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CHANGE DETECTION ANALYSIS TO STUDY NATURAL RESOURCE DEGRADATION AND RESILIENCE AROUND KUDREMUKH MINE

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ABSTRACT

Kudremukh, a prime part of Western Ghats is known for its rich biotic natural resources and iron ore deposit which was a subject of debate in the last decade. Extensive mining in this region has affected its vegetation resource for more than 25 years, which prompted the closure of mining activity in the year 2006. Since then the region has witnessed resilience by nature against human externalities. In this regard the study is focused on quantitative analysis of the phenomenon to know the temporal changes in quantity of different resources in an area of 175 km^2 encompassing the mine. Changes have been analyzed for years before and after the closure of mine. Remote sensing and satellite image processing techniques are employed for change detection analysis to evaluate changes in quantitative and physical condition of vegetation to track deprivation and resilience. Remotely sensed data in the shortwave infra-red, and red spectral region were exploited as the study area includes iron mine containing Hydrothermal alteration mineral assemblages which show unique reflectance signature in the shortwave infra-red region. Image classification results revealed the forest cover has suffered a loss of about 34.15 km^2 (30.70 %) between 1998 and 2003 while area of mine/tailings increased by 21.57 %. But between the years 2003 and 2014 a positive change was observed in forest cover which increased by 3.52 % even with a growth in mine/tailings area by 37.77 % during 2003 to 2006. From the perspective of physical condition of Vegetation, highest value of NDVI in the year 1998 was +0.812 which reduced to 0.561 in the next five years of active mining indicating increased stress on plant physiology around the mine. With continued degradation for another three years followed by a regeneration period of 7 years the highest value of NDVI increased to 0.558 in the year 2014. Statistical results indicate degradation of natural resources during mining and also corroborate resilience capacity of nature against anthropogenic activities.

Keywords: Remote Sensing, Satellite Image Processing, Change Detection, Iron Mine, Shortwave Infra-red, NDVI.

INTRODUCTION

Change detection is an important application of remote sensing technology. It is a method to ascertain the changes of specific features within certain time interval. It provides the spatial distribution of features and qualitative and quantitative information of features changes. It involves the type, distribution and quantity of changes, that is the ground surface types, boundary changes and trends before and after the changes. The use of remote sensing data in recent times has been of immense help in monitoring the changing pattern of vegetation. Change detection as defined by Hoffer (1978) is temporal effects as Variation in spectral response involves situations where the spectral characteristics of the vegetation or other cover type in a given location change over time. It is a process that observes the differences of an object or phenomenon at different times. This technique is widely used for range of applications such as land use analysis, environmental monitoring etc. Global warming and consequent changes in the climate has given momentum to investigate the causes of LULC [3].

Mineral exploration has also been a major factor which has altered natural vegetation cover, which in turn has left significant effects on local weather and climate. This activity causes two major environmental problems, First, the pollution of rivers and streams, decrease in quantity of water resource and second, alluvial erosion and deforestation [4]. Impacts of land-use and land-surface changes due open-cast mining are very severe as it includes changes such as deforestation, water resource degradation, agricultural intensification, road building and urbanization. Effect on natural resources like forest and water due to mining is not only in the excavated area but also in the area surrounding the mine. Open-cast mining all over the world is known to have devastating effects on ecosystems. Detailed knowledge of land use practice, land use pattern changes with time and its effects on environment and system are important to understand the importance of changes in land use. Around the globe impacts of mining has triggered social conflicts between miners and environmentalists. Monitoring the locations and distributions of land-cover changes due to mining activities and quantifying the effects on ecosystem is essential for establishing linkages between policy decisions, regulatory actions and subsequent land-use activities.

PROBLEM STATEMENT AND OBJECTIVE

Globally several mines were shut down due to increasing concern over environmental degradation. The surrounding environment generally experiences a positive change after terminating mining activities in any site, but the mechanism of reversal of environmental degradation is a slow affair. This study seeks to determine spatially how much of land cover has changed whilst mining and after closure of Kudremukh iron mine.

