MODIS NDVI TIME SERIES FOR IDENTIFICATION OF DEGRADED LAND HOTSPOTS

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ABSTRACT: Land degradation is recognized as a serious threat to environment. Restoring degraded lands and soils is one of the Sustainable Development Goals (SDGs) of the United Nations Development Programme (UNDP). Given the importance of the problem, many attempts have been made word wide to map the distribution, type and severity of degradation. In India, most of the country level frameworks for land degradation assessments are based on expert opinion and visual interpretation of satellite data and have provided estimates ranging from 47 m ha to 187 m ha. None of the studies in India have considered the crop phenology and productivity as an indicator of land degradation. Further, these approaches are subjective inconsistent and time and cost consuming. These delays in assessments lead to a delayed solutions. A quick, simple, robust, quantitative, cost effective and consistent method has been developed to identify and map degraded lands at regional scale. It utilizes MODIS (or Moderate Resolution Imaging Spectroradiometer) NDVI (normalized Difference Vegetation Index) time series data (16 days composite for 20 years) as a proxy indicator of land productivity. Time series NDVI data have been used successfully to identify land degradation using trend analysis and local NPP (Net primary Productivity) scaling methods. However, the trend analysis of time series NDVI cannot be expected to identify historically degraded areas. The other method classifies the degraded lands as land capability units. The present study identifies the degraded lands (both historic and ongoing) based on the assumption that the degraded lands exhibit a consistently low productivity over time, indicated by constantly low NDVI. In contrast, the healthy soils will show a cycle of increase and decrease of NDVI over time with crop phenology. This pattern can be well identified by applying principal component analysis (PCA) on the time series NDVI data to identify constantly low productive hotspot areas. Finally, the method relies on field observations along with other data available in public domain to validate the overall assessment. The methodology was tested in different agro-ecological regions of India including, alluvial plains (Indo-gangetic plains), coastal plains, deserts, rain forests, basaltic terrains and was found effective.

The simplicity and quantitative nature of method, use of freely available input data make it suitable for rapid assessment of land degradation on a national scale in a time and labour effective manner.

INTRODUCTION

Land degradation has been ranked as a major environmental and social issue in the coming decades (UN 1994). The agricultural land in India and elsewhere for production is shrinking (Bruinsma, 2003; FAO, 2005; Gelfand et al., 2013, Obi Reddy et al., 2018) and reclamation of degraded lands have often been suggested as a solution to issues of land scarcity to meet mounting global demands for agricultural goods (Gibbs and Salmon, 2015). UNCCD (2012) set a goal of "Zero Net Land Degradation" to meet out the global demand of food, fiber and timber (Grainer, 2015). Therefore, the identification and mapping of degraded lands with extent and severity is a primary objective for a number of scientific and policy organizations to achieve the said objective of achieving degradation neutrality by 2035.

Several estimates of degraded lands worldwide (Oldeman et al., 1990; Dregne and Chou, 1992; Bai et al., 2008; Cai et al., 2011, Gibbs and Salmon, 2015) and in India (NBSS&LUP, 1994; NRSC, 2012; Maji et al., 2010; SAC, 2016) have been made with different approaches having different definitions and classification systems resulting in different statistics. In India, there have been efforts to map land degradation for the country based on either GLASOD methodology (NBSS&LUP, 1994; Maji *et al.*, 2010) or visual interpretation of satellite imagery (NRSC, 2012, SAC 2016). These methods have been criticized for been qualitative, subjective, time consuming, and being hardly reproducible. Countrywide mapping of land degradation thus needs a fast and robust approach which is quantitative in nature and is reproducible. Isolated efforts to map land degradation or a type of land degradation have also been attempted for specific study areas, applying quantitative methods of digital image processing on moderate resolution satellite data obtained from Landsat, IRS, SPOT, etc (Kumar et al., 2019). However, these approaches are limited to smaller areas due to small coverage of these data and unavailability of cloud free data.

