# Community Carbon Forestry: Remote Sensing of Forest Carbon and Forest Degradation in Nepal

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# Community Carbon Forestry: Remote Sensing of Forest Carbon and Forest Degradation in Nepal

by

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## Disclaimer

## Abstract

The present study is focused on the capabilities of remote sensing data and techniques to help in better understanding the role of community forest ecosystems as carbon sinks and carbon sources, with special reference to distinguishing between forest degradation and deforestation, and well-managed forests. It examined the statistical relationships between satellite-derived spectral vegetation indices (SVI) data from ASTER and biomass field measurements carried out with the help of forest user groups in community forests. Statistically weak relationships were obtained when correlating these datasets from 30 plots surveyed. International definitions of forest degradation were compared with the definitions understood by local people and by national experts to determine common understandings of forest degradation. Reduced canopy cover and loss of biodiversity were most frequently used in defining of forest degradation. The suitability of satellite data (ASTER and Landsat ETM) in separating degraded national forests and non-degraded community forests was tested using statistical and graphical methods. The results did not reveal significant differences in spectral signatures of these forests. Moreover, forest canopy density (FCD) mapper was employed to determine the degree of forest degradation in these forests by predicting their canopy density. The results indicated that subtle forest degradation is not possible to be captured in the satellite images currently available. The possibility of detecting forest degradation, as opposed to deforestation, from remotely sensed data depends largely on the rate, magnitude and spatial extent of the degradation.

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## Table of contents

## List of figures

## List of tables

# 1. Introduction

## 1.1. International Concern for Climate Change

There is emerging evidence of an increasing trend in global climate instability due to greenhouse gases, which is one of the most pressing problems that the world is facing. The Bali Action Plan released by the UN Climate Change Conference in December 2007 reiterates that warming of the climate system is unequivocal, and that delay in reducing emissions of green house gases will increases the risk of more severe climate change impacts. The Fourth Assessment Report of International Panel on Climate Change (IPCC) states that anthropogenic factors are “very likely” to be the cause of climate change. For the past few hundred years, as a result of human activities, concentrations of greenhouse gases such as $CO_2$, $CH_4$, and $N_20$ have been increasing at an alarming rate, causing rapid changes in the climate and serious implications for human beings as well as for the environment surrounding them. .A study by National Aeronautics and Space Administration (NASA) has found out that there has been an increase in the world’s temperature by 0.2°C per decade in past 30 years (GEO year book 2007) and is expected to increase with more than 6° C over the next 100 years (IPCC 2007). According to the 4th Assessment Report of IPCC, eleven of the last twelve years (1995-2006) have been ranked as the warmest years recorded since 1850 (IPCC, 2007).

Efforts to control the climate change mainly focus on emission controls and on removal of carbon dioxide from the atmosphere. Carbon dioxide is believed to be the most important anthropogenic greenhouse gas causing global warming and climate change (IPCC 2007). Most attention has been focused on $CO_2$ as it is believed to contribute more than half of the increase in the global temperature in the next 100 years. The most important global instrument linked to mitigating adverse impacts of carbon dioxide and other greenhouse gases is the Kyoto Protocol to the United Nations Framework Convention on Climate Change, which entered into force in February 2005. The protocol is a legally binding international agreement that commits industrialized countries to reduce emissions of greenhouse gases by 2008-2012 and promote sustainable development.

## 1.2. Forest Carbon Reservoir

Forests form an integral part for scientific research as the “forest carbon reservoir” has a dynamic relationship with the climate system (Weaver 2007). Forests behave as a “carbon sink”, sequestering atmospheric carbon into biomass. According to Kyoto protocol, one of the mitigation strategies for reducing the greenhouse gases in the atmosphere is increasing the terrestrial sink for $CO_2$. Carbon sequestration, also known as “geo-sequestration” (Richard 2006), by plants is known to assimilate $CO_2$ from the atmosphere through the process of photosynthesis. The uptake of $CO_2$ by plants is referred to as gross primary productivity (GPP). At the same time the forest also acts as “carbon source” by releasing carbon into the atmosphere through processes such as respiration. During respiration, half of the GPP is respired with remainder referring to net primary productivity (NPP), which is the total production of biomass matter (IPCC 2006).

“**Reservoir**” means a component or components of the climate change system where a GHG or a precursor of a GHG is stored e.g., Forests, fossil fuels

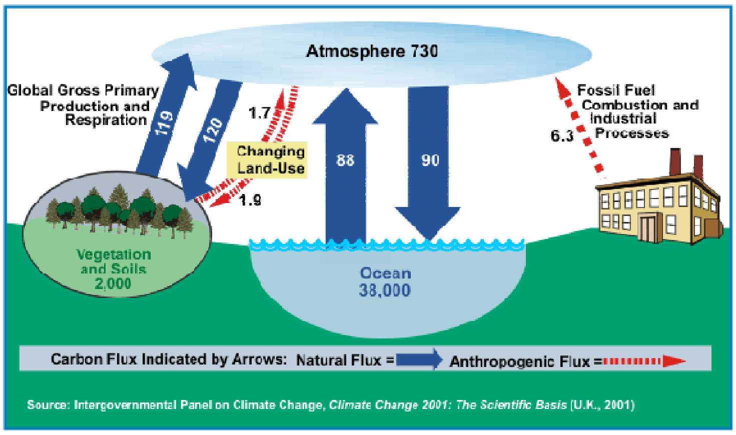
“**Sink**” means any process, activity which removes GHG, an aerosol or a precursor of a GHG from the atmosphere eg. Photosynthesis

“**Source**” means any process, activity or mechanism which releases GHG, an aerosol or a precursor of a GHG into the atmosphere. e.g. respiration

(Source: UNFCCC 2005)

## 1.3. Carbon Sinks and Biomass

Under Kyoto Protocol, forests are considered important for their unique role as carbon sinks because they are capable of capturing and storing carbon dioxide from the atmosphere (FAO 2005). According to FAO (2005), each time there is a forest growth of 2 cubic meters of wood; roughly 1 ton of carbon of the air is captured. Forests act as carbon sink by increasing above ground biomass through increased forest cover and by increased level of soil organic carbon content (Banskota et al. 2007). Biomass is defined as “mass of all organic matter per unit area at particular time (reported in $g/m^2$ or kg/ha)” (FAO 2008). The above-ground biomass (AGB) is described by IPCC Guidelines for National Gas Inventories (2006) as “all biomass of living vegetation, both woody and herbaceous, above the soil including stems, branches, bark, foliage, bark and stumps”. Forest biomass represents the largest terrestrial carbon sink and accounts for approximately 90% of all living terrestrial biomass (Dixon et al. 1994; Tan et al. 2007). The amount of carbon sequestered (or lost) by a forest can be estimated from the biomass accumulation since approximately half of forest dry biomass weight constitutes carbon (FAO 2008; Banskota et al. 2007; FAO 2005; Cairns et al. 2003; MacDicken 1997). Forest biomass can be measured both in terms of fresh weight or dry weight.



Source: Intergovernmental Panel on Climate Change, *Climate Change 2001: The Scientific Basis* (U.K., 2001)

**Figure 1.** Global Carbon Cycle (Billion Metric Tons Carbon)

## 1.4. Forest Degradation and Carbon Sources

Increasing tropical forest biomass contributes to increase in atmospheric carbon sequestration in the terrestrial biosphere, whereas the decrease in forest area due to deforestation and forest degradation causes emissions back to the atmosphere. Forest degradation is manifested mainly through decline in forest cover, and resulting in organic carbon losses (Sitaula 2005). Modification in the structure and composition of the forest is caused by forest degradation, which reduces the biomass/carbon content of the forest.

Release of carbon through forest degradation as a result of forest fire, pest infestation are fast while the sequestration of carbon through the photosynthesis process is quite slow taking ages (FAO 2006). Carbon emissions as a result of deforestation and degradation in tropical forests are the largest source of carbon emissions in developing countries but were unaccounted for in Kyoto Protocol. However, these emissions have now been acknowledged in UNFCCC Conference Of Parties (COP) 13 held in UNFCCC Bali (2007) under REDD (Reducing Emissions from Deforestation in Developing countries) Scheme, which reports that forest degradation needs to addressed when reducing emissions from deforestation and combating climate change.

### 1.5. Definition of Forest Degradation

The definition of forest degradation can be quite confusing as most of the literature and experts do not give a clear-cut distinction between degradation and deforestation. To understand both these phenomena it is important to understand the meaning of a forest first. According to FAO, “forest is a land spanning more than 0.5 ha, with a tree canopy cover of more than 10%, which is not primarily under agricultural or other specific non-forest land use”. The trees otherwise should have a potential of reaching a height of 5 m *in situ* and cover 10% crown cover in case of young forests.

The UN Commission on Sustainable Development established an Intergovernmental Panel on Forests (IPF) which addressed “Underlying Causes of Deforestation and Forest Degradation”. Deforestation here was defined as “changing forests into other land uses” and forest degradation as “deterioration of forest quality” (Verolme and Moussa 1999). Deforestation and degradation are both changes in forest landscapes, which can be both human induced or natural phenomenon. However, the way in which changes occur is not the same. Deforestation is a non-temporal change of land use from forest to other land use (e.g., forest land to settlement) or “the depletion of forest crown to less than 10 %”. Degradation defines changes within forest class, which negatively affect the stand or site, lowering the species composition, biological diversity, productivity. It is the depletion of forest crown to not less than 10 % (e.g. closed forest to open forest) (René 2007[1]).

Degradation of forest is a complex process (Lambin 1999) and a major source of carbon emission which can be taken care of with participation of communities (Verolme and Moussa 1999). Forest degradation is indicated by the reduction of canopy cover and/or reduction in quality of the forest through logging, fire, grazing, fuel wood collection, etc.

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[1] Siwe N. René (2007) over email correspondence.

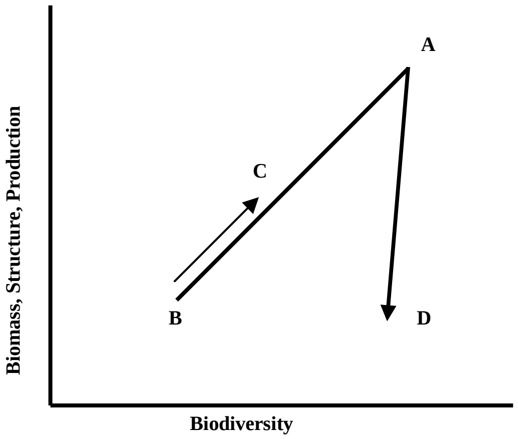

**Figure 2.** Different forms of forest degradation
(Lamb and Gilmour 2003, pg 12)
A: Undisturbed forest with certain level of biomass, structure and production.
B: Result of extensive clearing of A, where it has lost huge amount of biomass, structure and production.
C: B may or may not recover to the state C
D: Huge logging has taken place. However, significant level of biodiversity is still remaining

Forests are exploited for meeting various needs of the people as well as livestock's and hence impact the ecology in different ways. According to Nepstad et al. (1999) ranchers and farmers burn and clear-cut the forest in the process of preparing pasture land for their livestock; Loggers in the other hand damage the forests by harvesting. Forest degradation reduces overall supply of benefits from forest, which includes wood, biodiversity and other environmental services (FAO 2006).

Studies suggest that deforestation and forest degradation in Nepal were more a common phenomena 100 years ago and occurred in middle hills. However, forest degradation is still continuing in the hills (Verolme & Moussa 1999). Nepal suffers from a sequential process of degradation mainly in the non-managed forests because of lack of management inputs from the community people. The underlying causes of degradation in Nepal are illegal logging, fodder for livestock, grazing, forest fire and agricultural production. Other reasons such as unemployment, non existing governmental support shifting cultivations, fire and other natural processes also play their parts in it.

**Table 1.** Alternative Definitions of Forest degradation

| **Definition of Forest Degradation** | **References** |
|---|---|
| Change in forest attributes lowering productive capacity as a result of increase in disturbances and the process can occur from a few years to a few decades | Lambin 1999 |
| Degraded forests are the results of heavy logging which has caused drastic change in the forest structure and reduced biomass. | Lamb and Gilmour 2003 |
| A process leading to a 'temporary or permanent deterioration in the density or structure of vegetation cover or its species composition' | (Grainger 1993, p. 46).in Lambin |
| Degraded forest is heavily burned and heavily logged | Souza et al. 2003 |
| Changes in canopy cover, tree density and biomass density | Alan Grainger 1993 |
| A secondary forest that has lost, through human activities, the structure, function, species composition or productivity. It delivers a reduced supply of goods and services and has less biological diversity. | UNEP/CBD/SBSTTA 2001 |
| A long-term reduction of tree crown cover towards but not exceeding the minimum accepted `forest' threshold. | FAO 2002 |
| All biological, chemical and physical processes that result in loss of the productive potential of forest. Degradation may be permanent, although some forests may recover naturally or with human assistance. | World Bank 1991, European Environment Agency (EEA) |
| Changes within the forest which negatively affect the structure or function of the stand or site, and thereby lower the capacity to supply products and/or services. | FAO 2001, 2006 |
| Long-term reduction of the overall potential supply of benefits from the forest, which includes carbon, wood, biodiversity and other goods and services. | FAO 2003, ITTO 2002 |
| A direct human-induced loss of forest values (particularly carbon), likely to be characterized by a reduction of tree crown cover. | ITTO 2005, IPCC 2003a |
| A direct human-induced activity that leads to a long-term | IPCC 2003b |

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|---|---|
| reduction in forest carbon stocks. | |
| The overuse or poor management of forests that leads to long-term reduced biomass density (carbon stocks). | IPCC 2003c |
| A direct human-induced long-term loss (persisting for X years or more) of at least Y % of forest carbon stocks (and forest values) since time T and not qualifying as deforestation or an elected activity under Article 3.4 of the Kyoto Protocol. | IPCC 2003d |
| Degradation is the result of human interventions which occurs over a reasonable amount of time (i.e., decades) | Forest Stewardship Council (FSC) |
| A reduction of the canopy cover or stocking within the forest through logging, fire, wind felling or other events, provided that the canopy cover stays above 10%. In a more general sense, forest degradation is the long-term reduction of the overall potential supply of benefits from the forest, which includes wood, biodiversity and any other product or service. | FRA 2000. FAO 2002. (UN-FAOb 2000) |
| Reduction in tree density and/or increased disturbance to the forest that results in the loss of forest products and forest-derived ecological services. | WRI IN FAO |
| Temporary or permanent reduction in the density, structure, species composition or productivity of vegetation cover. | Grainger 1996 |
| The ecologically deleterious depletion by human activity of standing woody biomass and organic matter in forests often associated with over-utilization of the forest for fuel or timber. | UNDP, Climate Services in FAO |
| The deterioration of the health, quality and productive capacity of a forest. | People and the Planet 2000 - 2008 |
| Forests or grasslands that are have been overused or poorly managed and are likely to have reduced biomass densities. | IPCC 1996 |
| A loss of a desired level of maintenance over time of biological diversity, biotic integrity and ecological processes. | Lipper 2000 |
| A state which delivers a reduced supply of goods and services from the given site and maintains only limited biological diversity (CBD). | UNEP/CBD/COP/6 2006 |

| | |
|---|---|
| Degradation usually implies a loss of productivity. Operations such as thinning and salvage logging, while reducing the canopy cover, may not reduce the productivity of the land. In fact it may increase it. Thus over story reduction alone may not be regarded as degraded forest | Lund 2007 |
| Degraded primary forest is where the initial forest structure, productivity and species diversity of the primary forest has been affected by excessive and damaging wood exploitation and/or by such an intensity of harvesting of non-wood forest products that its structure, functions, processes and dynamics are noticeably altered beyond the resilience of the forest. | ITTO 2002 in UNEP-WCMC |
| Degradation concerns only human induced damages or site alterations. The origin of these damages become by ongoing or made in the past human actions and refers to irrational forest harvesting, fire, grazing, etc., which usually reduce permanently the site index and may negatively affect the stand. | Castellani, C., et al. 1983 in FAO website |
| Changes within the forest which negatively affect the structure or function of the stand or site, and thereby lower the capacity to supply products and/or services. | FAO 2001, 2006 |

(Source also from Schoene et al. 2007 and Lund 2007)

### 1.6. Community Forest Management in Nepal

Nepal is a land-locked, mountainous country, covering an area of 147 181 km$^2$, of which the forest area covers 55 180 km$^2$, which is approximately 37% of the total area. From the total forest area, over 25% of the forested land belongs to the local communities (Tamrakar 2003). The forest management system has significantly improved after the introduction of community forestry programmes in 1990s. In Nepal, National Forests are handed over to the local users as far as possible, where the users are responsible for the forest management. The handling over of the government-managed natural forests to local community user groups started from mid-1990s based on the Forest Act, 1993 and Forest Regulation 1995. FAO has also helped to communicate methods and tools to manage forests in a participatory way under the framework of sustainable development (Verolme and Moussa 1999). In these forests, local communities are responsible for the forest management and in such cases; communities have been seen to better manage the forests than the government (Banskota et al. 2007). Sustainable community management of the forests has not only met people's subsistence needs of fuel wood, fodder etc but also plays a major role in reducing deforestation and degradation and providing a global benefit of carbon sequestration. These roles of forest underscore a need of assessment of the magnitude of forests as carbon sinks for reliable estimates of biomass density of the forests. Storage of atmospheric carbon dioxide in the forests represents a long term pool for balancing the global carbon balance (Lez-Alonso 2006). Carbon sequestration can be significantly improved with improved forest management activities such as community forestry management and it is expected to play an important role for achieving targets of Kyoto Protocol (UNFCCC 1997). Although the amount of carbon sequestered by community forests could be relatively low (2-3 tons/ha/year), the costs associated with management are negligible (K:TGAL 2007). The mean carbon sequestration rate for community forests in Nepal has found to be around 2 t $ha^{-1}$ $yr^{-1}$ or 4 t $ha^{-1}yr^{-1}$ under normal management conditions (UNFCCC 2007). If local people were be given a financial return for their contribution towards carbon sequestration, it would act as a good incentive for more communities to be involved in sustainable management of their forests. REDD scheme emphasizes on crediting carbon from such forest management. Bali Action Plan (2007) recognizes that that the needs of local and indigenous communities should be addressed when action is taken to reduce emissions from deforestation and forest degradation in developing countries.

