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Assessment of Above Ground Biomass and Fire Risk Zonation in Selected Forest Areas of Ludhikhola Watershed Gorkha, District, Nepal

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SCIENCE PLEDGE

By my signature below, I certify that my, Thesis is entirely the result of my own work. I have cited all sources of information and data I have used in my thesis report and indicated their origin.

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Abstract

The drive for robust, accurate and cost-effective methods for biomass estimation over large areas is ever great with the launch of carbon crediting mechanisms in the developing countries such as UN-REDD. Traditional ground based measurement requires abundant manpower, resources, cost and time. Remote sensing based technologies pertinently answer the need of time in enhancing the successful implementation of such programs. The region growing and valley following algorithm used to delineate individual tree crowns produced a segmentation accuracy of 59.35% and 54.83% respectively. Both algorithms have similar approaches for delineation. Mainly *Shorea robusta* was identified in the image using a nearest neighbour classification approach with an overall accuracy of 85%. Above ground biomass (AGB) was calculated using allometric equation from DBH and height measured in the field. Linear regression models were applied to derive the relation of biomass with CPA, field measured height with biomass. All models were significant at 95% confidence level and the lowest RMSE% of 37.61% (*Shorea robusta*) and 33.33% (others.) The total amount of biomass stocks in the study area was approximately 94.52 Mg biomass ha^{-1}. For forest fire hazard Zonation an Analytic Hierarchy Process (AHP) method was used .The fire risk Zonation map is prepared on the basis of available data. This map shows that 11% of the study area falls under very low fire risk zone, 55 % falls under low fire risk zone and 30 % falls under moderate fire potential zone while 4% of area falls under high forest fire risk zone. The map is also validated through major past fire incidents. The results show that the predicted fire zones are found to be in good agreement with past fire incidents, and, hence, the map can be used for future forest resources management.

Key words: individual tree crown, region growing, valley following, crown projection area, Biomass stock, APH, Forest fire risk Zonation

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List of acronyms

AGB	Aboveground biomass
ANOVA	Analysis of variance
ANSAB	Asia Network for Sustainable Agriculture and Bio-resources
APH	Analytic Hierarchy Process
CF	Community Forest
CFUGs	Community Forest User Groups
CO_2	Carbon dioxide
CPA	Crown projection area
DBH	Diameter at breast height
DEM	Digital Elevation Model
DFO	District Forest Office
DoF	Department of Forests
DN	Digital Number
D_T	Transformed divergence
FAO	Food and Agricultural Organization
FRA	Forest Resource Assessment
GHG's	Greenhouse gases
GPS	Geographic Position System
HPF	High Pass Filtering
ICIMOD	International Centre for Integrated Mountain Development
IPCC	Intergovernmental Panel on Climate Change
Mg	Mega gram
MODIS	Moderate-resolution Imaging Spectroradiometer
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
UNFCCC	United Nations framework Convention on Climate Change
VDC	Village Development Committee
VHR	Very high resolution
WGS	World Geographical System

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CHAPTER 1: INTRODUCTION

Background

Reducing emissions from deforestation and forest degradation alongside with conservation and sustainable managing of forests in developing countries (REDD+) is emerging as an effective tool to mitigate and adopt the impacts of climate change (Angelsen, 2008; FAO, 2011). According to fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC) has estimated that the forest sector contributes 17.4% of all greenhouse gases from anthropogenic sources; most of this is due to deforestation and forest degradation (IPCC, 2007). Stern (2007) observed that curbing deforestation and forest degradation is a cost-effective way to reduce greenhouse gas emissions. Based on the scientific evidences, the Conferences of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC COPs) after the 13th session (COP 13) in Bali, Indonesia have outlined long-term cooperative action and called for enhanced national and international actions for operationalizing REDD+ to reduce greenhouse emission and address climate change adaptation and mitigation in developing countries.

