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Original Article

A Hybrid Clustering Method for Burnt Area Mapping of Forests

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Abstract - *Mapping the burnt forest areas presents a major challenge since it is impossible to collect the ground information (labelled data) for the supervised classification. In such cases, unsupervised classification techniques, which do not require any prior knowledge of the geographic area, can be used. This work maps the burnt areas of the forests of Bandipura forests in Karnataka (also known as Rajiv Gandhi National Park) using remotely sensed images obtained from LANDSAT-8. Part of the forests were destroyed in the forest fires of February 2019. Unsupervised k-means clustering algorithm is used to map the forest area. After that, the burnt areas are mapped using a hybrid approach comprising the Normalized Burn Ratio (NBR) and the Normalized Difference Water Index (NDWI). Additionally, the severity of the burns is also mapped using the threshold values in the difference Normalized Burn Ratio (dNBR). It was found that around 15,000 acres of forested land were lost due to forest fires.*

Keywords - *Forest Mapping, k-means clustering, Normalized Burn Ratio, Difference Normalized Burn Ratio, Unsupervised Learning.*

1. Introduction

Forests play a major role in environmental sustainability. Forest fires have the tendency to cause an imbalance in the forest ecosystem. It may also cause loss of humans and wildlife. The greenery or the green cover takes a direct hit with the forest fires, which in turn causes air pollution. Hence, monitoring the forest fires and surveying the burnt areas' severity becomes important. Remotely sensed images can be used to monitor forest fires and the regrowth of the forest land cover. This can be done remotely without being in touch with the forest land. This information can be used by the local and forest authorities for further planning and operations. The work discussed here can be used to analyze the burn severity over a vast expanse of the forests.

In the case of forest fires, it is not easy to take labelled data from the ground for doing supervised learning algorithms. Hence the need for unsupervised classification. Unsupervised algorithms classify the objects (land cover types, in this case) depending on the patterns identified by the system itself. The satellite sensors pick up the spectral signatures of each land cover class. The unsupervised algorithms consider this as the pattern and use them for clustering.

Using just the classification techniques on the pre-fire and the post-fire rasters does not give a clear picture of the burnt area. Using just the burnt area mapping misclassifies the water bodies as the burnt areas. Hence, a hybrid approach comprising the classification techniques and the burnt area mapping is necessary.

1.1. Study Area and Datasets used

The study area is the Bandipura forests, spanning Karnataka's Mysore and the Chamrajnagar districts. These forests are a part of the Western Ghats, which fall in the states of Karnataka and Tamil Nadu. The area considered is within the Karnataka state boundaries (Mysore and Chamrajnagar district).

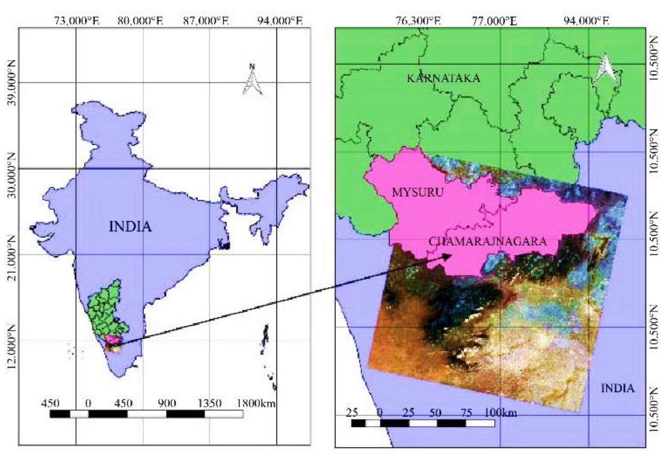

Fig. 1 Study area with respect to the state and national boundaries

Table 1. Details of the dataset used

Date of Acquisition	Spatial Resolution	Source	Format
8 January 2019	30 m	LANDSAT-8	GeoTiff
25 February 2019			

2. Literature Survey

Forests are important to maintain the balance in the ecosystem. Forests are rich in bio-diversity and are a source of livelihood and sustenance for a large number of the Indian rural population [1]. Uncontrolled forest fires play havoc with this delicate ecosystem and the rural economy, mainly dependent on forest products and produce. Remotely sensed images, along with geographic information systems, can be effectively used to monitor and manage these forest fires [2,3]. At the same time, quantifying the aftereffects of forest fires is equally important to understand the drivers and the edge effects of these fires [4]. Similarly, the loss of greenery and the ensuing pollution also have to be taken care of. [5].

