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RESEARCH ARTICLE

Inter comparison of post-fire burn severity indices of Landsat-8 and Sentinel-2 imagery using Google Earth Engine

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Abstract

Forest fires are significant catastrophic events that affect the landscape and vegetation in forested lands. They cause loss of biodiversity, land degradation & ecological imbalance. As the forest fires cause extreme damage to the habitat, it is of utmost necessity to assess the impact of fire on canopy/vegetation. Post-fire assessment is an essential element for finding the effects of fire on vegetation and implementing mitigation strategies. In this article, a Post-fire burn severity assessment was carried out with high-resolution multi-spectral images such as Sentinel-2 and Landsat-8 employing Google Earth Engine (GEE) to locate the burnt areas and fire severity. Three commonly used fire severity indices based on pre-fire Normalized Burn Ratio (NBR) and post-fire NBR, namely differenced Normalized Burn Ratio (dNBR), Relativized Burn Ratio (RBR), and Relativized dNBR (RdNBR) are computed and compared based on their accuracy with the active fire points provided by MODIS & VIIRS. Both Sentinel-2 and Landsat-8 exhibited a similar trend in mapping burn severity. The RdNBR resulted in high accuracy over heterogeneous landscapes with 61.52% for Sentinel-2 and 64.1% for Landsat-8 followed by dNBR (41.67% for Sentinel-2 and 47.44% for Landsat-8) and weak performance by RBR with 32.69% for Sentinel-2 and 26.92% for Landsat-8. Hence RdNBR burn severity maps are considered highly appropriate for mapping burnt areas. Even though severity analysis from both Sentinel-2 and Landsat-8 is at an acceptable level, the Landsat based burn severity maps provided an adequate assessment of the degree of damage.

Keywords Burnt area mapping · Fire severity indices · Post-fire mitigation · dNBR · RBR · RdNBR · Active fire points

Introduction

Forests are the significant resources of ecology and biodiversity. Forest fires are the substantial repetitive hassle occurring in forested lands, leading to land degradation and deforestation (Venkatesh et al. 2020a). Deforestation causes the emission of harmful greenhouse gases other than carbon dioxide, affecting climate change, thereby creating a threat to humans (DeFries et al. 2007; Venkatesh et al. 2020b). For effective forest resources management, it is critical to assess the impact of fire on the ecosystem. The degree of change in the soil and vegetation caused by a fire is known as burn severity. Burn severity indices are used to assess the impact of fire and burnt area extent. Once a forest catches fire, a series of spectrum changes occur in remote sensing data, such as (i) the severity of fire incidence on vegetation destroys chlorophyll content leaving the soil bare, thereby altering the soil moisture. ii) Post-fire incidence, the reflectance in the mid-infrared portion of the electromagnetic spectrum increases whereas the reflectance in the near-infrared region decreases. This variation in the electromagnetic spectrum's spectral reflectance values makes it possible to determine the forest cover loss using remote sensing techniques. Burn severity analysis is crucial for the forest departments to mitigate fire and restore the affected areas after the fire season.

Several methods have been listed in previous scientific studies to assess the impact of fire Cocke et al. 2005; Adagbasa et al. 2018; Suresh Babu et al. 2018; Konkathi

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and Shetty 2019; Konkathi et al. 2019; Yathish et al. 2019 had assessed the burn severity using Landsat 7 ETM + imagery to detect the changes in forest fire structure and moisture content caused by the forest fire. Lutes et al. 2006 evaluated the changes in landscape due to fire as a part of the Fire Effects Monitoring and Inventory System (FIREMON) program using the differenced Normalized Burn Ratio and sampled the severity to different categories. Escuin et al. 2008 determined the scope of NBR to assess the impact of fire by splitting up into burnt and unburnt pixels as most suitable. The classification accuracies resulted from the comparison of classes with thresholds of dNBR and RdNBR information for individual fires may be almost similar. Miller and Thode 2007 found that mapping burn severity using relativized dNBR is more suitable in heterogeneous landscapes. As an alternative to the most commonly used dNBR and RdNBR, Parks et al. 2014 proposed a Relativized Burn Ratio (RBR) to assess the fire severity. With the development of numerous spectral indices for mapping burn severity, there is a need to compare these indices to evaluate the most suitable index for mapping burn severity.

Recently, a cloud-based platform, i.e., Google Earth Engine (GEE), was introduced to handle and process substantial geospatial datasets (Wagle et al. 2020). Very few studies employed GEE for forest fire monitoring and assessment studies and less pieces of literatures have inter-compared various fire severity indices using high spatial resolution sensors for assessing burn severity which is of high importance for implementing mitigation strategies (Rahman et al. 2018; Cardil et al. 2019; Konkathi and Shetty 2019). Studies are needed to determine the efficiency of Sentinel-2 imagery for mapping burn severity compared to Landsat imagery. In the present study, efforts have been made to map burn severity by inter comparing Landsat 8 OLI images and Sentinel − 2 imagery to obtain the fire severity and burnt area. The most commonly used fire severity indices namely differenced normalized burn ratio (dNBR), relativized burn ratio (RBR) and relativized dNBR (RdNBR) are computed and compared based on their accuracy concerning active fire points provided by MODIS and VIIRS.

