Tropical Forest Degradation Assessment; A Case Study using CLASlite

Nabin Kumar Yadav[1], Hitendra Padalia[2], Sarnam Singh[2] and A. Senthil Kumar[2]

[1]International Centre for Integrated Mountain Development (ICIMOD), Nepal,

[2] Indian Institute of Remote Sensing (ISRO), 4 Kalidas Road, Dehradun, Uttarakhand, India

Abstract Detecting and monitoring forest degradation have implications for forest conservation and management. Mapping and monitoring deforestation have been an operational activity using satellite remote sensing. However, the mapping disturbance and degradation of forests is a major challenge. The present study attempted to quantify the forest disturbances in the Lachhiwala forest range situated in foothills of Himalaya in Uttarakahnd state, India. The study utilizes optical satellite data (Landsat TM, 2010 and Landsat 8, 2015) and spectral unmixing of these datasets gave fractional cover (proportion of vegetation, non-photosynthetic vegetation, and bare soil). An automated tool CLASlite was used to generate fractional cover which adopts Monte Carlo Spectral Unmixing techniques that combine spectral and spatial information was used to enhance the detection and mapping of canopy damage, exposed soil, and dead vegetation. Results show that study area has 86.82% intact forest,1.33% less degraded forest, 6.28% moderately degraded forest and 5.57% high degraded forest. Root mean squared error (RMSE) images were used to assess the performance of the Model. Landsat 8 OLI/TIRS has low RSME (i.e. 0-7%) than Landsat 5TM Landsat 5 TM (i.e. 1-10%).

Keyword: Landsat 8, Spectral Unmixing, Fractional Cover, Deforestation, Degradation

1. Introduction

Tropical forests have a vital environmental and socio-economic importance. They are habitat for about two-thirds of the Earth’s terrestrial biodiversity. They also provide a significant benefit to humans at the local and global scales (Risto Seppälä 2009). Tropical forests are affected by a range of anthropogenic disturbances such as transformation of forest land to agriculture, forest fire, selective logging, illicit felling, grazing etc. Such disturbances over time lead to degradation of forests thereby reduction of the capacity of a forest to provide goods and services. Forest degradation is defined as the quantities and qualitative loss of vegetation cover over a long period of time within the forest and gradual reduction in productivity (Singh 2010).

Forest changes, especially in tropical regions, are regarded as a major source of greenhouse gas (GHG) emissions. Deforestation and forest degradation are responsible for 12–20% of global GHG emissions per year (IPCC 2007) and are the second largest source, after the fossil fuels (van der Werf et al. 2009; Gibbs et al. 2010) which is a consequence of the rapid economic growth, increasing demand for agricultural land, forestry products, illegal logging and urbanization (Rudel et al. 2009). Reducing Emission from Deforestation and Forest Degradation (REDD) is a United Nations endorsed mechanism to mitigate climate change by assisting the developing countries in making strategies for the reduction of deforestation and forest degradation through implementing community forestry (Corbera et al. 2010). REDD focuses on the use of satellite remote sensing technology for collecting information about changes in stocks of forest carbon.

Remote sensing is a very powerful tool forest degradation studies. It involves the acquisition of information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, phenomenon or area under investigation (Lilesand and Kiefer, 1987). Remote sensing of subtle structural and physiological changes taking place in forested canopies are difficult to detect and map. Spectral unmixing a promising technique to generate fractional cover of forest canopies and its time-series study can indicate the various classes and levels of degradation. Recent development in digital image processing techniques particularly spectral unmixing technique provide a reliable method of forest degradation assessment. Spectral unmixing techniques quantify the proportion of proportion of vegetation, non-photosynthetic vegetation and bare soil for any forest area thereby is more sensitive to changes in forest structure over time.

The aim of this research work is to demonstrate mapping of degradation of Sal dominated forests in the Lachhiwala forest range using optical remote sensing data. The specific objectives of the research are (i)

Mapping fractional cover using CLASlite, (ii) To analyze forest disturbance based on spectral unmixing of temporal Landsat data and (iii) To generate forest degradation map of the study area

2. Study area

This study has been carried out in the Lachhiwala forest range falling in the East Dehradun Forest Division, Dehradun in the state of Uttarakhand, India (Figure 1). The geographic coordinates of the study area lie between 300 16' 06.38" N -300 10' 23.86" N and 780 01' 48.9"E-78074'6.39"E. The total area of the forest range is 5977 hectares. Physiography the study area has mountainous as well as plain area crisscrossed by rivers.

