

# Remote Sensing Based Deforestation Monitoring at the Change Hotspot Area in Hindu Kush Himalayan Region

*Kabir Uddin<sup>1</sup>, Mir A. Matin<sup>1</sup>, Hari Krishna Dhanju<sup>1</sup>, Birendra Bajracharya<sup>1</sup>, Africa Flores<sup>2</sup>, Eric Anderson<sup>2</sup>, Lee Ellenburg<sup>2</sup>*

<sup>1</sup> International Centre for Integrated Mountain Development, Kathmandu, Nepal;

<sup>2</sup> Earth System Science Center, University of Alabama in Huntsville, USA

Corresponding author: Kabir.Uddin@icimod.org

## Abstract

Forests play an essential role in providing sustainable ecosystem services and livelihood options for a growing population. In the Hindu Kush Himalayan (HKH) region, forests have been continuously reduced due to increasing demand for timber, fuelwood, and agriculture. Identification of deforestation hotspots and monitoring changes in those hotspots will be highly useful for forest managers to prevent illegal deforestation. In this paper, we identified forest cover change hotspots and areas for annual monitoring in those hotspots. For that factors like land cover from 1990 and 2010, shuttle radar topography mission (SRTM) digital elevation model (DEM), slope, curvature, and distance from the settlement and roads for all four countries which could influence loss in forest area and overlaid to determine forest hotspots, were considered. Land cover maps of 1990 and 2010 and other GIS layers were used for identification of hotspots using the model builder ArcGIS software. For monitoring of deforestation in the hotspot areas, Landsat 8 images (2013, 2014 and 2015) and geographic object-based image analysis (GEOBIA) technique was used. The method was validated in four study sites in Bangladesh, Nepal, Bhutan and Pakistan. The study revealed that the sites in Bangladesh have higher deforestation during 2013-2014 and 2014-2015 with forest loss of 1121.58 and 1773.18 ha respectively. The web-based forest monitoring system provides information on deforestation useful for forest managers to enforce annual management plans.

**Key words:** Forest hotspot, forest loss, forest monitoring, Landsat 8, remote sensing

## INTRODUCTION

Forests play a vital role in maintaining natural and ecological processes, water regulation and carbon storage (Bonan 2008; Bennett *et al.* 2009). On a global scale, forest change influences climate and rainfall patterns, and on a local scale, forests affect local microclimates (Eliasch 2008; Arx *et al.* 2013; Sheppard 2015). According to a 2015 global land cover assessment, forests cover about four billion ha, which was approximately 31 per cent of the total global land area (MacDicken *et al.* 2016). Globally, rates of forest loss is

reported at 0.6 per cent per year (Hansen *et al.* 2010), and studies have shown that the loss of forest through deforestation and degradation is recognised as a critical driver of human-induced climate change (Eliasch 2008).

During the last few decades, the Hindu Kush-Himalayan (HKH) region has also experienced high levels of deforestation and forest degradation (Ives 1987; Appanah *et al.* 2016). The changes in HKH forest cover due to population growth, forest management, harvesting and natural

disturbances may change the role and function of forest ecosystems (Kotru *et al.* 2015). Land use conversions from forest to other land use often results in substantial loss of carbon from the biomass pool and significant impact on the extent and condition of forests, causing a regional-scale decline in forest cover (Houghton 2003; Vadrevu *et al.* 2015). However, there is a significant gap in terms of a cohesive framework and information to assess and monitor these changes regularly across the HKH region (IPCC 2007). In view of the increasing deforestation rates and significant ecological and economic value of forests, reliable, timely and cost-effective monitoring of forests is very important. However, there is less precise information available in the region on the extent of current forest cover or deforestation rates, particularly the detailed information required for planning and assessing local level activities. It is particularly challenging to gather detailed information on forest extent at the ground level in remote and poorly accessible valleys of the HKH, and even more so to repeat measurements over time. In this context, a satellite based annual forest cover monitoring system would be highly useful for regular monitoring and management of forest cover.