Study area and data used

Kudremukh National Park in the Western Ghats of India spread across Chickmagalur, Udupi and Dakshina Kannada districts of Karnataka with a thick hilly forest near the coastal plains and huge shola vegetation towards the eastern portion. The Kudremukh National Park lies between latitude 13°01’00” N and 13°29’17” N, longitude 75°00’55” E and 75°25’00” E as shown in Fig. 1. The total area of the park is 780.009 km^2. The study area chosen is highly prone to fire based on historical data. Recently, Yathish et al. 2019 and Konkathi et al. 2019 predicted the fire susceptible zones in Kudremukh. To the best of our knowledge, no scientific studies have been reported to determine fire severity analysis, despite its importance as an eco-sensitive region.

The multi-spectral sensors namely Landsat 8 Operational Land imager (OLI) and Sentinel-2, are in rapid usage for many remote sensing applications due to their free availability. In the present study both Landsat 8 OLI and Sentinel 2 imageries are tested and compared to know their efficiency in computing the impact of fire. The Landsat 8 OLI acquires data in various bands of the electromagnetic spectrum. It contains 4 bands in the visible region, 1 band in the near-infrared region, 2 bands in the shortwave infrared region, 2 thermal bands, 1 circus band and 1 panchromatic image. The Landsat-8 is of 30 meters spatial resolution with a swath width of 185 km covering large portions of earth features. It has a temporal resolution of 16 days. Whereas Sentinel 2 has two satellites, namely Sentinel 2A and Sentinel 2B that acquires data in 13 bands of the electromagnetic spectrum from visible, NIR and SWIR regions. The spatial resolution of Sentinel 2 varies from 10 m to 60 m and has a temporal resolution of 5 days for Sentinel 2A and Sentinel 2B combination. A well-known cloud-based computing platform, namely GEE, was used to carry out burn severity analysis and perform batch operations. The historical fire hotspots (2005 to 2016) within the study area are analyzed to know the fire season, as shown in Fig. 2.

From Fig. 2, it is evident that most of the fires occur from January to May, therefore for the present study, the fire period is considered from January to May. As no data was available related to the fire occurrence in the region, the active fire points during the fire period acquired by Moderate Resolution Imaging Spectroradiometer (MODIS) Terra satellite (MOD14_NRT) and SUOMI NPP Visible Infrared Imaging Radiometer Suite (VIIRS) (VNP14IMGTDL_NRT) products data were downloaded from FIRMS NASA website (https://firms.modaps.eosdis.nasa.gov). These fire points are used to validate the burn severity maps. Table 1 displays the data used to generate burn severity maps.

Methodology

The area becomes extremely vulnerable to fire during the fire period. Hence there is a need for post-fire burn severity analysis. The flowchart of the methodology adopted for burn severity analysis is as shown in Fig. 3.