Numerous studies of similar nature that seek to analyze changes have been conducted in this area. However these works were concentrated on effects of mining on catchment hydrology, over-all land use change or environmental impacts. But this work mainly concentrates on studying changes in forest cover and water body with incremental changes in mine area and especially on positive changes in forest growth in recent years after closure of mining activities. Another aspect of this work is to ascertain the application of Short Wave Infra-Red bands of multispectral satellite data to spot iron rich areas or mines.

In this study the land use and land cover change is evaluated by considering four broad classes/ categories of land parcels namely, forest area, mine/tailings, water body, open soils/other. The changes in these categories between 1998, 2003, 2014 are evaluated by classifying satellite images of the area into above mentioned classes.

The objective of the work is:

- To create land use and land cover maps of Kudremukh area for three different years with four different LU/LC classes.
- To generate Normalized Difference Vegetation Index (NDVI) maps of the area for the particular time period.
- To carry out area-wise temporal change detection analysis to quantify changes in area of each class and changes in NDVI values during mining and after halting to analyze physical condition of vegetation.

STUDY AREA AND DATA

Kudremukh is a mountain range and name of a peak located in Chikkamagaluru district, in Karnataka, India. The Kudremukh National Park shares the boundary with iron mining area owned by Kudremukh Iron Ore Company Ltd (KIOCL). KIOCL owned 4,604.55 ha. area under lease for conducting magnetite mining operations for over 25 years until Dec 2005. Kudremukh situated at an altitude varying from 100 m to 1892 m above MSL has large extent of bio-diversity rich Shola-grassland ecosystems located in a hilly, high rainfall (6000-7000 mm yr^{-1}) region in the Western Ghats, a global biodiversity hotspot. In addition the Bhadra River and its tributaries are the habitat of several aquatic species limited to this area Kudremukh is widely known for its rich flora and fauna. An area of nearly 17500 ha. (Latitude 13°09'00" to 13°15'30" N, Longitude 75°11'00' to 75°19'00" E) is considered in this study which is aimed at evaluating forest decline in as a result of increased mining activity. In addition to the mine and forest reserves the study area consists of a huge tailings deposit area, holds backwaters of Lakya dam. It is also a point of origin for Bhadra River, and houses a township and a mega factory for primary processing of ores. Social conflict related to mining and environmental issues in this area is the motivation for carrying out a change detection study to understand the scenario.

The following remotely sensed datasets covering Kudremukh (13.1295° N, 75.2686° E) area are used in this study:

- Landsat 5 TM image for 1998
- Landsat 7 ETM+ image for 2003
- Landsat 8 OLI–TIRS image for 2014

All the images had same resolution of 30m. Images were taken between January to March considering the fact that study area is mostly cloud free in this period of the year.

Google Earth and Global Positioning System (GPS) data were used as ancillary tools to obtain geographic coordinates for Geo-referencing and rectification of the satellite images.

