

FOREST FIRE BURNT AREA EXTRACTION USING FUZZY INTEGRATION OF MULTI-SENSOR SATELLITE DATA FOR THE HIMALAYAN STATE

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KEY WORDS: Burnt area, Forest Fire, Fuzzy Logic, Characterization, Multi-sensor, Remote Sensing

ABSTRACT:

Burnt area assessment due to forest fires is an important aspect to estimate the extent of loss of biodiversity which has become feasible even in hilly and inaccessible areas with the help of geospatial technologies. But satellite data also has some limitations as it increases commission error by misclassifying non-burnt areas as burnt areas. To reduce this commission error, present study has attempted to integrate multi-sensor satellite data to characterize and extract forest fire burnt areas in Uttarakhand which is a fire prone hilly state in Western Himalaya. Landsat-8 and Sentinel-2 optical datasets have been used to calculate eleven vegetation/burn indices to identify burn patches for fire season of 2022 (February to June). These vegetation/burn indices have been calculated from Landsat-8 and Sentinel-2 datasets and integrated using Fuzzy Logic Modelling to get characterized forest fire burnt area maps. Accuracy assessment has been done using Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) active fire points for the characterized map of burnt area by Landsat-8, Sentinel-2 and combining indices from both sensors. The fuzzy map of burnt area using Landsat-8 showed the accuracy of 66.25%, while Sentinel-2 showed accuracy of 59.79% and the integration of fuzzy burnt area maps of both sensors showed the highest accuracy of 79.66%. This information of characterized burnt areas of a region can help forest managers to identify high vulnerable areas to focus on during the fire season to prevent the losses to natural resources, life and property in the region.

1. INTRODUCTION

Forest fire can pose threat to the biodiversity of the region either caused by natural or anthropogenic activities. Warming of the earth surface along the years have increased the frequency as well as the severity of the forest fires which has made it more important to evaluate the damage caused by the forest fire (Ryan, 2002). Assessment of the areas burnt due to forest fires is an important aspect to estimate the extent of loss of biodiversity and to monitor Land Use and Land Cover change (Shrestha et al., 2012). Forest fires generally occur over a large area which takes a lot of financial and human resources to estimate the damage caused by it. With the use of advanced geospatial tools, it has now become feasible to estimate the burnt area in the regions having complex terrain or are inaccessible (Key & Benson, 2006).

Several techniques have been used for burnt area assessment such as image classification (Zidane et al., 2021), indices-based methods (Liu et al., 2021), machine learning approach (Bastarrika et al., 2011), etc. Himalayan vegetation is highly prone to the forest fires due to the significant presence of pine forests. The loss of vegetation, having of char on the

leaves, changes in the moisture content of the soil and fuel, and other factors cause noticeable changes in the reflectance values, which are used to map the burn severity using satellite data.

Alves et al., (2018) have attempted to derive multispectral information from the forest fire-affected areas by fusing the optical imageries from Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) data over the tropical savannah in Brazilian Amazon. They have used Flexible Spatiotemporal DATA Fusion (FSDAF) algorithm by generating 60 fusion-derived images with good accuracy levels. Using a pixel-based random forest image classification approach, Abdikan et al., (2022) have combined data from optical sensors, thermal sensors, and Synthetic Aperture Radar (SAR) sensors to derive burnt area information from the Turkish Red Pine Forest in a Mediterranean Ecosystem. In their study, they demonstrated how features from Landsat LST, the burn index, and the coherence of L-band SAR data can be combined with several sensors.

The spectral reflectance characteristics of healthy vegetation and burnt vegetation or scar can be used for burnt area assessment. For forest fire detection, thermal differences

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between burning and background pixels have been studied by Giglio et al., (2018) and is frequently used. The thermal infrared bands on satellite sensors like MODIS, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Visible Infrared Imaging Radiometer Suite (VIIRS) can detect forest fires but at a coarse resolution that make the task of forest fire monitoring at regional scale challenging.

Major limitation of using optical dataset for the burnt area extraction is that it often misclassifies other regions also as burnt area such as cloud cover, cloud shadow, etc. which leads to its overestimation. To address this limitation, multi-sensor satellite data can be integrated to identify the areas affected by forest fire (Stroppiana et al., 2015). Geospatial data offers numerous benefits over traditional methods to monitor forest fires and estimate burnt areas at local, regional and even larger spatial scale along with multi-temporal scales. Medium-resolution sensors like the Landsat series and Sentinel-2A and 2B, provide free satellite imageries that are widely used for surface monitoring and burnt area assessment. These imageries can be used to quantify the burn severity of the areas affected by forest fires by utilizing the spectral information provided by these sensors related to vegetation characteristics, soil properties etc. (Keeley, 2009).

