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FOREST COVER MONITORING IN THE BARA DISTRICT (NEPAL) WITH REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEMS

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ABSTRACT

This study uses Landsat Thematic Mapper of 1989, Enhanced Thematic Mapper of 1999 and 2005 imagery to evaluate forest cover dynamics during 1989-2005 in the Bara district, located in the Nepal's Central Terai region. The aim of the study is to analyse the extent and trend of forest cover dynamics, spatial pattern of forest and their driving forces. Forest cover change analysis was performed using object-oriented classification approach applying a standard nearest neighbour algorithm to classify the image in eCognition. The overall classification accuracies were 85.71% and 88.23% for the year 1999 and 2005 respectively. Initially, land cover maps for the year 1989, 1999, and 2005 were produced with seven land cover categories prevalent in the study area. Classified images were further reclassified as forest and non-forest areas to analyse the forest cover dynamics effectively. Post-classification and time series analysis were carried out to detect the changes. Spatial metrics were computed for detecting the spatial pattern of forest. The classifications showed that the amount of forest land decreased by 11.56% during 1989-2005. The result of the spatial metrics reveals that forest area has been fragmented and deforested with an annual rate of 0.72%. The overall result demonstrates that forest area has experienced a significant shrinkage and mostly transferred into agricultural and bare land from 1989 to 2005. Expected change for the year 2021 was projected using Markov Chain Analysis (MCA). The MCA result showed that forest area including shrub will be decreased by 8.5% during 2005-21.

KEYWORDS

Change Detection

Geographical Information System

Land Cover Change

Object-oriented Image Classification

Remote Sensing

Spatial Metrics

ACRONYMS

BISEP-ST - Biodiversity Sector Programme for Siwaliks and Terai

C/FUG - Community / Forest User Group

CBS - Central Bureau of Statistics

CF - Community Forest

CFM - Collaborative Forest Management

CFMWG - Collaborative Forest Management Working Group

DDC – District Development Committee

DFO - District Forest Office

DFRS - Department of Forest Research and Survey

DOF - Department of Forests

FAO - Food and Agriculture Organization

GLS - Global Land Survey

GPS - Global Positioning System

HMG - His Majesty's Government (till 2006)

IDEA - Innovative Development Asia

LCCS - Land Cover Classification System

LRMP - Land Resources Mapping Project

MFSC - Ministry of Forests and Soil Conservation

MPFS/N - Master Plan for the Forestry Sector/Nepal

NDVI - Normalized Difference Vegetation Index

NFI - National Forest Inventory

NRSC - National Remote Sensing Centre

OFMP - Operational Forest Management Plan

USGS - United States Geological Survey

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1. INTRODUCTION

1.1 Background

Forest clearing represents a major driver of global warming and climate change. The world's forests, especially in the tropics, are dramatically shrinking (Apan, 1999). Tropical forests are being destroyed despite its ecological, social and economic importance. Deforestation is recognised as one of the pervasive ecological changes taking place in tropical regions (Lambin, 1994). In the late 1970s, tropical deforestation occurred at the rate of about 11.3 million hectares per year (Lanly 1982). During the period 1980–1990, FAO figures show that this rate has increased to about 15.4 million hectares per year (Singh 1993).

The conversion of forest cover in general and of tropical forest in particular has severe long term environmental and socio-economic consequences globally as well as locally. Many environmental problems caused by forest cover change are changes in global climate, habitat degradation and unprecedented species extinction (Goldsmith, 1998).

In recent decades, increasing awareness of the depletion of tropical forests, and the associated impacts on biodiversity and global climate in particular, have led to regional to global initiatives to halt or slow their decline. However, despite these initiatives, forests continued to be cleared, disturbed or degraded (directly or indirectly) at unprecedented rates. Given this continuing situation, there is an urgent need to provide up-to-date and timely evaluations of the state of tropical forests worldwide, to assess the impacts of past and present change on their functioning and survival, and to use this knowledge to better understand and predict the consequences of their future uses (Ustin, 2004).

The sound management of tropical forests and the conduct of related research require access to information, including spatial information. As with other natural resource management activities, the practice of forestry needs reliable information so that rational decisions during planning, at various management levels can occur. The capabilities of remote sensing to map and extract information about earth resources for various applications are well documented. On the other hand, Geographic Information System (GIS) is well known for its unique strength in handling, analysis, and management of geographic and land-related data (Apan, 1999).

Application of remotely sensed data to illustrate changes in land cover and particularly forest cover over time have been reported by many investigators (Singh, 1989; Mas, 1999). Reviews specifically addressing forest cover detection can be found in (Coppin and Baur, 1996). Used techniques are varied and depend on the data used and also on the type of landscape under analysis. These approaches include incorporation of geographic data, census data, texture features and structure or contextual information into remote sensing spectral data, use of expert systems and fuzzy classification, use of multi-sensor data, normalized difference vegetation index and the use sub-pixel information (Lu and Weng, 2001). With the advancement in remote sensing (RS) and geographic information system (GIS) techniques, characterizing a landscape and quantifying its structural change has become possible in recent years (Donnay et al. 2001; Maguire et al. 2005). With time series satellite data we can monitor long-term changes (Herold et al. 2003; Thapa et al. 2005) whereas GIS provides a framework for spatial analysis and modeling based on geographic principles and seeks to integrate the analytical capabilities to broaden the understanding of the real world system (Murayama 2001; Maguire et al. 2005).

Satellite remote sensing is one of the viable techniques to monitor the changing pattern of forest. Satellite data from several time points allows the creation of land cover maps over greater spatial extents and more frequent time steps than is possible with expensive and detailed field studies (Nagendra, 2001). Because these classifications are spatially explicit, they not only provide information on percent changes in forest cover, but also allow for evaluation of the spatial location of these changes and their association with environmental and biophysical landscape parameters that may be critical associates of this change (Nagendra et al., 2004).

The monitoring of forest cover change is a long-standing issue in remote sensing and geographic information system. Assessments of forest cover at country scale are useful for policy and management purposes, and for research. Monitoring of forest cover change in district level is useful in the preparation and implementation of forest management plan. Furthermore, updated forest maps obtained are the input for the harvest plan preparation and reforestation projects. This study, implemented in Tropical Forest located in the central Terai district (Bara) of Nepal has focused on monitoring forest cover dynamics, analysing spatial pattern of forest, and projecting future change with RS and GIS. This study has been specifically designed to explain the turnaround from deforestation to reforestation at district or operational scale.

Nepal encompasses diverse ecological zones and occupies mentionable places in natural resources and richness of biodiversity in world (FAO, 2000). Five major types of forest, i.e., tropical, sub-tropical, lower-temperate, upper-temperate and alpine forest are found in Nepal (Jackson, 1994). Timbers from commercially valuable hardwood forests of shorea robusta (and its associates) are continuously distributed throughout the country's lowland (Terai), inner-valleys and lower hills. More than 75% of all households and 90% of rural households rely on wood products for domestic purposes for their daily needs of timber, fuelwood, fodder, grasses, litter and traditional herbal medicines mainly from forests (Hobley, 1996). Nepal's forest is declining in both quantity and quality. Several proximate causes and underlying driving forces (Geist and Lambin, 2002) are responsible to accelerate the deforestation and forest degradation. Legal and illegal conversion of forest land for agriculture and infrastructure development, unplanned and overexploitation of forest products, free access for grazing and uncontrolled forest fire are major causes in depleting that create deficit of forest products in one hand and accelerate soil erosion, downstream sedimentation and decrease in agricultural productivity on the other hand (HMGN/DFRS, 1999; FAO, 2000). Some ecologists have predicted that forests of Nepal are in the threshold of degradation (Shah, 1998).

This study analyses the spatial and temporal pattern of forest cover change in the Bara district of the Central Terai region of Nepal during 1989–2005 based on a time series satellite images of Landsat TM in 1989, 1999 and ETM+ in 2005 using object- oriented image classification, time series analysis, spatial metrics, and land use change modelling.

1.2 Problem Statement

Forest plays a significant role in the livelihood of the rural people as they are highly depended on the forest resources. The forest resources of the country should be, therefore, well managed in a scientific way to meet of ever increasing population on the sustainable basis. In the contest of hilly country Nepal, forest is one of the most important resources for the rural development. Most of rural people live in or near the forest and are dependent for fuel-wood, fodder, timber and generate income from forest to maintain their daily needs. Forest is decreasing and deteriorating creating severe environmental problems. Forest, therefore, are the most important resources, and an extremely important component of the environment and plays a vital role in the improvement of the socio-economic condition of the rural people as well as in conserving the natural resource of the country. The current study of the woody vegetation cover of the country in 1992/1996 was 39.6% of the total area (DFRS, 1999).

Terai lies in the tropical region and occupies 14% land area of the country. Very productive forest with very high value timber species (*Shorea robusta* and its associate species) covers the majority of parts and were heavily degraded due to the unplanned export of timber to the neighbouring countries and official and unofficial conversion of forest land into agriculture and other land use (Joshi, 1993). Forest resources is depleting rapidly with a annual deforestation rate of 1.7%, if present rate of deforestation continue there will be only 19 % of forest cover remained by 2020, which was 38 % in 1978, and 29 % in 1994 (DFRS, 1999). The forest area of this region is decreasing both in size and stock (Skarner, 1998). The forest in Terai, Inner Terai and Siwaliks are depleting by 1.3% annually (HMGN/MFSC, 2000). A study shows that 99000 ha forest area lost in 12 years in 20 Terai districts between 1978/79 to 1990/91 (FRSC/MFSC and FRISP/FINNIDA, 1994). Further 0.7233 million ha of forest will be degraded to meet the national demand by 2010/2011 (HMGN/MFSC, 2000). Therefore, there is an urgent need to monitor forest cover dynamics in the Terai region.

Forest resources are depleting rapidly in Nepal due to the population growth and their dependency on forest resources for their livelihood. The people depend on forests for firewood as well as for timber, medicinal plants and other forestry products. Forest area including shrub has been decreased from 42.7% to 39.6 % during 1978/79-1994 in Nepal (Table 1). The increasing population is exerting heavy pressure on the forests of Nepal. It is estimated that the annual economic loss from the deforestation is eleven billion Nepali rupees per year. This situation shows that there is still good deal of pressure on forests especially those in the Inner Terai and Terai. The depletion of forests causes serious problem including declining agricultural productivity and environmental degradation. Woody vegetation sharply decreases in the Central Development Region (Table 2). Bara district is located in central Terai where deforestation rate is high in the one hand and population is increasing rapidly on the other hand. In these circumstances, study about forest cover monitoring is essential to assess the existing forest resources and to develop the effective strategy to halt deforestation and manage the economically valuable tropical mixed hardwood forest sustainably.

Vegetative Cover	**[1]LRMP**	**[2]NRSC**	**Master Plan**	**[3]NFI**
	1978-79	**1984**	**1985-86**	**1994***
Forest	38%	35.9%	37.4%	29.0%
Shrub	4.7%	Partly Included in forest	4.8%	10.6%
Total	42.7%		42.2%	39.6%

Table 1: Forest and shrub under different forest inventories in Nepal

(Source: NFI, 1999)

(*The NFI was implemented between 1989 and 1996 but it uses 1994 as the base year)

Development Region	**LRMP 1978 (1 000 ha)**	**NFI 1994* (1 000 ha)**	**Total change (percent)**
Far Western	1 049.9	951.3	-9.4
Mid Western	1 727.0	1 634.4	-5.4
Western	1 061.3	991.2	-6.6
Central	1 327.7	1 152.4	-13.2
Eastern	1 140.8	1 098.7	-3.7
Total	**6 306.7**	**5 828.0**	**-7.6**

Table 2: Change in forest cover between 1978-1994 by development region

(Source: NFI, 1999)

[1] Land Resources Mapping Project, 1986
[2] National Remote Sensing Centre of Nepal
[3] National Forest Inventory

Tropical Sal (*Shorea robusta*) forest is the dominant forest type found in the Bara district which is one of the most economically timber species in Nepal. But open forest areas of the district are depleting and degrading due to the rapidly increasing population and cattle pressure. Forest area of the district has been rapidly decreased from 41.58% in 1984 to 39.66% in 1990/91 (DFRS, HMG/N, 1999). This trend shows that forest area has rapidly been decreasing. No forest inventory has been carried out after 1994 in the Bara district. In these circumstances, the output of this study would provide useful information for the preparation, implementation and monitoring of the forest management plan in the study area. In addition, current information about the forest cover change would be useful in developing strategies for the protection and administration of forest area by the local authorities.

1.3 Research Questions

This research was designed to answer the following questions:

1. What are the distribution and rate of forest cover changes in the Bara district during 1989-1999 and 1999-2005?
2. What is the spatial pattern of forest cover change?
3. How much forest area will be converted into other land cover types in 2021?
4. What are the driving forces affecting forest cover changes in the period from 1989-2005?

1.4 Objectives

The research aims to analyse the trend of forest cover dynamics, fragmentation and their causes in Bara district, Nepal during 1989-2005.

The specific objectives targeted for monitoring forest cover dynamics in the Bara district are:

- To identify and map key forest cover types for the year 1989, 1999 and 2005
- To assess the trends of forest change over the period 1989-2005
- To analyse the spatial pattern of forest
- To analyse the relationship between the trends of forest cover changes and their underlying factors.
- To predict/ project the change of forest area for the year 2021

1.5 Hypotheses

The following hypotheses were formulated prior to this study:

1. Forest area has been decreased considerably over the period of 1989-2005
2. Conversion between land cover types (between-class changes) is significant
3. Spatial pattern of forest has been changed significantly

1.6 Research Approach

Nepal's forest land is gaining tremendous pressure from the extraction of timber from the forest, encroachment, agricultural expansion, population growth and infrastructure development. Therefore, forest cover monitoring is very important and essential not only to assess the impact of different forest management regimes but also to set the programme and policy on bio-diversity conservation as well as environmental and ecological balance. Integrated approach (Figure 1) of remote sensing and geographic information system such as image classification, change detection techniques, spatial metrics and land use change modelling was applied for monitoring forest cover in Bara district (Nepal). Forest resource assessment is the foundation of any sound forest management and this study will provide necessary information for scientific forest management.

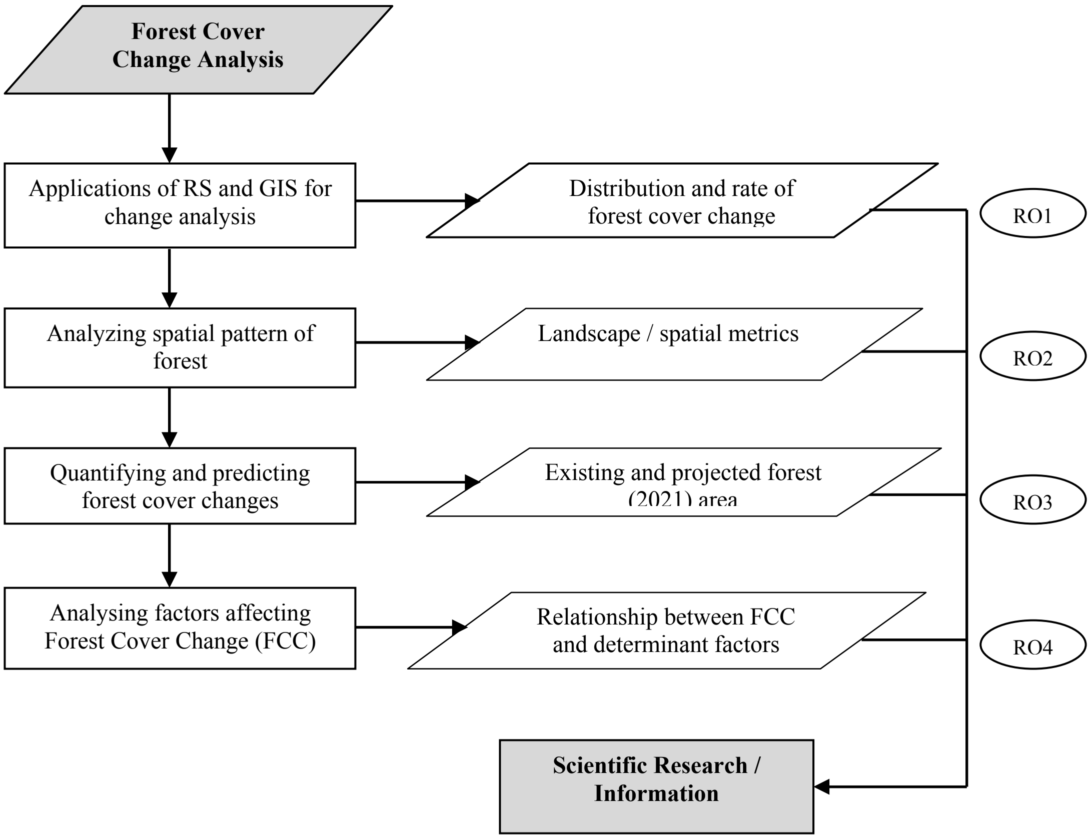

Figure 1: Research conceptual framework

1.7 Organization of the Thesis

It is important to have a mental roadmap about the relationship between various chapters. Chapter one deals with the general background; problem statement; research questions and hypothesis; and objective and research approach designed to monitor forest cover dynamics in Bara district (Nepal). Chapter two primarily deals with the state of art on remote sensing and sustainable forest management, land use classification, image classification and change detection techniques. In addition, spatial metrics and land use change modelling are described briefly. Chapter three describes the study area: the Bara district (Nepal) with respect to location, climate, population and forest resources distribution. Chapter four is concerned with the materials and methods used in this research such as image classification and change detection techniques applied as well as spatial pattern of forest and land use change modelling. Chapter five presents the result and discussion of forest cover monitoring .Chapter six summarizes overall results and discussion and recommends on the areas of improvements. Finally five appendices are also included in the back of the thesis to illustrate study area, data and output in detail.