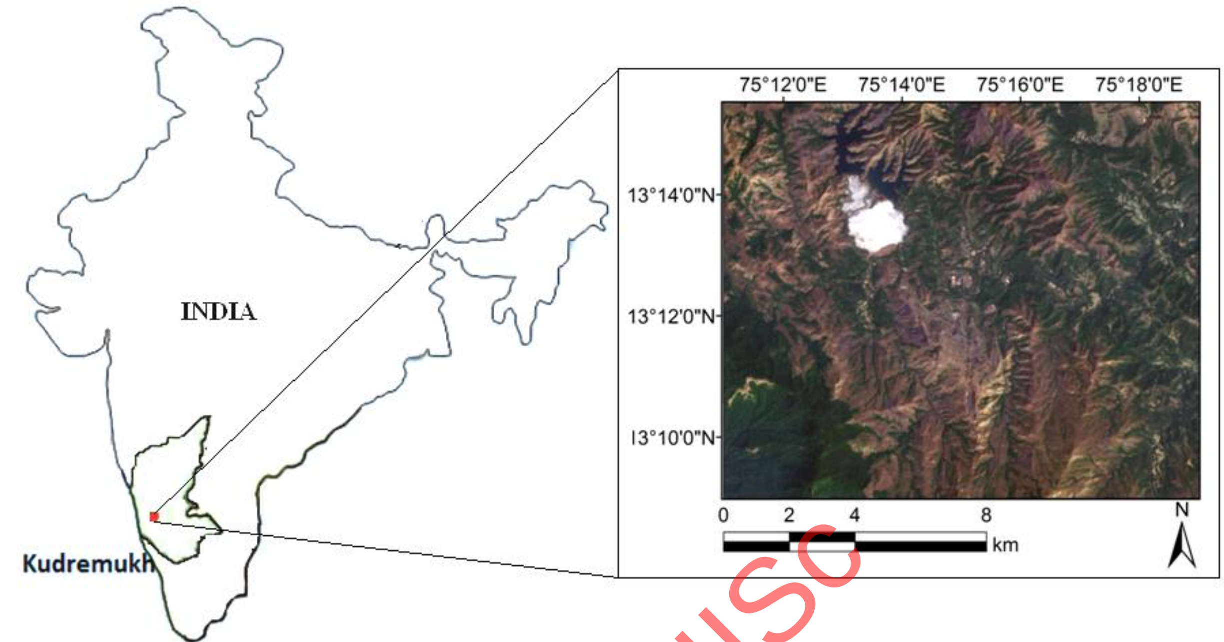

Figure 1. The geographic location the study area

METHOD

Method adopted in the study is outlined in fig. 2, involved following steps.

- Remote Sensing data acquisition, geo-referencing and rectification
- Image processing - NDVI calculation, Image classification and Accuracy assessment using Erdas Imagine
- Change detection analysis.
- Generating maps using ArcGIS.

ERDAS Imagine software package was used for all image processing procedures carried out in the current study which is popular for its varied types of tools to work on multispectral satellite data. Initially all the image bands obtained were layer stacked to visualize the best band combinations to discriminate mine area from its surrounding soil. The image was radiometrically correct as it was level-1 product from USGS earth explorer. Later the image is georeferenced using GPS coordinates and Google Earth. Geo-referencing and rectification was done using polynomial transformation and nearest neighbor interpolation which retains the original information in every pixel and offers advantage of computational simplicity. Then image was subset for chosen area of interest. The subset image was converted to false color composite to perform image classification. Prior to this NDVI was calculated separately.

A non-traditional false color composite was chosen for image classification. The RGB color composite was set to SWIR2, SWIR1, and Red as the study area is of iron mine containing hydrothermal alteration mineral assemblage such as phyllosilicates. These minerals produce diagnostic absorption signatures in the visible, and shortwave infrared (SWIR) regions [1] which make the mining/tailings area appear distinct from other soils. These features are produced by electronic or vibrational-rotational processes resulting from the interaction of electromagnetic energy with the atoms and molecules, which comprise the minerals that make up an ore [7]. This unique spectral characteristic of ores helps to classify mine area from surrounding soil with increased accuracy.

