***Original Research Article***

**Assessment of Vegetation Impact Using Vegetative Indices Due to Forest Fires in Uttarakhand**

**ABSTRACT**

Forest fires impact the forest ecosystems in the form of decline in forest cover, loss in biodiversity, and alterations in land use/land cover which further modifies the hydrological cycle, accelerating the runoff and soil erosion. All these problems require effective management strategies. This study estimates the impact of forest fires on soil moisture and vegetation in Uttarakhand, using Landsat 8 imagery and four vegetation indices: NDVI, NDMI, NBR, and MSAVI based on different forest types. Data from 42 forest fire sites spread across five forest types were analysed to assess the changes in vegetation loss, moisture depletion, and burn severity. Results show significant decline in NDVI in Subtropical Pine Forests. NBR effectively shows burn severity and it was found highest in Subtropical Pine Forest and Tree Outside Forest types. NDMI index shows considerable decreases in soil moisture, while MSAVI detected considerable vegetation cover loss, especially in Subtropical Pine forests. Statistical analysis highlighted NDMI index’s sensitivity to moisture changes and shows the highest M-statistics with 1.55 followed by NBR's, which is reliable in assessing burn severity. The study highlights the effectiveness of different indices in assessing the impacts of forest fires which may be of immense utility to establish strategies for post-fire forest management, monitoring, and rehabilitation.

***Keywords:*** *Forest fire****,*** *Vegetative indices, Forest type, Remote sensing, NDVI*

1. **INTRODUCTION**

Forests are vulnerable to both gradual and sudden disruptions that differ in frequency, intensity, and extent. Worldwide, fire is a major cause of forest disturbances (Kasischke et al., 2013). According to van der Werf et al. 2006, fire affects over 350 million hectares worldwide each year, potentially having a significant impact on the amount of carbon released from terrestrial ecosystems (Andreae & Merlet, 2001; Simmonds et al., 2005)**.** Fires cause enduring changes to vegetation composition, impact vast area worldwide, leading to severe consequences such as decline in biodiversity, a reduction in forest cover, alterations to the landscape, soil degradation, an increase in greenhouse gas emissions, and disruption of ecosystem functioning and landscape patterns, all of which promote the processes of desertification. Evaluating the effects of fire is crucial for understanding the fire-induced degradation, improve our understanding of ecosystem recovery after fire, and quantifying the related economic losses. Various approaches have been developed to assess fire severity, such as spectrum mixture analysis (Veraverbeke & hook, 2013; Quintano et. al., 2013), simulation methods (De Santis et. al, 2010; De Santis et. al., 2007), and spectral indices (SIs) (French et. al., 2008). The most popular method is spectral indices because of its ease of use and computational effectiveness (Veraverbeke et. al., 2011). Fire severity is expressed by fire severity indices, which measure the extent of environmental alteration caused by fire and provide the amount of organic matter lost above and below ground. According to optical perspective, there is a significant decrease in visible to near-infrared surface reflectance (i.e., 0.4–2.5 µm) when vegetation is burned. The extent of reduction is linked to the vegetation damage caused by the fire severity, which is represented by a change in the spectral index values **(**White et. al., 1996**).**

The study of vegetation index is essential to comprehend how forest fires affect ecosystem. The health and quantity of vegetation in the given area can be assessed using vegetation indices, which are mathematical computations based on aerial or satellite photography. However, satellite remote sensing (SRS), which collects input across wide regions at a regular interval, offers rapid and affordable means for estimating fire intensity and vegetation recovery. These spectrum indices are based on normalised difference spectral indices (NDSIs), like commonly used Normalised Burn Ratio (NBR) (Epting et. al. 2005, Key and Benson 2006, Miller and Thode 2007) and the Normalised Difference Vegetation Index (NDVI) (e.g. Chafer et al. 2004). Whereas the NBR correlates with vegetation wetness by merging the NIR and SWIR (short wave infrared) reflectance, the NDVI measures the quantity of green vegetation by combining the reflectance in the R (red) and NIR (near-infrared) spectral regions. Indices that correct for atmospheric and background distortion perform better than the NDVI. For instance, the modified soil-adjusted vegetation index (MSAVI) surpasses NDVI in performance (Veraverbeke et. al., 2012, Qi et. al., 1994, Rogan & Yool, 2001, Schepers et. al., 2014) and reduces soil spectral interference (Huete, 1988). NDMI index is essential for estimating vegetation moisture levels, which can indicate conditions like drought that could increase the risk of fire (Ochtyra et. al., 2020). MSAVI index reduces the effect of soil brightness which increases the precision of vegetation analysis in area with little plant cover. When combined, these indices offer thorough data that supports forest fire detection, evaluation, and management, resulting in more efficient fire prevention, response, and recovery plans. This study primarily aims to evaluate the variations in vegetation indices before and after fire. This will provide insight into vegetation recovery and fire's effects on forest ecosystems. Each of them leads to a different Normalised Difference Vegetation Index (dNDVI) (Chafer et. al. 2004), a different Normalised Burn Ratio (dNBR) (Key and Benson 2006), a different Normalised Difference Moisture Index, and something else entirely. This study attempts to investigate the mechanisms of forest health and recovery following fire using a variety of measures.