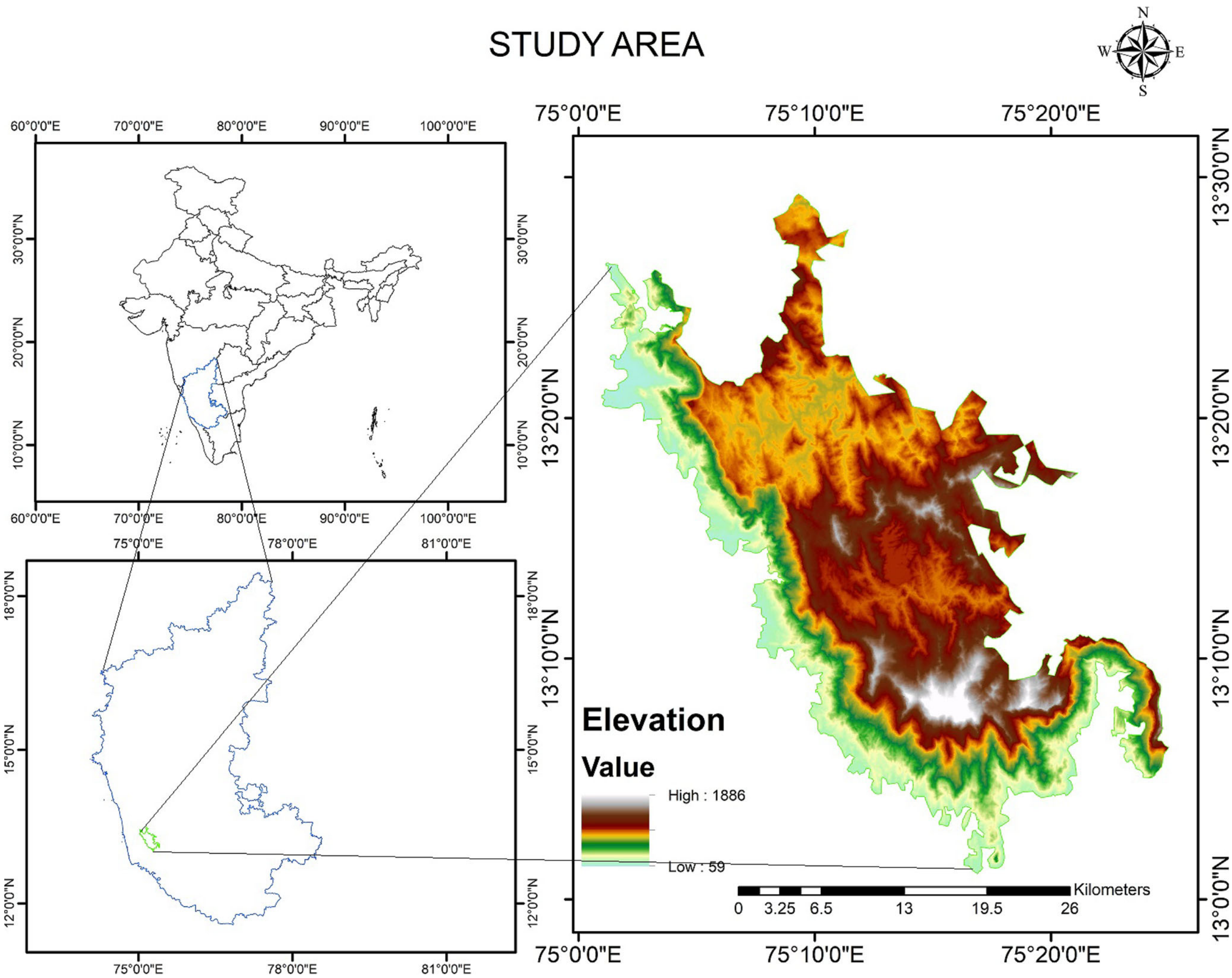

Fig. 1 Location of Kudremukh National Park, India

GEE is a JavaScript-based online cloud computing platform. An algorithm was developed for post-fire burn severity analysis using different fire indices such as NBR, dNBR, RBR, and RdNBR. Initially, geometry was imported into the code editor to locate the region of interest and then image collection is loaded into it. In the present study, cloud-free image collections of Sentinel-2 and Landsat 8OLI for both pre-fire (before January) and post-fire (post May) are filtered and loaded into the code editor. Normalized Burn Ratio was calculated using Eq. (3.1) for both pre-fire and post-fire to highlight the areas with fire (Lutes et al. 2006; Tran et al. 2018)

$$\mathrm{NBR} = \frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})} \tag{3.1}$$

The NBR value ranges from − 1 to + 1 with maximum values for vegetation and minimum values for burnt areas. The NBR difference is used in many studies to map the burn severity (Cocke et al. 2005; Escuin et al. 2008; Adagbasa et al. 2018; Rahman et al. 2018). The differenced Normalized Burn

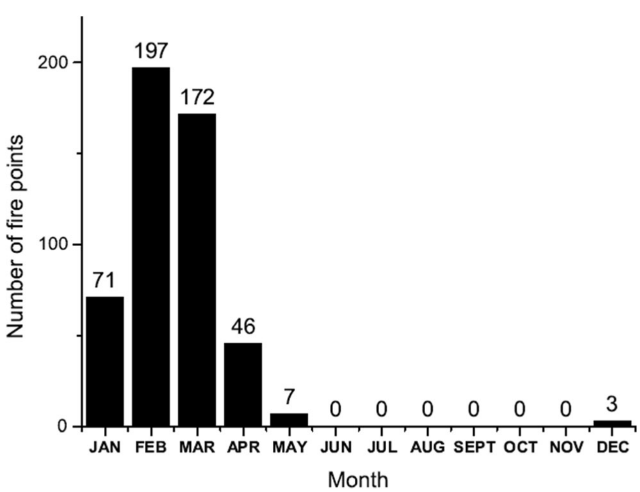

Fig. 2 Cumulative number of fires occurred during each month of 2005 to 2016

Table 1 Satellite datasets used in the present study

Name of the datasets	Product ID	Spatial Resolution	Temporal resolution
Landsat imagery	Landsat 8OLI	30 m	16 Days
Sentinel imagery	Sentinel 2A and 2B	10 m-60 m	5Days
Fire & Thermal Anomalies	MOD14& VNP14IMGTDL(NRT)	1 km &375 m	Daily

Ratio was calculated from Eq. (3.2) for pre-fire NBR and post-fire NBR. The value of dNBR increases with an increase in burn severity.

$$dNBR = NBR_{Prefire} - NBR_{Postfire} \tag{3.2}$$

Relativized Burn Ratio (RBR) was calculated using Eq. 3.3, which is the ratio of dNBR and pre-fire NBR adjustment (Parks et al. 2014).

$$RBR = \frac{dNBR}{NBR_{Prefire} + 1.001} \tag{3.3}$$

A value of 1.001 was added to the denominator to ensure that it will never tend to zero (Parks et al. 2014). The Relativized differenced Normalized Burn ratio (RdNBR) was a distinct dNBR variant that takes into account the relative amount of pre-fire shift by dividing dNBR with the pre-fire NBR value (Miller et al. 2009). Because of the form and density of vegetation pre-fire, this index was suggested to eliminate the bias. RdNBR was calculated using Eq. (3.4) (Cardil et al. 2019).