Satellite remote sensing has become a major source of reliable forest cover information (Foley *et al.* 2005). At the global level, numerous efforts have been made to provide satellite-based land cover and forest cover information (Schweik *et al.* 1997; Reis 2008; Xian *et al.* 2009), including GlobCover land Cover Maps (GLOBCOVER) (Arino *et al.* 2007; Bontemps *et al.* 2009), annual MODIS

Land Cover (Friedl *et al.* 2002; Friedl *et al.* 2010), MODIS Vegetation Continuous Fields (VCF) (DiMiceli *et al.* 2011), and 30 meter global tree cover change data obtained from the University of Maryland and Global Forest Watch (World Resources Institute 2013). There are however some challenges in reporting forest loss at local scales using global datasets (Tropek *et al.* 2014). Global-scale training sets have shown less success in distinguishing forest-shrubland, forest-agriculture and forest-grassland eco-tones across different topographic regimes at local scales (Chen *et al.* 2015). Part of this challenge lies in the differing definitions of “forest” versus “tree cover,” as evidenced in comparisons of the Global Forest Watch product with local-scale data.

The objective of this study is to develop a deforestation monitoring system using multi-temporal Landsat data for annual monitoring of changes in designated four sites in the HKH region. This study contributes to forest loss information for efficient management of the forest. The results will provide relevant data to facilitate and support informed decision making on the future management of forest hotspot in the HKH region.

## Materials and Methods

The study consists of three components. Firstly, forest change hotspots were identified based on published land cover, topographic and physical features data. Secondly, a set of decision rules were developed based on Landsat 8 images to analyse annual forest loss. Thirdly, validation of the resulting forest loss products was conducted.

## Description of the Study Area

The study area includes four locations in four countries in the HKH region: These

include Bandarban in Bangladesh, Paro in Bhutan, Sarlahi in Nepal, and Swat district in Pakistan (Figure 1).



Figure 1: Map of the Study Area: the Red Highlighted Area used for Deforestation Monitoring

### Bandarban

Bandarban district of Bangladesh falls between latitudes  $21^{\circ} 10' 48''\text{N}$  to  $22^{\circ} 21' 2''\text{N}$  and longitude  $92^{\circ} 3' 36''\text{E}$  to  $92^{\circ} 40' 48''\text{E}$ . Bandarban district is bordered internationally with Myanmar to the east and is bordered nationally by Cox's Bazar and Chittagong to the west, Rangamati to north. The total land area of Bandarban district is  $4,479 \text{ km}^2$ .

### Paro

Paro district of Bhutan falls between latitudes  $27^{\circ} 10' 48''\text{N}$  to  $27^{\circ} 46' 48''\text{N}$  and longitude  $89^{\circ} 7' 30''\text{E}$  to  $89^{\circ} 32' 60''\text{E}$ . The total land area of the Paro district is  $1288 \text{ km}^2$  with predominantly hilly areas and slopes between 0 and  $63.94$  degrees.

### Sarlahi

Sarlahi district of Nepal falls between latitudes  $26^{\circ} 44' 24''\text{N}$  to  $27^{\circ} 11' 24''\text{N}$  and longitude  $85^{\circ} 19' 12''\text{E}$  to  $85^{\circ} 48' 36''\text{E}$ , and is bordered internationally by India to the south and bordered nationally by Rautahat to the west, Mahottari to the east and Sindhuli district of Nepal to the north. With a total land area of  $1263 \text{ km}^2$ , Sarlahi district is a predominantly flat area.

### Swat

Swat is a valley and an administrative district in the Khyber Pakhtunkhwa province of Pakistan. It is the upper valley of the Swat River, which rises in the Hindu Kush range. Swat district lies between

latitudes 34° 33' 36"N to 35° 55' 48"N and longitude 72° 7' 12"E to 72° 47' 60"E. Swat is surrounded by Chitral, Upper Dir and

Lower Dir in the West, Gilgit-Baltistan to the north and Kohistan, Buner, and Shangla to the east and southeast.