The forest fires are major global concern, especially in countries like India where vast area of forested cover are exposed to different degrees of fire threat. In India, the recorded cases of forest fires were assessed as 345,989 by SNPP-VIIRS (Suomi-National Polar-orbiting Partnership - Visible Infrared Imaging Radiometer Suite) and 52,785 during the year 2020 to 2021 through MODIS (Moderate Resolution Imaging Spectro-radiometer) (Forest Survey of India, 2021). Forest types, like dry deciduous forests, are susceptible to severe fires; evergreen, semi-evergreen, and high-temperate forests are relatively less vulnerable (Forest Survey of India, 2015). According to estimates, forest fires frequently occur in more than 36% of the nation's forest cover. About 4% of the nation's forest cover is extremely prone to fire, while 6% is assessed to be very highly prone to fire (Forest Survey of India, 2019).

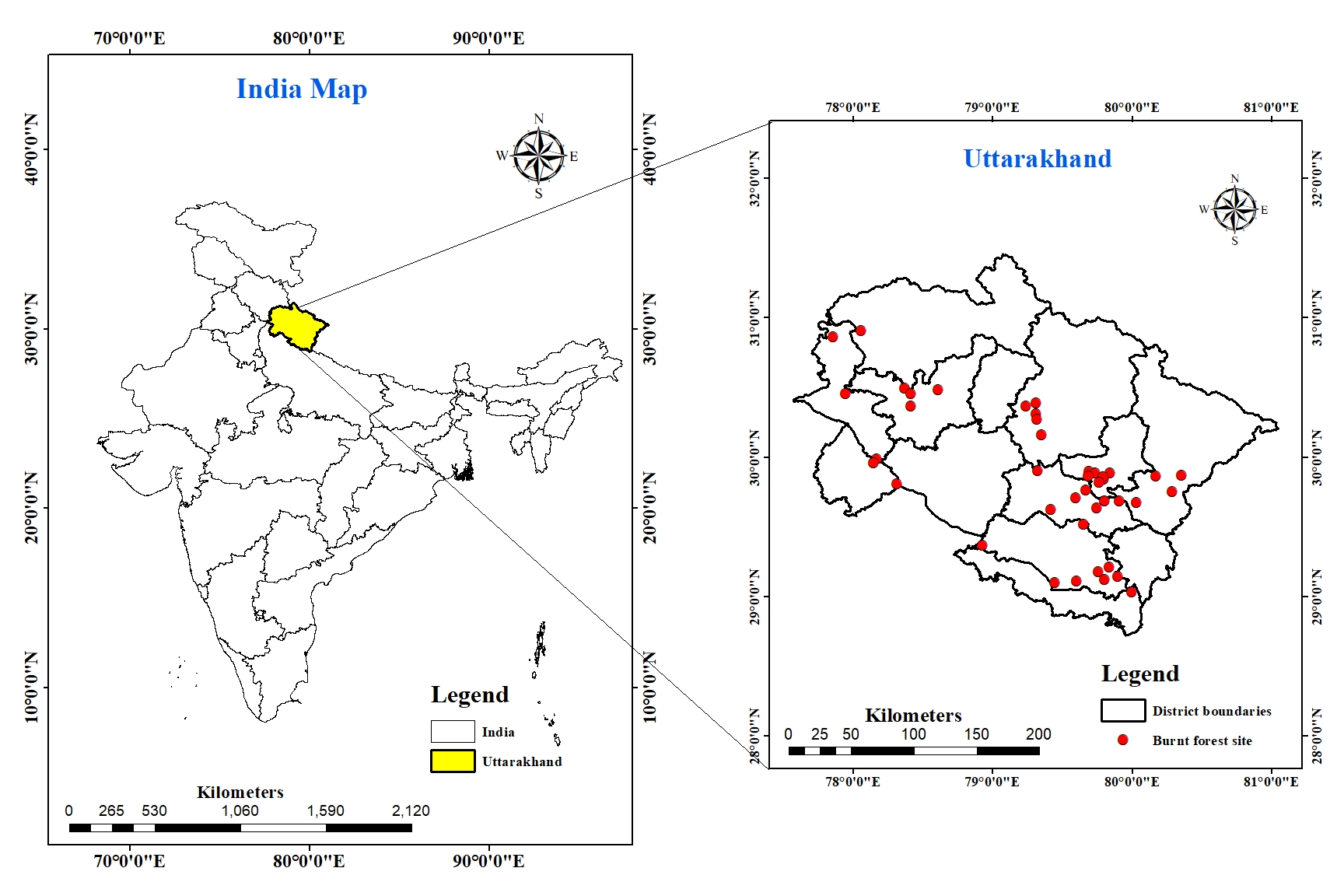
Forest fires are a primary driver of extensive ecological and socioeconomic disruptions in Uttarakhand, contributing significantly to rural outmigration. Approximately 45.44% (24,305 km²) of Uttarakhand’s total geographical area has experienced high fire incidences in recent years (Forest Survey of India, 2021). Between the years 2010 and 2023, the state witnessed multiple forest fire events, with the most severe fire season recorded in 2019. During that year, 2,158 fire incidents impacted 2,981.55 hectares of forest land, predominantly in the Garhwal and Kumaon regions (Negi, 2019). The impact was particularly severe in Chir Pine (Pinus roxburghii) forests due to the high resin content and accumulation of dry leaf litter during summer, increasing their susceptibility to combustion. While no human fatalities were reported, 15 individuals sustained injuries, and wildlife populations also suffered significant adverse effects from the fires.