2. REMOTE SENSING AND SUSTAINABLE FOREST MANAGEMENT: CONCEPTS AND DEFINITIONS

2.1 Introduction

Remote sensing has played a pivotal role in informing national governments and organization and the international community of the rapid and unprecedented decline in tropical forests over the past 50 years (Ustin, 2004). Routine observations by satellite sensors such as the Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper (ETM^+) drew attention to unprecedented changes in forest extent. Substantial advances in remote sensing technologies and data processing capabilities have allowed a more rigorous and quantitative assessment of the human impact on forest extent and condition. In this chapter concept of remote sensing with respect to sustainable forest management; satellites/sensors used in forestry; broad overview of land cover classification system, digital image interpretation and changed detection techniques are discussed briefly. Moreover, spatial metrics used to quantify and assess spatial pattern of forest, and land use change modelling are discussed. Concepts and definition about remote sensing for sustainable forest management and commonly used terminologies relevant for this study are then briefly defined.

2.2 Remote Sensing

Remote sensing is defined as the art and science of obtaining information about an object without being in direct physical contact with the object (Jensen, 2000). It is a scientific technology that can be used to measure and monitor important biophysical characteristics and human activities on earth. The world has entered the electronic information age which, now more than ever before, includes spatial information. People responsible for managing the Earth's natural resources and planning future development recognize the importance of accurate, spatial information residing in a digital GIS. Many of the most important layers of biophysical, land use/ land cover, and socioeconomic information in a GIS database are derived from an analysis of remotely sensed data (Jensen, 2000).

Image interpretation is defined as the examination of images for the purpose of identifying objects and judging their significance (Philipson, 1997). Multi-temporal analyses of surface properties are desired in order to monitor the various changes occurring at the Earth surface. Remote sensing data collected by various instruments constitute a unique data basis ensuring a systematic local, regional, and global coverage for a range of ground spatial resolution. The examination of multi-temporal remote sensing data set is often confined to simplified change analysis schemes.

The examination of multi-temporal remote sensing datasets is often confined to simplified change analysis schemes. More powerful procedures are offered by trend analysis techniques requiring quantitative or semi-quantitative input data (Elmore et al., 2000). Application of remotely sensed data to illustrate changes in land cover and particularly forest cover over time have been reported by many investigators (Coppin and Baur, 1996). Trend analysis can be employed to calculate numerous parameters that may be derived from time series of satellite data. A combination of different parameters reveals additional information, which is not easily comprehensible through other processing schemes.

Vegetation is one of the most important components of ecosystems. Knowledge about variations in vegetation species and community distribution patterns, alterations in vegetation phenological (growth) cycles, and modifications in the plant physiology and morphology provide valuable insight into the climatic, edaphic, geologic, and physiographic characteristics of an area (Jones et al., 1998). Scientists have devoted a significant amount of effort to develop sensors and visual and digital image processing algorithms to extract important vegetation biophysical information from remotely sensed data (Huette and Justice, 1999).

The potential role of remote sensing as an information resource to support sustainable forest management appears enormous and immediate based largely on two facts:

- Sustainable forest management requires synoptic and repetitive biophysical and biochemical vegetation data for large geographic areas over long periods of time, and
- Remote sensing is the only way to acquire such data.

Landsat Thematic Mapper

Landsat Thematic Mapper (TM) is the second generation of the Landsat satellites that was launched on 16th July, 1982 (Landsat 3) and March 1, 1984 (Landsat 5). The TM sensor provides several improvements over the MSS sensor including: higher spatial and radiometric resolution; finer spectral bands; seven as opposed to four spectral bands; and an increase in the number of detectors per band (16 for the non-thermal channels versus six for MSS). Sixteen scan lines are captured simultaneously for each non-thermal spectral band (four for thermal band), using an oscillating mirror which scans during both the forward (west-to-east) and reverse (east-to-west) sweeps of the scanning mirror. Spatial resolution of TM is 30 m for all but the thermal infrared band which is 120 m. All channels are recorded over a range of 256 digital numbers (8 bits). Table 3 outlines the spectral resolution of the individual TM bands and some useful applications of each.

Channel	Wavelength Range (μm)	Application
TM 1	0.45 - 0.52 (blue)	soil/vegetation discrimination; bathymetry/coastal mapping; cultural/urban feature identification
TM 2	0.52 - 0.60 (green)	green vegetation mapping (measures reflectance peak); cultural/urban feature identification
TM 3	0.63 - 0.69 (red)	vegetated vs. non-vegetated and plant species discrimination (plant chlorophyll absorption); cultural/urban feature identification
TM 4	0.76 - 0.90 (near IR)	identification of plant/vegetation types, health, and biomass content; water body delineation; soil moisture
TM 5	1.55 - 1.75 (short wave IR)	sensitive to moisture in soil and vegetation; discriminating snow and cloud-covered areas
TM 6	10.4 - 12.5 (thermal IR)	vegetation stress and soil moisture discrimination related to thermal radiation; thermal mapping (urban, water)
TM 7	2.08 - 2.35 (short wave IR)	discrimination of mineral and rock types; sensitive to vegetation moisture content

Table 3: Characteristics of Landsat Thematic Mapper (TM) Spectral Bands

Landsat 7 was launched on April 15, 1999. Landsat 7 is a three-axis stabilized platform carrying a single nadir-pointing instrument, the ETM^+. The ETM^+ bands 1-5 and 7 are identical to those found on TM and have the same 30 × 30 m spatial resolution. The thermal infrared band now has 60×60 m spatial resolution (instead of 120×120 m). Most notable is the new 15×15m panchromatic band (0.52-0.90 μm).

Data from the MSS, TM and ETM^+ sensors are used for a wide variety of applications, including resource management, mapping, environmental monitoring, and change detection.

2.3 Land use / Land cover Classification

According to FAO (2000): "Land cover is observed (bio) physical on the earth's surface". The FAO defines the land use as the arrangements, activities and inputs that people undertake on a certain land cover type. According to these definitions, land cover corresponds to the physical condition of the ground surface, e.g. forest, agricultural land, grassland, urban, while land use reflects human activities such as the use of the land like industrial zones, residential zones, and agricultural fields.

The above definitions establish a direct link between land cover and the actions of people in their environment i.e. land use may lead to land cover change. Generally, land cover does not coincide with land use. A land use class is composed of several land covers. Remote sensing data can provide land cover information rather than land use information.

Land cover change can be divided into two forms as follows (FAO, 2000):

- Conversion from one land cover category to another, e.g. from forest to grassland.
- Modification within one category, e.g. from dense forest to open forest.

Land cover is a fundamental variable that impacts and links many parts of the human and physical environment. Land cover changes can be readily detected using satellite imagery based on changes in spectral reflectance or the introduction of spatial features such as vegetation, roads or field outlines. Natural and human disturbances, ecological succession, and recovery from the previous disturbances are all the forces that modify ecosystem patterns and processes within the landscape, causing changes in land cover (Franklin et. al, 2002) . Knowledge of these changes and of their driving forces can provide insight into regional landscape dynamics (Hall et al., 1991). Land cover changes can be analyzed either visually (Skole and Tucker, 1993) or through digital analysis (Yuan et al. 1998). In general, two dates of imagery are sufficient to document a set of land cover changes which have occurred between the two image acquisition dates.

A universal land use/land cover classification system does not exist. Instead, a number have been developed to reflect the needs of different user(s). Typically, the systems are hierarchically arranged with the ability to consolidate lower level classes into the next highest level and with a consistent detail for all classes at a given level in the hierarchy. In selecting a classification system for use with remotely sensed data, the classes must have a surface expression in the electromagnetic spectrum. For example, a crop such as pineapples reflects electromagnetic radiation, but an automatic teller machine (ATM) on the side of a building cannot easily be detected, especially from most down-looking sensors.

The U.S. Geological Survey Land-use/Land-cover classification system (Anderson et al., 1976; USGS, 1992) was originally designed to be resource oriented (land cover). Anderson's classification system is summarized in Appendix 1.

2.4 Image Classification

According to Jensen (1996), digital image classification is the process of assigning pixel to classes. Usually, each pixel is treated as an individual unit composed of values in several spectral bands. By comparing pixel to one another and to pixel of known identity, it is possible to assemble groups of similar pixels into classes that match to the informational categories of interest to users of remotely sensed data. In recent year, many advanced classification approaches; such as artificial neural networks, fuzzy sets and expert systems, have been widely applied for image classification (Lu and Weng, 2007). Cihlar (2000) discussed the status and research priorities of land cover mapping for large areas. Franklin and Wulder (2002) assessed land cover classification approaches with medium spatial resolution remotely sensed data. In general, image classification approaches can be grouped as supervised and unsupervised, pixel-based and object-oriented, hard and soft classification based on whether training samples are used or not, spatial unit of analysis, and whether parameters are used or not respectively.

Object oriented image classification

Per pixel procedures generally perform classification by using spectrally based decision logic that is applied to each pixel in an image individually and in isolation. In contrast, object-oriented classifiers use both spectral and spatial patterns for image classification. This is a two-step procedures involving (i) segmentation of imagery into discrete objects, followed by (ii) classification of those objects. The basic assumption is that the image being classified is made up relatively homogenous “patches” that are larger in size than individual pixels. This approach is similar to human visual interpretation of digital images, which works at multiple scales simultaneously and uses colour, shape, size, texture, pattern, and context information to group pixels into meaningful objects.

The scale of objects is one of the key variables influencing the image segmentation step in this process. For example, in case of forested landscape, at a fine scale the objects being classified might represent individual tree crowns. Segmentation at an intermediate scale would produce objects that correspond to stands of trees of similar species and sizes, while at a still coarser scale, large areas of the forest would be aggregated into a single object. Clearly, the actual scale parameter used for an object-oriented classification will depend on a number of factors, including the resolution of the sensor and the general scale of features on the landscape that the analyst is seeking to identify.

Once an image has been segmented, there are many characteristics that can be used to classify the objects. These characteristics fall into two groups. One set of characteristics is intrinsic to each object- its spectral properties, its texture, its shape etc. Other characteristics describe the relationship among objects, including their connectivity, their proximity to objects of the same or other types, and so forth.

Object oriented analysis can also be used to facilitate land cover change in that the approach is capable of preserving the “parent-child” relationships among objects. For example, a large agricultural field containing only one crop type at an early time period might be classified as a single object. If multiple crop types are present in the field at later date, the parent field will be split into numerous child objects. This approach has been proven to be able to provide better classification results than pixel-based classification approaches, especially for fine spatial resolution data. The eCognition method is so far the most commonly used object-oriented classification (Wang et al. 2004).

2.5 Change Detection and Analysis

Analyzing an individual date of remote sensor data to extract meaningful vegetation biophysical information is often of value. However, to appreciate the dynamics of the ecosystem, it is necessary to monitor the vegetation through time and determine what changes in succession are taking place. Relatively medium to high temporal resolution satellite data is often useful for such type of study.

Researchers involved in change detection studies using satellite images data have conceived a large range of methodologies for identifying environmental changes. Change detection procedures can be grouped under three broad headings characterized by data transformation procedures and analysis techniques used to delimit areas of significant changes: (1) image enhancement, (2) multi-date data classification and (3) comparison of two independent lands cover classifications (Mas, 1998). The enhancement approach involves the mathematical combination of imagery from different dates such as subtraction of bands, rationing, image regression or principal component analysis (PCA). Thresholds are applied to the enhanced image to isolate pixels that have changed. The direct multi-date classification is based on the single analysis of a combined data set of two or more different dates, in order to identify areas of changes. The post-classification comparison is a comparative analysis of images obtained at different moments after previous independent classification.

Change detection techniques using remote sensing techniques involve the use of multi-temporal satellite data sets to discriminate areas of land cover change between dates of imaging (Lillesand a Kiefer, 2008). It can provide up-to-date spatio-temporal information about forest resources status that supports in making decision on appropriate intervention (policy formulation, planning and management). Change detection can be applied for various purposes like land cover change analysis, monitoring of shifting cultivation, assessment of deforestation and forest degradation, study of change in vegetation phenology, seasonal changes in pasture production, damage assessment, crop stress detection, disaster monitoring, environmental changes etc.(Roy, 2003). The basic principle of change detection using remote sensing is that changes in the land cover result in changes in radiance values (Mass, 1999). Analysing spectral differences in signatures of an object (land cover change can be detected. Thus change detection in remote sensing play a key role in improving spatial and temporal change information resulted by natural and anthropogenic activities in terms of time and cost effectiveness

The applicability of semi-automated and object-oriented approaches for satellite remote-sensing data has been the subject of many recent studies (Zhan, 2003).There is great interest in change detection using high-spatial resolution multispectral imagery. Some researchers have been working on change detection using high-spatial resolution imagery using object-oriented image segmentation techniques. For example, Walter (2004) performed an object-based change detection using pre-existing objects placed in a GIS database. His change detection method was based on maximum likelihood classification (MLC) and utilized input training data extracted from the GIS database.

Much current work focuses on the application of object-based analysis to temporal studies (Walter 2004, Zhou et al. 2008). For instance, Im et al. (2008) compare various pixel- and object-based change detection techniques, concluding that advanced object-based approaches are superior. Object-based change detection has been applied to various environmental concerns, including urban growth (Zhou et al. 2008) and shrub land encroachment (Stow et al. 2008).

2.6 Spatial Metrics

Different representations of space have led to a variety of spatial metrics for the description of spatial structure and pattern For each application, they have to be selected , interpreted, analysed, and evaluated according to the context of the study, given the thematic classification and inherent processes of change(Gustafson, 1998). The basis of the spatial metric calculation is a thematic map representing a landscape comprised of spatial patches categorized in different patch classes.

In general, spatial metrics can be defined as quantitative and aggregate measurements derived from digital analysis of thematic-categorical maps showing spatial heterogeneity at a specific scale and resolution. This definition emphasizes the quantitative and aggregated nature of the metrics, since they provide global summary descriptors of the individual measured or mapped features of the landscape (patches, patch classes, or whole map). Furthermore, it has to be considered that the metrics always represents the spatial heterogeneity at a specific spatial scale, determined by the spatial resolution, the extent of the spatial domain, the thematic definition of the map categories, and at a given point in time. Many of the quantitative measures are implemented in the public domain statistical package FRAGSTATS (Mc Garial et al., 2002).

Forest cover pattern characterization involves its detection and quantification. Spatial metrics are algorithms used for quantifying spatial characteristics of patches, classes of patches, or entire landscape mosaics (McGarial et al., 2002). The term patch defines scale-independent homogenous regions in a landscape (e.g., forest, grassland etc.). They were developed in the late 1980s for landscape ecology studies and included measures from information and fractal theory (Herold et al., 2003). Landscape metrics are used to quantify the spatial heterogeneity of the individual patches sharing a common class, and the landscape as the Selected spatial metrics of classified scenes have already been used in previous researches (*Herold*, et al., 2003; Cabral, et al., 2004) and were calculated using FRAGSTATS public domain software(McGarigal, et al., 2002).

Very recently there has been interest in applying spatial metrics to the analysis of the forest fragmentation. Soutworth et al. (2004) summarized the utility of spatial metric for land cover change and landscape fragmentation. Previous work has emphasized the use of spatial metrics to describe structure and pattern in land cover change and landscape fragmentation. Soutworth et al. (2004) evaluated fragmentation of landscape using landscape metrics. At the class level, descriptive metrics of land cover pattern between forest and non-forest classes were compared across four dates (1987, 1991, 1996, and 2001). These metrics can be grouped into categories of area, shape, core, diversity and contagion / interspersion. Thapa and Murayama (2007) proposed spatial metrics for spatial structure of land use dynamics in Kathmandu valley. Four land use maps were prepared from the images for the year 1967, 1978, 1991, and 2000. A set of landscape metrics was used to evaluate temporal dynamics of land uses from the maps at class and landscape levels. GIS and landscape metrics provided the spatial structure of land use dynamics quantitatively in Kathmandu valley.

Fragmentation of a landscape occurs when land cover patches are dissected by disturbance (Forman, 1995). Fragmentation leads to smaller patches, more distant patches, and increases in edge area ratios and has been associated with the spatial density of roads, pipelines, and other dissection factors that divide patches and serve corridor.

Forest fragmentation can be defined as “division of large, comparatively homogenous tracts of forest into a heterogeneous mixture of much smaller patches” (Reed et al., 1996: p.267). No single landscape metric captures all aspects of fragmentation (Davidson, 1998; Jager, 2000); instead, a suit of selected metrics may be useful in interpretation of landscape change, and must be carefully considered relative to the type of change (the patches) and the background matrix (the forest mosaic).