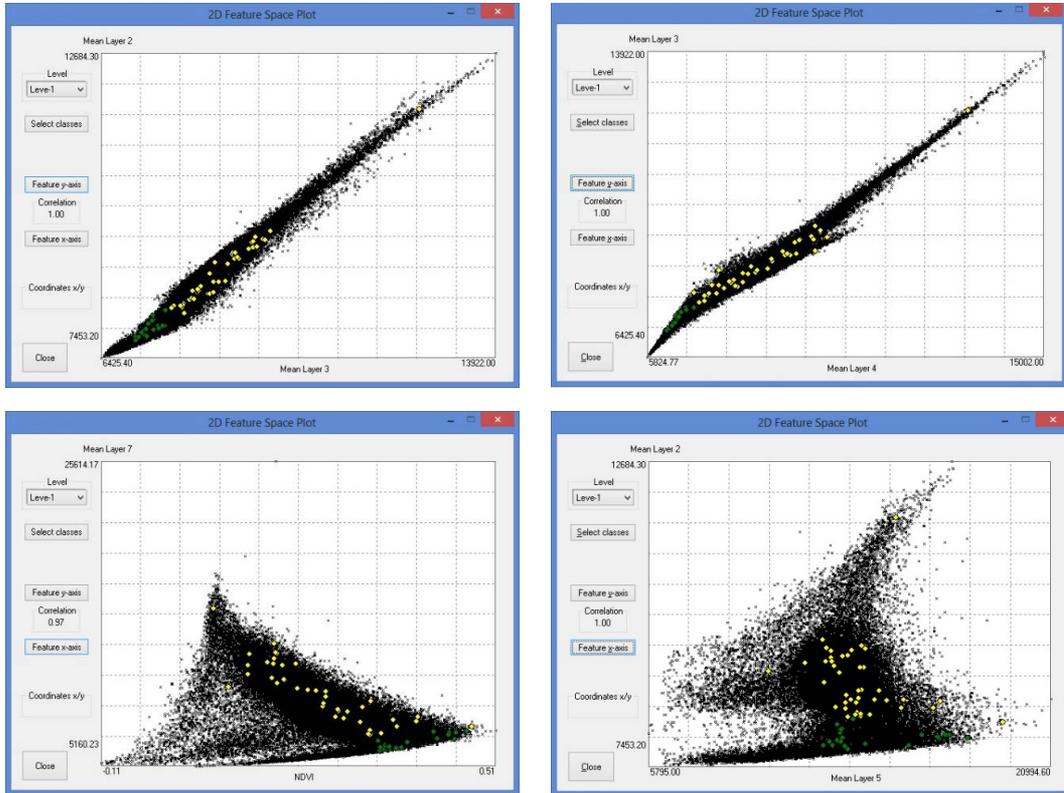


Figure 2: 2D Scatter Plot Created Based on the Training Sample from the Forest and Non-forest Segments.

## Land Cover Mapping

Land cover change hotspot is defined as areas that are more susceptible to change while also being important for biodiversity, human health, and sustainability (Sanchez-Cuervo and Aide 2013). According to Lambin and Ehrlich (1997) land cover change hotspots can be identified at three levels: high rates of land cover change

which are observed at present; or have been observed in the recent past, or areas where land cover changes are likely to occur shortly. Here, land cover maps for 1990 and 2010 that were prepared from analysis of the Landsat TM and ETM+ images (Gilani *et al.* 2015; Uddin *et al.* 2018) were used as one of the layer to identify forest change hotspots.

## Identifying Hotspots

A decadal land cover map was available to provide forest change statistics for the HKH region, but they are very limited in providing information on year-to-year changes. We used 2010 land cover (Gilani *et al.* 2015; Qamer *et al.* 2016; Uddin *et al.* 2018) as a baseline to estimate annual forest loss in hotspot areas for 2013, 2014, and 2015. For forest loss mapping, the Geographic object-based image analysis (GEOBIA) classification technique using Landsat 8 images were run in eCognition software. All Landsat 8 images were downloaded from the United States Geological Survey (USGS) archived data portal. Previously, image classification of all the spectral bands were normalised by reflectance to radiance conversion using metadata information, i.e. gains, offsets, solar irradiance, solar elevation, and acquisition of date/time given in the image. A recent study confirmed that GEOBIA technique could accurately classify Landsat images for forest and land cover mapping (Beuchle *et al.* 2015; Mitchell *et al.* 2016; Yu *et al.* 2016). GEOBIA can produce improved forest map in the steep mountainous terrain based on Landsat (Dorren *et al.* 2003). Recently object-

based image analysis has been increasingly used for classification of moderate and high resolution images including Landsat (Blaschke 2010; Uddin *et al.* 2015b). GEOBIA provides a methodological framework for the machine-based interpretation of complex classes defined by spectral, spatial, contextual, and hierarchical properties, which has been shown to yield more accurate classification results when compared to pure pixel-based methods (Blaschke and Lang 2008; Duro *et al.* 2012; Uddin *et al.* 2015a). The fundamental basis of object-based image analysis is the segmentation of satellite images; there are several algorithms that can be used to do this.

