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MAPPING OF DEFORESTATION AND FOREST DEGRADATION ASSOCIATED WITH RESPONSIBLE DRIVERS IN THE MAN RIVER BASIN, CENTRAL INDIA

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Abstract. In developing countries, both deforestation and forest degradation are of serious environmental concern due to various driving factors. This can be more difficult to manage due to the lack of quality data and the unavailability of appropriate mapping techniques. Based on remote sensing data, this study examined an integrated approach to improve the mapping capability of forest change monitoring for data deficient areas. The study is carried out integrating ground-based information with Landsat 5 TM, Landsat 8 OLI and TIRS in the Man River Basin, India. The findings of the current study suggest that the integrated approach enhances the ability of modeling to estimate deforestation and forest degradation associated with responsible drivers, especially in countries such as India where grassroots data are infrequent.

Keywords: deforestation, forest degradation, drivers, integrated approach, remote sensing.

Introduction

Tropical deforestation and forest degradation are at alarming levels due to natural and human related activities (Ravindranath et al., 2012; Indrabudi et al., 1998; Margono et al., 2012). It is one of the most serious environmental concerns in developing countries as well as globally. Tropical deforestation has a significant impact on global climate change (Dale, 1997; Deborah & Karen, 2015), biodiversity issues (Specht et al., 2015), livelihood opportunities (Foley et al., 2005) and forest ecology (Dale, 1997). India is also one of the countries in the world where forest destruction is a serious concern. (Ravindranath et al., 2012; Tian et al., 2014).

In central India, the large forest area of the Man River Basin has been severely affected by forest loss due to human and natural causes over the past few decades. (Madhya Pradesh State Government, 2007; Narmada Valley Development Authority [NVDA], 2008; Tamgadge et al., 2001). Most of the forest areas in the region are largely degraded by the permanent shifting of agriculture, which is even more difficult to reverse as the state government gives land ownership licenses to local farmers (Banerjee, 2010).

In this context, it is necessary to develop an effective approach that has the potential to measure the entire landscape of forest changes to control further loss of forest and forest degradation in such areas. In the scientific literature, there are many new tools and techniques based on satellite data to measure the pattern and process of forest change and its responsible factors (Lambin, 1999; Ringrose et al., 1990; Hellden, 1991; Tucker et al., 1991).

In the context of remote sensing data, the forest change assessment process can be classified into two distinct groups: (1) direct assessment and (2) indirect assessment. The direct assessment process uses aerial photographs or spectral imagery with very high resolution to measure the forest change. While the same, indirect assessment uses automatic multispectral classification to analyse the change (Achard et al., 2008). Direct methods have some limitations due to the limited availability of high-resolution imagery in a temporal manner and the expensive cost of data. Inadequate availability of these data is not sufficient to assess the activation of forest changes which occur quickly or at least annual mapping is required. Furthermore, this approach is time consuming and cannot be applied universally (Wertz-Kanounnikoff, 2008; Souza et al., 2009; DeFries et al., 2007). However, the actual estimation of forest changes and forest degradation is still a challenging task in which even indirect assessment process leads to a very high degree of error. At the same time it becomes more difficult to identify and quantify the complex symptoms of forest degradation through remote sensing data (GOFC-GOLD, 2010; Broadbent et al., 2008; Asner et al., 2005; Asner & Warner, 2003; Lambin, 1999).

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Therefore, integration of ground-based information with remote sensing data is an appropriate approach to effectively estimate forest changes that have a greater level of accuracy. This means that the integration of spectral, spatial and temporal domains is an important requirement for correctly assessing deforestation and forest degradation Lambin (1999). A good number of scientific literatures recommend a similar approach in this context. (Herold et al., 2011; GOFC-GOLD, 2010; Broadbent et al., 2008; Hansen et al., 2008; Wertz-Kanounnikoff, 2008; Saatchi et al., 2007; Asner et al., 2005; Lambin, 1999). Thus, the aim of the present study is to develop an integrated approach adopting Remote Sensing data for the Man River basin of central India to estimate deforestation and forest degradation with responsible drivers.