2.7 Land Use Change Modelling

Scenarios of future land cover are important for a number of conservation and restoration goals, including targeting areas for restoration, assessing the impacts of possible restoration and mitigation scenarios, and determining the vulnerabilities of various resource lands to future land conversion.

Landuse and land cover models can be used for different purposes. These models can be categorised according to amount of information they contain. These are whole landscape models, distributional landscape models or spatial landscape models (Baker, 1989). Landuse and land cover change is influenced by various natural and human activity processes. Spatial details plays important role in these process (White et al., 1997). Therefore spatial modelling has more relevance than other methods of modelling in research.

Models of land use change are tools to support the analysis of the causes and consequences of land use changes in order to better understand the functioning of the land use system and to support land use planning and policy. Models are useful for disentangling the complex suite of socio-economic and biophysical forces that influence the rate and spatial pattern of land use change and for estimating the impacts of changes in land use. Furthermore, models can support the exploration of future land use changes under different scenario conditions. Summarising, land use models are useful and reproducible tools, supplementing our existing mental capabilities to analyse land use change and to make more informed decisions.

Description and modelling of land systems highly depends on the data availability and quality. With recent advances in land use modelling research, the discrepancy of data types between human and biophysical disciplines are obvious (Veldkamp et al., 2001).

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Different approaches have been attempted in spatial modelling, to name a few models, based on approaches: Markov Chain Analysis, Cellular Automata models, and GEOMOD.

2.8 Remote Sensing for Sustainable Forest Management

Forestry is concerned with the management of forests for wood, forage, water, wildlife and recreation. Because the principle raw product from forest is wood, forestry is especially concerned with timber management, maintenance and improvement of existing forest stands, and fire control. Forests of one type or another cover nearly a third of the world's land area. They are distributed unevenly and their resource value varies widely (Lillesand et al., 2008).

Sustainable forest management is the process of managing permanent forest land to achieve one or more clearly specified objectives of management with regard to production of a continuous flow of desired forest products and services without undue reduction of its inherent values and future productivity and without undue undesirable effects on the physical and social environment (FAO, 2000).

Remote sensing can be designed to support sustainable forest management in the presentation and reporting on the criteria and indicators of sustainable forestry, and in the modelling and projections at a variety of scales based on common understanding of biophysical and ecological principles (Berry and Ripple, 1996). Remote sensing, together with GIS and computer simulation models, appear poised to make significant contributions to the way in which the remaining forests of the world are managed. Recently Remote Sensing and GIS are considered as real tools for use by those concerned with the whole process of forest planning, operations and management.

Satellite remote sensing plays an important role in the monitoring of deforestation due to its capability to observe forest change in a repetitive and consistent manner over large areas (Alves et al., 1999; DeFries et al., 2002). Remote sensing technology in combination with GIS can render reliable information on vegetation cover. The use of remote sensing data in recent times has been of immense help in monitoring the changing pattern of vegetation..

The remote sensing of vegetation trends in the absence of land cover change is more challenging than standard land cover change analyses. Vegetation growth typically exhibits some type of annual cycle, with a period with low (or no) growth and a period of active growth and decline. Vegetation vigour and growth cannot be analysed using a single year image. An analysis of vegetation trends would be substantially improved if a sufficient number of images were included in the analysis to track the vegetation growth pattern. Some frequently used forestry terminologies relevant for this study are defined below.

Forest fragmentation

Forest fragmentation occurs when large, continuous forests are divided into smaller blocks by roads, agriculture, urbanization, or other development. This process reduces the forest's function as a habitat for many plant and animal species. In addition, it reduces the forest's effectiveness in performing other functions, such as water and air purification. Fragmentation not only reduces the area that is left as forest but also affects other biophysical aspects of forest such as forest structure, temperature, moisture and light regimes. It disturbs the habitat to which all forest animals and plants have adopted over millennia.

Afforestation

Afforestation is the process of establishing a forest on land that is not a forest, or has not been a forest for a long time by planting trees or their seeds. The term may also be applied to the legal conversion of land into the status of forest.

Reforestation

Reforestation is the restocking of existing forests and woodlands which have been depleted, with native tree stock. The term reforestation can also refer to afforestation, the process of restoring and recreating areas of woodlands or forest that once existed but were deforested or otherwise removed or destroyed at some point in the past. The resulting forest can provide both ecosystem and resource benefits such as: pollution control, dust control and has the potential to become a major carbon sink.

Deforestation

Deforestation is the conversion of forested areas to non-forested land, for uses such as: agriculture, pastures, urban use, logging purposes, and can result in arid land and wastelands. Deforestation implies the long-term or permanent loss of forest cover and implies transformation into another landuse. Such a loss can only be caused and maintained by a continued human-induced or natural perturbation. Deforestation results from removal of trees without sufficient reforestation, and results in declines in habitat and biodiversity, wood for fuel and industrial use, and quality of life. The term specifically excludes areas where trees have been removed as a result of harvesting or logging.

Forest degradation

It implies the changes within the forest, which negatively affects the structure or function of the stand or site, and thereby lowers the capacity to supply products and/or services (FAO, 2000).

Forest improvement

It implies the changes within the forest, which positively affects the structure or function of the stand or site, and thereby increases the capacity to supply products and/or services (FAO, 2000).

2.9 Conclusions

Remote sensing is a scientific technology that can be used to measure and monitoring important biophysical characteristics on earth. Multi-temporal analyses of surface properties are desired in order to monitor the various changes occurring at the earth surface. Remote sensing together with GIS and computer simulation models contribute significantly with the whole process of forest planning, operations and management. The information on the forest status such as quality, quantity, type, spatial distribution etc. can be assessed using remote sensing data.

Land cover changes can be readily detected using satellite imagery based on changes in spectral reflectance or the introduction of spatial features such as vegetation, road or field outlines. Digital image data are frequently the basis to derive land use / land cover information over large areas. A universal land use / land cover classification system does not exist. Land use and land cover data are needed in the analysis of environmental processes and problems. USGS Land Cover Classification System (LCCS) and FAO, LCCS are most commonly used land use system in remote sensing.

The most obvious method of change detections is a comparative analysis of spectral classifications for time t_1 and t_2 or series of time independently. Forest cover pattern characterisation involved its detection and quantification. Spatial metrics provide a means for quantifying spatial heterogeneity of individual patches, all patches in class, and over the whole landscape as a collection of patches. Important applications of spatial metrics include the detection landscape pattern, biodiversity, and habitat fragmentation.

Models of land use change are important tools to support the analysis of the cause and consequences of land use changes. Land use and land cover change is influenced by various natural and human activities and spatial details plays important role in these processes and therefore spatial modelling has more relevance than other methods of modelling.

3. STUDY AREA: THE BARA DISTRICT, NEPAL

3.1 Introduction

Nepal is situated on the southern slopes of the central Himalayas and represents about one third of its whole length (Figure 2). The country lies between China to the north and India to the east, south and west. It is located between the latitudes 26^{o} 22' and 30^{o} 27' N and the longitudes 80^{o} 40' and 88^{o} 12' E. It is roughly rectangular in shape and occupies a total area of 147181 square Km. From east to west the average length is 885 Km and north- south width varies from 145 to 241 Km with a mean of 193 Km. About 83% of its total land area is occupied by high mountains and wavy hills, and the remaining 17 percent by flat lands of the terrain. The altitude varies from some 60 m above the sea level in the Terai to 8848 m in the Mt. Everest, the highest peak of the world (CBS, 2001).

Nepal is divided into five major physiographic regions which run in more or less parallel bands from northwest to southeast. Each of these regions has a distinctive agricultural and forestry land utilization pattern. These regions are known as Terai, Siwaliks, Middle Mountains, High Mountains and High Himal from south to north direction. Nepal was once extensively covered by forests. Demand for fodder, overgrazing and uncontrolled cutting of timber and fuel wood, have significantly reduced the original forest cover. The composition of vegetation is closely related to the climate, which in turn is related to the physiographic region. There is not only a difference in vegetation from north to south, but also from east to west. The latter is caused by the decrease of monsoon rains in the western part and to some extent by the latitudinal differences between the eastern and western regions of Nepal.

Bara district is located in the central Terai of Nepal with few are on Siwaliks. Terai represents only 14% of the total area of Nepal but it contains about 42% of the total cultivated land of the country. The forests consist mainly of high value Sal and a mix of tropical and subtropical species. The Siwaliks - its hillslopes have little potential for agricultural production. Soils are shallow and erodable. The forests consist mainly of chir pine (*Pinus roxburghii*) and tropical mixed hardwoods of which Sal is often a major component.

3.2 Location and Physiographic Characteristics

Bara District is located in the south-central lowland Terai of Nepal which borders India in the south. The district lies between and Rautahat to east, Parsa to west, Makawanpur to the north and Bihar, India to south (Fig 2). It is located between the latitudes 26^{o} 61' and 27^{o} 02' N and the longitudes 84^{o} 51' and 85^{o} 16' E It occupies 0.87% of the 14.5 million hectares area of Nepal's land surface, includes 1.8% of country's farmland, and bears 1.9 % of Nepal's 24 million people with an average population of 7.5 per ha (CBS, 2001).

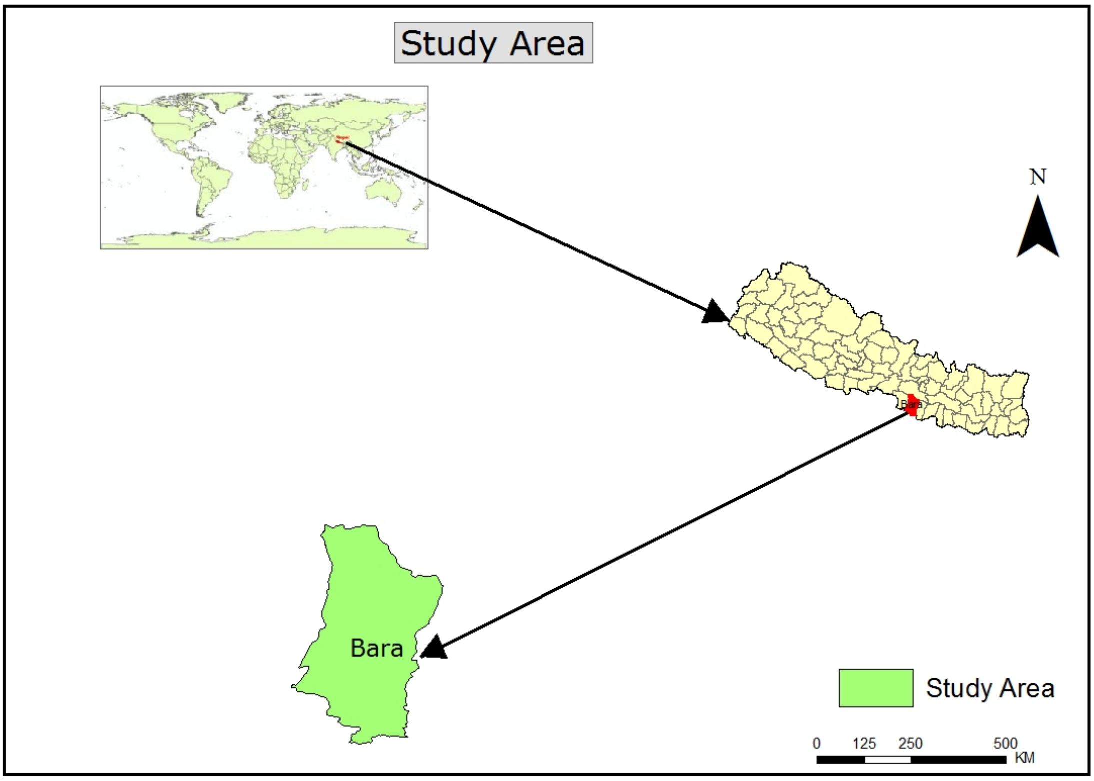


Figure 2: Study area

Government published estimates of the total area of the district are not consistent. This study utilizes a shape file obtained from the Department of Survey (DOS) of Nepal to delineate the area of the district that shows its area as 127,292 ha. Out of the total area, 6.3% is undulated gravelly hills called the Siwalik which are located in the north, while the other 93.7% lies in the south Terai plain (MDM 1971), which constitutes 5% of Nepal's plain land area. Most of the district's forests are located in the north, with more extensive farmland in the southern plain.

With the decline of government forests and increasing environmental awareness among people and due to the government incentives to individual farmers for farm plantations, many individual farmers in the southern part of the district have planted trees in their farmlands.

3.3 Climate

Most of the area (>90%) of the study area lies in tropical and remaining few areas in subtropical region. Maximum average temperature of the district is 31.2^0 C in summer and minimum 18.1^0 in winter. Maximum rainfall occurs during mid-June to mid-September with a high intensity during mid-June to mid-July. Average annual rainfall is approximately 1683 ml (CBS, 2001).

3.4 Population

Bara district has been experiencing rapid land use and land cover dynamics after the development of roads in 1960s. Two highways, east-west and north-south and the district level roads passing north-south from forests have been blessing on landuse dynamics. The population increased from 0.25 million in 1971 (MDM, 1971), 0.412 million in 1990(CBS, 1995), to 0.55 million in 2000(CBS, 2001), with 5 ha per family. The new migrant population living in the north, mostly along the forest fringes located near highways and commercial centres, strongly influences local and regional forest use practices of the district. According to CBS, 2001; total population of the district is 559,137 with total households 87,706. Out of the total population, 289,397 are male and 269, 738 female respectively.

3.5 Forest Resources

According to FRA-2005, forest area of Nepal has been changed significantly during 1990-2005(Table 4). Forest area has been shrunk with an annual rate of 2.1% and 1.4%   during 1990-2000, and 2000-2005 respectively. On the contrary, other wooded land has been increased during 1990-2005.

S.N.	Year	Forest(1000 ha)	Other wooded land(1000ha)
1	1990	4817	1180
2	2000	3900	1753
3	2005	3636	1897

Table 4: Change in extent of forest and other wooded

Forest types:

The forests found in the Bara districts mainly are composed of tropical and sub tropical species (IDEA, 2004). Sal (*Shorea robusta*) the dominant forest type in Bara and Tropical Mixed Hardwood (TMH) forest. In the northern part of the district, Hill Sal and Chir-pine (*Pinus roburghii)* forest occurs. Other forest types found in the study area are: riverine forest (*Dalbergia sissoo, Acacia catechu*) along the river. *Pseudosteppe* with *graminae*, tropical elephant grasses are found sparsely in a smaller quantity. Proportion of species found in the study area is tabulated below (Table 5) and forest types are illustrated in Figure 3.

S.N.	Scientific Name	Local Name	Coverage (%)
1	*Shorea robusta*	Sal	53.15
2	*Dalbergia sissoo*	Sissoo	14.39
3	*Tectona grandis*	Teak	10.65
4	*Dillenia pantagyna*	Tatari	3.67
5	*Eugenia jambolana*	Jamun	3.19
6	*Adina cordifolia*	Karma	2.47
7	*Lagerstromia parviflora*	Botdhayaro	2.46
8	*Careya arborea*	Kumbhi	2.23
9	*Mallotus Philippinesis*	Sindhure	1.55
10	*Hymenodictyon exelsum*	Bhurkut	1.32
11	*Mysine semiserrata*	Kalikath	1.31
12	*Gurga pinnata*	Dabdabe	0.24
13	*Eugenia operculata*	Kyamuna	0.07
14	*Phyllanthus emblica*	Amala	0.03
15	N/A	Other	1.90
Total			100

Table 5: Species composition in the Bara district (Source: IDEA, 2004)

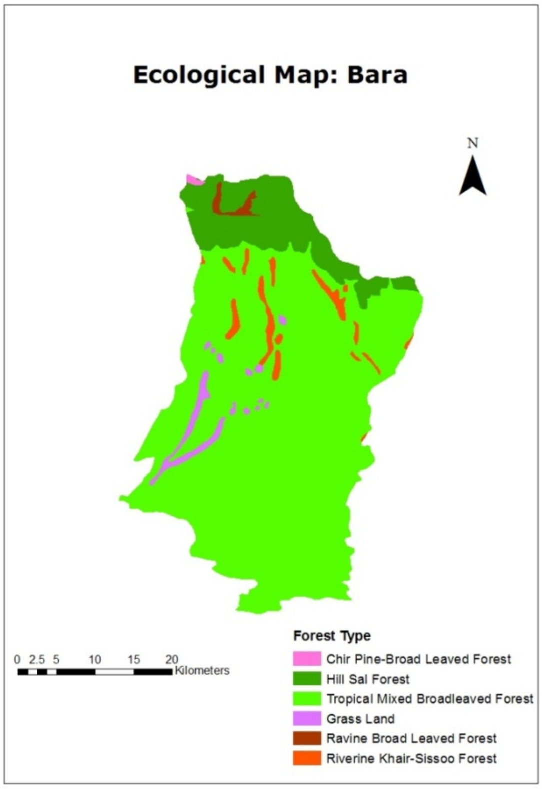


Figure 3: Ecological map of the Bara

Forest management regime:

Forests and shrub cover about 29% and 10.6% of total land area of country respectively (DFRS, 1999). Forests in Nepal is depleting at an annual rate of 1.7% from 1978 to 1994 (DFRS, 1999).