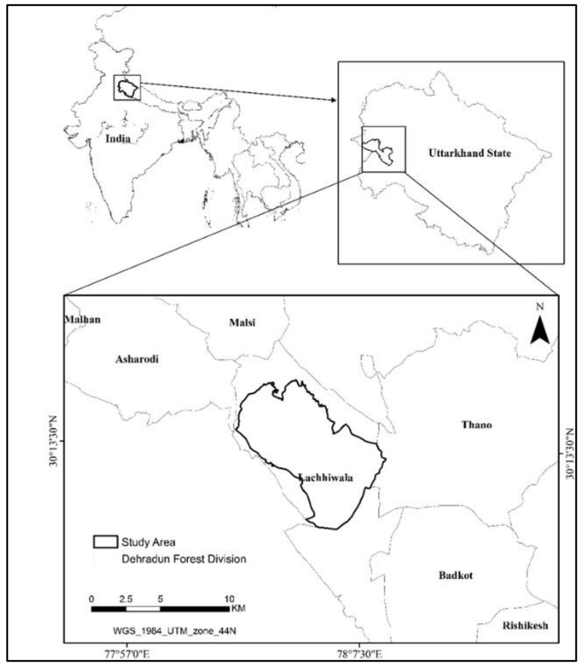

Fig. 1 Map of study area

Climatically the study area is a subtropical monsoon. The mean annual rainfall of the study area is about 2080 mm and bulk of it occur during in July-September. The hottest months are May and June and coldest are December and January. The elevation in the study area varies from 466m to 806 m above mean sea level. The study area is characterized by very large boulder present in debris flow and river deposits, comparatively less weathered and in the incipient stage of soil formation. The soil in the study area varies from coarse loamy to loamy sand throughout the depth with embedded gravels and pebbles.

According to Champion and Seth (1986), the study area has dominance of moist Siwalik Sal forests in the hills and plain areas. The quantity of Sal is usually poor and is generally III/IV quality. Its typically associate are Terminalia alata, Anogeissus latifolia. Other important associates are Haldina cordifolia, Kydia calycina, Lannaea coromandelica, Syzium cumini, Terminalia bellerica. The underwood is usually light and consists of Mollotus phillipinensis, Casia fistula, Ehretia laevis, bauhinia variegate, Ougenia oojeinensis, etc. The undergrowth's in various proportion are murraya koenigini, clerodendron viscosum, Adhatoda vasica, Woodfordia fruticose, milentia auriculata, Baunia vahlii etc. The study is also heavenly infested by undergrowth of Lantana camara, Cassia tora, Ageratum conizoids in degraded sites of Sal forest. The drier areas also have dry Siwalik Sal forests. In addition, there plantation of teak and eucalyptus in the peripheral areas. The riverine forests are found near the bank stream and river. There is also incidences mortality of Sal trees by the Sal heartwood borer, Hoplocerambyx spinicornis (Coleoptera: Cerambycidae), however in small areas. The forest range is surrounded by agriculture and rural settlements. There is disturbance due to grazing by cattle, illicit felling, road widening and dying trees in flooding of low lying areas.

3. Methodology

The optical data for this study are Landsat TM of 2010 and Landsat 8 OLI&TIR of 2015. Criteria for the selection of the multi-temporal Landsat data set involved assessment of cloud cover percentage, time of acquisition, and sensor type so that mapping and change detection scope was optimized. Google Earth, Aster DEM and topographical map (scale 1:25000) of the study area were used for extracting Area of Interest from whole map and ground truth information was required for validation of satellite image and defining threshold value.