1. Method

1.1. Study area

The study area extends to 1557 km^2 covering the Man River Basin, a tributary of the Narmada River in central India. It lies between latitude 22° 9′ 15′′ N to 22° 35′ 45′′ and longitude 75° 0′ 15′′ E to 75° 24′ 50′′ E (Figure 1). Geographically, the river basin extends across three types of topographies such as plateaus, mountain ranges, and valley areas. The increase in availability of water and electricity in the last few years promotes intensive agricultural activities by small and marginal farmer communities which is an important concern for landscape change in this rainfed area.

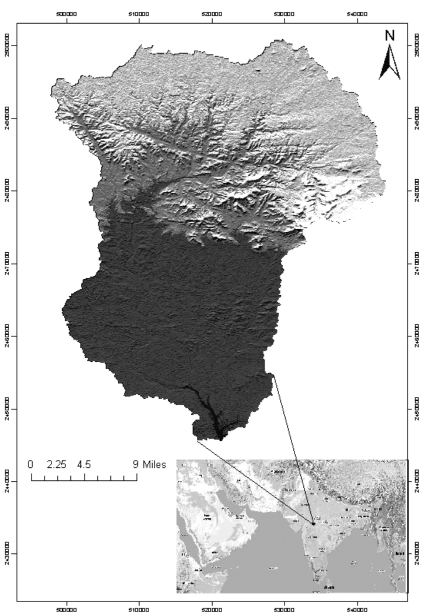

Figure 1. Location of Man River basin in Central India

1.2. Material

For this study, Landsat Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery were obtained from the US Geological Survey for the years 2009 and 2013 (Table 1). While ground reference databases for forest and non-forest cover lands were collected using GPS from the study area. Altogether, two hundred and fifty (250) GPS plots for the years 2009 and 2013 were obtained to provide a better understanding of the filed. In addition, Google Earth imagery, NDVI, and EVI imagery were also used to support the mapping process as needed.

1.3. Data processing

To improve the quality of Landsat imagery, a geometric correction and dark object subtraction (DOS) algorithm was implemented. Landsat imagery was also put forward to generate the Normalized Difference Vegetation Index (NDVI), which was used to guide forest and non-forest classes (Rouse et al., 1973). In addition, the Enhanced Vegetation Index (EVI) was also prepared using Landsat 8 imagery used to delineate the boundaries of deforestation and forest degradation within the forest mask (Huete et al., 1997).

A total of six major categories of land use and land cover, including forest cover, were created following the IPCC guidelines (Intergovernmental Panel on Climate Change (2003). The forest class includes an area of evergreen and deciduous trees with 10% canopy cover as well as degraded forest types that have 10% canopy cover. Deforestation maps for the period 2009–2013 were also validated with the help of Google Imagery. Whereas, the Enhanced Change Matrix approach was implemented to produce a thematic layer of deforestation for the years 2000–2013 (Manandhar et al., 2010; Teferi et al., 2013).

1.4. Integrated assessment

In the next phase of assessment, the study area was divided into a series of regular 1×1 km space grids for systematic wall-to-wall mapping. Whereas, the deforestation thematic layer (2009–2013) was further updated, overlaying the

Table 1. General characteristics of Landsat scenes used for study area

Landsat image	Date Acquired	Band Quality	Cloud Cover	Path	Row	Data Type	Level	Resolution (m)
Landsat 8 OLI &TIRS	Feb 2013	9	0%	147	44	MS	L1T	30
Landsat 8 OLI &TIRS	Feb 2013	9	0%	147	45	MS	L1T	30
Landsat 5 TM	Nov 2009	9	0 %	147	44	MS	L1T	30
Landsat 5 TM	Nov 2009	9	0%	147	45	MS	L1T	30