Given the critical need for effective fire management systems and prevention strategies, their development and implementation have become a focal point. However, the phenomenon of forest fires in Uttarakhand has been relatively underexplored in scientific literature. This research aims to assess the impact of forest fires in the region and formulate comprehensive mitigation and control strategies. The study holds significant relevance in advancing fire management policies and strategic interventions that not only safeguard local populations but also ensure the preservation and resilience of the broader ecosystem.

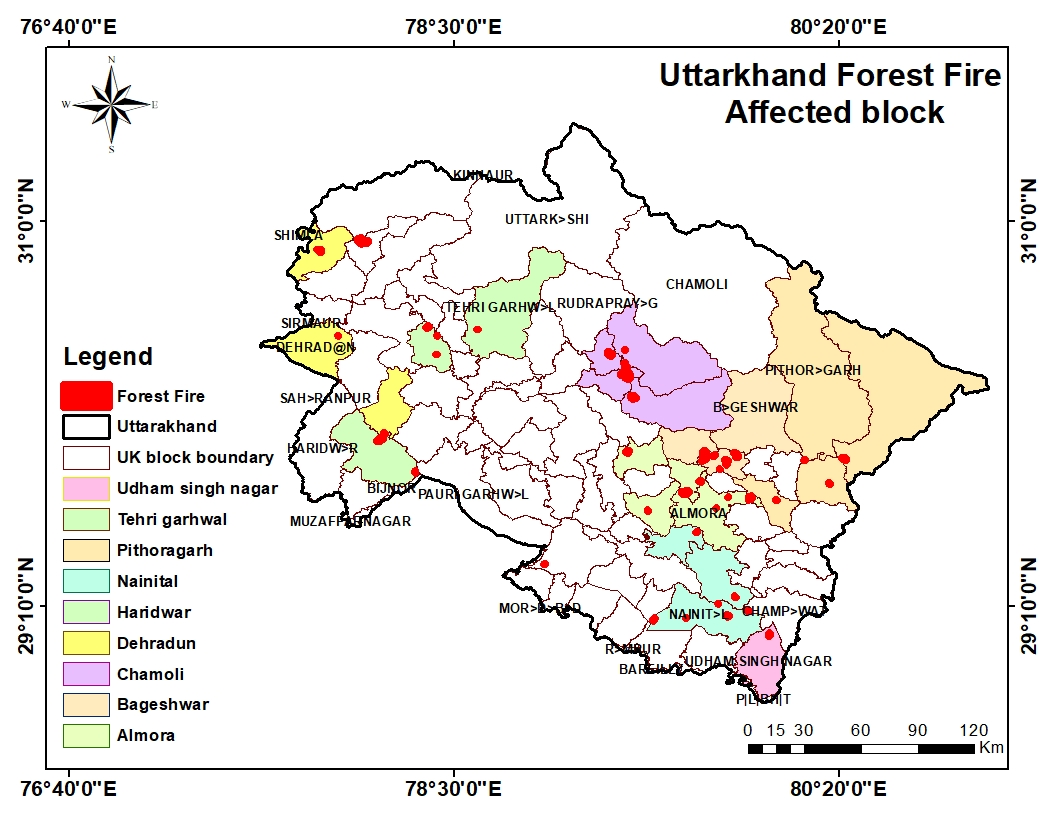
1. **MATERIAL AND METHODS**

**2.1 Study Area**

The study was carried out in the Uttarakhand State of India (Fig 1). It is situated on the southern slope of the Himalayan range, spanning 53,483 km2 and lying between latitudes 28° 44' and 31° 28' N and longitudes 77° 35' and 81° 01' E. Uttarakhand can be categorised geographically into three zones: The Terai region, the Siwaliks, and the Himalayas. Uttarakhand's climate is distinctly divided into two zones: the limited lowland plains and the predominantly hilly terrain that constitutes the majority of the state. The state is characterised by steep slopes, extensive snow-covered regions, and predominantly mountainous topography. Uttarakhand's climate is distinctly divided into two zones: limited lowland plains and the predominantly hilly terrain that constitutes the majority of the state. The southern foothills experience a subtropical climate with summer temperatures of roughly 30°C and winter temperatures of roughly 18°C. The Middle Himalayan valleys experience warm, temperate weather, with summers typically hitting around 25°C and winters being milder. In the highest regions of the Middle Himalayas, cool temperate weather predominates. Summer temperatures often range from 15°C to 18°C, while winter temperatures fall below freezing. According to ICFRE (2013), the state receives about 1,547 mm of rainfall on average per year. The State's total area covered by forests is 24,305 km2, or 45.44% of its total land area. According to forest canopy density classes, the State has 6,482 km2 of Open Forest (OF), 12,768 km2 of Moderately Dense Forest (MDF), and 5,055 km2 of Very Dense Forest (VDF) (Forest Survey of India, 2021).



(a)



(b)

**Fig. 1 (a) Map of Uttarakhand and location of 42 burn sites (b) Map of Forest Fire-Affected Blocks in Uttarakhand**

**2.2 Data**

Official data concerning forest fires, including specific locations and dates, has been made available for the study region by the Forest Research Institute (FRI). Utilizing GPS technology, burnt plots were identified and polygons were created accurately delineating boundaries of the burned areas. This dataset includes 42 forest sites vulnerable to forest fire; many additional variables such as forest type, district, division, block/range, beat, and the forest canopy cover and its degree of damage have been included. The area measurement measures the extent of the areas that have been targeted for burning and the FCM deals with the burnt areas and the remaining forest. The table 1 categorizes five forest types and analyses the extent of fire-affected areas, highlighting regions with extreme and moderate burn severity. This classification illustrates the varying degrees of fire impact across different forest ecosystems.

