AIRBORNE LIDAR DATA AND VHR WORLDVIEW SATELLITE IMAGERY TO SUPPORT COMMUNITY BASED FOREST CERTIFICATION IN CHITWAN, NEPAL

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February, 2013

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Enschede, the Netherlands, February, 2013

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resource Management

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ABSTRACT

The sustainable management of forest (SFM) cannot be done without understanding of the ecosystem as a whole. In doing so, SFM demands accurate and up-to-date information, which usually involves a system of criteria and indictors. The certification system of SFM based on criteria and indictors has emerged as powerful tool to produce progress reports towards monitoring and assessment of SFM. However, studies have proved that there is still lack of an accurate estimation of criteria and indictor to support SFM, particularly using high resolution remote sensing techniques. This study aims therefore to explore the role of LiDAR and Worldview-2 satellite imagery using object based image analysis (OBIA) for estimating and mapping of three criteria and five indictors to assess the current community forest condition and sustainability in part of subtropical forest of Chitwan, Nepal.

The LiDAR point clouds data was pre-processed to generate a Digital Surface Model (DSM) and Digital Terrain Model (DTM). The DSM was generated from LiDAR first return data and DTM was derived from LiDAR last return. A tree Canopy Height Model (CHM) was computed as a difference between the DSM and DTM. The LiDAR derived tree height was plotted against the field measured tree height for accuracy assessment which was found to be RMSE of 3.2m and R^2 of 0.77.

Multi-resolution segmentation was used to extract the individual tree crowns from both LiDAR and Worldview-2 images in eCognition developer. An overall segmentation accuracy of 79% in 1:1 correspondence and 69% segmentation accuracy from D value were found. The resulted segmented polygons were further used for forest cover and tree species classification using the OBIA technique. Forest cover classification was done into two classes: forest area and non-forest area with accuracy of 94% and kappa statistics of 0.75 in Devidhunga, 86% accuracy and kappa of 0.72 in Janprogati and 82% accuracy and kappa of 0.7 for Nebuwater. Tree species were classified into six species and one broader classes “others” and resulted with accuracy of 67% and kappa statistics of 0.52.

A non-linear regression model was used to estimate and map Above Ground Biomass (AGB). The model resulted R^2 of 0.71 and RMSE of 22 Mg for *Shorea robusta* and R^2 of 0.79 and RMSE of 51 Mg for the other species. The power model was found to be best with R^2 of 0.74 and RMSE of 9.2 to predict DBH and in turn to estimate timber volume. The linear regression showed R^2 of 0.73 between the observed timber volume and predicted timber volume. Statistical methods were used to analyse indictors for forest condition and sustainability assessment. With regard to the rating of indictors, the species diversity and composition were comparatively low in Janprogati, and high in Devidhunga. However, the amount of above ground biomass and timber were found to be high in Nebuwater.

Together, airborne LiDAR remote sensing and Worldview-2 satellite imagery offers the ability to estimate and map these indictors and its associated criteria with reasonable accuracy for SFM and forest certification in tropical forest.

Key words: LiDAR data, Worldview-2 satellite, OBIA, C and I, Sustainable forest management, remote sensing

ACKNOWLEDGEMENTS

All praise goes to God the almighty, who has gave me the strength, health and determination to complete my MSc study, while living very far from home.

I would like to thank the Netherlands Government and the Netherlands organization for international cooperation in higher education (NUFFIC) for awards of fellowship to pursue my MSc study at ITC, Netherlands.

I am deeply indebted to Dr Yousif Ali Hussin, my first supervisor, for his patience guidance, continuous and positive suggestion and repeated correction, fatherly encouragement throughout the course of this study. Without his guidance this research would hardly have to come to completion.

I am very much indebted to Dr. Michael.J.C.Weir, my second supervisor for his excellent and motivating comments from very beginning till the compilation of this study and for your guidance and concern for all NRM students throughout the course.

Dr Hussin and Dr Michael, I will always remember both of you in those hard times and when you were encouraging me to work hard.

I am pleased to extend my sincere thanks to Dr.ir .C.A.J.M. (Kees) de Bie, for his critical constrictive comments during proposal and mid-term defence that assisted me to shape my research.

I cannot forget all my fellow NRM students: It has been a pleasure and good experience working with a diverse group from different parts of the world. I would like to extend my heartfelt thanks to my fieldwork mats: Marnes Rasel and Getachew Mahari, who shared together the tough and cheerful moments and for always working together and help each other during the field work.

I would like to thank ICMOD project in Nepal for providing the necessary data and facilitated our field work.

I would like to dedicate my words for my beloved ones, my father and mother, for their prayer, my spouse Dawit for your patience during my absence, my sisters and brother: you have provide me much moral support to complete my MSc study from abroad. You have always special place in my heart. God bless you

Last but not least, I would like to thank all my friends here and abroad for their continuous support and for making me feel at home.

Metadel Fentahun Asmare
Enschede, the Netherlands
11th February, 2013

Dedicated to my father, mother and my little brother "Abraham"

"You are every reason and dream I have ever had"

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LIST OF ACRONYMS

AGB	Aboveground biomass
ANOVA	Analysis of variance
ANSAB	Asia Network for Sustainable Agriculture and Bio-resources
CBD	Convention on Biological Diversity
CF	Community Forest
CFUGs	Community Forest User Groups
CHM	Canopy Height Model
CO_2	Carbon dioxide
C & I	Criteria and indictors
CPA	Crown projection area
DBH	Diameter at breast height
DEM	Digital Elevation Model
DFO	District Forest Office
DoF	Department of Forests
DN	Digital Number
DSM	Digital Surface Model
D_T	Transformed divergence
DTM	Digital Terrain Model
FAO	Food and Agricultural Organization
FRA	Forest Resource Assessment
GHG's	Greenhouse gases
GPS	Geographic Position System
HCS	Hyperspherical Colour Sharpening
HPF	High Pass Filtering
ICIMOD	International Centre for Integrated Mountain Development
IHS	Intensity, Hue and Saturation
IPCC	Intergovernmental Panel on Climate Change
LiDAR	Light Detection and Ranging
MOFSC	Ministry of Forest and Soil Conservation
MSS	Multispectral data
NIR	Near Infrared band
NTFPs	Non-Timber Forest Products
OBIA	Object based image analysis
REDD+	Reducing carbon emission form deforestation and forest degradation and foster conservation, sustainable management of forests, and enhancement of forest carbon stocks
RGB	Red, Green and Blue
RMSE	Root Mean Square Error
SFM	Sustainable Forest management
VDC	Village Development Committee
VHR	Very high resolution
WGS	World Geographical System

1. INTRODUCTION

1.1. Background

The year 2011 was designated as 'The International Year of Forests' by the United Nations General Assembly. This has raised awareness of forests significant role particularly in global carbon cycle and climate change. Forests are regarded as a carbon sink. Photosynthesis is one of the processes by which it absorbs CO_2 and stores it as carbon in plants steam, leaves, twigs and roots. World forests ecosystem provide wide range of ecosystem services, which are vital on supporting life on earth (FAO, 2011b). Moreover, 31% of the world land surface is covered by forests which contain 283 Gts of carbon in biomass, 38Gts in dead wood and 317Gts in soil (top 30 Cm Litter) which exceed the amount of carbon in the atmosphere (IPPC, 2007).

However, forests are more than a carbon sink. They have been also increasingly important for local livelihood across the tropics that are living in and outside the forest. Local people use forest resources by clearing lands for agriculture and cutting trees to meet their daily needs for timber, shelter, fuel wood, fodder and traditional herbal medicines (FAO, 2003). Subsequent in time, the valuable ecosystem in recent decades has experienced a rapid decline in the total coverage area and species composition mainly due to deforestation and degradation (Santilli et al., 2005). Notably in tropical countries, since colonization, the negative result of tropical deforestation and degradation has been recognized (Fuller, 2006). Timber logging has exhausted tropical timber resources, which accounts together with deforestation for 12% of global anthropogenic CO_2 emission (Lagan et al., 2007). However, forests are renewable and still can be sustained through proper management. In doing so, forest management should focus on integrating state of the art with traditional ecological knowledge, generated and practiced by traditional societies over time (Tian et al., 2012).Traditional knowledge is a term that combines the knowledge, innovations and practices of indigenous peoples and local communities. It also includes the understanding of the use and management of forest species, and the broader understanding and management of forest ecosystem.

Nepal is a pioneer of handing over forest to local communities. Nepal's community forest has a long history of managing forest resource using collective efforts of the community. The management type has been taken as innovative community based approaches. Consequently, it has made significant contributions to poverty mitigation (FAO, 2011a). However, all tropical countries including Nepal are developing rapidly. This often causes great pressure on natural resources and especially on forest ecosystems. Developing indictors for forest status has been became a prerequisite which can be used as tool to monitor the progress of sustainable management of forest (ITTO, 2000). However, these indictors should not indicate the miss-use of forest resource; rather they should also highlight the extent of the problem that can allow the monitoring deforestation. They would also provide information on the trend and status of forest ecosystems for further monitoring of forest to decision makers. So in many instance practising SFM (Sustainable forest management) and forest certification requires precise and documented data about forest resource at a range of spatial and temporal scale. Remote sensing can provide a wealth of data that can support sustainable management of forest over large area (Rajitha et al. (2007). However SFM has been experiencing many problem due to lack of data in terms spatial and temporal scales which is vital for forest trend assessment over a large area (Held, 2001). This resulted in greater effort and interest to explore role of remote sensing in supporting sustainable community forest management and forest certification.

1.2. Definition and Concepts

1.2.1. Sustainable forest management

The Rio de Junerio Earth summit incited the world attention on sustainable forest management in 1992. Since then world international efforts towards implementing sustainable forest and ecosystems management have shown considerable development at different level (Jalilova et al., 2012). Many organizations have defined sustainable forest management in many ways, particularly to point out their objective. However all definitions share the essential elements of ensuring that the ecological functioning of forest resources that all living things enjoy today are available now and in the future. Moreover “Sustainability” is a concept specifically designed to bring together the different environmental, economic and social interests (Rametsteiner et al., 2003).

Two major “Post-Rio” moves of SFM

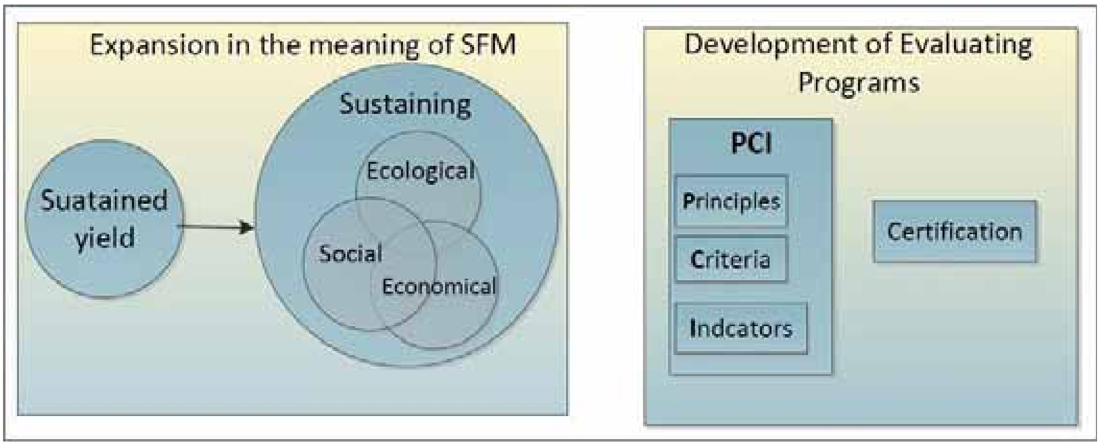


Figure 1 *Components of sustainable forest management (Source FAO, 2005)*

According to ITTO (2005) SFM is defined as “the process of managing permanent forest land to achieve one or more clearly specified objective of management with regard to the production of continuous flow of desired forest product and service undue reduction of its inherent values and future productivity and without undue undesirable effects on the physical and social environment”. SFM can also be defined as “It is the stewardship and use of forests and forest lands in a way, an at a rate of, that maintains their biological diversity, productivity, regeneration capacity, vitality and their potential to fulfill, now and in the future, relevant ecological economic and social functions, at local, national and global levels, and that does not cause damage on other ecosystems” (FAO, 1996) (Figure 1). To be able to apply the concept in a clearly and simply manner, different organizations of different regions and nations have developed their own guiding principles, criteria and indicators.

1.2.2. Forest certification system, Criteria and Indictors

Forest certification is relatively new concept which aim to promote sustainable forest management (FAO, 2002). However, it becomes a major activity in many developed countries and in number of tropical timber-producing countries. The principles of forest certification are almost similar to those of SFM. The aim of SFM is measuring and monitoring the status of forest while forest certification is a market-driven approach aimed at auditing and improving forest practice at forest level (Marx et al., 2010). Forest certification denotes two distinct processes: Certification of forest management and a chain of custody certification. This involves system of forest examination plus a means of assessing timber and non-timber forest product from raw material to finished product phase. Under the certification of forest management, “the certifier who is third party - gives a written assurance that guarantee environmentally, socially and economically viable forest product"(FAO, 2002). The chain of custody certification of forest product from certified forest is an important element of any certification. A certificate or label on the forest product indicates the consumer a confirmation that the product is coming from certified forest. At the global level, there are two certification schemes with different operating modalities. The Program for the Endorsement of Forest Certification (PEFC) is one among certification schemes which operates as a system for mutual recognition between national certification systems. Almost two-third (65%) of the world certified forests carry PEFC certificate, (Cashore et al., 2003) the Forest Stewardship Council (FSC), which provides all the necessary elements of certification through integrated decision-making system. All the forest certification systems based on a framework of criteria and indictors for sustainable forest management. Criteria and indictors are tools for assessing trends in forest condition and forest sustainable management (ITTO, 2005).

Criterion: It describes the essential aspect of forest ecosystem. Criterion is a principal element of sustainable forest management against which the forest features and sustainability is assessed (FAO, 2002)

Indicator: It measure specific quantitative and qualitative forest attributes and values. It show changes over time for each criterion and confirm how well each criterion reaches the objective (FAO, 1996). It helps to monitor trends in the sustainability of forest management over time (ITTO, 2005).

1.3. Forest and Forest management in Nepal

Forests have always been an essential part in the livelihoods of the rural people in Nepal. They are the source of fuel wood, timber, fodder, organic fertilizer and around 80% of energy in the country (FAO, 2011a). From the management viewpoint, Nepal's forest can be classified into: Government managed forest, community forest, leasehold forest (LF), religious forest (RF) and national park and reserve (NPR). However Community forest (CF) is one of the priority programs which were initiated in 1978. The program has been found to be effective to preserve the natural forest cover and improve its condition (SDC, 2010).The community forest program is aiming to achieve sustainable management of forest resource by converting national forests into community managed forest in step wise manner in Nepal. The involvement of stakeholder to manage forests as community forestry has become widely accepted along with the sustainable forest management framework.

1.4. Sustainable forest management and forest certification in Nepal

Forest certification plays a vital role in Nepal community forest. It is used as a vehicle to progress sustainable management of community forest and improves the livelihood of Community Forest Users Groups (CFUGs) by promoting forest products to the outside market. Targeting only Non Timber Forest Products (NTFPs) 10,045 ha of community managed forest were certified within the framework of FSC standard for implementing the forest management activity (ANSAB, 2010). Criteria and indictors(C&I) have been known as powerful tools in implementing SFM internationally (Jalilova et al., 2012). More than 150 countries are participating in timber certification (Wijewardana, 2008). All these member countries are arranged according to the region. These are

- The Pan-European and the Montreal processes for temperate and boreal forests
- Dry zone Africa process for arid zones forests
- The African Timber Organization (ATO) Process.
- The Near-east process
- Dry foresters in Asia

Dry forest Asia process was evolved in 1996 at Indian Institute of Forest management (IIFM) in Bhopal, involving representative of nine countries such as Bhutan, China, India, Mongolia, Myanmar, Nepal, Srilanka and Thailand. The Bhopal-Indian process is branch of ITTO. However, the experience of using C and I is rare in Nepal. There were no formal and official agreed set of national level C and I until FAO launched the process workshop in 1996 (FAO, 2000). After this FAO workshop, many have tried to develop criteria and indicator to implement and assess sustainability of community forest in Nepal. But still, a comprehensive and organized methodology is needed to involve all stakeholders and to increase the commitment of these stakeholders to use C & I for evaluating and assessing of sustainability in community based managed forest at any level (Khadka et al., 2012). The previously developed ITTO C and I of SFM has adopted at local level; under different donor assisted projects including ANSAB, FECOFUN, UNDP-IHEP, and CIFOR, all of which have been reviewed by FAO (FAO (2010). In addition to this recently Nepal also participated in the Bhopal-Indian process which aims to update the C and I dry Forest Asia process in line with ITTO Guidelines.

1.5. Reason for the choice of criteria and indictors

Different organizations are involved in certification of community forest of Nepal. Most international certification system includes seven criteria (FAO 2011b) which are:

1. Extent of forest cover and tree cover
2. Maintenance and enhancement of ecosystem function and vitality.
3. Maintenance and enhancement of forest resource productivity
4. Maintenance and conservation and enhancement of biodiversity
5. Conservation and enhancement of soil and water resource and other environmental function
6. Social-economic, cultural and spiritual needs
7. Policy and legal and institutional framework

However, there is a need to adjust C&I to fit the objective of sustainable forest management at local level (Orsi et al., 2011). For the sake of this study the C and Is used are re-phrased and adjusted in line with Bhopal-Indian process as well as the ITTO principles and guidelines to fit the objective and approach of Community forest management in Nepal and other prevailing local condition based on different studies and published literatures (ANSAB, 2010; Chiranjeewee et al., 2012; Khadka et al., 2012; Tambe et al., 2011). The present studies C & I's were adopt directly from ITTO and dry forests of Asia. Thus, in this study, three criteria and five indictors will be used to assess sustainability of selected community managed forests (*Table 1*).

Table 1 Selected criteria and indicators

Criterion	Indictor	Verifier
1. Extent of forest and tree cover	1.1. Forest cover types	- Area and forest types in the study area (ha).
2. Maintenance & enhancement of ecosystem function & vitality	2.1. Diameter Distribution(m) 2.2. Tree Species 2.2. Biomass (kg/tree)	- Tree species diversity and composition - Amount of AGB in the study area (kg).
3. Maintenance & enhancement of forest resource productivity	2.3. Timber Volume (m^3)	- Amount of timber volume in the study area (m^3).

Source:-(ANSAB, 2010; Indian Forest Reseach Institute and FAO, 2009; ITTO, 2011)

1.6. Extent of forest area

Extent of forest refers the concern of maintaining adequate forest type, cover and stocking to support the social, economic and environmental function of SFM. The extent of forest should be managed properly to reduce or deforestation. Thus the conservation of degraded forest, forest sustainability and function of carbon sequestration can be achieved. Information on the extent of forest the backbone of all global forest resource assessment (FAO, 2005).

1.6.1. Maintenance and Enhancement of Ecosystem Function and vitality

Maintenance and vitality of ecosystem refers to the concern about the conservation and management of all flora and fauna living in and outside the forest, which is directly linked with forest health, productivity and function at ecosystem level, species level and genetic level. This criterion also refers the management of forest in a way that maintains their regenerative capacity and ecosystem resilience. It specifically lists broad categories of ecosystem diversity, species diversity, and genetic diversity. The present study was done specifically on flora living inside the forest.

1.6.2. Maintenance and enhancement of forest Productivity

Timber volume is a one significant indictor in forest sustainable management. Basically, forest managers require such information to estimate the growing stock, which in turn is used to evaluate timber and plan for forest area allowed to be for harvested. However there is a problem in the development of volume function for natural forest due to heterogeneity in species composition and structure of forest. Akindele et al. (2006) proposed three ways to address this problem. The first approach is developing species wise timber volume equation, the second approach is the general formula (combining data for all species) and developing a single set of allometric equation for all species and the last approach is classifying species into groups and develops the equation for the each groups. In this study the species was divided into two major class based on their dominancy (Bell et al., 2007). The local allometric equation was employed to estimate the total timber volume for the entire study area.

1.7. Application of Remote sensing In Sustainable forest management

The earth is continuously under observation from many satellites orbiting the planet and collecting data. They are involved in "remote sensing", which is the act of obtaining information about object, areas or phenomena without being in direct contact with them (Boyd et al., 2005). Remote sensing has facilitated robust up-to date forest information to support sustainable forest management. Different remote sensing data have been used to measure the extent, quantities, composition and condition of forest resources. Typical applications of remote sensing involve either using images from passive optical systems, such as aerial photography and Landsat Thematic Mapper or to a lesser degree, active radar sensors such as RADARSAT (Lefsky et al., 2002).

Studies have used optical remote sensors such as Landsat-ETM to assess criteria and indictors such as tree diversity, selective logging and damage and forest extent for forest certification and sustainable forest management (Hussin (2004). However, Landsat and other passive imagery can be affected by cloud cover. Optical sensors produce only two-dimensional (x and y) images which is largely insensitive to vertically distributed attribute such as height and volume of biomass because their spectral signature saturates at lower biomass level than active sensors.

1.8. LiDAR in Sustainable forest management

LiDAR remote sensing, which is directly measures vertical forest structure is a breakthrough technology with many applications in forest resource management. LiDAR stands for Light Detection and Ranging is uses a pulsing laser to send out the signal. Basically LiDAR is an active airborne remote sensing technique. The systems measure a round-trip time of scattered light energy to find range between distant target and sensor, From the ranging information several structural metrics can be calculated (Drake et al., 2002). Radio Detection and Ranging (RADAR) is also remote sensing technique which is based on microwaves.