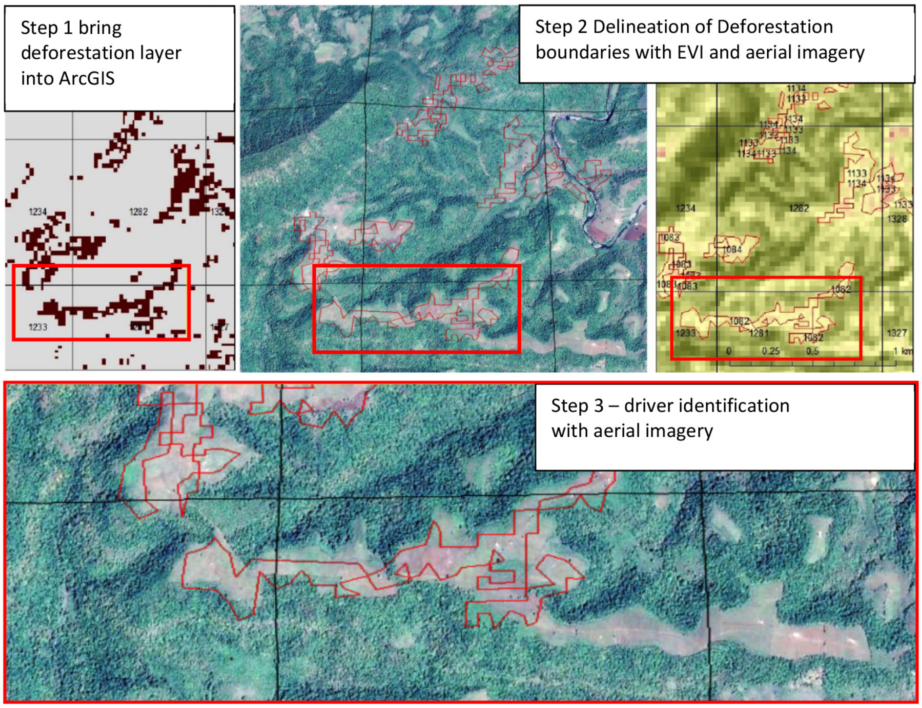

Figure 2. Decision steps for deforestation and forest degradation mapping associate with drivers

Google Earth Imagery Year (2013) and the EVI thematic layer. This assessment consists of two major phases; the first phase involves delineation of forest area, while phase two includes drivers of deforestation (Figure 2).

Aerial imagery was used to re-delineate and verify deforestation and forest loss areas that had already been mapped by multispectral imagery. Additionally, EVI inspections were also conducted in non-forest areas to further refine the delimitation of deforestation and forest degradation, which were characterized by aerial imagery. Major drivers of deforestation and forest degradation have also been identified such as agriculture encroachment, deforestation, development of water bodies, and forest fires, and have been associated with appropriate activities.

Considering the importance of the Minimum Mapping Unit for forest change analysis, (Olofsson et al., 2014; Knight & Lunetta, 2003; Saura, 2002) in the present study, two different sizes of MMUs were applied. Firstly, an MMU of 30×30 m was adopted to prepare a classification map of forest changes for the year 2009–2013. Here it was intended to produce a more accurate classification map that has the potential to provide sufficient information about small patches (smaller than one hectare). Secondly, a minimum mapping unit of one hectare was implemented to further update the deforestation layer and measure deforestation and forest degradation.

2. Results

Accuracy assessment of forest and non-forest change shows that deforestation has overall accuracy of (95%), while user accuracy was (84%). However, (85.8%) of the producer's accuracy indicates a warning for classification.

As this study uses two different Minimum Mapping Units (e.g. 30×30 m MMU and 1 ha MMU), which has a significant impact on forest area estimation. Over the four years of the study period, the total area under deforestation is estimated at (7618) ha by the Integrated Approach (1 ha MMU). Implementing larger size (1 ha) of MMU and more accurate delineation of deforestation area with grassroots verification may be a major reason for this estimation. Whereas, the estimated area of deforestation by the Automated Pixel Based Approach is

Table 2. Estimated deforestation areas using three different approaches

Approach	Deforestation area (ha)	Minimum Mapping Unit	Accuracy	Sources
Landsat based automatic classification	25 108	30×30 m	84%	Landsat multispectral classification along with vegetation index, GPS plots and aerial imagery.
Integrated wall to wall mapping	7615.19	1 ha	100%*	Polygon delineation of Landsatmultispectral classification map using Vegetation index and aerial imagery.