$$RdNBR = \frac{dNBR}{\sqrt{|NBR_{Prefire}|}} \tag{3.4}$$

All burn severity indices are further analysed using Arc map to determine burnt area and their accuracies are computed using active fire points (described in Section 2). All the

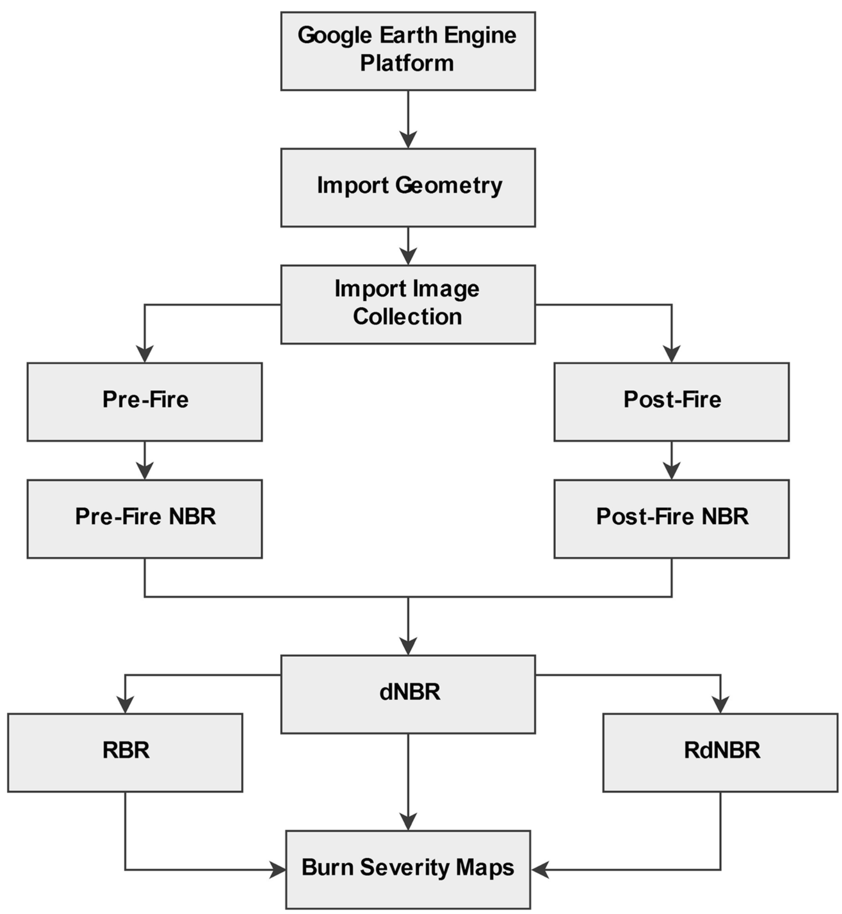

Fig. 3 Flowchart of methodology for burn severity analysis

Table 2 Severity level assigned to each class

S.no	Severity Level	Range
1	Enhanced Regrowth, High	<-0.25
2	Enhanced Regrowth, Low	-0.25 to -0.1
3	Unburnt	-0.1 to 0.1
4	Low Severity	0.1 to 0.27
5	Moderate-Low Severity	0.27 to 0.44
6	Moderate-High Severity	0.44 to 0.66
7	High Severity	> 0.66

determined fire indices from Landsat-8 and Sentinel-2 are intercompared to determine their efficiency in mapping burn severity.

Results and discussion

The burn severity analysis was performed to map the regions according to their rate of damage due to the fire. The burn severity analysis was executed by generating three different fire severity indices namely, Differenced Normalized Burn Ratio (dNBR), Relativized Burn Ratio (RBR), Relativized Normalized Burn Ratio (RdNBR) from two different satellite images (Landsat 8 and Sentinel-2 imagery) with varying spatial and temporal resolutions. These indices were calculated and inter-compared after segregating them into different fire severity levels. The obtained burnt area maps were validated using active fire points. The values of burn severity indices were classified into different severity levels as shown in Table 2 (Lutes et al. 2006; Rahman et al. 2018) to obtain the burn severity map.

The burn severity maps using dNBR, RBR and RdNBR were depicted in Figs. 4 and 5 for Sentinel-2 and Landsat-8 respectively.