The 15th session (COP 15) held in Copenhagen in December 2009 has decided to flow US $ 30 billion from the North to the South which has raised the expectation to reduce emission from deforestation and forest degradation and generate other co-benefits (livelihood improvement, poverty reduction, biodiversity conservation and adaptive capacity of ecosystem and local people) in developing countries. During COP 15, a consensus was reached that, while undertaking REDD+ actions, a number of safeguards should be designed and promoted both nationally and globally. This consensus was later turned into an agreement during COP 16, held in Cancun, Mexico. The COP 16 was considered one of the most important breakthroughs in the climate change negotiations.

It built a necessary foundation for REDD+, on which a more comprehensive structure could be implemented in the future. The Cancun conference has also outlined the three distinct phases that need to be included in the REDD+ implementation process: readiness, demonstration and implementation. It has decided on a phased approach to REDD+ implementation adopting with the following steps: i) development of national strategies or action plans, policies and measures, and capacity building; ii) implementation of national policies, measures, strategies or action plans for further capacity building, technology development and transfer, and results-based demonstration activities, evolving into; iii) results-based actions to be fully measured, reported and verified. Finally, the agreements highlighted the need to address related issues by requesting that parties, when developing their national action plans or strategies for REDD+, address “the drivers of deforestation and forest degradation, land tenure issues, forest governance issues, gender considerations and the safeguards” whilst ensuring effective and full participation of the relevant stakeholders including indigenous peoples and local communities.

Outcomes for REDD+ from COP 17 held in Durban, South Africa, relates to financing options, safeguards and reference levels. The same decision includes guidance on reference levels and/or reference emission levels. These form the benchmarks against which to measure forest-related emissions per year and are thus essential to environmental integrity when assessing future performance. This provided a strong basis for a robust Measurement, Reporting and Verification (MRV) scheme, essential for the development of REDD+. It was decided that reference levels should be consistent with each country’s greenhouse gas inventories, referring to anthropogenic forest-related greenhouse gas emissions by sources and removals by sinks.

The decision provides guidance on a transparent, flexible approach, in which reference levels are periodically reviewed in conjunction with any advancement in methodologies; and sub-national reference levels can be elaborated as an interim measure whilst transitioning to a national level. MRV and REDD+ financing were the main areas of debate on REDD+ during COP 18, held in Doha, Qatar where technical issues regarding MRV were addressed under the Subsidiary Body for Scientific and Technological Advice (SBSTA). This included:

(i) How to design national forest monitoring systems;

(ii) How to create an appropriate MRV framework for result-based payments;

(iii) How to link MRV with reference levels;

(iv) The need for additional guidance on designing REDD+ safeguards and

(v) The drivers of deforestation. Furthermore, the COP 19 held in Warsaw of Poland brought a Warsaw framework that includes decisions on modalities for national forest monitoring systems; modalities for MRV; technical assessment of proposed forest reference emission levels/forest reference levels (RELs/RLs); safeguards information systems; and addressing the drivers of deforestation and forest degradation.

According to the decision of COP 19 under the Warsaw framework for REDD+, developing country party may nominate a national entity to obtain and receive results-based payments (UNFCCC, 2013). This national entity will be a main responsible institution for the effective implementation of REDD+ program at national level. In the context, the Government of Nepal through its Ministry of Forest and Soil Conservation (MoFSC) have been preparing for REDD+ initiatives since 2008. Presently, Nepal is in the first phase; the readiness phase within which the Government of Nepal (GoN) develops a national REDD+ strategy and builds the capacity of forestry stakeholders.

Nepal's REDD Preparedness Plan (RPP) 2009 has envisioned a hybrid approach including both a robust and comprehensive MRV framework at national and sub-national levels for implementing REDD+. Similarly, MoFSC through REDD Implementation Center (REDD-IC) has been implementing the emission reduction program with support from the Forest Carbon Partnership Facility of the World Bank (FCPF) in twelve Terai districts of Nepal. Similarly, different civil society organizations have been piloting REDD+ at sub-national level in different parts of Nepal. The first REDD+ pilot project was implemented through a consortium of ANSAB, International Centre for Integrated Mountain Development (ICIMOD) and Federation of Community Forest Users in Nepal (FECOFUN) in three sub-watersheds of Nepal with financial assistance from the Norwegian Agency for Development Cooperation (NORAD).