Studies have shown that spatial patterns of forest hotspots are dependent upon the topography and human settlement characteristics (Mendoza and Dirzo 1999; Pandit *et al.* 2007; Etter *et al.* 2008). Following factors were considered: a) land cover from 1990 and 2010, b) shuttle radar topography mission (SRTM) digital elevation model (DEM), c) Slope, d) Curvature, and e) Distance from the settlement and roads for all four countries which could influence loss in forest area and therefore forest hotspots.

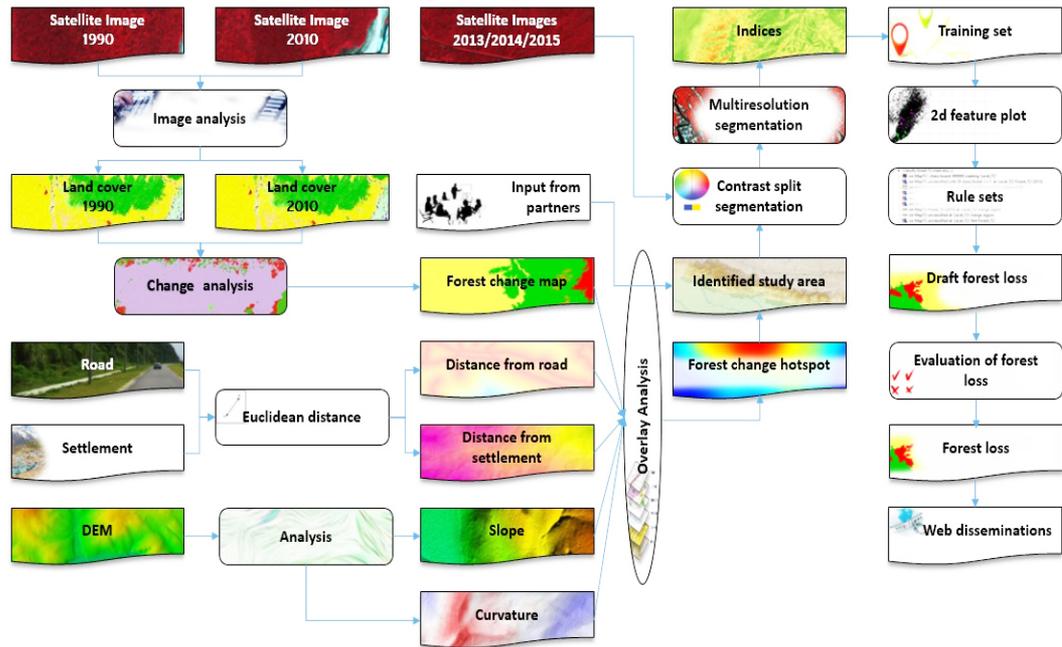


Figure 3: Flow Diagram of the Overall Study.

### Monitoring Forest Loss

In the present analysis for forest loss identification, Contrast Split Segmentation algorithm with near-infrared (NIR) bands were used to create image segments. The contrast split segmentation can distinguish and group bright and dark objects. The algorithm aims to optimise the separation between forest and non-forest areas by considering different pixel values, within the range provided by the parameters (scale parameters 16, shape 0.1 and compactness 0.5). During the image segmentation process, objects brighter than the set threshold (Minimum relative area dark 0.1, minimum relative area bright 0.02) were classified as a non-forest, and dark objects were classified as forest. Secondly, the multi-resolution segmentation algorithm was used within the non-forest area produced by contrast split segmentation.

During the multi-resolution segmentation, homogeneous areas resulted in larger objects and heterogeneous areas in smaller ones. The multi-resolution segmentation algorithm helps to merge pixels with their neighbours based on relative homogeneity criteria (Batz *et al.* 2006). After that forest and non-forest sample (training set) assigned to the image objects to develop 2D scatter plots for 2013 Landsat 8 scene. The image layers were chosen based on their relative importance and potential to delineate the class. The thresholds for each layer were fixed iteratively by 2D scatter plots (Figure 2) and validated with reference segments. After that ascertained rules were executed to obtain a non-forest area for each hotspot area. Finally, classified non-forest areas and base forest area intersected to produce forest loss area (Figure 3).