LiDAR uses the same principle as RADAR, but its shorter wavelength makes the data useful in quite different ways. A variety of LiDAR systems have been used in forestry applications. This is mostly based on three characteristics: 1) whether they record the range to the first or last return or fully digitized the return signal; 2) whether they have small footprint (typically a few centimetres) or large footprint; and 3) their sampling rate and scanning pattern.

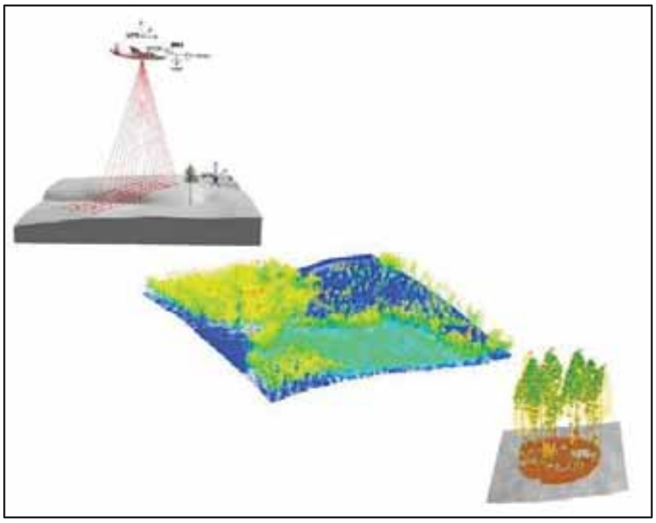


Figure 2: LiDAR application in forestry (Source: Esri June 2010)

Nearly all commercial LiDAR systems have a small-footprint high pulse rate and are ; first-or last-return-only airborne systems that fly at low altitudes (Andersen et al., 2005). Large foot print and full wave form digitized system are also other forms of LiDAR which can provide greater vertical detail about the vegetation canopy (Wulder et al., 2008). However, many studies rely on the small-footprint to estimate vegetation parameters, such as height, tree density and crown dimensions accurately in a variety forest types. In particular higher laser sampling density can provide not only tree height but also other important biophysical parameters such as timber volume and aboveground biomass of forest Takahashi et al. (2010) using allometric relationship mainly based on heights (Lefsky et al., 2002). These structural description of forest (vertical and horizontal) are essential parameters of forest in assessing the status of forest ecosystems and forest productivity and function (Sun et al., 2000).

However, LiDAR can only provide limited information. For example, forest stand parameters such as tree species diversity and health attributes cannot be derived directly from LiDAR data alone. But LiDAR can be combined with very high resolution/VHR) optical sensors, which is quite promising and useful forest inventory information, In addition, the integration of LiDAR with VHR optical imagery will result in more accurate forest classification than using either data set independently.

Recent MSc studies have done their research in the same study area in Nepal, strongly advocated the integration of images such as GeoEye and Worldview-2 image with LiDAR data for estimation of forest parameters in mountains tropical forest (Karna, 2012) and (Mbaabu, 2012). Very high resolution imagery has proven capability for the detection of individual tree crown diameter to estimate many forest inventory attributes (Falkowski et al., 2009). Object based image classification was used because individual pixels does not represent the characteristics of targeted forest stand and tree crown since a target is composed of many pixels in VHRs images.

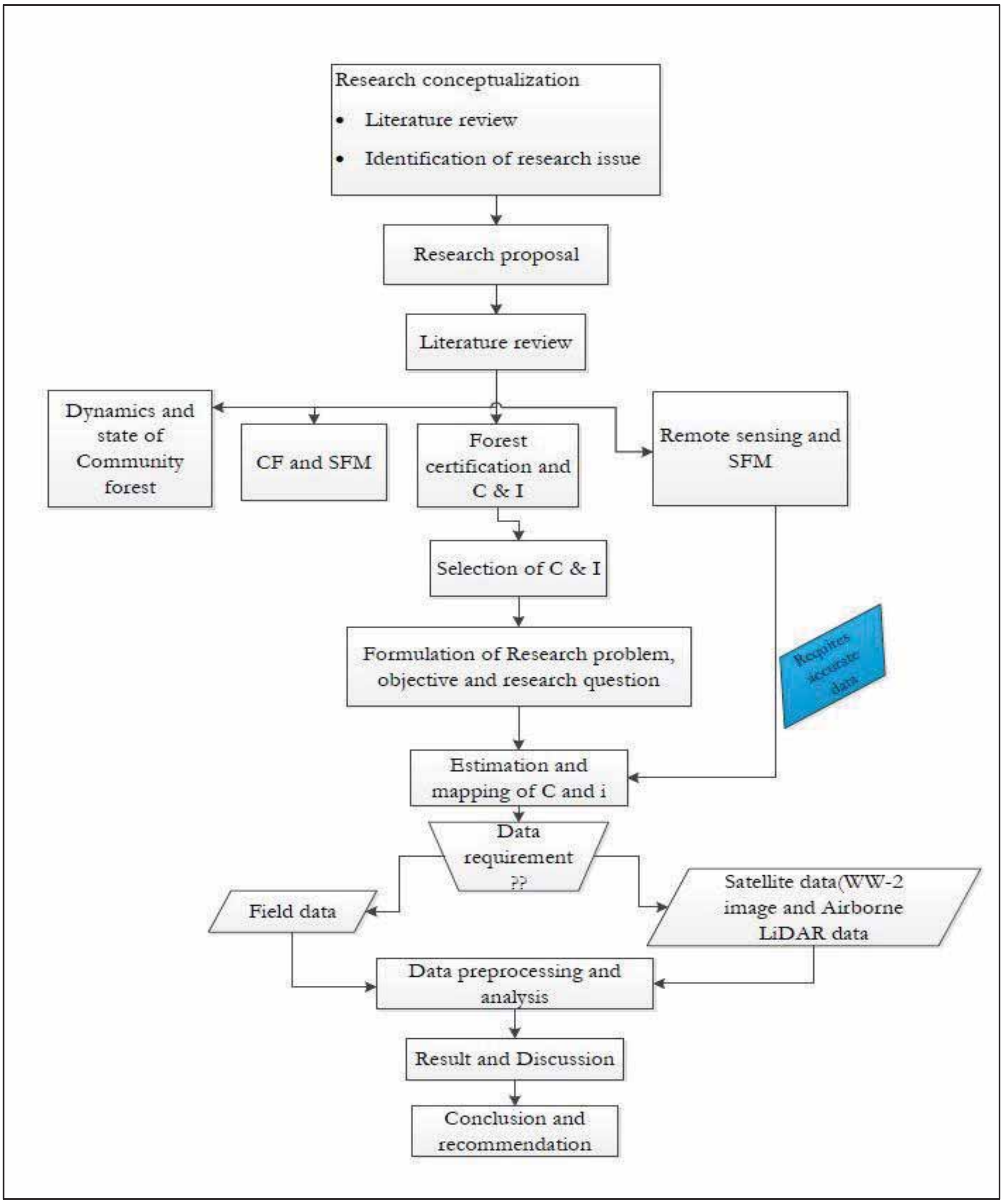


Figure 3: Research theoretical framework

1.9. Problem statement

Tropical deforestation and degradation have had a major harmful effect on the environment and significantly on the forest resources which results in the massive loss of biodiversity, loss of an important sink for atmospheric carbon and negative effects on the livelihoods of people (Foody, 2003). Tropical timber production is still a threat to long term viability of tropical forest and a cause of deforestation. But timber production may also provide positive input through environmentally, economically and socially sound forest management and promotion of forest certification. Sustainable management of forest resource has been used as one of the main tool by many researchers and international organizations to achieve social, economic and environmental goals. In doing so, it also promotes certification of forest products as approach to preserve the remaining world forest biodiversity. For this, countries throughout the world established criteria and indictors that can measure and monitor the sustainability of current management practices. Most studies have used many criteria and have proposed indictors to assess SFM often in relation to specific needs of a particular study. In Nepal, some studies have been intended to evaluate the community forest by using multi criteria analysis and hybrid approach that use both top-down & bottom-up approach (Chiranjeewee et al., 2012) together with the statistical analysis on environmental aspect (Stephen R. Kellert, 2000). However they failed to analyses the sustainability of forest by integrating different data about ecological, social and economic aspect (Wolfslehner et al., 2005).

Although, tropical countries have shown progress in using criteria and indictors for monitoring and assessing the sustainability of community forests, the data availability is still low, particularly at the species and also at ecosystem level (Basuki et al., 2009). Criteria and indictors demands accurate and continuous Information on the status and trends of the forest to assess and monitor SFM as well as forest product certification process (FAO, 2005). The ground-based measurement and remote sensing have been used as information source to describe and measure forest attributes and in turn can feed the information requirement for SFM and forest certification. The ground measurements would have been the most direct and accurate method, however for large and remote forest area, they are expensive and logistically challenging (Newton et al., 2009). Remote sensing has been recognized as an attractive data source for forest monitoring as no other data acquisition system can match the timeliness and consistency with large spatial coverage via satellite platform (Franklin, 2001). Given the spatial and temporal scale of concern, satellite remote sensing is the only cost-effective and feasible means of acquiring the necessary information about forest environment, and thus to evaluate C & I for SFM (Win et al., 2012).

Studies have proved that most of the indictors can be assessed using remote sensing technique at scales that are useful for sustainable management purposes. For instance indictors associated with different criteria such as- extent and type of forest resource, condition of forest stands, land cover change due to encroachment and condition of flora and fauna species diversity can positively be assessed by using Landsat and Spot data (Boyd et al., 2005), (Hussin, 2004). Moreover studies of (Yijun, 2003), Aguma (2002) and Dahal (2002) have noted that, the data from fine spatial resolution optical sensors were limited particularly because of cloud cover and smoke, which constrained these studies to assess only a few criteria and indictors. In contrast, few studies have used very high resolution, VHR optical sensors to identify and delineate individual tree crowns with low to medium uncertainty in the tropics (Gibbs et al., 2008). The crown projection area (CPA) delineated from very high spatial resolution satellite imagery can be related to biomass estimation using allometric equation (Marshalla et al., 2012). However, unlike active sensors, they are as largely insensitive to vertically distributed attribute such as height and volume of biomass because their spectral signature saturates at low biomass level. LiDAR data has been used as tool to characterize vertical forest structure, such as diameter , height, and volume which are key indicators of forest sustainability (Lim et al., 2003).

Wulder et al. (2008) have noted that LiDAR has limited capacity for few indictors associated with spectral information such as vegetation species estimation. While several studies have showed that the combination of VHR satellite images and airborne LiDAR data provides an accurate and efficient estimate of forest attribute(Ke et al., 2010) and (Zhao et al., 2009). For this reason, this study aims to explore the potential of LiDAR data in assessing indictors and criteria by including VHR Worldview-2 data to support SFM and forest certification in Chitwan district of Nepal.

1.10. Research Objective, Research questions and Hypotheses

1.10.1. General objective

The general objective of this study is to assess the conditions of community managed forest based on selected criteria and indictors using VHR Worldview-2 satellite images and airborne LiDAR data to support sustainable forest management and forest certification.

Table 2: specific research objectives and questions

Specific Objectives 1: To assess the segmentation accuracy of OBIA on the combined datasets (LiDAR data and Worldview-2) for estimating criterion and indictors to support sustainable forest management.	
Research Question	Hypothesis
1.1. How accurate is the segmentation of CPA from LiDAR data in combination with Worldview-2 satellite image?	HI: Image segmentation can be done with ≥ 70% accuracy using object based image analysis (OBIA) from LiDAR data and Worldview-2 satellite image
Specific Objectives 2: To map, estimate and asses the - Forest type/area, tree species, AGB and timber volume using LiDAR in combination with Worldview_2 satellite images of the Community Forest Users Groups (CFUGs).	
Research Question	Hypothesis
2.1. How accurate the forest covers and tree species classified from Worldview-2 satellite images and LiDAR data sets?	H1: Forest cover and species classification can be done ≥ 70% accuracy using object based image analysis (OBIA) from LiDAR data and Worldview-2 satellite image
2.2. What type of forest and tree species found in the each CFUG?	
2.3. How much AGB stored in the study area?	
2.4. What is the timber Volume in the study area?	
Specific Objectives 3: To assess the condition of CFUGs based on the selected criteria and indictors assessed using remote sensing to support sustainable forest management and forest certification	
Research Question	
3.1. What is the existing condition of the CFUGs based on the selected criteria and indictors assessed using remotely sensed data?	

2. DESCRIPTION OF THE STUDY AREA

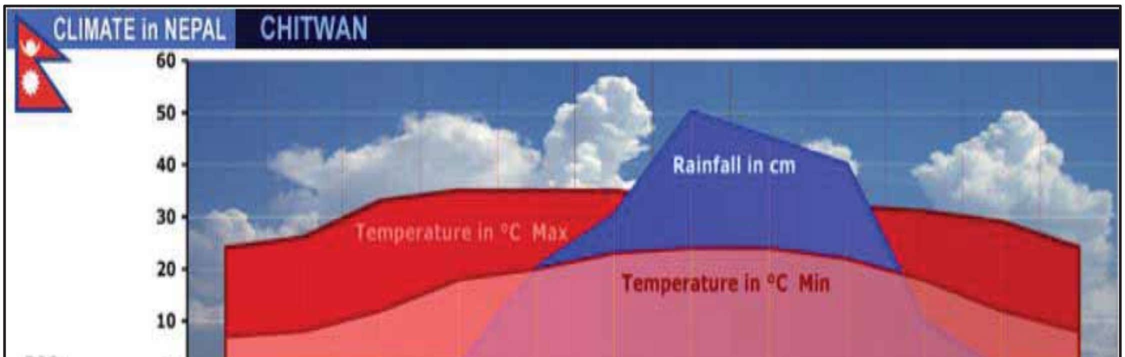
2.1. Overview of Chitwan district

2.1.1. Geographical location and topography

Chitwan district is one of the 75 administrative districts of Nepal, located approximately 80 kilometres south west (260°) of the capital, Kathmandu. Chitwan district shares a common boundary with Dhading, Gorkha and Tanahun Districts in the north, Narayani River in the west, Rapti and Makawanapur district at east and the international border of India in the southern part. Geographically, the district lies between latitude of 27^{0}30'51''N - 27^{0}52'01 N and between 83^{0}55'27''E - 84^{0}48'43''E longitude. The elevation of the area ranges from 300m to 1200m above sea level. The land is characterized by many steep gorges and slope varies from 30% to more than 100%. The area is drained by Kayerkhola stream having many small tributaries feeding into it.

2.1.2. Climate

Due to the latitude variation from south to north, Chitwan has a diverse climate and rainfall over forest and the landscape. The district enjoys both tropical to sub-tropical climate with fertile soils which generally favours for the luxuriant growth of the vegetation and crops. The average annual rainfall of the district is 1510mm/year (ANSAB, 2010). It is typically hot and wet during the summer and cold dry during winter. The average maximum and minimum temperature of the district is 30.3 and 16.6 Celsius respectively as shown in (Figure 4). Consequently, Chitwan has different forest types ranging from subtropical to alpine (Panta et al., 2008).



	January	February	March	April	May	June	July	August	September	October	November	December
Temperature in °C Max	24	26	33	35	35	35	33	33	32	31	29	24
Rainfall in cm	1.0	1.0	1.0	1.5	20.0	30.0	50.0	45.0	40.0	10.0	0.5	0.5
Temperature in °C Min	7	8	12	18	20	23	24	24	22	18	12	8

Figure 4: Chitwan district climate

(Source: RAO-online http://www.raonline.ch/pages/np/visin2/np_climate00.html)

2.1.3. Land Cover /Land use

The district occupies large amount of forested area, which is used to provide timber and other forest products and which constitutes 60% of the total area. The rest 40% is covered by agricultural and urban areas. Chitwan National Park, enlisted in world heritage which covers an area of 970km^2 and part of Parsa Wildlife reserve is in the district(Panta, 2003).

2.1.4. Social, economic and demographic

The actual population of Chitwan district is estimated to be population of 623,677. Chitwan district has several castes and ethnic groups, which includes both indigenous to elite people. The main centre of the district, Narayangadh, is famous for the business activities though most of the people economy is based on agriculture.

2.1.5. Vegetation

This district is very famous for its rich natural resource and quality timber. The study area has three dominant cover types of forest.

1). Sal (*Shorea robusta*) forest
2). Hardwood forest
3). Riverine Khair-Sissoo forest

Sal (*Shorea robusta*) is dominant tree species found in the study area and covers nearly 70% of forest composition (Gautam et al., 2002). Other dominate tree species found in the study area are *Terminilia bellirica*, *Schima wallichii*, *Semicarpus anacardium*, *Mallotus phillippensis*, *Cassia fistula*, *Cleistocalyx operculatus, Careya arborea, Holarrhena pubescens, Syzygium cumini, Aesandra butyracea, Terminalia chebula*.

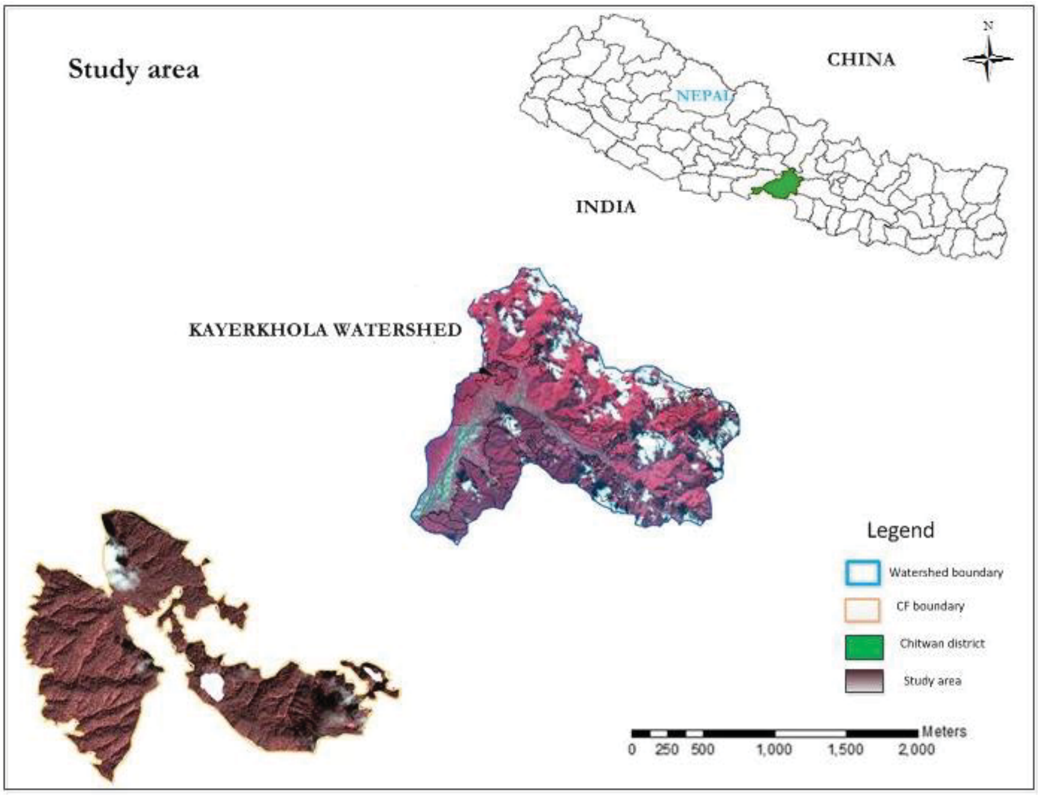


Figure 5: Map of study area: Kayerkhola watershed

2.2. Description of Kayerkhola watershed

The watershed consists of 15 CFUGs out of which three CFUG namely Devidhunga, Nebuwater and Janprogati were selected for this study. The forest is managed by the community of four village development committees (VDCs), namely Shiddi, Shaktikhor, Chainpur and Pithuwa have been involved in the forest management activities and REDD+ pilot project. Within the CF 1902.72 ha is considered as dense forest whereas 479.19 ha are regarded as sparse forest type. Land use profile of the watershed is mainly divided into five parts according to the classification done by ICIMOD.

3. MATERIALS AND METHODS

3.1. Matrial

3.1.1. Remote sensing data

Two different data sets were used for the present study, namely Worldview-2 (MSS and Panchromatic) images and Airborne LiDAR data.

Worldview-2 satellite image

Worldview-2 satellite is the commercial earth observation satellite owned by Digital Globe. It provides panchromatic imagery of 0.46 m resolution and eight-band multispectral imagery (visible to near infrared range) with 1.84 m. Worldview-2 image was acquired on 25th October 2010.

Airborne LiDAR data

The raw LiDAR (las file) data was received from Forest Resource Assessment (FRA) project under the Ministry of Forests and Soil Conservation. The data were collected by Arbonaut Ltd., Finland between 16 March and 2 April 2011 (leaf-off season) using a Leica ALS -40 (Airborne Laser Scanner-40) sensor with mounted on an aerial platform.

Table 3: List of performance of parameters for LiDAR data and Worldview_2 image

Parameter	Sensor	
	LiDAR	Worldview-2
Costumer	Forest Resource Assessment (FRA) Nepal, Ministry of Forests and Soil Conservation	International Centre for Integrated Mountain Development (ICIMOD), Nepal
Projection	UTM 45 N zone	UTM 45 N zone
Datum	WGS 84	WGS 84
Aerial Platform	Helicopter (9N-AIW)	Satellite sun synchronous
Band wavelength	NA	Costal Blue(400-500nm) Blue(450-510nm) Green(510-580nm) Yellow(585-625nm) Red(630-690nm) Red-age(705-745nm) NIR1(770-895nm) NIR2(860-1040nm)
Flying height(above the ground)	200m	NA
Flying speed	80kontos	NA
Sensor scan speed	20.4 lines/second	NA
Sensor plus rate	52.9 kHz	NA
Scan FOW half-angle	20 degree	NA
Nominal outgoing pulse density At ground level	0.8 points per sq. m	NA
Point spacing	Max. 1.88 m across, max. 2.02 m down	NA

3.1.2. Field instruments

In addition to the data set, several types of field equipment were used to collect the field data during fieldwork period mid-September to mid-October 2012.