Similarly, WWF Nepal established baseline of forest carbon for implementing REDD+ in Terai Arc Landscape. Similarly, RECOFTC (The Center for People and Forests) and Nepal Federation of Indigenous Nationalities (NEFIN) piloted some capacity building projects on REDD+. These pilot projects have contributed to the ongoing national REDD+ process by providing learning in various aspects, namely reference level/reference emission level, methodologies for forest carbon measurement and benefit sharing mechanisms and forest carbon stock to ensure the ecological, economic and socio-cultural integrity of the region and design a successful REDD+ project activities in the future. When properly designed, REDD+ schemes can provide a sound bridging mechanism in the transition towards a low carbon economy. They can contribute to improving rural livelihoods, promoting good forest governance, delivering biodiversity objectives and increasing resilience and adaptive capacities to climate change.

1.2 Technique for Forest above Ground Biomass Estimation

According to FAO (2010) biomass is the organic material both above and below the ground, and both living and dead trees, crops, grasses, dried litter root etc. This is considered one of the important indicators for analyzing the ecosystem productivity. Most of the biomass assessments are done for AGB of tree which is due to their large account for the total living biomass and which can be easily and readily measured in the field (Brown, 1997), Hence above ground measuring have drawn the considerable attention these days. Biomass can be readily converted to carbon storage and quantifying carbon storage which is important to understand carbon cycle (Malhi et al; 2002). Remote sensing, especially satellite-based approaches, provides the most practical option for monitoring land cover change over large areas.

The appropriate use of remotely sensed data combined with a forest resource inventory provides the practical means to generate this information and supplies synergistic answers the important questions of where, how, and by what amount resources are changing over time . Remote sensing is the study and activity of collecting and interpreting information about features from a distant location. It is the only means to obtain continuous data over large areas at an effective cost. With the advancement in spaces science and technology there is are also different methods and technique in practices to measure AGB and consequently the carbon stock of forest. Studied conducted by lu (2006) summarized that some Remote Sensing and Geographic Information System with Field based measurement could be the effective and cost effective measure for the forest biomass estimation. Based on field data like diameter at breast height (DBH) and tree height can be further converted to estimate to estimates of forest carbon stock with the application of allometric relationship (Gibbs et al; 2007) .

The most accurate method to estimate forest biomass is based on field measurements, but collection of field measurements is time-consuming and labor-intensive, and it is impossible to census large geographic areas (Wang et al. 2009). Geographic Information System (GIS)-based biomass estimation models using environmental variables cannot provide accurate biomass estimates because forest biomass often has weak relationships with environmental variables (Lu 2006; Chen 2012). In case of GIS-based methods which required data like Land cover type, site quality and forest age in order to establish indirect relationship for biomass of a particular area.(Lu, 2006). However such methods are difficult to implement because of problem in obtaining good quality of ancillary and compound effect of environmental factors on biomass accumulation (Brown, 2002, Lu, 2006). Statistical relationship between satellite extracted variables and ground based are used in biomass estimation with application of remote sensing (Gibbs et al; 2007). It is necessary to keep in mind that remote sensing does not measure biomass itself but it rather measures forest characteristics like spectral reflectance reflected form the tree canopy and which is the base for deriving variables and ground data are necessary for to develop biomass productive model calibration and validation (Gibbs et al; 2007).

Combination of this approach could be the best alternative and cost effective to traditional methods (Patenaude et al; 2005). Because of which UN-REED+ program and Kyoto Protocol height lights the advantage of using Remote sensing based data for obtaining spatial, temporal and spectral information to obtain reliable information for above ground carbon estimation (Andreson et al; 2009). During last decade different types of optical sensor data have been available for the biomass estimation such as Landsat, SPOT, ASTER, CBERS, QuickBird, MODIS, and AVHRR (Fuchs et al. 2009; Lu et al. 2012; Song 2013; Du et al. 2014). Optical sensor data have various spatial, spectral, radiometric, and temporal resolutions.