Table 1 Description of total burnt sites according to forest types

|  |  |  |  |
| --- | --- | --- | --- |
| **S. No.** | **Forest type** | **Burnt Severity** | |
| **Moderately Burnt** | **Low Burnt** |
| **1.** | Group 3- Tropical Moist Deciduous Forests | 4 | 2 |
| **2.** | Group 5- Tropical Dry Deciduous Forests | Nil | 2 |
| **3.** | Group 9 -Subtropical Pine Forests | 18 | 2 |
| **4.** | Group 12- Himalayan Moist Temperate Forests | 9 | 2 |
| **5.** | Group- TOF/Plantation | 1 | 2 |
| **Total** | | **32** | **10** |

The method of estimating vegetative indices was performed in a number of steps. First of all, the landsat 8 pre and post fire images of the year 2019 with a cloud cover percentage of less than 10% were downloaded from Earth Explorer. To remove atmospheric distortions and errors from the satellite data, an atmospheric correction was performed using ACP plugin in QGIS 3.34.11. The ArcGIS applications were consequently used for the interpretation of the data sets respectively. Four different vegetation indices were computed from bands 4, 5, 6 and 7 which were used in this study.

**2.3 Analysis of Vegetative Indices and Computation**

Out of the several spectral indices and image processing methods that have been documented in the literature, we have chosen four distinct methods that were created for the Landsat sensors and are frequently employed to determine the extent of burns. For every Landsat data set, VI equations were used (Table 2). Lastly, SI values were estimated at each of the 42 burned sites from the newly formed layers.

Table 2List of Vegetative indices *Red* = visible red Landsat TM band 4; *NIR* = near infrared Landsat TM band 5; *SWIR* = shorter shortwave infrared Landsat TM band 6; *lSWIR* = longer shortwave infrared Landsat TM band 7.

|  |  |  |  |
| --- | --- | --- | --- |
| **Vegetative Indices** | **Abbreviation** | **Equation** | **Reference** |
| Normalized Difference Vegetation Index | NDVI |  | Rouse et. al. (1974) |
| Normalized Burn Ratio | NBR |  | Key & Benson 2006, Lopez & Caselles 1991, Koutsias & Karteris 2000 |
| Normalized Difference Moisture Index | NDMI |  | Wilson & Sader 2002; |
| Modified Soil Adjusted Vegetation Index | MSAVI |  | Qi et. al. (1994) |

NDVI is an index that measures the change in the level of greenness of vegetation, NBR determines the level of burn, NDMI helps in the determination of moisture content of vegetation and MSAVI reduces the effects of soil on vegetation cover analysis on less vegetated areas. Therefore, these certain indices are used in tandem due to their ability to fully demonstrate fire, and post-fire recovery mechanisms. Their efficiency has also been demonstrated in the contexts in which fire-impacted forest ecological change has been unit of measure in numerous studies. All of the abbreviations used in this section, along with the VI equations and literature references, are presented in Table 2 and the accompanying legend. The indices that were chosen are described in the following sections.

The significance of each vegetation index (VI) in differentiating pre-fire, and post-fire, and also the Change in VI values could be understood through the various statistical metrics that measure the spectral distance of two distributions. Among these, the M-statistic was found to be the most powerful of all parameters in measuring class separateness. This statistic is the difference between the two classes' means (μ) and standard deviations (σ). The M-statistic can also be seen as a form of signal to noise ratio. Here the signal is the difference between the means while the noise is the sum of standard deviations. The degree of separation between two distributions is computed quantitatively by the M-statistic and hence provides an objective way of evaluating vegetation indices as change detection factors. It was revealed in the analysis that with highest M-statistic, separateness as well as degree of relative changes increases. Alternatively, with a lower M-statistics it was note that class separateness as well as the degree of relative changes were also reduced. The M-statistic has already found application and been employed by many researchers in the area of fire effect and burned area discrimination, in some well-known works (Melchiori et. al., 2015; Lasaponara 2006, Libonati et. al., 2011; Smith et. al., 2007). The *M*-statistic is expressed as

*Equation* (1)

Where: n is the number of sites, the numerator represents the difference between mean pre and post fire values and the denominator represent the sum of standard deviation between mean pre and post fire values.

**2.4 Modified Formula for Pre and Post-fire Vegetative Indices**

Equation (2)

Equation (3)

Equation (4)

Equation (5)

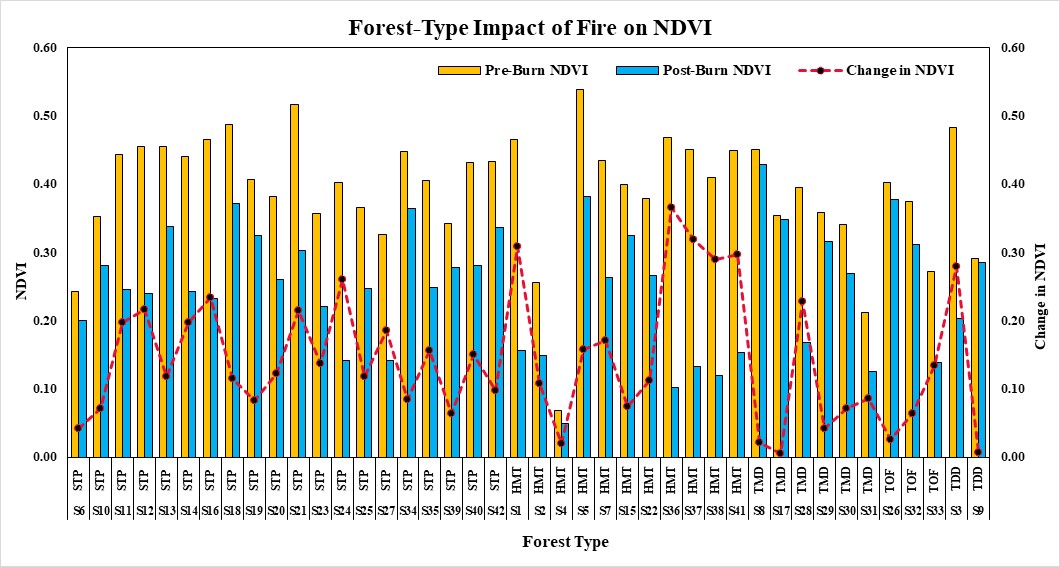
Here: Mpre and Mpost are M-Statistics for Pre and Post-fire.