Table 4: List of instruments used for the data collection

Instruments	Purpose
Garmin GPS Map 60 CSx and iPAQ	Navigation (location of plots)
Haga altimeter	Height measurement of tree
Diameter tape (5m)	DBH measurement of trees
Measuring tape (30m)	Radius measuring of plot
Spherical densiometer	Canopy density measurement of trees
Field work dataset	Field data collection

3.1.3. Software and tools

Table 5: List of software used in the research is presented below

Name of Software	Purpose of usage
ENVI 4.8	Image processing
Erdas Imagine 2011	
ArcGIS 2010	GIS analysis
LAStools	Processing of LiDAR raw data
Quick Terrain Modeller	Processing and visualization of LiDAR data
eCognition Developer 8.7	Object based image analysis and Classification
SPSS	Statistical analysis
R software	
SPSS 16 and R stat	
MS office	Thesis writing & editing
Adobe Acrobat professional	

3.2. Methods

3.2.1. Pre-fieldwork

Before the field work, the pan-sharped Worldview-2 image was converted and compressed to ECW format to reduce the file size and exported to iPAQ for tree identification in the field. In the image, a buffer of 500m^2 (radius of 12.62m) was created and printed in all sample plots considering each sample points as centre point. Field data collection format and field materials were also prepared and borrowed accordingly.

3.2.2. Sampling Design

Stratified random sampling is the most preferred sampling method in forestry inventory work, because stratification reduces the variation within the forest sub-division and increase the precision of the population estimate (Husch, 2003). Moreover, there are gains in reliability over that of simple random sample. For this reason stratified random sampling was used to layout sample plot in the study area. The sampling design developed by Nepal Department of Forestry (DOF) was adopted. Kayerkhola watershed consists of 15 Community Forests (CF). The stratification of the study are was achieved by sub-dividing the whole community forest area into strata (CF) on the basis of criteria such as forest type, altitude, slope, aspect, age, species composition and stand structure. Stratification was done on the basis of these characteristics so that each CF was considered as one stratum and hence homogeneity prevails. However prior knowledge of the area is the prerequisite to determine the sample size, in that case preliminary study has been conducted to establish reasonable information of population parameters (Husch, 2003). The total number of plots units required was calculated using the following formula developed by (DOF, 2004).

$$\text{Area of sample (A)} = \text{Sampling intensity} * \text{total area of} \frac{\text{stratum(A)}}{100} \quad \ldots\ldots\ldots \quad \text{equation 1}$$

$$\text{Number of plot (n)} = \text{area of sampling} \frac{a}{t} \text{area of one sampling plot (p)} \quad \ldots\ldots \quad \text{equation 2}$$

The study was conducted in three community forests which cover 662ha, with total plot of 65 and each community forest considered as one stratum.

3.2.3. Field work

In practice, the sample plots are most often of circular, square or rectangular shape. In this study a circular plot of 500 m2 area with 12.62 m radius was delineated based on sample plot on the map. A circular plot was used because it has two advantages over other plot shapes. (1) It represents the geometric shape within the smallest parameter which allows producing lowest number of borderline tree than other plots shape of the same size, (2) In forest stands without undergrowth, the plot boundaries can be conveniently located with the help of optical device. The plot radius was adjusted for the area when the slope is greater than 5^0 using a slope correction table. The XY coordinate of the centre tree of all sample plots were located in the iPAQ. Then all tree parameters within the circular plot such as tree height, DBH, crown diameter, canopy cover, slope, aspect and altitude were recorded in the field data sheet In addition all trees above 10cm DBH were selected for measurement. This is because- it is assumed that trees with DBH < 10cm contribute less to the total biomass Brown (2002) of the plot. However all tree species were recorded for further species diversity and richness analysis.

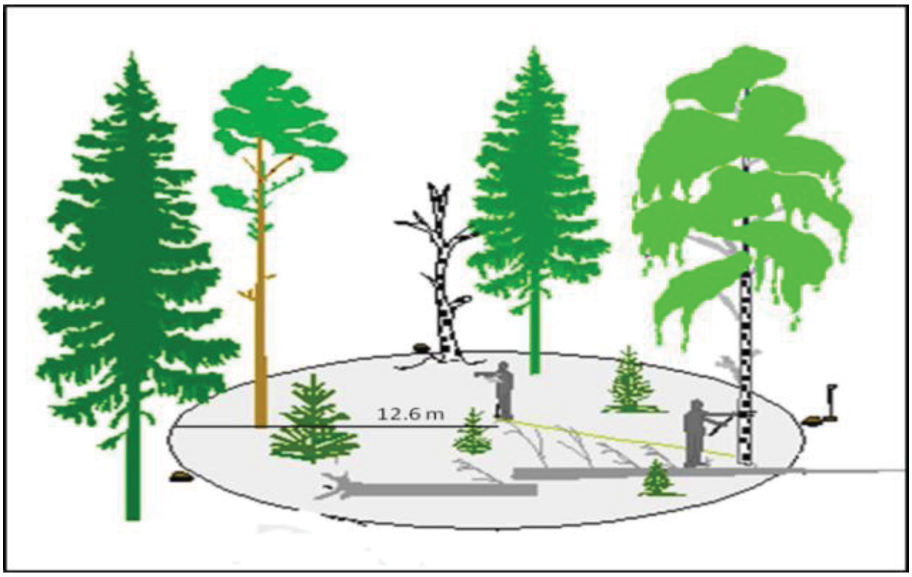


Figure 6: Circular plot measurement (Source modified from integrated monitoring system 2011, Sweden)

3.2.4. Post field work

Descriptive statistical analysis of forest parameters were made to visualize and analyze the distribution of field data using box plots. The remote sensing data of LiDAR and Worldview-2 image were pre-processed before starting any work. Geo-referencing and registration of image and LiDAR data was done to UTM 45 N zone projection and WGS 84 datume field data was used for the validation with the parameters derived from Worldview- 2 image and LiDAR data. The field parameters such as height CPA and DBH were used to build a model and estimate AGB and timber volume of study area.

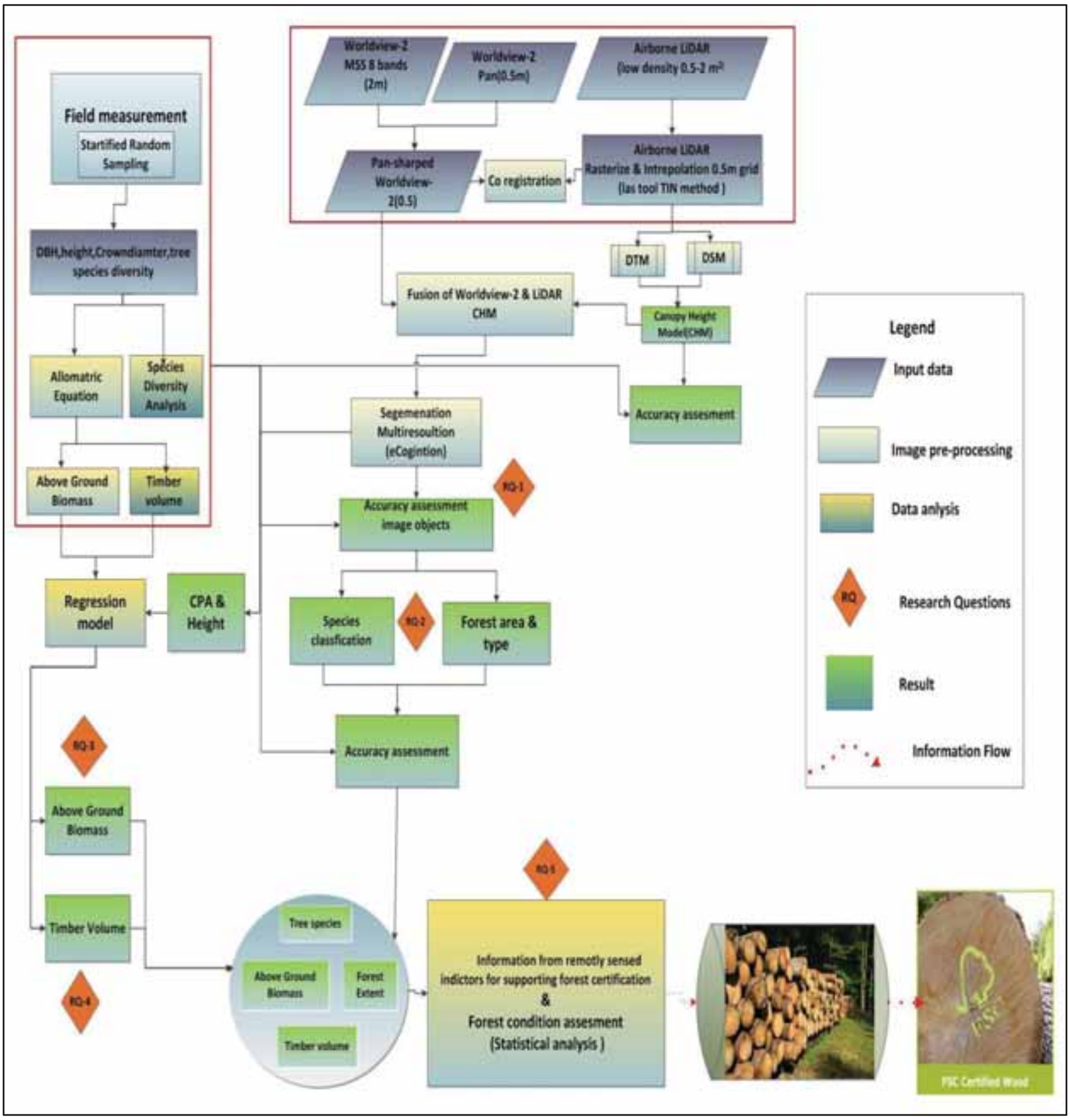


Figure 7: Research Method work flow

3.3. Image preprocessing

3.3.1. Image fusion

Image fusion is the process of combining two or more images, through which greater information can be obtained. The fusion of the panchromatic with multispectral images of Worldview-2 scenes was done using Hyperspherical Colour Sharpening (HCS) pan- sharping method (ERDAS, 2011), resulting in a multispectral image with 0.50 m spatial resolution. In addition, LiDAR derived CHM was fused with Worldview-2 (0.5m) image and filtered using Gaussian filtering method. The use of the Gaussian filter eliminates the variations and noise in the spectral values as well as in the height values in the fused image. Thus both the fused image of the Worldview-2 image and LiDAR derived CHM are crucial to estimate forest attribute such as height, crown diameter, steam volume and tree.

3.4. Canopy height generation (CHM)

LiDAR data was checked for any inconstancy before the start of any analysis. The data was provided in point format .las. The LiDAR point cloud was consisted of nine classes as shown in Table 6. Based on the code class, extraction of ground and vegetation was performed.

Table 6: Class code and classification of point code

Class Code	Classification Code
0	Created, never classified
1	Unclassified
2	Ground
3	Low vegetation
4	Medium vegetation
5	High vegetation
6	Building
7	Low points (noise)
8	Model key
9	Water

A digital surface model (DSM) was generated from the LiDAR first return data and Digital terrain model (DTM) was derived from the LiDAR last return data. The DSM represents the tree canopies of the forest while DTM represent the ground. The crown height model (CHM) was computed as the difference between DSM and DTM using appropriate thresholds. To derive CHM, the digital surface model (DSM) was subtracted from digital terrain model (DTM). For this different commands were used. The steps are presented as follows.

DTM

- *Step 1: Generating a DTM (blast2dem tool)*

Command

blast2dem -i cloud_ points.las -o-sub_ dtm .tif -v -step 0.5 -keep_ class 2

DSM

- *Step 2: Generating a DSM (lasgrid tool)*

Command

Lasgrid -i cloud_points.las -o sub_dsm.tif –first_only -highest -step 0.5 -fill 5 -mem 2000

CHM

- *Step3: Generate Canopy Height Model (CHM)*

Command: *Difference between DSM to DTM*

The two commands were to generate the raster's, whereas the third step was performed in the raster calculator of ArcGIS software. Finally, a CHM with 0.5 m spatial resolution was computed which contains pixel values of the height of trees.

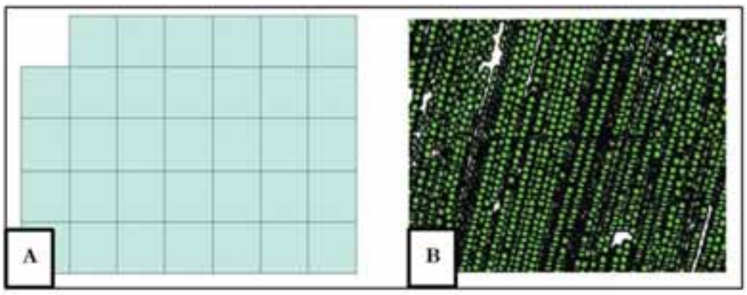


Figure 8 Point cloud and las file from LiDAR data

3.5. Manual delineation of trees

Manual delineation was done on both panchromatic and pan-sharpened image for those trees recognized during field work. The scale of 1:250 and 7:4:3 band combinations were used; while the field measured CPA was used as reference to correct the delineation of crowns. The delineated tree crown was then used for segmentation accuracy assessment and model validation. Out of the total measured trees only one third were identified for manual delineation.

3.6. Image segmentation

Image segmentation is the process of dividing remotely sensed images into homogeneous units using spatial or spectral information. The segmentation process reduces spectral variation of VHR imagery, and can increase the classification and statistical accuracy if conducted at an appropriate scale (Blaschke, 2003). Segmentation can be done using different parameters in eCognition. The most important parameter is the scale parameter, which is the maximum allowed heterogeneity in the resulting segments- the higher the value, the larger the objects, though it also depends on the image type and DN range (Drăguţ et al., 2010).

3.6.1. Scale Parameter (ESP)

The estimation of the scale parameter (ESP) is programmed in eCognition Network Language (CNL) in the eCognition software, a modular programming language for OBIA applications (Baatz et al., 2008). The ESP tool generates iterative image objects at different scales to calculate the LV values for each scale. Then thresholds are shown in the ROC of LV (ROC-LV) curve, which indicate the scale were the image can be segmented with more precise values (Drăguţ et al. (2010) as its shown in (*Figure 9*). In this particular case, there is only one threshold at scale parameter 21).

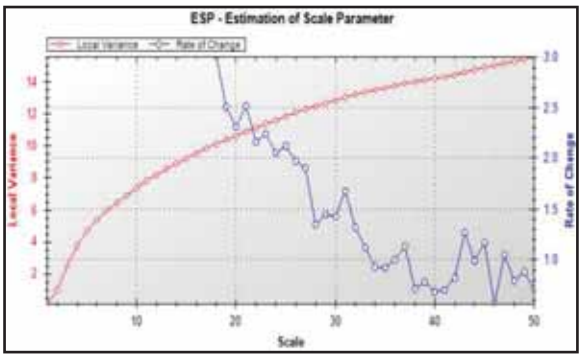


Figure 9: Tool for estimation of Scale Parameter

3.6.2. Multi-resolution segmentation

Multi-resolution segmentation is a bottom up region based segmentation approach in which the grouping decision is based on the local homogeneity criteria. In multi-resolution segmentation, segment size was determined firstly by scale parameter measuring the maximum possible homogeneity.

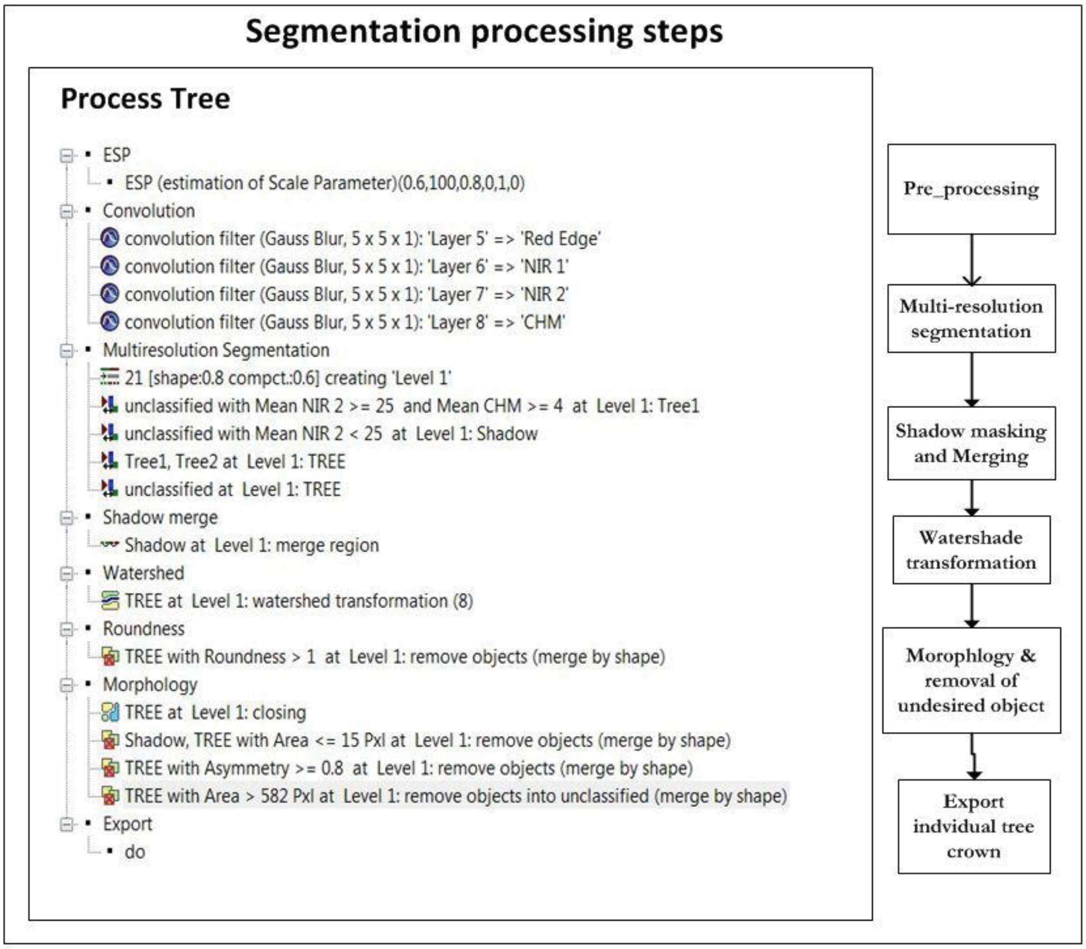


Figure 10 : Multi-resolution segmentation workflow

Homogeneity criteria were set up using color and shape parameters. Color describes the digital value of the image objects, and shape defines the textural homogeneity of the object (Listner and Niemeyer 2010). The shape criterion represent of two parameters: smoothness was used to improve the objects smoothness of the borders, and compactness to enhance the image objects compactness. Because of the absence of any generally accepted criteria for segmenting a particular forest area or tree crown; these factors were defined based on trial and error approach until the appropriate image objects of interest is found (Mathieu et al., 2007). A multi-resolution segmentation to the first hierarchal level using the criterion of reference scale 20, shape 0.7, and compactness 0.5 was conducted. Using the brightness information for band six and the criterion established for each class, another multi-resolution segmentation with scale of 21, shape 0.8 and compactness 0.6 was conducted. Throughout the process segmentation was carried out more than 15 times using different parameter (scale, shape and compactness) and different image segmentation algorism and classification were applied to preform hierarchical classification.

Table 7: image segmentation hierarchy

Hierarchy	Scale	Shape	Compactness
Level 1	18	0.9	0.7
Level 2	21	0.8	0.7
Level 3	24	0.5	0.5

3.6.3. Watershed transformation

Watershed transformation is a well-known segmentation method which considers the image as a topographic surface; this surface is flooded into minima, thus generating different catchment basins dams are built to avoid merging water from two different catchments basin (Derivaux et al., 2010). The segmentation result defined by the location of the dams (i.e., the watershed lines) as illustrated in (*Figure 11*). In this algorism, overlapping trees, big crowns and clusters of crowns were split into individual tree crowns (Yazid et al., 2008). In processing of watershed transformation 8 pixels was used as a parameter because all the trees were ≥ 4 meter (8 pixels).but the shape of the segmented polygon may not be the same. Thus refining algorism was used to refine the segments to obtain the approximation of the shape of trees. A morphology algorithm was employed to improve the tree shape.