Relying on remotely sensed images becomes all the more important when the burnt or burning areas become inaccessible. Remotely sensed images are hyperspectral or multispectral [6]. If the burnt areas have to be mapped at a macro level, then multispectral images can be used. The downloaded images must be corrected for atmospheric and other defects caused by the sensor equipment [7]. Further, machine learning classification techniques can be used to map the burnt area. A brief survey of these algorithms and their relative performance is given by [8].

Supervised classification techniques based on Maximum Likelihood algorithms have been traditionally used for burnt area mapping [9]. Burnt area mapping can also be done using SVM [10]. Artificial Neural Networks [11] and Logistic Regression [12]. Out of the many classification algorithms, [13] has shown that the Random Forest classifier performs better in the burnt area mapping classification. In a real-time scenario, getting labelled data for supervised classification algorithms is a tedious job. Fuzzy set theory and a region-growing algorithm have been used on Sentinel images to map the burnt areas [14]. These classification algorithms sometimes confuse between the water bodies and the burnt areas because of the spectral similarities. Hence, water body masking has been done by some authors [15].

Even though these techniques produce a highly accurate burnt area map, they do not lend themselves to automation. In a large country like India, where forest fires are a norm, there has to be a technique which can be applied effectively and quickly to assess the burnt area. This can be done using the spectral signatures, which are derived from the sensor values [16]. Burnt areas can also be mapped using different spectral indices like chlorophyll level, leaf tissue damage and moisture content [17]. Classification accuracy depends mainly on the source image and the availability of labelled datasets. Burnt area mapping using MODIS images is generally less accurate because of the coarse resolution of this imagery [18]. In India, only a small percentage of forest fires were identified by images from MODIS due to the coarse spatial resolution of these images [19]. The accuracy of the assessment also depends on the time and date of the acquisition of the remotely sensed images. Studies [20, 21] have shown that the change in the spectral signatures of the components of the forest can be exploited to examine the extent of the damage. This is because the burnt areas will be converted to healthy vegetation within a few days [22]. In this work, burnt forest areas are mapped using a combination of clustering techniques (unsupervised classification) and spectral indices based on water content on a LANDSAT-8 image, which has a resolution of 30 meters.

3. Methodology

The methodology adopted for mapping the burnt areas is shown in Figure 2. The methodology can be broadly classified into two stages. In the first stage, the forest cover map is identified in the given geographic area using an unsupervised classification technique. The burnt forest area is mapped in the second stage according to different intensities.

3.1. Data Acquisition

The burnt areas are mapped using remotely sensed images captured by LANDSAT-8. Two data sets were downloaded, one for the pre-fire date (8 January 2019) and the other for the post-fire (25 February 2019). A major fire broke out in the forests of Bandipur in February, which continued well till the 3rd week of February. In order to analyze the severity of the burns, it is important to consider the images of the dates after the fire has been extinguished.

3.2. Pre-Processing

Since the forest cover map has to be compared in a temporal manner, pre-processing to remove the effects of the atmosphere has to be done. In this work, Atmospheric corrections have been done using the DOS-1 algorithm.

3.3. Classification Stage

This stage is important as it helps us to eliminate the non-forest area. The main aim of this work is to map the burnt forest areas, but the raster downloaded also has other land cover classes. Classifying them helps eliminate all the non-forest classes from further processing. Unsupervised learning can be implemented in the form of clustering algorithms or associative algorithms. The advantage is that it does not require any manual labelling of the ground points, which is beneficial in the present scenario. Unsupervised classification using k-means clustering has been implemented to get a forest map. Clustering algorithms generally tend to discover the hidden patterns in the dataset. Hence, these algorithms are generally used when the ground truths are unavailable. The main disadvantage of unsupervised learning is the difficulty in checking for the accuracy of the classifier, as there is no labelled data [23].

