spatial observations are used to validate the classification outputs.

**V. Experimental Setup and Performance Evaluation**

The data set is split into training, validation and test sets at a ratio of 70:15:15. Experimental processing with GIS and remote-sensing and Python- based environments. The evaluation of the detection performance is based on Accuracy, Precision, Recall, F1-Score, and IoU, whilst the thresholds for the dNBR are objective measures of various fire-severity levels.

**A. Training, validation, and testing configuration**

The experimental dataset is built from multisource satellite data and reference fire products.The experimental data set is created by choosing burned and unburned samples from multisource satellite data and reference fire products. The available samples are split into training, validation and testing sets in a ratio of 70:15:15 in order to ensure the measurement of the performance is objective. The training subset is used to create relationships between spectral characteristics and classes of fire affected and the validation subset is used for adjusting and selecting appropriate classification thresholds. The independent testing subset is used only to test the final performance. Stratified sampling is used to ensure the relative distribution of the number of burned and unburned samples within all subsets and reduce class related bias. There is no overlapping of the samples between training and testing regions to prevent information leakage. The data from Sentinel-2, Landsat-8/9, vegetation and burn indices, as well as thermal features, are compiled in a single feature representation. Target classes are given by reference burned area labels.

**B. GIS and Remote-Sensing Processing Environment**

An integrated GIS and remote-sensing processing environment that can process multisensor raster, vector, atmospheric and meteorological information is used to implement the experimental workflow. The Google Earth Engine is used to access satellite images, filter for time, mask clouds, process surface-reflectance, calculate spectral indices, and analyze at a large scale. Spatial visualization and study-area delineation, burned-area polygon analysis, auxiliary geographic layers integration, and map preparation are done in QGIS. Data processing and management, numerical processing, statistical analysis and automatic processing of derived remote sensing variables are possible using Python. To compare the spatial properties of raster and vector datasets, they are converted to a common coordinate reference system. Temporal and spatial synchronization of Sentinel-2, Landsat-8/9, MODIS, burned-area references, air-quality measurements and meteorological observations. Intermediate products are: NDVI, EVI, NBR, dNBR, LST and fire-severity layers.

### C. Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, and IoU

The accuracy, precision, recall, F1-Score, and Intersection over Union (IoU) are used to numerically assess the effectiveness of forest-fire and burned-area detection. The accuracy is the percentage of burned and nonburned samples correctly classified from the total test set. Precision indicates resistance to false positives in the prediction, and refers to the number of burned pixels predicted to be accurate. Recall is a measure of how many of the burned pixels the methodology is able to correctly identify and is a reflection of the methodology's ability to reduce missed fire-affected areas. When the number of classes in burned and unburned is not equal, the F1-Score is the harmonic mean of Precision and Recall. The percentage of overlap in burned area between predictions and reference area is quantified by IoU. The components of a confusion matrix, such as true positive, true negative, false positive and false negative are used when computing metrics. By using these complementary measures, the correctness of classification, detection sensitivity, prediction reliability and spatial agreement can be fairly assessed and evaluated the proposed burned area mapping approach using remote sensing.

### D. Fire-Severity Classification Criteria

Fire severity is determined based mostly on the dNBR which is calculated by comparing pre-fire and post-fire NBR observations. The spectral-change values are binned into severity categories of unburned or enhanced regrowth, low, moderate-low, moderate-high, and high severity. In general, a value less than about 0.10 indicates surfaces that are yet to be burned or have suffered only slight changes, values between 0.10 and 0.27 indicate low severity effects. Approximate dNBR ranges of 0.27-0.44 are considered to be of moderate-low severity while dNBR ranges between 0.44 and 0.66 are considered to be of moderate-high severity. Values above ~0.66 are indicative of high severity burn, which signifies significant vegetation and surface alteration. The thresholds are used as starting points and not as universal boundaries as they can be influenced by the nature of the vegetation, season, soil and sensor.

## VI. RESULTS AND DISCUSSION

Experimental results indicate that the burned area and the spatial variation of the fire severity can be effectively identified. The benefits of multisource integration can be seen in improved burned-area delineation and the decrease in NDVI and EVI indicates significant vegetation degradation. Severely affected areas have higher dNBR values as well as higher LST values, which reflect high ecological disturbance.