**3. Results and Discussion**

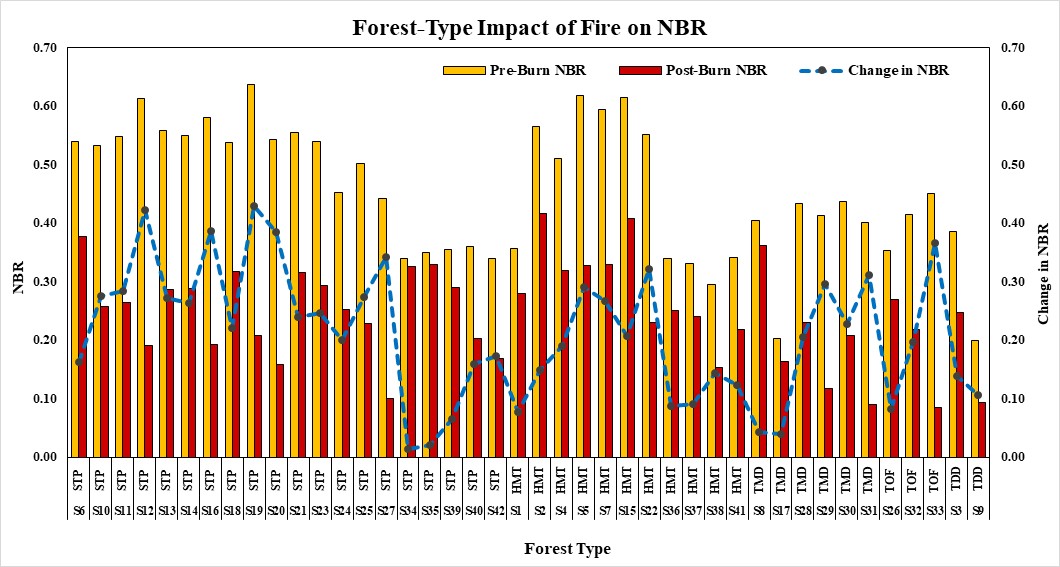
**3.1 Response of Vegetative Indices**

Figure 2 depicts the trends of vegetative indices (NVDI, NBR, NDMI, MSAVI) over different areas S1 to S42, where burned area values are represented using bar graphs and the change of the mentioned indices is presented using line graphs, where the effect of forest fires on the vegetation properties such as health, moisture and coverage is established. The analysis of vegetative indices (NDVI, NBR, NDMI, and MSAVI) unveils the consequences of forest fires affecting across different sites S1 to S42. The pre-burn NDVI values were between 0.07 and 0.54, with highest at S5, while S4 had the lowest, while the post-burn NDVI values range from 0.05 to 0.43, the highest being S8 and the lowest remaining at S4. The most significant change in NDVI, which constitutes a remarkable 0.37, was at S36, wherein S36, S37, S1, S41 and S38, sustained the highest level of vegetation loss. Pre-burn NBR values are also within the range of 0.20 and 0.64, including the highest values at S19, S5, S15 and S12, and the lowest NBR value at S9, showing limited vegetation cover. Post-burn NBR values decline significantly, found between 0.42 to 0.08, highest values were noted for sites S2, S15, S6 and S8, which are also subjected to the most intense fire. The NDMI values, which reflects soil moisture content, show a significant decrease after fire, with pre-burn, values ranging from -0.012 to 0.685 highest at S39 and lowest at S8, post burn value ranges from -0.09 to 0.30. Most NDMI changes, which are around 0.66, occur at S19, S39, S36 and S12 indicating severe moisture depletion. The MSAVI, which measures vegetation density or greenness, also shows substantial impacts, with pre-burn values highest at S21, S18, S3, and S16, and post-burn values lowest at S35, S4, S34, and S9. The largest changes were around 0.47 for S35 corresponding to the site as most effected. As a group these indices demonstrate the importance of the vegetation decline, estimates burn severity, moisture losses, density changes after forest fire, offering essential information for monitoring post-fire recovery, forest management and supervisory restoration efforts.