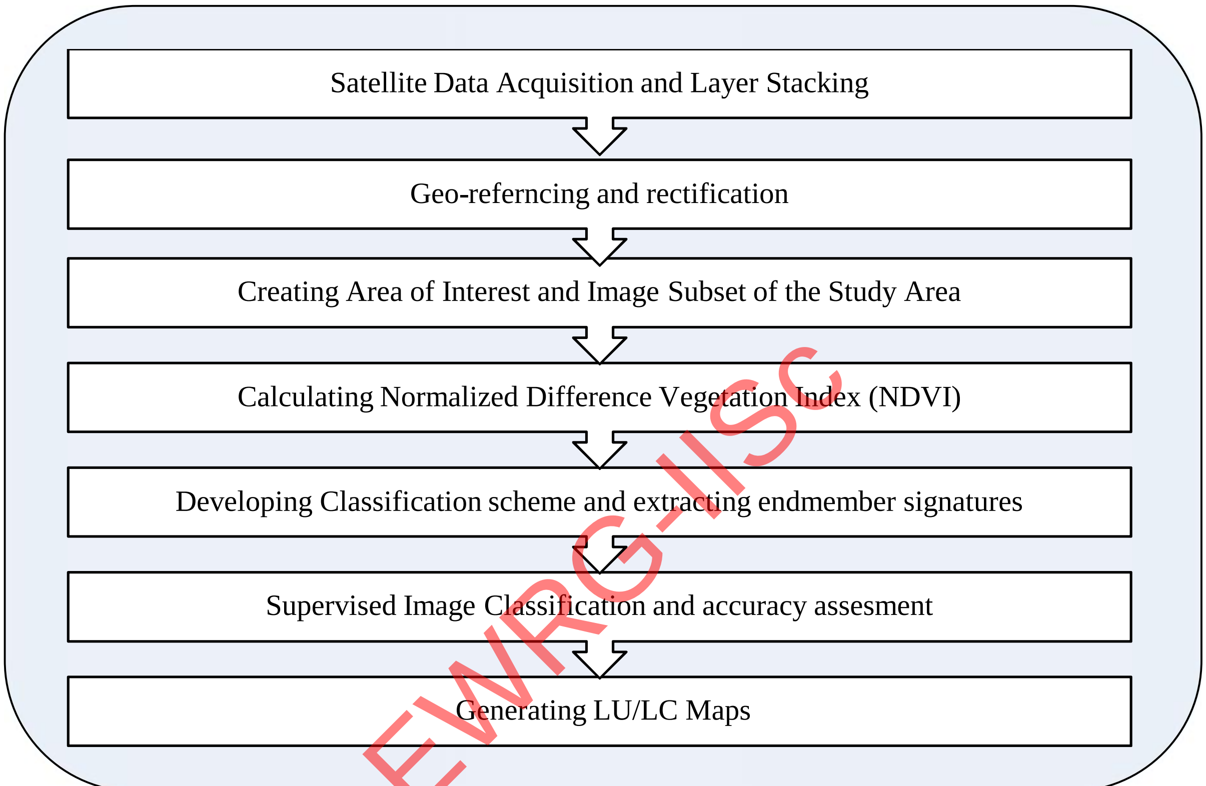

Figure 2. Flow chart of methodology adopted

Analysis was carried out using a pixel based supervised pattern classifier called Gaussian maximum likelihood algorithm which quantitatively evaluates the variance and covariance of the category spectral response patterns while assigning a pixel into a class. The classifier delineates equiprobability contours of each class based on training samples provided and applies a weight associated with cost of misclassification ensuring a theoretically optimum classification [2]. Prior to classification training samples were selected from the false color composite image for all the four classes described in table 1. Training polygons were selected such that they were uniformly distributed over the entire study area and represent pixels which seemed pure. GPS was useful in locating respective training polygons in the field.

Accuracy assessment is carried out for all the classified images. This is important for post-classification type change detection analysis. Classification accuracy assessment is a method to evaluate the performance of classification algorithm in transforming image to thematic map. It is the process of measuring the spectral classification accuracies by set of reference pixels. Overall accuracy (OA) is the summed average accuracies of individual classes. The OA provides a measure of the overall classification accuracy of all and is expressed as percentage (%). OA represents the probability that a randomly selected point is classified correctly on the map. And the kappa coefficient k expresses the proportionate reduction in error generated by a classification process compared with error of completely random classification [2].

TABLE I: CLASSIFIATION SCHEMA OF LAND USE CATEGORIES

Class	Land use included in class
Forest Area	Forest and any other vegetation
Water Body	Reservoirs, Lakes, Tanks, Streams
Open soil/ Other	Open ground, Built-up area, Sparse shrubs, Mixed pixels etc.
Mine/ Tailings	Mining area and tailings deposit

Along with image classification, Normalized Difference Vegetation Index (NDVI) images were generated for each year and exported to ArcGIS for representing as maps. The year-wise ranges of this index along with generated maps are presented and discussed in the next section. NDVI is a numerical indicator varying from -1 to +1 derived from reflectance of the pixels in Near Infra-red and Red region of the electromagnetic spectrum. The magnitude of the index indicates the amount of vegetation present in the pixel or level of photosynthetic activity by green vegetation [6]. Generally healthy vegetation absorb most part of the red light and reflects most part of the Near Infra-red light incident on it for photosynthesis, whereas stressed or sparse vegetation reflects lesser portion of Near Infra-red light. This behavior of foliage helps in deriving the index.

$$\text{Normalized Difference Vegetation Index} = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \qquad (1)$$

Pixels with higher reflectance in the NIR range will have positive NDVI value, generally values over 0.6 indicate dense vegetation.