### 1.7. Estimation of Biomass/Carbon in Forests

Biomass level is an important indicator of a forest's potential to store carbon and has received much attention since the adoption of Kyoto protocol. High uncertainties for estimating forests as carbon sinks exists (Houghton 2005). Estimation of the magnitude of forest as sinks requires accurate and reliable measurements to quantify the biomass density of the forests (Cairns, 2003). The role of tropical forests in the global carbon cycle and its potential to reduce increasing carbon dioxide by photosynthesis has increased the importance in estimation of biomass/carbon pool of these forests (Brown 1997). Estimates of biomass give a direct measurement of carbon sequestration in the forests and help to "quantify the anthropogenic impacts on climate change and to validate carbon models" (FAO 2008).

According to FAO (2008), there are four main methods of monitoring biomass:

- destructive sampling;
- non-destructive sampling,
- inference from remote sensing, and
- models

Accurate measurement and mapping of distribution of forest biomass can be carried out with appropriate biomass estimation methods using detailed field inventory data (Fang and Wang 2001). With the advancement of earth observing satellites, biomass can be estimated from field based observation using community participatory methods with the combination of remote sensing tools as well as statistical instruments to further understand the correlations associated with ground data and remotely sensed data.

### 1.7.1. Insitu Measurements and Modelling of Biomass/Carbon

Conventional methods of measuring biomass values in the field are so far the most accurate and reliable method although they are often time consuming, labour demanding and can not cover spatial distribution of biomass in larger areas (Lu 2006; Houghton 2005; de Gier 2003). Biomass can be estimated in a destructive and non-destructive means in the field based surveys. The destructive method is to fell down specific number of sample trees, which are weighed to make a biomass equation which is not considered as a practical solution (Brown 1997). In non-destructive methods, regression equations are developed (Foody et al. 2003) based on data from felled trees using some easily measurable dimension such as diameter (Brown 1997). Biomass and trunk diameter are highly correlated and therefore regression models can be used that convert trunk diameter data to biomass data (Brown 1997 in de Castilho 2006). The allometric equations that relate biomass of several tree components to diameter at breast height (dbh) are used to calculate biomass values. Other variables such as height can also be used in the regression equations. However, it is not always necessarily that input of these variables will contribute to improvement of the equation based on dbh (Wang 2006). Hence, the most simple and commonly used technique for deriving forest above ground biomass is through the use of dbh -based allometric equations (Popescu 2007; Wang 2006).

The most commonly used biomass model is,

$$W = aDBH^b$$

Or, $$\text{Ln } W = a + b \text{ Ln } DBH$$

where, W is biomass in Kg; DBH is overbark breast height (measured 1.3 meter above ground) in cm , a and b are regression coefficients of the biomass model that vary according to different species types and their climate, management and disturbances (Fehrmann and Kleinn 2006; Zianis and Mencuccini 2004).

In order to obtain carbon value from the biomass calculated, it is assumed that 50 percent of it is carbon and hence biomass value is multiplied by 0.5 to obtain the corresponding carbon value (Garzula and Saket 2003; Malhi and Grace 2000). This conversion factor is used for all species of trees as it is believed that carbon concentration of biomass varies only slightly between different tree types (Garzula and Saket 2003).

### 1.7.2. Remote Sensing for Mapping of Biomass/Carbon

State-of-the-art of remote sensing techniques have been identified as potentially an important tool, in support of the Kyoto Protocol and its signatories, in quantification of above-ground biomass stocks and associated changes therein (Tomppo et al. 2002; Rosenqvist et al. 1999). Remote sensing data however are useful for indirect estimation of biomass/carbon value, should be complemented with the ground truth data with some measurements of the trees carried out, which is used in the empirical biomass equations (Zianis et al. 2005).

A major benefit of using remote sensing data is that it can cover a large area and provide systematic observation systems and historical archives of data (Rosenqvist et al. 2003). Remote observations in combination with *in situ* measurements can be useful in a developing country (like Nepal) where huge uncertainties exist in estimation of biomass/carbon values (FAO 2008).

For remote sensing studies at the local or regional level, satellite images with finer resolution instruments has been used, such as Landsat (Krankina et al., 2004; Tomppo et al. 2002; Mabowe 2006; Foody et al. 2003; Zheng et al. 2004; Lu 2005; Franco-Lopez et al. 2001; Tomppo et al. 2002; Foody et al.2003), ASTER (Heiskanen 2006; Muukkonen and Heiskanen 2005), IKONOS (Mabowe 2006; Thenkabail et al. 2004). Biomass cannot be directly measured from remote sensing data, however remotely sensed reflectance can be related to the biomass estimates based on in situ measurements (Dong et al. 2003). Reflections of the red, green and near infrared radiances contained considerable information about forest biomass. Two main approaches predicting biomass using satellite images are (1) Use of Solar radiation and (2) Use of Reflection Coefficients (Namayanga 2002), which is primarily determined by the green foliage biomass (Christensen and Goudriaan, 1993).

Using reflection coefficients, indirect estimates of carbon can be generated with most relying on empirical relationships established with vegetation indices such as the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) based on photosynthetically active radiation (PAR) and up-to-date reliable *in situ* data on biomass (carbon) stocks in the forests (Rosenqvist et al. 1999). Many studies have demonstrated that vegetation indices (VIs) or simple band ratio obtained from satellite data provide useful estimates of carbon biomass content (Foody et al. 2003). High correlations between spectral bands and vegetation parameters makes it possible to use satellite images for estimating biomass in inaccessible areas such as mountainous regions.

Direct biomass estimation may also be possible with vegetation Light Detection and Ranging (LIDAR) observations (Popescu 2007; Drake et. al 2002). The potential of forest biomass mapping has also been explored using Radar (Gaveau et al., 2003; Tomppo et al. 2002) along with JAXA ALOS-PALSAR L-band (24 cm wavelength) which gives lower range of biomass (upto 50-80 t/ha). The BIOMASS mission, which is expected to launch around 2014 by ESA uses a longer wavelength (68 cm) and shows potential of estimating higher levels of biomass (FAO 2008).

### 1.8. Monitoring Forest Degradation Using Satellite Images

Forest degradation and its associated impacts have drawn the attention of the scientific, environmental and policy making bodies. Spatial distribution of forest is large and hence some places are inaccessible. Uncertainties exist in current estimates of forest degradation, mainly due to confusing definition of forest degradation with that of deforestation and general lack of quantitative, spatially explicit and statistically representative data. The implementation of incentives for Reducing Emissions from Deforestation and Degradation in developing countries (REDD) requires robust and reliable methods for estimating forest degradation (UNFCCC 2007).

For this reason, the importance of satellite images to identify forest degradation, at both national and international levels is increasing. However, these means have not been entirely effective to identify or contribute to reducing forest degradation. The role of remote sensing as a tool for degradation monitoring is an essential in natural resource management and is still in a testing phase. Remote sensing data can support inventory approaches by informing on degradation patterns in forests in combination with ground-based monitoring of forest degradation. Mapping forest degradation and related carbon emissions is more challenging than mapping deforestation (Souza 2005). Identification of small and gradual degradation is often not easy using remote sensing data alone and contemporary *in situ* information is necessary. Images with spatial resolutions less than ~20-25 m can be used to detect changes in land as small as 0.05 ha (Rosenqvist 2003).

## 1.9. Research Problem

Community managed forests of the Himalayan region are considered to be an important carbon pool (Banskota et al. 2007). With increasing area of forests being brought under community management, forests in Nepali Himalayas are improving and thus are becoming major carbon sinks. Sustainable community forest management has been a success story in Nepal with involvement of local communities that avoids the deterioration and deforestation of existing natural forests thereby contributing to increase in carbon sequestration (Banskota et al. 2007).

Biomass information is uncertain for many developing countries, including Nepal. It is important to study the forest biomass of the forests to know its role in the national and global carbon budgets and climatic system (Wang 2006; Tan et al. 2007). Many recent studies have analyzed and estimated the carbon sequestration potential of forests in the context of the flexible mechanisms of the Kyoto Protocol using ground measurement and remote sensing in large-scale forests. However, there are not many studies carried out in the same field in the framework of community carbon forestry programs with integration of ground truth data and satellite images.

Biomass estimation is necessary as emissions of carbon from the deforestation and degradation is based on the biomass content of the forest that has been degraded (Huoghton 2005). Many studies on biomass have mainly focused on tropical, temperate and boreal forests and not many studies have focused on sub-tropical forests (Zhang et. al 2007). The study area considered for the research also comprises of sub-tropical forests and considerable uncertainties exist in the estimation of carbon as well as degradation in these forests.

Nepal is a landlocked mountainous country and the feasibility of measurement of carbon in small patches of community forests spread all over the mountainous is not only difficult but is expensive. In such a case, remote sensing could be the only cost effective and reliable measure for the carbon assessment at local as well as national level.

Satellite imageries might also be useful to detect the damages caused to the forests by over extraction of the forest products in the non community-unmanaged national forests. Although much research has been carried out in the deforestation scenario, not many studies have been focused on forest degradation. Hence, this study aims at integrated use of remote sensing and ground carbon biomass data to estimate the total carbon stored in the community forests of Nepal and to find out the differences between the carbon values estimated by these methods. The study also focuses on determining if degraded non-community forests can be distinguished from non degraded community forests.

## 1.10. Limitations

The study was carried out with limited budget and hence recent satellites images could not be purchased for the study. Due to the steep terrain in the study area, limited number of sample plots had to be established. There was also an insecurity problem in the forest as a result of robbery and Maoist incidents previously. There was lack of sufficient and reliable source information in the field since the data was collected from another source.

## 1.11. Research Objectives

### 1.11.1. General Objective

- To assess the feasibility of satellite imagery in estimating above-ground biomass/carbon stocks and identifying forest degradation.

### 1.11.2. Specific Objectives

- To determine the relationship between the carbon values derived by satellite sensor and the carbon biomass content from community field measurements by community and to examine the correlation between calculated carbon value and estimated carbon value.

- To examine the definitions of forest degradation of local people and national experts compared with those defined by the International standards

- To determine if the managed community forests can be distinguished from an unmanaged national forest using remote sensing.

### 1.12. Research Questions

- What is field estimated average biomass value for 2007 from the community forest under study?

- Is there a significant relationship between the carbon estimated from the satellite image compared to the field measurement of biomass/carbon?

- What is the most commonly used definition of forest degradation by the International bodies and national forest experts? How similar is it with those understood by the community forest user groups?

- Can degraded forests be easily distinguished from non-degraded forests using satellite imagery?

### 1.13. Hypothesis Tests

In the present study, it is hypothesized that there is no significant difference between the ground measurement and satellite measurement of carbon data. The second hypothesis is that satellite imagery can be used to distinguish naturally growing "degraded" forest from the community managed "non-degraded" forests.

### 1.14. Research Approach

The research has been initiated with an extensive literature review on the existing scientific papers, books on the use of remote sensing for estimating carbon balance in the forests and using remote sensing for studying forest degradation. Research problem has been formulated for which research objectives, research questions and hypothesis have been identified. The study area has been selected in Nepal and field data on biomass from years 2004-2006 was made available through a parallel research done by a Ph.D. student in Twente University. The field work was conducted for a period of 3 weeks from October to November 2007. Local people were involved in the measurements of dbh in the community forest for estimating the biomass in the field. ASTER and Landsat images were employed for the study. The satellite image was pre-processed by applying geometric and radiometric correction. Pre-processed images were then used to calculate VIs. Statistical tests such as correlation and regression analysis were used to study the relationships between field measurements of biomass and remote sensing data (Ob1). The field work also concentrated on finding out a non-community forest that was degraded. Forest user groups (FUGs) as well as the forest experts were interviewed regarding their perception on forest degradation as well as indicators / criteria used to measure degradation of the forest (Ob2). Different methods were adopted to find out the possibility to differentiate community forests from non-community forests using the satellite images (Ob3). Finally the findings were integrated into the results followed by the discussions, conclusion and recommendations.

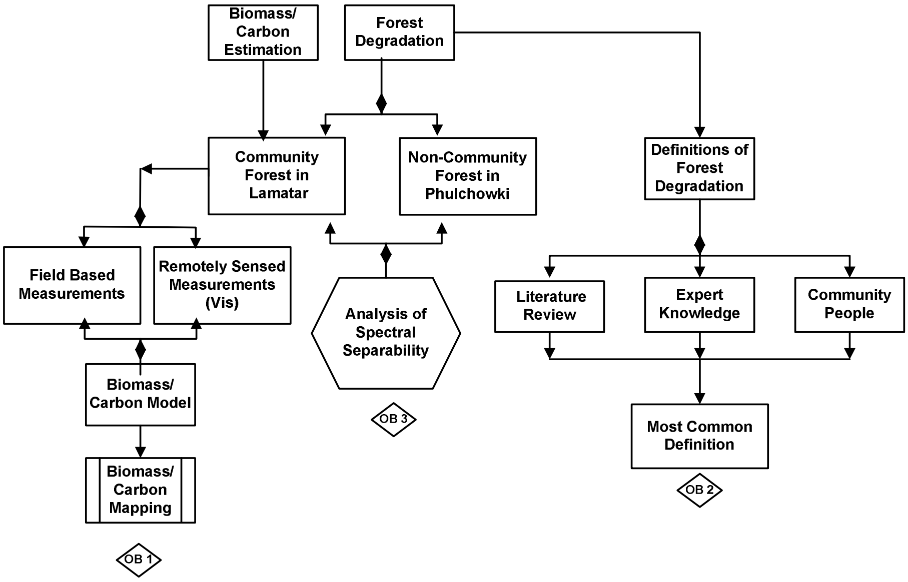

**Figure 3.** Flowchart of conceptual framework of the study

## 2. Methods and Materials

### 2.1. Site Description and Land Use History

The research was conducted in the sub-tropical forests of Nepal. Nepal is a small landlocked mountainous country surrounded by India on the East, West and South and by China on the North. Ecologically the country is divided mainly into three regions-Low land (about 17% of the land), Hill belt (about 68% of the land) and High land (about 15% of the land). Accordingly to the 2001 National Census, Nepal has a total population of 23.4 million residing in the country. Nepal has an area of 147 181 km$^2$, of which 55 180 km$^2$ is covered by forests, that corresponds to approximately 37% of the total area (Tamrakar 2003). The research site chosen for the study is located South of Kathmandu in the Lamatar Village Development Committee (VDC) in Lalitpur District as seen in Figure 4.

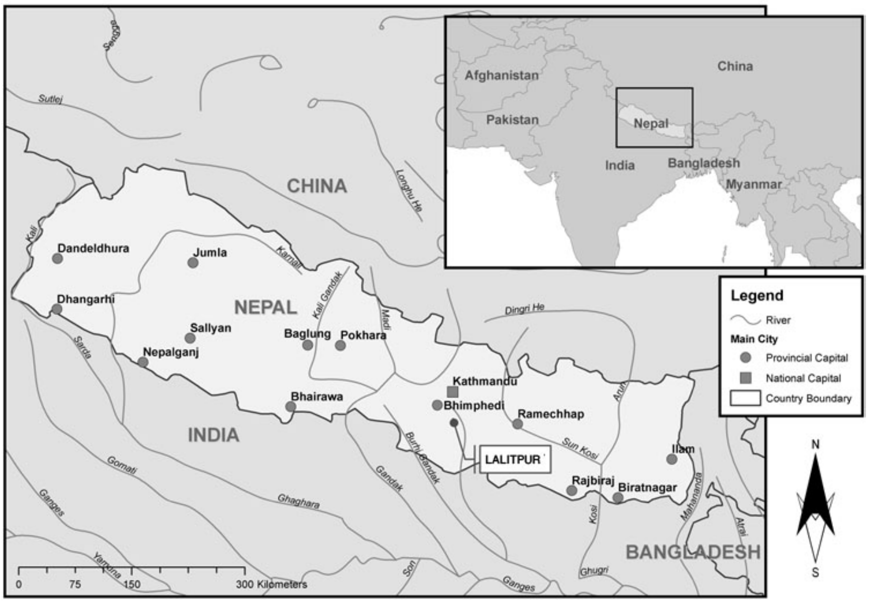

**Figure 4.** Map of Nepal showing the location of study area

(Source: Murdiyarso and Skutsch 2006)

Lalitpur district comprises of 15,253 ha of forest of which 9,993 ha are managed by 162 CFUGs. There are nine community managed forests in Lamatar VDC that covers 525 ha and involves 670 households. Kafle Community Forest (KCF) is one of the community managed forest that has been chosen as a study site for this research. The community forest was established in the year 1994 and covers an area of 96 ha. The total number of households in the CF is 60 and total forest user group is 390. The elevation of the KCF ranges from 1830 to 1930 m above sea level and is dominated by lower temperate broad-leaved species, particularly *Schima-Castanopsis*. Mean annual temperature varies from Min $3^0$C- $30^0$C Max. The mean annual precipitation is 160 cm.