The percentage of the area that fell in each severity class for all indices was represented in Fig. 6. From Fig. 6, it can be observed that very little regrowth has been occurred within the fire period considered. In the case of RBR, vegetation subjected to high severity was not observed, whereas for dNBR, very less vegetation (0.23% for Sentinel-2 and 0.26% for Landsat-8) is subjected to high severity level

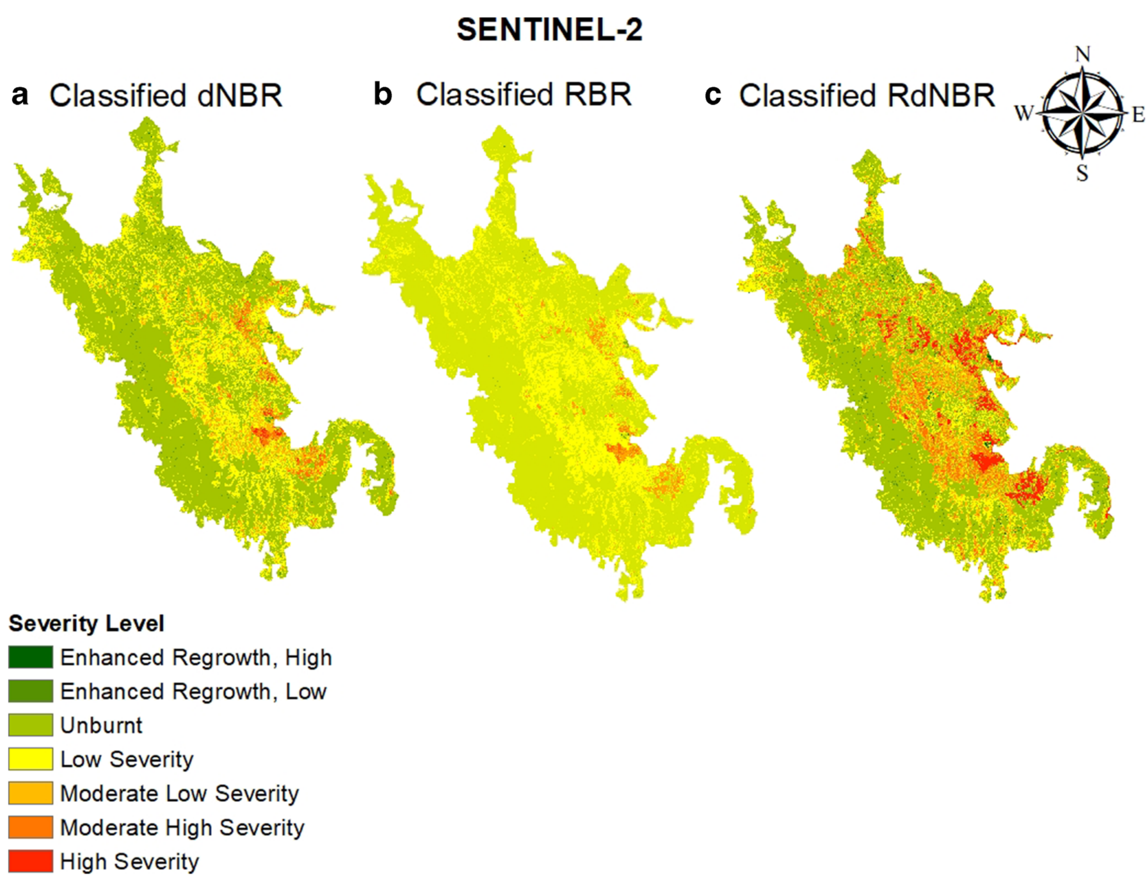

Fig. 4 Burn severity maps using SENTINEL-2 for (**a**) dNBR (**b**) RBR (**c**) RdNBR indices