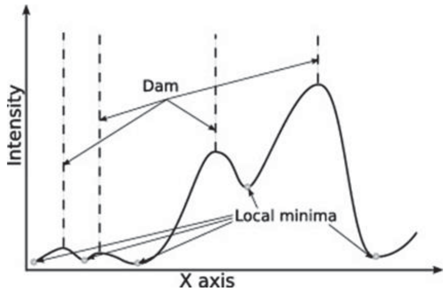


Figure 11 Illustrations of the watershed segmentation principle (Derivaux et al., 2010)

3.6.4. Morphology

Morphology was done to refine, reshape and to smooth the boundaries resulted segments. The method is based on two basic operations: (1) remove pixels from an image object that are irregular in shape; (2) adds surrounding pixels to an image object to fill small holes inside the segmented area as shown in (*Figure 12*).

a) Image object after multi-resolution segmentation   b) *Image object after watershed*   c) *Image object after morphology*

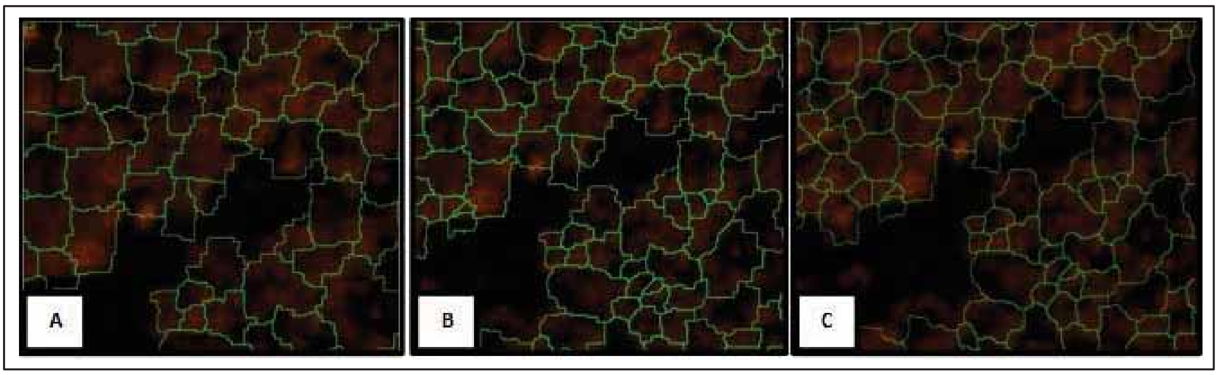


Figure 12 :multi-resolution, morphology and watershed algorism during segmentation

3.6.5. Removal of undesired objects

This operation was done to remove undesired objects after morphological operation. The tiny objects were removed on the basis of shape (roundness) and pixel number thus the segmented polygons looks like tree crown. The elongated segmented polygons with a high asymmetry were also removed.

3.6.6. Segmentation validation

The accuracy assessment of segmentation result is very important for further image analysis. For this study geometrical relationship was used for comparison of training polygons with the segmented polygons (Zhan et al., 2005). Thus quality of segmentation was determined by over and under segmentation as well using "D" value. The D value was calculated to evaluate the matching of the segmented objects relative to the over and under segmentation. The value of over segmentation and under segmentation ranges between 0 and 1 where the over segmentation -0 and under segmentation -0 is considered as the prefect segmentation (where the training objects matches the segments exactly). The equation developed by Clinton et al. (2010) was used as described in (Equation 3-5).

$$UnderSegmentation_{ij} = 1 - \frac{area(x_i \cap y_j)}{Area(Y_i)}, y_i \epsilon Y_i^*$$

Equation3: Under segmentation

$$OverSegmentation_{ij} = 1 - \frac{area(x_i \cap y_j)}{Area(X_i)}, y_i \epsilon Y_i^*$$

Equation 4: Over segmentation

And "D" value was calculated using the following formula

$$D_{ij} = \sqrt{\frac{OverSegmentation_{ij}^2 + UnderSegmentation_{ij}^2}{2}}$$

Equation 5: D Value formula

Where,

X_i is the training objects or reference polygons

Y_j is the set of all segments in the segmentation

The accuracy assessment was done for each CFUGs based on 1:1 correspondence. The 1:1 correspondence based on manually delineated polygons and segmented. The validation process was performed polygon by polygon by the GIS overlay operation in Arc GIS and manual delineated tree crown which are obtained from field sampling points were used as reference.

3.7. Object based image classification

The analysis and interpretation of remotely sensed images can be done in different ways. The statistical analysis of each pixel's spectral values is one the conventional pre-pixel method (van der Werff et al., 2008). However, it is quite limited when used for very high resolution imageries because these procedures mostly ignore the spectral reflectance characteristics of neighboring pixel. OBIA arose through the realization that image object hold more real-world value than pixel alone (Gamanya et al., 2007). Image objects are a group of pixels in a map. Each object represents a definite space in a scene and object can provide information about this space. Procedurally, OBIA is based on three major steps: the first and foremost step is segmentation of an image into serious of non-overlapping, meaningful and homogenous image objects: the second step is the feature set constriction and optimization to remove unrelated feature, while retaining the useful information to identify the target objects: the last step is to classify the object into categories. The outcome of segmentation phase is controlled by user-defined parameters (scale, shape and compactness) that must be assigned accurately according to feature being extracted (Molinier et al., 2011).

3.8. Image classification and accuracy assessment

Following multi-resolution segmentation, the resulting image objects was used to carry out image classification. The neighbourhood approach was used because it is simple classification algorithms for predicting the class of a test example and its non-parametric model (Lamonaca et al., 2008). It was used to classify the forest cover types and species level. The forest covers were classified as forest and non-forest area. The same procedure was undertaken classifying image objects into six tree species and one broad class “other”. The mean value of NIR1, NIR2 and Red-Edge band of pan-sharpened image and maximum value of CHM was chosen in object features for the classification. Classification results were evaluated using training sample which is 30% field data while the remaining 70% was used as training sample. The accuracy assessment was undertaken in ERDAS 2011 and confusion matrix, kappa statistics and overall accuracy report was derived to assess the classification image result.

3.8.1. Transformed divergent (D_T)

The transformed divergent is the statistical distance between pairs of signature to maximize the separability. Transformed divergent was done to define the separability and to decide the number of classes to be used for image classification. According to Jensen (1996), the D_T value ranges from 0-2000. If D_T value is greater than 1900, then the species classes can be separated. When D_T value is between 1700 -1900, then the separability is good and below 1700, the separability is poor. If the TD value equal to 2000, then the class signature are totally separable in the bands being used. Consequently the expected classification accuracy would be high.

3.8.2. Spectral separability of tee species classes

Spectral separability analysis is quantitative way of measuring the spectral propriety of an object based on the bands of image (Holmgren et al., 2008). This method was used to decide on the number of tree species class to be used in the classified of image. It was carried out using ERDAS 2011 software.

3.9. Regression analysis

Regression models were used to develop equation relating to LiDAR data and satellite image derived forest parameters. Forest parameters include DBH, CPA and heights were used to develop the regression model and estimate AGB and timber volume. DBH cannot be measured directly from both LiDAR data and Worldview-2 image. Studies shows that LiDAR and image parameters are well correlated with DBH (Popescu, 2007). Nonlinear and linear relationship were established to determine the relationship between dependent and independent variables (Husch, 2003). The field data were divided into training and testing datasets, were the training data set was used to build models and the testing data set was used to evaluate the model performance (Foody, 2003). The performance of the model was evaluated by using a Root Mean Square Error (RMSE) and coefficient of determination (R^2). To calculate the RMSE, the values of observed (field data) and predicted (derived from the model) were compared using (Equation 6).

$$RMSE = \sqrt{\sum \frac{(Yp-Yo)^2}{N}}$$

Equation 6: RMSE calculation

Where,
RMSE = Root mean square error
Y p = predicted
Y o = observed

N = Number of observations

3.10. The Shannon-Weiner Diversity Index

Shannon-Weiner diversity index was used to characterize and both species richness and relative abundance of each species. It is most commonly used and acceptable index assessing species composition. It is symbolized by H, which range from 0 to about 4.5 (high uncertainty as species are relatively evenly distributed) (Shannon, 2001). In each plot, the number of tree species with DBH more than 10 cm and DBH less than 10cm was used to calculate the tree diversity index. It was computed by using *(Equation7).*

$$\boldsymbol{H'} = \sum \boldsymbol{Pi} * \boldsymbol{ln}\ \mathrm{p}_{\boldsymbol{i}} \ldots \ldots \quad \textit{Equation 7}$$

Where:

H' = Shannon diversity index,
p_i = the proportion of individuals belonging to i^{th} species, and
Ln =natural log (*i.e.* base 2.718)

3.11. Above ground biomass estimation : Allometric equations

Allometric equation is known one of the standard methods to estimate AGB. It is a statistical way of relating biomass with one or more tree parameters of trees, such as diameter at breast height (DBH) or height. Allometric equation for biomass usually include information on trunk diameter at breast height DBH (cm), total tree height h (in m), and wood specific gravity (in g/cm). The selection of an appropriate allometric equation is one of vital step in estimating AGB (Banskota, 2007). In this study the general equation developed by (J. Chave et al., 2005) was used since, there is no detailed floristic information for allometric equation to relate to DBH and height.

$$AGB = 0.0509 * pLD^{2.} \ \ldots\ldots\ldots \quad \textit{Equation 8}$$

Where,

AGB = above ground biomass (kg
P = wood specific gravity [kgm^{-3}];
D = tree diameter at Brest height (DBH) [cm]; and
H = tree height /m/

According to J. Chave et al. (2005) the above equation can be used for the area which covered by hardwood forest and tropical rain forest which receive annual rainfall between 1500-3500mm/yr. The present area under study was mostly covered by hard wood forest and rain fall of 2250mm/yr (ICMOD 2010).

3.12. Timber Volume

The volume of a stand is the most essential tree parameter; both economically and environmentally, as it interacts with the total stand biomass. It also used as a potential contributor factor for understanding carbon dynamics (Franklin, 2001). The merchantable timber volume of the study area was estimated through the field inventory data using tree DBH and height measured with the circular plot. The Local allometric equation developed by Sharma (1990) was used which combine tree height and DBH of tree. However the DBH of tree cannot be derived directly from the remote sensing data to predict the total volume of the timber in the study area. For this reason the model was developed to predict DBH interims of CPA and height. Predicted volume was generated from the predicted DBH and height while the observed timber volume was generated from field data. The model parameters of *Shorea robusta* and the general class “other” are described in (*Appendix 6*).

$$\boldsymbol{V = a + b * ln(DBH^2 + c * ln(H)} \;\; \ldots\ldots \quad \textit{Equation 9:}$$

Where,
V is the timber volume
a. b. c model parameters
DBH is diameter at breast height and
H, is height

3.13. Forest condition assessment using remotely sesned indcitors

The characterization and vertical analysis of tree variable are vital to assess and evaluate the sustainability of the forest condition. The selected criteria and indictors were used to assess the condition of each of the CFUGs. Statistical analysis was used to analysis indictor’s distribution in the entire forest. All data related to each indictor were subjected to Shapiro Wilk normality analysis test to determine whether or not the distribution of each indictor was normal in each management regime. If the data did not follow a normal distribution, the Mann-Whitney (non-parametric test) was used (Aguilar-Amuchastegui et al., 2007). Then indictors were assessed based on their performance against the result from remote sensing analysis and field data which was used as verifiers and then forest status was assessed.

4. RESULTS

4.1. Descriptive analysis of field data

Descriptive statistics were used to summarize and present the surveyed field data. The study area is composed of three CFs, from which 1233 trees were recorded from 67 plots. As presented below, there are seven most dominant species, representing 85 % of the study area, and "others" which is consists of 19 species representing the remaining 15%. The dominance of *Shorea robusta* is clearly observed followed by others species, *Lagerstroemia parviflora* and *Schima wallichii* representing 61%, 15%,10% and 6% respectively. The details of the occurrence of species distribution and descriptive statistics are presented in the pie chart *(Figure 13 and Table 8).*

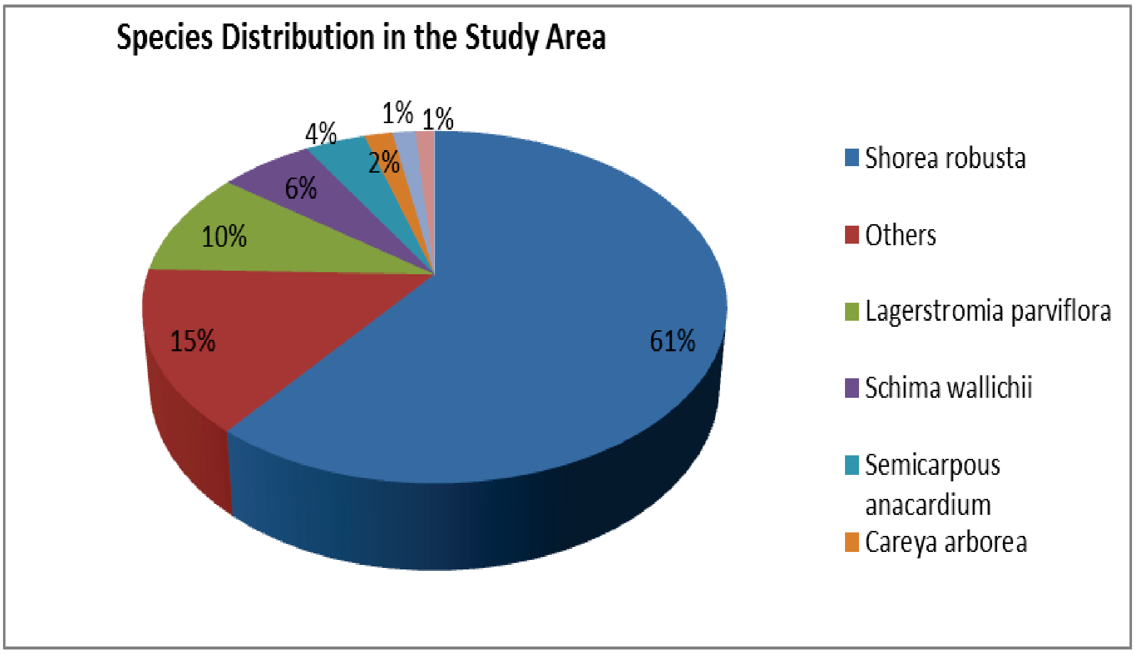


Figure 13 pie chart showing tree species distribution in the study area

Among the three CFUGs, Nebuwater is the largest (329ha) followed by Devidhunga (253 ha) and Janprogati (78.57 ha). In all three CFUGs together 1233 trees were measured and 333 trees were recognized in the image as shown in (*Table 8*). For this study, any tree with DBH>10cm was counted as tree as small trees (i.e. with DBH <10cm) contribute little to the total AGB and timber volume.

Table 8: Detail of field sample measurement

Name of CF	No of plots	No of tree species	No of tree measured
Nebuwater	32	17	453
Devidhunga	28	27	568
Janprogati B	7	29	212
Total	67	73	1233

The field data includes the basic stand parameters such as tree height, DBH and crown diameter. All the three parameters were measured for every tree inside the plots. As shown in the box plot, on average *Schima wallichii* has the largest DBH while *Lagerstroemia parviflora* has the lowest. The mean height of *Shorea robusta* was found to be the highest followed by *Schima wallichii* and *Terminilia tomentosa.* For the highest variability of DBH and height was observed due to the dominancy of the species in the sample plot.

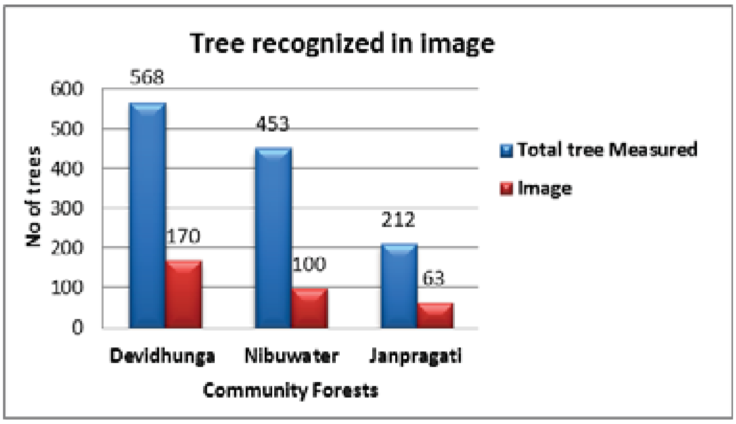


Figure 14: Tree measured vs. Tree recognized in the image

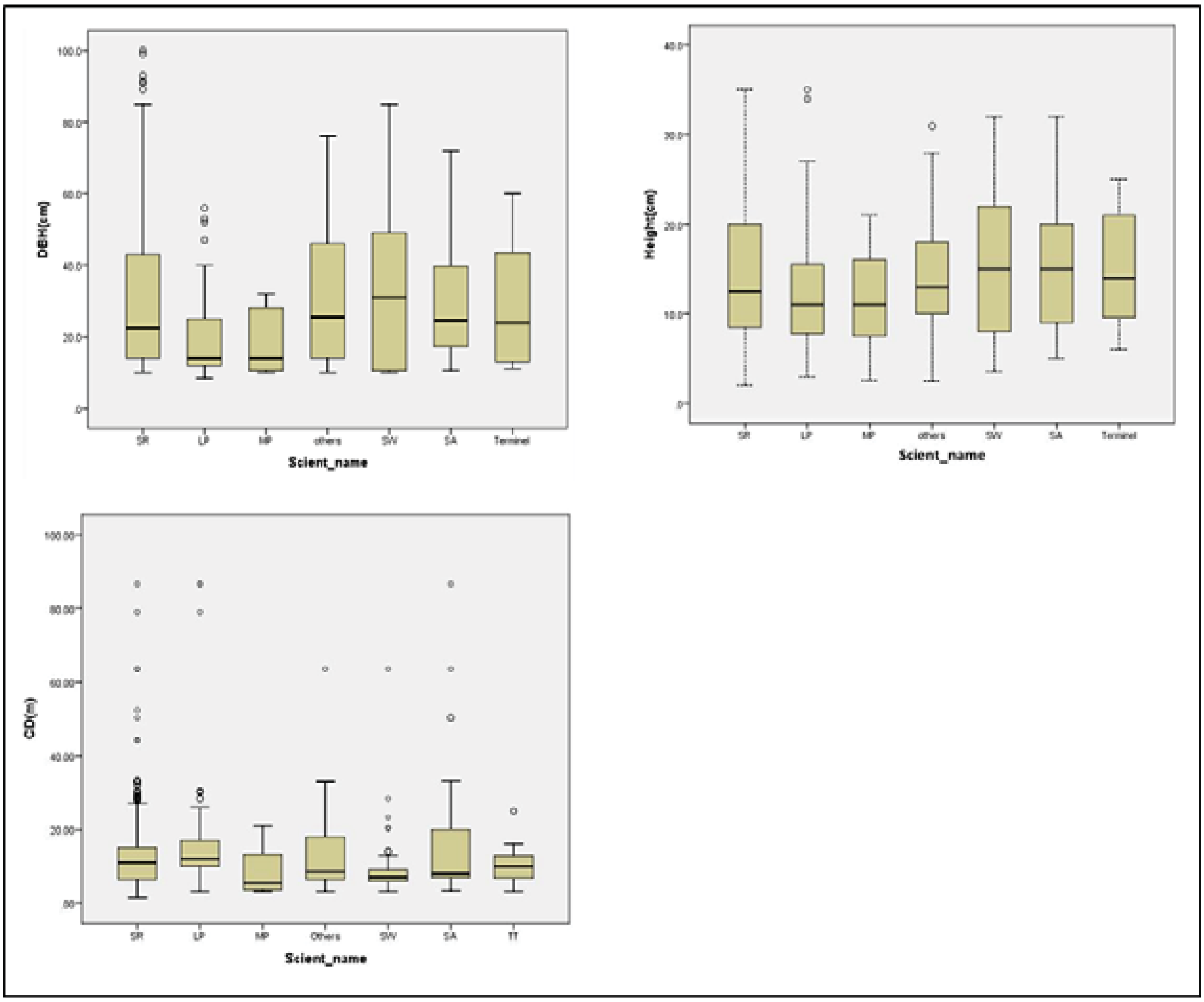


Figure 15: Box plot of DBH (cm), height (m) and crown diameter (m) of major trees

In summary, the DBH of the trees have a mean and standard deviation of 27 cm and 17cm respectively. Similarly, the height of the trees has mean and standard deviation of 14 m and 7m respectively as shown in (Table 9).

Table 9: Descriptive statistics of DBH, height and CD

Field variables	N	Minimum	Maximum	Mean	Std. Deviation
DBH(cm)	1233	8.5	100	27.77	17.78
Height(m)	1233	2.0	37	14.11	7.12
CD(m)	983	1.5	32.1	9.84	5.12

4.1.1. Shannon-Weiner diversity index

Tree species diversity for all three CFUGs was assessed by means of the Shannon-Weiner diversity index. All regeneration (seedlings), saplings and trees found in inside the plot were counted and summarised for each CF per ha. The Shannon diversity index was calculated for every plot and then averaged for each CF. Devidhunga is the most diverse CF with a 0.954 diversity index (DI), 3.006 species richness and followed by Nebuwater with 0.721 and 2.514 respectively. On the other hand, Janprogati CF has the least number of species with 0.210 DI and 2.038 species richness (*Table 10.*)

Table 10: Tree diversity index of each CF

Name CF	Diversity index	Species richness	No tree
Devidhunga	0.954	3.006	41
Nebuwater	0.721	2.514	38
Janprogati	0.210	2.038	20

4.1.2. Above ground biomass calculation

The above ground biomass of each tree was calculated from field measured DBH, height and constant “g” which is a species specific wood density using the allometric equation for the whole area. AGB of each plots were also calculated based on the average AGB of each tree inside the plot. The detailed descriptive statistics are presented in (*Table 11*).