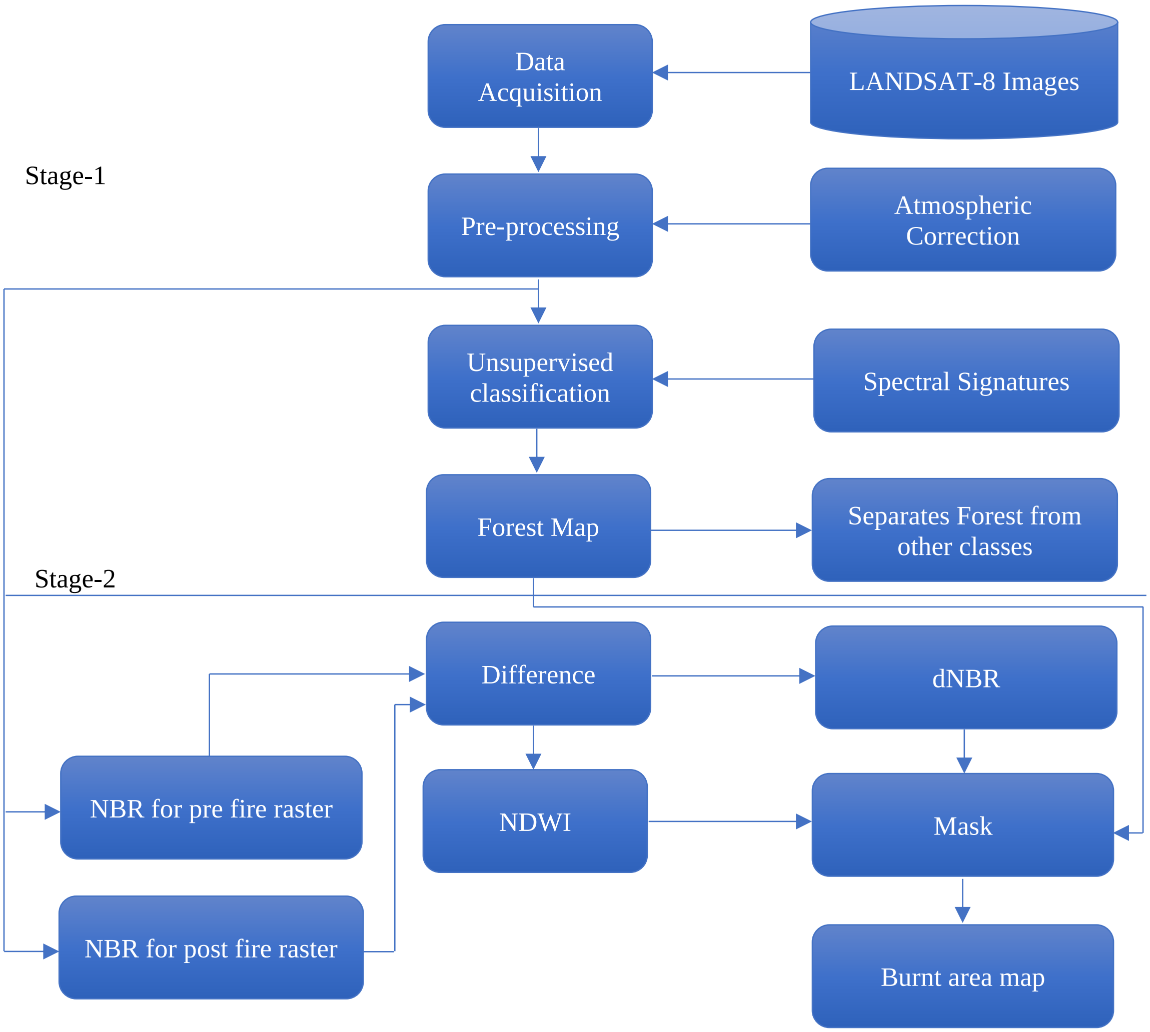

Fig. 2 Workflow for the proposed method

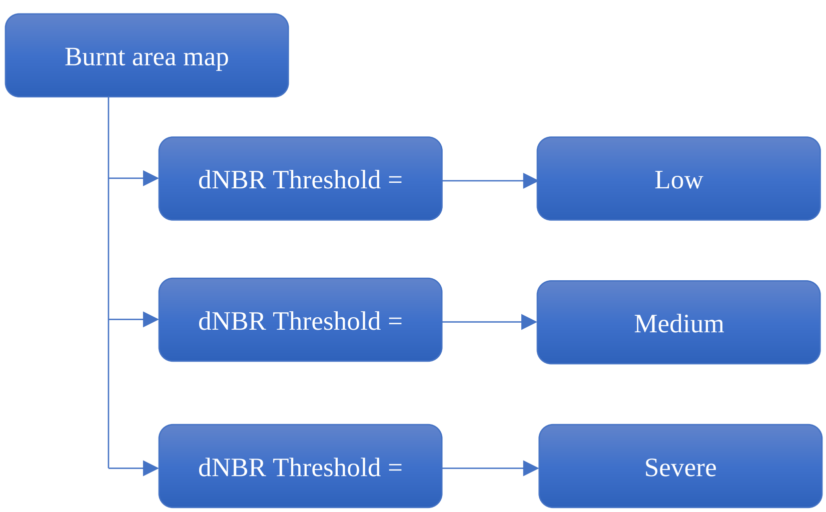

Fig. 3 Burn area severity map

3.3.1. k-means Clustering

k-means clustering is a centroid-based model that uses the Euclidean Distance to classify the test points to their respective clusters. It is an exclusive clustering scheme in which a data point under consideration can exist in any one cluster only. It can also be referred to as hard clustering. The value of ***k*** indicates the number of clusters required. Here, k is chosen to be four, indicating the 4 forest cover classes that have to be mapped. The classes chosen are Water Forest, Sparse Vegetation and Urban. The class Sparse vegetation includes the agricultural areas, bare soil and minimum vegetation. This class need not be used for further processing, but as explained in the subsequent sections, the class water is needed. K-means clustering requires a centroid point or a starting seed point, chosen randomly here. A cluster diagram indicating the clusters belonging to 4 classes is shown in Figure 5. These clusters are formed from the spectral signatures of the data points taken in a band combination of 4-3-2. For clarity, only a 2D image with only two bands is shown here. The steps involved in the implementation are given below.

1. Let number of clusters k = 4 (4 classes)
2. Randomly choose the centroid point for each class and randomly assign the data points to the nearest centroid.
3. Compute the centroids by averaging all the data points allotted to a particular cluster.
4. Reassign the data points to the nearest centroid calculated in Step 3.
5. Recompute the centroids.
6. Repeat Steps 4 and 5 till there are no further changes in successive iterations (or the difference between successive iterations is below a threshold value).

The classification result separates the forest region from the other areas. The next stage is only to determine the effect of forest fires in the forested area.