The present study has attempted to integrate multi-sensor satellite data to characterize and extract forest fire burnt areas in Uttarakhand state of India, a fire prone hilly state located in the Western Himalayan region. Multi-sensor data have been used to utilize the unique characteristics of both the sensors to estimate the spectral signature of different levels of burn severity. Medium resolution Landsat-8 and Sentinel-2 optical datasets are used to calculate various vegetation/burn indices to identify burn patches for fire season of 2022 which is from February to June. The vegetation/burn indices involve use of spectral bands in different regions like visible region, near infra-red region, short-wave infrared region and thermal region. There is no consensus about which vegetation/burn index is most suitable to assess burn severity, so multiple indices have been calculated in this study. Eleven vegetation/burn indices are calculated from both the sensors and integrated together using Fuzzy Logic Modelling approach, which is a logical mathematical procedure.

2. STUDY AREA

The present study involves the forest fire burnt area extraction in the forests of Himalayan state, Uttarakhand. It is a highly fire prone area due to the presence of sub-tropical pine forest and the pre-monsoon dry weather conditions. It is a hilly state in Western Himalayan region, situated on the northern part of India (Figure 1). It covers the geographical area of 53,483 square kilometers. It shares the international border with Nepal in the east and Tibet and China in the

north, while national border with Himachal Pradesh in the west and Uttar Pradesh in the south.

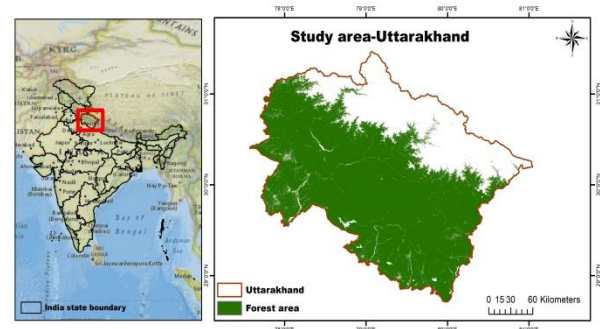


Figure 1. Study area map

It has huge diversity in the flora and fauna with approximately 45% of the area covered with forests out of which around 33% is moderately to extremely fire prone (ISFR, 2019). Fire proneness of the forests in Uttarakhand is primarily due to the presence of sub-tropical pine forests. Dry pine needles are very flammable in nature (Gupta et al., 2018) which makes it very easy to catch fire during the pre-monsoon or dry season in Uttarakhand that is from February to June every year.

3. MATERIAL AND METHOD

3.1 Dataset used

In this study, medium resolution satellite datasets of Landsat-8 and Sentinel-2 have been used to calculate various vegetation/burn indices to identify burn patches in Uttarakhand for the forest fire season of 2022 which is from February to June. These satellite datasets have been retrieved from the data catalogue of Google Earth Engine (GEE) (Gorelick et al., 2017) which provides Level-1C orthorectified top-of-atmosphere reflectance and Level-2A orthorectified atmospherically corrected surface reflectance data for Sentinel-2 and atmospherically corrected surface reflectance, calibrated top-of-atmosphere (TOA) reflectance and raw images with DN values, representing scaled, calibrated at-sensor radiance for Landsat-8.

Active fire data provided by MODIS and SNPP VIIRS have been downloaded from Fire Information for Resource Management System (FIRMS-https://firms.modaps.eosdis.nasa.gov/active_fire/) and used for the validation of the results. It has been downloaded for the same time period i.e. fire season of 2022 for Uttarakhand state shown in Figure 2.