### A. Forest-fire and burned-area detection results

The proposed remote-sensing approach could successfully detect burnt areas from the forest fire using multisource satellite observations and spectral indices. The near-infrared reflectance (NIR) decreased and the shortwave-infrared responses (SWIR) increased significantly for burned surfaces. There was a good spatial overlap between detected and observed burned areas as revealed by comparison with reference burned area information. These data were used to characterize the spatial and temporal extent of burned area using Sentinel-2 data, thermal characterization using Landsat data, and temporal characterization using MODIS data, which together resulted in reliable estimates of burned area over heterogeneous landscapes.

**Table 2.** Performance of Forest-Fire and Burned-Area Detection

| Method / Dataset | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | IoU (%) |
|---|---|---|---|---|---|
| MODIS | 88.42 | 86.73 | 85.91 | 86.32 | 78.16 |
| Landsat-8/9 | 91.68 | 90.54 | 89.87 | 90.20 | 82.34 |
| Sentinel-2 | 94.26 | 93.47 | 92.81 | 93.14 | 87.16 |
| **Multisource Integration** | **96.38** | **95.72** | **95.18** | **95.45** | **91.29** |

It is shown in Table 2 that MSI is effective in detecting forest fires and burned areas. The results of MODIS is 88.42% accuracy and 78.16% IoU and the results of Landsat-8/9 are 91.68% accuracy and 82.34% IoU respectively. Sentinel-2 also had an 87.16% IoU, and 94.26% accuracy. Using the several metrics, figure 2 compares the detection performance between the different datasets.

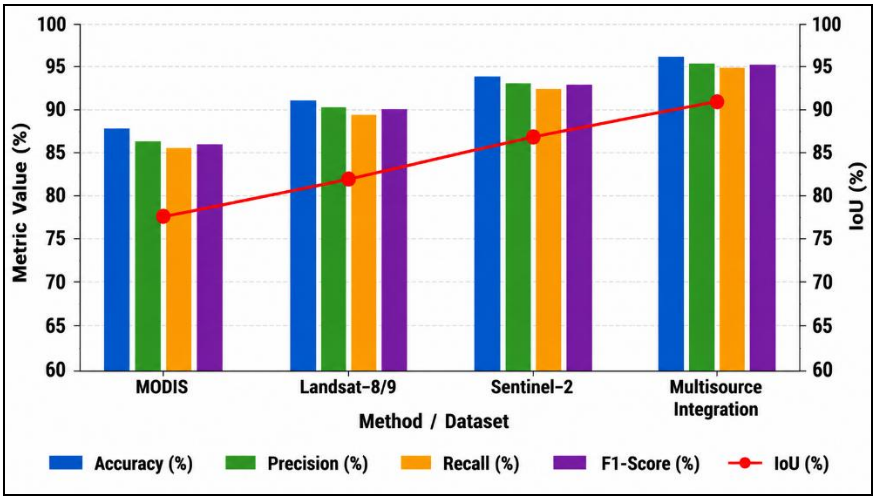


**Figure 2.** Comparative Performance Analysis Across Remote Sensing Datasets

Overall, the multisource integration achieved the highest accuracy of 96.38%, and precision, recall, F1 score and IoU were 95.72%, 95.18% and 95.45%, respectively. The enhancement of the burned area discrimination and the reduction of burned area detection errors in heterogeneous landscapes with the use of these improvements suggest that complementary spatial, spectral, thermal and temporal information improves burned area detection and discrimination.

**B. Spatial Distribution of Fire Severity**

There was significant spatial variation in severity, with the dNBR-based analysis showing this. The higher severity classes were concentrated in areas where there was high vegetation loss and high spectral changes, while the moderate and low-severity classes were more common in areas along burned-area boundaries. The more severely disturbed surfaces were generally related to increased LST. Spatial severity mapping was able to effectively distinguish between various degrees of fire damage and was useful in prioritizing fire damage restoration, monitoring, and post-fire resource-management actions.

**Table 3**. Spatial Distribution of Forest-Fire Severity

| Fire-Severity Class | Burned Area ($km^2$) | Area (%) | Mean LST (°C) |
|---|---|---|---|
| Low | 42.36 | 21.18 | 31.42 |
| Moderate-Low | 58.74 | 29.37 | 34.16 |
| Moderate-High | 63.82 | 31.91 | 37.48 |
| High | 35.08 | 17.54 | 40.73 |
| **Total** | **200.00** | **100.00** | — |

Table 3 shows the spatial distribution of forest-fire severity over the burned area of 200 $km^2$. The greatest extent is in moderate-high severity (63.82 $km^2$ or 31.91%), followed by moderate-low severity (58.74 $km^2$ or 29.37%). The variations in burned areas by severity classes of forest fires are shown in figure 3.