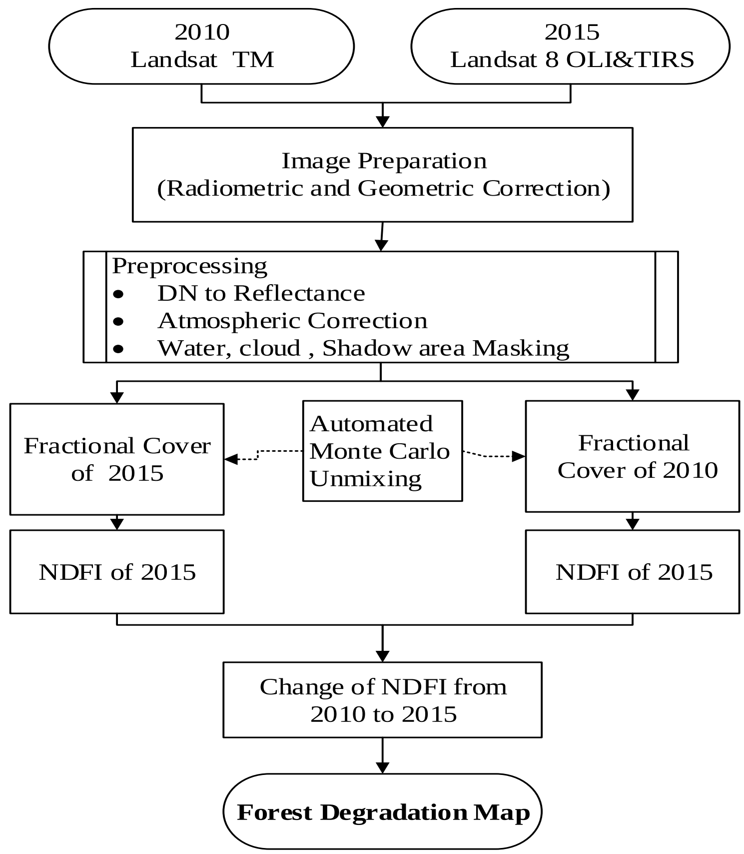

Fig. 3 Overall flow chart of methodology

3.1 Field Data Collection

A reconnaissance survey was carried in order to get the general understanding of forest status of the study area before starting the field work. Field surveys were conducted to identify land use and cover type on degradation locations spread across the study area. The surveys used roads, secondary roads, and logging trails to access areas of human-induced disturbances in forests and intact forest areas. Coordinates (latitude, longitude) of the locations of clear cutting, disturbance, road widening, land conversion etc. were marked using GPS (Trimble Zuno SD).

3.2 Pre-processing of Landsat Satellite Data

The raw Digital Number (DN) images downloaded from USGLOVIS (www.glovis.com) are calibrated to reflectance using gain and offsets value available in metadata. The result of radiometric calibration is an image in units of radiance (i.e. watts per square meter per unit of solid angle), also known as the energy measured by the satellite-based sensor. The main atmospheric players are aerosols, water vapour and other gases, like oxygen and ozone. These constituents scatter and absorb radiated energy to various extents at different wavelengths. This means that the sensor cannot detect everything that gets reflected off the Earth's surface. CLASlite applies an automated atmospheric correction and converts the results to reflectance images.(Allnutt et al. 2013). In some cases, the atmospheric correction model does not work perfectly. For example, in shaded areas or areas obstructed by heavy aerosol content, the reflectance value may turn out to be negative. In contrast, some pixels can exceed 100%. This can happen if the atmospheric correction model fails to remove radiation reflected off the atmosphere as opposed to the land's surface. So, the masking is done to eliminates clouds, cloud shadows, topography shadows, and water.

3.4 Analysis of Fractional Cover

The claslite tool is used to generate fractional cover. CLASlite adopts a Monte Carlo method, whereby the possible combinations of the endmember spectra are pre-computed and are applied during the Automated Monte Carlo Unmixing run. An advantage of the Monte Carlo approach is that the per-pixel iterations produce a standard deviation of the estimate for PV, NPV and bare substrate fractions. The process of random selection is repeated up to 50 times or until the solution converges to a mean value for each surface cover fraction. This technique considers that each pixel is a combination of certain pure elements (i.e. vegetation (PV), Soil-vegetation(S), Non-Photosynthetic vegetation(NPV), shade burnt) that combine to produce a given response per pixel.