The Bara district has national, community and privately owned forests, and collaborative forests, each with different forest management practices. National forest includes government managed, protected, leasehold, and religious, community and collaborative forests. In community and collaborative forests, land ownership titles stay in government, users have the usufruct right only.

Community Forest

Community Forest (CF) means a national forest handed over to a users' group for its development, conservation and utilization for the collective interest (Forest Act 1993). CF is one of the most popular and successful program in Nepal. In CF, users are the people living near to and traditionally using forest and also called local user. Due to difficulties in the identification of local user in the densely populated and heterogeneous society and existence of larger blocks of valuable natural forest, CF is not fully implemented in the Terai region of Nepal. Only small and isolated patches of natural forest and plantation forest are handed over to local user as community forest. About 1.2 million hectares of forested land (more than 25 percent of the total) has so far been handed over to over 14,000 CFUGs which constitute about 35 percent of the total population of Nepal. So far, only 1818 ha forest is handed over as community forest to 13 Community Forest User Group in the Bara district (DOF, CFUG Database, Sept-10, 2007).Lack of the effectiveness of CF in Terai such as Bara, government launched the alternative forest management program *viz*. Collaborative Forest Management which is discussed below.

Collaborative Forest Management

Collaborative Forest Management (CFM) is an approach of sustainable forest management in Collaboration with the local people to achieve multiple benefits maintaining ecological balance, generating economic returns and improving livelihood from the government managed forests (CMWG, 2003).

In the Community Forestry model, individual houses are associated with particular patches of forest. In the Terai such associations are impossible (or at least impractical) to define, not only because of the large numbers of households involved, but also because there are conflicting claims over access rights. In the Terai, generally, the forests stretch out in the northern Terai up to the Churia hills range. This suggests that in the Terai a different organisation model of users' participation in forest management is needed. Realizing this, Government introduced the CFM as new forest management model for Terai.

Figure 4 shows a schematic sketch of Bara, a typical Terai district with the Churia range in the north, Terai block forests just south of that, and densely populated areas towards the Indian border. In the figure below, we can see agricultural land, forest users, and stakeholders (forest industries, line agencies etc.) are confined to the southern part of the district while forest is confined around east-west highway in the north. In the figure we can see three categories of user viz. close users, occasional users and distant users. Although, Terai districts vary geographically, with regard to forests' access rights, all Terai districts have the same pattern of large block forests and a complicated socio-economic lay-out. Community forest which is one of the successful people cantered forestry program in Nepal only recognize individual houses (close users) that are associated with particular patches of forest and ignore both occasional and distant users. Therefore, government of Nepal introduced new model of forest management, CFM, a working partnership between the key stakeholders in a management of the given forest: key stakeholders being local forest users, line agencies, local government, civil society, non-governmental organization and private sector. This approach includes close versus distant users and all stakeholders that fit the forest and population distribution pattern in the Terai.

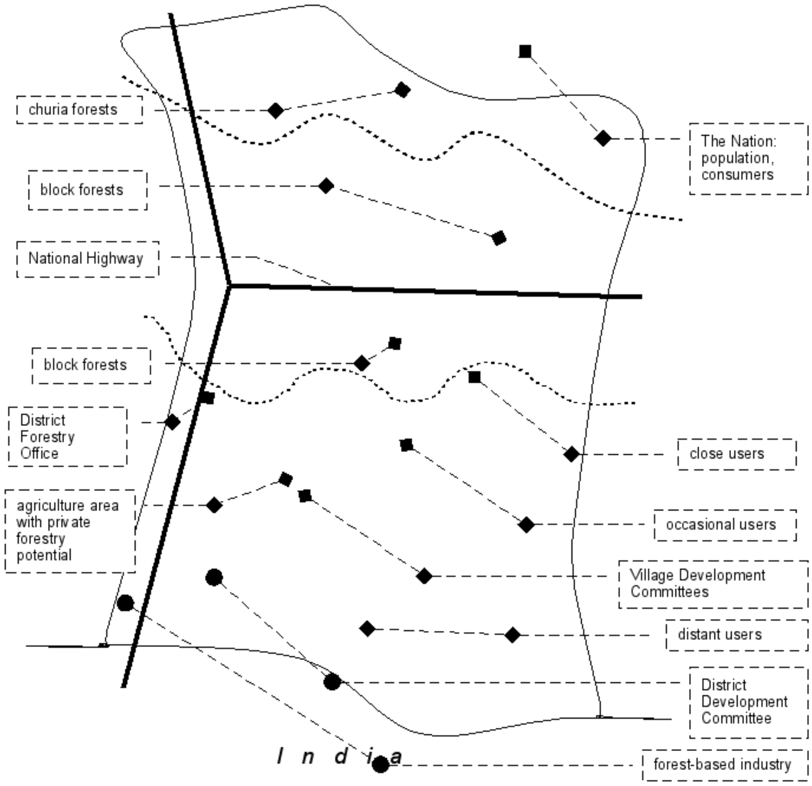


Figure 4: Distribution of forest resources and population in Bara

(Adopted from Schoubroeck and Karna, 2003*)*

Sajahnath CFM is currently operational (Table 6) in the study area. In addition, approximately 2500 ha forest has been proposed as Tamagadhi CFM (BISEP-ST, 2005).

Name	Sahajnath
Area of Forest(ha)	2058.00
No of households	17527
Population	110313
VDCs	26
Per ha Growing Stock (cu.m.)	130
Average annual increment per ha	3.2

Table 6: Present status of Collaborative Forest Management in Bara

(Source: BISEP-ST/RSU, 2005)

3.6 Conclusions

Tropical and sub-tropical forest found in the Bara district. Dominant forest type is Sal (*Shorea robusta*) and Tropical Mixed Hardwood Forest. Most of the region's forest is located in the north with extensive farmland in the southern plain. Bara district is an exemplary site to monitor the forest cover dynamics with RS and GIS because the region has the most economically important forest type in one hand and forest has been rapidly decreasing due to increasing population and excessive exploitation forest products. In addition, no official forest inventory has been carried out after 1990/91 in the Bara district.

4. MATERIALS AND METHODS

4.1 Materials

4.1.1 Data

Landsat TM and ETM+ satellite imageries were selected for forest cover change analysis of the Study area during a period 16 year (1989-2005). The reasons for selecting the Landsat images are due to the free access, appropriate spatial and spectral resolution, and relevancy to the objectives of the study. The main data used in the study included three Landsat satellite images acquired (Table7) for the years 1989 (TM), and 1999 (ETM+) and 2005(ETM+). 1989 and 1999 images were downloaded from the Global Land-Cover Facility site hosted by the University of Maryland and 2005(Landsat decadal, GLS-2005) image was downloaded using the USGS Global Visualization Viewer.

Satellite	**Date**	**Resolution**
Landsat TM	1989-10-31	30 m ,7channels
Landsat ETM^+	1999-11-04	30 m, 8 channels
Landsat ETM^+	2005-11-04	30 m, 8 channels

Table 7: Database Description

Three Landsat images for the year 1989, 1999 and 2005 were used in this study allowed us to provide an explicitly temporal perspective, and to examine the forests in Bara.

4.1.2 Software

The following softwares were used for this study for different purposes:

- eCognition (version 3.0) : for object-oriented image classification,
- Idrisi Kilimanjaro: for time series change analysis and predictive change modelling, and image differencing.
- ArcGIS 9.3: for vector data analysis and management.
- FRAGSTATS: for spatial metrics calculation

4.2 Methods

An integrated approach of remote sensing and GIS was applied in this study to generate land cover map and analyze the forest cover changes of the Bara district. Three remote sensing images (1989, 1999 and 2005) from Landsat satellites were processed for evaluating the forest cover dynamics. Image classification was carried out using object-oriented classification approach applying a standard nearest neighbourhood algorithm. Forest cover change was analysed by the post classification analysis, time series analysis and spatial pattern of forest was quantified by calculating spatial metrics.

4.2.1 Satellite image pre-processing

Three nearly cloud-free Landsat TM images were selected to analyze changes in forest cover between 1989, 1999 and 2005. Two images (1999 and 2005) were taken in the same day (November-4), and 1989 was also taken within a week that reduces the error due to variation in phenological characteristics of vegetation. A false colour composite image of the study area is illustrated in Appendix-5.

All the images downloaded were already projected into Universal Zone 45 N using WGS, 1984 datum. Since most of maps of Nepal are projected in the modified UTM (Zone 44.5 N), the projected images are re-projected into modified UTM (Zone 44.5 N, Spheroid: Everest-1830). The 1999 image was georeferenced using 1:25 000 scale topographic maps obtained from the Topographic Survey Branch of Nepal; the 1989 and 2005 images were georeferenced using the image-to-image registration against the 1999 image with an RMS error of 0.25 pixels. This enabled us to overlay information from different images within a GIS to evaluate forest change. We realized the radiometric correction is not required for this study since all the images were taken in the same season within a difference of one week. Autumn (October-November) is the appropriate season for acquiring cloud and dust free satellite images for Nepal. Generally atmosphere appears clean in autumn in the study area.

4.2.2 Description of land cover classes

The land cover classes applied in this study are defined considering USGS LCCS (Appendix-1), and land use land cover classification systems used in Nepal.

For this study, image classification was performed by emphasizing seven main categories. They are: Upper Mixed Hardwood (UMH), Mixed Forest, Shrub, Scatter Trees, Agricultural land including settlements, Bare Soil and Water Bodies respectively (Table 8). Since objective of the study is to monitor forest cover dynamics, residential area is not treated as separate class and it was included in agriculture.

Landover classes	Descriptions
Upper Mixed Hardwood	It includes upper mixed hardwood forest with >10% canopy cover, also include small pockets of plantation and burned areas
Mixed Forest	Includes lower tropical Sal and mixed broadleaved forest with >10% canopy cover, also include small pockets of plantation and burned areas
Shrub	Same as forest with < 10 % canopy covers but well defined stems cannot be found
Scatter Trees	It comprises trees scattered in agricultural and marginal land
Agriculture	Crop, irrigated land, bare soil, residential areas are included in this category
Bare Land	Includes sands, silt mainly along stream and river
Water	Water courses, water bodies are included in this class

Table 8: Land cover class nomenclature

4.2.3 Image classification and accuracy assessment

In order to quantify recent changes in vegetation cover in the study area, it is necessary to map the vegetation cover at present and at some time in the past. Change in vegetation cover was quantified during 1989- 2005. It is apparent that successful detection of forest cover changes requires effective classification methods. In various empirical studies, different classification methods are discussed e.g. supervised/unsupervised, pixel or object-based classification, etc. It is rather difficult to clearly extract objects of interest with pixel based classification. The advent of object-oriented method provides a tool for effective land use/land cover mapping (Blaschke, 2005). This method considers group of pixels and geometric properties of image objects. Therefore, to avoid the mixed pixel problem associated with pixel based methods and easily detect the change, an object-oriented method was applied in this study.

Object-Oriented classification

Object-oriented processing techniques segments the imageries into homogenous regions based on neighbouring pixels' spectral and spatial properties. Image analysis techniques that consider both the measure of reflectance values and neighbourhood relations (object-oriented analysis) are available in eCognition. One technical solution to overcome the pixel view is image segmentation. The aim of segmentation is to generate the most meaningful objects possible. For this purpose, an object-oriented analysis tool, eCognition, was employed. Image classification methodology is similar for all three images, so classification methodology is illustrated for 1989 image in the figure 5 below.

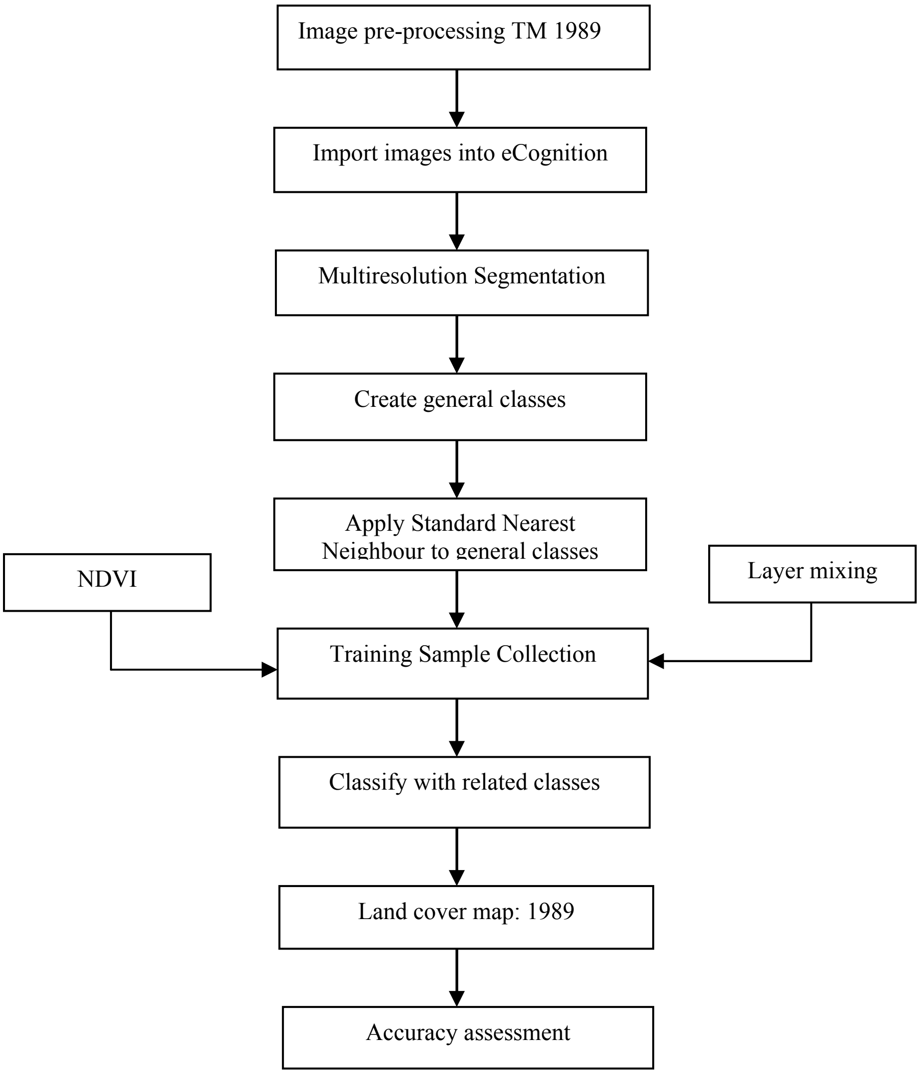


Figure 5: Image classification methodology

Image segmentation and classification

The first step in the object-oriented image classification is the segmentation of the image into discrete objects. A multi-resolution segmentation tool which is based on "region growing" approach (i.e. from small objects to super objects) was applied to create the image objects. There are many criteria that can be used to select how the objects in the image will be determined. For this project, colour was chosen as the main attribute that was used to segment the image. The other option that is important to keep in mind is the scale parameter, which determines how big we wish to grow our objects. Different scale parameter was attempted and a scale parameter of 10 was selected based on visual interpretation of the image segmentation results and nature of land cover classes used for this study for all three images. For the analysis and classification of image objects, in eCognition, the land cover class has to be defined in a class hierarchy. The seven classes shown in Table 8 were created in a class hierarchy.

There are two types of classifiers (nearest neighbour or membership functions) available in eCognition. Same scale parameter (i.e. 10) was applied for all three date images. After satisfied with the segmentation, standard nearest neighbours was inserted for all classes and then 440 training sample objects(Table 9) were collected using the topographic maps (Appendix –5) and other reference data (e.g. Google map). Normalized Differential Vegetation Index (NDVI) was calculated to improve the result and assist the classification. The training samples are typically representative of the seven classes created in class hierarchy. After constructing the resource based sample collection, a standard nearest neighbour algorithm was applied to classify the image. Based on these procedures, land cover maps of the study area were produced several times in order to improve the classification accuracy.

S. N.	**Class**	**Number of Samples**
1	UMH	35
2	Mixed Forest	140
3	Shrub	15
4	Scatter Trees	15
5	Agriculture	180
6	Bare land	30
7	Waterbodies	25
	Total	440

Table 9: Training samples collected for image classification

Accuracy assessment

It is necessary to assess accuracy to quantitatively assessing classification accuracy if remote-sensing derived land-use or land cover maps and associated statistics are to be useful (Meyer and Werth, 1990). The accuracy assessment in remotely sensed image classification is necessary for evaluating the obtained results (Congalton 1991). This will allow a degree of confidence to be attached to those results and will serve to indicate whether the analysis of objectives has been achieved. Randomly selected reference points lessen or eliminate the possibility of biasness. Reference points represent geographic points on the classified image for which actual data are known. The reference data are often derived from field survey, high resolution satellite imageries or aerial photographs. A set of reference points is usually used in accuracy assessment.

The accuracy assessment was carried out using 270 stratified random reference points. Random reference points were created representing all the land cover classes proportionally for each class separately using Idrisi. These points were verified with Google earth, topographic maps (1:2500) prepared in 1999-2001.

4.2.4 Change detection and analysis

Post classification comparison and time series analysis (Cross tab) were applied for the change analysis. Methodology applied for change detection is illustrated in Figure 6 below.