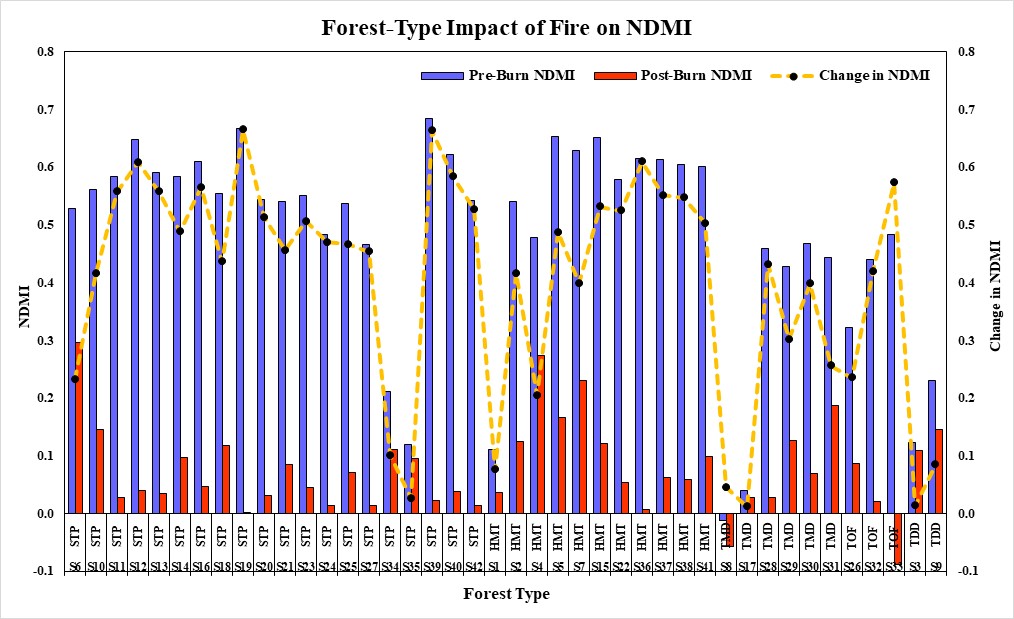
The figure provides a through comprehensive overview of how forest fires affect vegetation health, burnt severity, and moisture content as determined by various vegetation indices namely NDVI, NBR, NDMI, and MSAVI in various forest types and locales. The different forest types include Himalayan Moist Temperate (HMT), Subtropical Pine (STP), Tropical Moist Deciduous (TMD), Tropical Dry Deciduous (TDD) and Tree outside the Forest (TOF). NDVI, which measures the greenness of vegetation, indicates a decrease in post burn for all sites signifying the loss of vegetation due to fire. It shows that there is a larger loss of vegetation in the HMT forest type especially in the regions S36, S37, and S1 indicating these regions had the most depleted vegetation. Similarly, the highest NBR declines are seen in STP forests (e.g., S19, S12, S16) and TOF forests (e.g., S33). This is because NBR is sensitive to changes in vegetation structure and soil exposure brought on by fire, these alterations highlight the intensity of burns in these sites. This is consistent with pine biomass's high flammability, which promotes rapid fire spread and damaging effects. The vegetation moisture content is measured by NDMI, which makes it a crucial indicator for evaluating the impact of fire. Two types of forests have had a noticeable drop in NDMI after the fire, but Sub-Tropical Pine (STP) especially those at sites S19 and S39 have seen the sharpest drops. Additionally, there is a noticeable change in HMT forests, including site S36, suggesting that there was a significant reduction of vegetation moisture in these areas during the fire. Significant decreases in MSAVI, are seen at STP forest, especially at S35 and S16, whereas at TMD S8 is also affected by fire, these sites experienced the biggest alterations, suggesting a severe fire impact and showing a drastic decrease in the health of vegetation after the fire. In the Himalayan Moist Temperate (HMT), site S2 exhibits a higher MSAVI, indicating localized loss of vegetation. The data visualization reveals that STP sites are the most severely affected by fire, displaying the greatest changes in NDMI. Specific locations within HMT and TOF follow in terms of impact, while TMD and TDD forest types show more subdued effects.



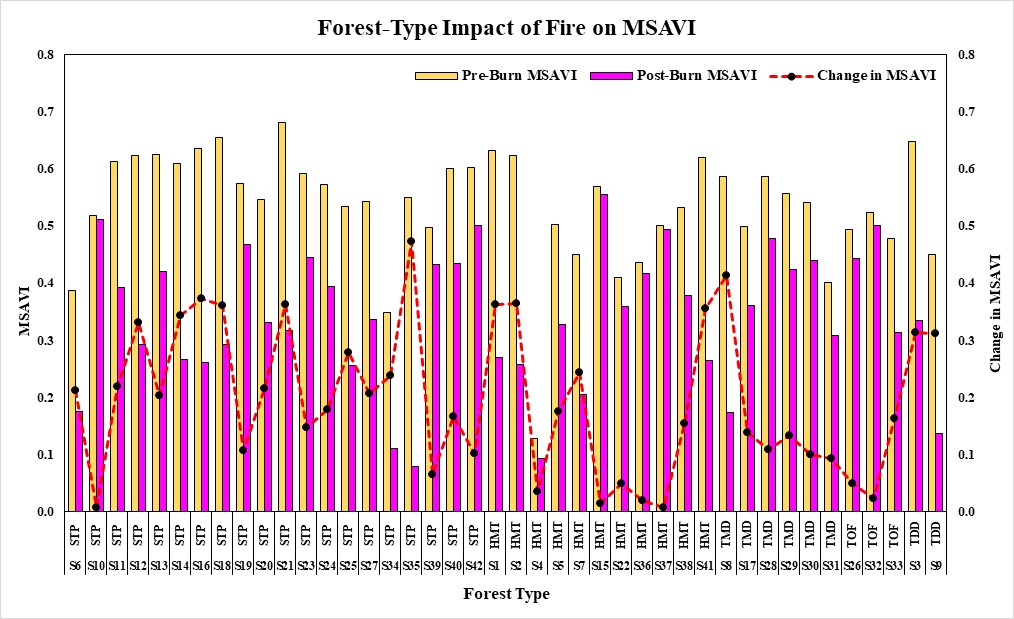
(a)