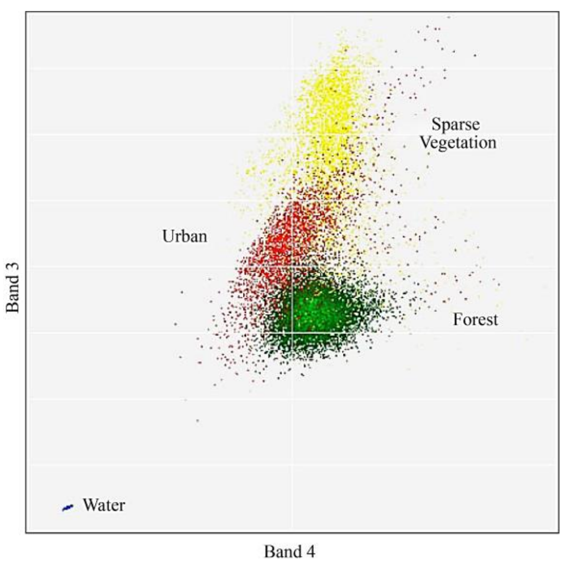

Fig. 5 Clusters of the 4 classes with a band combination of 4-3-2

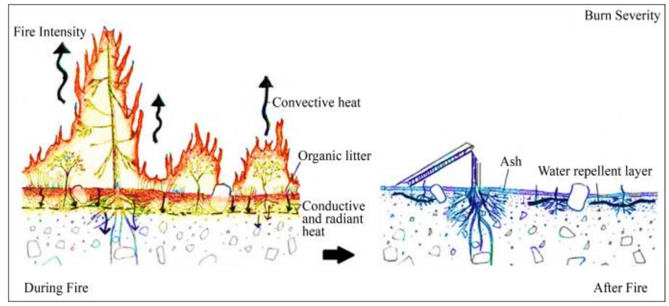

Fig. 6 Illustration of fire intensity versus burn severity

Source: U.S. forest service

3.4. Normalized Burn Ratio (NBR)

It is important to note the difference between the fire's severity and the burns' severity. While the severity of the fire generally refers to the state of the fire when it is still active, the severity of the burns refers to the state of the ground and the ecosystem, in general, after the fire [24]. The difference is shown in Figure 6.

Different ecosystems react to the fires in a different way. Hence, the Normalized Burn Ratio (NBR) is utilized to quantify the damage done by the fires. It is a raster derived from the following equation.

$$\mathrm{NBR} = \frac{\mathrm{NIR-SWIR2}}{\mathrm{NIR+SWIR2}} = \frac{\mathrm{Band5-Band7}}{\mathrm{Band5+Band7}} \qquad (1)$$

The healthy vegetation and their burnt versions can be distinguished from the RS images depending on their spectral signatures. Healthy vegetation has a good reflectance in the NIR band and a bad reflectance in the SWIR2 bands. Vice-versa is true for the burnt vegetation. Hence, the difference between the healthy vegetation and the burnt vegetation reaches a peak in these two band differences. The concept is shown in Figure 7.

NBR is calculated for both the pre-fire and the post-fire rasters. The difference between the two rasters is dNBR. After calculating the dNBR, the severity level is mapped depending on the guidelines given by USGS, shown in Table 1.

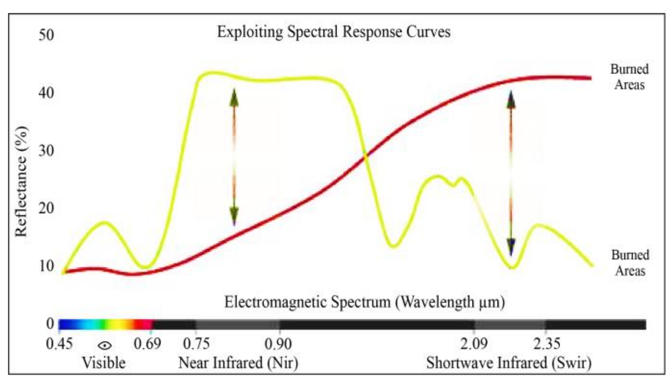

Fig. 7 Comparison of the spectral response of healthy vegetation and burned areas

Source: U.S. forest service

Table 1. Burn severity levels were obtained by calculating dNBR, proposed by USGS

	Severity Level	dNBR Range (scaled by 103)	dNBR Range (not scaled)
	Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
	Enhanced Regrowth, low (post, fire)	-250 to -101	-0.250 to -0.101
	Unburned	-100 to +99	-0.100 to +0.99
	Low Severity	+100 to +269	+0.100 to +0.269
	Moderate-low Severity	+270 to +439	+0.270 to +0.439
	Miderate-high Severity	+440 to +659	+0.440 to +0.659
	High Severity	+660 to +1300	+0.660 to +1.300

4. Results and Discussion

The output of the k-means clustering algorithm for both the pre-fire and the postfire scenes is shown in Figure 8a and Figure 8b. It can be seen that a majority of the area is forested, whereas there are some other land cover classes also, like water bodies urban and sparse vegetation. This classification is necessary since it is important only to analyze the damage in the forest area.

Comparing Figures 8a and 8b, the loss in greenery is evident in the lower part and the right part of the images. But it is difficult to determine, just with the help of a land cover map, if this loss in greenery is because of forest fires or something else. Hence, the NBR rasters have to be mapped. The results of the dNBR are shown in Figure 9.