1.3 Geospatial Approach for Fire RiskZonation

Forest fires are one of the most important sources of forest land degradation that lead to deforestation and desertification processes. Forest fires occur throughout Nepal and result deforestation of around 1.7 per cent of the total forest area annually (DFRS, 2014). Along with destruction and degradation of forests, wildfires are emitting huge amount of GHGs to the atmosphere during thus serving for global warming. To mitigate such impacts and for effective response, fire risk assessments prior to the disaster events are taken as an important tool (IPCC, 2014).These fires cause economic losses and environmental degradation throwing dedicates ecosystems out of balance. It is also threatening valuable and endangered flora and fauna, degrading the forest, soil and inducing flood and landslide. Most of the fire incidents are caused by negligence of the people. Hunting practices, negligence by cigarette smoker, intentional fire to accelerate growth of grasses to feed livestock, intentional fire setting by herb and charcoal collectors and children playing with fires are some of the reasons for forest fires. Certain type of trees especially Sal (*Shorea robusta*) is particularly other susceptible to fire. About 86 per cent of the population of the country inhabit in the rural areas mainly in thatched houses closely clustered where fire hazards are likely to be common (MoH 2009).

Forest fires are one of the most important sources of land degradation that lead to deforestation and desertification processes. Forest and wild land fire are considered vital natural processes initiating natural exercises of vegetation succession. However uncontrolled and misuse of fire can cause tremendous adverse impacts on the environment and the human society. A wildfire risk model can serve as an early warning system to predict the severity level of future fire risks which significant for wildfire prevention and fighting strategies. Developing a GIS-based wildfire hazard modeling which aim to identify geographic locations with the highest wildfire hazards and risks.

Fire hazard is defined as a fuel condition or state that may result in an undesired wildfire event. Risk is defined as the probability of an event occurring. For example, dense housing within a high wildfire hazard area may have a higher probability or risk burning than home s within a patchy fuel complex. In the literature the words hazard and requirement have different meanings. Hazard includes both risk and danger component (risk is associated to prevention and ignition, danger corresponds to spread and fighting actions) (Wybo, et al 1995).

However it is impossible to control .It is impossible to control nature, but is possible to map forest fire risk zone and thereby minimize the frequency of fire. The model deals to combine geospatial data by Geographic Information System (GIS) technology to construct the map forest fire risk zone. Study conducted by (Noson, 2004) state that hazard mapping is essential to understanding and addressing risks that can interfere with a community's ability to achieve that vision in which can minimize and reduce the risk of forest fire and better management of forest fire. The integration of satellite data into GIS can be very useful to determine risky places and to plan range management after fire that this result coincide with study of Erten et al. (2005) as it mentioned in the study. (Mahdavi et al. 2012, Ariapour et al; 2014) have been used AHP technique for zoning map of wildfire risk in forest areas and referred that it is useful to define priority of affecting factors of fire, so this study used AHP also because it is fast and simple to use.

1.4 Problem Statement and Justification

To obtain reliable tree information of forest biomass different effort has been done (Maier et al; 2008). Accurate quantification of biomass is important baseline information required to identify the amount of carbon stored in any ecosystem. The quantification of biomass has been made possible by the use of conventional methods. The conventional methods for quantifying biomass face some challenges such as high cost involved in data collection, accuracies of the collected data, and it is time consuming. Due to these shortcomings biomass quantification had been based on the local biomass allometric equations (Chamshama et al., 2004; Munishi and Shear, 2004). Although biomass allometric equations provide a general biomass content of an area based on the sample data of particular tree size. Also, the applications of allometric equation require verifying for their applicability to a forest area to be measured.