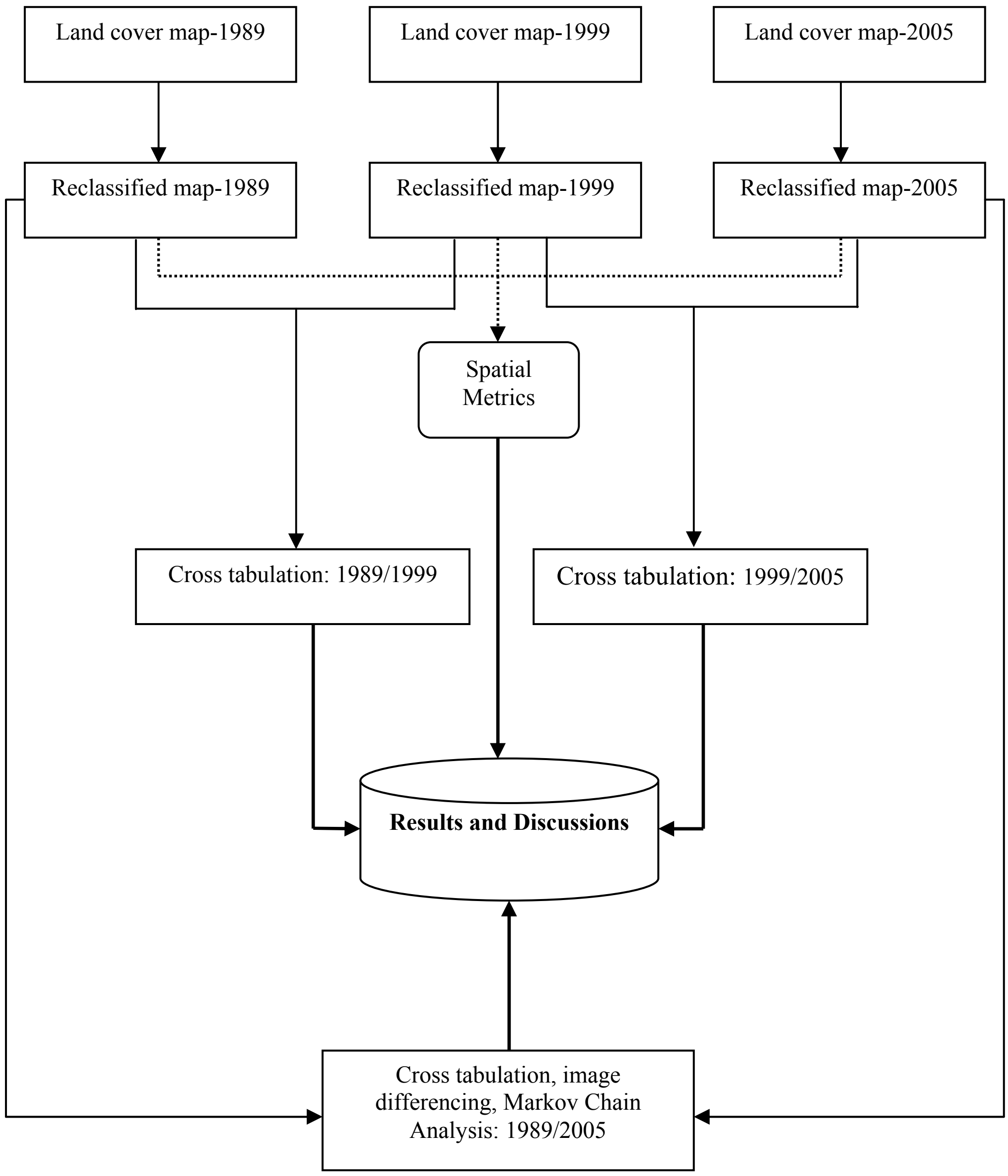


Figure 6: Flow diagram of change analysis, spatial heterogeneity and change projection

Post classification analysis

In the last few decades various detection and analysis techniques have developed and been applied in remote sensing studies to determine the spatial extent of land cover changes. Although there are a wide variety of techniques, most of land cover change detection analysis is performed using the simple techniques of post classification comparison (Blaschke, 2005). Following classification of imagery from the individual years, a post-classification, approach of subtracting the classified maps, 1989-1999, 1999-2005 and 1989-2005, was applied. This approach provides 'from-to' change information.

Time Series/Change Analysis

With qualitative data, CROSSTAB is the tool used for change analysis between image pairs and there are several types of output that can be useful. The crosstabulation output shows the frequencies with which classes have remained the same (frequencies along the diagonal) or have changed (off-diagonal frequencies). The Kappa Index of Agreement (KIA) indicates the degree of agreement between the two maps, both in an overall sense and on a per-category basis. Finally, the cross classification image can readily be reclassified into either a change image or an agreement image.

4.2.5 Spatial metrics

Forest cover changes can be well described using information from spatial metrics. Landscape metrics are quantitative indices used to describe structures and pattern of landscape (Herold *et al*., 2003). Therefore, spatial metrics were applied in this study to quantify and analyze the spatial and temporal changes of the forest land cover changes during 1989-2005. In this study, seven spatial metrics parameters were adopted and used for analyzing the spatial pattern of forest (Table 10).

Metric	Description/calculation scheme	Units	Range
CA- Class area	CA equals the sum of the areas (m^2) of all urban patches, divided by 10,000(to convert to hectares); that is, total forest area in the landscape.	Ha	CA>0, no limit
NP- Number of patches	NP equals the number of forest patches in the landscape.	None	NP≥, no limit
ED-Edge density	ED equals the sum of the lengths(m) of the edge segments involving the forest patch type, divided by the total landscape area (m2), multiplied by 10,000(to convert hectares)	Meters per hectare	ED≥, no limit
LPI- Largest patch index	LPI equals the area ($m^{2)}$ of the largest patch of the corresponding patch type divided by total area covered by forest (m2), multiplied by 100(to convert to a percentage).	Percent	0<LPI≤100
MNN- Euclidian mean nearest neighbour distance	MNN equals the distance(m)mean value over all forest patches to the nearest neighbouring urban patch, based on the shortest edge-to-edge distance from cell centre to cell centre	Meters	MNN>0, no limit
AWMPFD- Area weighted mean value of fractal dimension	Area weighted mean value of the fractal dimension values of all forest patches, the fractal dimension of a patch equals two times the logarithm of patch perimeter(m) divided by the logarithm of patch area(m^2); the perimeter is adjusted to correct for the raster bias in perimeter.	None	1≤AWMPFD≤2
CONTAG-Contagion	CONTAG measures the overall probability that a cell of a patch type is adjacent to cells of same type.	Percent	0<CONTAG≤100

Table 10: Spatial metrics used in the study (Adopted from McGarigal et al., 2002)

4.2.6 Land Use Change Modelling

Markov Chain Analysis

A Markovian process is one in which the state of a system at time 2 can be predicted by the state of the system at time 1 given a matrix of transition probabilities from each cover class to every other cover class. The MARKOV module can be used to create such a transition probability matrix. As input, it takes two land cover maps. It then produces the following outputs:

- A transition probability matrix. This is automatically displayed, as well as saved. Transition probabilities express the likelihood that a pixel of a given class will change to any other class (or stay the same) in the next time period.
- A transition areas matrix. This expresses the total area (in cells) expected to change in the next time period.
- A set of conditional probability images—one for each land cover class. These maps express the probability that each pixel will belong to the designated class in the next time period. They are called conditional probability maps since this probability is conditional on their current state.

Projected change mapping

Group file listing probability images yielded from MARKOV was normalized using NORMALIZE module and then Stochastic land cover map was created using STCHOICE in Idrisi respectively. Different filters were applied iteratively in order to generalize salt and pepper maps created. 3*3 median filter yields good result so it is used to generalize forest cover maps.

4.3 Conclusions

Multidate Landsat satellite images were used (1989, 1999 and 2005) were used to monitor forest cover dynamics in Bara. Image classification was carried using object-oriented classification approach. Forest cover change was monitored using post classification analysis and time series analysis. Spatial metrics were calculated to quantify change and evaluate landscape heterogeneity. Markov Chain Analysis was used to project forest cover for the year 2021.

5. RESULTS AND DISCUSSION

5.1 Land Cover Mapping and Accuracy Assessment

Multi-spectral images from Landsat TM and ETM$^+$ images of 1989, 1999 and 2005 were used to evaluate the forest cover changes in the study area. Training objects were collected and used to create classification of the satellite image using eCognition software. Land cover maps produced are presented in the Figure 7, 8 and 9 for the year 1989, 1999 and 2005 respectively. Initially, images were classified into seven land cover classes viz. Upper mixed hardwood (UMH), mixed forest, shrub, scatter trees, agriculture, bare land and water bodies prevalent in the study area. To simply the change analysis, classified images were reclassified into two classes: forest and non-forest. Upper mixed hardwood, mixed forest and shrub were reclassified as Forest and remaining all land cover classes as Non-forest. Reclassified maps are illustrated with the land cover maps in the figure below. The figures show proportion of each land cover classes.

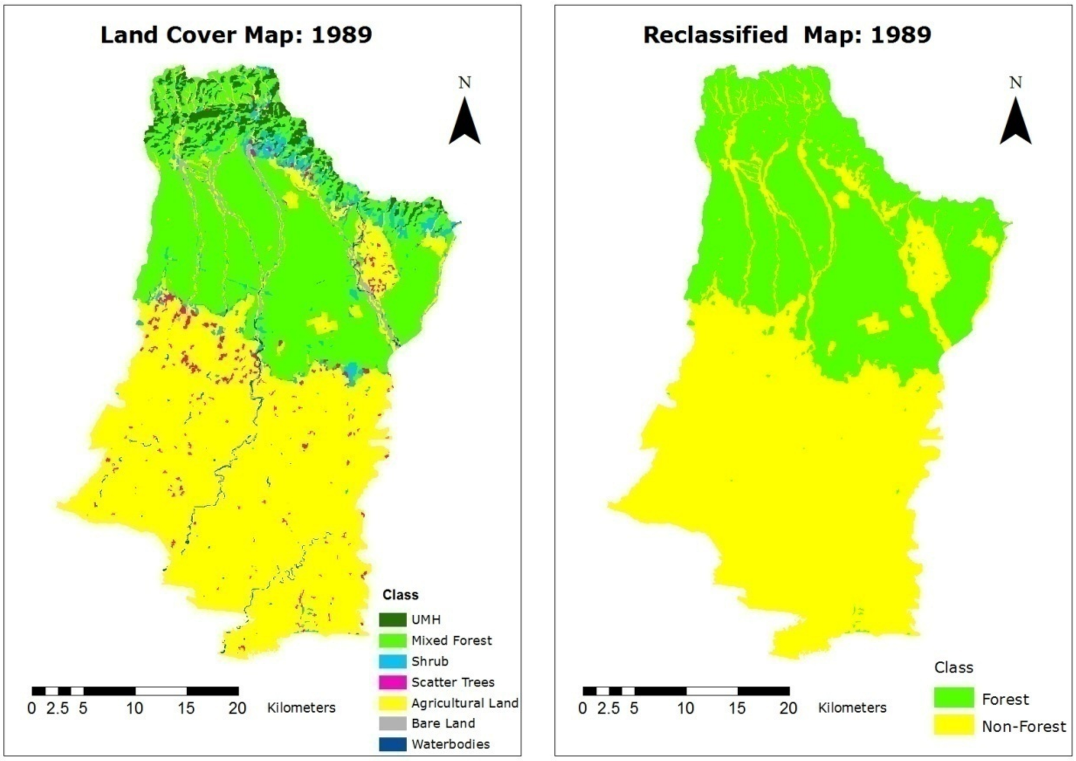


Figure 7: Land cover and reclassified map, 1989

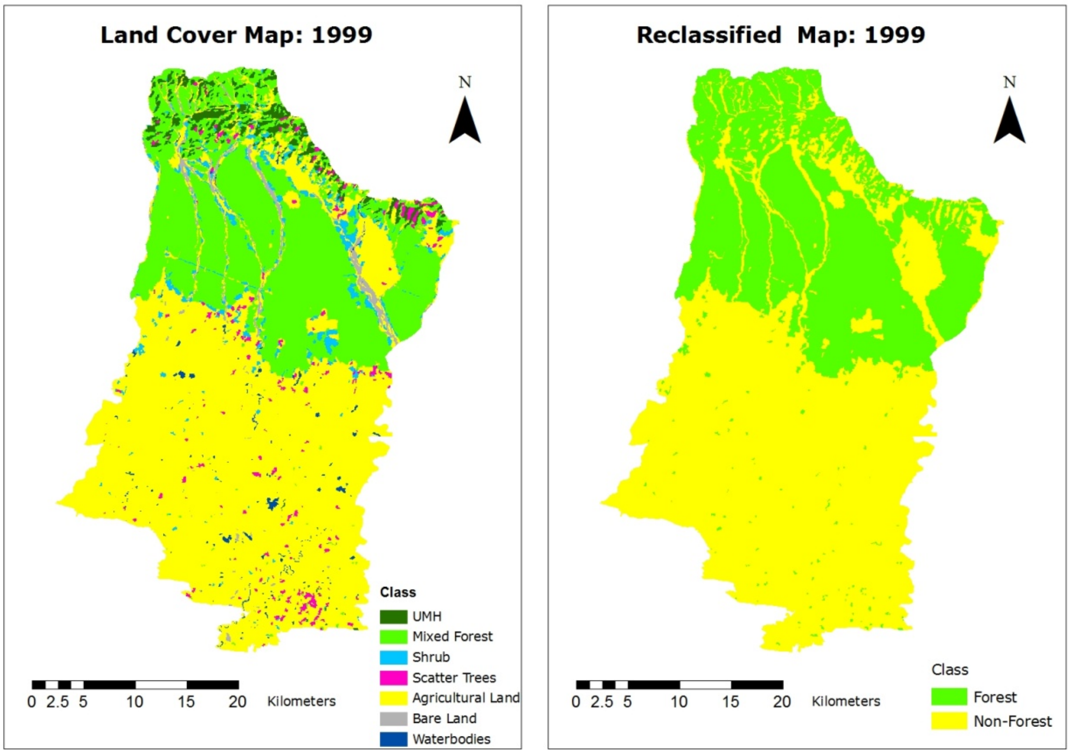


Figure 8: Land cover and reclassified map, 1999

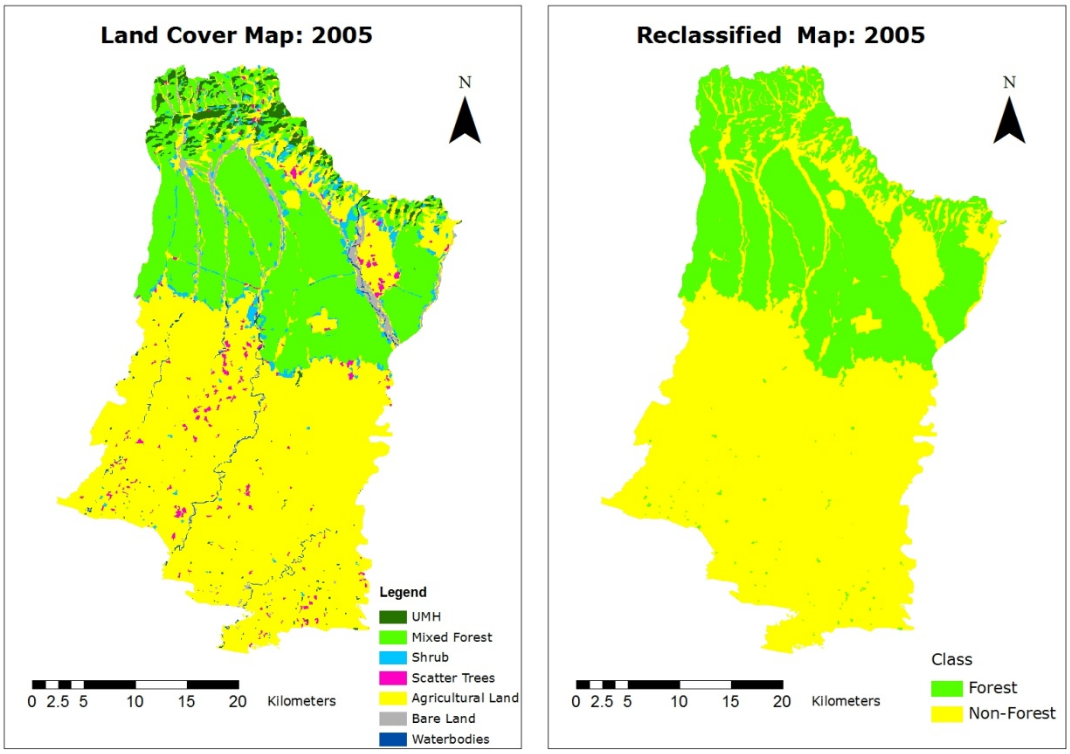


Figure 9: Land cover and reclassified map, 2005

Accuracy assessment

Classification accuracy was assessed using overall accuracy and kappa coefficient as well as producer's and user's accuracy which were calculated for the year 1999 and 2005. Overall accuracy, producer's accuracy and user's accuracy was assess by cross tabulating two values (ground observation and interpreted map of land cover) into a matrix, known as the confusion matrix. Kappa index was computed for each classified map to measure the accuracy of the results. The Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification. Kappa accounts for all elements of the confusion matrix and excludes the agreement that occurs by chance. Consequently it provides a more rigorous assessment of classification accuracy. Kappa Coefficient is a measure of agreement that compares the observed agreement to agreement expected by chance if the observer ratings were independent.