3.4 Normalized Difference Fraction Index (NDFI)

A technique that combines spectral and spatial information to enhance the detection and mapping of canopy damage, exposed soil and dead vegetation has been used. The Equation given below is used to calculate NDFI. The output layers of CLASlite i.e. PV, NPV and Bare Soil is used as input parameters.

$$NDFI = \frac{PV - (NPV + Bare\ Soil)}{PV\ + (NPV + Bare\ Soil)}$$

Where, PV is photosynthetic Vegetation, NPV is non-Photosynthetic Vegetation.

3.5 Forest Degradation Map

The difference between 2015 and 2010 images was used to prepare change map. The layers were reclassified into the intact forest, less degraded forest, moderately degraded forest and highly degraded forest on the basis of the threshold collected from the ground. These layers were simply overlaid using raster calculator of ArcMap 10.3.

4. Result and Discussion

4.1 Fractional cover of 2010 and 2015

Fig. 4, shows the fractional cover of 2010 in which PV, NPV and bare are expressed in percentages (0-100%).In 2010, there is 0-96% of bare, 0-100% vegetation and 0-58% of non-vegetation.

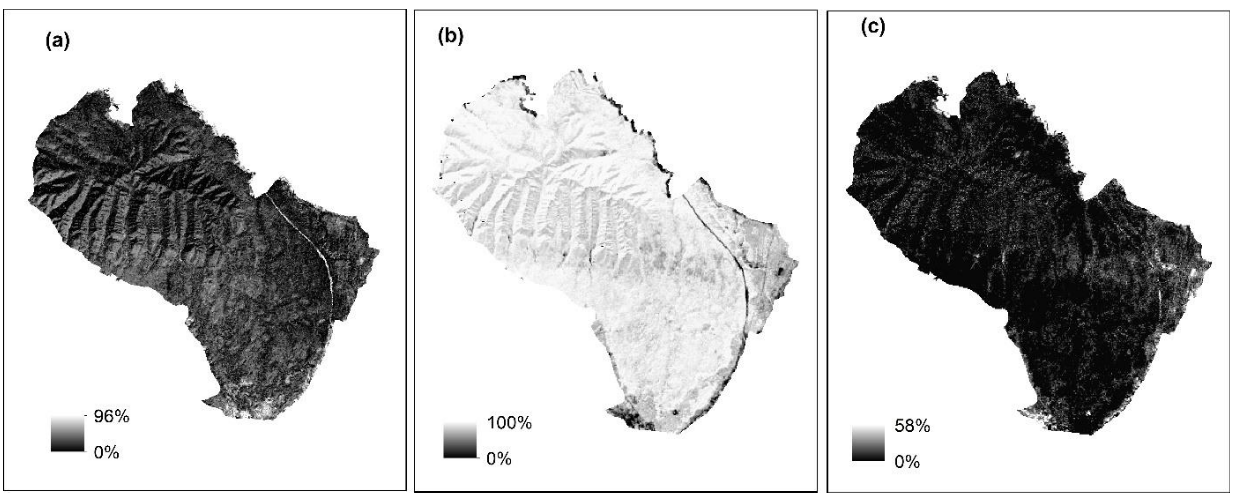

Fig. 1 (a) Bare (b) Photosynthetic Vegetation (PV) (c)Non-Photosynthetic Vegetation(NPV)

In Fig.5(b) and Fig. 8(b), Band 1 (Fractional cover of S) is displayed in red, Band 2 (Fractional cover of PV) is displayed in green, and Band 3 (Fractional cover of NPV) is displayed in blue. The intensities of each color represent the presence of each cover type in each pixel. For example, greener pixels have a higher percentage of PV, yellow pixels indicate the presence of both S and PV, while bluer pixels represent higher fractional coverage of NPV.

The RMSE image (Fig. 5 c) shows the geographic areas of relatively high overall uncertainty in the modeling; for example, hill area and road have the largest errors approaching 10%(Fig.6). In contrast, degraded area shows very low error close to 1-3%.