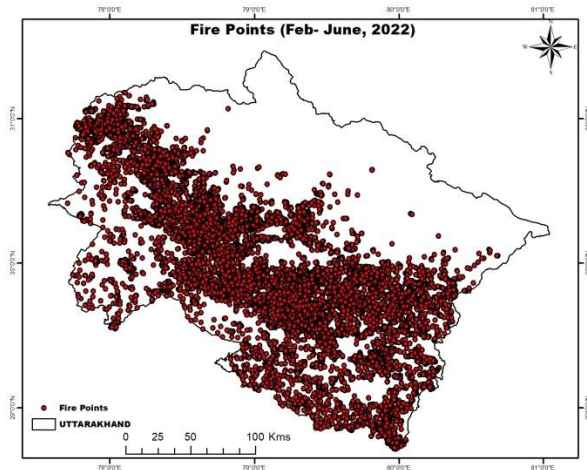


Figure 2. Active fire locations for February-March, 2022 in Uttarakhand

3.2 Methodology

To extract the forest fire burnt areas using multi-sensor satellite data, Landsat 8 Operational Land Imager (OLI) data and Sentinel 2 MSI data have been used. These datasets have

been retrieved using GEE, which provides a cloud computational platform. The data has been retrieved for the fire season of 2022 for Uttarakhand region and masked for the forest areas using Normalized Differenced Vegetation Index (NDVI) thresholding method. The vegetation/burn indices involve the use of spectral bands in different regions like visible region, near infra-red region, short-wave infrared region and thermal region. As there is no consensus about which vegetation/burn index is most suitable to assess burn severity, so multiple indices have been calculated in this study. A total of eleven vegetation/burn indices are calculated for Landsat-8 and 10 for Sentinel-2 data (Table A1) using GEE which is based on JavaScript programming language (Shelestov et al., 2017).

Normalized Burn Ratio Thermal (NBRT) has not been calculated for Sentinel-2 due to the lack of thermal band. Other indices calculated include Burn Area Index (BAI), Enhanced Vegetation Index (EVI), Char Soil Index (CSI), Two-band EVI, Mid-Infrared Burn Index (MIRBI), Normalized Burn Ratio (NBR), Normalized Burn Ratio 2, NDVI, Soil Adjusted Vegetation Index (SAVI) and Normalized Burn Ratio Plus (NBR+).

S. no.	Dataset	Spatial resolution	Temporal resolution	Time-period
1	Sentinel-2	10 m	5 days	2022 (Feb-June)
2	Landsat-8	30 m	16 days	
3	Active fire points	MODIS-1 km SNPP-VIIRS-375 m	Daily	

Table 1. Details of the geospatial datasets used in the study

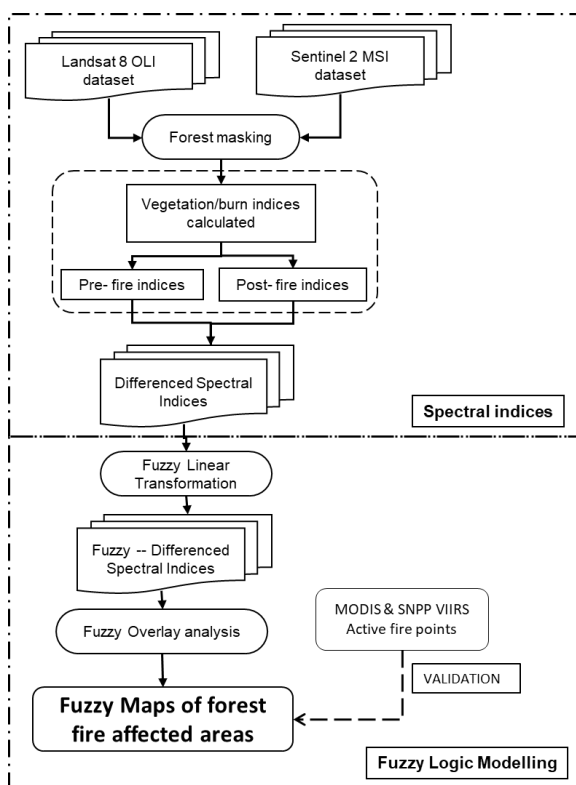


Figure 3. Methodology flow chart

All the spectral indices calculated have different value ranges to highlight the different levels of burn severity, so before integrating them together, it is an important step to normalize the values in a uniform range. So, the indices have been converted to fuzzy membership function to get the probability of burnt area in the range 0 to 1 (Figure 3). The fuzzy membership function for each index for both the sensors are then integrated using Fuzzy Logic Modelling by fuzzy overlay analysis to get the characterized forest fire burnt area maps. These maps have been validated for their accuracy using the active fire points provided by the MODIS and VIIRS. These active fire points can be downloaded from the FIRMS website in the form of CSV, KML or shapefile. For this study, active forest fire points in the format of shapefile have been downloaded for the fire season of 2022 for Uttarakhand.

4. RESULTS AND DISCUSSION

Integration of multi-sensor satellite data for the characterization of the forest fire burnt areas shows that the areas which are marked as highly affected by forest fires with high burn severity from Landsat-8 as well as Sentinel-2 are

retained in the integrated map thereby reducing the commission error.