The overall accuracy and Kappa index of classification results achieved for 1999 were 85.71 % and 0.72 and for 2005 were 88.23 % and 0.76 respectively (Table 11). Results of the accuracy assessment are presented in Appendix-4. Kappa is 1 for perfectly accurate data and zero for accuracy no better than chance. Different people have different interpretations as to what is a good level of agreement. Kappa index 0.60 to 0.80 is interpreted as good agreement in the literature.

Producer's accuracy can be defined as the number of correct pixels in a category divided by total number of pixels from reference data (measure of omission error). User's accuracy can be defined as the total number of correct pixels in a category / total number of pixels that were actually classified in a category (measure of commission error, is the probability that a pixel classified on the map actually represents that category on the ground). In our study producer's accuracy is poor for scatter trees, shrub and bare land (Table 13). Discriminating scatter trees from forest, agriculture and shrub is experienced difficult with the available ancillary data (Google earth and topographic map). Discriminating bare soil from rainfed agriculture was also experienced difficult. User's accuracy is poor for shrub, scatter trees and upper mixed hardwood (Table 12) since it is intermixed with mixed forest and both are broadleaved forest type and difficult to discriminate them each other.

	1999	***2005***
Overall accuracy	85.71	88.23
Kappa	0.72	0.76

Table 11: Overall accuracy and Kappa

	1999	2005
Upper Mixed Hardwood	50.00	75.00
Mixed Forest	84.10	84.78
Shrub	50.00	81.82
Scatter Trees	61.54	61.54
Agriculture	87.96	89.42
Bare Land	85.71	87.8
Water	84.85	100

Table 12: User's accuracy (%)

	1999	2005
Upper Mixed Hardwood	55.56	75.00
Mixed Forest	95.35	96.3
Shrub	27.27	54.5
Scatter Trees	20	20
Agriculture	96.3	97.16
Bare Land	41.67	50
Water	66.67	66.67

Table 13: Producer's accuracy (%)

5.2 Rate and Distribution of Forest Cover Change

5.2.1 Rate of change

Multi-date Landsat images (1989, 1999 and 2005) were classified and area was calculated for each land cover classes. Percentual change of landuse change during 1989-2005 is accompanied in Table 14 and land use trend in Figure 10 respectively. During 1989-1999, forest area has decreased rapidly with loss of 11.49% upper mixed hardwood forest, 6.47 % mixed forest, and 3.21% shrub land respectively. Mixed forest has decreased by 5.61% followed by gradual decrease of upper mixed hardwood forest by 1.15%, and shrub by 5.89% respectively during 1999-2005.

Similarly, upper mixed hardwood forest has decreased by 12.51%, mixed forest by 11.72%, shrub by 8.91% during the entire study period, 1989-2005. Scatter trees slightly increased (8.75%) during 1989-1999 then decreased by 19.44% during 1999-2005 and decreased by 12.39% during the entire study period (1989-2005). Agricultural land has been increased by 7.59% during 1989-2005. In the figure trend is similar for all three dates, only observable difference is the amount of change is larger during the 1999-2005. Waterbodies decreased with a minimum quantity during the study period. Forest area has been decreased from 36% to 33.5% during 1989-1999 and 33.5% to 31.7% during 1999-2005. Similarly, forest cover has been decreased by 11.56 % (Table 15) during 1989-2005.

Year / Classes	1989	1999	2005	% Change (89-99)	% Change (99-05)	% Change (89-05)
UMH	4095	3625	3583	-11.49	-1.15	-12.51
Mixed Forest	41658	38963	36778	-6.47	-5.61	-11.72
Shrub	3982	3854	3627	-3.21	-5.89	-8.91
ST	1906	2073	1670	8.75	-19.44	-12.39
Agriculture	70366	74687	75705	6.14	1.36	7.59
Bare Land	2282	2077	2793	-8.97	34.45	22.39
Waterbodies	845	836	806	-1.12	-3.53	-4.61

Table 14: Percentual variation of land cover change

Year / Class	1989	1999	2005	% Change (89-99)	% Change (99-05)	% Change (89-05)
Forest	49736	46442	43988	-6.62	-5.28	-11.56
Non-forest	75399	79673	80974	5.67	1.63	7.39

Table 15: Percentual variation of forest cover change

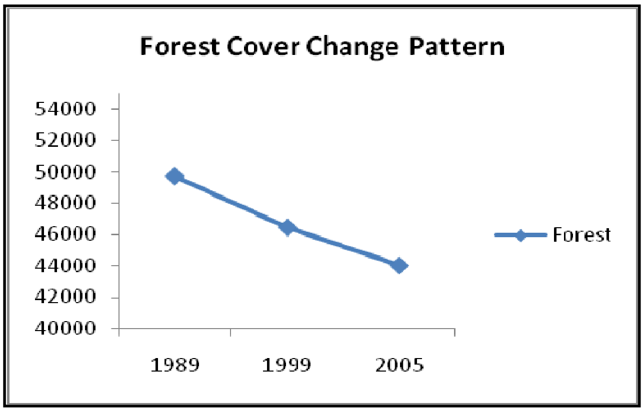


Figure 10: Forest cover change pattern

Land use proportion is illustrated in the figure 11 below. Out of the total area, forests cover 36%, 33.5%, and 31.7% in 1989, 1999 and 2005 respectively. Waterbodies decreased with a minimum quantity during the study period. Forest area has been decreased from 36% to 33.5% during 1989-1999 and 33.5% to 31.7% during 1999-2005.

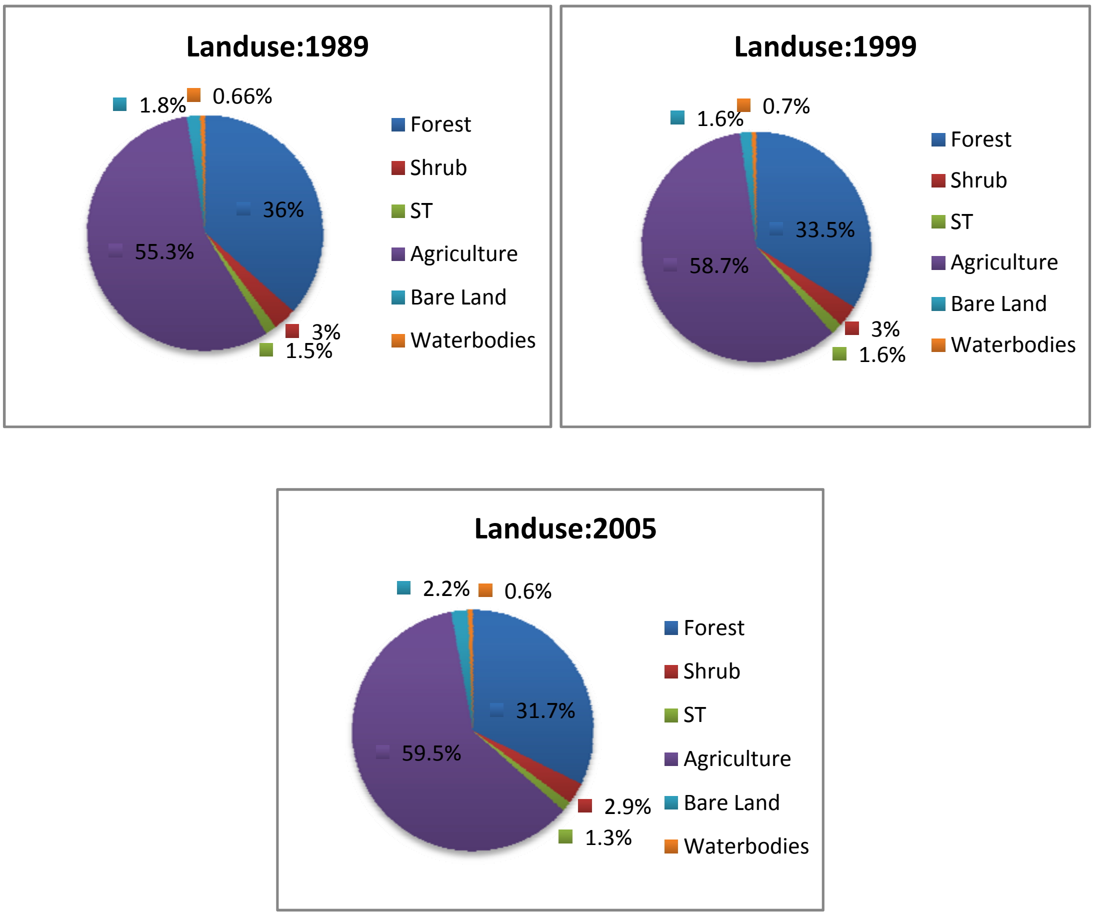


Figure 11: Land use proportion: 1989, 1999 and 2005

5.2.2 Distribution of change

Each pixel for the first year was compared to the same pixel location in the second year and similarly second year to the third year. During the first period, 1989-1999 (Table 16), considerable amount of forest land has been converted into cultivated land (upper mixed forest- 496 ha. mixed forest-2078 ha. and shrub- 1853 ha was converted during the period of 1989-1999). About 212 ha of mixed forest were also transferred to bare land. A mutual land conversion is observed among upper mixed hardwood, mixed forest and shrub, for example about 1471 ha of upper mixed hardwood forest to mixed forest, 2156 ha of mixed forest to shrub, 1510 ha of mixed forest to upper mixed hardwood forest and 1042 ha of shrub to mixed forest was transformed respectively. Some ha of forest land was transformed into other land use/cover categories but with a very low proportion of change. Conversion of agricultural land into scatter trees was also significant during 1989-1999.

1989/1999	1	2	3	4	5	6	7	8	Total
1	1676	1510	256	14	136	0	1	31	3625
2	1471	34980	1042	80	985	154	47	204	38963
3	126	2156	570	58	786	74	23	61	3854
4	145	452	162	47	1244	1	0	22	2073
5	496	2078	1853	1672	65645	944	625	1374	74687
6	25	212	26	18	600	1048	108	41	2077
7	5	28	14	3	697	17	39	32	836
8	150	242	58	15	273	43	3	360	1144
Total	4095	41658	3982	1906	70366	2282	845	2125	127259

Table 16: Result of cross - tabulation (1989/1999)

1-Upper mixed hardwood, 2- Mixed forest, 3- Shrub, 4-Scatter Trees, 5- Agriculture, 6-Bare land, 7-Waterbodies, 8-Unclassified area.

During the second period, 1999-2005(Table 17), about 340 ha of upper mixed forest, 2278 ha of mixed forest and 1376 ha of shrub land was converted to agricultural land respectively. About 272 ha forest including shrub was also transferred to bare land. A mutual land conversion is observed among upper mixed hardwood, mixed forest and shrub, for example about 964 ha of upper mixed hardwood to mixed forest, 1686 ha of mixed forest to shrub, and 921 ha of mixed forest to upper mixed forest and 1213 ha of shrub to mixed forest was transformed during 1989-1999 respectively. Conversion of agricultural land into scatter trees was also significant during 1999-2005.

1999/2005	1	2	3	4	5	6	7	8	Total
1	2121	921	41	74	278	1	42	105	3583
2	964	33403	1213	243	759	18	9	169	36778
3	115	1686	901	30	832	14	14	35	3627
4	9	111	78	51	1403	9	3	4	1670
5	340	2278	1376	1651	68434	590	662	373	75705
6	2	146	123	6	1123	1310	34	48	2793
7	8	27	44	6	579	93	43	5	806
8	65	390	77	11	1279	42	29	405	2297
Total	3625	38963	3854	2073	74687	2077	836	1144	127259

Table 17: Result of cross tabulation (1999/2005)

The most obvious changes were the conversion of forest land (upper mixed forest, mixed forest and shrub) into cultivated land (upper mixed forest- 563 ha, mixed forest-3392 ha. and shrub- 2305 ha was converted during 1989-2005). About 425 ha of mixed forest were also transferred to bare land. A mutual land conversion is observed among upper mixed hardwood, mixed forest and shrub, for example about 1285 ha of upper mixed hardwood to mixed forest, 2354 ha of mixed forest to shrub, 1231 ha of mixed forest to upper mixed forest and 776 ha of shrub to mixed forest was transformed during 1989-2005 respectively (Table 18). Some ha of forest land was transformed into other land use/cover categories but with a very low proportion of change.

1989/2005	1	2	3	4	5	6	7	8	Total
1	1937	1231	156	13	221	6	12	7	3583
2	1285	33789	776	45	698	152	34	0	36778
3	194	2354	501	41	452	75	9	1	3627
4	37	167	162	102	1181	9	10	2	1670
5	563	3392	2305	1679	66267	728	545	227	75705
6	40	425	54	10	927	1218	115	2	2793
7	6	55	22	11	497	91	117	7	806
8	34	245	6	5	123	3	2	1879	2297
Total	4095	41658	3982	1906	70366	2282	845	2125	127259

Table 18: Result of cross-tabulation (1989/2005)

To sum up, forest area has been converted to agricultural land considerably with about 6260 ha followed by the bare land with 520 ha during 1989-2005 (Table 19). The trends of conversion of forest into agriculture and bare land during two different periods are not much difference. The annual rate of conversion is higher during 1999-2005. Distribution of change is illustrated in the Figure 12 below.

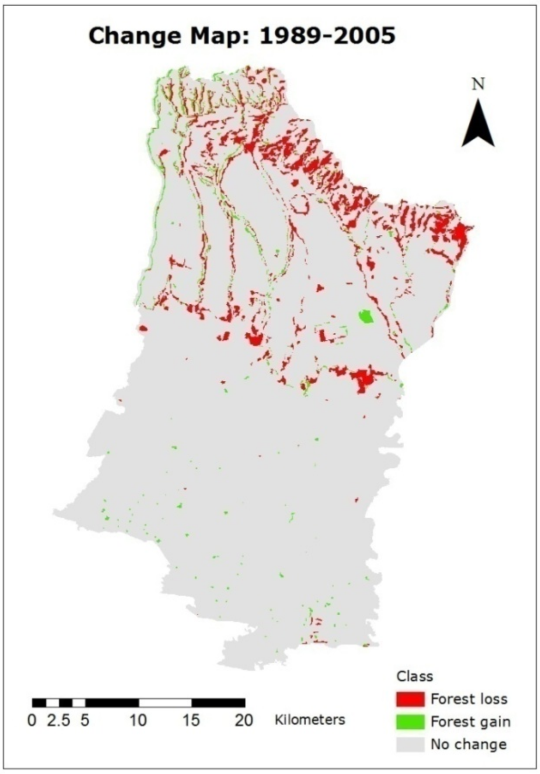


Figure 12: Forest cover change map, 1989-2005

5.3 Spatial Pattern of Forest

Spatial pattern of the forest area was evaluated calculating landscape metrics using the software FRAGSTATS 3.3 for each individual image classification (1989, 1999, and 2005). FRAGSTATS provides a very comprehensive set of spatial statistics and descriptive metrics of pattern at the patch, class, and landscape levels (Chopping, 1996). At the class level, descriptive metrics of land cover pattern between forest and non-forest classes were compared across the three dates. The spatial metrics obtained and their dynamics are presented in Table 19 and 20 respectively shows the result of the class metrics of both forest and non-forest areas with reference to the seven spatial metrics *viz.* Class Area (CA), Number of Patches (NP), Edge Density (ED), Largest Patch Index (LPI), Mean Euclidian Distance Neighbour (ENN_MN), and Area Weighted Mean Fractal Dimension (FRAC_AM).

Metrics \ Classes	1989		1999		2005	
	Forest	**Non-forest**	**Forest**	**Non-forest**	**Forest**	**Non forest**
CA- Class Area	49735.53	75399.03	46442.07	79673.22	43987.77	80974.26
NP- Number of patches	76	113	161	175	157	109
ED-Edge Density	7.3817	7.8211	10.3518	10.6285	9.4003	9.7919
LPI- Largest patch Index	28.9549	54.2380	14.5572	59.5356	10.8126	61.0966
FRAC_AM	1.1964	1.1707	1.1926	1.2056	1.1458	1.2155
ENN-MN	760.6497	314.4310	632.1205	196.3891	609.6734	253.1699
CONTAG	62.955		64.0693		63.2	

Table 19: Result of spatial metrics (1989/1999/2005)

Percentual variation of the seven spatial metrics calculated are tabulated in the table 20 and shown in the figure 13 respectively.

The indices of LPI and NP correspond to area metrics. Together with ED, these provide indications of the degree of fragmentation for different land cover types and change images. The result of the CA analysis shows that forest area has been converted to non- forest area significantly during 1989-2005. 3293 ha (6.62%) forest during 1989-1999, 2454 ha (5.28%) during 1999-2005 and 5748 ha (11.56%) during 1989-2005 has been converted into non-forest area respectively.