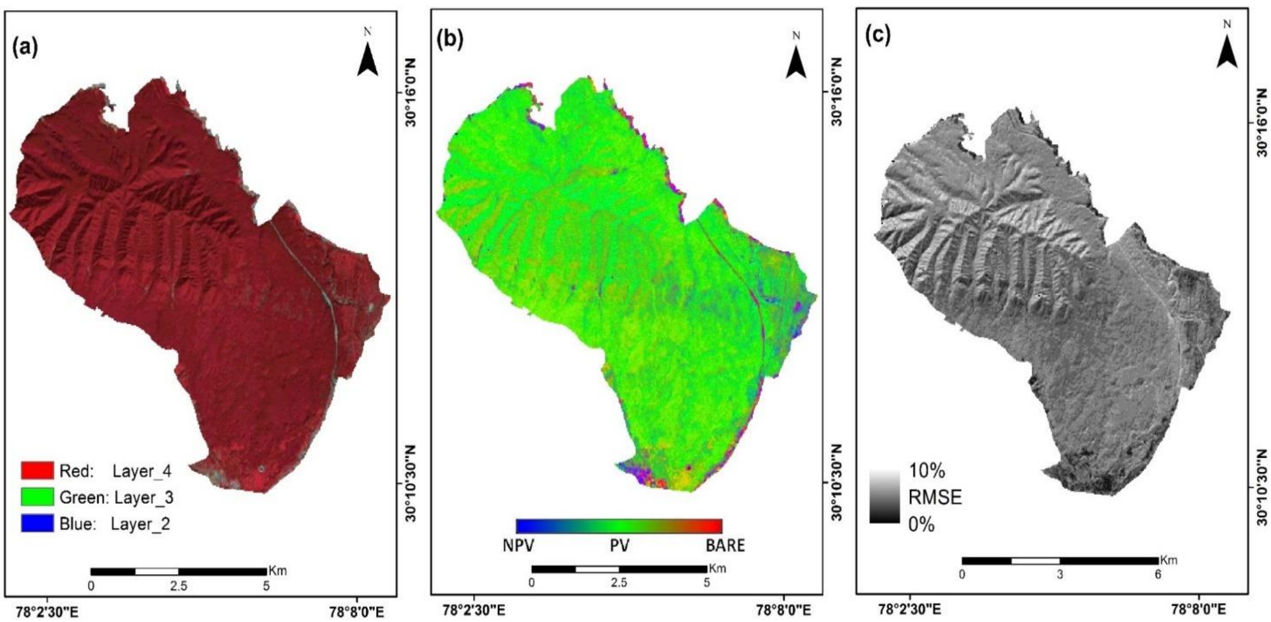

Fig. 2 (a) FCC of 2010 **(b)**Fractional cover of 2010 **(c)** RMSE image of 2010

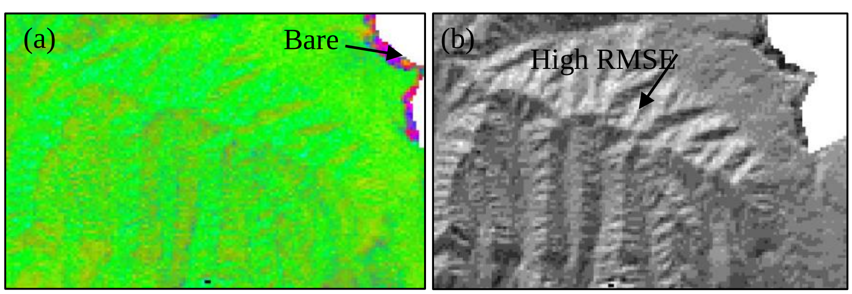

Fig. 3 (a) showing bare **(b)** High RMSE in the hill area.

In fig. 7 are the fractions of PV, NPV and bare expressed in percentages (0-100%). In 2015, there is 0-100% of bare, 0-100% vegetation and 0-58% of Non-vegetation which shows there is more open and clear cut area.