A recent approach to identify degraded lands is using proxy indicators (Bai *et al.*, 2008; Gibbs and Salmon, 2015). This is a quantitative method based on the hypothesis that the degraded lands have lower biomass productivity reflected in terms of lower Normalized Difference Vegetation Index (NDVI) (Bai *et al.*, 2008; de Jong *et al.*, 2011). This utilizes data from sensors like Advanced Very High Resolution Radiometer (AVHRR), SPOT Vegetation, and Moderate Resolution Imaging Spectro-radiometer (MODIS) which provide time series data at a regular interval. The degraded areas have been identified by trend analysis (Wessels *et al.*, 2012; Eckert *et al.*, 2015), Local NPP Scaling (LNS), and local variance method (Budde *et al.*, 2004). The trend analysis of time series NDVI approach identifies negative trends in vegetation production through time. This method cannot be expected to identify historically degraded areas (Wessels et al., 2008, 2012). Further, a significant negative trend can only be visible when there is a sharp decrease in NDVI. The other method, LNS, is capable of detecting historical degradation. It identifies degradation by comparing the NPP (growing season ΣNDVI) of a particular pixel to the maximum observed NPP in the homogeneous unit - in terms of terrain, climate, and soils – to which it falls (Pickup 1996; Wessels et al., 2008; Prince et al., 2009). Thus, it first requires the study area to be divided into different homogeneous unit such as land capability units (LCU). Furthermore, it assumes that sufficient non-degraded land exists in each LCU to allow the relative scaling procedure (Prince et al., 2009).

The present study attempts to utilize the coarse resolution MODIS NDVI time series data as a proxy of land degradation based on the assumption that, the degraded lands exhibit a consistently low NDVI in the time series (Kumar, 2018; Kumar and Singh, 2018). In contrast, the healthy soils will show a cycle of increase and decrease of NDVI over time with crop phenology. This pattern can be well identified by applying principal component analysis (PCA) on the time series NDVI data to identify constantly low productive hotspot areas.

MATERIALS AND METHODS

Study Area

The methodology was developed and tested in different physiographic regions of India, one district each, including Kanpur Dehat, North -24 Parganas, Wardha, and Jaisalmer. Kanpur Dehat represents the Indo-Gangetic Plains (IGP) where soil erosion and salinity/sodicity is the main problem. Wardha represents the basaltic terrains of central India where soil erosion is main problem. North 24-Parganas represents the eastern India having wetlands as the main problem. The district Jaisalmer represents the deserts of Western India.

Data Used

In this study, open data of Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation indices (250 m, 16 days composite) for 18 years (2001-2018) were used for identifying the degraded lands. Landsat 8 Operational Linear Imager/ Thermal Infrared Sensor (OLI/TIRS) multispectral (30 m) data, high resolution Google earth data, and legacy data on land degradation from land degradation database of National Remote Sensing Centre, Hyderabad at 1:50000 scale have been used for validating the research.

Pre-processing of MODIS data

Pre-processing of MODIS data includes: extraction of the NDVI layer from the 12 layered data, calculation of original NDVI values from the scaled data, and conversion of projection system and data format. Thus all the 414 images were converted into workable format. Savitzky-Golay filter (Savitzky and Golay 1964) was applied for smoothing the time series data. All the processes were done in R (R Core Team 2018).

Identification of Degraded Land Hotspots

All the processed and smoothened data were stacked into a single file for PCA. The layer stacked time series MODIS NDVI data was used to identify the regions with constantly low biomass productivity. It is based on the hypothesis that the consistent low NDVI was shown by the degraded lands and the permanent features. PCA was used for identification of continuously low productive areas based on the hypothesis that the higher values in first principal component (PC 1) highlights the regions that do not change significantly over the years (Lasaponara, 2006). These included the habitations and water bodies along with the degraded lands. Similarly, the cropped areas with changing NDVI will show lower values in PC1.

Validation

Three approaches were applied to validate the results obtained for the area under degraded lands: filed verification, use of Landsat OLI and Google earth, and use of legacy data on land degradation provided by NRSC-NBSS&LUP (NRSC, 2012).