Burnt area extraction using Landsat-8 and Sentinel-2

Burnt area extraction has been done firstly individually for each of the sensor. Since, there is no crisp boundary defined for the indices to discriminate between burned and unburnt areas, so fuzzy linear transformation has been done to normalize the values ranging from 0 to 1. Fuzzy overlay analysis using AND has been done to integrate the transformed layers. The fuzzy burnt area map for Landsat-8 (Figure 4(a)) highlights that the part of Dehradun, Pauri and Nainital districts have the highest possibility of having high burn severity areas. These areas frequently experience forest

fires every year during the forest fire season (Bargali et al., 2017; Mamgain et al., 2022).

While fuzzy burnt area extraction for Sentinel-2 shown in Figure 4(b), highlights some patches in the mid-elevation zones also which are retained in the burnt area extraction using fuzzy integration of multi-sensor data of Landsat-8 and Sentinel-2. Visual interpretation of the output fuzzy burnt area maps from both sensors shows that Landsat-8 output is slightly overestimating the burnt areas and thus has a high commission error while Sentinel-2 output emphasizes on the patches of parts of Uttarakhand forest. This variation can be due to differences in the spatial and radiometric parameters of both sensors

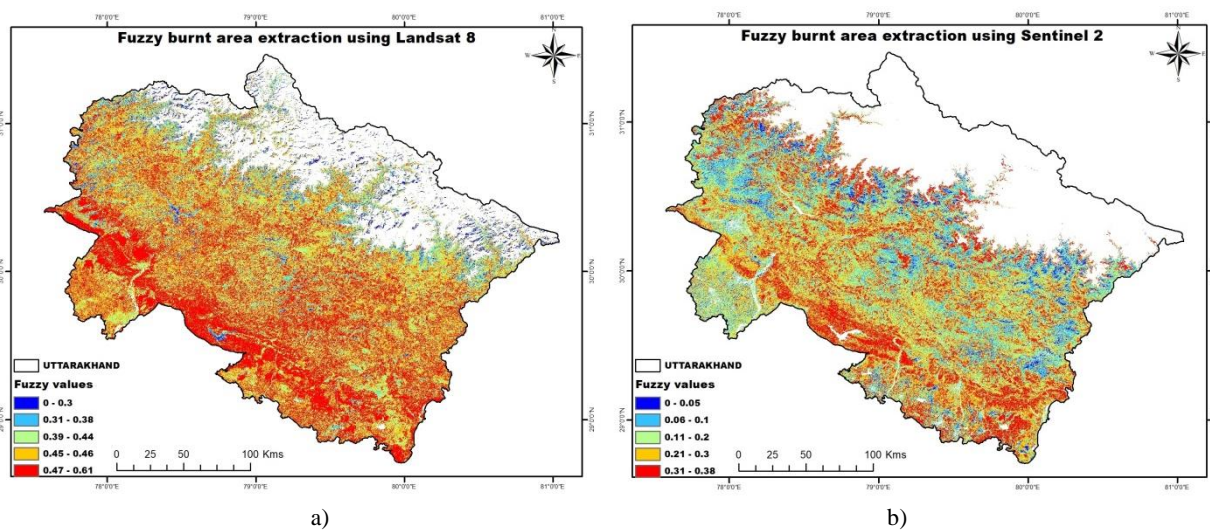


Figure 4. Fuzzy burnt area extraction using a) Landsat-8 and b) Sentinel-2

Integrated burnt area map from multi-sensor satellite data

Burnt area estimation by integrating multi-sensor imageries from both sensors i.e. Landsat-8 and Sentinel-2 has been done using AND approach of fuzzy overlay analysis which highlights the areas characterized as high burn severity probable areas from both the sensors. Figure 5 shows the integrated fuzzy burnt area map that highlights the forest areas in Uttarakhand that are prone to forest fires at different severity levels. Integrated map of fuzzy burnt area can easily determine and characterize the high burn severity areas for the fire season of 2022. Since, the outputs area masked for the forest areas so non-forest areas are excluded. 2022 has been an unusually warm year for the Indian sub-continent and thus experienced severe forest fire episode and thus most of the forest area is showing moderate to high burn severity.