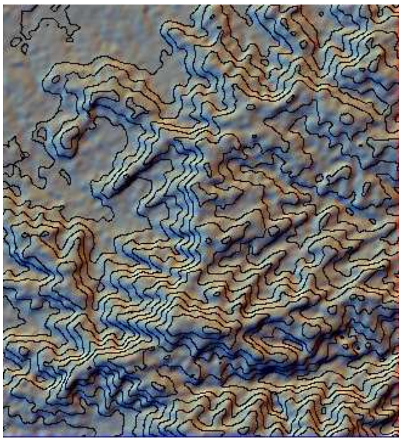

**Figure 5.** Contour lines and DEM in Study area

The particular study area was chosen as this research is carried out in the line with the project “Kyoto: Think Global Act Local” which is working in this community forest since 2004 for field based estimation of biomass/carbon values in Nepal. This Community Forests User Groups (CFUG's) managed forest sites had been chosen from among other several surveyed community forests based on the willingness of the community members to participate in the training exercises for carbon estimation (Banskota et al. 2007). The data necessary for estimation of carbon was collected in collaboration with the local people who were trained on forest survey techniques by the Nepal Trust for Nature Conservation (NTNC), a Non Governmental Organization in Nepal.

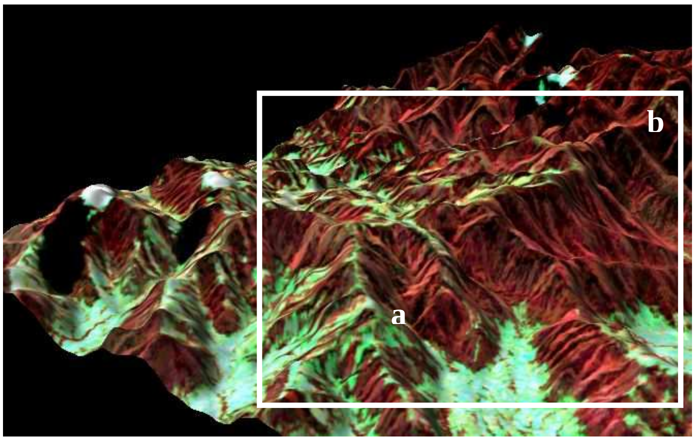

**Figure 6.** DEM of study areas (a) Managed Forest (b) Unmanaged Forest

The study area for assessing forest degradation using remote sensing was chosen near Kafle Community Forest (KCF) so that the difference in these two forests can be observed in the satellite imagery. Phulchowki National Forest is a government owned “open access” forest in Lalitpur district, which is exploited illegally by many communities from several villages for fuel wood and grazing. This forest is not well managed or protected against people who have been misusing it. People have easy access to Phulchowki national forest covering an area of over 1,200 ha. Forest degradation here is mainly due illegal logging and free grazing. Vegetation characteristics of forests were measured in managed and unmanaged forests and it was observed that National Forests (NF) managed by the government had the lowest number of tree species (Shah, 1998). The maximum elevation of this forest is 2800 m above the sea level. The forest is mainly covered by lower temperate broad-leaved species, particularly *Schima-Castanopsis.*

The Kafle CFUG has a five-year Operation Plan that explains the forest management procedures and rules. KCF has been effectively managed by the user groups to ensure that there is no illegal fodder and litter collection; timber and fuel wood extraction; hunting, grazing livestock. This forest has several springs, which has markedly increased with the rejuvenating forest biomass and as a result it plays an important role in providing an environmental service of carbon sequestration (Banskota et al. 2007).

## 2.2. Pre-Field Work

Prior to conducting fieldwork, an intensive literature review was done to obtain knowledge on the background of the study and methods to be adopted to achieve the objectives of the research. The study is in parallel research with a Ph.D. student, Bhaskar Singh Karky in Twente University, who is working with the community people in Lamatar for measuring biomass using field based methods from 2004-2006. The community methods for establishing random sample points within the forest and measuring biomass were observed and compared with different literatures. Updated information in the field of Remote Sensing and GIS and their role in biomass estimation and study of forest degradation were also sought.

Literature review on the definition of forest degradation was carried out to get a beforehand knowledge of forest degradation for identifying the indicators of forest degradation in the field and to interview local users as well as the forest experts in Nepal.

## 2.3. Field Work

Field work was undertaken from mid-October to mid-November for about 3 weeks to collect ground data. The main organizations who were involved in Nepal for the project Kyoto: Think Global Act Local (K:TGL) were visited. The regional member in Nepal for the project is the International Centre for Integrated Mountain Development (ICIMOD) and the NGO who works for the field measurements of biomass is National Trust for Nature Conservation (NTNC). The community forest study area was visited with the Forest User groups (FUGs). Informal meetings were carried out with FUGs to collect information on land use history, socio economic activities and land/forest ownership. The forest condition in the Lamatar was observed and literatures on community forests of Nepal were studied. Nepal Survey Department was visited for the topographical map and the aerial photograph, which covers both the study area.

### 2.3.1. Sampling Design

Community managed forests were not stratified for selecting random sampling plots because the area of forest was relatively small having uniform forest cover (Banskota et al. 2007). A sampling design of sampling units of size 10 m x 10 m

(100 m$^2$) was framed in reference to the previous years' sampling unit size used by the KTGL studies. The permanent plots had been laid out in 2004 by using random assignment on the map for a total sampling area of 96 ha. Sampling plots were later located in the field using a GPS device. The use of GPS receivers enables in efficient and accurate placement of the plots (MacDicken 1997). The use of permanent sample plots is the most common method of evaluating changes in forest conditions (Sampson 2002). For convenience of the community investigators in annual biomass/ carbon monitoring, centre of the plot was taken as a tree (marked with white paint) and the radius of the circular plot taken from the centre of this tree. The area of the circular permanent plots varied in different sites as the radii of the plots were determined by the area per tree as described by MacDicken (1997) (Table 1.) For Lamatar, the plot radius taken was 5.64 meters.

**Table 1.** Plot radii for carbon inventory plots

| **Plot size in square meters** | **Plot radius in meters** | **Typical area per tree (m$^2$)** | **This size of plot is usual for:** |
|---|---|---|---|
| 100 | 5.64 | 0 to 15 | Very dense vegetation, stands with large numbers of small diameter stems, uniform distribution of larger stems |
| 250 | 8.92 | 15 to 40 | Moderately dense woody vegetation |
| 500 | 12.62 | 40 to 70 | Moderately sparse woody vegetation |
| 666.7 | 14.56 | 70 to 100 | Sparse woody vegetation |
| 1000 | 17.84 | > 100 | Very sparse vegetation |

(Source: MacDicken, 1997, pp54)

As a general rule, about 20 and 30 sampling plots should be established and measured to test for statistical results (Sampson 2002). Hence, in addition of 8 permanent plots, 22 plots were randomly selected in the field with the help of the expert knowledge and FUGs. These selected random sampling plots are overlaid in an ASTER image as shown in Fig. 2.

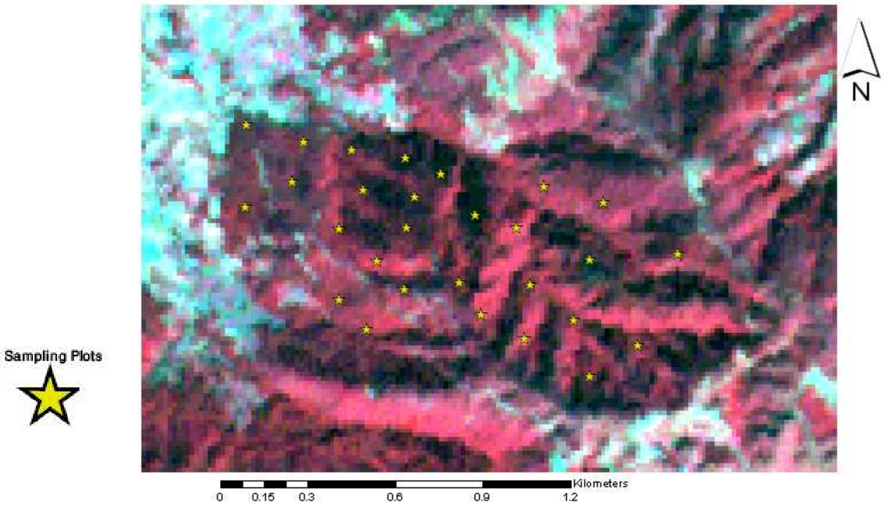

**Figure 2.** Distribution of random sampling plots in KFC displayed in ASTER

Due to limitation of available time and accessibility of the study area, measurement on more plots could not be conducted. Data on tree diameter at breast height (1.3 m) were collected at 30 circular sample plots each with a radius of 5.64 m representing an area of $100m^2$. From these data, the biomass (Kg.) of each tree with a diameter > 5 cm was estimated using standard allometric equations for sub tropical forests of Nepal. Smaller trees <5 cm dbh were not considered since they contribute a relatively small quantity of biomass. The data on tree biomass were then used to estimate the biomass of each sample plot. For the purpose of comparing the canopy cover density in these forests, ocular estimation of forest canopy density (in percentage) was also carried for each sample plot.

Coordinate points using GPS were taken in the Phulchowki National Forest, where there were signs of forest degradation such as logging, reduced canopy cover. Due to limited time, the quantitative measurement of the degradation in the field could not be carried out. All these measurements were taken with the help of three trained members of the communities who had sufficient knowledge in taking field measurements, correctly noting down the readings, and using GPS for taking the coordinate points for the plots. It was observed that the local people with primary level of education were efficient in carrying out such measurements (Banskota et al. 2007).

Working with the local users helped in learning the participatory methodology that the local communities had adopted for assessing and monitoring carbon sequestered in their forests and the reliability of their data recording method was assessed visually. After completion of measurement of tree dbh in the community forest, the boundary coordinates were noted down by Garmin GPS to demarcate the study area

### 2.3.2. Interviews

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For the definition of what is meant by “forest degradation” in Nepal, foresters from the Forest Department, Ministry of Forest and ICIMOD were interviewed for their perception, criteria and definition of “forest degradation” in Nepal.. The open-ended discussions carried out during single interview session were very useful in getting a snapshot of their own definitions of degradation. After consulting with National foresters, Phulchowki National Forest was chosen as the study site for identifying the forest degradation in this forest using remote sensing data. FUGs in the study area were also interviewed in a group on their perception of forest degradation.

## 2.4. Data Preparing and Processing Tools

The instruments used for field work were dbh tape, Garmin GPS, iPAC. Computer programs that were used for the data preparation and analysis were ERDAS 9.1, ENVI 4.4, ArcGIS 9.2, FCD Mapper Ver.2, SPSS 15.0, Microsoft Excel and Microsoft Visio.

## 2.5. Post-fieldwork

### 2.5.1. Remote Sensing Data

Biophysical, chemical properties of the features along with surface roughness are recorded by a sensor. A large number of sensors are present and a sensor can be chosen depending on the types of application, availability of data, resolution and cost. It is important to take into account the spatio-temporal characteristics of the problem that is going to be analyzed. For mapping and monitoring at a local scale, Landsat systems, ASTER images can be utilized.

In this study, ASTER scene acquired on October 14, 2004 was used. ASTER data was chosen for the study because it has relatively high spatial resolution in the visible to near infrared bands (Heiskanen 2006). The study requires calculating several vegetation indices (VIs), which mostly uses red and near infrared wavelengths such as NDVI and Simple Ratio (SR). The research is also based on study of spectral response of the features on the earth which needs surface reflectance values. Hence, ASTER On-Demand L2 Surface Reflectance was also used, which contains atmospherically corrected surface reflectance data. Furthermore, not many studies of forests have been carried out using ASTER image (Muukkonen and Heiskanen 2005; Heiskanen 2006). Till date, most frequently used remote sensing data has continued to be Landsat ETM+ (Lu 2006). However keeping in regard the small size of the study area, an image with finer resolution such as IKONOS or Quickbird would have been better but could not be purchased due to limited budget.

The study also requires measuring forest canopy density of the area using FCD mapper as a measurement of indicator of forest degradation in the area. Since only Landsat data can be used for this software, Landsat ETM image from December 27, 2001 was acquired.

Subsets of the images were prepared in ERDAS. Subsets should be large enough to cover context required for specific analysis (Campbell 2002). The subset was made not only to cover the community forest and national forests but a small region surrounding to provide sufficient number of training sites for image classification.

### 2.5.2. Image Processing

The distortion in the image maybe caused due to the rotation of the earth and it maybe rectified with the use of data on monitoring of the satellite path and the properties of scanning system (Gibson and Power 2000). ASTER and Landsat images have been rectified to the national coordinate system using ground control points (GCPs) collected from 1:25000 scale digital topographic maps with first order polynomial equation and the nearest neighbour resampling method. A spectral image never depicts the true radiance of the surface (Adams and Gillespie 2006) because of the errors in it as a result of defective sensors, data loss during transmission and recording at ground based receiving centre. So image analysis process can not proceed without performing radiometric correction (Gibson and Power 2000). In order to obtain accurate and reliable results, atmospheric corrections or radiometric calibration of the satellite images were carried using ATCOR3 in ERDAS. ATCOR3 correction algorithm uses digital elevation models (DEM) to carry out atmospheric and topographic correction in a rugged topographical surface as found in Lamatar and Phulchowki study areas. During radiometric calibration, raw radiance from imaging spectrometer is converted into reflectance data. (San and Suzen 2007; Goetz, et al. 2002).

### 2.5.3. Allometric Biomass Equations

Allometric Biomass equations are regression equations that provide a relationship between tree fresh weight biomass and a tree dimension(s) such as dbh. In order to compare the efficacy of remote sensing in estimating carbon sequestered in the study area, field aboveground measurements of biomass must be carried out. This requires cutting down the vegetation, but fortunately in this study, allometric equations were found to exist for the study area during the literature review.

Allometric equations are preferably species-specific and locally derived (UNFCCC 2006). Regional tree biomass equation for sub-tropical forests of Nepal was collected from Forest Department in a booklet named “Common Tree Species: Field manual for Community and Private Forests in Nepal” prepared by NG[2]/UNDP/FAO, which had simplified biomass equations. These equations required only dbh as a single input variable to calculate biomass. The allometric relationships were applied to estimate the biomass for the sample plots. Foresters were consulted for choosing the allometric equations for the different tree species. Not all the species in the study area had its own allometric equation for biomass calculations, so using the expert knowledge; they were grouped into the similar type of plant species with similar morphology.

### 2.5.4. Forest Biomass/Carbon Estimation

#### 2.5.4.1. Ground Measurements

The individual dbh value for each plot was converted to biomass using allometric biomass tables. Biomass equations are important to relate dbh with the number of plants per ha to total biomass (MacDicken 1997). The above ground biomass of each tree in the plots was estimated using the field measurements of dbh. For each site, the biomass (expressed in Kg per ha) of each sample plot was taken to be the sum of the total above ground biomass of its component trees (Kg) estimated using standard allometric equations developed for the local forests. To enhance the direct comparability of the data sets, a standardized methodology used in previous years

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[2] NG here is Nepal Government

were used. Here, data from 8 plots surveyed in the field from 2004-2006 were also taken into account to see the correlation with the remote sensing data long with the 30 points collected in 2007.