(b)



(c)



(d)

**Fig. 2 Spectral Indices changes over forest type and sites: pre- and post-fire, and change in Vegetative indices. The plots represent 4 vegetative indices values for the pre, post fire and change in VI of all sites (a) Forest type impact of fire on NDVI (b) Forest type impact of fire on NBR (c) Forest type impact of fire on NDMI (d) Forest type impact of fire on MSAVI**

**3.2 Response of M-Statistics and Statistics Summary**

Table 3 exhibited a separability index (M-statistic) for the four VI and figure 3 exhibited statistical summary for vegetative indices. The four vegetation Indices for 42 burnt sites of Uttarakhand react differently to forest fire and show dissimilar patterns. These patterns can be observed in the VI trajectories, and can be quantified by comparing the values of *M*-statistic. Among them, we can notice that STP and HMT tend to more effected by forest fire. This pattern is found in all the VI. All plots were burned during the dry season between 2019 and 2020, which is described as one of the most severe forest fires in Uttarakhand. The extreme climate conditions had a significant impact on vegetation and soils, such as pronounced decreases in moisture content. The primary cause of forest fires in Uttarakhand is the accumulation of dry biomass from pine trees, which is highly flammable. This dry matter acts as a potent fuel, making it easier for fires to ignite and spread rapidly. The situation is further aggravated during the dry season, characterized by heatwaves and rising temperatures, which create ideal conditions for forest fires to occur.

The M-statistics for the spectral indices NDVI, NBR, NDMI, and MSAVI give more insight on their separability and also their effectiveness in assessing the vegetation’s overall change due to fire. Immediately after the fire incident, as observed over the 42 burnt sites, NDMI was found to change greatly from a mean of 0.142 before the fire to a mean of 0.994 after the fire. The very high value of M (1.55) that measures separability indicates that NDMI has increased capacity to detect changes in moisture content and assess fire severity. This is consistent with its use in estimating post-fire increase or decrease in moisture content. NBR that was developed specifically to measure fire severity also had very good separability with a magnitude of change of 1.05. Its performance underscores its reliability in locating and mapping of burn areas and burn severity accurately. MSAVI, which adjust for soil background impacts, also performed well by M value of 0.88, which means moderate sensitivity to changes in vegetation due to fire in sparse/soil-dominated areas. On the other hand, NDVI showed an M value of 0.81 and this can be explained as good separation for areas characterized by vegetation being lost and recovering being strong. NDVI's sensitivity to green vegetation highlights its role in capturing the initial reduction in biomass and subsequent regrowth. Overall, the various indices showed degrees of separability and ecological sensitivity, with NDMI outperforming better than the other indices moisture content detection and NBR did much better in terms of mapping the burn severity index. The computed M-statistics validate the selection of these indices for post-fire impact assessment, which findings have earlier been reported by Key and Benson, 2006 that emphasize their usability in fire-prone ecosystems. Together, these indices augment the understanding of fire behavior and the pattern of recovery of the affected ecosystems.

The graph illustrates the statistical data for vegetative indices denoted as NDVI, NBR, NDMI and MSAVI with respect to six measures of central tendency: i.e. mean, standard deviation, sample variance, coefficients of skewness and kurtosis including confidence level. The mean NDVI is low (0.14) implying negative kurtosis of -0.55 which means that such a distribution is with thin tails. The NBR best performed demonstrating the greatest range and also highest skewness at 0.55. This signifies that the results are variable and asymmetrical. NDMI has a skewness of 0.47 which is just moderate coefficient therefore other factors must be consider, NDMI shows low (-0.28) kurtosis of which leans on slightly skewed distribution. MSAVI returns the best value of the coefficient of skewness at 0.26 and extreme -1.00 for the coefficient of kurtosis; this essentially means that heavy-tailed data is expected. Based on the statistical description, NBR appears to be the most effective for distinguishing burn severity due to its high variance and skewness, which signify its sensitivity to changes in burn severity conditions.

Table 3. Separability index (*M*-statistic) for the four VI

|  |  |  |  |
| --- | --- | --- | --- |
| **M-Statistic- 42 Burnt Sites (Mean)** | | | |
| **Spectral Index** | **Pre-Fire** | **Post-Fire** | **Changes in VI** |
| NDVI | 0.050 | 0.130 | 0.81 |
| NBR | 0.061 | 0.116 | 1.05 |
| NDMI | 0.142 | 0.994 | 1.55 |
| MSAVI | 0.035 | 0.124 | 0.88 |