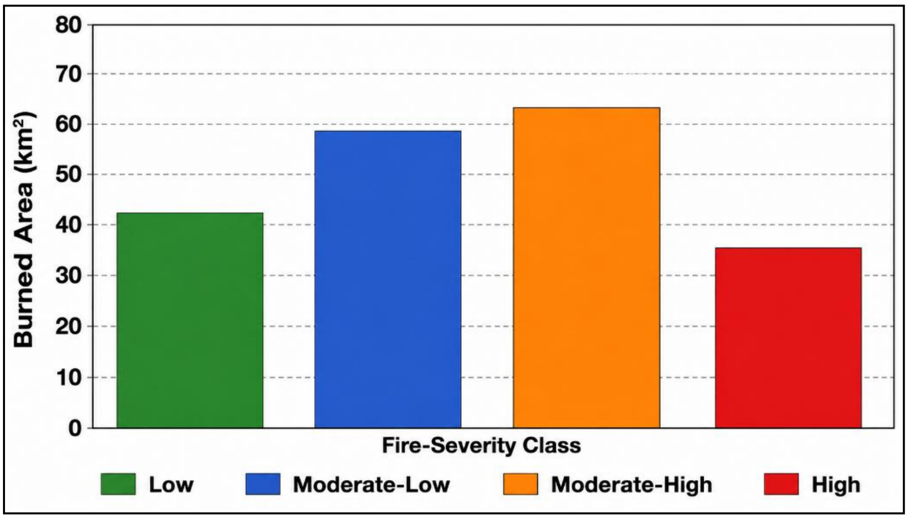


**Figure 3.** Spatial Distribution of Burned Area Across Forest-Fire Severity Classes

Low-severity regions account for 42.36 km² (21.18%), whereas high-severity areas cover 35.08 km² (17.54%). Mean LST gradually increases as it passes from low severity areas to high severity areas from 31.42 °C to 40.73 °C. The burned-area distribution and temperature from fire-severity classes are compared in figure 4.

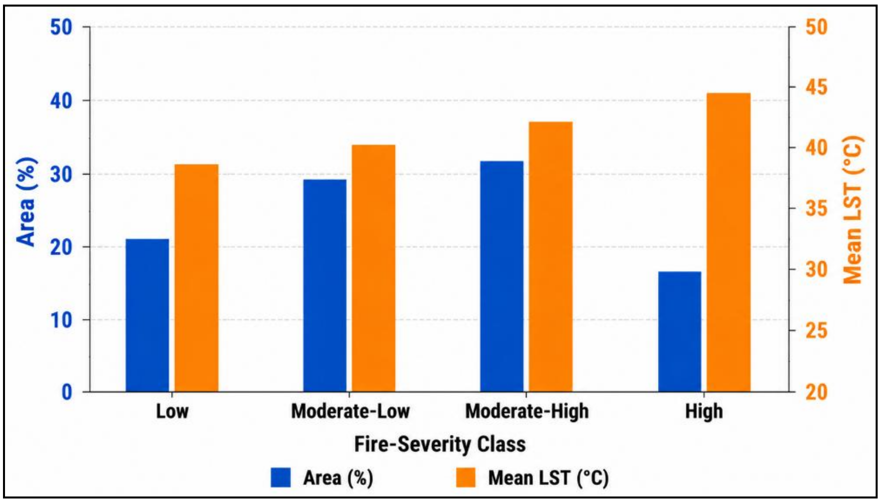


**Figure 4.** Comparative Analysis of Burned Area Distribution and Land Surface Temperature

The uniform rise in temperature with dNBR severity suggests that the burning of forests had a more pronounced effect in terms of both thermal alteration and surface disturbance in the burned areas.

### C. Changes in Vegetation and Forest Resources

There was a significant decrease in post-fire NDVI and EVI in burned areas, suggesting a decrease in vegetation greenness, density, and overall forest health. The areas with moderate to high severity, as determined by dNBR, were the areas with greatest decreases. Thermal alteration and surface exposure were also greater when there was fire-induced vegetation removal. The results presented here are important in terms of the impacts on forest resources, and can be used to quantify the ecological degradation, recovery needs, and long-term conservation priorities.