#### 2.5.4.2. Remote Sensing Measurements

Satellite images have been used in several studies at various spatial and temporal scales for estimating and mapping forest biomass (Heiskanen 2006; Lu 2006; Foody et al. 2001; Muukkonen and Heiskanen 2005; Tomppo et al. 2002; Foody et al. 2003; Mabowe 2006; Thenkabail et al. 2004; Foody et al. 2003;  Zheng et al. 2004, Lu 2005; Franco-Lopez et al. 2001; Tomppo et al. 2002; F. Gonza´ Lez-Alonso 2006; Wicks and Curran 2003; Dong et al .2003) Due to the difficulty in collecting field data of below-ground biomass (Lu 2006), biomass estimation has focused only on above-ground biomass (AGB) The remotely sensed data from visible-near-infrared detectors (such as ASTER) is most common for estimating biomass in the field (Brown 1996). The coordinate points of the sample plots taken by the GPS were converted into a point shape file and were laid over the corrected ASTER image. The reflectance values from ASTER were extracted for each sample plot using ENVI. Reflections of the red, green and near infrared radiances contain considerable information about forest biomass. Vegetation reflectance properties were then used to derive spectral vegetation indices (SVIs). SVIs are constructed from reflectance measurements in red and NIR bands to analyze specific characteristics of vegetation in the area (Asner 1998; Mather 1999). SVIs attempt to enhance the spectral contribution of vegetation while reducing that of the background (Heiskanen 2006). Vegetation indices have been recommended to remove variability caused by canopy geometry, soil background, sun view angles and atmospheric conditions when measuring biophysical properties (Tucker 1979). Vegetation indices (VIs) were used in the present study as they are commonly used to produce estimates of biomass (Schlerf et al. 2005) and they usually have good correlation with the biomass as biomass represents the good health of the plants (Pinter Jr. et al. 2003). However, some studies have also shown that VI has poor correlation with biomass data such as of Mabowe (2006). Most popular VIs using red and near infrared wavelengths are simple ratio (SR) (Heiskanen 2006) and the normalised difference vegetation index (NDVI) (Brown 1996; Heiskanen 2006; Foody et al. 2003; Myeong 2006). Many vegetation indices and band ratios have been used in the relation with biomass since past 30 years. The ones that have been used in this study are mentioned in Table 2. Other vegetation indices that reduce the effect of soil background and atmosphere such as Soil Adjusted Vegetation Index (SAVI), Perpendicular Vegetation Index (PVI) were not considered as there was no bare soil background in the study area.

**Table 2.** SVIs used in the study

| Vegetation Indices | Formula | References |
|---|---|---|
| DVI | NIR - R | Tucker 1979 |
| SR | NIR/R | Lu 2004; Schlerf et al. 2005; Heiskanen 2006; Jordan 1969 |
| MSR | (NIR/Red -1)/((NIR/Red)$^{0.5}$ + 1) | Chen 1996 |
| NDVI | (NIR- R)/ (NIR+R) | Lu et al. 2004; Jensen 1986; Heiskanen 2006; Rouse et al. 1973 |
| RDVI | $\sqrt{NDVI * DVI}$ | Roujean and Breon 1995 |

(Note: MSR: Modified Simple Ratio, DVI: Difference Vegetation Index, TVI: Transformed Vegetation Index; RDVI: Re-normalized Difference Vegetation Index)

#### 2.5.4.3. Statistical Modelling

When the vector layer of 30 sample plots was placed over the corrected ASTER image, it was observed that some of these points failed to fit into the correct location within the study area. The reason is most likely due to the error in the GPS reading as a result of poor satellite signals during field work. Therefore, out of 30 points, only 28 points were considered in the statistical analysis.

Linear regression analysis was employed in the statistical modeling of the relationship between the forest variables and ASTER data (Heiskanen 2006; Muukkonen and Heiskanen 2005; Foody et al. 2003). Plot wise reflectance values from the ASTER image were derived using ENVI 4.4, which used to calculate the vegetation indices such as NDVI, SR in Excel worksheets. Empirical relationships between plot biomass data and VIs were developed using correlation and linear regression analysis, which were used for developing a biomass model. The coefficient of determination ($R^2$) was used to evaluate a regression model performance because it measures the percentage of variation explained by the regression model (Lu 2005).

$Y = aX + b$ (Biomass model)

Where, Y is response variable (Biomass in Kgs)
X is an explanatory variable (VI)
a and b are coefficients of explanatory variable.

Indirect estimates of biomass/carbon values were generated with empirical relationships established between vegetation indices and in situ data on biomass (carbon) stocks in the forests. The biomass proportions from all the sites were added to give the total aboveground tree biomass, which was divided by 0.5 factor to get the carbon values. These values were again converted into carbon in ton/ha using the area of the plot. Finally, VI for the biomass model was chosen in terms of best coefficient of determination ($R^2$) for biomass/carbon mapping of the study area.

Although validation of the estimated results is an important part in the AGB estimation procedure (Lu 2005), sufficient data for validation could not be collected during field work.

### 2.5.5. Defining Forest Degradation

Forest degradation results from various causes and understanding these underlying drivers of degradation are important for identifying measures to reduce degradation. There are many definitions of forest degradation relating to the causes of degradation, loss of environmental services, changes within the forest structure within certain time frame etc. Forest degradation is mainly caused by direct and indirect impacts from the human activities and leads to a reduction in forest biomass in an unsustainable manner (Defries et al. 2006) without reducing the area of the forest.

The definition of forest degradation were sought from numerous literature reviews, which were combined with the definitions given by the community people and forest experts in Nepal to determine the most commonly understood International and local definition of forest degradation

### 2.5.6. Identification of Forest Degradation from Remote Sensing

During the field work, both community forests and national forests were visited. It was observed that national forests had more indicators of forest degradation such as logging, invasion by alien species, reduced crown cover density. The objective is to observe whether these two forest types can be distinguished in a satellite image; various remote sensing tools have been applied to attempt this distinction. These tools are briefly described in the paragraphs below.

#### 2.5.6.1. Spectral Signature Separability

A common method of monitoring vegetation disturbances and pattern is to categorize the pixels in an image to different land cover classes and compare the size and extent of the classes (Wulder and Franklin 2007). This is the main reason for employing classification in this study. Classification is the most common single-date image analysis techniques for change detection (Wulder and Franklin 2003). Classification or image segmentation is the process of grouping the pixels of the image into a finite number of individual classes based on their data values. If a certain set of criteria are satisfied by the pixel, it is assigned to the class corresponding to that criteria. The software needs training to define these criteria according to which the image will be grouped into several classes. Classification assigns color to group of pixels having similar spectral reflectance (Gibson and Power 2000). Supervised and unsupervised classifications are two types of classification approaches that were applied on ASTER image.

Image classification can form a basis for investigating the difference in the structure of degraded and non degraded forest by assigning different classes to these two forest types. An unsupervised classification using the ISODATA clustering algorithm was performed. The ISODATA algorithm uses minimum spectral distance to assign a cluster for each candidate pixel. This algorithm is highly successful at finding the spectral clusters that are inherent in the data (ERDAS 2005). Knowledge of the area is not necessary during image segmentation due to which the high accuracy of classification may not be achieved (Tso and Mather 2001). Since the aim of the classification was to analyze the difference in signatures of community and non community forests only, the class numbers were limited to 4(community forest, non community forest, agriculture and bare), to examine whether both community and national forests get classified into the same or different classes. In this study, terms “degraded, unmanaged, national forest” imply the same meaning and in the same way terms such as “non-degraded, managed and community forest” provide the same understanding.

Supervised classification was carried out in the second stage where calibration data (50) and validation data sets (100) were collected during field work. Supervised classification is the process where the analyst selects pixels that represent certain land cover type with the help of field data, aerial and other sources of information and knowledge of the area being classified. Supervised classification attempts to classify each pixel, based on spectral information in one or more spectral bands, to classes or themes. Minimum distance to means is one of the mathematical approaches for spectral pattern recognition, where pixel of unknown identity is classified by computing the distance between the value of the unknown pixel and each of the category means, which has been used in this case. To make the study simple and easy to understand, the number and the name of the classes were kept the same as the unsupervised classification in this case too.

Spectral signatures of both managed and unmanaged forests were analyzed using ENVI 4.4 and ERDAS 9.1. Every natural and synthetic object on the earth's surface reflects and emits electromagnetic radiation (EMR) over a range of wavelengths in its own characteristic way according to its chemical composition and physical state. These objects (features) usually exhibit the spectral response pattern that is unique like a fingerprint, which allows for the identification of different objects on the earth in a satellite image. This unique spectral characteristic is known as a spectral signature of that feature. Each spectral signature corresponds to a class and assigns the pixels in the image file to a class during classification (ERDAS 2005).

The basic principle to identify different earth features is to observe if these features are spectrally and statistically separable or not. The spectral signatures can be plotted as curves to represent the spectral response of a certain type of features as a function of wavelength in a graphical way. These curves are defined by the varying percent of reflectance. The spectral reflectance curves were constructed by plotting the image pixel value (reflectance or DN values) of both forest types as the function of band number (wavelengths) to determine which bands are most useful for discriminating these two feature types.

#### 2.5.6.2. Statistical and Graphical Method of Feature Selection

Features are the "statistical characteristics" of the image data that carries information about the variation within the scene (Campbell 2002). Training statistics were collected for the class of interest for each band to determine which bands were most effective in separating the classes. This process is known as feature selection (Jensen 1996). Feature selection involves both statistical (parametric) and spectral (non-parametric) methods (Tso and Mather 2001; Jensen 1996). Both methods were used to analyse the difference between managed and unmanaged forests, because both graphical display of the statistical data as well as spectral presentation of data are equally important

### Statistical Method of Feature Selection

A parametric signature defines the class probability based on statistical parameters (e.g., mean, standard deviation, covariance) extracted from the samples of multispectral pixels in the image space (ERDAS 2005). Parametric signatures can be generated both in supervised and unsupervised classification

Statistical methods of feature selection were used to quantitatively select the subset of band or features that provides statistical separability (Jensen 1986) between the managed forest and unmanaged forest classes. There are many options for evaluating the separability of signatures using statistical method and these formulas take into account the covariances of the signatures in the bands being compared, such as divergence, transformed divergence and Bhattacharya distance.

Univariate statistical analysis gave the values of Minimum, Maximum, Mean and Standard Deviation (SD) for all sample points taken for both managed and unmanaged forests in each band, which were analysed and interpreted using Excel worksheet.

#### 1. 2D Scatterplot

A 2D scatterplot visualizes a relation between two variables. Individual data points are represented in two-dimensional space where X axis and Y axis represent the variables. A set of 100 random points were generated inside the boundary of both managed and unmanaged forest in ArcGIS. The reflectance value of the 100 random points were extracted from managed and unmanaged forests in ASTER image and were compared for two bands at a time in a 2D scatterplot till all possible combinations became exhausted.

#### 2. Box Plots

Box plot graphs are efficient means of displaying summary of the data. It displays five number data in the graph: maximum value, minimum values, median, upper quartile and lower quartiles. Using box plots, the reflectances data can be analysed by studying their location and their spread. Box plots were studied using both managed forest and unmanaged side by side on the same graph to compare 2 data sets in 3 bands. Hence the box plot was made for managed and unmanaged forests for band 1, band 2 and band 3.

### 3. Coincidence Bi-spectral plots

One way of two dimensional display of training class statistics is plotting spectral plots in a bar graph format for each band (Anuta 1977 in Jenson 1986,pp192).

Coincident bi spectral plots were generated where training statistics for 2 forest types were displayed in all 3 bands. This display can be used to identify between-class separation between each class in each band (Jensen 1979 in Jenson 1986, pp193) using the mean and the variance of the data sets.

### 4. Transformed Divergence

As mentioned before, statistical methods of feature selection involve use of different separability measures like Divergence, Bhattacharya distance, Transformed Divergence (TD). Divergence was one of the first measures of statistical separability used in remote sensing data for feature selection (Jensen 1986). Transformed Divergence is an advanced divergence method, which was used in the present study to identify statistical separability of 4 training classes in 3 bands. This statistic gives an exponentially decreasing weight to the increasing distance between two classes. Larger the value, better the separability between the classes will exist (Jensen 1986).. The range of the values is from 0-2000

The Transformed Divergence is given by the following equations:

$$TD(i,j) = 2*[1-\exp(-D(i,j)/8)]$$

Where

TD (i,j) = Transformed Divergence between classes i and j
D (i,j) = divergence between classes i and j

$$\begin{aligned} D(i,j) = {} & 0.5*T\,[M(i)-M(j)]*[InvS(i)+InvS(j)]*[M(i)-M(j)] \\ & + 0.5*Trace[InvS(i)*S(j) + InvS(j)*S(i) - 2*I\,] \end{aligned}$$

Where,

M(i) = mean vector of class i, where the vector has Nchannel elements (Nchannel is the number of channels used)
S(i) = covariance matrix for class i, which has Nchannel by Nchannel elements
InvS(i) = inverse of matrix S(i)
Trace[] = trace of matrix (sum of diagonal elements)
T[] = transpose of matrix
I = identity matrix

### 5. Bhattacharya distance or Jeffries-Mastusuta

Bhattacharya distance was also calculated for determining the separability between two classes at a time**.** The Bhattacharrya (or Jeffries-Mastusuta (JM)) Distance is calculated using the following formula:

BD(i,j) = 2*[1-exp(-a(i,j))]

where

BD(i,j) = Bhattacharrya Distance between class i and j
a(i,j) = 0.125*T[M(i)-M(j)]*Inv[A(i,j)]*[M(i)-M(j)]
+ 0.5 *ln{det(A(i,j))/SQRT[det(S(i))*det(S(j))]}

Where,

M(i) = mean vector of class i, where the vector has Nchannel elements (Nchannel is the number of channels used)
S(i) = covariance matrix for class i, which has Nchannel by Nchannel elements
Inv[] = inverse of matrix
T[] = transpose of matrix
A(i,j) = 0.5*[S(i)+S(j)]
det() = determinant of a matrix
ln{} = natural logarithm of scalar value
SQRT[] = square root of scalar value

The value of JM ranges between 0 and 1414. Jensen (1996) suggested using TD or JM distance measures whenever possible. Hence these two measures were also selected for the current study.

The signature editor in ERDAS Imagine was used to carry out signature separability test using distance measures and the result was given in a report of the computed divergence of every pair of signature in each band set. The numbers for each pair of signatures were compared to determine which classes were mostly separable and which set of bands is the most suitable for separability of signatures.

### 6. Dendogram

A study was also undertaken to find out the spectral separability between classes using a dendrogram. Dendrogram is one of tools that ArcGIS Spatial Analyst provides, which was used to study the statistical distribution of the classes stored in a signature file in the attribute space.

The Dendrogram tool uses a hierarchical clustering algorithm. The program first computes the distances between each pair of classes in the input signature file. The closest pair of classes is merged first and the next closest pair of class gets merged and so on, till all the classes get merged. After each merging, the distance between all pairs of classes gets updated. The distances at which the signatures of classes are merged are used to construct a dendrogram (ArcGIS Desktop Help)

The distance $d_{mn}$ between a pair of classes m and n (in this study, managed and unmanaged forests) was measured as a distance between their means and variances using the following formula.

$$d_{mn} = \sum_{i=1}^{N} \frac{(\mu_{mi}-\mu_{ni})^{2}}{\sqrt{V_{mi}V_{ni}}}$$

Where,
m, n = IDs of classes, i = layer number
μ = mean of class m or n in layer i
V = variance of a class m or n in layer i.

The spectral signatures were created for the training areas in all bands, which was used as an input signature file for dendrogram function to create an ASCII file that graphically depicted the distance relationships between the classes in the signature file.

### Graphical Method of Feature Selection

A nonparametric signature is not based on statistics, but on discrete objects (polygons or rectangles) in a feature space image (ERDAS 2005). These feature space objects define the boundaries for the classes. The pixels are assigned a class depending on their location either inside or outside the area in the features. Non-parametric signatures were generated using supervised classification (Kloer 1994), which were plotted in the feature space.

### 1. Eclipse Diagram and Scatter Plots

The evaluation of non-parametric signatures was carried out based on the concept of feature space. The feature space of an image is the N-dimensional space which encompasses all the data values of the image (Tso and Mather 2001). Since N-dimensional space cannot be easily represented, the feature space of an image is calculated and visualized in a multiple 2-dimensional ellipse plots which are known as spectral plots or scatter plot or feature space images. The feature space images displays the distribution of the pixel values for the sample points using combination of 2 bands each time, which provided useful visual between the class separability information for different band combinations (Jensen 1996). In this feature selection method ellipses are calculated based on the means and standard deviations stored in the signature file and displayed in 2-dimensional features space. By observing whether the ellipses for different signatures for one band pair overlapped or not on the feature space image, it was determined if the signatures represent similar groups of pixels.