RESULTS AND DISCUSSION

The resulted first component images for Kanpur Dehat district obtained from the application of PCA to NDVI temporal series is shown in figure 1. The PC1 represents the weighted mean pattern of 414 images of NDVI for the years 2001–2018. As expected, PC1 patterns are based on long-term stable productivity. High PC1 values tend to be distributed around the permanent features (habitation, water bodies) and the degraded lands with constant NDVI, whereas PC1 values become lower for cropland with changing NDVI values over the year. This is a direct result of the high correlation that exists among images for regions that do not change significantly and the relatively low correlation associated with regions that change substantially (Lasaponara, 2006).

A similar pattern was observed in images of all the districts. From the analysis, this can be pointed out that PC1 distinguishes between areas whose vegetation development behaves similarly and the areas with changing vegetation in the time series. And therefore can differentiate the areas with constant NDVI from the areas with variable NDVI over the year. This was confirmed by overlaying the land degradation polygons from NRSC (2012) on the PC1 of each district in the study area.

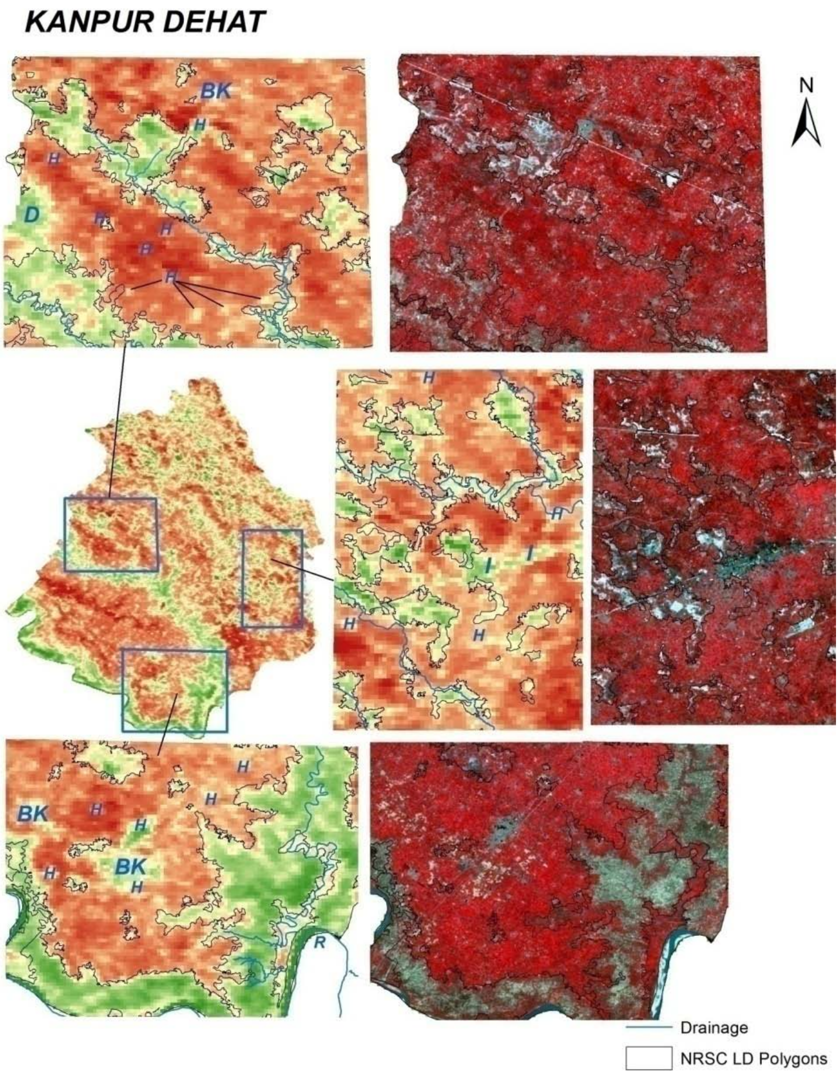

Figure 1: Figure showing the PC1 and the degraded patches overlaid by NRSC land degradation polygons for Kanpur Dehat, Uttar Pradesh

Figure 1 also shows some selected window areas with land degradation polygons from NRSC (2012) overlaid. For reference, Landsat data of the same areas are also shown. The figures clearly indicated that the regions with high PC1 values are strikingly similar in spatial distribution to that of the degraded land polygons. The higher values are also associated with the permanent features including the rivers (R), settlements (H), industrial areas (I), and brick kiln areas (BK), indicated in the figure.