Spatial Metrics	**Percentual Variation (Δ %)**		
	1989-1999	**1999-2005**	**1889-2005**
CA	-6.62	-5.28	-11.56
NP	111.84	-2.48	106.58
LPI	-49.72	-25.72	-62.66
ED	40.24	-9.19	27.35
FRAC_AWMN	-0.32	-3.92	-4.23
ENN_MN	-16.90	-3.55	-19.85
CONTAG	1.77	-1.36	0.39

Table 20: Percentual variation of spatial metrics

Specifically, NP is an excellent measure of the fragmentation of a given class within the landscape since the landscape size is constant. Quite simply, the greater the number of patches, the greater the degree of fragmentation. Because this statistic is not an average (rather it is a count and so not skewed by outliers), it is a good indicator of the entire landscape, and not just the extremes. The number of patches on the other hand increased 111.84% during 1989-1999, and then decreased by 2.48% during 1999-2005. This reflects that forest area has been fragmented during 1989-2005 due to deforestation in new area. During 1999-2005, Number of patches decreased by 2.48% indicates the aggregation of non-forest area where small patches of forests fused into non-forest area. Thus, forest area has been isolated and fragmented rapidly initially during 1989-1999 and gradually during 1999-2005.

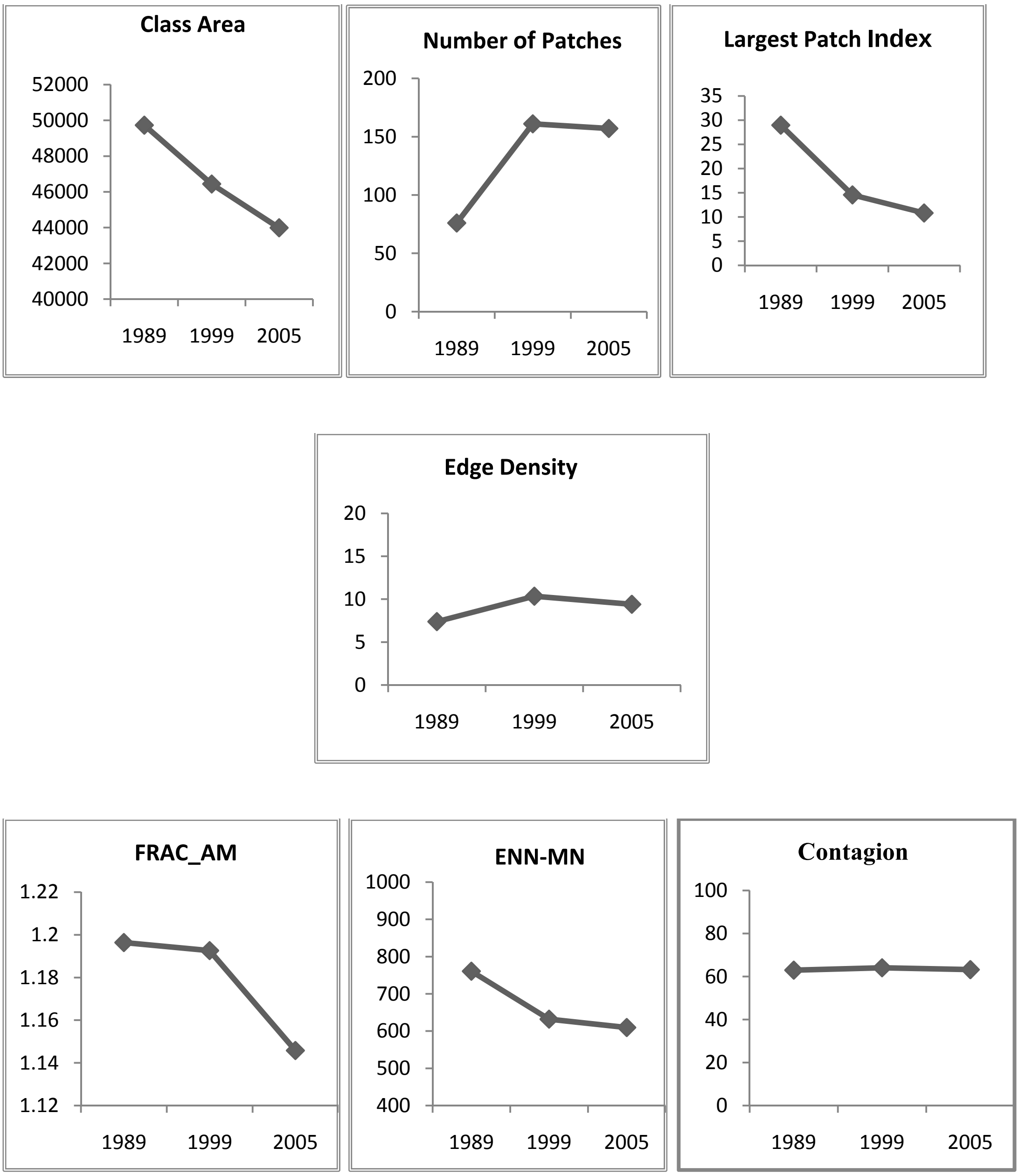


Figure 13: Landscape structure change in Bara (1989-2005)

The largest patch index (LPI) quantifies the percentage of total landscape area comprised by the largest forest patch. The LPI value of the forest area has been decreased during 1989-2005 that reflects the isolation and fragmentation of the forest area. Its evolution indicates two moments in the forest degradation and fragmentation: during 1989-1999, LPI index decreased by 49.72% reflects rapid fragmentation of forest area while during 1999-2005, LPI is decreased by 25.72% reflects the gradual fragmentation of forest patches in the later years. It may be due to agriculture sprawl into shrubs and forest lands forming bigger patches in the landscape in the later years.

The most remarkable difference in the change of forest area is given by the LPI. Continuous decrease of LPI during 1989-2005 reflects the continuous isolation of larger blocks of forest. In the Figure13, sharp decrease of LPI in the beginning followed by gradual decrease in the later year reflects that forest area has rapidly fragmented due to agriculture sprawl and extension of road network. The ENN_MN also follows the same trend of LPI and confirms that the fragmentation of the forest area has been decreased in the second period.

Edge Density (ED) can be defined as the length of the forest boundary divided by the total landscape. ED has increased by 40.24% during 1989-1999 indicates the larger number of smaller patches that justify the further fragmentation of forest area. During 1999-2005 ED decrease by 9.19%. It may be due to the conversion of smaller patches of forest into agriculture. The Euclidian mean nearest neighbour distance represents the average minimum distance between the individual forest areas. The ENN_MN has been reduced by 16.90% during 1989-1999, by 3.55% during 1999-2005 and by 19.85 % during entire period (1989-2005) respectively indicates that the forest patches are getting closer to each other during the study period. The closer the distance to the nearest neighbouring patches of the same land use type, the larger the number of patches and vice-versa. The number of patches is a good index of fragmentation since the area of the landscape is constant, more patches equates to more fragmentation.

The fractal dimension index is calculated by regressing the log of patch perimeter against the log of the patch area for each patch on the landscape. The index equals twice the slope of regression line. FRAC_AM value greater than 1 indicates the increase in shape complexity. Gradual decrease of the area weighted mean patch fractal dimensions (FRAC_AM) and amplified later reflects that the shape of the patches is becoming a bit simple results the decrease and fragmentation of forest area due to biotic influence such as population pressure, rural-urban migration and agricultural expansion. Contagion expresses the probability that land cover is more “clumped” than the random expectation. The contagion metric is a general measure of landscape heterogeneity often getting lower when the forest/non-forest configuration is more dispersed and fragmented. The contagion index slightly increase during 1989-1999 and decrease slightly during 1999-2005. Contagion value slightly increases first and then decrease. It shows the strange behaviour during 1989-1999 since other metrics such as NP, LPI shows fragmentation of the forest cover. It may be due to aggregation of agricultural land though rate of change is too small. In addition, Contagion is not only a measure of aggregation but also measure diversity and it is more sensitive to diversity than pattern in some instances. There can be many instances where contagion metrics does not measure contagion.

Regarding the extent and pattern of forest cover changes, forest area has been considerably decreased and fragmented during 1989-2005. With the increase of population, agricultural sprawl, migration and expansion of road networks, rapid decrease of forest area has been reported near highways such as Amlekhjanga and Pathlaiya. In these areas, there has been an attempt to convert forest into agricultural land due to proximity to east-west highway, industrial area and access to market. Evaluating the result of the spatial metrics, most of the forest area has been converted into agriculture and bare land. Another reason for the conversion of forest land into agriculture is due to the encroachment which is one of the most serious issues for deforestation in the Terai region of Nepal.

5.4 Land Use Change Modelling

Based on the changes that have occurred during 1989-2005, changes of forest cover for the year 2021 has been projected using Markov Chain Analysis module in Idrisi. A Markovian process is one in which the state of a system at time 2 can be predicted by the state of the system at time 1 given a matrix of transition probabilities from each cover class to every other cover class with the help of two land cover maps as input .

Results of the Markovian module are presented in Figure 14 below. Forest area including shrub will be decreased by 8.5% during 2005-21. On the other hand, non-forest area will be increased by 4.62%. In terms of the ratio of the forest area to the total area of the study area, forest including shrub bears 34.6% and 31.63% in the year 2005 and 2021 respectively.

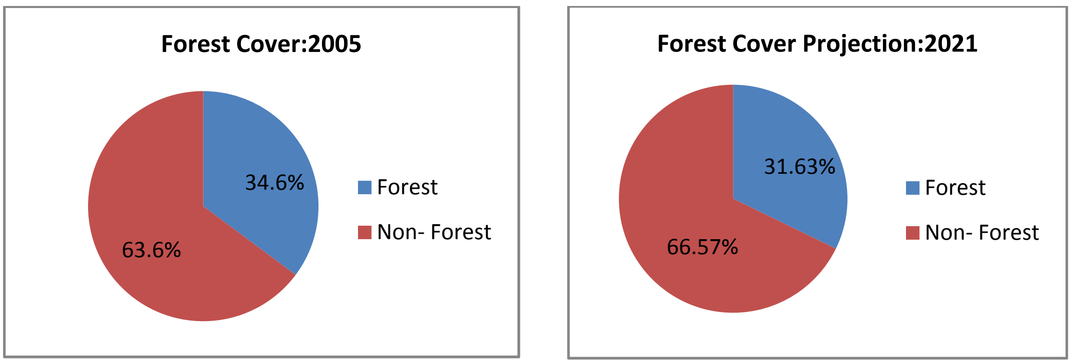
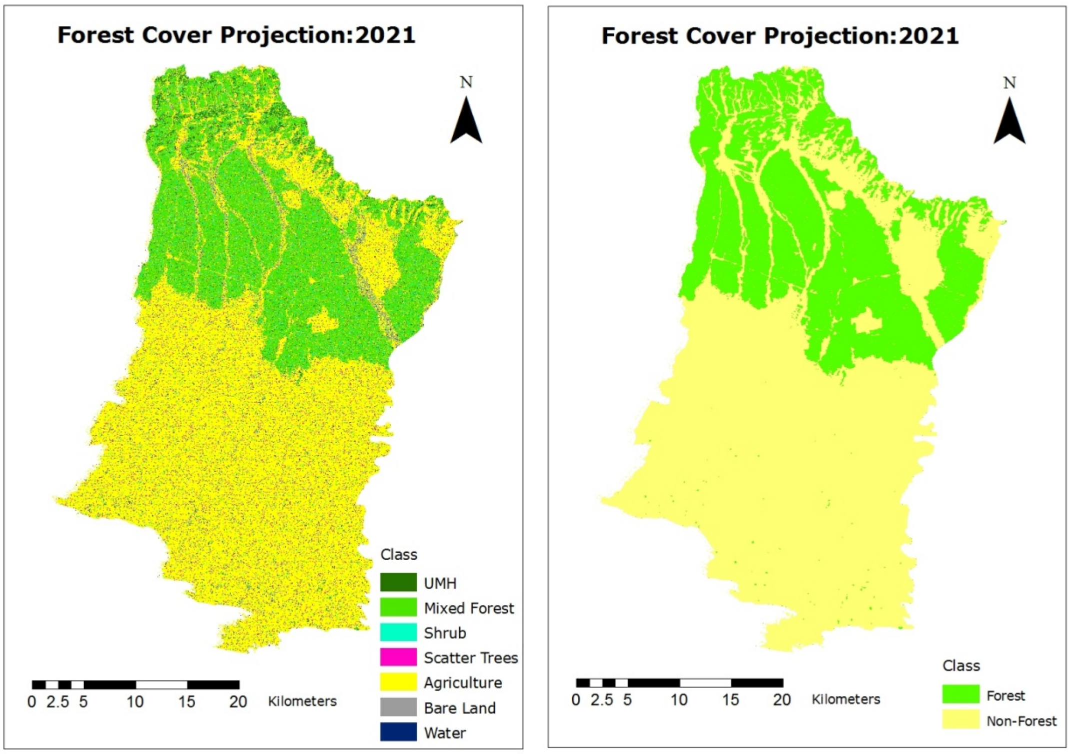


Figure 14: Projected forest cover for 2021

Projected changed was mapped using STCHOICE module in Idrisi. In the map (Figure 15). we can see that small isolated and scattered fragmented patches have been cleared due to the excessive exploitation by rapidly grown population . Salt and pepper map produced by STCHOICE and reclassified filter maps are displayed in the in the figure-13 below.



(a) Before filter (b) After filter

Figure 15: Forest cover projection map for 2021

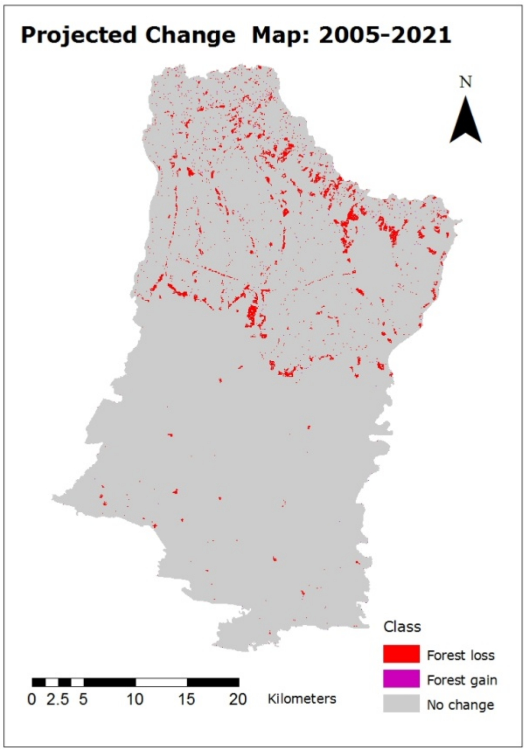


Figure 16: Projected change map

5.5 Discussion of Results

Distribution and rate of forest cover change

Classification of multi-date Landsat satellite images for the year 1989, 1999 and 2005 reveals that Bara district has been experiencing rapid land cover dynamics. Considerable amount of forest area (5748 ha) including shrub has been decreased during the entire study period, 1989-2005 with an annual deforestation rate of about 383 ha. In the first period (1989-1999), 3293 ha of forest has been converted into other land cover types with an annual deforestation rate 329 hectare. Similarly, 2454 ha of forest has been transformed into other classes with a loss of 409 ha annually during 1999-2005. Result shows that forest area has been decreased rapidly during 1999-2005.It may be due to bad security situation in the country and lack of patrolling by local authorities. As illustrated by the cross-tabulation result, most of the forest area has (6260 ha) been converted into agricultural land and the bare land (520 ha) during 1989-2005. Rapid conversion of forest area into agriculture seen near highways and residential areas due to proximity to east-west and north-south highways, access to market and larger number of migrant from the hilly area.

Spatial pattern of forest cover change

To glean more information not just on extent, but also pattern of land cover changes, analysis of spatial pattern is crucial. From the result of the seven metrics calculated, it is found that forest has been fragmented during the study period. During the first stage, large patches of forest have been fragmented. It may be due to the encroachment, agriculture sprawl into shrubs and forest lands breaking larger blocks of forest into smaller patches irregularly, extension of road networks and frequent change of their courses by rivers in the study area. During the second stage (1999-2005), fragmented forest patches have been deforested due to the exceesive biotic pressure on forest. From the evaluation of the metrics, we can conclude that forest has been deforested in two stages, during the first stage (1989-1999), fragmentation and deforestation occurred simultaneously and during the second stage fragmented patches has been cleared rapidly. Higher annual rate of deforestation as discussed in the research question 1 further justify it.

Projections of forest cover change

Evaluating the transitional area metric produced by the MARKOV module, considerable amount of forest area (3740 ha) will be cleared during 2005-21. The expected area to be changed in the future (2021) follows the similar trend as in 1989-2005 but the rate of change is gradual than in the past. The projected rate and amount of change is slightly lower as compare to 1989-2005. Since, scattered small patches had already deforested, encroachment and excessive exploitation will reduce in the core and compact forest in future. Moreover, government will pay much attention to conserve the valuable natural resource. For these reason, the projection is realized reliable though the output from MARKOV has only very limited spatial knowledge.