This is because, the relationships between biomass and tree parameters differ with geographical location, land cover type and forest management practices. On the other hand, remote sensing has an added advantage of estimating and spatially distributing biomass over the wider area of interest. This research study intend to add up to the baseline information that will aid the government, policy makers, local stake holder , different organization working on development and implement of REDD+ in Nepal basically for identifying the amount of biomass present in each forest types as well as most deforested and degraded area within the forest ecosystem. In addition to the baseline information, this study focused with the application of freely available medium resolution images that can be used widely and freely and broadens the knowledge on techniques of estimating AGB which are simple and has low costs. The Ministry of forest and soil conservation is the key beneficiary from the output of this study, although other stakeholder will benefit on information generated regarding the forest.

Among the forest deforestation and degradation forest fire are key factors so it is urgent and necessary to develop forest fire Zonation map so emission due to this factor can be minimize. The results of this study are expected to enlight the local people on how much their forest is capable to store biomass per unit area, which part of their forest are degraded and deforested heavily and perhaps they can be easily display the deforested and degraded forest area, Which location, area are more risk to fires and can give the biomass content of an area in maps, forest fire risk Zonation Map and develop their forest working operation and forest management plan accordingly.

1.5 Aims and Objectives

The overall Aims of the study were to assess forest biomass stock and forest fire hazard Zonation of Ludhikhola Watershed Gorkha Nepal. The specific objectives of the study was

1. To assess and classify the community forest based on the spatial distribution of forest above ground biomass.
2. To determine the relationship between fields measured tree height, Crown Projection Area (CPA) and aboveground biomass in the study area.
3. To develop spatial Forest fire risk Zone map for study area.

1.8 Research Question

Major research question of this study were what are the relationship between CPA and above ground biomass, amount of biomass in study area, accuracy level of species classification , how accurate forest fire hazard Zonation could be with past forest fire incidence.

1.9 Organization of the Report

Chapter 1

The general background of the research problem, general overview technique for forest above ground biomass estimation, general overview on geospatial approach for fire hazard Zonation, and problem of statement, Research question and objectives follows thereafter.

Chapter 2

The description of study area in terms of its geographic location, climatic conditions and vegetation characteristics, and criteria for the selection of location are covered.

Chapter 3

This chapter discusses the materials and methods used in this research to achieve the research objectives.

Chapter 4

Results of the Above ground biomass estimates including the tree crown delineation approaches and regression modelling, AHP approach for the forest fire hazard Zonation are described.

Chapter 5

Discussion of the results obtained in this study. It includes, image segmentation, classification of tree species, regression modelling, mapping of above ground biomass, relationship between CPA and above ground biomass, Forest fire risk hazard Zonation. Finally recommendations are drawn in this chapter.

CHAPTER 2: AN OVERVIEW OF STUDY AREA

2.1 Criteria for the Selection of Study Area

2.1.1 Nepal REED+ Implemented Area

Among different three watersheds Ludhikhola watershed is also one of the REED+ pilot projects implemented by the community forest user group. The project area is funded by different agencies under the Climate Forest Initiative. In this area near about 1888 hectors of forest are managed by community for the better management of forest and forest biomass.

2.1.2 Data Availability

Different data sets for the community forest and additional information are lacking in many part of the forestry sector area in Nepal, But in case of this watershed some basic data information were made available by ICIMOD data like Forest fire data, delineated community forestry boundary 2010 land use land cover and forest cover etc. so they were obtained from ICIMOD.

2.1.3 Accessibility

Study area is located in accessible area from the nearby city which was good for researcher to complete all field work in limited time and budget.

2.1.4 Variation in Forest Types

The forests are mostly young forest by age. The forests are mixed forest and there is variation in tree species with change in aspect and altitude. Sal (*Shorea robusta)*is the most dominant species in southern aspects and northern aspect of low altitudes. Where *Schima wallichi* (Cheluna) and *Castanopsis indica* in northern upper part. Additionally there are some needle leaf tree species like *pinus roxburghi* in the southern aspect and few species like Ficus, Terminalia, syzgium, bombox are also distributed across the study area.

2.2 Location and General Characteristic

Ludhikhola watershed is located in the Gorkha district of the western development Region of Nepal. This watershed is having hill physiographic region with wide ranges of altitude ranging from 318m to 1714 m from mean sea level. It have occupied 31 community forest user groups and managing about 1888 ha of forest area. Among 31 only 5 community forest were selected for this study.