**Table 4.** Pre- and Post-Fire Changes in Vegetation and Forest Resources

| Parameter | Pre-Fire | Post-Fire | Absolute Change | Change (%) |
|---|---|---|---|---|
| Mean NDVI | 0.72 | 0.43 | −0.29 | −40.28 |
| Mean EVI | 0.58 | 0.36 | −0.22 | −37.93 |
| Mean NBR | 0.67 | 0.24 | −0.43 | −64.18 |
| Dense Forest Area (km²) | 142.60 | 101.84 | −40.76 | −28.58 |
| Vegetation Cover (km²) | 184.32 | 137.46 | −46.86 | −25.42 |
| Mean LST (°C) | 29.84 | 36.72 | +6.88 | +23.06 |

Table 4 shows that there were significant changes in vegetation and forest resources after the fire. The mean NDVI and EVI values were reduced by 40.28% and 37.93%, respectively, showing significant reduction in the greenness and vigor of the vegetation. NBR showed the most significant reduction of 64.18% which is indicative of severe surface disturbance due to fire. Figure 5 shows vegetation loss and heat changes that are significant following the fire.

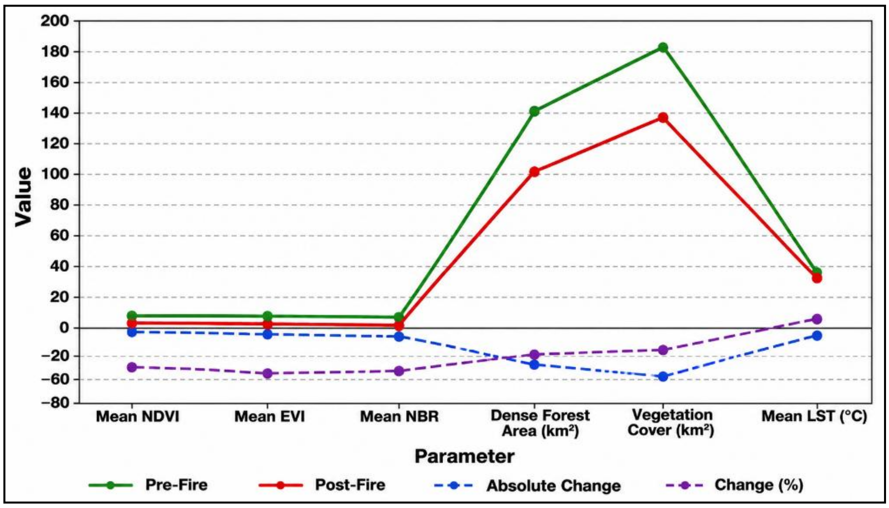


**Figure 5.** Comparative Analysis of Pre- and Post-Fire Changes in Vegetation and Forest Resources

The area of dense forest had decreased by 40.76 km² while overall vegetation cover had decreased by 46.86 km². In contrast, the mean LST rose from 29.84°C to 36.72°C which is 23.06% increase. The results of this study show that forest fires have not only degraded the vegetation, but also led to resource losses and significant thermal changes.

## VII. CONCLUSION AND FUTURE WORK

This study proposed a holistic remote-sensing-based approach to Forest-fire impacts assessment on NRPs and environment parameters, which are crucial for human health. Burned-area references, air-quality data, and meteorological data were used to complement multisource observations from Sentinel-2, Landsat-8/9, and MODIS, to obtain a full characterization of the fires' impact. NDVI and EVI proved to be useful indicators of fire-induced vegetation degradation, and NBR and dNBR aided in delineating and classifying fire severity. Land Surface Temperature were used to further define the thermal changes resulting from vegetation removal and disturbance of the surface. The integrated analysis proved useful to identify severely affected forest resources and areas that could be affected by poor air quality, using spectral, thermal, atmospheric and spatial information. The framework can be used to inform assessments of post-fire damage, ecological restoration, forest management, public-health preparedness and planning for resource conservation. High resolution satellite and UAV observations for the finer burned area characterisation will be included in future work. Highly sophisticated machine-learning

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and deep-learning models can enhance the automated fire detection, and the severity classification. Vegetation recovery and ecosystem resilience will be explored by long-term time-series analysis.