Table 11: AGB of each CF

Name of CF	No plots	No trees	Average AGB/ plot	Area of CF(ha)
Nebuwater	28	453	1583.26	329
Devidhunga	32	568	837.72	254
Janprogati	7	212	436.85	79

4.1.3. Timber volume calculation

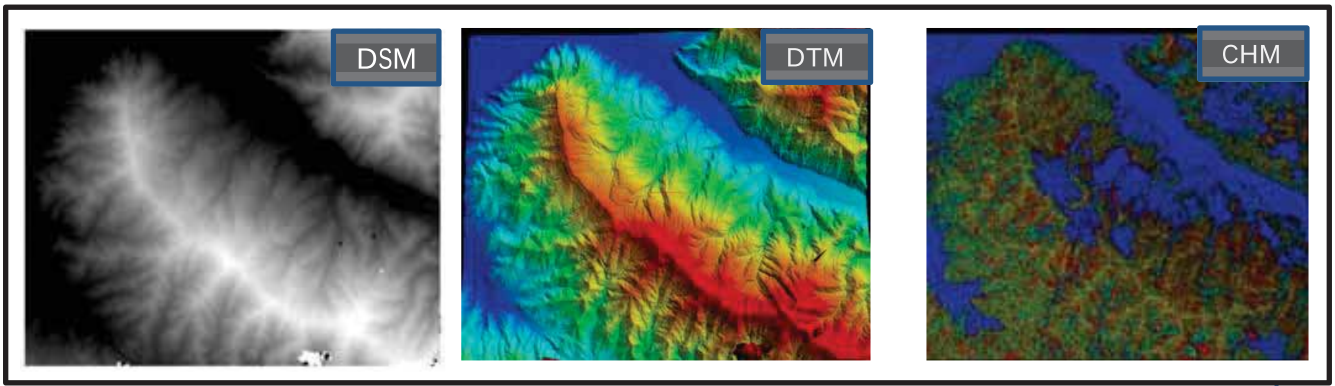
The actual (observed) timber volume calculation was determined by using the equation developed by (Sharma, 1990). Mostly, the individual tree volume is calculated as function of DBH, height and tree form. However, for practical reasons the local equation that involves only DBH and height was used. Summing up all individual trees volume gave the total timber volume per plot. The standing timber volume in each plot was calculated from ground measurement for each individual tree. The summed timber volume in each sample plot was calculated in terms of volume in cubic meter (m3). The average timber volume was calculated by averaging sample plot with in each CF. Total volume was also computed as the sum of individual tree volumes (*Table 12*).

Table 12: Timber volume per plot and CF

Name of CF	No plots	No tree measured	Total timber volume per plot (m^3)	Average timber volume per plot
Nebuwater	28	453	428.7	13.7
Devidhunga	32	568	227.9	8.3
Janprogati	7	212	59.5	5.5

4.2. CHM generation

The LiDAR data point clouds were used to generate the Digital Terrain Model (DTM) and Digital Surface model (DSM). As it is shown in (Figure 16) the tree height or canopy height model was found by subtracting the DTM from the DSM.



(Generated from first return) 2D *(Generated from last return) 3D* *(Canopy height Model) 3D*

- In the DSM, the bright area shows the terrain (trees)
  While the darker shows the ground surface.
- In the DTM, the yellow shows high elevation and blue area shows low elevation
- In the CHM, the red area shows the highest elevation (height tree) and the blue the ground.

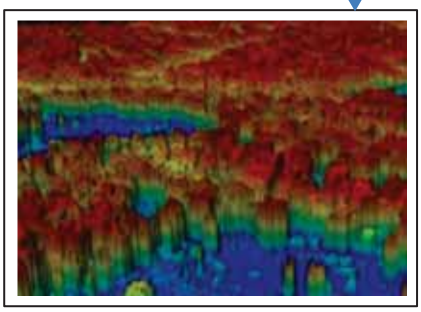


Figure 16: 3D (DTM left), 2D (DSM middle) and 3D (CHM right) *(Subset of CHM) 3D*

4.2.1. Accuracy assessment

Tree height derived from LiDAR data and height measured from field were plotted to see whether tree heights derived from field measurements were significantly different from the LiDAR height (*Table 13*). The mean heights from LiDAR and the field were 6.73 and 6.34 respectively. The LiDAR derived height was 0.39m greater than the field measured height (*Figure 17*).

Table 13: Tree height from LiDAR and field measured height

Data source	Mean	R	R^2	t –test	RMSE
Height LiDAR	6.73	0.88	0.77	0.67	3.22
Height-field	6.34				

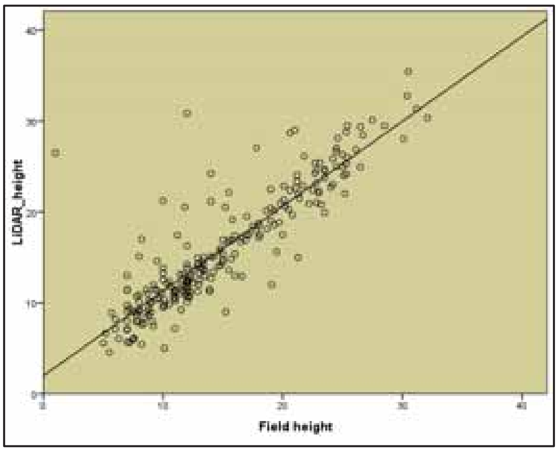


Figure 17: height values from LiDAR and field measured tree height

4.3. Multiresolution segmentation

Image segmentation was done on the panchromatic Worldview-2 image and canopy height model (CMH) data. In segmentation of an image, one cannot identify which scale parameter is suitable prior to the segmentation. The image objects were generated based on several adjustable criteria such as scale, shape and compactness. The change to one of these three parameters indirectly influences the object size (Rejaur Rahman et al., 2008). Therefore, for this study, the image segmentation was undertaken many times at different levels. For example: In level one segmentation the criterion scale parameter was set to 20, with 50% of the criterion depending on colour and 50% on shape. The later factor was divided between smoothness and compactness, with the criterion dependent being 25 % and 75 % respectively. In level two segmentation more emphasis was given to shape, which was increased from 50% to 75% and the colour factor was decreased from 50% to 25 %. In the same way compactness was decreased from 75 % to 60 % and smoothness was increased from 25% to 40% and the scale parameter was also increased from 20 to 21. Based on the visual inspection of segmented polygons and field data, scale of 21, shape 0.8 and compactness 0.6 were selected as the suitable parameter combination for segmenting the Worldview-2 and LiDAR CHM for the present study area. Red, Red-edge, NIR-1 and NIR-2 from Worldview-2 image and CHM from LiDAR data were used as bands and ranked accordingly.

4.3.1. Segmentation validation

Segmentation accuracy assessment can be done using different methods. In this study, A set of manually digitized objects was overlaid on segmentation results to check how the segmented polygons much with the reference polygons, thus to assess the accuracy of the results.

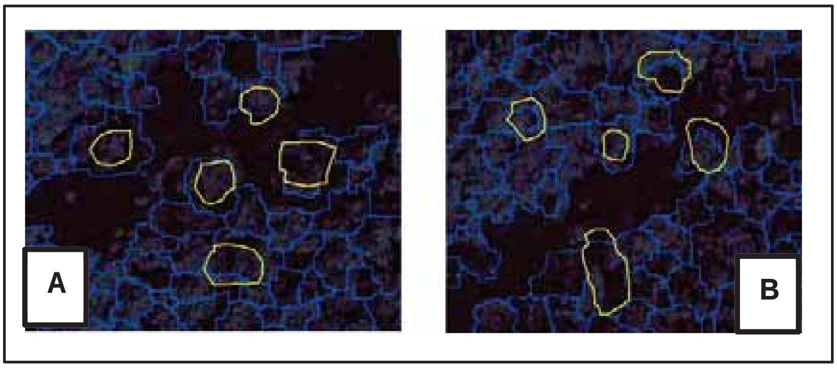


Figure 18: Matched cases of extracted segmented object

(*Figure 18*) shows the matching condition of different objects. In figure a) there is more than 50% match; while in (b) an extracted object matches with the same position but differs in its spatial extant. The quality of segmentation outputs were defined in terms of over- and under segmentation as well as goodness of fit (D) as described in (*Figure 19*).

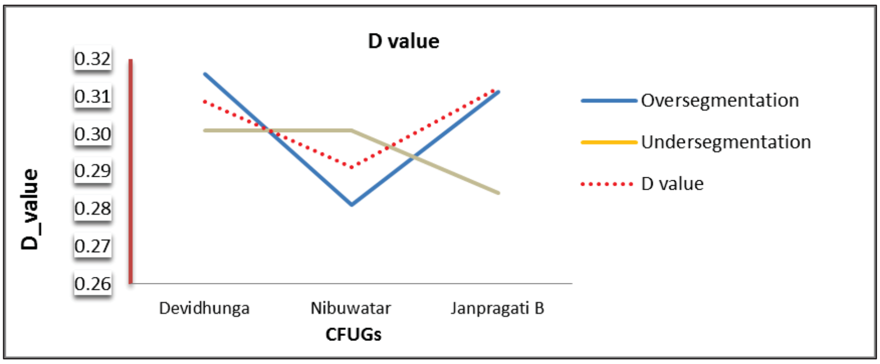


Figure 19: Measure of closeness (D value) for accuracy assessment of segmentations

Over segmentation, under segmentation and the resulting D values were 0.34, 0.29 and 0.31 respectively. The total tree crown delineation accuracy was 69% with 31% of segmentation error. D value was calculated using the formula below.

$$D_{ij} = \sqrt{\frac{OverSegmentation_{ij}^2 + UnderSegmentation_{ij}^2}{2}}$$

For accuracy measure of 1:1 spatial correspondence, matching of reference and segmented polygons was observed on one to one basis. In total, 212 reference polygons which were found from manual delineation were used, Among these, only 167 were found to have a one to one relationship with the segmented polygons. The detailed description is presented in (*Table 14*).

Table 14: D value for accuracy assessment of segmentation

CFUGs	Total reference polygons	1:1 match	Correctly matched
Devidhunga	78	63	80.7%
Nebuwater	102	79	77.5%
Janprogati B	32	25	78.0%
Overall accuracy	212	167	78.8%

4.4. Extent of the forest : Forest type and area

The estimates of the extent of forest and forest types are required for a complete understanding of forests and their sustainable use. Forest cover type classification was done based on segmented tree crown using the nearest neighborhood function in eCognition. Each community forest cover was classified into two classes: forest area and non-forest area. The forested area covers more than 90% of the CF whereas non forest covers has less than 10% of total area. Training samples, which were identified from the field, were then compiled into a spectral library use the statistics for supervised classification. In Nebuwater 43 ha non-forest area and a small area in Janprogati was found whereas in Devidhunga almost area was covered by forest trees and their crown *(Figure 20 and Figure 21).*

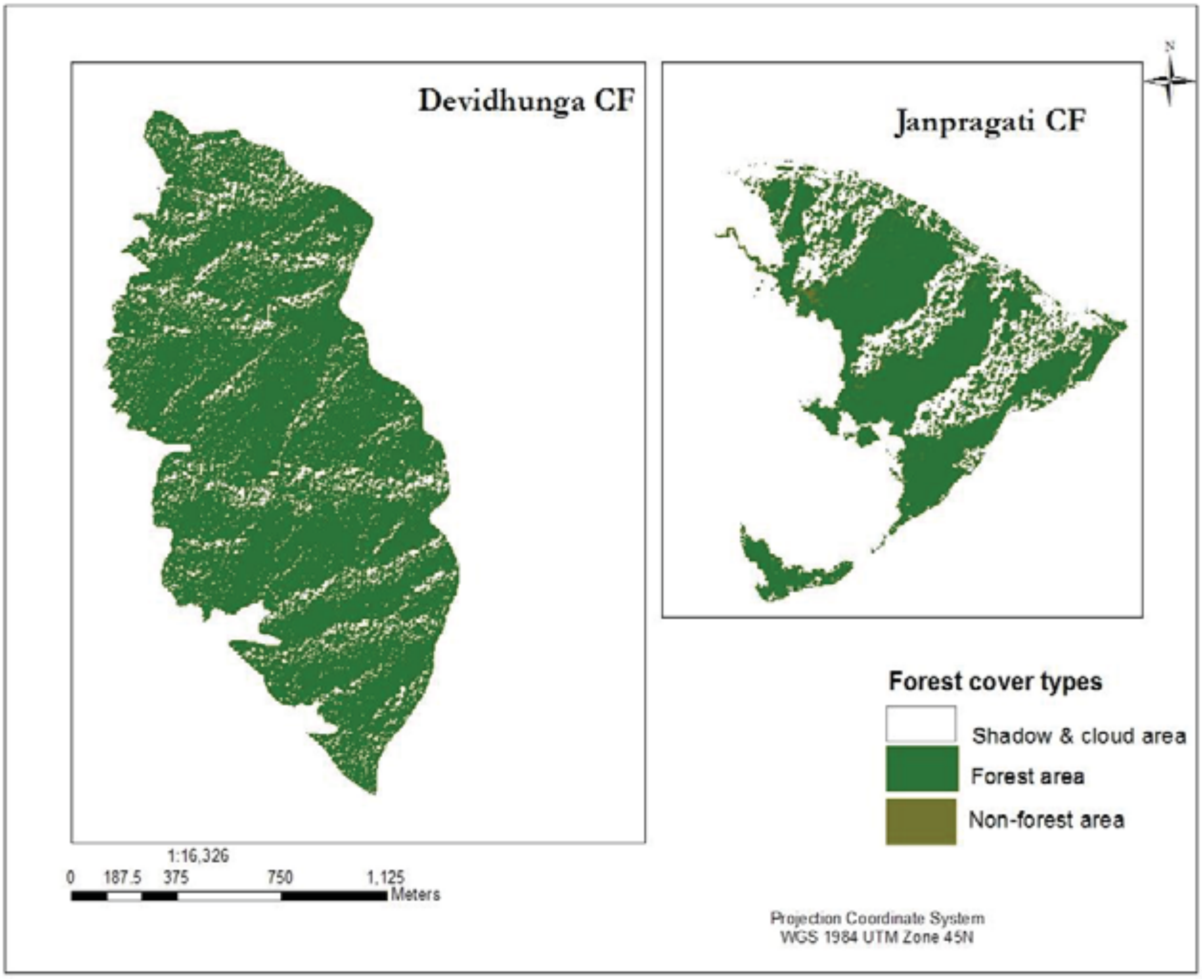


Figure 20: forest cover maps of Devidhunga and Janprogati

The accuracy assessment was done using an Error Matrix or Confusion Matrix and kappa statistics. The error Matrix indicates accuracy of each sample category with the actual category from field data. Kappa statistics were used to show the level of agreement in the classification (García et al., 2011). The detail overall accuracy information and forest type map is shown in (Table 15). The classification result was validated using a total of 145 trees from all three CFUG (23: Janprogati, 55: Devidhunga and 67: Nebuwater).

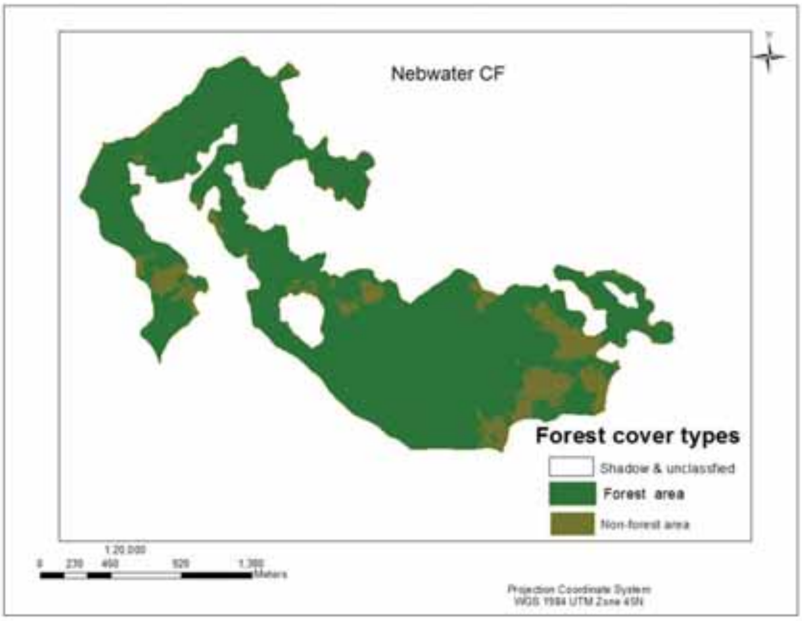


Figure 21: forest cover map of Nebuwater

The overall accuracy indicated that Devidhunga CF has the highest overall accuracy and Kappa statistic followed by Nebuwater CF and Janprogati CF which is 94%, 86% and 82% respectively.

Table 15: Overall accuracy for forest classification

CF name	Class name	Producer accuracy	Users accuracy	Overall accuracy of CF	Kappa(K^)
Devidhunga	Forest area	89.33%	100%	94%	0.75
	Undetectable area *	-	-		
Janprogati	Forest area	83%	100%	86%	0.72
	Non-forest area	92%	75%		
Nebuwater	Forest area	93%	100%	82%	0.70
	Non-forest area	86%	68%		
The undetectable area was found as class due to shadow in case of Devidhunga					

4.5. Transformed divergent (D_T)

Transformed Divergence was used to determine the statistical separability between tree species. The D_T value was calculated using the field training datasets and all eight bands of pan-sharped image. The species class pair with the highest D_T maximizes the possibility of high classification accuracy. As it is shown in (*Table 16*) the average separability was found to be 1976, which is the best separability of the image within the species classes. D_T with value 2000 (Excellent separability) was obtained between *Shorea robusta* and *Terminalia tomentosa*, *Shorea robusta* and *Mallotus phillippensis* and between *Shorea robusta* and others, While the tee species class “others” has separability of 1809 with *Lagerstroemia parviflora* and 1836 with *Mallotus phillippensis*. The separability of *Shorea robusta* falls in the range of 1992-2000 which is considered as excellent separability among all species. Almost all tree species have as D_T value greater than 1800, which indicated that the species can be separated distinctly.

Table 16: Transformed divergent of Worldview-2 image

Best Average Separability=1976.09							
Signature Name	*Shorea robusta*	*Schima wallichii*	*Semicarpus anacardium*	*Terminalia tomentosa*	*Lagerstroemia parviflora*	*Mallotus phillippensis*	*others*
Shorea robusta	0	1995.87	1992.87	2000	1998.66	2000	2000
Schima wallichii	1995.87	0	1910.74	1976.71	1819.68	1990.54	1992.44
Semicarpus anacardium	1992.87	1910.74	0	1999.24	1998.53	2000	20000
Terminalia tomentosa	2000	1976.71	1999.24	0	1988.95	1998.15	1999.38
Lagerstroemia parviflora	1998.66	1819.68	1998.53	1988.95	0	1999.74	1809.95
Mallotus phillippensis	2000	1990.54	2000	1998.15	1999.74	0	1836.47
Others	2000	1992.44	2000	1999.38	1999.95	1836.47	0

4.6. Spectral separability of tree species

The mean DN values of tree species in each band of Worldview-2 image were examined to decide the number of species classes to be selected in the image classification. The spectral curve was derived for six dominated species and one broad class called "other". The spectral separability was made on the ERDAS. The mean DN values of tree species were extracted from the spectral profile of each species in all eight bands of Worldview-2 image. As shown in (*Figure 22*) *Shorea robusta* was separated from rest of the species, while, *Semicarpus anacardium* and "other" species showed different characteristics in NIR-1 and NIR-2. This is due to the merging of species as one class (others) and small number of observation. The tree species were distinctly separated in the Red-edge, NIR-1 and NIR-2 bands.