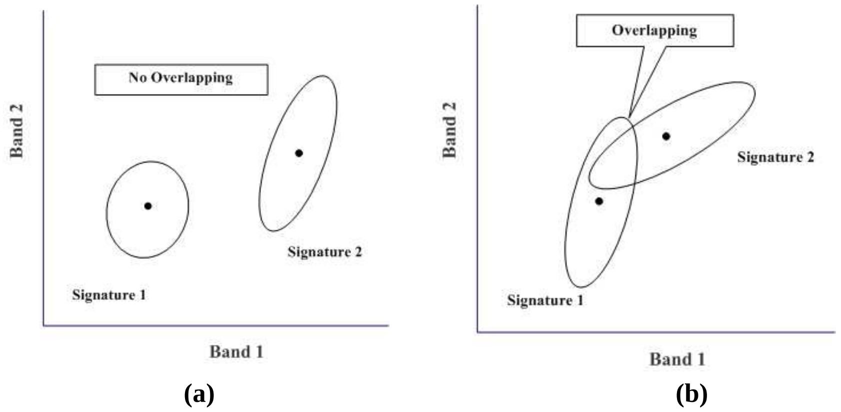


**Figure 7.** Ellipse diagram plotted between 2 bands.

**(a)** No overlapping between the signatures

**(b)** Overlapping between the signatures

(Centre points in figures are the mean of the vector image)

### 2.5.6.3. Forest Canopy Density (FCD) Modelling

The status of forests can be determined by its canopy density. Forest degradation, by many definitions is described as the reduction in canopy cover is the most readily observed in a satellite image. Damage to forest canopy can be detected through visual interpretation and advance image processing algorithms (Defries et al. 2006). FCD mapper is one such model that employs forest canopy density as a primary parameter for determining the condition of the forest thereby indicating the degree of forest degradation (Rikimaru et al. 1999). The advantage of FCD mapper is that intensive ground truthing is not required.

FCD mapper estimates the index of canopy density using reflectance properties of Landsat TM (Baynes 2005). Therefore, Landsat ETM of December 2001 was acquired for analysis. FCD mapping and monitoring model is a semi expert system, which considers four factors into the model: vegetation, bare soil, thermal radiation and shadow which are derived from advanced vegetation index (AVI), bare soil index (BI), thermal index (TI) and Shadow Index (SI) or Scaled Shadow Index (SSI). The combination of these indices into the model produces a FCD map. Forest canopy density here is expressed in a percentage scale for each pixel in the image, where 0 implies no forest and 100 means maximum canopy density.

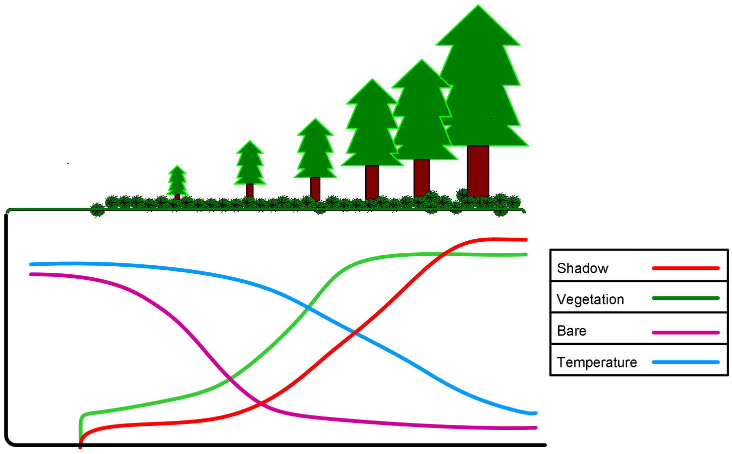


**Figure 8.** Concept of Forest Cover Density Mapper

Advanced vegetation index (AVI) reacts sensitively for the vegetation and increases with increasing forest canopy. Shadow index increases with the increase in forest density. Thermal index increase as the forest density is reduced and bare soil index increases as the bare soil exposure degrees of the forest floor increases (Fig. 8).

As an intermediate step VI and BI were combined into vegetation density (VD) value using principal component analysis and VI and SI were combined into scaled shadow index (SSI) by linear transformation of SI. Finally, VD and SSI were synthesized into a forest canopy density value to produce a FCD map (Joshi et. al 2006).

$$FCD= (VD * SSI + 1)^{1/2} - 1$$

The FCD map with categorical value of forest canopy density expressed in percentage was finally exported as TIFF and analysed used ArcGIS 9.2. The main purpose of using the FCD mapper in this study is to examine if there is a difference in the canopy cover density in managed and unmanaged forests. The assumption is that managed forest would have more canopy density than the unmanaged forest.

The total FCD value of all the pixels was added up for both the forest types and statistical analysis was carried out to measure mean and variances of both the forest types to see if degraded unmanaged forest had lower canopy cover density than the managed forests. In addition, the predicted against observed carbon values were plotted and the agreement was tested by a simple linear regression and the variance of the observed carbon value explained by the predicted value was used to assess the random errors in the model.

The coefficient of determination ($R^2$), slopes (ß) and intercepts (α) were used to evaluate the performance of predictors. An unbiased predictor would be expected to have a slope (b) of 1 and intercept (a) of zero (Joshi et. al 2006).

For more details in the theory and operation of the model FCD Mapper User Guide Ver. 2 can be studied.

### 2.5.7. Accuracy Assessment

Validation is critical to both biomass mapping and classifications and is an integral part of this research. Classification or feature identification using remote sensing requires an accuracy check with independent sets of training and testing data (Stehman 1997). Estimation of accuracy measures tells us the magnitude of error and its impact on a model. Accuracy assessments can be achieved with application of specific formulas and tests to the statistical observations (Sophia 2007).

The accuracy assessment statistics for the FCD mapper included the root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \Big/ n}$$

Where, $Y_i$ is observed value of FCD; $\hat{Y}_i$ is estimated value of FCD by the models and n is number of sample observations.

Training and testing sites were developed from the ground truth data obtained by using a GPS during field work which was used for validation of the supervised classification results. Accuracy assessment report was generated using ERDAS 9.2 with user accuracy, producer accuracy, overall accuracy and kappa coefficient.

### User Accuracy

The user accuracy or object accuracy was calculated, which compares the map with the field data. For each class, the probability that a randomly chosen point on the map has the same class value in the field

### Producers Accuracy

The user accuracy or object accuracy was calculated, which compares the map with the field data. For each class, the probability that a randomly chosen point in the field has the same class value on the map

### Overall accuracy

The simplest accuracy measurement "overall accuracy or total accuracy" was calculated by dividing the total number of correctly classified sample points by the total number of points. It reflects the probability that a randomly selected point on the map is correctly classified.

### Kappa Statistics

Precision refers agreement between observations and is often reported as a kappa statistic. Kappa statistics give a quantitative measure of the magnitude of agreement between observers. The Kappa coefficient was calculated, which allows us to quantify this randomness of the data prepared by the influence of chance. Kappa estimates the influence of chance on the estimated map accuracy. Kappa estimate of 1 indicates perfect agreement, whereas a kappa of 0 indicates agreement equivalent to chance. Interpretation of Kappa is given below.

| | **Poor** | **Slight** | **Fair** | **Moderate** | **Substantial** | **Almost perfect** |
|---|---|---|---|---|---|---|
| **Kappa (κ)** | 0.0 | .20 | .40 | .60 | .80 | 1.0 |

# 3. Results

## 3.1. Relationship of Field Based Measurement and Remotely Sensed Measurements of Biomass/Carbon

### 3.1.1. Tree Species in the Study Area

In October 2007, a total of thirty 10m ×10m sample plots were established randomly throughout the Kafle community forest. *Schima Wallichii* and *Castonopsis Indica* were the most abundant tree species observed in the sample plots as depicted in (Fig.9). All the trees with dbh ≥5cm were measured in 30 plots of the study area. The total number of sample trees taken was 443 and 59% of these trees had dbh ranging from 5-10 cm and 3% had dbh below 30 cm (Fig.10).

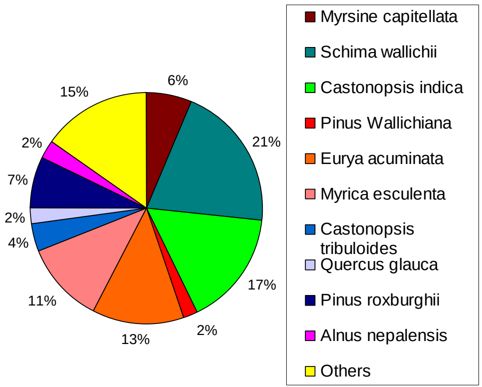


**Figure 9.** Tree species of the area

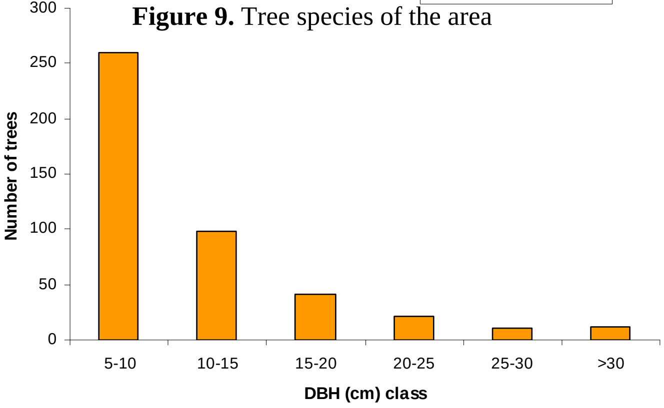


**Figure 10.** Distribution of trees according to dbh class

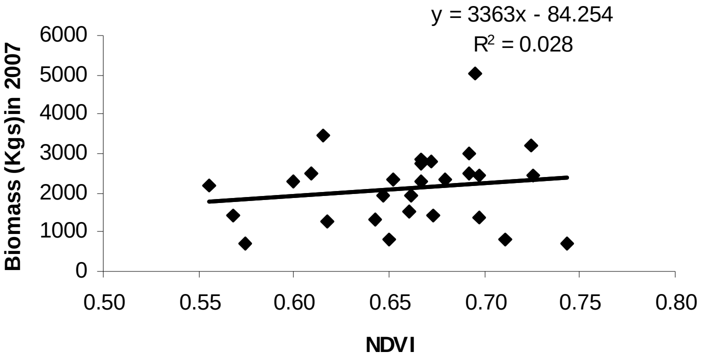
### 3.1.2. Statistical Results from Exploratory Field Data Analysis

As mentioned previously, empirical relationships between plot biomass data and SVIs were developed using correlation and linear regression analysis. The allometric relationships were applied to estimate the AGB for the 28 sample plots.

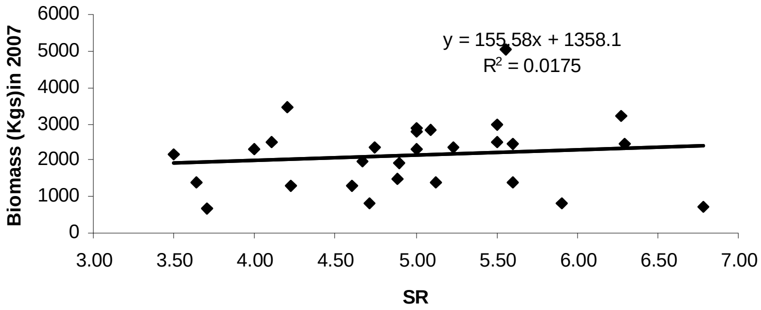
In the present study, the correlations between SVIs calculated from the ASTER image for 28 plots and field biomass data showed poor relationship which is shown in Table 3 and Fig. 11.

**Table 3.** Linear regression model between SVIs and plot wise biomass data

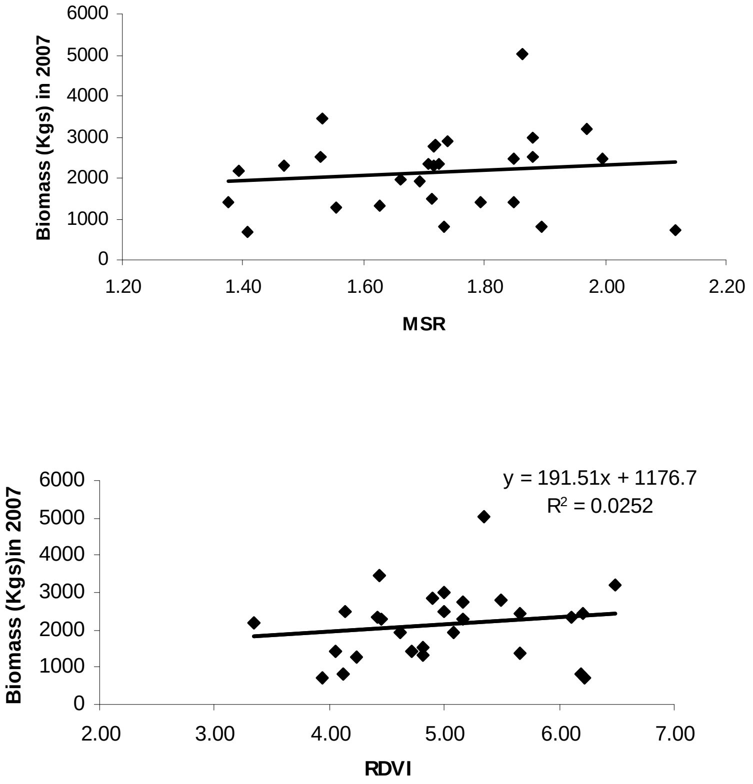
| SVI | Linear Model | $R^2$ |
|---|---|---|
| NDVI | 3363x - 84.254 | 0.028 |
| SR | 155.58x + 1358.1 | 0.0175 |
| MSR | 667.46x + 986.01 | 0.0166 |
| RDVI | 191.51x + 1176.7 | 0.0252 |



(a)



(b)



(c)

(d)

**Figure 11.** Linear regression analysis of SVIs (a) NDVI (b) SR (c) MSR (d) RDVI with plot wise biomass values in Kgs. in 2007

Due to the poor values of coefficient of determination ($R^2$) between biomass data and SVIs, this dataset was not considered for biomass/carbon mapping. The biomass data from previous years from 2004-2006 with 8 sample plots were plotted against the ASTER SVIs. Linear regression models and coefficients of determination ($R^2$) obtained between VIs and biomass data over the winter period of 2004-2006 are shown in Table 4.

**Table 4.** Linear regression models and $R^2$ between VIs and biomass data in 8 plots from 2004 -2006

| **Year** | | **NDVI** | **SR** | **MSR** | **RDVI** |
|---|---|---|---|---|---|
| 2004 | $R^2$ | 0.3273 | 0.4452 | 0.3109 | 0.4401 |
| | Eqn | 8774x - 3929.6 | 646.93x - 1340.4 | 2432.9x - 2352.9 | 530.95x - 688.6 |
| 2005 | $R^2$ | 0.506 | 0.5981 | 0.4421 | 0.5859 |
| | Eqn | 8704.2x - 3881.3 | 598.26x - 1106.9 | 2314.6x - 2151.4 | 88.78x - 494.01 |
| 2006 | $R^2$ | 0.3303 | 0.3772 | 0.2598 | 0.4085 |
| | Eqn | 7684.7x - 3152.9 | 519.18x - 660. | 1939x - 1450.8 | 445.99x - 227.96 |

Results indicate that the relationships obtained between vegetation indices and biomass data showed better correlation, obtaining the best relationships in year 2005 with $R^2$ value of 0.59 for SR. $R^2$ values of the linear models varied between 0.25 and 0.59 for biomass.

Given that the ASTER image in this study was from the year 2004, the biomass data from the same year was considered to be the best one for drawing the conclusion on previous data. The correlations between the reflectance in ASTER VNIR spectral bands and the AGB of trees from 2004 were significant, although not mostly strong. The best relation was observed with SR ($R^2$=0.44) among other tested VIs.

## 3.2. Different Definition of Forest Degradation

### 3.2.1. Forest Degradation in Literatures

Different definitions of forest degradation were sought from various literature reviews, which are summarized below according to the parameters used for defining forest degradation by the authors and the International bodies.