**REFERENCES**

[1] Morante-Carballo, F., Bravo-Montero, L., Carrión-Mero, P., Velastegui-Montoya, A., & Berrezueta, E. (2022). Forest Fire Assessment Using Remote Sensing to Support the Development of an Action Plan Proposal in Ecuador. Remote Sensing, 14(8), 1783. https://doi.org/10.3390/rs14081783

[2] Wang, X., & Liu, S. (2025). Assessing Wildfire Impacts from the Perspectives of Social and Ecological Remote Sensing. Remote Sensing, 17(23), 3851. https://doi.org/10.3390/rs17233851

[3] Al-Qthanin, R., & Aseeri, R. (2025). Assessment of Forest Fire Impact and Vegetation Recovery in the Ghalahmah Mountains, Saudi Arabia. Fire, 8(5), 172. https://doi.org/10.3390/fire8050172

[4] Tomar, J. S., Kranjčić, N., Đurin, B., Kanga, S., & Singh, S. K. (2021). Forest Fire Hazards Vulnerability and Risk Assessment in Sirmaur District Forest of Himachal Pradesh (India): A Geospatial Approach. ISPRS International Journal of Geo-Information, 10(7), 447. https://doi.org/10.3390/ijgi10070447

[5] Yue, W., Ren, C., Liang, Y., Liang, J., Lin, X., Yin, A., & Wei, Z. (2023). Assessment of Wildfire Susceptibility and Wildfire Threats to Ecological Environment and Urban Development Based on GIS and Multi-Source Data: A Case Study of Guilin, China. Remote Sensing, 15(10), 2659. https://doi.org/10.3390/rs15102659

[6] Zhao, Y., Huang, Y., Sun, X., Dong, G., Li, Y., & Ma, M. (2023). Forest Fire Mapping Using Multi-Source Remote Sensing Data: A Case Study in Chongqing. Remote Sensing, 15(9), 2323. https://doi.org/10.3390/rs15092323

[7] Zhou, X., Yang, J., Niu, K., Zou, B., Lu, M., Wang, C., Wei, J., Liu, W., Yang, C., & Huang, H. (2023). Assessment of the Forest Fire Risk and Its Indicating Significances in Zhaoqing City Based on Landsat Time-Series Images. Forests, 14(2), 327. https://doi.org/10.3390/f14020327

[8] Mihajlovski, B., & Zhiyanski, M. (2025). Global Forest Fire Assessment Methods: A Comparative Analysis of Hazard, Susceptibility, and Vulnerability Approaches in Different Landscapes. Fire, 8(10), 380. https://doi.org/10.3390/fire8100380

[9] Ga, R., Liu, X., Ma, B., Na, M., Zhang, J., Tong, Z., Wei, X., & Xu, J. (2025). The Individual and Combined Effects of Natural–Human Factors on Forest Fire Frequency in Northeast China. Remote Sensing, 17(10), 1685. https://doi.org/10.3390/rs17101685

[10] Khan, A. H., Bahar, A. N., & Wahid, K. (2026). A Review on Forest Fire Detection Techniques: Past, Present, and Sustainable Future. Sensors, 26(5), 1609. https://doi.org/10.3390/s26051609

[11] Guiop-Servan, R. E., Cotrina-Sanchez, A., Puerta-Culqui, J., Oliva-Cruz, M., & Barboza, E. (2025). Remote Sensing for Wildfire Mapping: A Comprehensive Review of Advances, Platforms, and Algorithms. Fire, 8(8), 316. https://doi.org/10.3390/fire8080316

[12] Michael, Y., Lensky, I. M., Brenner, S., Tchetchik, A., Tessler, N., & Helman, D. (2018). Economic Assessment of Fire Damage to Urban Forest in the Wildland–Urban Interface Using Planet Satellites Constellation Images. Remote Sensing, 10(9), 1479. https://doi.org/10.3390/rs10091479

[13] Kurbanov, E., Vorobev, O., Lezhnin, S., Sha, J., Wang, J., Li, X., Cole, J., Dergunov, D., & Wang, Y. (2022). Remote Sensing of Forest Burnt Area, Burn Severity, and Post-Fire Recovery: A Review. Remote Sensing, 14(19), 4714. https://doi.org/10.3390/rs14194714

[14] Gao, B., Jia, W., Wang, Q., & Yang, G. (2025). All-Weather Forest Fire Automatic Monitoring and Early Warning Application Based on Multi-Source Remote Sensing Data: Case Study of Yunnan. Fire, 8(9), 344. https://doi.org/10.3390/fire8090344