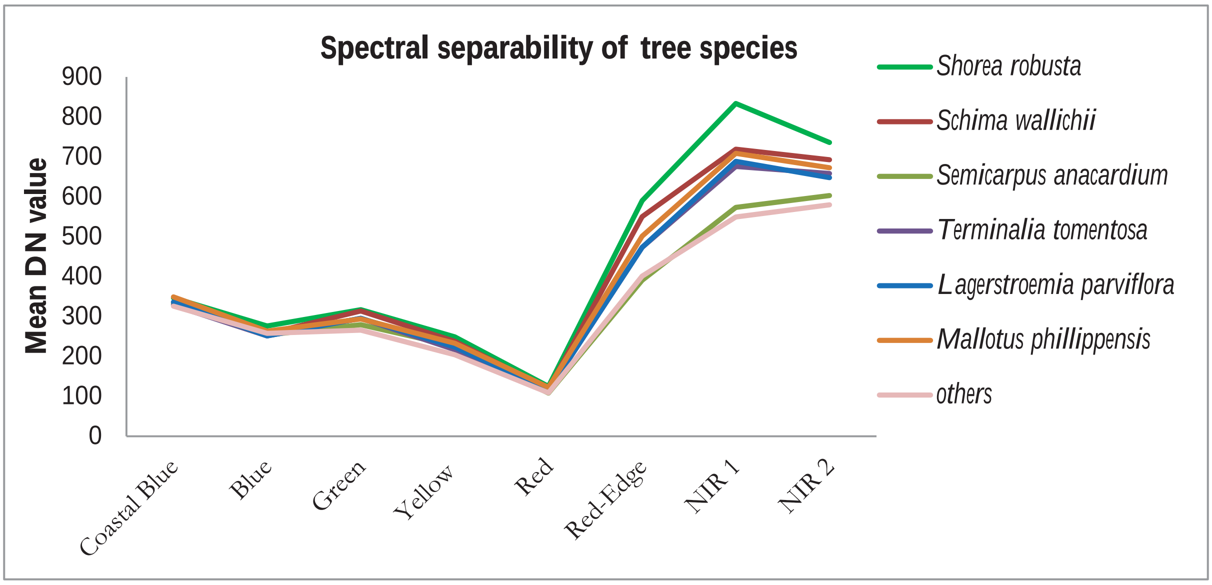


Figure 22: Spectral separability of dominate tree species

4.7. Specie classification

Tree species composition is among the important indictors in conservation of ecosystem function and vitality. It is also an essential part of SFM in line with global commitment concerning halting the loss of biodiversity (Wijewardana, 2008). In the study area six major dominate species class were identified: namely *Shorea robusta, Lagerstroemia parviflora, Terminalia tomentosa, Schima wallichii, Semicarpus anacardium, Mallotus phillippensis* and one general class called "others". Procedurally, the study followed two steps for species classification. First, image segmentation process and second the classification of segmented tree crown into appropriate species class. Supervised classification was done in eCognition which helps taking representative samples from each class. A neighbourhood classifier was used for object categorization. The segmented tree crowns were classified into six species and one class called "other" were found in Devidhunga, five species were identified in Nebuwater and two species were found in Janprogati. The result of the classification indicated the heterogeneity of species distribution across each stratum (CF). Particularly, a high diversity of species distribution was observed in Devidhunga while in Janprogati more than 70% of the area was covered by *Shorea robusta* and the remainder by other species. *(Figure 23 and 24)* shows the classified maps for the three CFUGs along with the overall classification accuracy in (*Table 17 and 18).*

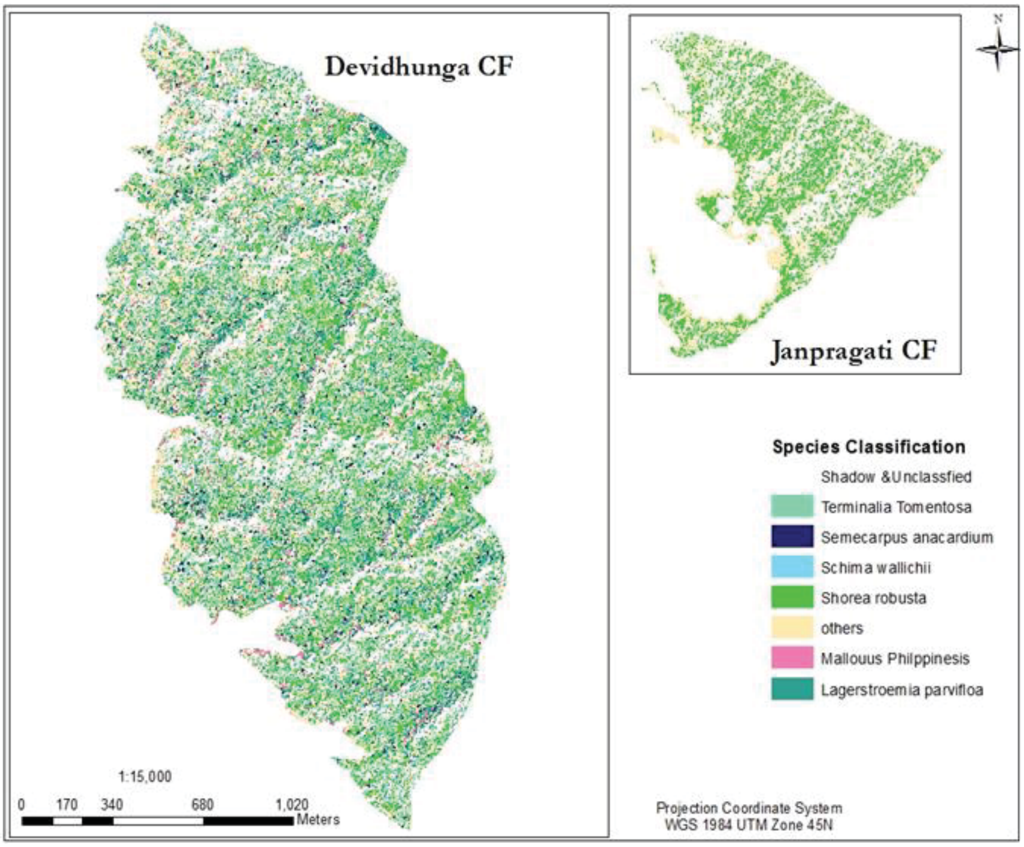


Figure 23: species classification map of the study area

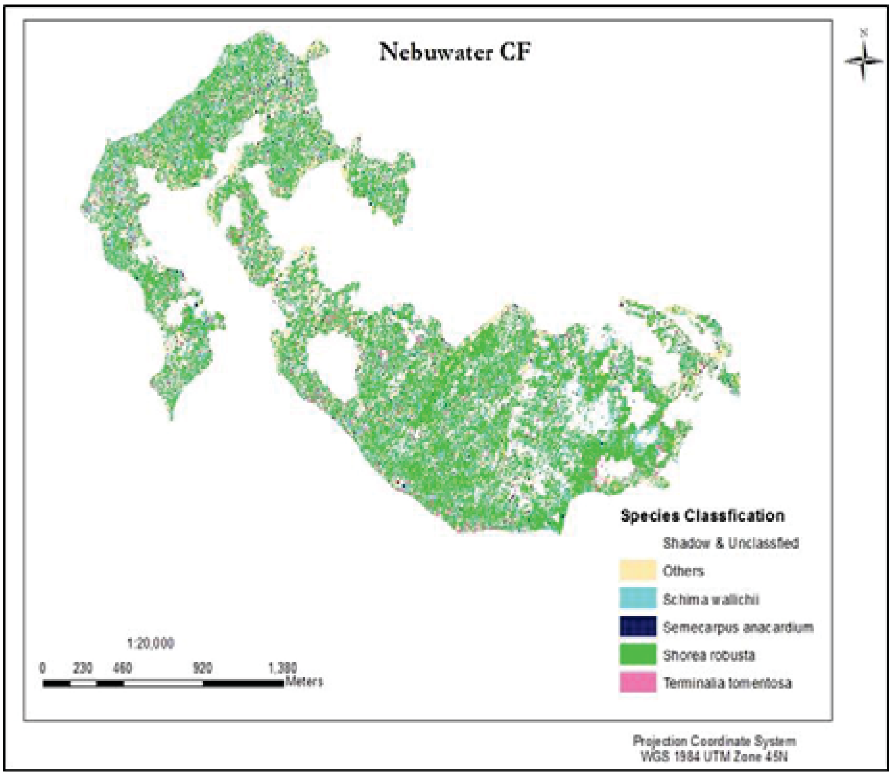


Figure 24: Nebuwater species classification

4.7.1. Accuracy assessment

The accuracy assessment was carried out and assessed based on the error and confusion matrix which summarizes the comparison of map species class labels with the reference data labels. A total 153 trees: 24 in Janprogati, 60 in Devidhunga and 64 in Nebuwater were used for accuracy assessment. The accuracy assessment was assessed based on the overall accuracy, user's accuracy and producer's accuracy. The classification showed that Janprogati CF had the highest accuracy followed by Nebuwater and Devidhunga as shown in (*Table 17* and *Table 18*).

Table 17: Overall accuracy for each CF

Name of CFs	Number of species classified	Overall Accuracy (%)	Kappa statistics
Janprogati B	2	86	0.71
Nebuwater	5	75	0.69
Devidhunga	7	67	0.52

Table 18: The user and producer accuracy of species class

Class Name	Janprogati B		Nebuwater		Devidhunga	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Shorea robusta	78%	94%	68%	57%	61%	58.1%
Schima wallichii	-	-	75%	77%	72%	100%
Mallotus phillippensis	-	-	-	-	60%	53%
Terminalia tomentosa	-	-	100%	78%	50%	100%
Semicarpus anacardium	-	-	87%	77%	65%	51%
Lagerstroemia parviflora	-	-	-	-	71%	94%
Others	95%	86%	58%	78%	64%	32%

4.8. Above ground biomass

A number of previous studies have attempted to produce a general AGB regression model and species wise models in present study area. Karna (2012) developed a multiple regression model for five dominant species. These species are *Shorea robusta*, *Lagerstroemia parviflora, Terminalia tomentosa, Schima wallichii* and Others , Mbaabu (2012) predicted AGB based on two models by dividing species into *Shorea robusta* and *others*. For this study, the second model was used because, *Shorea robusta* was found to be the dominant species in the study area and others only constitute of less than 20% of the study area. The relationship between CPA, height and AGB of *Shorea robusta* and others species are shown in (*Table 19* and *Table 20*)

Model 1: *Shorea robusta*: AGB= -1087+67.83CPA+10.67+3.0CPA*H

Table 19: Regression analysis for Shorea robusta in the CFUGs (source (Mbaabu, 2012)

Shorea robusta				
Regression statistics		Coefficients	T stat	P-value
Multiple R	0.91	Intercept -1087.14	-1.02621263	0.311115
R Square	0.83	H 10.67	0.210231962	0.834581
Adjusted R Square	0.82	CPA 67.83	1.375055618	0.176963
Standard Error	1139.55	CPA*H 3	1.507918018	0.139634
Observation	43			

Model 2 others species- CFUGs forest: AGB=-733.55+50.87CPA+5.63H+0.29CPA*H

Table 20: Regression analysis for other species in the CFUGs (source (Mbaabu, 2012)

Others				
Regression statistics		Coefficients	T stat	P-value
Multiple R	0.84	Intercept -733.55	-10.51457391	0.611038
R Square	0.71	H 5.63	0.116261631	0.908306
Adjusted R Square	0.67	CPA 50.87	0.728834943	0.472378
Standard Error	546.78	CPA*H 0.29	0.12685353	0.899996
Observation	31			

4.8.1. Model validation

The model validation was based on the calculation of the root mean square error (RMSE) and co-efficient of determination (R^2) to see goodness of fit. The observed AGB was plotted against the predicted AGB as shown in *(Figure 25).*

Shorea robusta *Other species*

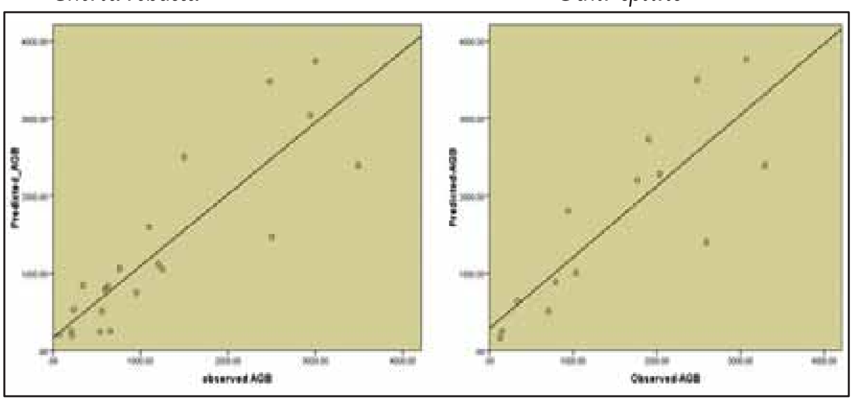


Figure 25*: Scatter plot for AGB model validation*

In addition to this, root mean square percentage (average field measured AGB divided by RMSE) was calculated. The *Shorea robusta* model explained 71% of the observed AGB with RMSE of 22, while of the observed AGB explained 79 % of the model for other species with RMSE of 51(*Table 21*). The models were validated using randomly selected independent data sets.

Table 21: AGB estimation model validation and RMSE (kg/tree)

Species	Coefficient of determination(R^2)	Sample size	RMSE
Shorea robusta	0.71	14	22.01
Others species	0.79	21	51.43

4.8.2. Mapping Above ground biomass

The regression model was used to estimate the AGB for the study area for both *Shorea robusta* and other species. The AGB map was produced in ArcGIS 2010. The amount of AGB ranges between 1500 kg/tree and 9500 kg/tree. A few trees with larger CPA and height have showed more than 9500kg/tree. In the study area an average of 367 $Mgha^{-1}$ was found. *(Figure 26 and 27)* show the AGB map for the three CFUGs.

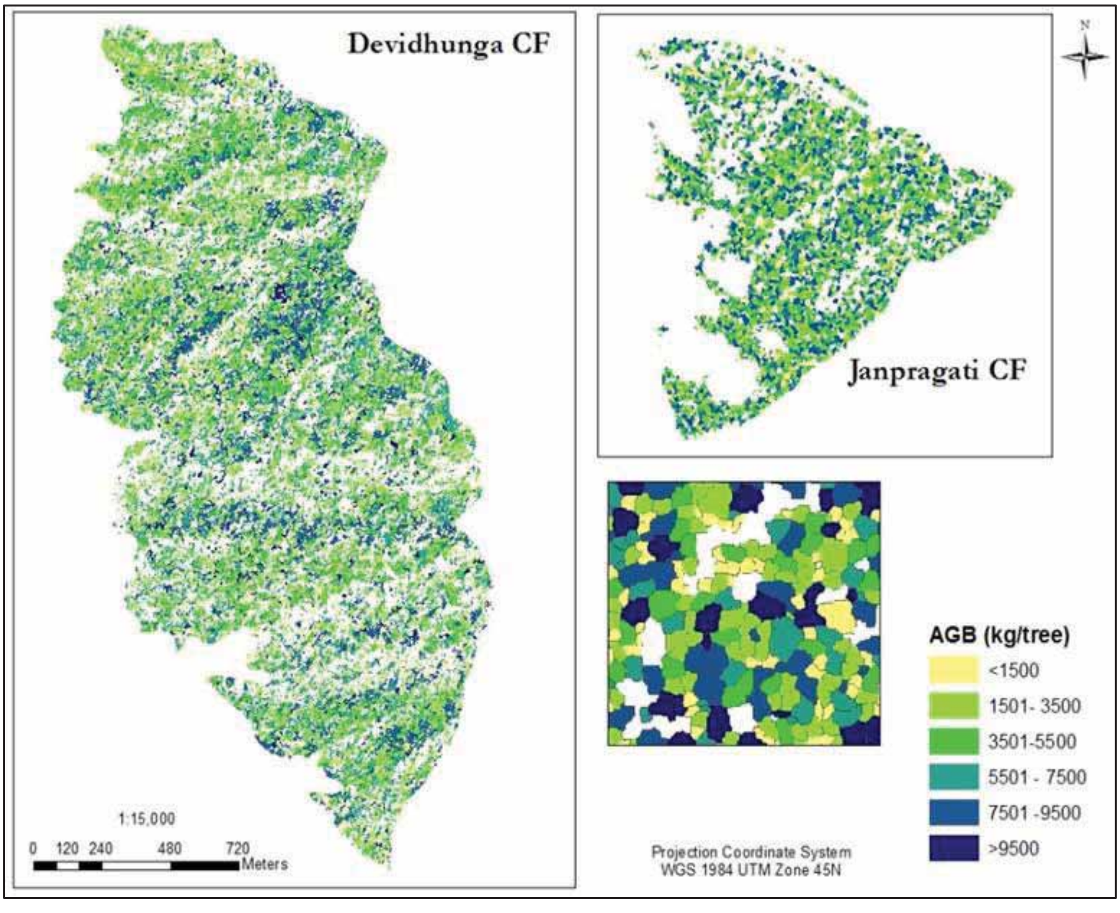


Figure 26: AGB stock (kg/tree) in Devidhunga and Janprogati

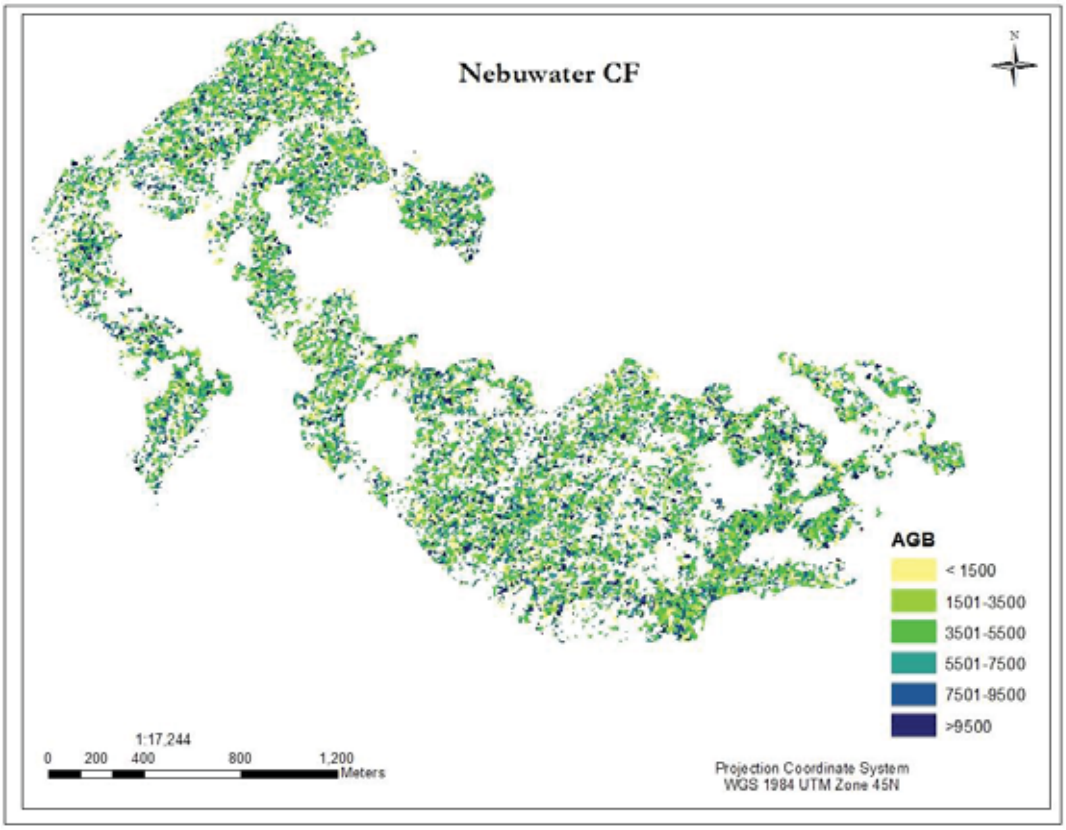


Figure 27: AGB stock (kg/tree) in Nebuwater CF

4.9. Relationship between CPA and DBH

The relationship between the crown projected (CPA) and diameter at breast height (DBH) was performed to see how accurate DBH can be predicted using CPA values and then to calculate timber volume of tree. For this reason cubic, logarithmic, linear and power models were developed and the results are presented in (*Table 22*).

Table 22: Model for DBH estimation

Model type	Model	R^2	RMSE	r
Linear	DBH(cm)=0.0.715*CPA+20.627	0.646	11.95	0.80
Logarithmic	DBH(cm)=18.904*log(CPA)-14.754	0.742	10.49	0.86
Power	DBH(cm)= 6.829*$CPA^{0.5569}$	0.738	9.24	0.86
Cubic	DBH(cm)=-0.0042*CPA^2+0.6743*CPA +2.3516	0.744	10.29	0.86

The results showed that cubic and power models have the lowest value of error. Finally, only one model was selected for the DBH estimation, which is based mainly on the lowest RMSE value, thus the power model was selected as most appropriate. The first analysis is a comparison of results only within the observed data to see the relationship between CPA and DBH derived from field data (*Figure 28*).

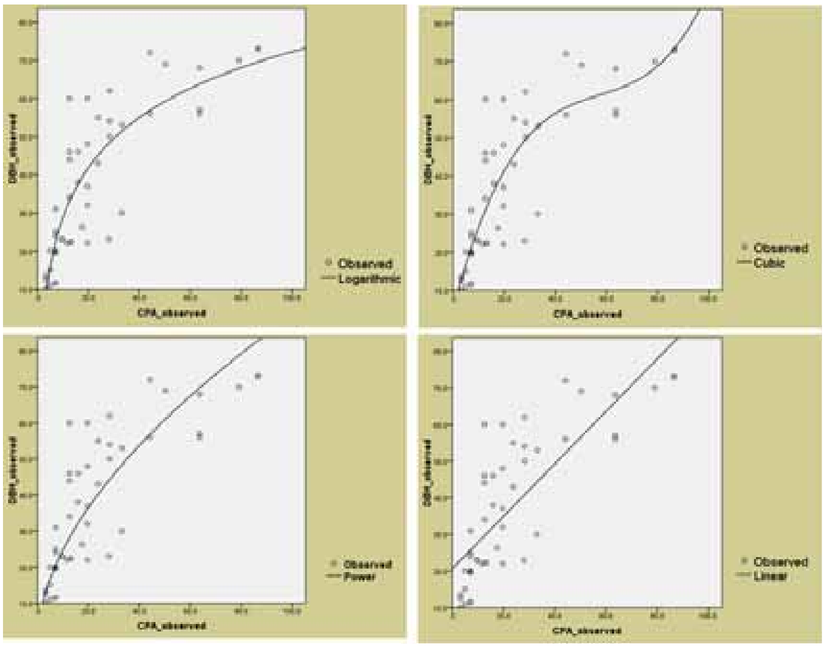


Figure 28: Relationship between Observed DBH and observed CPA

A one way analysis of variance (ANOVA) test was employed to test the significance of the power model and the result, shown in (*Table 23*) indicted that explanation of DBH by referenced CPA was statically significant at 95% confidence level.

Table 23: ANOVA test of model

ANOVA _ DBH					
Summary	df	SS	MS	F	Significance F
Regression	1	19409564	6469854.542	126.64028	2.38401E-07
Residual	45	8072266	298972.831		
Total	46	27481830			

4.9.1. DBH Model validation

A linear regression model was applied to validate the relationship using evaluation data set. The observed and predicted DBH were plotted against each other. The coefficient of determination and the RMSE values were used to evaluate the model *(Figure 29).* Modeling DBH using segmented CPA as explanatory variable resulted in higher (R^2=0.73) and less RMSE (9.03) when the power model was employed.

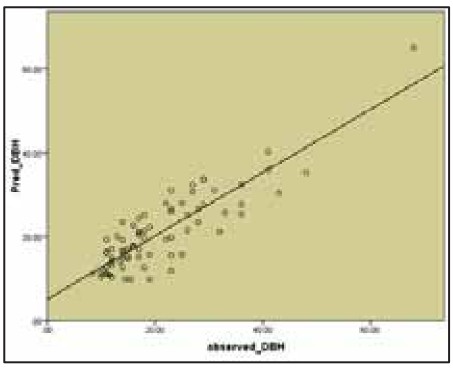


Figure 29: Scatter plot of predicted and observed values of validation DBH

4.10. Timber volume estimation

The timber volume was estimated based on the DBH and height for the entire study area. The DBH was derived from power model and height was from LiDAR CHM. The observed timber volume was plotted against the predicted timber volume to determine the linear relationship and it was found to be $R^2=0.73$ as shown in (*Figure 30*).