Note: *All deforestation patches over study area were validated and updated with ground reference.

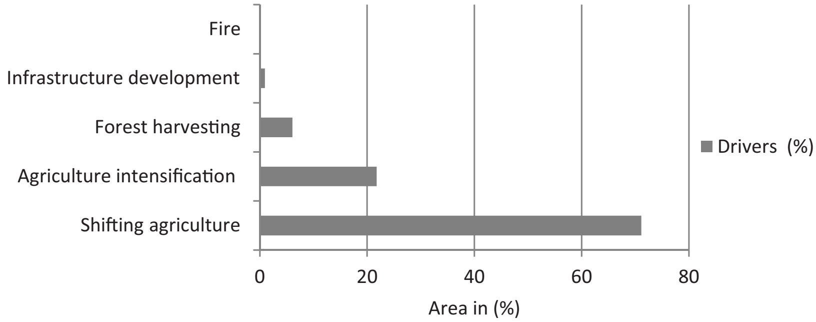

Figure 3. Distribution of the deforestation and forest degradation drivers for period (2009–2013)

(17,491) ha. This area under the deforestation is greater than the area estimated by the Integrated Approach. (Figure 4 and 5, Table 2). This means that small patches of deforestation (less than one hectare) are not effectively captured by the Integrated Approach.

The results demonstrate that agricultural expansion over the past four years is the leading contributor to deforestation (7082.6 ha or 92.9%), followed by deforestation (462.7 ha) and infrastructure development (71.5 ha) (Figure 3). Analysis of the spatial distribution of deforestation suggests that it is mostly spread in small patches (1–5 ha) due to shifting cultivation and permanent transformation of agriculture in hilly areas (Figure 4).

The estimated area of degradation (5,418 ha) is due to permanently shifted agriculture which accounts for 71.1% of all degradation area (Table 3). The findings also suggest that the estimation of forest degradation using medium resolution optical remote sensing data does not work effectively. However, the Integrated Approach provides the potential for effective measurement of degradation areas and potential drives (Figure 5).

Table 3. Drivers of deforestation and forest degradation in the Man River basin from 2009 to 2013 by integrated assessment

Drivers	Deforestation (ha)	Degradation (ha)	(%)
Shifting agriculture	5418	5418	71.12
Permanent agriculture	1660	–	21.8
Forest harvesting	462	–	6.06
Development of water bodies	72	–	0.94
Forest Fire	6	–	0.08
Total	7618	5418	100

3. Discussion

The findings of this study show that the integrated approach performed very well in exploring spatial patterns of deforestation in the study area, which have a strong relationship with shifting agriculture and deforestation. It has been observed that medium-sized irrigation projects

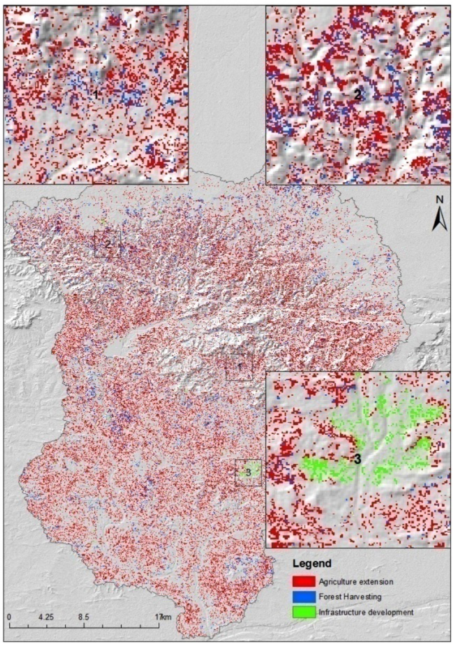

Figure 4. Mapped deforestation areas using automatic change detection analysis (2009–2013)