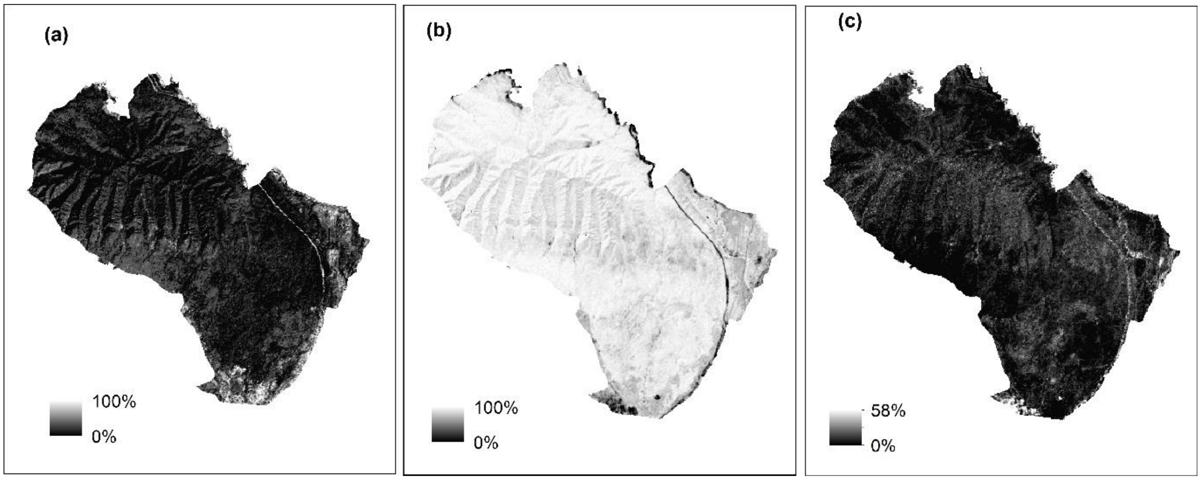

Fig. 4 **(a)** Bare **(b)** Photosynthetic Vegetation(PV) **(c)**Non-Photosynthetic Vegetation(NPV)

The RMSE image (figure 8 d) of 2015 ranges from 0 to 7% indicating the highly accurate classification of PV, NPV, and Bare.

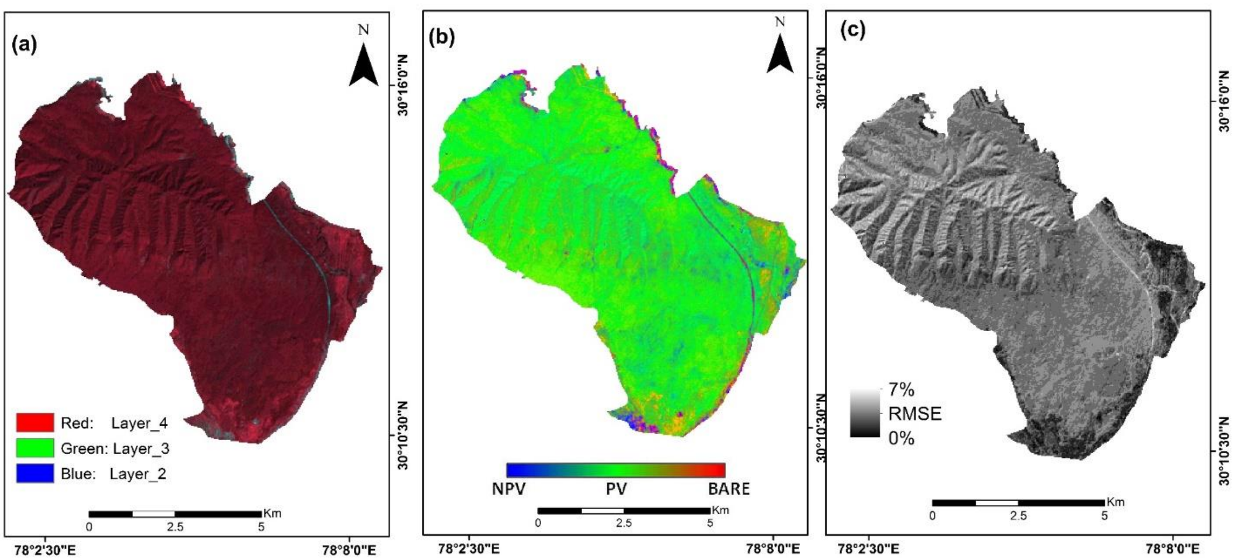

Fig. 5 (a) FCC of 2015 (b) fractional cover of 2015 (d) RMSE image

4.3 Normalized Difference Fractional Index (NDFI)

The range of NDFI lies between -1 to +1. A positive value shows high PV implying less NPV and bare soil indicating less disturbed forest while a negative value shows high NPV and bare soil indicating highly disturbed forest. Figure-10 (a) shows that the range of NDFI in 2010 lies between -1 to 1 while in 2015 Figure 10 (b) the range is between -0.90 to 1.