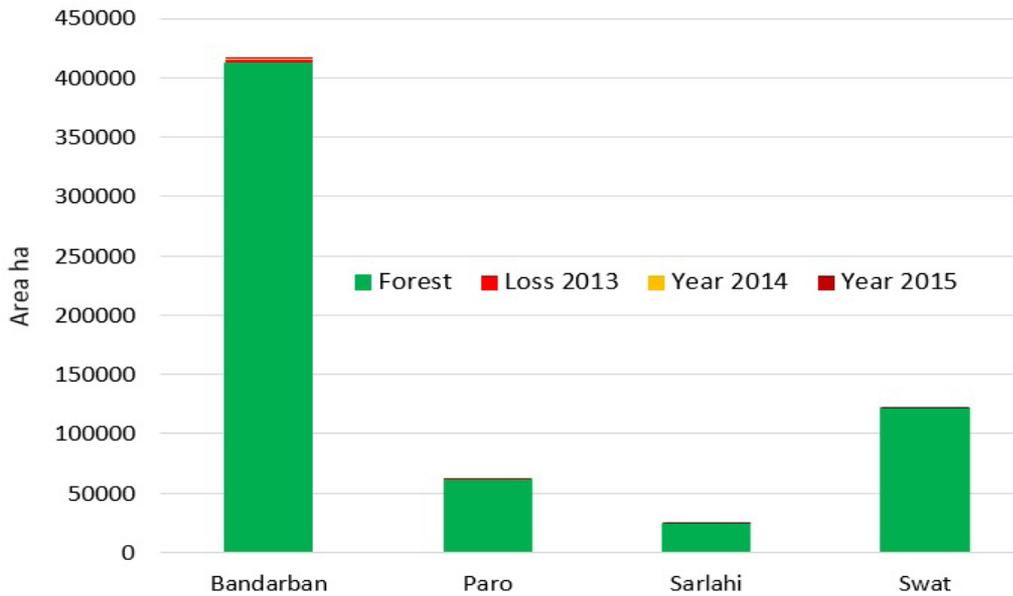


Figure 4: Annual Forest Loss in the Study Areas

The same process was applied for all of the forest hotspots to map forest loss for 2013 using site-specific training sets. The rules developed in eCognition were used for 2014 and 2015 to produce annual forest loss estimates per forest hotspots.

### Validation of Forest Monitoring

The quality of the forest loss produced by the study was assessed using three different approaches: 1) a team of experts who had not participated in the classification process provided an independent assessment. 2) hotspot site-specific visual analysis of the classified output was conducted using the maximum 20 windows of 1x1 km in size

by comparing with high-resolution images of GeoEye. 3) quantitative accuracy assessment using sample points from high-resolution images. The overall accuracy of 2013 forest cover was 93.33 per cent, 96.00 per cent, 95.24 per cent and 91.67 per cent, in Bandarban, Bangladesh; Paro, Bhutan; Sarlahi, Nepal; and Swat, Pakistan respectively. The forest loss maps and statistics were disseminated online to ensure stakeholders could access the information. For onward years (2014 and 2015) forest loss was validated by visual verification using high-resolution images from Google Earth given the lack of sufficient field data (Figure 5).