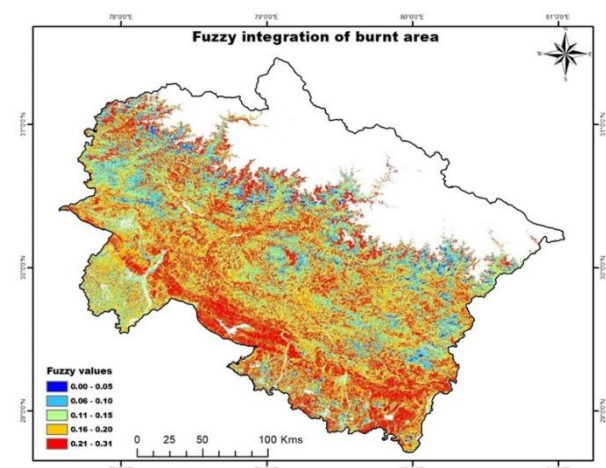


Figure 5. Fuzzy burnt area map from integrated multi-sensor data

Validation

Accuracy assessment has been done using MODIS and VIIRS active fire points for the characterized map of burnt area by Landsat-8, Sentinel 2 and combining indices from both sensors. The fuzzy map of burnt area extraction using Landsat-8 data showed the accuracy of 66.25% but high commission error can be observed through visual interpretation. While Sentinel-2 data showed the accuracy of 59.79% and the integration of the fuzzy burnt area maps of both the sensors showed the highest accuracy of 79.66%. Active fire locations for February to June, 2022 for Uttarakhand state (Figure 2) shows that the middle part of the state has the highest frequency of forest fires. A patch can be seen on the integrated fuzzy burnt area map near the waterbody present in the southern part of the state where very high probability of having burnt area can be seen as per the output. But the active fire locations are very less in this region, which could be because this region comes under the Corbett National park area and thus there is no anthropogenic activity allowed here and thus it can account for low forest fire occurrence here.

5. CONCLUSION

Forest fire burnt area extraction using geospatial data techniques can help in estimating the area damaged by forest fires even in the inaccessible areas. The present study, thus concludes that various vegetation/burn indices calculated from the optical datasets have the possibility of high commission error for extraction of burnt areas. This error can be reduced by integrating different indices and the multi-sensor data. The information of characterized burnt areas of a region can help forest managers to identify high vulnerable areas to focus on during the fire season to prevent the losses to the natural resources, life and property in the region.

DATA AVAILABILITY

In this study, publicly available optical datasets from Landsat-8 and Sentinel-2 have been used which has been accessed through GEE data catalogue using the links given below:

Landsat-8- https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_L2
Sentinel-2- https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED

ACKNOWLEDGEMENTS

We express our sincere thanks to Google Earth Engine for providing the necessary satellite datasets through its data catalogue and the platform for carrying out the current study. We are also thankful to Ms. Bhoomika Ghale, Ph.D. Scholar, IIRS, for reviewing this article and providing her invaluable comments.

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APPENDIX

Table A1. Details of various vegetation/burn indices calculated in the study. These indices have been calculated for Landsat-8 OLI as well as Sentinel-2 MSI sensors.

<u>S. no.</u>	<u>Vegetation/Burn Index</u>	<u>Formula</u>
1	Burn Area Index	$1/((0.1 - R)^2 + (0.06 - NIR)^2)$
2	Enhanced Vegetation Index	$2.5 * ((NIR - R) / (NIR + 6 * R - 7.5 * B + 1))$
3	Char Soil Index	$NIR/SWIR1$
4	Two-band EVI	$2.5 * ((NIR - R) / (NIR + 2.4 * R + 1))$
5	Mid-Infrared Burn Index	$(10 * SWIR2) - (9.5 * SWIR1) + 2$
6	Normalized Burn Ratio	$(NIR - SWIR2) / (NIR + SWIR2)$
7	Normalized Burn Ratio 2	$(SWIR1 - SWIR2) / (SWIR1 + SWIR2)$
8	Normalized Difference Vegetation Index	$(NIR - R) / (NIR + R)$
9	Soil Adjusted Vegetation Index	$(NIR - R)(1 + 0.5) / (NIR + R + 0.5)$
10	Normalized Burn Ratio Plus	$(SWIR - NIR - G - B) / (SWIR + NIR + G + B)$
11	Normalized Burn Ratio Thermal	$(NIR - (SWIR * T / 1000)) / (NIR + (SWIR * T / 1000))$

R- Red band, B- Blue band, G- Green band, NIR- Near Infra-red band, SWIR- Short Wave Infra-red band and T- Thermal band