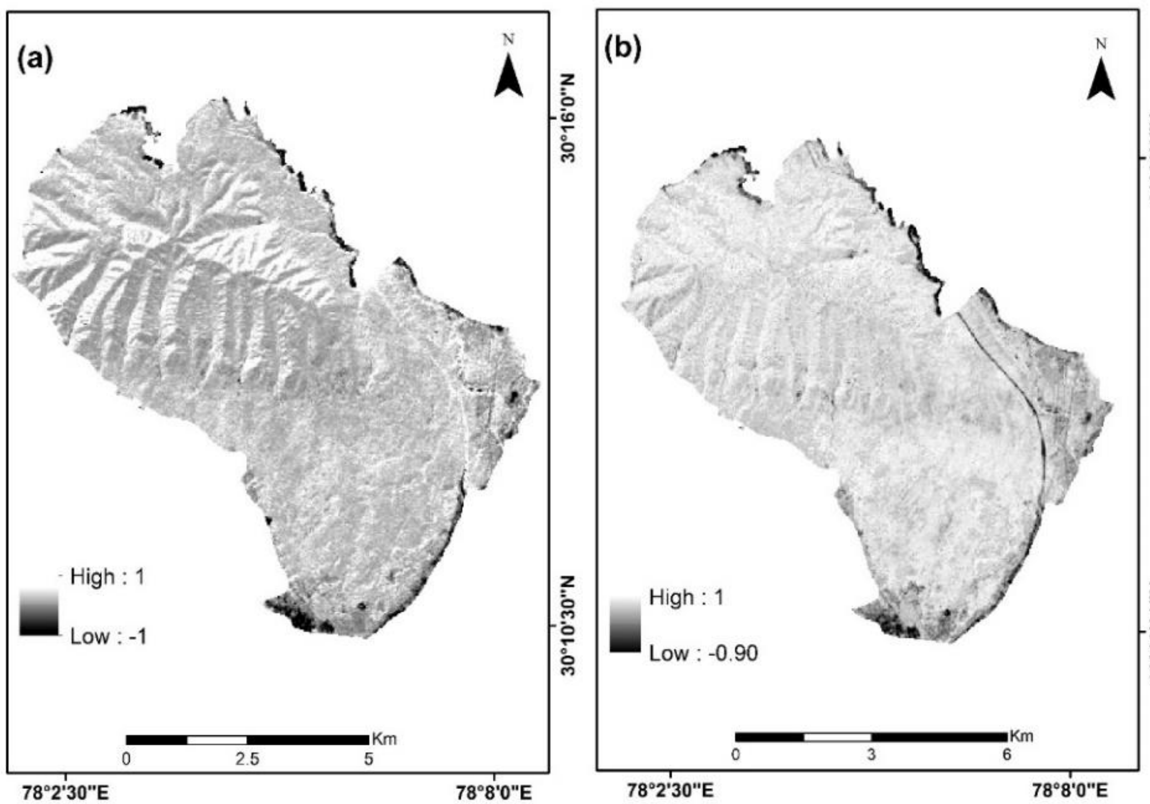

Fig. 9 (a) NDFI map 0f 2010 (b) NDFI map of 2015

4.4 Forest Degradation Map

In the figure, it's showing the of forest degradation which is composed by overlaying of reclassifying change map of NDFI.The result shows that shows that 86.82% intact forest,1.33% less degraded forest, 6.28% moderately degraded forest and 5.57% high degraded forest percentage of area in change NDFI.