**Table 5.** Parameters covered by different definitions of forest degradation from literature review.

| **Parameter** | **Definitions Covering the Parameters**<br>**(References)** |
|---|---|
| **Changes within the forest** | |
| **Structure** | FAO 2000, FAO 2001, FAO 2006, UNEP/CBD 2001, Grainger 1993, UNEP/CBD/SBSTTA 2001, Grainger 1996, ITTO 2002 in UNEP-WCMC |

| | |
|---|---|
| **Crown cover** | FAO 2000, ITTO 2005, IPCC 2003°, Grainger 1993, FAO 2002 , FRA 2002, Grainger 1996, UN-FAOb 2000, Lund 2007 |
| **Species composition** | FAO 2001, FAO 2006, UNEP/CBD 2001, Grainger 1993, UNEP/CBD/SBSTTA 2001, Grainger 1996, ITTO 2002 in UNEP-WCMC |
| **Biodiversity** | FAO 2000, FAO 2003, FAO 2002, UNEP/CBD 2001, ITTO 2002, UNEP/CBD/SBSTTA 2001, FRA 2002, UN-FAOb 2000, USFS, UNEP/CBD 2006 |
| **Stocking** | FAO 2000, FAO 2001, FAO 2006, UN-FAOb 2000 |
| **Soil degradation** | FAO 2001, FAO 2006 |
| **Tree density** | Grainger 1993, WRI IN FAO, Grainger 1996 |
| **Forest health** | People & the Planet 2000 – 2008 |
| **Reduction of capacity to provide:** | |
| **Productivity** | Lambin 1999, UNEP/CBD/SBSTTA 2001, World Bank 1991, EEA, WRI IN FAO, Grainger 1996, People & the Planet 2000 – 2008, Lund 2007, ITTO 2002 in UNEP-WCMC |
| **Goods** | FAO 2000, FAO 2001, FAO 2006, UNEP/CBD 2001, ITTO 2002, UNEP/CBD/SBSTTA 2001, UNEP/CBD 2006 |
| **Services** | FAO 2000, FAO 2001, FAO 2006 ,UNEP/CBD 2001, ITTO 2002 UNEP/CBD/SBSTTA 2001 |
| **Wood** | FAO 2003, ITTO 2002, FAO 2002 , FRA 2002, UN-FAOb 2000 |
| **Carbon stocks/biomass** | FAO 2001, FAO 2006, FAO 2003, ITTO 2005, IPCC 2003°, IPCC 2003b IPCC 2003c, IPCC 2003d, Grainger 1993, UNDP, Climate Services in FAO, IPCC1996, IPCC1996 |
| **Other functions** | FAO 2000, FAO 2001, FAO 2006, FAO 2003, ITTO 2002, FAO 2002 , FRA 2002, UN-FAOb 2000 |
| **Time scale** | |
| **Long Term** | FAO 2000, FAO 2003, ITTO 2002, IPCC 2003b, IPCC 2003c, IPCC 2003d, Lambin 1999, FAO 2002, FSC, FRA 2002, UN-FAOb 2000 |
| **Short Term** | Lambin 1999 |
| **Permanent** | Grainger 1993, World Bank 1991, EEA, Grainger 1996, Castellani, C., et al 1983 |

| | |
|---|---|
| **Temporary** | Grainger 1993, Grainger 1996 |
| **Causes** | |
| **Logging** | FAO 2000, FAO 2001, FAO 2006, Souza et. al 2003, FAO 2002 , FRA 2002, UN-FAOb 2000, Lund 2007 |
| **Harvesting** | ITTO 2002 in UNEP-WCMC, Castellani, C., et al 1983 (2) |
| **Thinning** | Lund 2007 |
| **Fire(s)** | Souza et. al 2003, FAO 2002, FRA 2002, UN-FAOb 2000, Castellani, C., et al 1983 |
| **Wind-felling** | FAO 2002, FRA 2002, UN-FAOb 2000 |
| **Over grazing** | FAO 2001, FAO 2006, Castellani, C., et al 1983 |
| **Landslides/erosion** | ITTO 2002 |
| **Over exploitation for fuel wood or timber** | FAO 2001, FAO 2006, IPCC 2003c, UNDP, Climate Services in FAO, IPCC1996 |
| **Attacks by insects** | FAO 2001, FAO 2006 |
| **Diseases** | FAO 2001, FAO 2006 |
| **Plant parasites** | FAO 2001, FAO 2006 |
| **Invasive Species** | FAO 2001 |
| **Cyclone** | FAO 2001, FAO 2006 |
| **Poor managements** | IPCC 2003c, IPCC1996 |

The analysis suggests that most of the definition of forest degradation from literature includes reduced crown cover of the forest as well as loss of biodiversity in their descriptions.

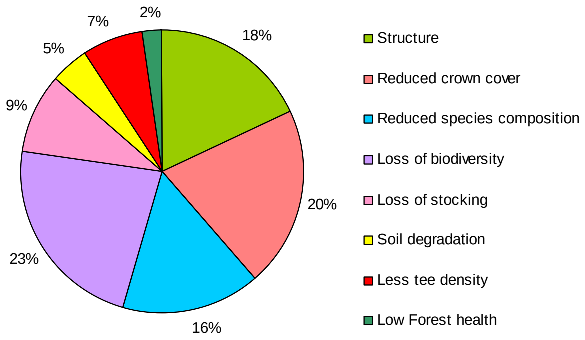


**Figure 12**. Parameters of forest degradation mostly covered by literature review

### 3.2.2. Community Perception on Forest Degradation

Analysis of the interview data revealed that most of the FUGs were not clear about the distinction between "deforestation' and "degradation". The forest definitions as described by the local users were mainly concentrated on forest fire and timber smuggling.

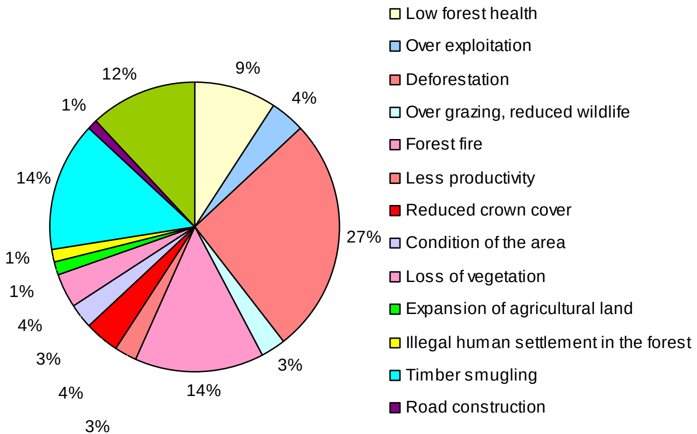


**Figure 13.** Parameters of forest degradation mostly described by FUGs

### 3.2.3. Expert Knowledge

About 10 foresters were interviewed with an open ended questionnaire to gain their perception on the definition of forest degradation as well the underlying causes and indicators of degradation. It was noticed that same as literature review, their description of forest degradation mainly focused on reduced canopy cover and loss of biodiversity.

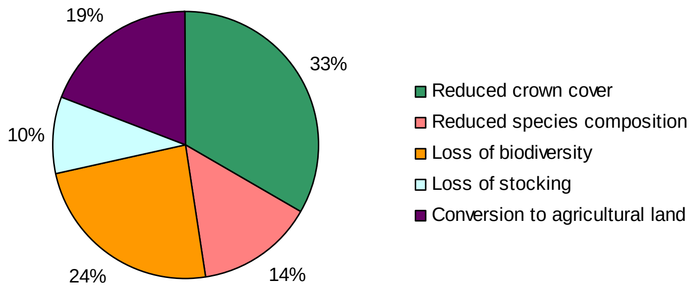


**Figure 14.** Parameters of forest degradation mostly defined by national experts

### 3.2.4. Comparison of Results

Comparison of the results was based on graphical analysis of degradation definitions as regards to causes of degradation, observed changes in the forest due to it, reduction in its capacity to provide functions on a temporal scale and the results are illustrated below.

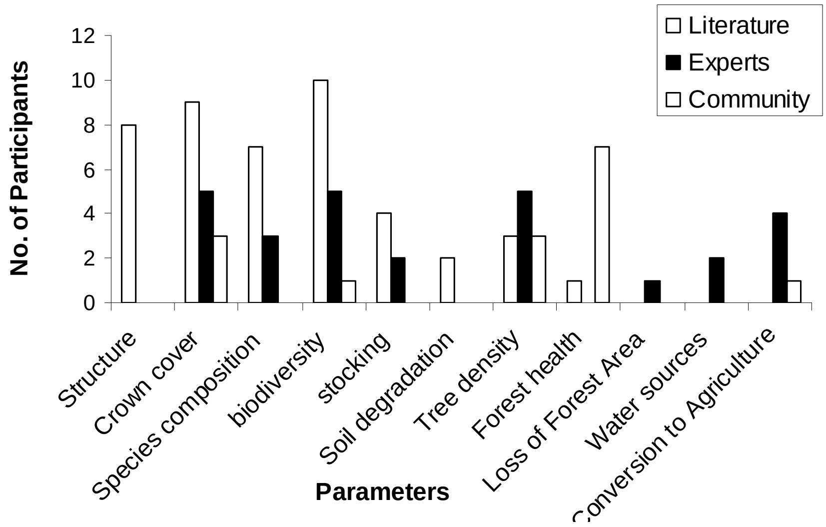


**Figure 15.** Changes within the forest as the result of degradation

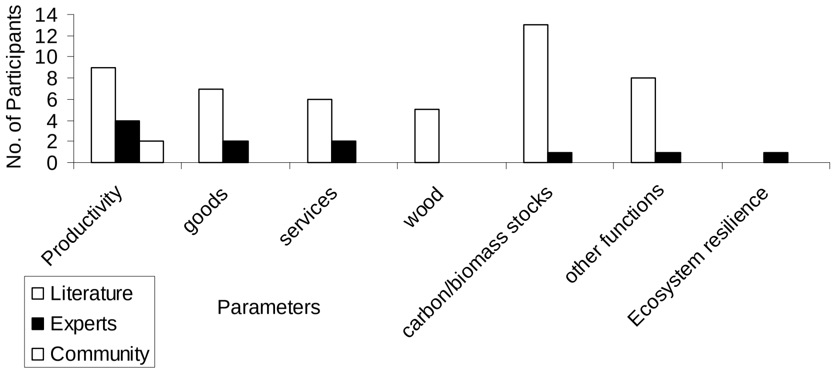


**Figure 16.** Forest services lost due to forest degradation.

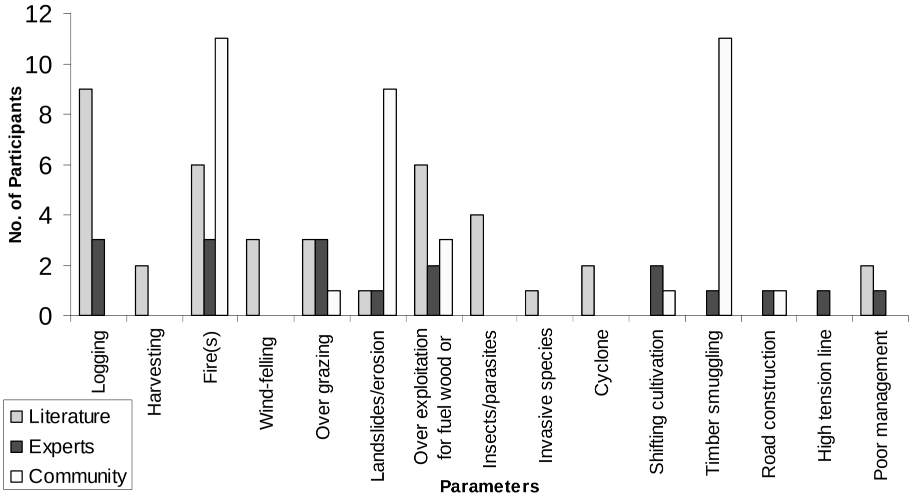


**Figure 17.** Causes of forest degradation.

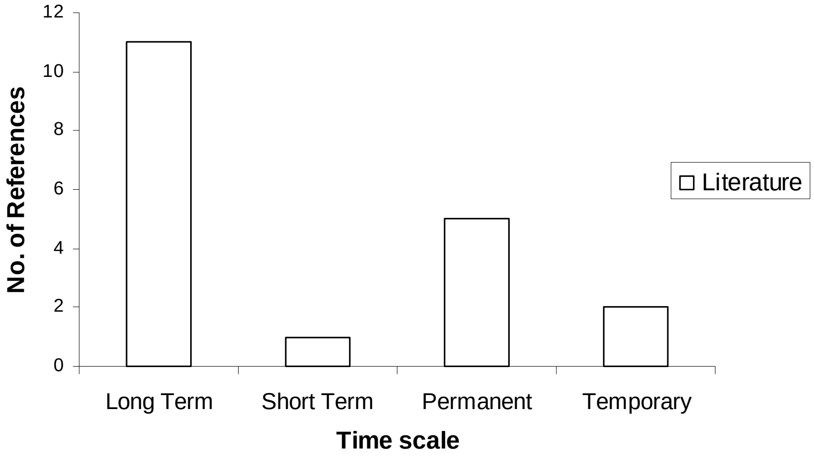


**Figure 18.** Duration of forest degradation according to the literature

**Most common definition** of the forest degradation according to Literatures, Expert and Local People:
Forest degradation is "**change in crown cover and loss of biodiversity**" caused as a result of "**logging and forest fire**s" which reduces the "**carbon stock and productivity**" of the forest for a "**long term**".

### 3.3. Distinguishing Managed and Unmanaged Forest using Remote Sensing Data

Remote sensing and GIS tools were employed in analyzing degraded and non-degraded forests, which requires knowledge of the structure and function of forest and their condition that varies their reflectance properties.

### 3.3.1. Spectral Signature Separability

The classification phase started with the unsupervised classification to observe if the pixels of both degraded and un-degraded forests in the image would be classified into the same category. Results revealed that there was not much distinction in distribution of the classes for both the forest types, which is shown in the image below (Fig. 19). During classification some clusters fell into both the classes which were identified as crossovers.

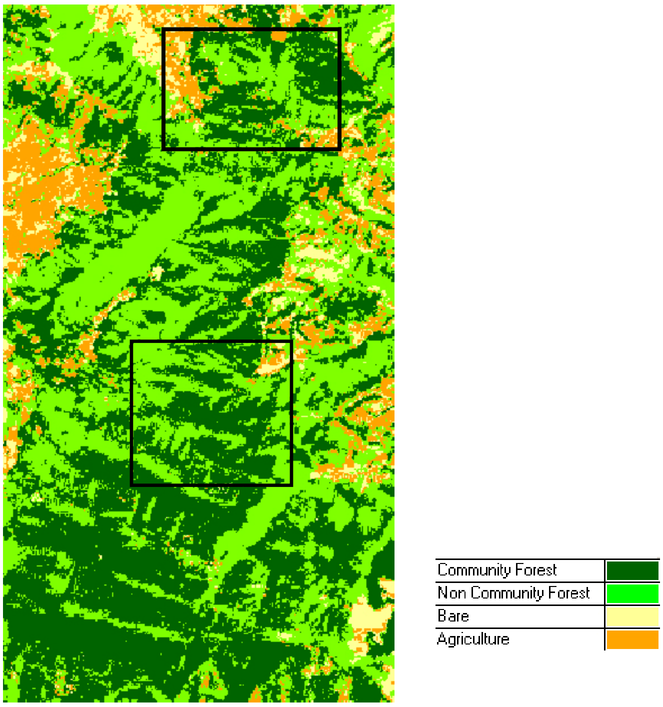


**Figure 19.** Unsupervised Classification of ASTER image showing CF and NF

Supervised classification was carried out in the second stage where 50 datasets were taken for calibration and 100 sets for validation data (Figure 19). Degraded and non-degraded forests were assigned into 2 different classes to analyze their spectral separability using statistical and non-statistical measures.

### 3.3.2. Accuracy Assessment

The accuracy assessment and Kappa statistic suggests good classification (supervised) results that has been presented in the Table 6 below.

**Table 6.** Accuracy Assessment of Supervised Classification

| Class | Managed Forest | Agriculture | Unmanaged Forest | Bare |
|---|---|---|---|---|
| Producers Accuracy | 77.5 | 100 | 86.21 | 85 |
| Users Accuracy | 88.57 | 83.33 | 71.43 | 100 |
| Kappa for each Category | 0.8082 | 0.8146 | 0.5959 | 1 |
| Overall Accuracy | 83.84% | | | |
| Overall Kappa | 0.7713 | | | |

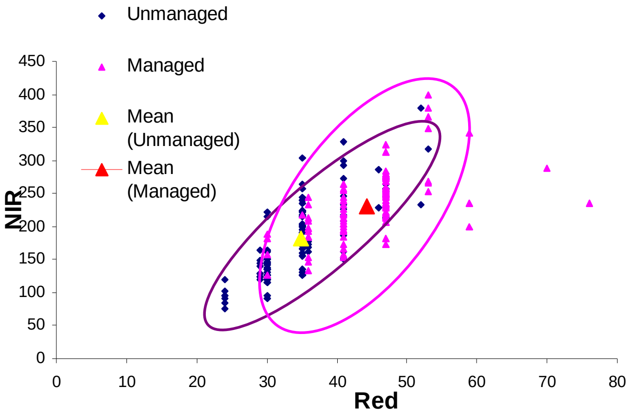
The overall accuracy is 83.84% while the overall Kappa is 77.13% i.e. 77.13% better than chance. The cell size used here was 15m i.e., the cell size of ASTER image.

### 3.3.3. Statistical Method of Feature Selection

The results of identification of managed and unmanaged forest features analyzed spectrally and statistically are explained below.

**1. 2D Scatterplots**

The reflectance value of the 100 random points were extracted from managed and unmanaged forests in ASTER image and were compared for two bands at a time till all possible combinations became exhausted.