Land degradation varies for each location under different land management practice. Therefore, land degradation assessment at the national level- the intended main focus of this study- should be verifiable to other terrains of the country. The applicability of the method to other terrains were tested and found effective in three other terrains namely, the basaltic terrain of central India and the deserts of western India, and the wetlands of eastern India.

Figure 3 shows some of the degraded patches affected by salinity with Google earth and Landsat images. Some of the filed photographs taken during field verifications are shown in figure 4 with their location on Google Earth.

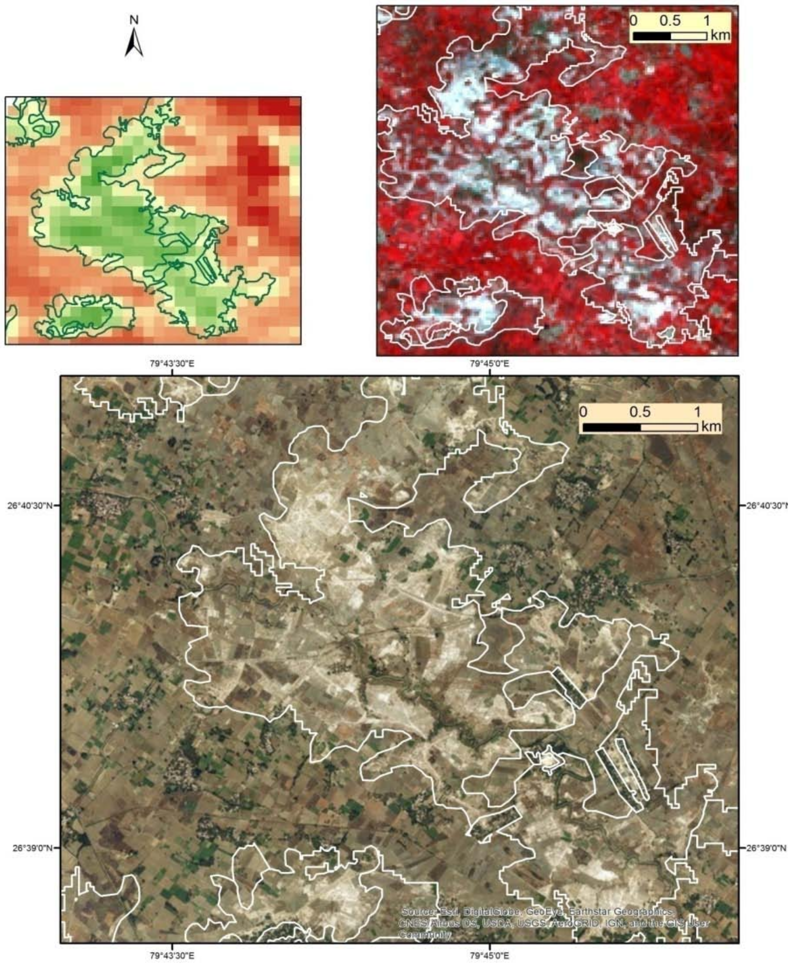

Figure 2: Figure showing some salt affected patches identified on MODIS time series data PC1, Landsat, and Google Earth

Figure 3: Field photographs of some of the degraded areas with Google Earth locations of Kanpur Dehat with

Figures 4 and 5 show the methodology applied on MODIS time series images of districts North 24-Parganas and Jaisalmer, respectively along with the Landsat 8 data. The wetlands areas in the district North 24-Parganas can be very distinguishably identified having higher values in PC1. Similarly, the desert area in the district may be differentiated from the irrigated area of the Indira Gandhi Canal Command area. The irrigated areas are the areas with fluctuating NDVI and can be seen as red patches in the figure 5.