2.2.1 Topography

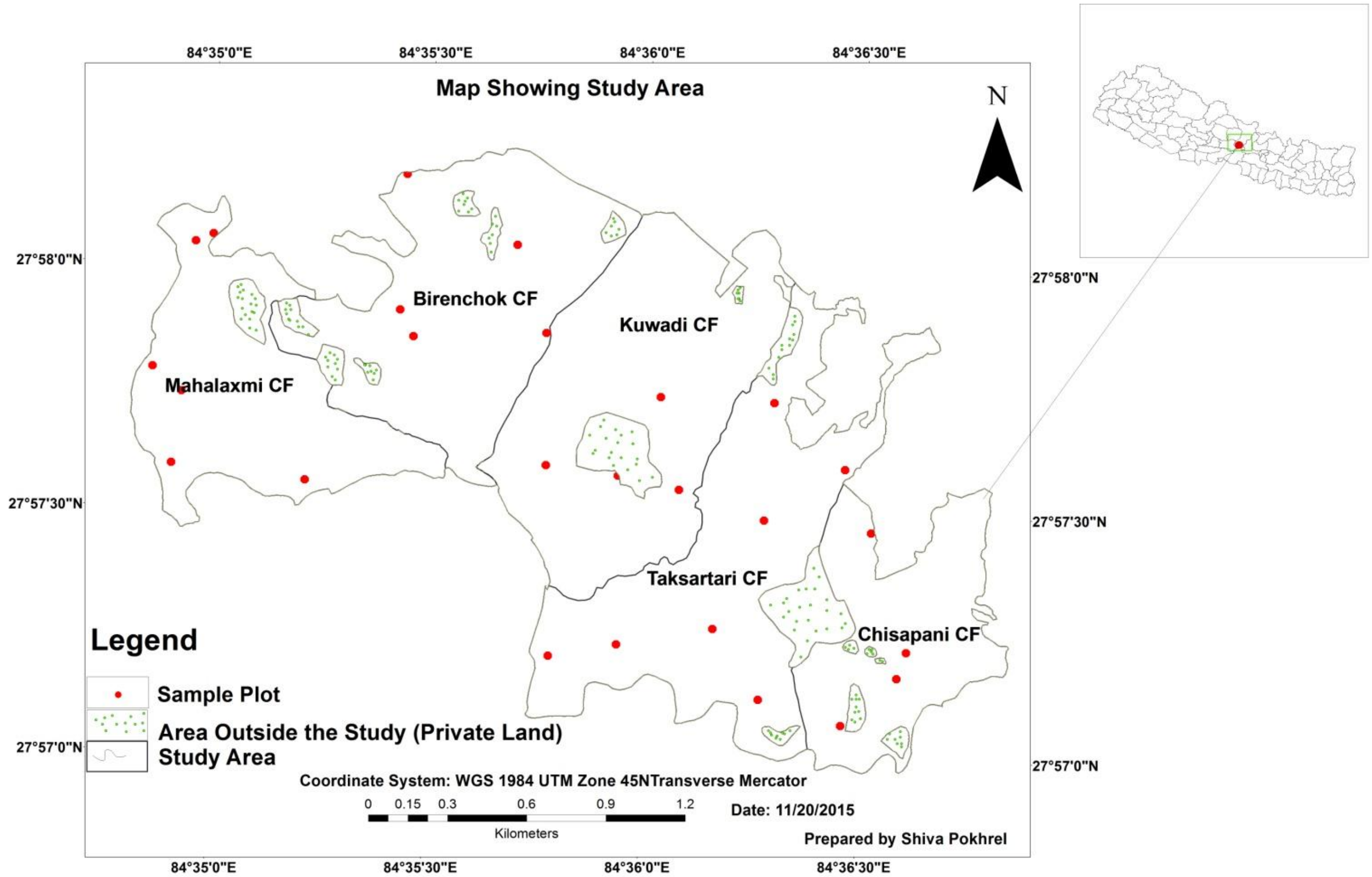
All most all parts of this watershed lie in Middle Mountain Ecological Zone with varying altitude ranging from 600m to 1100m. Out of total area 61% of the land is steep slope with 30 to 60% slope and the Remaining land with slope less than 30%. This watershed has four major river systems that run within and along it. Which are BudhiGandaki, Marsyangdi, Daraudi and Chepe.