(a)

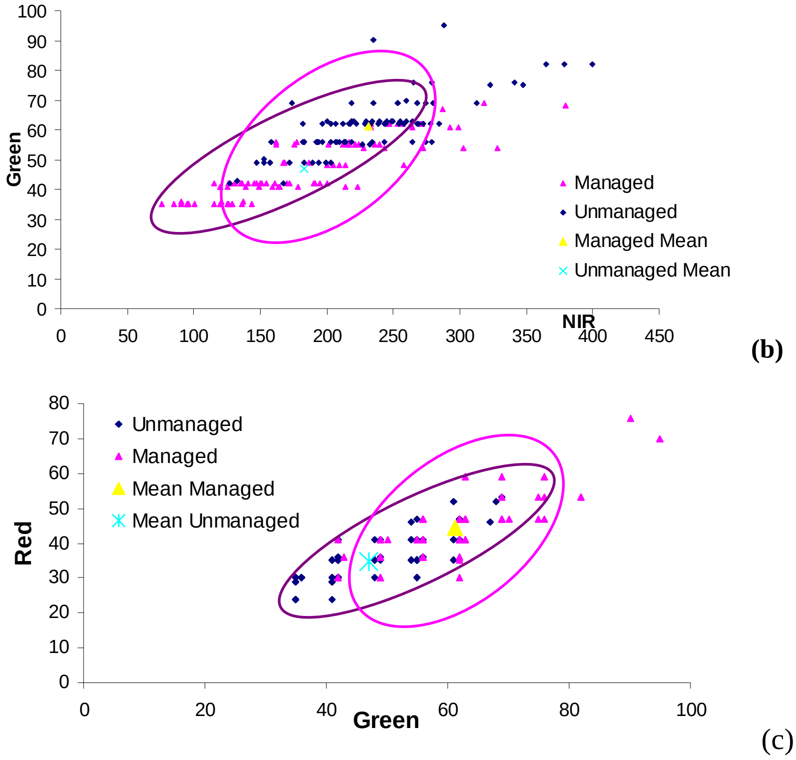


**Figure 20.** 2D Scatter plots of the reflectance values plotted between (a) NIR and R band (b) Green and NIR (c) Red and Green

It was observed that there was significant overlapping between the reflectance values in all band combinations. The drawback of 2D scatter plot is that each graph has to be prepared and evaluated for each band combination and it is possible to visualize the training statistics only in 2 bands at a time (Jenson 1986).

### 2. Box Plot Diagram

Box plots were constructed which graphically depicted groups of reflectance data of managed and unmanaged forests through their five-number summaries (the smallest observation, lower quartile (Q1), median, upper quartile (Q3), and largest observation) (Fig. 22). The indicated outliers can be seen as text in the figure.

Box plot graph shows difference in 2 datasets, without making any assumptions of the underlying statistical distribution. The spacing between the different parts of the box specify variance. Third quartile of the reflectance in band 3 of unmanaged forest is near to the median of the reflectance in the managed forest in the same band. This might suggest slightly higher reflectance in managed forest than unmanaged forest. However, in Band 1 and 2, there was no distinction.

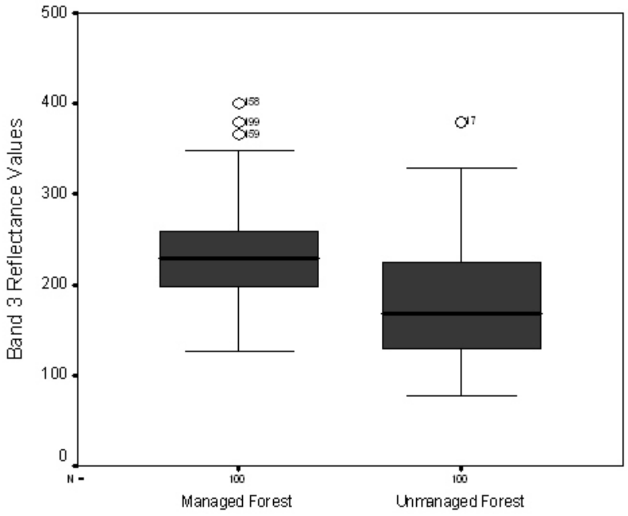


**Figure 21.** Box plot diagram of Band 3 reflectance of CF and NF

### 3. Coincident Bi Spectral Plot

Coincident bi spectral plots were constructed where training statistics for 2 forest types were displayed in all 3 bands. This display was used to identify between-class separation for each class and band (Jensen 1979) using the mean, lower and upper threshold values for each class in each band. This display revealed separation between each class in each band using the mean and the variance of the data sets was not applicable in this case.

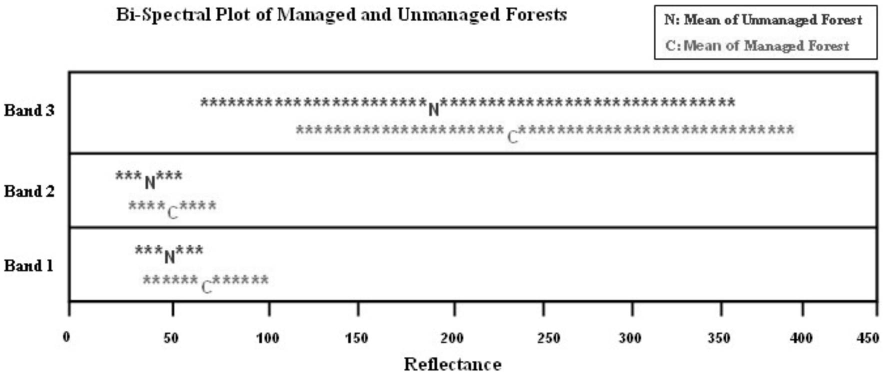


**Figure 22.** Coincident bi spectral plot

### 4. Transformed Divergence

The values of transformed divergence are presented below:

**Table 7.** Values of transformed divergence

| | **Bands** | | |
|---|---|---|---|
| **Class Pairs** | **1** | **2** | **3** |
| **CF_NF** | **999** | **432** | **1439** |
| CF_Bare | 2000 | 901 | 106 |
| CF_AGR | 1993 | 2000 | 1735 |
| NF_Bare | 2000 | 2000 | 1639 |
| NF_AGR | 2000 | 2000 | 538 |
| Bare_AGR | 2000 | 2000 | 1740 |

As mentioned in the methods section, transformed divergence value of 2000 suggests excellent separability between classes; 1700 to 1900 means good separability and below 1700 is poor separability. The values of transformed divergence in all bands were below 1700 suggesting there is a poor separability between these classes

### 5. Jefferies-Matusita

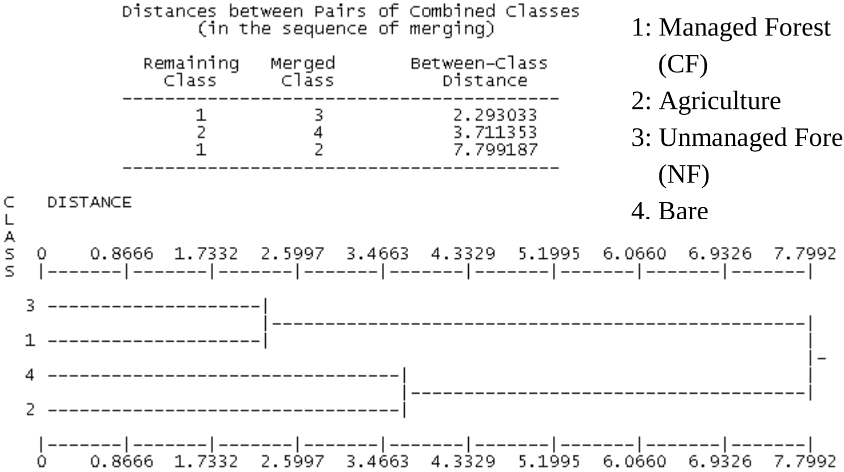
**Table 8.** Values of Jefferies-Matusita

| | **Bands** | | |
|---|---|---|---|
| **Class Pairs** | **1** | **2** | **3** |
| **CF_NF** | **727** | **486** | **817** |
| CF_Bare | 1335 | 1385 | 105 |
| CF_AGR | 1302 | 1369 | 995 |
| NF_Bare | 1361 | 1391 | 853 |
| NF_AGR | 1393 | 1393 | 639 |
| Bare_AGR | 1187 | 1216 | 1015 |

The values of Jefferies-Matusita range from 0-1414. The results showed poor separability between managed and unmanaged forests. This indicates that the two signatures are statistically very close to each other.

**6. Dendogram**

The output dendrogram is given below:



```
          Distances between Pairs of Combined Classes
               (in the sequence of merging)

            Remaining   Merged        Between-Class
              Class      Class           Distance
          ----------------------------------------
              1          3             2.293033
              2          4             3.711353
              1          2             7.799187
          ----------------------------------------
C   DISTANCE
L
A
S  0    0.8666  1.7332  2.5997  3.4663  4.3329  5.1995  6.0660  6.9326  7.7992
S  |-------|-------|-------|-------|-------|-------|-------|-------|-------|

  3 --------------------|
                        |--------------------------------------------------|
  1 --------------------|                                                  |
                                                                           |-
  4 --------------------------------|                                      |
                                    |--------------------------------------|
  2 --------------------------------|

   |-------|-------|-------|-------|-------|-------|-------|-------|-------|
   0    0.8666  1.7332  2.5997  3.4663  4.3329  5.1995  6.0660  6.9326  7.7992
```

**Classes**

1: Managed Forest (CF)

2: Agriculture

3: Unmanaged Forest (NF)

4. Bare

**Figure 23.** Dendogram of CF (1), NF (3), Bare (4) and Agriculture (2)

The results suggest that classes 1 (managed forest) and 3 (unmanaged forest) are the nearest neighbours in attribute space; therefore, they are merged at level 2.293033. This value indicates the relative degree of similarity, which can also be viewed as the distance in multidimensional space.

### 3.3.4. Graphical Method of Feature Selection

After creating the signatures of four classes (Managed, Unmanaged, Bare and Agriculture) during supervised classification, these signatures were evaluated between all VNIR band combinations in a feature space and the results are presented in Fig. 24. Scattergrams provided an in-depth understanding of the spectral nature of the signatures being analyzed. Examining the graphs suggests that there is substantial overlap between class 1 and 2 in all bands.

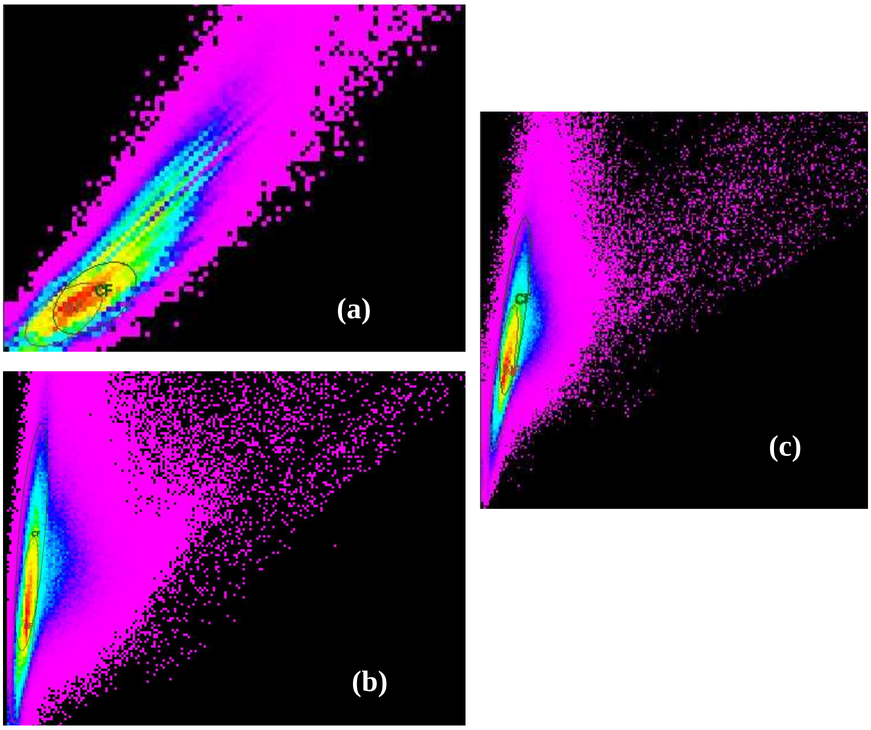


**Figure 24.** Feature space images with two band combinations (a) 1-2 (b) 2-3 (c) 3-1

### 3.3.5. FCD Modelling and Mapping

Since most of the literatures and experts explained forest degradation as loss of canopy cover, FCD mapper was approached as an image processing technique to analyse canopy cover density in both managed and unmanaged forests. The larger subset of radiometrically corrected Landsat image (from 2001) was taken so that both managed and unmanaged forests were covered in the image being processed.

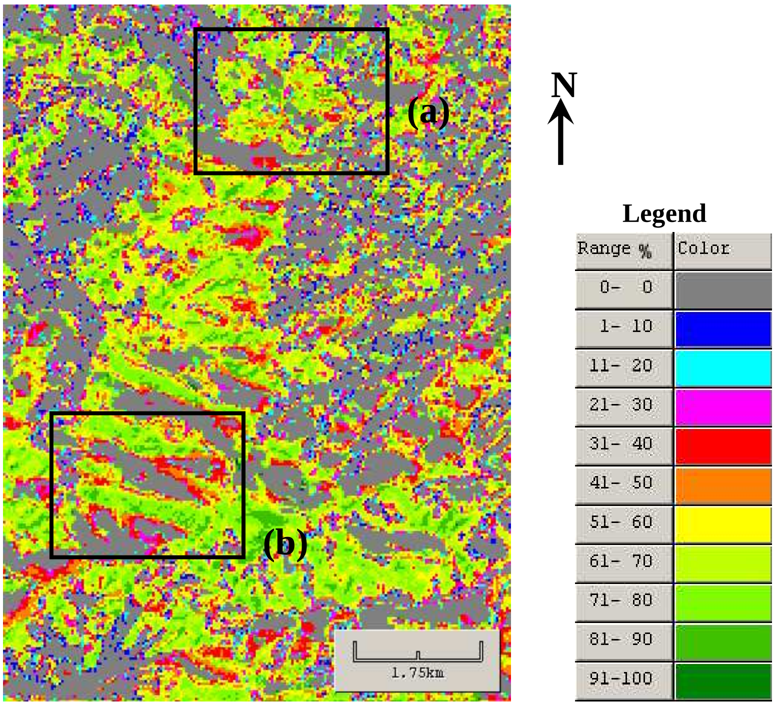


**Figure 25**. FCD map showing values ranging from 0-100% as shown in the Legend. Here, (a) Managed Forest and (b) Unmanaged forest

Using four indices i.e., AVI, BI, SI and TI, the canopy density for each pixel was calculated in percentage. The output was 10 canopy density classes ranging from 0-1, 1-10,…….., 9-10 in both managed and unmanaged forests as seen in Fig. 2 The descriptive statistics of the FCD data are presented in the table below.

**Table 9.** Results of FCD data showing descriptive statistics

| Class | Min (%) | Max (%) | Mean | Standard Deviation | Sum of total pixel values | No of Pixels | Avg FCD value of pixel (%) |
|---|---|---|---|---|---|---|---|
| Managed Forests | 9 | 99 | 56.88 | 24.54 | 70680 | 897 | 78.79 |
| Unmanaged Forests | 7 | 99 | 60.01 | 23.30 | 165577 | 1964 | 84.30 |

The error statistics of the linear regression models are given in Table 10. The table shows the coefficients of determination ($R^2$) between the estimated and observed FCD values. The $R^2$ of observed and predicted FCD was 0.026 showing very poor relations. RMSE value obtained was 50.97 %. An unbiased predictor would be expected to have a slope (b) of 1 and intercept (a) of zero (Joshi et. al 2006). The results show that there is biasness in the prediction.

**Table 10.** Error statistics of FCD mapper

| **Method** | **$R^2$** | **Intercept (α)** | **Standard error$_α$** | **$t_α$** | **Slope (ß)** | **Standard error$_ß$** | **$t_ß$** | **Standard error of estimation** | **RMSE** |
|---|---|---|---|---|---|---|---|---|---|
| **FCD mapper** | **.026** | **70.23** | **5.48** | **12.81** | **-.077** | **.092** | **-.835** | **19.071** | **50.97%** |

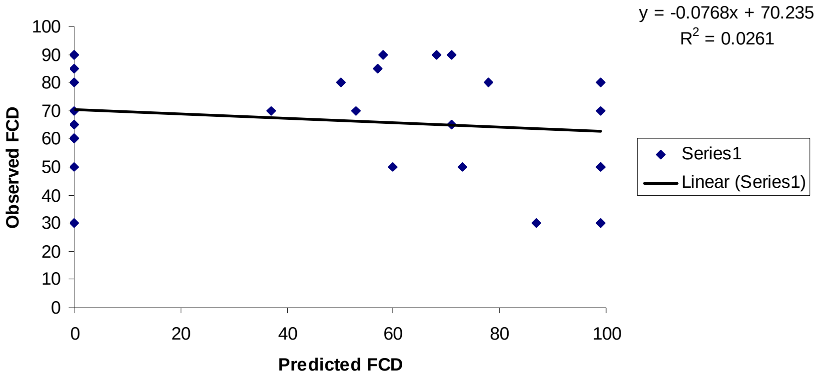


**Table 11.** Linear regression between observed and predicted FCD values in the sample plots.

# 4. Discussions

## 4.1. Biomass Estimation by FUGs Vs. Satellite Images

**Research Question 1.** What is field estimated average biomass value for 2007 from the community forests?

**Research Question 2.** Is there a significant relationship between the carbon estimated from the satellite based image compared to the field measurement of biomass/carbon?