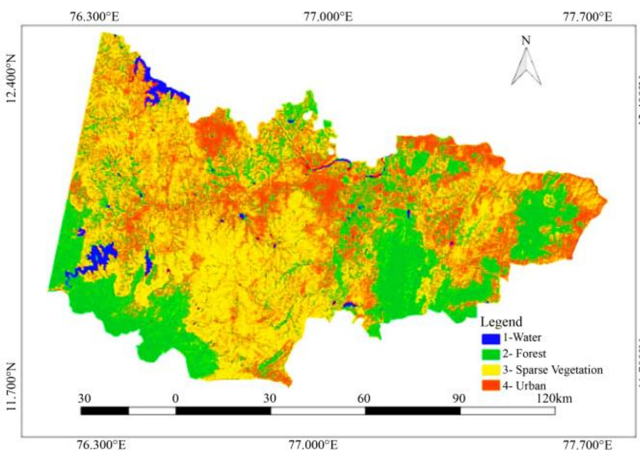

Fig. 8(a) Land Cover map of the study area using k-means clustering algorithm (pre-fire)

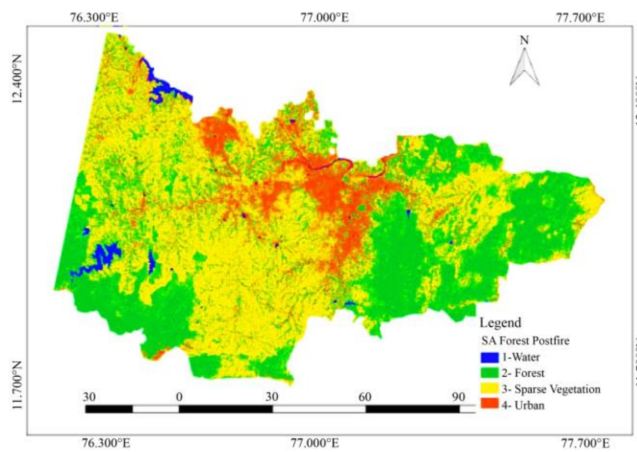

Fig. 8(b) Land Cover map of the study area using k-means clustering algorithm (postfire)