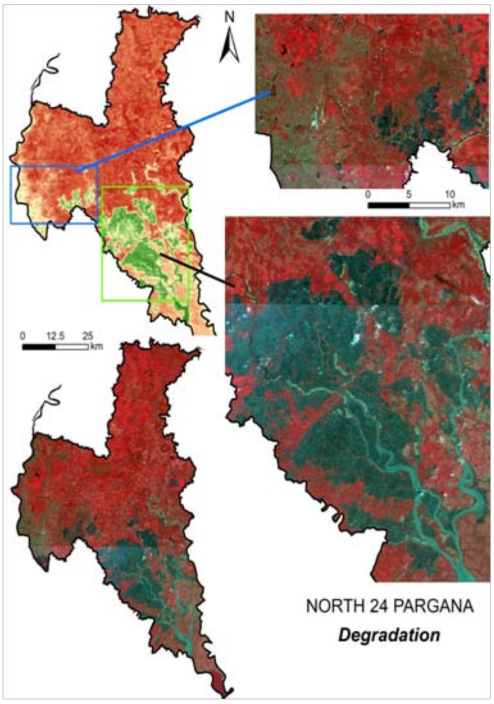

Figure 5: Wet lands in North 24-Parganas district

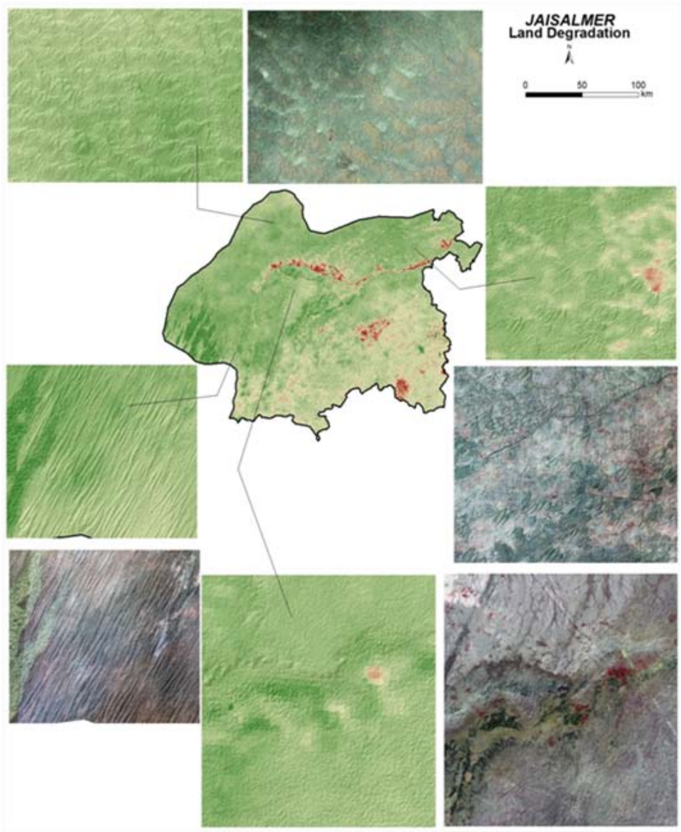

Figure 4: Deserts and sand dunes of Jaisalmer district

Thus, the raster of PC1 resulted from the PCA analysis of the time series MODIS NDVI data can be used to map the degraded lands. However, permanent features had to be identified and masked to get actual figures of degraded lands. Further, the results were in a raster format with a low resolution similar to the parent raw data (250 m).

CONCLUSION

The objective of the study was to develop a method which is quick, quantitative, and cost effective in identifying degraded lands. The use of coarse resolution (250 m) MODIS NDVI time series data as a proxy to identify the degraded lands was tested. The assumption was that the permanent features and the degraded lands will show small variations in the time series (continuous features), whereas, crop lands will show a varying trend with a high NDVI in the growing seasons and a lower NDVI equivalent to the other features during the breaks in growing periods. The continuous features showed high correlation between the time series images which were identified by higher values in PC1. These patches were identified as hotspots of degraded lands which could be delineated with exact boundaries using high resolution satellite data. The method developed was equally effective for mapping the eroded land in all the physiographic regions.

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