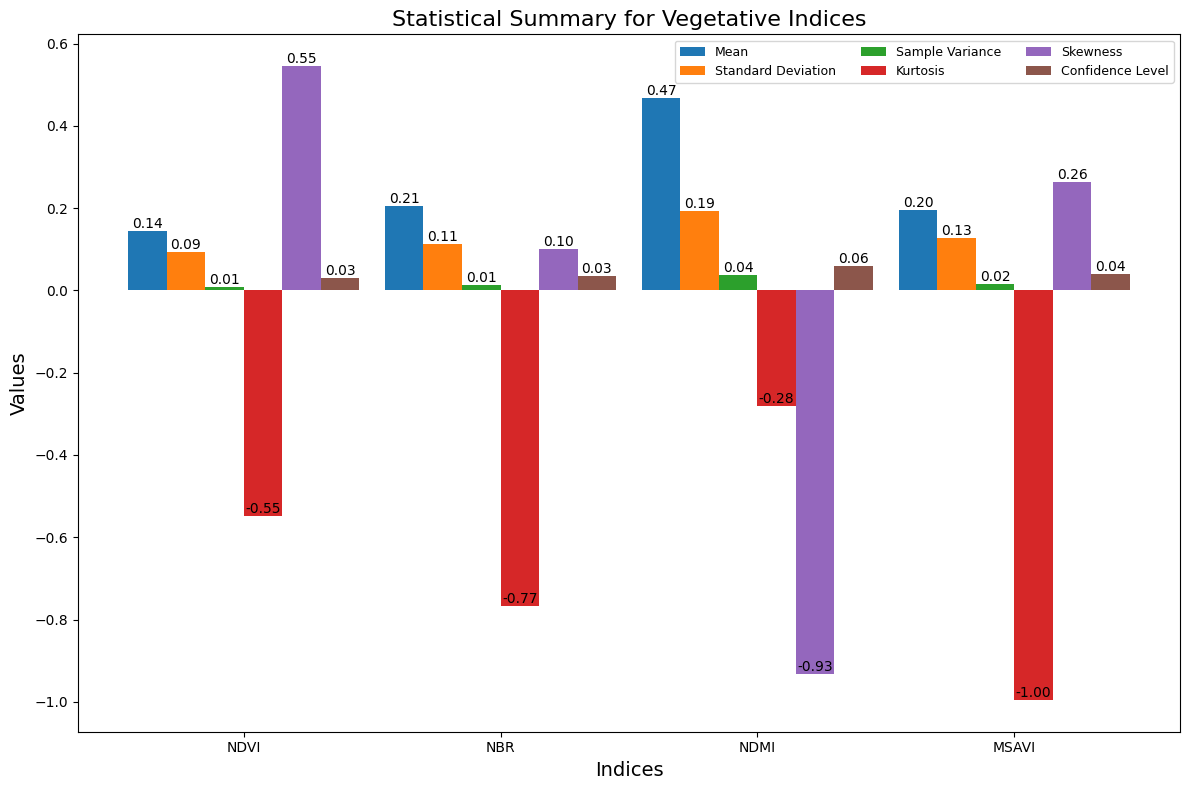


Fig. 3 Statistical Summary for vegetative indices

1. **Conclusion**

This study provides an in-depth analysis of the effects of forest fires on vegetation health, burn severity, and moisture content across different sites and forest types. The study evaluates four important vegetative indices, include MSAVI, NDMI, NBR, and NDVI to assess the spatial and temporal dynamics of ecosystems impacted by fire. The analysis revealed significant differences in vegetation indices before and after the fire occurrences. We observed a significant decline in NDVI values, which reflect vegetation greenness, which was consistently seen across all the sites. The greatest loss was found in Himalayan moist temperate (HMT) forests, indicating destructive vegetation damage at these sites. NBR applied to mapping burn severity also shows significant decline, especially in STP and Tree Outside Forest (TOF) sites showing higher values, indicating regions of destructive fire impact. NDMI, as a measure of soil moisture content, revealed drastic alterations after the fire particularly in STP forests, indicating the impact of fires on soil moisture. MSAVI, as a well-known implicit, which is sensitive to vegetation cover and bare soil, also displayed a sharp reduction in STP sites, thus confirming the extensive impact to forest ecosystem. Statistical analysis, including M-statistics and data analysis revealed that NDMI was the most sensitive index to post-burn moisture changes, while NBR was the most reliable index capable of predicting burn scars. having higher application in the assessment of vegetation cover loss and extent of the burn area respectively and NDMI being superior in the estimation of the moisture content. assessment. These observations suggest that the application of these indices complements each other in the post fire evaluation and management of forest resources. In this way complementing each other in the case of how best to plan the rehabilitation efforts.

This research shows the interesting relationship between vegetation burning, burn severity caused by forest fires and soil moisture of diverse forest ecosystem. Aspects of vegetative change caused by fire could be evaluated with NDVI, NBR, NDMI, and MSAVI as vegetation health indicators. Among the indices, NDMI was the most sensitive to moisture deficiency that followed the fire and NBR was relatively the most appropriate for burn severity mapping especially in STP and HMT forests which were the most affected. Different index values which were obtained after the fire in the forest indicating that fire has different effects in different forest types, STP forests were the worst damaged with the most vegetation cover and moisture loss. The usage of the indices was confirmed in the statistical analysis, NBR performed well for burn severity analysis with a high degree of separability, while MSAVI did well when changes in vegetation were detected. Overall, the study highlights the importance of using multiple indices to gain a holistic understanding of fire impact assessments and in the design of strategies for rehabilitation, monitoring and management of the forests after forest fire. These findings point towards increasing recognition of the need for distinct strategies for forest management and restoration taking into consideration the different levels of damage inflicted by fire to various forest types.

**CONSENT (WHERE EVER APPLICABLE)**

NOT AVAILABLE (N.A.)

**ETHICAL APPROVAL (WHERE EVER APPLICABLE)**

NOT AVAILABLE (N.A.)

**Disclaimer (Artificial intelligence)**

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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