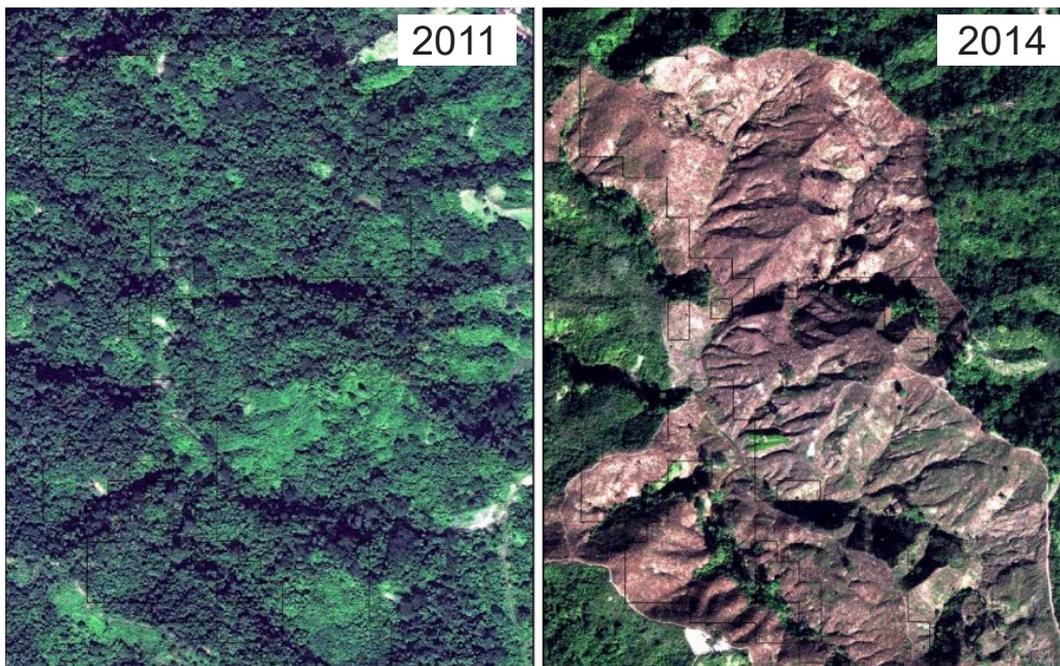


Figure 5: Forest Loss Validation using Very High-resolution Images, Green Colour Represent the Forested Area and Brown Colour Showing Forest Loss Area.

## RESULTS AND DISCUSSION

The forest hotspot monitoring results are presented in figure 4. The results show that in 2010 forest area covered 412,364.07 ha of the total geographical area of the Bandarban district. Loss of forest area was 2520.99 ha, 1121.58 ha, and 1773.18 ha during the period of 2010-2013, 2013-2014, and 2014-2015, respectively. Bandarban district has seven Upazilas (sub-district), and among them, maximum forest loss

was found in Naikhongchhari Upazila during 2010-2013.

The study shows that between 2010 and 2015, there was little forest loss in Paro district, Bhutan. Between 2010 and 2013 forest loss was 10.44 ha. From 2013 to 2014 the forest loss was 53.19 ha, and from 2014 to 2015 the loss was 67.14 ha. In Paro, most of the forest losses were due to development activities, mainly due to the construction of new roads.

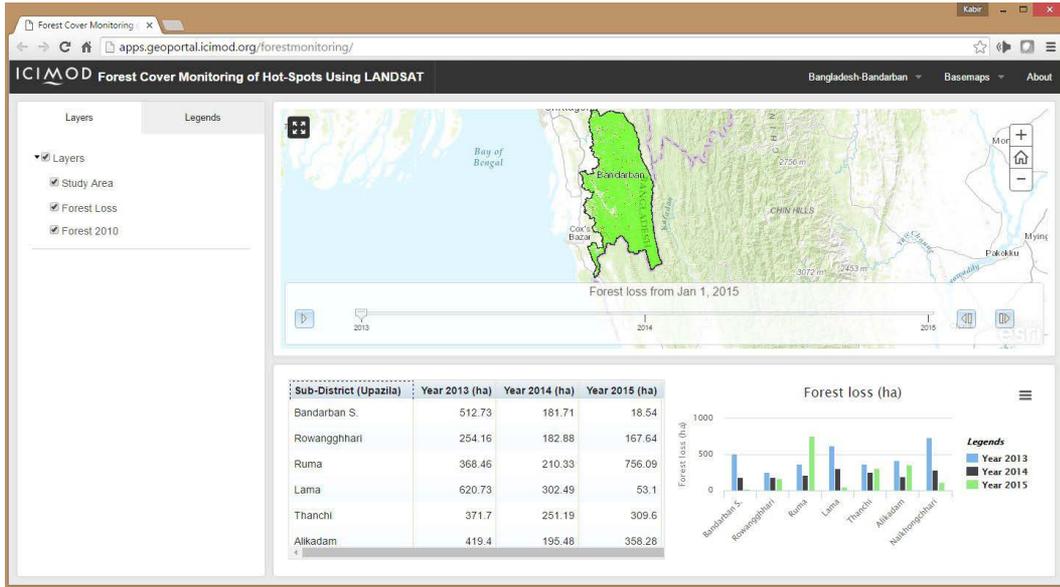


Figure 6: Forest loss validation using very high-resolution images

In Sarlahi district of Nepal, forests covered 24,385.14 ha in the year 2010. However, the total forest loss was 96.21 and 22.95 ha during 2013-2014 and 2014-2015 respectively. Village development committees (VDC) level analysis shows that maximum forest loss happened in Bhaktipur VDC of Sarlhai district. Some level of forest loss was also observed in Gaurishankar, Ghurkauli, Janaki nagar, Kalinjor, Lalbandi, Netraganj, Parwanipur, Pattharkot, and Raniganj VDC. There was very little forest loss seen in the Swat district, Pakistan. Loss of forest area in the period 2010-2013 was 7.65 ha and between 2014 and 2015 forest loss was 27.11 ha.