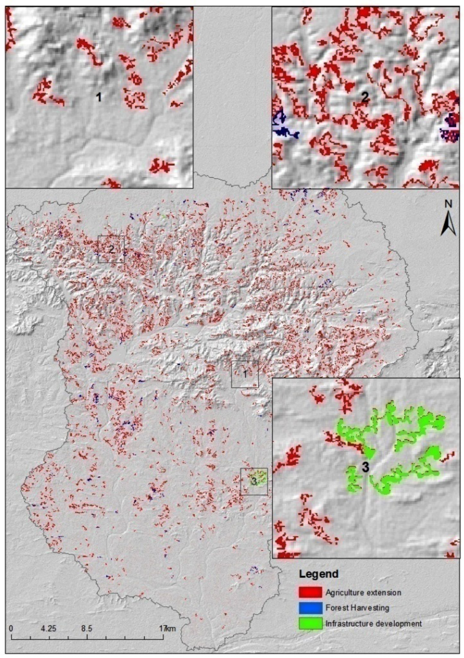

Figure 5. Mapped deforestation and forest degradation associate with responsible driver using GIS based direct interpretation approach (2009–2013)

such As Man River Dam Project and large sized farm ponds for irrigation are accounted in the area (72 ha), which has a significant impact on deforestation (Figure 3). This study estimates the forest erosion area in the river basin as a result of agricultural intensification (5418).

The, wall to wall mapping approach performs excellently to map deforestation and associated responsible drivers. Whereas the Normalized Difference Vegetation Index (NDVI) and Advanced Vegetation Index (EVI) allow better delineation of deforestation and forest degradation areas. Similarly, Google Earth aerial imagery helps to identify the attributes of forest transformation that are extremely difficult to map with medium-sized multi-spectral imagery such as Landsat alone.

In the present study, two different estimation approaches to estimate forest change were investigated, resulting in two different outputs that raise an interesting question among the research community as the selection of the Minimum Mapping Unit and effective delineation by polygons in the forest loss may affect field estimates. The results of the current study provide some valuable suggestions for developing a mapping approach according to user requirements and the availability of remote sensing data.

The findings suggest that the MMU of one (1) ha is more reliable and consistent in terms of accurate estimation of forest loss area with responsible drivers. Whereas, it has also been observed that the MMU (30×30 m) adopted in the first stage of the mapping process was found to be a suitable decision helping to capture small patches of deforestation.

In comparison, this study performs more reliably in recently published research (e.g. Manandhar et al., 2010; Olofsson et al., 2011). For example, the Global Forest Change (GFC) mapping by Hansen et al. (2013) shows that forest loss in the Man River Basin was estimated at 2.93 ha over a 12-year period from 2000 to 2012, whereas in the present study it was 7615.19 hectares in only a period of four years (2009–2012). The GFC maps in this area were not validated as the current study was verified following the GOFC-GOLD guidelines. In this context, the study raises an important question about the quality and use of GFC data for various environmental modelling. The results of the present study were also compared with another nationally conducted study in India, in which the LULC datasets were developed from Advanced Wide-Field Sensor (AWiFS) of RESOURCESAT-1, along with the inventory LULC dataset during 1880–2010 (Tian et al., 2014). The deforestation trend has been found to be similar to a current study which indicates that deforestation has reached an alarming level in recent years in the study area.

Conclusions

The findings of this study recommend some valuable options for improving the mapping potential of forest change in India, where availability of grassroots data is always an issue in remote areas. Primarily based on remote sensing data, the study provides a valuable solution for mapping forest changes in data spare region. The combination of Landsat imagery and aerial photographs with the vegetation index performs effectively to map forest changes and potential drivers.

This study suggests that the integrated approach is a better option for performing forest transformation mapping at a deeper level rather than adopting automated change analysis of multispectral imagery at medium resolution scale. The results of the present study also demonstrate that forest loss in the Man River Basin is significantly affecting local biodiversity and livelihood which is subject to further study in the region.

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