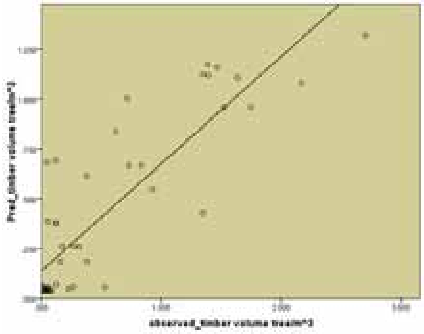


Figure 30: predicted timber volume vs. observed timber volume

The timber volume map was generated based on the formula developed by Sharma (1990) which contains the DBH and height. The timber volume of the three CFUGS is shown in (*Figure 32 and Figure 33*). The amount of timber volume ranges between $0.02m^3$ g/tree and $1.3m^3$/tree and the timber volume of the study area was 222143 m^3. However the few trees that have a larger DBH and height have showed more than $1.35m^3$/tree. In the study the average timber was 0.79m3/tree.

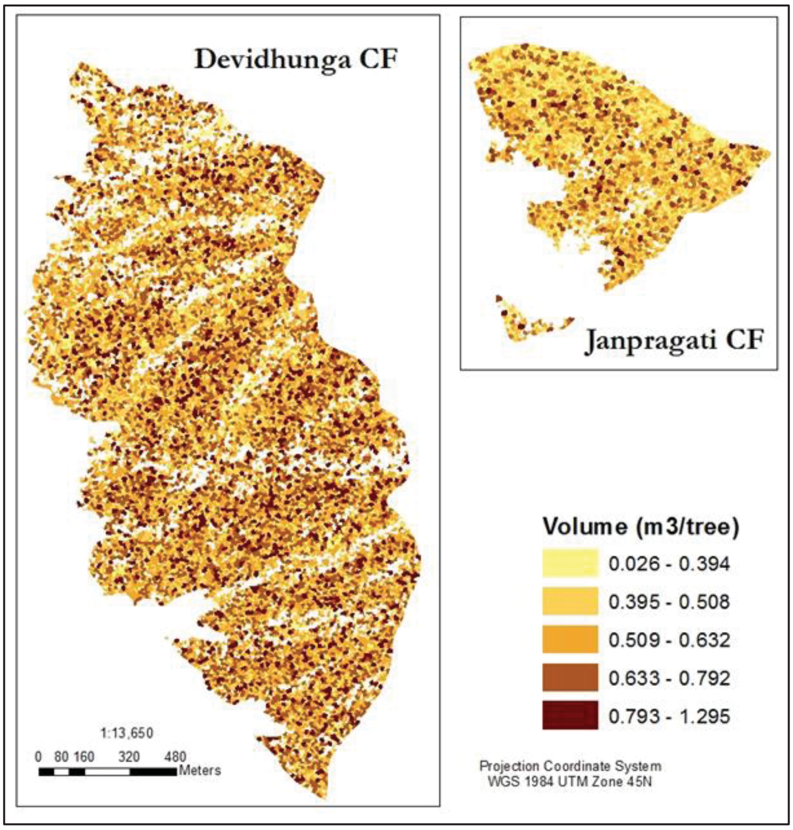
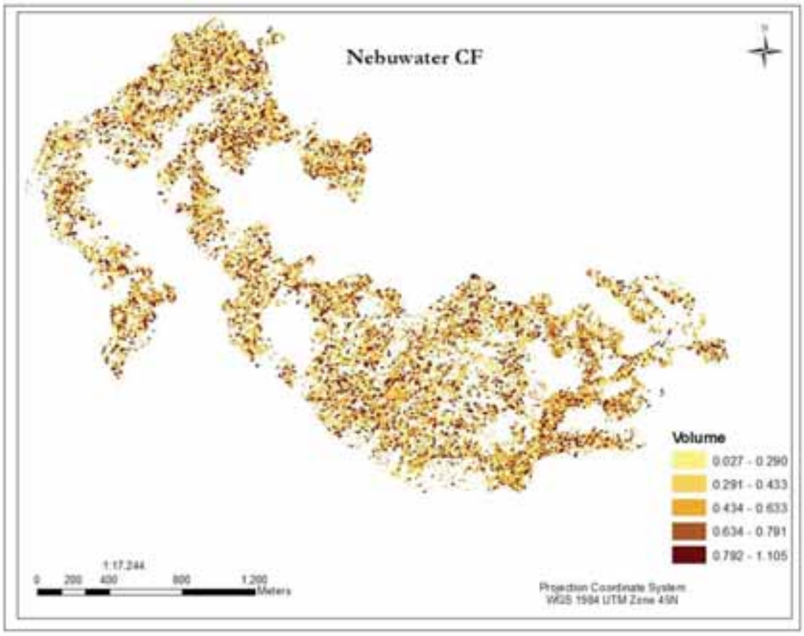


Figure 31: Timber volume map of Devidhunga and Janprogati



4.11. Forest condation assesement

Statistical method was used to analyze indictor's distribution for the entire forest and thus to assess the forest condition and its sustainability based on the field and remotely sensed data. These parameters were analyzed and compared among the three CFs. For the sake of interpretation, trees species with DBH> 10 were considered which allow the analysis of the size distributions. All the indictors were checked for the normality using the Shapiro Wilk test since the sample size is < 2000. The test was done at 95% significance level. As shown in the *Table 24* almost all parameters (height, DBH, AGB and timber volume) showed a normal distribution in Devidhunga and Nebuwater. However, this it was not the case in Janprogati for DBH, AGB and timber volume while height was normally distributed. The p-value was smaller than alpha =0.05.

The non-normality of the distribution indicted the trees present were not uniform in their distribution which further signifies that the stand composition is not a following similar pattern all over the area as its natural forest. The distribution in height and DBH results in high variability in AGB and timber volume (Patenaude et al., 2005). In Devidhunga and Nebuwater, (*Figure 33*) the frequency of trees increased in the larger DBH class (40cm -50cm). While in Janprogati the reverse was observed: an increase in the frequency of tress in the small DBH class (10cm-30cm) and a decrease in large DBH-class. Nebuwater CF has significantly higher mean DBH, AGB and timber volume than Devidhunga and Janprogati which means the stand composition is better in terms of growth and stock.

The species distribution of the CF is shown in (Figure 26 and Figure 24). *Shorea robusta* dominated in all the three CFs but the composition of *Shorea robusta* was significantly different in all three forests. For instance in Devidhunga a high diversity (0.95) of species was found (total six species) which indicate the heterogeneity of the CF. While in Janprogati more than 70% of area was coved by *Shorea robusta* with low diversity value(0.21) and in Nebuwater total of five species was found and diversity was high(0.72). In summary, Janprogati CF was found be the lowest in species composition, mean AGB stock and timber volume per tree. Devidhunga CF was the highest in species composition and diversity and Nebuwater possess the highest AGB stock and timber volume per unit area.

Table 24 Statistics of Indictors

Indictors	Devidhunga				Janprogati				Nebuwater			
	Mean	Stand deviation	Stand. Error	P. Value	Mean	Standard deviation	Stand. error	P. Value	Mean	Stand. deviation	Stand. Error	P. Value
Height	15.08	10.38	0.78	0.15	11.2	5.2	0.63	0.53	17.07	9.5		0.137
DBH	23.3	16.30		0.21	20.2	18.41	2.27	0.04	28.97	24.40	4.20	0.21
Diversity index	0.954				0.210				0.954			
Species richness	3.006				2.514				2.038			
AGB/tree	1053.1	1567.2		0.21	877.8	1024.3	108.45	0.010	1740.7	1077.4	103.4	0.28
Timber .V m^3/tree	0.92	1.27		0.17	0.64	1.82	4.72	0.032	0.59	0.64	27.23	0.15

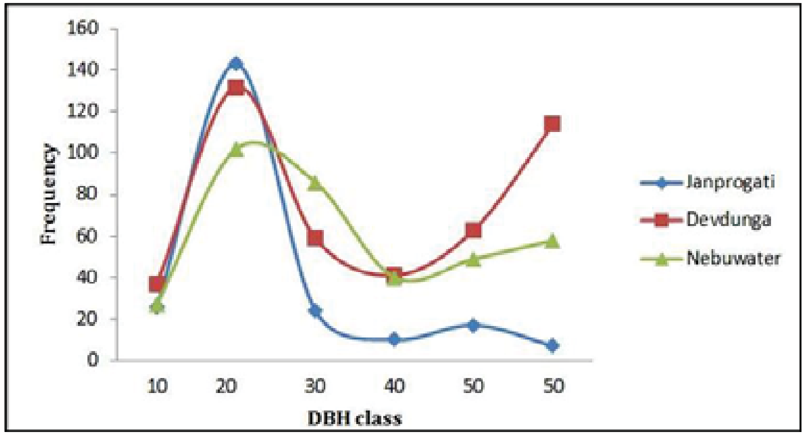


Figure 33: DBH class distribution

5. DISCUSSION

5.1. Introduction

Criteria and indictors are the basic units of SFM. Several studies have been done on segmentation of remotely sensing images for feature extraction (Hou et al., 2013). In this study, multi-resolution segmentation was used since it is a well-known method for the extraction of meaningful image objects from high resolution imagry (Baatz et al., 2000). Particularly, the combination of LiDAR data and VHRS images has brought a more robust application for precise estimate of forest biomass and timber volume than the former lower resolution of optical imagry. Forest stand parameters such as DBH, CPA and tree species have been used to estimate the AGB and timber volume which in turn, were very important to assess the forest condition and sustainability. However, the use of criteria and indictors for monitoring SFM is relatively rare in tropical conditions (Aguilar-Amuchastegui et al., 2007). In line with REDD+, which advocate SFM in tropical developing countries, the present study was conceived with the intention of estimating and mapping indictors using VHR Worldview-2 imagery and LiDAR data to assess the sustainability of community forest in Chitwan, Nepal.

5.2. Segemenation accuracy of tree crown

Together, the LiDAR derived layer (CHM) and the spectral information from Worldview-2 image contributed to an improved segmentation process. The CHM data were used to extract trees in shadow areas which would be missed if only spectral values were used. In particular in Janprogati CFs the LiDAR CHM contributes a lot to extract trees in the shadow area. However the segments were relatively larger in size and at the same time lots of polygons (tree crowns) were removed during shadow masking and morphological thinning of the tree crowns (Erikson, 2004). This has contributed to over segmentation. According to (Leckie et al., 2004) this process should have removed dead trees and unhealthy trees. Minimum and maxima pixel value of CHM were used for height information to separate small trees (height >4m) and tall trees (<4m) in the study area. The multispectral bands from the Worldview-2 images also allowed a more detailed discrimination of target tree crown by using the brightness and mean values of the bands, especially; the red-edge, NIR-1 and NIR-2.

The overall accuracy was assessed based on 1:1 correspondence and D-value (measure of closeness). In 1:1 spatial correspondence an overall accuracy of 79% was found. Out of 212 reference polygons, only 167 were found to have a 1:1 relationship with the segmented tree crowns (*Table 14*). Over segmentation, under segmentation and the resulting D values were 0.34, 0.29 and 0.31 respectively (*Table 14*). The validation result shows 50% overlap between the segmented polygons and the manually digitized polygons, which is considered correctly classified as done by (Zhan et al., 2005). The accuracy of segmentation was determined and constrained by several factors. The most important factors were the segmentation criteria and the segmentation technique. The segmentation technique can be region based, region growing and region merging (Ke et al., 2010). A multi-resolution segmentation (region based) technique was chosen among other segmentation methods, hence it is considered as the best method in heterogeneous forest (Lamonaca et al., 2008). In addition to this, the study area is a complex natural forest which consists of multi-scale variation (age, shape of branches, size of tree crowns) among trees, which normally causes over segmentation of images (Jing et al., 2012). The second factor is segmentation criteria which include scale, shape, compactness; colour and smoothness. These are the most important parameters in the segmentation process. In this study the segmentation was done many times using different combinations of these parameters at different levels. However, based on the visualization of the segmented polygon and field data, scale of 21, shape 0.8 and compactness 0.6 were selected for segmenting the Worldview-2 and LiDAR CHM.

Different authors have obtained different segmentation accuracy. The segmentation accuracy result achieved in this study similar to Karna (2012) who obtained an accuracy of 76 % using Worldview-2 image and LiDAR data and Baral (2011) who obtained an accuracy of 74 %, using a Worldview-2 image in the same study area. Similarly, Maharjan (2012) found an accuracy of 72% based on matching of manually delineated tree crown to automated segments and the D value was 0.31. In this study the improvement in accuracy is due to the use of different rule set and the inclusion of height information during the segmentation process.

5.3. Object based image classfication

Segemented tree crowns were frurther used for forest type and species classfication. An OBIA was conducted using a nearest neighbour classifier. OBIA is useful to minimize the local spectral variation caused by crown texture and gaps when it is compared with pixel based methods (Q. Yu et al., 2006). The mean intensity value of red-edge, NIR-1, and NIR-2 were tested for input signature as described in section (4.5). In this study, the forest cover classification was found to be 94% and kappa of 0.75 in Devidhunga, 86% and kappa of 0.72 in Janprogati and accuracy of 82% and kappa of 0.70 in Nebuwater *(Table 15).* The species classification achieved an overall accuracy of 67% and kappa 0.52 for classifying six species and one broader class “Others” in Devidhunga, while it was 75 % and kappa of 0.69 for classifying five species in Nebuwater and 86 % and Kappa of 0.71 for classifying two species (*Table 17* and *Table 18*). According to the classification result the classification accuracy was decreased as the number of species class increase (Immitzer et al. (2012). The user accuracy of all the five species (*Shorea robusta Lagerstroemia parviflora, Schima wallichii, Terminalia tomentosa* and *Mallotus phillippensis*) was more than 61% in each CF except for *Terminalia tomentosa* which had only 50%. This could be due to the small number of samples used for validation.

The overall accuracy obtained in this study is comparable to the results that were obtained by Maharjan (2012) who achieved 75% classification accuracy to classify two classes of tree species namely: *Shorea robusta* and others using a digital camera image and GeoEye images in Gorkha, Nepal. The user accuracy achieved for *Shorea robusta* was 77% and for other species it was 71%. Another author, Karna (2012) obtained an accuracy of 58% and kappa of 0.46 for classifying six species, an overall accuracy of 63% and Kappa of 0.48 for classifying five species and overall accuracy of 73 % and Kappa 0.62 for classifying three species using Worldview-2 and LiDAR in the same study area. Similarly, Holmgren et al. (2008) obtained an accuracy of 96% for classifying three tree species using LiDAR data (50 points/m^2) and multispectral images (4 Bands).This study used multispectral images which comprise a high resolution panchromatic image (0.1 pixel size on the ground) and a colour NIR image (0.6 m pixel size on the ground). The LiDAR generated tree crown segments and the corresponding pixel from the multispectral images were used for species classification. Compared to their research the present study uses low density LiDAR data (0.5 points/m^2). The overall accuracies obtained in this study fall in the acceptable range, although there is not yet any fixed standard for the method of assessment and style of reporting for any result derived from remotely sensed data (Congalton, 2001).

There are several factors that affect classification accuracy. In this study three major factors were identified. These are: data acquisition time, effects of shadow and cloud and segmentation quality. (i) **Data acquisition time**: the two images were acquired at different date. The LiDAR data was acquired in March, 2011 while the Worldview-2 image was acquired in October, 2010. ii) **Effect of shadow and**

cloud: eCognition did not perform well due to the presence of shadow and cloud of in the Worldview-2 image.

Figure 34: Worldview image distortion (left) and cloud and shadow (right)

In addition to this, the classification accuracy was affected by distortion in Worldview-2 image (*Figure 34*). Finally (iii), **Segmentation quality**: The effect of shadow and cloud have a direct impact on individual tree recognition in segmentation process (Brandtberg et al., 2003), which also affects the classification accuracy.

5.4. Model Development

Nonlinear regression and linear equations were tested to explain the relationship between CPA, height and DBH as described in section 4.6 and 4.7. However, a nonlinear relationship was found to be the best in explaining the relationship between theses tree parameters. According to Shimano (2000), nonlinear models are the best, particularly in dense and diverse natural forest conditions, in which trees growth does not follow a linear relationship between diameter and tree crown. The nonlinear regression model developed by Mbaabu (2012) therefore was used. In the model, CPA and height were used as independent variable for explaining the variation in AGB (dependent variable). Two different models were developed according to tree species classification (*Shorea robusta* and others) (*Table 19* and *Table 20*). The resulted models were validated using 30% of sampled data. The coefficient of determination (R^2) was 71% for *Shorea robusta* and 79% for other species. The coefficient of determination (R^2) showed that height and CPA explained 71% and 79% of variance in AGB for *Shorea robusta* and others respectively. The RMSE values of “other” species were higher (51%) than the value of *Shorea robusta* (21%).The result of this study is comparable with the result obtained by (Baral, 2011). She obtained R^2 of 0.65 for *Shorea robusta* and 0.8 for other species.

There are numerous studies about the relationship between DBH, CPA and height. For example García et al. (2010) discussed the non-linear relationship between height and CPA with AGB for four dominant species in lowland rain forest, southeast Brazil. They developed a general model for all species together based on height derived from LiDAR intensity data. The model yields R^2 of 0.8 and RMSE value of 28.89 for branch and foliage biomass. A study by Alves et al. (2002) also the relation between height and DBH and CPA with height. In their study they tested a non-linear regression model to show the relationship between DBH and CPA. The study reported R^2 of 0.91 which is higher than the output from models developed by our study (R^2 =0.7). This is due to the clustering of tree species into one class. It is the case for tree with large crown and DBH like in case of *Terminalia tomentosa* and *Schima wallichii*. However for some trees like *Semicarpus anacardium* which are small trees with low AGB compared to big trees in Chitwan, Nepal. Besides, the sample for validation was small.

5.5. Above ground biomass estimation

The result from this research shows that the AGB of the study area was approximately 367 Mg AGB per ha or 172 $Mgha^{-1}$carbon. The result found in this research was higher than the result of ICIMOD (2010) which is 153.10 Mg of carbon or 325 Mg of AGB per ha and lower than study by (Karna, 2012) who found 217 Mg carbon or 461 Mg of AGB in the same study area. These lower estimation in this study could be the due to the aggregation of many species in a general allometric equation which might introduce error in the estimation of AGB.

5.6. Timber volume estimation

The timber volume estimate was calculated using DBH and height of the trees. The DBH cannot be derived directly from both LiDAR data Worldview-2 image. Many studies have reported that DBH is best correlated with CPA (Lamonaca et al., 2008). Thus, four different nonlinear regression models were developed to estimate DBH: namely logarithmic, power, cubic and exponential models. The results show that the relatively highest RMSE value was obtained in the linear model with 11.9, followed by the logarithmic model with 10.4 and, finally, cubic model with 10.1. The power model was used to explain 74 % DBH based on CPA with a lower RMSE =9.2 from LiDAR data and Worldview-2 image *(Table 22).*The cubic and power models were found to have with less error. As a result, both the models were tested to estimate timber volume. However, the cubic model was unable to extrapolate to predict DBH values for those trees with CPA>200. Similarly, the study by Shimano (2000) examined both power and exponential model for DBH-class prediction in broadleaved forest and study found a correlation coefficient of 0.92 and 0.15 respectively.

In this study, the timber volume map was generated using the allometric equation developed by (Sharma, 1990). The mean and total timber volume was found to be 0.79m^3/tree and 222143m^3 respectively. The linear relationship between the predicted and observed timber volume was R=0.74%. Similarly a study by Sorin et al. (2004) in Virginia (USA) was done using the regression model and cross validation to estimate timber volume at plot level which resulted in an R^2 value of 0.39 and RMSE of 52.84 m^3/ha for deciduous trees and R^2 of 0.83 and RMSE of 47.9 m^3/ha for pine trees. This study also noted that using the fused data of multispectral and LiDAR always improves the result for both pine and deciduous trees. Another study by Sorin et al. (2004) obtained 83% of R^2 and RMSE of 47.90 m3/ha using small-foot print airborne LiDAR data with optical data. The study by (X. Yu et al., 2010) compared the plot level volume estimate using individual tree-based and area based timber volume estimation. They obtained an RMSE of 21% for area based level timber estimation and RMSE of 18% for individual based timber volume estimation using airborne scanner data in south Finland. The individual tree-based method gave relatively low RMSE, while in case of the area based method the mean volume was influenced most by the generalization error which also depends on individual tree detection (Franklin, 2001).

5.7. LiDAR data and Worldview-2 satellite image for SFM

In this study, the role of LiDAR and Worldview-2 was proven in estimating and assessing the associated indictors positively with reasonable accuracy. The chosen indictors (i.e. timber volume and green biomass) demands input from the vertical dimension of the tree. The accurate measurement and estimation of this variable is a very essential component to forest maintenance and productivity. Airborne LiDAR was used to derive canopy height which was the greatest interest of this study. The regression analysis was done to evaluate the linear relationship between the LiDAR derived CHM and field measured tree height which resulted in a coefficient of determination (R^2) of 0.77 and RMSE of 3.2.

The result of this study was higher than those by (Persson et al., 2002), (R^2=71), Lim et al. (2003),(R^2=0.68) and Clark et al. (2004), (R^2= 0.51) who estimate the canopy height in spruce forest , deciduous and coniferous forest respectively. compared to the results of Clark et al. (2004) , the accuracy of our study is low. They obtained R^2=95% and 55% for abandoned pasture trees and old growth tress. In the case of pasture trees, there is broad area without tree canopy, which permits more laser energy to reach the ground and return to the sensor, resulting in better height accuracy. In our study the reason for the poorer results might be due to the random error generated during field measurement from the field data (standard deviation =7.1). However there are also other reasons why direct comparison cannot be done. For instance the differences in forest type, composition of tree species and the quality of LiDAR data should be consider into account (Kwak et al., 2007).