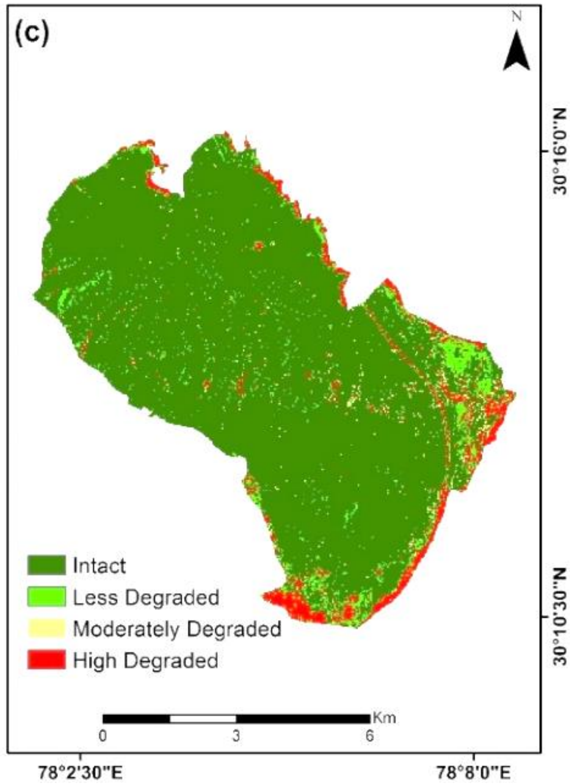

Fig. 10 Forest Degradation map

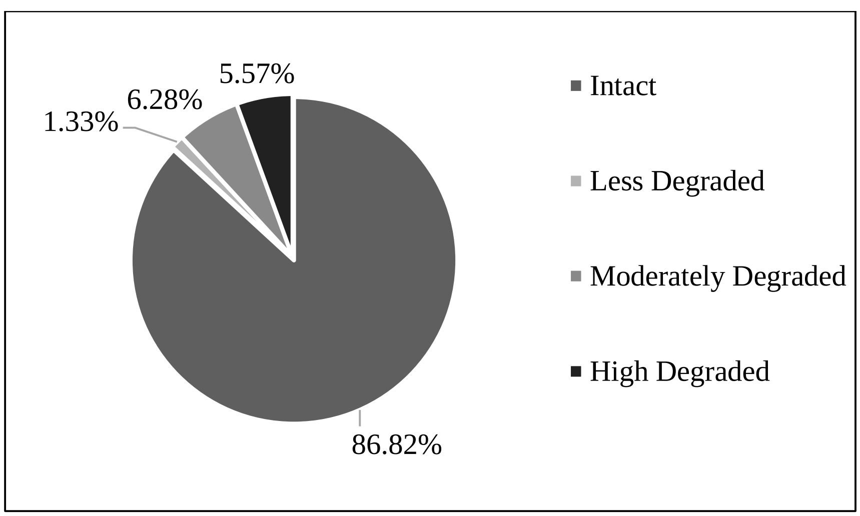

Fig. 11 Pie chart showing the percentage of area in reclassifying change of NDFI from 2010 and 2015.

5. Conclusion

The Lacchiwala which is dominated by deciduous forest is subjected to degradation due to various factors-natural and man-made. Natural factors include forest fires whereas lopping, conversion of forest land to agricultural land, widening of roads are the anthropogenic factors that are the main causative factors behind forest degradation. LANDSAT images are better suited for studying about forest as it has NIR, SWIR, thermal bands. CLASlite is an automated tool based on Automatic Monte Carlo Unmixing (AutoMCU) for separating PV, NPV and Bare using pre-computed spectral signature. An advantage of the Monte Carlo approach is that the per-pixel iterations produce a standard deviation of the estimate for PV, NPV and bare substrate fractions. It also generates a root mean squared error (RMSE) image of the model versus observed reflectance signature which expressed in percentage. The RMSE and the standard deviation images provide a way to assess the performance of the AutoMCU on a pixel by pixel basis, allowing to identify areas of concern.

Results show that study area has 86.82% intact forest,1.33% less degraded forest, 6.28% moderately degraded forest and 5.57% high degraded forest. The fractional cover of study area shows that Landsat 8 OLI/TIRS of 2015 has low RSME (i.e. 0-7%) than Landsat 5TM of 2010 (i.e. 1-10%) because it has two thermal bands in which one of them is used for quality assessment(QA). The hill area and road shows largest error i.e. 10% while degraded areas show very low error close to 1-3 % show high RMSE while degraded forest has low RSME.

The change in fractional cover from one time to other includes change in natural (felling, logging, lopping) as well as anthropogenic change (conversion of forest to agriculture). The study suggest that NDFI considers only PV, NPV, and bares whereas fails to analyze the structural changes in vegetation, this disadvantage is overcome by using SAR and high-resolution satellite images. Claslite automated tool will be much useful for operational purpose, which need limited classification but has greater impact to protect forest degradation

6. Acknowledgement

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