Factors affecting forest cover change

Results obtained from the post classification analysis, cross tabulation and spatial metrics reveals that areas of upper mixed hardwood, mixed forests and shrubs have been decreased in successive periods. Main causes of deforestation are agricultural sprawl, population growth, increased need of firewood, forage for livestock, migration, expansion of road networks, and the impact of rivers. There are also other reasons which include political instability, politician's attitude, fire, shifting cultivation, natural process, forest rewards, attitude of individuals, donors role and government policy.

Bara district has been experiencing rapid population growth due to due to fertile land and hill migration. The population increased from 0.25 million in 1971(MDM, 1971) to 0.55 million in 2000(CBS, 2001), with increasing landholding disparities ranging from 0.5 to over 5 ha per family. Most of the people are dependent on subsistence farming in sustaining their livelihood. Increased in population results the increase in demand on forest products. Overdependence of this increasing and impoverished population on forest resources for firewood, timber and forage continue to endanger forest resources.

Two highways (east-west and north-south) and several district roads have had major impacts on Bara’s forest. Settlements near or along roads such as Amlekhganj, Pathlaiya and Nijgadh, mixed forest has been deforested. Moreover, most of the rivers are seasonal and they frequently change their course results deforestation along rivers.

5.6 Conclusions

Forest cover dynamics was monitored using object oriented classification; post classification comparison, time series analysis and spatial metric. Results and discussion are presented in this chapter. The overall classification accuracies were 85. 71 % and 88.23% for the year 1999 and 2005 respectively. Classification result showed that forest land has been decreased by 6.62% during 1989-99, 5.28 % during 1999-2005, and 11.56% during the entire study period respectively. The annual rate of deforestation is 0.662 % during 1989-1999 and 0.877 % during 1999-2005. The result shows that annual rate of deforestation is higher in the second stage. Result of the spatial metrics reveals that forest area has fragmented and deforested considerably. The overall result demonstrates that forest area has decreased significantly. Most of the forest area has been converted into agricultural land and bare land. Land change modelling reveals that forest area will be decreased by 8.5% during 2005-2021. Key factors responsible for deforestation are: population growth, agricultural sprawl, and expansion of road networks.

6. CONCLUSIONS AND RECOMMENDATIONS

Evaluating the result obtained by post classification analysis, spatial metrics and land use change modelling, following conclusions are drawn with respect to each research questions formulated in the beginning of the study.

6.1 Conclusions

Research questions and hypothesis are discussed with respect to research and the hypotheses set prior to this study.

6.1.1 Discussion on research questions

Research question 1: Distribution and rate of forest cover changes during 1989-1999 and 1999-2005

- The change analysis revealed the two important changes: deforestation and fragmentation of forest area.
- Rate of fragmentation is higher in the first stage(1989-1999), while rate of deforestation is higher during second phase(1999-2005)
- Rapid shrinkage of forest coverage has been experienced along highways and near settlements. It is due to the concentration of migrants from the hill and proximity to highways (east-west and north-south)
- Most of the forest area has been converted into agricultural land and bare land during 1989-1999 and 1999-2005 respectively.
- Annual rate of deforestation was 0.66%, 0.87% and 0.72% during 1989-99, 1999-2005 and 1989-2005 respectively. Forest area has been rapidly decreased during 1999-2005.

Research question 2: Spatial pattern of forest cover change

- Spatial pattern of forest has been change significantly during 1989-2005. Spatial metrics such as CA, NP, and LPI reveals forest area has been fragmented and deforested.
- Fragmentation and deforestation occurs simultaneously during 1989-1999, while during 1999-2005, rapid deforestation occurred due to loss of fragmented small forest patches.
- Agricultural sprawl, population growth and expansion of road networks are primarily responsible for the fragmentation and decrease of forest area
- Extensive fragmentation and deforestation close and along main highways and along river
- The degree of fragmentation may also indicate long-term degradation of forests. Estimates of degree of fragmentation could be considered as an indicator of the current change process. Output of the spatial metrics clearly indicates that forest area has been fragmented rapidly.

Fragmented and isolated patches have been cleared due to encroachment and excessive exploitation of forest products such as timber, fuelwood, and forage.

Research question 3- Projection of forest cover change for 2021.

- Magnitude and rate of the forest cover change for the next period (2021) follow the same trend to that of 1989-2005 with slightly lower rate of deforestation.
- The result of the MCA reveals that forest area will be decreased by 8.5% during 2005-2021 with a 0.53% annual rate of deforestation.
- Markov Chain Analysis is simpler to calculate. Only two input map is required for calculation but it has only very limited spatial knowledge.

Research question 4 Main factors affecting forest cover changes

- Major factors responsible for the deforestation and fragmentation are: agricultural sprawl, rapid population growth , expansion of road networks, and emigration
- Due to rapidly increasing populations, return cycle times for shifting cultivation and burning are reduced. The areas under cultivation are increased, and the use of less suitable terrain for agriculture becomes common place for agriculture. In addition, most people are dependent on subsistence agriculture and forest resources for their livelihood, agricultural land is aggregated and expanded causing forest area fragmented and shrunk
- New road construction typically leads to an influx of populations and initiates forest clearance. With increased agricultural profitability, further road construction subsequently attracts more migrants and promotes further clearance of forest area. Expansion of road networks firstly fragment forest areas itself in the one hand and most of the migrated people settled down close and along highway due to the proximity to road, market and employment. Rapid deforestation and urbanization along the highway and densely populated areas such as Amlekhjanga and Pathalaiya.
- Because of the fragile soil in the Churia and Siwalik, there are many seasonal river and streams in the study. These rivers frequently changed their course resulting conversion of forest into bare lands.

6.1.2 Discussion on hypotheses

Results from the post- classification, cross-tabulation and spatial metrics have revealed that forest area including shrub has been decreased significantly (5748 ha) during the entire study period (1989-2005). Evaluating the cross-tabulation result, it is clear the lager amount of forest area has been converted to agriculture and bare land. Results obtained from different spatial metrics clearly reflect that forest area has been fragmented and deforested. Landscape becomes more heterogeneous and complex during the study period. Based upon the result obtained from different tools and techniques applied for this study, we can conclude that following hypothesis have been accepted.

- Forest area has been decreased considerably over the period of 1989-2005
- Conversion between land cover types (between-class changes) is significant
- Spatial pattern of forest has been changed significantly

6.2 Recommendations

Existing situation about forest cover dynamics have been evaluated with RS and GIS. Based on the result and existing condition, some areas of improvement about the applicability of RS and GIS for sustainable forest management are recommended:

- It is realized that object-oriented image classification is an efficient method especially in more complex landscape having problems of deforestation and encroachment where accurate estimate is required to delineate forest boundaries. So, this approach would be very reliable to produce land cover especially in the Terai region of Nepal where deforestation and encroachment is the serious problem.
- Time series analysis, spatial metrics and predictive change modelling are the reliable GIS tools for in evaluating and quantifying forest cover dynamics. It would be better to utilize these tools to assess quantity and rate of change (e.g. deforestation, encroachment, illicit felling etc) accurately and efficiently.
- Collaborative Forest Management (CFM), new and innovative approach targeted especially to the Terai region like Bara. It is mandatory to prepare forest cover maps and conduct inventory. Remote sensing and GIS tools like spatial metrics, time series analysis and predictive change modelling would be very much useful forest resource assessment, forest cover mapping, inventory and growth modelling in order to manage CFM sustainably.
- More efforts needs to be taken to halt deforestation through extensive implementation of CFM and identifying alternative energy sources to buffer the excessive pressure on forest for fuelwood and timber.

- Due to lack of ancillary data for creating suitability map, Markov Chain Analysis is used to project change, CA_MARKOV is recommended to predict the quantity spatially accurately (i.e. where, when and how much) since output from MARKOV has very limited spatial knowledge.

6.3 Limitations and Future Works

Limitations

The limitations experienced in this study are:

- Availability of data is the major problems for this study. Identifying and discriminating sub-category with satellite images is difficult without ground truth data and other ancillary data.
- Due to lack of ancillary data such as land cover maps, aerial photographs, Digital Elevation Model, it is difficult to apply effective modelling tools such as CA-MARKOV, GEOMOD to model forest cover dynamics and have to depend on Markov Chain Analysis
- Accuracy assessment for 1989 map was realized on the accuracy of 1999 and 2005 since there was no ground truth data available for this study to assess 1989 image accuracy. However, classification methods were similar to all images (1999 and 2005) and were collected in autumn season at the same time of the day.

Future Works

Much of work can still be done both in the monitoring forest cover dynamics and land use change modelling. Analysing spatial pattern of forest and land use change modelling would provide detailed information about the forest cover dynamics and its spatial distribution. Due to the limitation on availability of required data, Markov Chain Analysis was carried to project forest cover change in this study but it has limited spatial information. Land use change simulation model: GEOMOD is proposed for predictive change modelling. It is a grid-based land-use and land-cover change model, which simulates the spatial pattern of land change forwards or backwards in time. GEOMOD simulates the change between exactly two land categories such as forest and non-forest. Only a map of a beginning time and information concerning the number of grid cells of each category at an ending time. GEOMOD selects the location of the grid cells to classify as one of the two categories for the ending time.

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APPENDICES

Appendix 1 - Bara District: An Introduction

1. **Geographical Location**

Latitude:	26^0 51' N – 27^0 02' N
Longitude:	$84^0$51' E – $85^0$16' E
Area:	1190 Km^2
Altitude:	152 – 915 m

2. **Boundary**

East:	Rautahat
West:	Parsa
North:	Makawanpur
South:	Bihar, India

3. **Climate**

Climate zone: Tropical; Sub-tropical

Average maximum Temperature: 31.3^0C

Average Minimum Temperature: 18^0C

Average Rainfall: 1760.6 mm

4. **Political and Administrative Division**

Development Region:	Central
Zone:	Narayani
Headquarter:	Kalaya
Number of Electoral Region:	6

5. **Population**

Total:	559,135
Male:	289,379
Female:	269,738
Number of Households:	87,706
Population Density:	470/Km^2
Average Population Growth:	2.7%
Life Expectancy:	58.58 year

6. Religion

S.N	Religion	Population	%
1	Hindu	448,149	81.94
2	Islam	45.051	8.06
3	Kirat	132	0.02
4	Jain	16	0.00
5	Christian	82	0.00
6	Sikh	57	0
7	Whoi	13	0
8	Other	30602	5.47
Total		559,135	100

7. Education

Literacy: 42.7%

Male: 55.2%

Female: 29.1%

8. Health

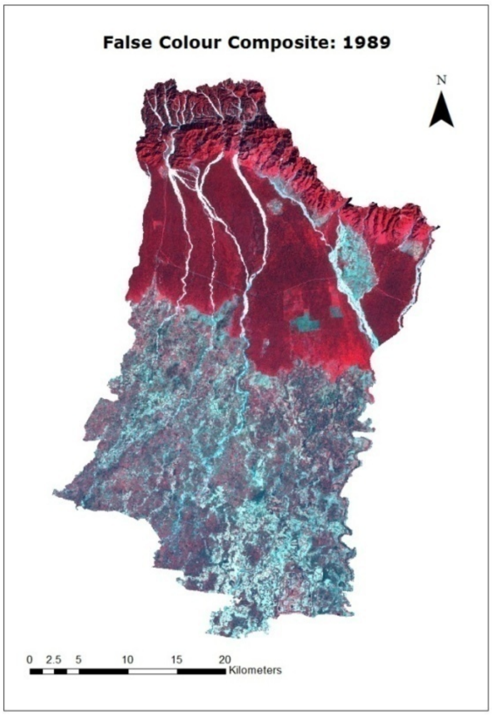
S.N.	Particular	Number
1	Hospital	1
2	Health Post	11
3	Health Centre	3
4	Ayurved	2
5	Homeopathy	2
6	Sub-health post	84

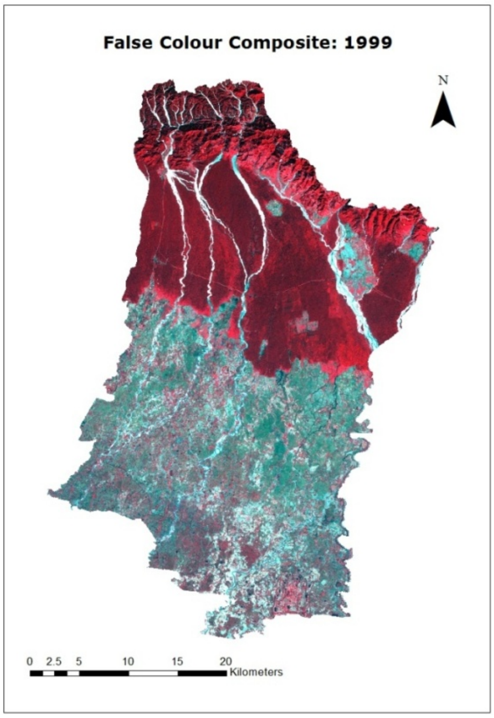
(Source: District Development Committee, Bara)

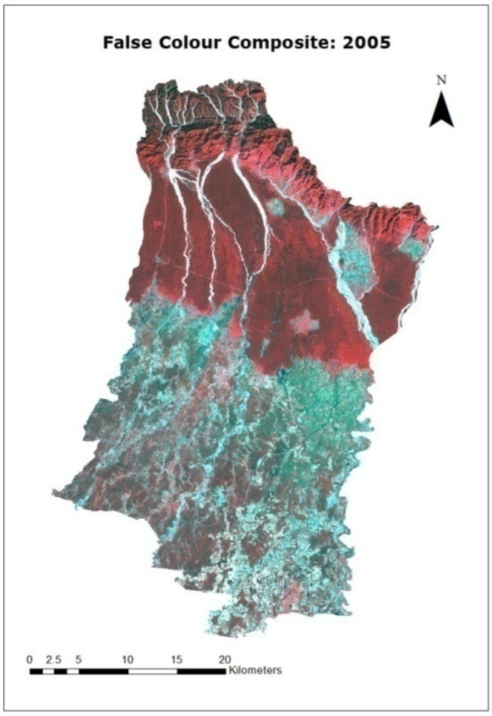
Appendix 2 - Land Use and Land Cover Classification System for use with Remote Sensor Data (Adopted from Anderson et al., 1976)

Level I		**Level II**	
1	Urban or Built-up Land	11	Residential
		12	Commercial and Services
		13	Industrial
		14	Transportation, Communications, and Utilities
		15	Industrial and Commercial Complexes
		16	Mixed Urban or Built-up Land
		17	Other Urban or Built-up Land
2	Agricultural Land	21	Cropland and Pasture
		22	Orchards, Groves, Vineyards, Nurseries, Ornamental Horticultural Areas
		23	Confined Feeding Operations
		24	Other Agricultural Land
3	Rangeland	31	Herbaceous Rangeland
		32	Shrubs and Brush Rangeland
		33	Mixed Rangeland
4	Forest Land	41	Deciduous Forest Land
		42	Evergreen Forest Land
		43	Mixed Forest Land
5	Water	51	Streams and Canals
		52	Lakes
		53	Reservoirs
		54	Bays and Estuaries
6	Wetland	61	Forested Wetland
		62	Non-forested Wetland
7	Barren Land	71	Dry Salt Flats
		72	Beaches
		73	Sandy Areas other than Beaches
		74	Bare Exposed Rocks
		75	Strip Mines Quarries and Gravel Pits
		76	Transitional Areas
		77	Mixed Barren Land
		81	Shrub and Brush Tundra
		82	Herbaceous Tundra
		83	Bare Ground Tundra
		84	Wet Tundra
		85	Mixed Tundra
9	Perennial Snow or Ice	91	Perennial Snowfields
		92	Glaciers

Appendix 3 - False Colour Composite Images (Bands: 4, 3, 2) of the study area







Appendix 4 - Result of the Accuracy Assessment (1999, 2005)

4.1. Confusion Matrix, 1999

		Reference Map								
		UMH	Mixed Forest	Shrub	Scatter Trees	Agriculture	Bare Land	Water	Grand Total	**User's Accuracy (%)**
Classified Map	UMH	5	2	3					10	**50.00**
	MF	4	164	18	4	5			195	**84.10**
	Shrub		4	9					18	**50.00**
	ST				8	5			13	**61.54**
	Agriculture		2	3	28	650	42	14	739	**87.96**
	Bare Land					5	30		35	**85.71**
	Water					5		28	33	**84.85**
	GT	9	172	33	40	675	72	42	1043	**85.71**
Producer's Accuracy (%)		**55.56**	**95.35**	**27.27**	**20**	**96.3**	**41.67**	**66.67**		

Kappa=0.72

4.2. Confusion Matrix, 2005

		Reference Map								
		UMH	Mixed Forest	Shrub	Scatter Trees	Agriculture	Bare Land	Water	Grand Total	**User's Accuracy (%)**
Classified Map	UMH	6		2					8	**75**
	MF	2	156	12	4	10			184	**84.78**
	Shrub		4	18					22	**81.82**
	ST				8	5			13	**61.54**
	Agriculture			3	28	685	36	14	766	**89.42**
	Bare Land					5	36		41	**87.8**
	Water							28	28	**100**
	GT	8	162	33	40	705	72	42	1062	**88.23**
Producer's Accuracy (%)		**75**	**96.3**	**54.5**	**20**	**97.16**	**50**	**66.67**		

Kappa=0.76

Appendix 5 - Topographic Maps of the Study Area