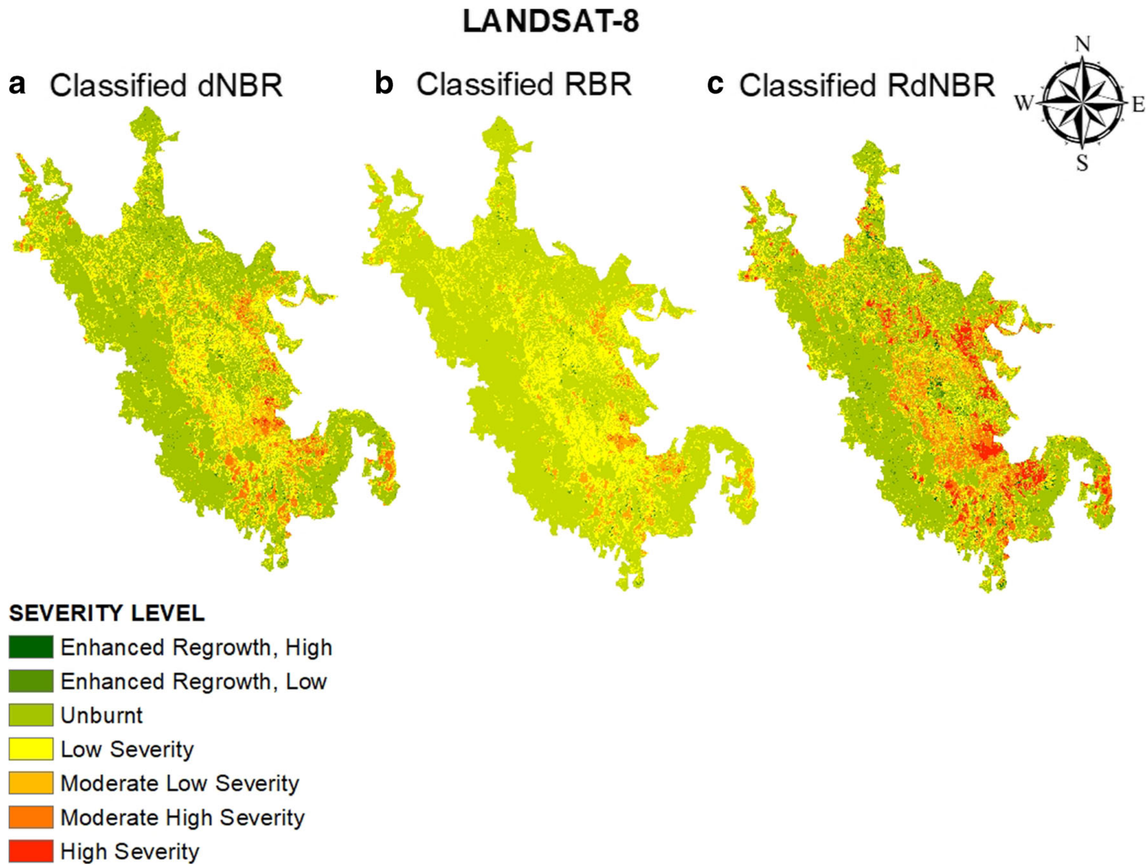

Fig. 5 Burn severity maps using LANDSAT-8 for (**a**) dNBR (**b**) RBR (**c**) RdNBR indices

assigned to each class and the percentage area subjected to high severity for RdNBR is slightly greater than dNBR (4% for both Sentinel-2 and Landsat-8). Percentage area remained un-burnt was more in RBR followed by dNBR and RdNBR indices.

The effect of fire is negligible from enhanced regrowth-low severity to low severity levels; therefore they are classified into unburnt regions whereas the impact of fire is high from moderate-low severity to high severity levels with soil organic damage layer to tree mortality. Hence they are classified as a burnt region. The burnt area maps are generated with burnt and unburnt classes overlaid with active fire points during the fire period, as shown in Figs. 7 and 8. The accuracy of these severity maps was validated using active fire points from the FIRMS NASA website which provides hotspot locations of fire events after the satellite's overpass. The active fire points within burnt and unburnt classes are extracted to calculate the accuracy of severity maps. The percentage of active fire points within burnt and unburnt levels for all indices are shown in Fig. 9 for Sentinel-2 datasets and Fig. 10 for Landsat-8 datasets. The accuracy obtained for dNBR was 41.67% for Sentinel-2 and 47.44% for Landsat-8, whereas in the case of RBR, 32.69% was observed for Sentinel-2 and 26.92% for Landsat-8, and finally, for RdNBR 61.52% was noticed for Sentinel-2 and 64.1% for Landsat-8. From these results, it can be identified that RdNBR has proven its accuracy in heterogeneous landscapes when compared to the other two indices. The results are in agreement with previous studies on the performance of fire severity indices by Miller and Thode 2007; Rahman et al. 2018 and Konkathi and Shetty 2019.

From these results, it can be concluded that RdNBR can be considered as more appropriate indices for mapping burnt area. The Landsat- 8 performed slightly more accurate than Sentinel-2 for predicting the burnt area. This may be due to the variation in the date of acquisition and misclassification of the unburnt pixels in the Sentinel-2. The results obtained are in coherence with the results of the scientific study conducted by Quintano et al. 2018, where they performed burn severity analysis using both Sentinel-2 and Landsat-8.

Conclusions

Post-fire burn severity analysis was carried out using multispectral high spatial resolution sensor imageries. Sentinel-2