Based on the estimated biomass of the plots, the average biomass per hectare basis was calculated to be 94.75 tones/hectare of AGB for 2007. The estimated biomass for the forest in the present study was comparable to those in previous studies for similar forest types. The biomass value detailed by Fang et al. (1996) in (Zhang et al. 2007) and Zhang et al. (2007) for ever green broad leaved forest were 133 tones/per ha and 89.19 tones/per ha respectively, which shows some degree of similarity to the values estimated in this study.

Empirical relationships between plot biomass data and SVIs were developed using correlation and linear regression analysis. The visual interpretation and $R^2$ of the scatter plots of these correlations fail to depict any relationship between biomass estimated from the field and the reflectance variables from ASTER, which corresponds to the results of Mabowe et al. (2006).

The underlying cause for the weak correlation between the biomass data from 2007 and ASTER SVI could be attributed to many factors, one of which is an increase in biomass density in the study area over the past 4 years from 2004 to 2007, which was revealed in the Table 12 and Figure 26. Moreover, seasonality and the time difference between the year of image acquisition and field data collection may have introduced some error (Joshi et al. 2006). Also factors such as shadows cast by larger tree crowns greatly influence the reflectance (Lu 2005) and leads to spurious estimates of carbon value. After the initiation of community forest program in the region, forest density has improved significantly contributing to an increase in biomass volume as well. This increase in forest biomass carbon can be noted as evidence that this community forest is functioning as a significant carbon sink.

**Table 12.** Increase in Biomass (Kgs) in the Permanent plots from 2004-2007[3]

| Plot No. | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|
| Plot 1 | 1946.48 | 1969.88 | 2128.98 | 2339.82 |
| Plot 2 | 1793.88 | 1407.41 | 1673.65 | 2174.33 |
| Plot 3 | 1436.93 | 1553.05 | 1300.81 | 1410.87 |
| Plot 4 | 1908.56 | 2236.19 | 2799.13 | 2817.02 |
| Plot 5 | 1770.31 | 1750.83 | 1819.50 | 1951.68 |
| Plot 6 | 3402.13 | 2945.59 | 2745.57 | 3210.54 |
| Plot 7 | 653.20 | 892.85 | 980.57 | 795.87 |
| Plot 8 | 832.16 | 1015.14 | 899.73 | 689.21 |

(Source: Data from 2004-2006 from Karky, B.S. 2007 Karky, B. S. 2007)

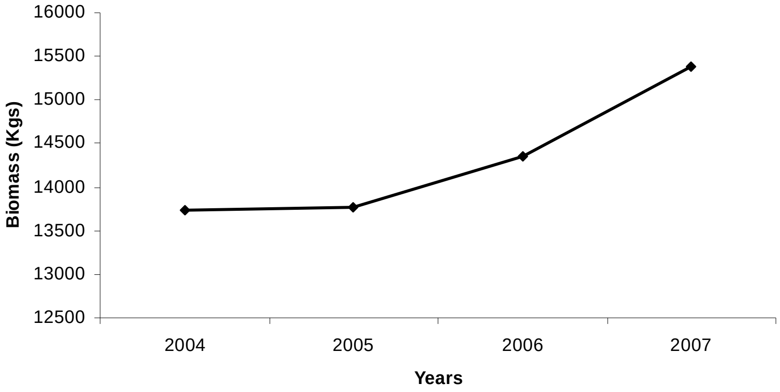


**Figure 26.** Increase in total biomass in permanent plots from 2004-2007

All of the SVIs were moderately correlated with the 2004-2006 data. However, this correlation coefficients results can be misleading due to very small size of the sample size considered for the statistical analyses. Due to the lack of sufficient field measurements data of biomass from previous years, validation of the result was not possible in this study.

The best relation was observed with SR ($R^2$=0.44) among other tested VIs in the year 2004. The results are in agreement with Heiskanen (2006) and Lu et al. (2004), who found the strongest correlations between biomass and SR. Mutanga and

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[3] Biomass value converted from 100m$^2$ to 225m$^2$ to match with ASTER pixel size

Skidmore (2004) also had similar results where SR yielded the highest correlation coefficients with biomass as compared to NDVI and TVI.

There is numerous vegetation indices developed and used in many studies. However choosing the best VI for biomass estimation model using remote sensing data hasn’t been properly understood (Lu et al. 2003). Some SVIs like NDVI exhibit a saturation problem in the relation between biomass showing its limitations in correct estimation of biomass. NDVI reaches a saturation level after certain biomass density increase (Tucker 1977; Gao et al. 2000; Smith et al. 2005). This problem is well explained by Mutanga and Skidmore (2004) that when forest canopy cover increases upto 100%, there is an increase in NIR reflection because of increase in leaf numbers but decrease in the red reflection because the amount of red light that can be absorbed by leaves reaches a peak. This imbalance between the increase in NIR and slight decrease in red contributes to a change in NDVI value yielding poor biomass estimates (Tucker 1977; Thenkabail et al. 2000). The community forest under study had high canopy density. The linear equation found in this study also implied this limitation. Mutanga and Skidmore (2004) suggest that SR may be a better index for estimating biomass in dense canopies.

A high-quality source of data is a prerequisite for developing biomass estimation models using remote sensing data (Lu 2006). The allometric equations that relate biomass of several tree components to diameter at breast height (dbh) are used to estimate biomass values (Foody et al. 2003; Brown 1997; Popescu 2007; Wang 2006). Many uncertainties exist in this method (Ketterings et al. 2001 in Lu 2006) because of different means of field measurements adopted, inconsistency of data collection dates/years with that of the image, complex tree species composition for developing allometric equations. Therefore, validation of the calculated AGB is necessary (Lu 2006).

Estimation of biomass also relies on other factors such as economic circumstances of the researcher, limitation of remote sensing data in spectral, spatial, and radiometric resolutions, forest structure, quality and quantity of sample plots, selection of suitable variables along with the proper modelling algorithms (Lu 2006). Logistic factors have directly influenced this study with the limited number of collected biomass sample plots which affect the calibration of AGB estimation models and validating the estimation results. Also the images from the year of the field work could not be purchased for the study due to limited budget.

In remotely sensed data, radiometric and atmospheric correction is an important task (Lu 2006; Mather 1999). In a mountainous region like Nepal, “topographic factors such as slope and aspect can considerably affect vegetation reflectance, resulting in spurious relationships between AGB and reflectance” (Lu 2006). It is also important to ensure that satellite images, ancillary data, and sample plots are accurately registered before implementing biomass estimation (Lu 2006). The topographic effect on vegetation reflectance as well as probable errors in the geometric correction and GPS reading could also be accounted for other reasons of weak results in the current study. Atmospheric factors and other sources of error can lower the accuracy of GPS receivers (Garmin 2008).

## 4.2. Definition of Forest Degradation

**Research Question 3.** What is the most commonly used definition of forest degradation by the International bodies and national forest experts? How similar is it with those understood by the community forest user groups?

Analysis of the interview data from the community revealed that most of the FUGs were not clear about the distinction between “deforestation’ and “degradation”. The reason behind this is lack of awareness among the community over different criterias set by the International standards in defining forest degradation and deforestation.

The definition of forest degradation can be quite confusing as most of the literature and experts do not give a clear-cut distinction between degradation and deforestation To understand both these phenomena it is important that the community understand the meaning of a forest first. Most commonly understood definition of forest degradation by the International body and the national forest experts are related to change in crown cover and loss of biodiversity. The definitions provided by the local users on forest degradation include low forest health, deforestation, forest fire, less productivity, reduced crown cover, condition of the area, loss of vegetation, expansion of agricultural land, illegal human settlement in the forest, timber smuggling, road construction, etc. The result indicates description of forest degradation given by FUGs include important indicators of forest degradation as set by the International bodies and those understood by the forest experts such as reduced crown cover and reduced biodiversity. However, there lies a difference in basic understanding of difference in degradation and deforestation among the forest user groups.

## 4.3. Indentification of Degraded Forest using Remote Sensing Data.

**Research Question 4. Can degraded forests be easily distinguished from non-degraded forests using satellite imagery?**

Forest degradation is believed to be more serious in national forests than in community forests in Nepal (Pandit and Thapa 2004). And the assumption of the study was that the changes between these two forests types could be detected using remote sensing data.

However, it was not possible to distinguish spectral reflectance of these two forest types using statistical and graphical method.. The possible reasons are explained in the paragraphs below.

### 4.3.1. Statistical and Graphical Method of Feature Selection

During feature selection with use of statistics, degree of overlap was noticed in all band combinations. This indicates that the two signatures are statistically very close to each other. Examining the ellipsoids also suggests that there is a substantial overlap between class 1 and 2 in all bands. Had these 2 forest types shown sufficient difference in spectral responses, image pixels consisting of these classes would have formed two separate clusters of data points in the feature space allowing individual identification of each forest types. The overlapping of the cluster in the ellipse implies that in this case, feature selection method failed to represent distinct sets of pixels in the two bands (combinations) being plotted. Low signature separability is usually caused because the training sites have large internal variability within each class as stated by Richards (1986).

Community forest in this study is the forest which is sustainably managed by the local users hence there are no indicators of forest degradation. On the other hand, national forests taken into account for the study are not managed by the local users. Also due to lack of proper institutional arrangements, including the lack of a comprehensive government policy framework for sustainable use and management (Pandit and Thapa 2004), forest degradation is a major issue in these forests.

Identifying forest degradation using remote sensing data is more difficult than identifying deforestation. Reflectance data from different forest types (degraded and non-degraded) are expected to vary in terms of their reflectance values. However, differences in reflectance between degraded and non-degraded forests are subtle than in the case of deforestation (Wulder and Franklin 2007). Moreover, patches of forest degradation are generally small compared with deforested areas. Due these reasons, methods for monitoring degradation have not been well established as those for monitoring deforestation (DeFries et al. 2006).

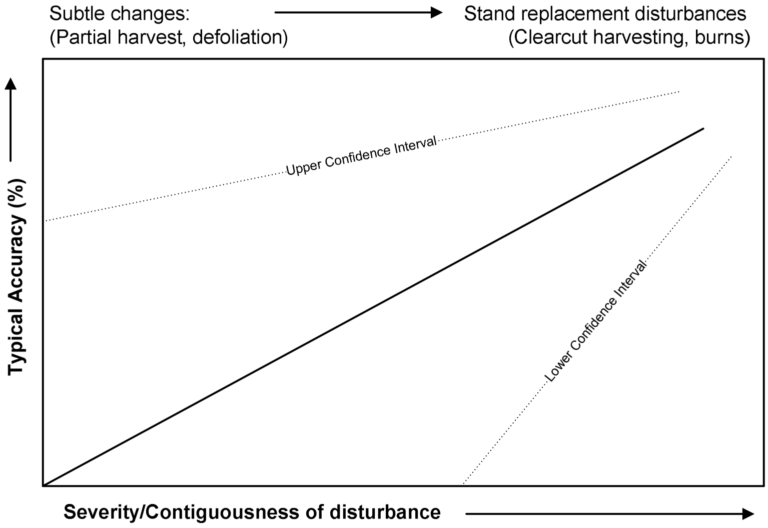

**Figure 27.** Theoretical representation of the increase in accuracy and decrease in confidence intervals (assuming equal sample sizes) associated with forest disturbance detection as disturbances on the forest landscape become more severe (e.g. increase in size) or more contiguous. (Source: Wulder and Franklin 2007, pp55)

Distinguishing managed and unmanaged forests was not possible as the results did not exhibit unique multivariate properties that were separable from each other. This has been pointed out by Wulder and Franklin (2003) that separating spectral signature approach in forests has been less successful as the vegetation canopies tend to be made up of the same organic compounds and canopy architecture has greater impact on canopy and the reflectance. The authors added that “additional” environmental data are required to add dimensionality for discriminating closely related classes of interest.

The possibility of detecting forest degradation in a remotely sensed data depends largely on the rate, magnitude and spatial extent of the forest degradation. Stand replacements such as forest fire and clear cut logging are easily detectable due to its large visible extent and major vegetation changes. Whereas subtle changes such as selective logging, partial harvesting are difficult to be captured using satellite images (Wulder and Franklin 2007). Moreover the spectral variability of these disturbances is greater, making it for difficult to detect using remote sensing data (Wulder and Franklin 2007). For instance logging of 100 ha of forest area has “higher detection likelihood” than logging that has occurred in 10 ha of forest. Hence, the accuracy with which subtle changes in the forest is mapped is lower than mapping large changes. The detectability factor of forest degradation also depends on the relationship between spatial resolution of the sensor used and the objects of interest (Wulder and Franklin 2007). For instance a fine resolution image such as IKONOS or Quickbird might have been successful in identifying degraded forest in smaller area, whereas the same changes cannot be easily captured in an image having less resolution such as ASTER and Landsat which were used in this study.

### 4.3.2. Estimation of Forest Canopy Cover using FCD Model

FCD mapper was used to examine the degree of degradation in the national forests as canopy density is based on the growth phenomenon as mentioned by Rikimaru et al. (1999). The result indicates absence of huge variation within 2 datasets as shown in the table 9. However, the average pixel FCD values from the unmanaged forest tend to be higher than that of managed forest. The reason can be well explained by the fact that these values are based on 2001 Landsat image. Community forest programs initiated during mid-1990s in Nepal. Hence, the condition of forests compared to the present situation was not of good quality. Higher FCD value in unmanaged National forests could be as a result of forest guarding carried out by the Nepalese Army, whose headquarter is based at the peak of this forest area.

The main reasons for errors in the model is due to a huge time difference between the date of image acquisition (2001) and field data collection (2007), which is explained by Joshi et al (2006) as well.

The main drawback of using FCD model is requirement of preliminary knowledge of the study area to input the threshold values according to vegetation type and terrain condition of the area, which seem to be in agreement in studies carried out by Joshi et al. (2006). This method has not been considered reliable or accurate but has been proposed to be used as a quick estimation method in cases where there are no alternatives by Joshi et al. (2006). Therefore, it has been used for the same purpose in this study.

# 5. Conclusions and Recommendations

## 5.1. Conclusions

The summary of conclusion of the study is listed below.

1. Based on the field estimated biomass of the plots, the average biomass (from the plots) on per hectare basis was calculated as 94.75 tonnes/hectare of AGB for 2007. The study showed that KCF is relatively stable in terms of the forest carbon storage since 2004.

2. This research indicates that satellite-based biomass estimation methods does not exhibit good correlation with the field based measurements in community forests and could not provide reliable and accurate information about forest carbon in the study area. However, given that the seasonality and the time difference between the year of image acquisition and year of field data collection is not too long, the coefficient of determination can be improved.

3. International and expert definitions of forest degradation slightly differ with those described by the local users. Loss of biodiversity and loss of forest canopy cover are the most common indicators of forest degradation according to the International definitions on forest degradation as well as expert knowledge. However, the community users are not aware about the distinction between deforestation and degradation.

4. Distinguishing managed and unmanaged forests using remotely sensed data using the statistical and graphical feature selection methods didn’t reveal any separability between two forest classes. The possibility of detecting forest degradation using remotely sensed data depends largely on the rate, magnitude and spatial extent of the forest degradation. Stand replacements such as forest fire and clear cut logging are easily detectable due to their large visible extent and major vegetation changes. Whereas subtle changes such as selective logging, are partial harvesting are difficult to be captured using satellite images. New RS tools are under development (see below in future direction).

However, in spite of inaccuracies and uncertainties, satellite images can still be an effective tool for understanding forest environment in Nepal, where use of traditional methods based on field measurements might be not be viable because the feasibility of study of forests spread all over the mountains is not only difficult but is expensive. In such a case, remote sensing could be the only cost effective and reliable measure for the forest study at local as well as national level.

## 5.2. Future Direction

Future research is needed to improve the AGB estimation as well as identification of forest degradation using remotely sensed data. Hyperspectral images may improve AGB estimation performance because of its large number of spectral bands with very narrow wavelengths. The potential of forest biomass mapping has also been explored using RADAR (Gaveau et al., 2003; Tomppo et al. 2002) along with JAXA ALOS-PALSAR L-band (24 cm wavelength), which gives lower range of biomass (upto 50-80 t/ha). According to FAO (2008), BIOMASS mission, which is expected to launch around 2014 by ESA uses a longer wavelength (68 cm) and shows potential of estimating higher levels of biomass/carbon.

The basic principles employed as a part of this study, in identifying forest degradation using remote sensing data should be used for future investigation of the new methods to allow more comprehensive study on differentiating managed and unmanaged forests. It is essential that research continues to improve the detection and mapping of forest degradation by making significant progress in improvement, development and implementation of approaches to integrate satellite remote sensing methods in forest inventory, survey and monitoring. Analyses of time-series satellite images can one of the measures to address these information needs. Likewise development of state of the art technologies like LIDAR, RADAR represents a significant milestone in ongoing research of forest degradation under REDD.

Finally, fostering cooperation between communities and government, to promote knowledge and understanding of forestry degradation, and to find methods for rehabilitation of the degraded forests would help increase the potentiality of community forests as a carbon sink.

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