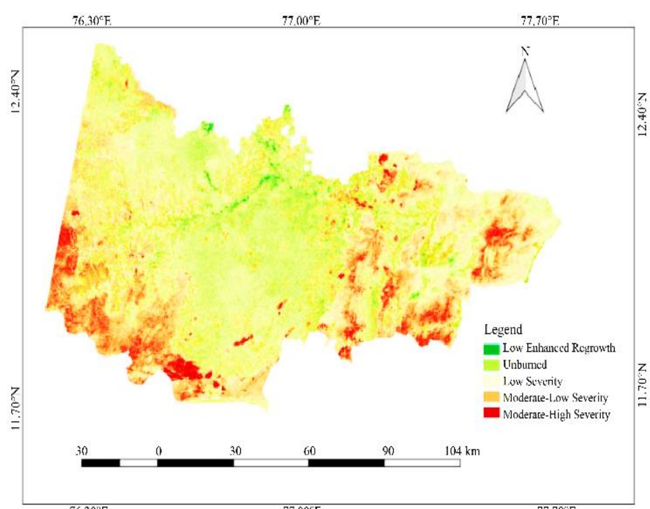

Fig. 9 Burnt area map

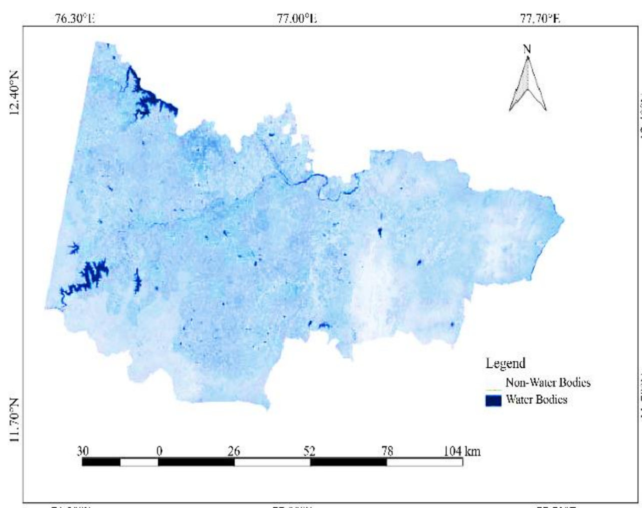

Fig. 10 NDWI Raster

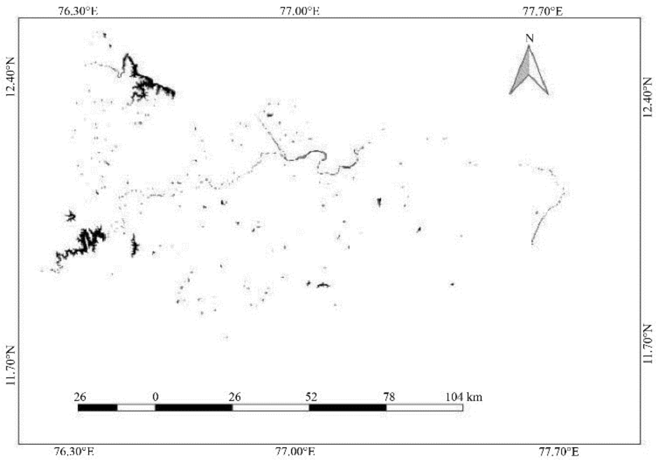

Fig. 11 NDWI mask

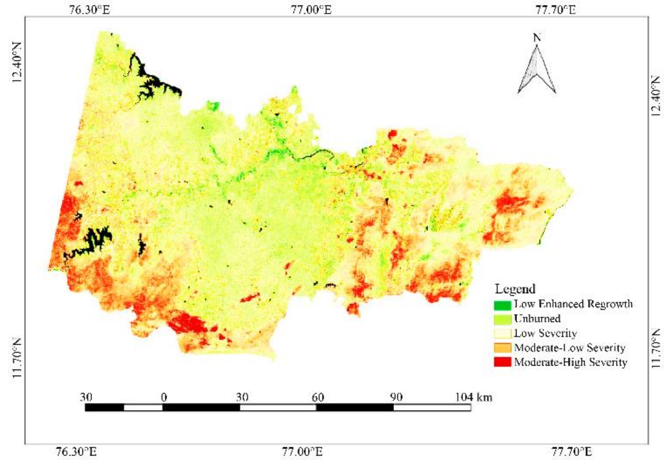

Fig. 12 Burnt areas map with water bodies masked

Category Information	acres
-1	18,457.717
0	246.338
1	342.751
2	2561.638
3	14,437.898
TOTAL	36,046.342

Fig. 13 Burn severity in terms of acres of forest land

The problem with this approach is that the water bodies also show up as the burnt areas on the map. In the case of ground truth knowledge of the geographic area, this does not create a problem, as the mapper is well aware of the water bodies' presence and location. But, in the case where the ground truth of the study area is not known, these water bodies have to be alienated so that they do not turn up as burnt areas. To circumvent this problem, an NDWI raster has been created here. This raster is then vectorized so that it can be used to mask the water bodies in the burnt areas. This gives a better picture of the burnt areas. The NDWI raster is shown in Figure 10. The mask created with this raster is shown in Figure 11. Finally, the burnt areas map, with the masked water bodies, is shown in Figure 12.

The percentage areas with varying degrees of burn severity are obtained after reclassifying the dNBR raster, the results of which are shown in Figure 13. Approximately 14,437 acres of forest land were burnt with high severity, as indicated in red. The results obtained here agree with the analysis done by Ananth et al., 2019 and that reported by the National Remote Sensing Centre [25]

5. Conclusion and Future Work

The main aim of this work is to map the burnt areas of the forest. For doing so, first, the forest area is identified using the k-means clustering algorithm with 4 classes. Then, the dNBR raster is mapped using the formula stated in the work. The intensity of burns is also mapped using the Burn Severity Table. The water bodies in the dNBR raster are masked using the NDWI masking vector.

This is an important aspect of this work since, without the masking, even the water bodies turn up as burnt areas and may lead to misinformation if the geographical area is unknown. With the help of this burnt area mapping, the forest authorities can prioritize their action plans for monitoring and reforestation. The limitation of the work is that the accuracy of the classification and the burnt area mapping cannot be ascertained. As a future work, this can be incorporated into the mapping process.

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