Considering the unavailability of regular field-based monitoring, the study results demonstrated that the proposed method and results could be used as an alternative to field-based monitoring. In the present study, a set of rules were developed using

Landsat images for each study area by semi-automatic object base analyses. This enables the detection of forest cover analysis with high overall accuracy. An advantage that we have demonstrated is that once rules have been developed they can be re-used for subsequent years for the same study area (Uddin *et al.* 2015b; Tompoulidou *et al.* 2016). Several authors confirm that object-based analyses techniques provide higher accuracy than other algorithms in classifying forest cover. Cui *et al.* (2008) noted that it is a robust method which can extract objects and boundaries smoothly. The online application (Figure 6) provides easy access to forest loss information for four forest hotspots and provides user friendly tools for generating statistics to understand the forest change processes and to support better forest management (Uddin *et al.* 2015c). The area of each forest loss can be viewed for 2013, 2014 and 2015 separately, with the option to make charts

on a selected country. The forest cover and loss of different years can be viewed using a swipe tool which helps to explore the changes in an interactive manner.

The results indicate that tree cutting remains an ongoing problem in the hotspots, especially cutting of planted mature trees for shifting cultivation. Reddy *et al.* (2016) addressed these activities during a study of the past eight years in Bangladesh where semi-evergreen forests show losses of 56.4 per cent of forest cover followed by moist deciduous forests (51.5%), dry deciduous forests (43.1%) and mangroves (6.5%). According to Gilani *et al.* (2015), during the last three decades, there have been some alterations in forested areas, but the net forest has increased in Bhutan. A recent study on Nepal land cover (Uddin *et al.* 2015c) shows that patch and edge forests constitute 23.4 per cent of national forests and are highly impacted due to anthropogenic factors. Likewise, Qamer *et al.* (2016) show that the time series of forest cover maps revealed extensive deforestation in the Western Himalaya, Pakistan.

Remote sensing-based forest cover monitoring globally provides both opportunities and challenges for generating accurate information on forest cover monitoring. Within the high elevation mountain zones, deep shadows affect the accuracy of the classification (Bishop *et al.* 2003; Ye *et al.* 2006). The topographic regimes increase the effect of shadows and influence the classification with more complexity on higher elevations (Tan *et al.* 2013; Li *et al.* 2016). These shadows specific areas need to be assessed for the quantum of errors and approach to improve them.

The study results were validated using a high-resolution image from GeoEye and Google Earth systems. Additional validation with field data may yield slightly different accuracy statistics, but given the extremely high spatial resolution of images used for validation, we do not expect significant disparities.

## CONCLUSIONS

Forest loss used to provide negative consequence on earth which not only sequesters carbon dioxide but also serves the purpose of heat-trapping. Periodic forest cover monitoring systems are critical to support forest adaptation and mitigation strategies. Previous efforts using Landsat images to derive the decadal land cover change in the HKH region have proven inadequate to provide information necessary to monitor and make decisions for forest management on a yearly scale. In this context, we developed an appropriate methodology for the regular monitoring of forest cover changes over designated hotspots using Landsat data. In the future, we expect the methodology to continue to be improved by further validation with field data and high-resolution imagery. Given additional training and capacity building, this method can be extended to additional forest hotspot areas in the HKH region.

## ACKNOWLEDGEMENTS

This work was funded by the US Agency for International Development (USAID) and the US National Aeronautics and Space Administration (NASA), through the SERVIR-Himalaya initiative. We are grateful to the MENRIS-Geospatial team of ICIMOD. The authors express their

sincere gratitude to the Department of Forests of Bangladesh, Bhutan, Nepal, and Pakistan for their active support needed for this study. Special thanks to Mr. Gauri Dangol for cartographic support for map preparation. We also thank the editors and the anonymous reviewers for their valuable comments on the manuscript.

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