Change detection involves comparison of statistics obtained from satellite image processing sense changes. In this study, Post-classification change detection technique was applied to detect and quantify the extent of change in forest and other classes' areas as well as differences in NDVI values are analyzed to learn the changes in vegetation reflectance characteristics. Change in the area of mine and tailings have caused subsequent changes in other classes. This phenomenon is quantified and comparison of areas is done for various years and represented and discussed in next section.

RESULTS AND DISCUSSION

NDVI values varied greatly from 1998 to 2003 and from 2003 to 2014. In the year 1998 least value of NDVI was -0.551 and highest value was +0.812, after five years of intensive mining the NDVI values changed to a least value of -0.575 and highest value of +0.561 which indicates a significant reduction in maximum value by 30.91%. Mining was continued for three more years and the NDVI values might have seen a further declination during this period. After eight years of closure the NDVI values showed an increase in vegetation density or physical condition as NDVI varied between -0.089 to 0.588 in the year 2014 i.e. increase by 4.81%. Fig. 3 represents spatial variation of NDVI in the study area. Since changes in maximum values of

NDVI best portrays the changes in foliage density or condition it is tabularized in table 2.

TABLE II: CHANGES IN MAXIMUM VALUE OF NDVI

NDVI	1998 to 2003	2003 to 2014
Change in Maximum Value	+0.812to +0.561	+0.561 to +0.588
%Change in Maximum Value	Decreased by 30.91 %	Increased by 4.81 %