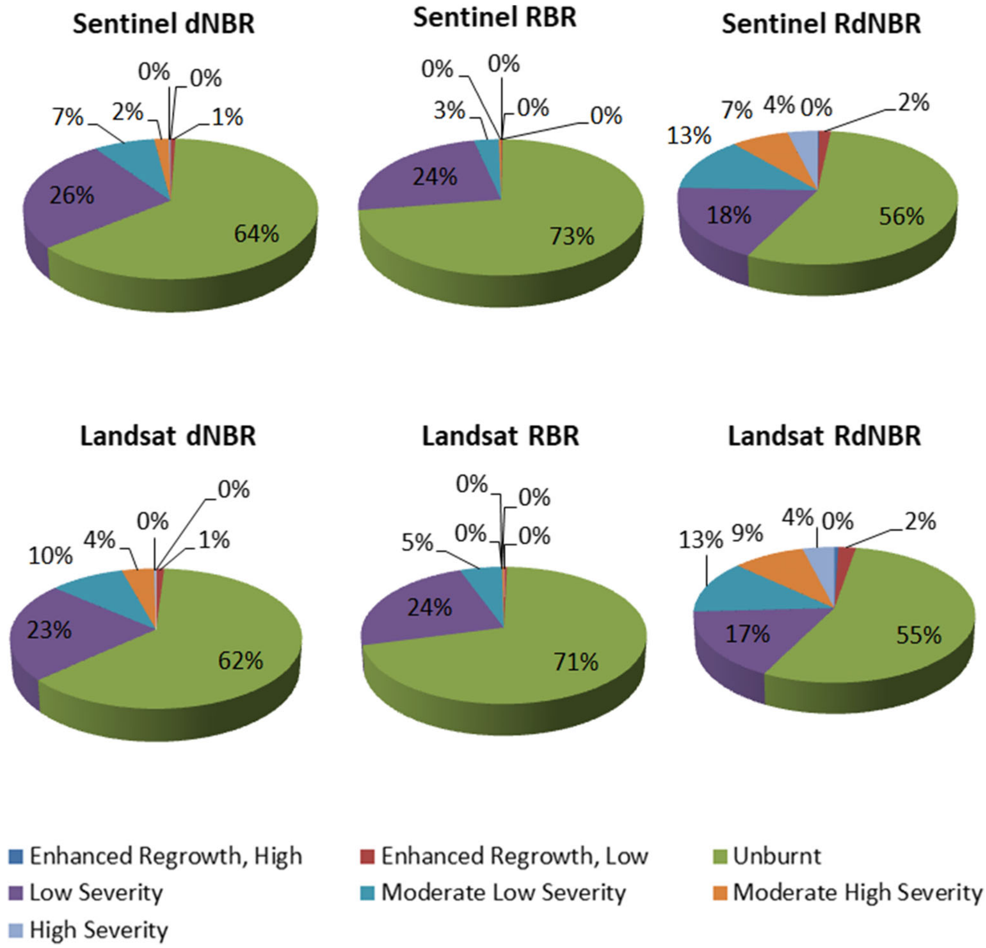

Fig. 6 Percentage of area in each severity class of burn severity indices

and Landsat 8OLI images were used to assess the burn severity from three different fire indices. Pre-fire NBR and post-fire NBR were calculated to obtain a differenced Normalized Burn Ratio, Relativized Burn Ratio and Relativized differenced Normalized Burn Ratio. These indices were classified into various severity levels to get burn severity maps. The classes

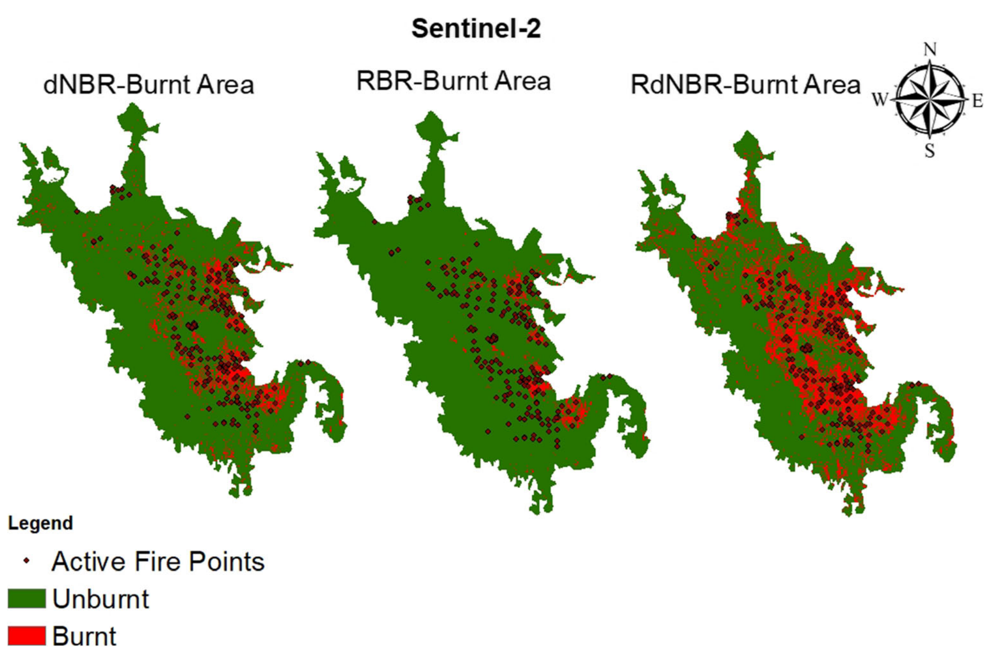

Fig. 7 Burn Area Maps generated using SENTINEL-2 overlaid with Active fire points