The spectral information from the Worldview-2 image was used to improve the identification and measurement of individual trees (Sorin et al., 2004). Indictors such as forest cover and species classification were derived from the spectral information. Among the multispectral variables, the red, red-edge; NIR1 and NIR2 bands play a key role. VHR multispectral data has even great potential in providing textural information at stand level that is better than information obtained from lower resolution optical imagery. The textural analysis of remote sensing images provides significant information for sustainable forest management (Corona, 2010). Generally, based on the indictors result, higher species diversity was observed in Devidhunga CF (0.95) and also six dominant species were found. Nebuwater took the second place in terms of species composition (five species) and species diversity (0.72). Janprogati CF was the lowest in species diversity value (0.21) and only two species were found. The amount of AGB and timber volume was found to be high in Nebuwater and low in Janprogati (*Table 11*).

5.8. Sources of Error or Uncertainities

5.8.1. Global positioning system (GPS) error

A handheld GPS receiver was used to record the location of centre of sample plot and individual tree. It was also used for navigation and GIS data capture. However, it has introduced some positional error starting from transmitting signal to recording the coordinates of points and plots. According to Sinha (2002) positional error is related to the satellite's position along with its orbital track.. The accuracy of GPs was 4m to 6m on average (Sinha, 2002). The study also noted that the topography of the area also has influence on the GPS signal and thus on the accuracy.

5.8.2. Error from LIDAR and Worldview_2

In this study, two processes were identified in which error could be propagated: i) the process of CHM generation and ii) the registration of LiDAR data to Worldview-2 image. The LiDAR CHM was plotted against field height (R^2=0.77), which indicates 77% of variation in the field height can be explained by LiDAR derived height and the RMSE was 3.2m (*Table 13*). This error has also influenced the later analysis in the research. Registration of the LiDAR data with the panchromatic and multispectral band of Worldview-2 was performed to build-up a relationship and to extract the maximum information from both data sets which results in an RMSE of 1.5m (Karna, 2012). This creates a slight shift and discrepancy to both data sets, which could results in errors in both the segmentation and the species identification processes.

5.8.3. Error in segmentation process

In spite of the great potential of VHR Worldview-2 imagery and LiDAR data, the shape of tree crown was not easily recognized as expected. A fixed scale of 1:1500 was employed during digitizing process. However, the shape of tree crown could have introduced some error either to over or under segmentation. It was difficult to digitize two intermingled trees, which look like one tree in the image even after field observation. However this error was minimized because we employed the LiDAR height information in the rule set. Nevertheless, the LiDAR laser cannot see all the trees from above. As a result the small trees (understory vegetation) could not be detected or merged with nearby trees, causing under-segmentation. On the other hand, some trees with larger branches may be identified as two or more segments, causing over segmentation in tree detection. Bothe under and over segmentation can cause errors in the estimation of AGB as well as of timber volume.

Image acquisition time also was one of the factors influencing the propagation of error. The Worldview-2 image was acquired in October, 2010 (autumn) while the LiDAR data was acquired in March 2011which is the leaf fall season in tropical countries areas of Nepal. Leaf falls gives an opportunity to record the understory by remote sensing, which make tree identification difficult. In addition, the time difference (more than two years) may have a seen changes in the size of trees crown Song (2007) as some tropical trees have yearly growth rate of 3-5 cm. However the coupling of LiDAR data with multispectral imagery has minimized the error during segmentation as the LiDAR CHM was used for those small trees.

5.8.4. Error propagation in AGB and Timber estimation

According to Jerome Chave et al. (2004), the uncertainty in AGB estimation error can be introduced in different ways. Tree height and DBH are the most commonly used variables in both AGB and timber estimation. The first potential error could be from the process of tree measurement during fieldwork. The irregular shape of trees during measurement of DBH and height of individual tree may generate error. In addition to this, error can be introduced due to incorrect use of the instrument or imprecision of the instrument by itself, for instance positional error due to the GPS receiver and height measurement error from Haga altimeter can be mentioned. The allometric equation has also its own part in introducing error in both AGB and timber estimation, particularly in tropical forests which have high tree diversity (Asner et al., 2010). The general allometric equation does not include the variation in stand structure and species diversity (age and CPA) and the difference in location (topography, soil type and climate). In addition to this, the sample size used had also its own effect on AGB estimation (Sierra et al., 2007). (*Figure 35*) shows the summarized errors and their propagation which influence the overall pre and post results in this study.

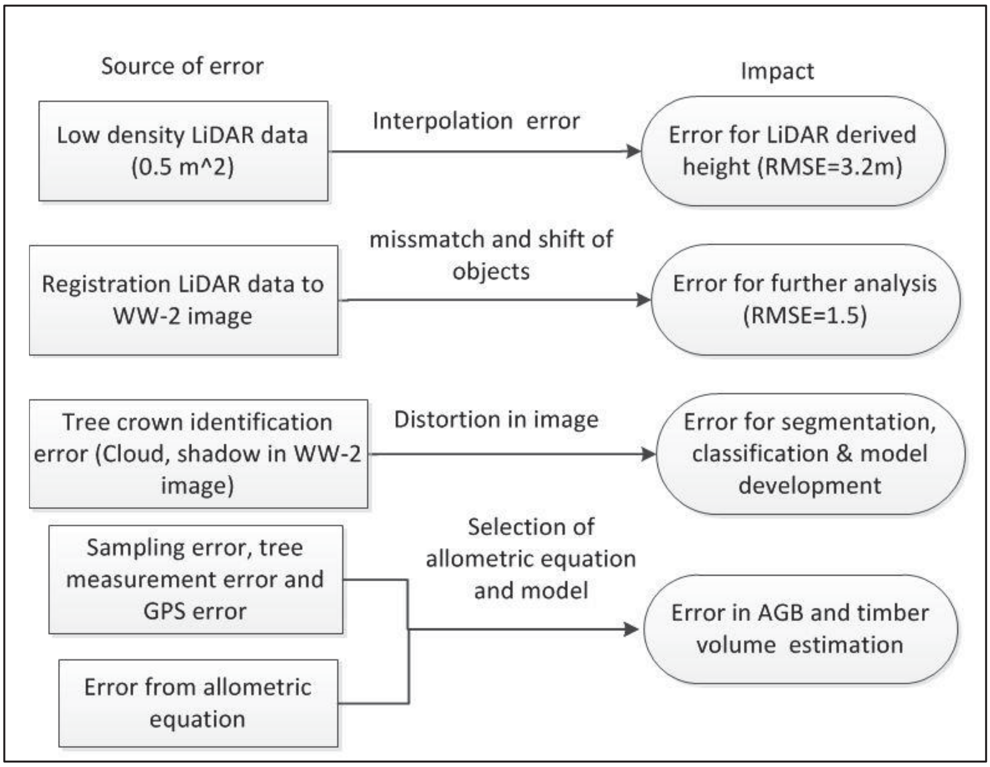


Figure 35: Source of error and its propagation

5.9. Strengths and Limitations of the study

Strengths

- The use of criteria and indictors facilitates the assessment of forest condition and sustainability of community forest.
- The integration of LiDAR data with the VHR Worldview-2 satellite imagery reduces the effect of shadow and cloud, both of which are common in most high resolution multispectral imagery.

Limitations

- Lower density LiDAR data can contribute to individual tree height estimation in some place where the high density LiDAR point data is missing.
- There was a 25^0 off-nadir view in the Worldview-2 image, which created distortion in the image and contributed to the error in segmentation process.
- Personal error and GPS error (due to dense canopy, steep slope and atmospheric conditions) in tree recognition in the field can contribute to errors in measurement of field measured parameters and final estimation of AGB and timber volume.
- The acquisition date of the image was not the best as it was during tree leaves fall period which can contribute to the reduction in the size of the tree crown (Song, 2007). Consequently, it would create a problem in separating undergrowth from the tree tops.
- There was no clear local species allometric equation for timber volume, which can contribute to error in the estimation of timber volume.
- Pervious field survey data (e.g. historical data) of the indictors were not available, and for this reason, it was not possible to verify the indictor's trend.

6. CONCLUSIONS

6.1. Conclusions

The integration of LiDAR data and Worldview-2 imagery was evaluated for estimating and mapping indictors using OBIA to assess the condition three community forest area of Chitwan, Nepal. In this research, the selected five indictors were positively assessed with reasonable accuracy using LiDAR data and Worldview-2 imagery. With respect of addressing the research objectives and research questions, the following conclusion were made accordingly.

How accurate is the segmentation of CPA from LiDAR data in combination with Worldview-2 imagery?

The segmentation accuracy was assessed using two methods. The 1:1 relationship showed an overall segmentation accuracy of 79% while D value (measure of closeness) resulted in segmentation accuracy of 69%.

How accurate is the forest type and species classification from LiDAR data and Worldview-2 imagery?

The OBI classification method was used for both forest type and species classification. For forest cover the following overall classification accuracies were found: 94% for Devidhunga, an accuracy of 86% for Janprogati and 82% in Nebuwater. Whereas, the species classification resulted in the accuracy of 86% for classifying two species, 75% for classifying five species and 67% for classifying six species.

What type of forest cover and tree species found in each CFUG'S?

Two major forest cover types were found: forest and non-forest area. While, at more detailed species level six dominated species were found in the study area. They include *Shorea robusta, Terminalia tomentosa, Schima wallichii, Lagerstroemia parviflora, Semicarpus anacardium and Mallotus phillippensis.*

How much AGB stored in the study area?

The total of 243079 Mg of AGB and on average 367 $Mgha^{-1}$ above ground biomass was found in the study area.

How much Timber stored in study area?

The total timber volume of the study area was 222143$m^{3,}$ While, the mean timber volume was 0.79m^{3}/tree.

What is the existing condition of the CFUG'S based on the selected criteria and indictors assessed using remotely sensing?

Results of forest parameters i.e., forest cover and areas, species composition, AGB, timber volume were used to assess the condition of each CFs. For instance; the species diversity was comparatively low in Janprogati, and high in Devidhunga. Forest extent indicated that in Devidhunga and Janprogati almost more than 90% of these two areas were covered by the forest whereas in Nebuwater 48 ha of non-forest area was found. However, Nebuwater CF also has significantly higher AGB and timber volume than Devidhunga and Janprogati. In summary the result of this study does not actually asses the sustainability as this needs historical data to be able to assess the trend of each indictor in the forest.

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APPENDIXES

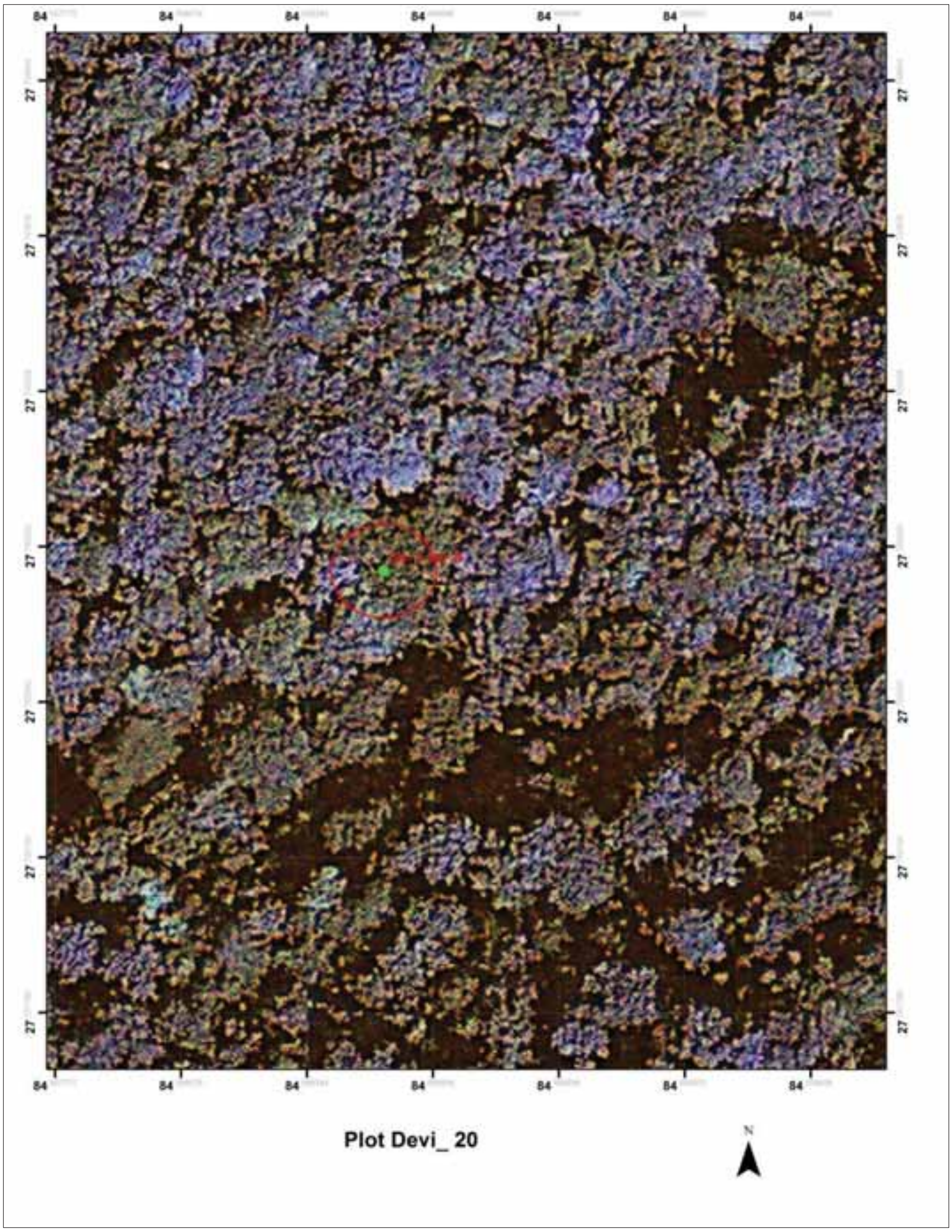
Appendix 1: Sample of data collection sheet

Data Collection Form For Kayerkhola Watershed, Chitwan, Nepal						
Name of Recorder:				Date:	Plot Radius Size: 12.62m	
Sample Plot No.		Coordinate		Elevation	Slope	Aspect
		X	Y		%	
Management Type:						
Strata Name:						
Forest Type:					Crown Cover%	
			DBH	Height	Crown	Remark
Tree No.	Species		(cm)	(m)	diam.(m)	
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						

Appendix 2: Diversity index

S. N.	Species	Sapling/ Regeneration	No. of individuals	Relative abundance	Remarks

Appendix 3: Map of sample plot used for tree identification in the field



Appendix 4: Sample plots

Strata Name	PLOT ID	X coordinate	Y coordinate
Devidhunga	Plot_1	262408.5568	3067439.145
Devidhunga	Plot_2	262445.3984	3067727.911

Devidhunga	Plot_3	262663.1734	3067570.423
Devidhunga	Plot_4	262597.8357	3067459.882
Devidhunga	Plot_5	262736.922	3067632.284
Devidhunga	Plot_6	262524.884	3067436.31
Devidhunga	Plot_7	262536.5033	3067702.457
Devidhunga	Plot_8	262836.3457	3066845.636
Devidhunga	Plot_9	262662.5489	3066840.648
Devidhunga	Plot_10	263076.972	3067549.265
Devidhunga	Plot_11	263077.8721	3067355.889
Devidhunga	Plot_12	263083.712	3067325.01
Devidhunga	Plot_13	262926.8847	3067337.459
Devidhunga	Plot_14	262876.3414	3067321.745
Devidhunga	Plot_15	262323.7264	3066915.696
Devidhunga	Plot_16	262784.8837	3067041.952
Devidhunga	Plot_17	262414.2338	3067009.531
Devidhunga	Plot_18	262633.1235	3067114.18
Devidhunga	Plot_19	262759.07	3066841.129
Devidhunga	Plot_20	262880.0772	3066968.182
Devidhunga	Plot_21	262803.4671	3067103.577
Devidhunga	Plot_22	262464.5566	3067916.385
Devidhunga	Plot_23	262452.5596	3067924.82
Devidhunga	Plot_24	262656.8071	3067096.024
Devidhunga	Plot_25	262321.5985	3067258.509
Devidhunga	Plot_26	262834.838	3067792.567
Devidhunga	Plot_27	263070.727	3067609.231
Devidhunga	Plot_28	263023.9645	3067604.836
Nebuwater	Plot_1	264527.2245	3067484.213
Nebuwater	Plot_2	265867.075	3066300.368
Nebuwater	Plot_3	265045.1369	3065838.82
Nebuwater	Plot_4	265230.6615	3065746.394
Nebuwater	Plot_5	264635.4538	3066244.669
Nebuwater	Plot_6	265598.7091	3065648.738
Nebuwater	Plot_7	264775.0235	3066125.869
Nebuwater	Plot_8	264309.7574	3067849.785
Nebuwater	Plot_9	264099.5451	3067784.047
Nebuwater	Plot_10	263844.8768	3067764.533
Nebuwater	Plot_11	263665.5795	3067706.69
Nebuwater	Plot_12	263729.1404	3067595.35

Strata Name	Plot ID	X coordinate	Y coordinate
Nebuwater	Plot_16	263848.1105	3066783.015
Nebuwater	Plot_17	263748.2385	3066845.18
Nebuwater	Plot_18	263906.583	3066695.145
Nebuwater	Plot_19	265902.1165	3066110.487
Nebuwater	Plot_20	265898.2376	3065987.943
Nebuwater	Plot_21	265937.5111	3065876.419
Nebuwater	Plot_22	265906.943	3066151.553
Nebuwater	Plot_23	264303.4265	3067494.151
Nebuwater	Plot_24	263609.5503	3066934.342
Nebuwater	Plot_25	263792.3002	3066681.248
Nebuwater	Plot_26	264215.3571	3066924.909
Nebuwater	Plot_27	264329.9246	3067006.266
Nebuwater	Plot_28	264402.8745	3066832.389
Nebuwater	Plot_29	264465.7832	3066749.683
Nebuwater	Plot_30	264304.0535	3066886.337
Nebuwater	Plot_31	264217.485	3067154.819
Nebuwater	Plot_32	264601.473	3066862.263
Janprogati	Plot_no1	263419.8644	3068574.768
Janprogati	Plot_no2	263852.0444	3068506.839
Janprogati	Plot_no3	263715.361	3068341.657
Janprogati	Plot_no4	263565.8843	3068335.945
Janprogati	Plot_no5	263406.5378	3068190.31
Janprogati	Plot_no6	263201.102	3068121.534
Janprogati	Plot_7	263362.7311	3068107.389

Appendix 5: List of tree species in the study area

S.N.	Species	Scientific name		S.N.	Species	Scientific name
1	Asare	*Mussaenda frondosa*		15	Chilaune	*Schima wallichii*
2	Asna	*Terminalia tomentosa*		16	Chiuri	*Bassia butyracea*
3	Badkaule	*Caseria graveolens*		17	Dabdabe	*Bassia butyracea*
4	Bandare	*Cynocardia odorata*		18	Dhalnekatus	*Castonopsis indica*
5	Banpipal	*Sapium baccatum*		19	Dhangero	*Dillenia aurea*
6	Bansupari	*Ophiopogon wallichianus*		20	Dolikath	*Dillenia aurea*
7	Barro	*Terminalia belerica*		21	Dumari	*Ficus benjamina*
8	Bhalayo	*Semicarpous anacardium*		22	Gayo	*Bridelia retusa*
9	Bhalukath	*Sida rhombifolia*		23	Gindari	*Premna latifolia*
10	Bhalukath	*Sida rhombifolia*		24	Guelo	*Elaeagnus latifolia*
11	Bhorla	*Bauhinia vahilii*		25	Harro	*Terminalia chebula*
12	Bilaune	*Maesa chisia*		26	Jamun	*Syzygium cumini*
13	Botdhairo	*Lagerstromia parviflora*		27	Jhakrisyaula	*Actinodaphne angustifolia*
14	Champ	*Michelia champaca*		29	Jamun	*Syzygium cumini*

S.N.	Species	Scientific name	S.N.	Species	Scientific name
30	Kadam	*Anthocephalus cadamba*	46	Kyamuna	*Syzygium serasoides*
31	Kadam	*Anthocephalus cadamba*	47	Latikath	*Cornus oblonga*
32	Kalikath	*Myrsine semiserrata*	48	Madane	*Randia dumetorum*
33	Kalo Siris	*Albizia lebbek*	49	MasureKatus	*Castonopsis tribuloides*
34	Karma	*Adina cordifolia*	50	Mayankanda	*Tetrameles nudiflora*
35	Khamari	*Gmelia arborea*	51	Nimaro	*Ficus roxburghii*
36	Khasreto	*Ficus hispida*	52	Mayankanda	*Tetrameles nudiflora*
37	Khirro	*Holarrhena pubescens*	53	Nimaro	*Ficus roxburghii*
38	Kummi	*Careya arborea*	54	Padake	*Albizzia julibrissin*
39	Kutmiro	*Litsea polyantha*	55	Padake	*Albizzia julibrissin*
40	Kyamuna	*Syzygium serasoides*	56	Sal	*Shorea robusta*
41	Khamari	*Gmelia arborea*	57	Sandan	*Ougeinia oojeinensis*
42	Khasreto	*Ficus hispida*	58	Simal	*Bombax ceiba*
43	Khirro	*Holarrhena pubescens*	59	Sindure	*Mallotus phillippensis*

Appendix 6: Model parameters for volume estimation

$$\ln(V) = a + b * \ln(DBH) + c * \ln(Ht)$$

Species	a	b	c
Shorea robusta	-2.4554	1.9026	0.8352
Others species	-2.3293	1.8836	0.9402

Appendix 7: Fieldwork work in Chitwan