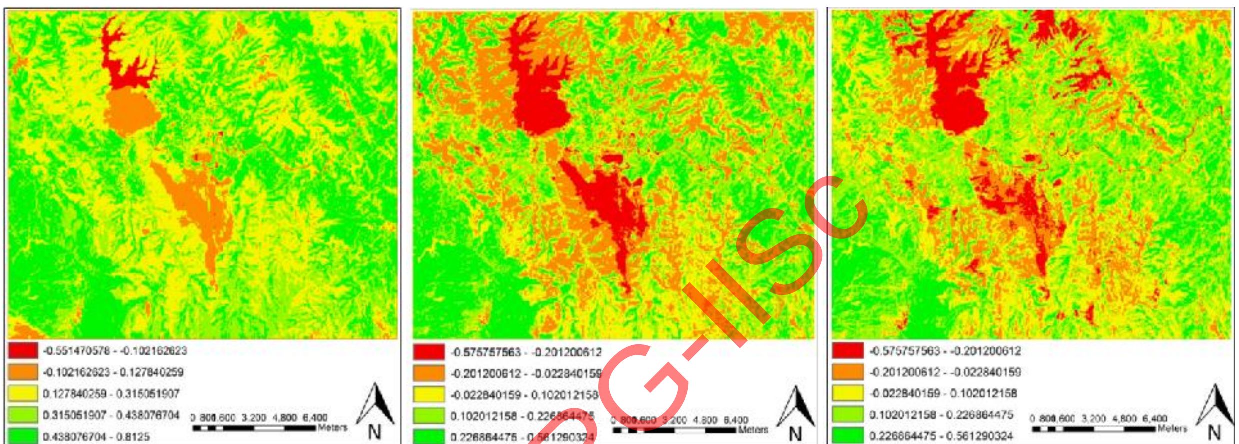

Figure 3. Spatial variation of NDVI in the year 1998, 2003 and 2014 respectively

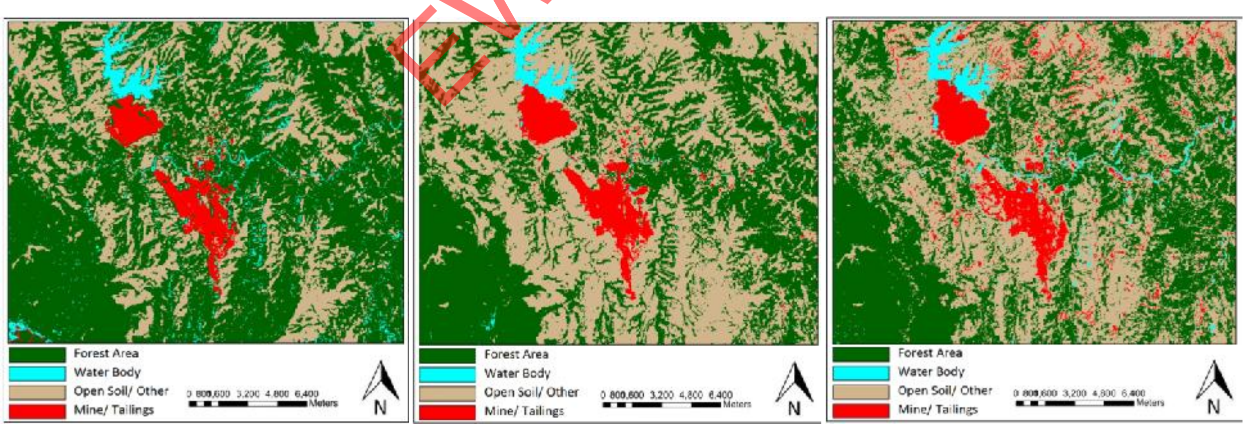

Figure 4. Land use maps of the year 1998, 2003 and 2014 respectively

Fig. 4 shows LU/LC maps developed by satellite image classification. The variations in classes can be easily identified from one map to other due to the fact that the magnitude of spatial change from time one study time to other is significant. There has been a significant increase in mining from 1998 to 2006 which has led to a drastic drop in the total area forest cover and water body and simultaneously increasing open land area. The forest cover has suffered a loss of about 34.15 km^2 in just 5 years from 1998 to 2003 because of large scale externalities caused by mining and in anticipation of possible closure of mine in near future. A steep decrease in water body was also seen which is majorly because of increased tailing dump in the northern part of the study area which holds back-water of Lakya Dam. In the year 1998 the forest cover was 64.11 % of the total area which reduced to 44.43 % in the year 2003. Similarly, a drop of about 56.10 % was observed in water body in the same time period. On the other hand a reversal of degradation was witnessed in the period 2003 to 2014 which might have started only after 2006 when the mining works was banned by the Supreme Court of India in the end of 2005 i.e. three years of further degradation and 7 years of effective resilience. The increase in the area of mine/ tailing between years 2003 and 2014 is due to full paced running mine in its last three years of activity.

TABLE III: LAND USE DURING 1998, 2003 AND 2014

Class	Forest Area		Water Body		Mine/ Tailings		Open soil/ Other	
Year	km^2	%	km^2	%	km^2	%	km^2	%
1998	111.28	64.11	6.00	3.46	7.23	4.17	49.06	28.26
2003	77.12	44.43	2.63	1.52	8.79	5.07	85.02	48.98
2014	79.83	45.99	4.20	2.42	12.11	6.98	77.43	44.61