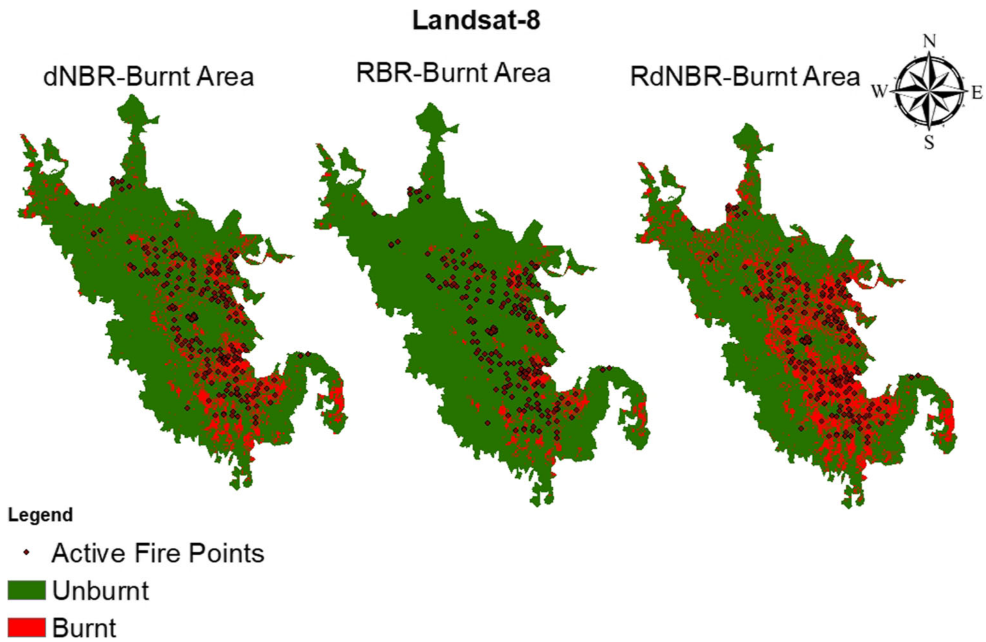

Fig. 8 Burn Severity Maps generated using LANDSAT-8 overlaid Active fire points

with moderate-low severity to high severity levels have a high impact on fire; hence, they are considered burnt region and rest as unburnt region due to negligible fire damage. The burnt area maps are validated using active fire points (MODIS & VIIRS) during the fire period. Sentinel-2 and Landsat-8 exhibited similar characteristics in determining burn severity. The RdNBR has proven its accuracy over heterogeneous landscapes with 61.52% for Sentinel-2 and 64.1% for Landsat-8, followed by dNBR (41.67% for Sentinel-2 and 47.44% for Landsat-8) and weak performance for RBR with 32.69% for Sentinel-2 and 26.92% for Landsat-8. Results showed that Landsat based burn severity maps provided an adequate assessment of the degree of damage, although maps based on both sensors reached an acceptable level of detecting burnt area. The Landsat-8 performed slightly more accurate than Sentinel-2 in predicting burnt area due to the variation in the date of acquisition and misclassification of the unburnt pixels. Future research should adjust the implemented classification thresholds for burn severity analysis to avoid misclassification of unburnt pixels. It is observed that the regrowth of vegetation was significantly less within the fire period considered. Hence the generated maps are useful for planning mitigation measures for recovery of vegetation losses.

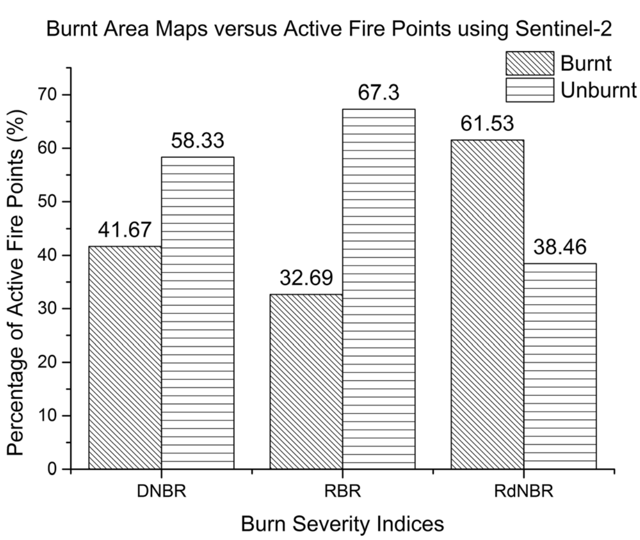

Fig. 9 Percentage of the active fire points fell in burnt area maps generated from severity indices using SENTINEL-2

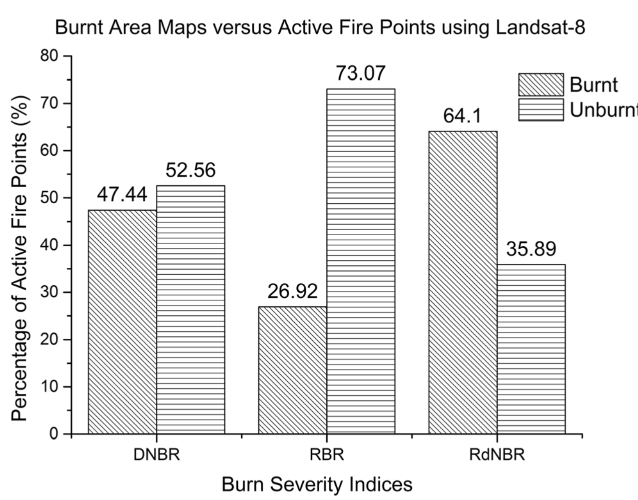

Fig. 10 Percentage of the active fire points fell in burnt area maps generated from severity indices using LANDSAT-8

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