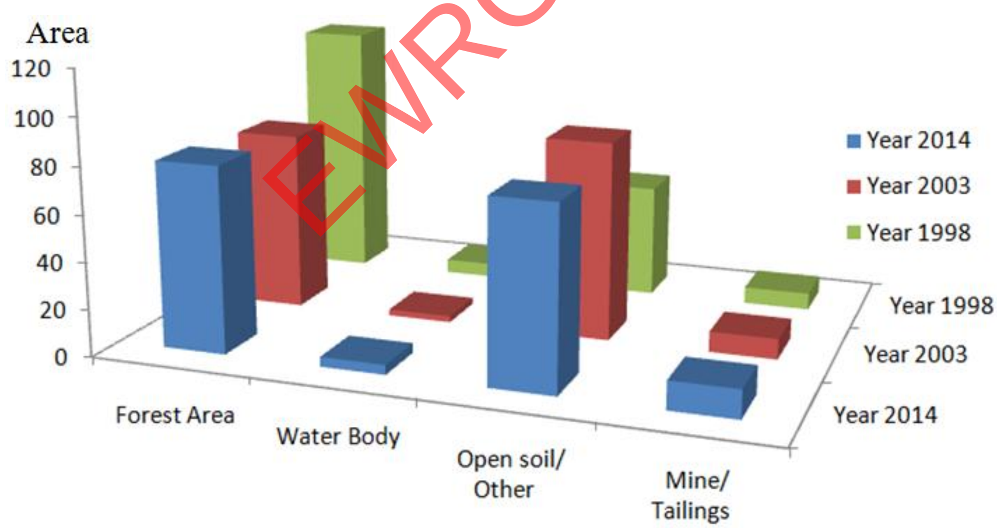

Figure 5. Graph showing year wise changes in area (area in km^2)

From the year 1998 to 2003 the mining area and tailing dump area has risen by 1.56 km^2 (21.57%) resulting a loss in forest area by 34.15 km^2 (30.70%). In the same time span area of water body decreased by 3.36 km^2. Between 2003 and 2014 there was a significant increase in water body by about 1.56 km^2 of surface area which is about 59.69 % more than what was in 2003. An improvement in forest area and decline in open soil is also observed over the years.

These statistics proves the resilience by nature against externalities. Accuracy assessment was done for classified image for all the years. In all the three classified maps 1.593 km^2 of area remained unclassified. The average overall accuracy was 83.2%, with average overall kappa statistics 0.76, which is acceptable.

TABLE IV: CHANGES IN AREA OF EACH CLASS BETWEEN THE STUDY YEARS.

Class	1998 - 2003	2003 - 2014
Forest Area	-30.70 %	+3.52 %
Water Body	-56.10 %	+59.69 %
Open soil/ Other	+73.29 %	-8.93 %
Mine/ Tailings	+21.57 %	+37.77 %

TABLE V: ACCURACY ASSESSMENT

Year	Overall accuracy %	Kappa
1998	78.62	0.71
2003	81.33	0.75
2014	89.64	0.84

CONCLUSION

Understanding the effects of anthropogenic activities on environment is essential for future policy making from the perspective of better sustainability of natural resources. Employing historical remotely sensed data and image processing techniques help achieving this in a better way. Kudremukh suffered huge loss in its both biotic and abiotic natural resources like forest and water during the years of active mining. But there was an increase in the area of water body as well as forest cover in the previous decade. Fig. 6 depicts effect of mineral exploration and halting on each of the land-use land-cover class area with good proximity to the mine.

These statistics helps us to draw a conclusion that, mining is certainly a cause for natural resource degradation and the nature has the resilience capacity to overcome the negative impacts caused by anthropogenic activities if they are halted. This study benefits future policy makers with insights of risks attached extensive mining around sensitive eco-systems to maintain feasible trade-off between mineral exploration and conserving the ecological entities.

Another conclusion which can be drawn from good classification accuracy obtained in image classification is the potential of shortwave infrared bands of a multispectral data to map iron ores which will help studying locations of ore deposits or to estimate exploration with easily available multispectral data.

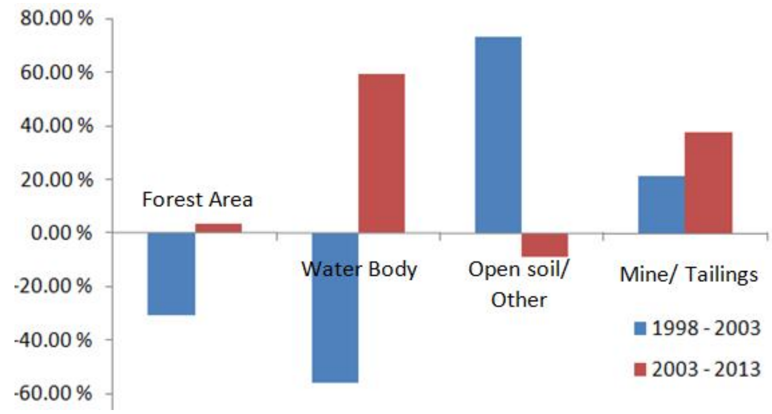

Figure 6. Graph showing % changes in each class during and after mining

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