2.2.2 Climate

Because of the varying altitudinal topography and ecological region climate of this area are dominate by subtropical at lower altitudes to sub-temperate to temperate at higher altitude. Average daily temperature of this watershed observed 23.3˚C.The minimum temperature is 5 ˚C and the maximum 33˚C In terms of hottest and driest days are in March, April and May while June and end of August are heavy rainfall month with an average annual rainfall of 1972 to 2000m (DHM, 2012).

2.2.3 Settlements

The total population of this area is 23197 with 3800 household Watershed is occupied by diverse ethnic group namely Magar, Gurung, Dalit (marginalize caste in Nepal), and few households of Brahmin and Chhetri (ICIMOD, 2010).



Map: 1 Map showing Study Area

Table 1 Table showing CF Name and area

S.No.	C.F Name	Area (Ha)	Area (%)
1	Birenchok C.F	83.576	22.05
2	Chisapani C.F	50.036	13.10
3	Kuwadi C.F	92.269	24.34
4	Mahalaxmi C.F	63.965	16.88
5	Takasartari C.F	89.207	23.53
Total		379.153	100

CHAPTER: 3 LITERATURE REVIEW

3.1 Forest Biomass and Its Measurement

Forest play significant role in global system (UNFCCC, 2012). Forest is the sources of wide range of goods and services which include timber, fuel wood and food products (berries, nuts mushrooms, and many wild edible fruits and vegetables) and fodder. As regards important services, forests and trees play a vital role in the conservation of ecosystems in maintaining quality of water and in preventing or reducing the severity of floods, avalanches, erosions and droughts. Forests provide a wide range of economic and social benefits, such as employment, forest products and protection of sites of cultural value (FAO 2010). Forests are the most important carbon sinks, storing more carbon than the world's oil reserves; they also constantly remove carbon from the atmosphere through photosynthesis that converts atmospheric carbon to organic matter. Forests are absorbing atmospheric carbon, deforestation is putting carbon right back into the atmosphere at an annual rate of 5.9Giga tone (Gt) CO_2. In other words, 60 percent of the carbon that is absorbed by forests is emitted back into the atmosphere by deforestation (Erin C. Myers Madeira 2008*).*

Biomass is commonly estimated by applying conversion factors (biomass expansion factors) to tree volume (either derived from field plot measures or forest inventory data) (Kurz et al. 2002, Lenhtonenet al. 2004). The use of existing forest inventory data to map large area tree AGB has been explored conversion tables were developed to estimate biomass from attributes contained in provincial forest inventory data, including species composition, crown density and dominant tree height. Guidance on the selection, development and application of appropriate biomass factors and allometric equations for large-scale biomass estimation was provided (Somogvi et al. 2007).

Different approaches mainly based on field measurements, remote sensing and GIS modeling has been utilized largely applied for AGB estimation (Geotz et al. 2009, UNFCCC 2008, Lu D2006). AGB estimation and mapping using remotely sensed data has been explored and widely appreciated during the past few decades. According to the Intergovernmental Panel on Climate Change Good Practice Guidance (IPCC GPG) (IPCC 2003), remote sensing methods are especially suitable for independent verification the national Land Use, Land-Use Change and Forestry (LULUCF) carbon pool estimates, especially for the aboveground biomass.IPCC report of 2007 accepted that GHG emissions since pre-industrial time have increased more than 70% between 1970 and 2004. Intensive use of fossil fuels in industries of developed countries and increasing rate of deforestation and forest degradation in developing countries are to be considered major cause increase for emission carbon dioxide gas.

Definitely its impact is inevitable to different biophysical and socio-economic system. Several researches have been conducted to show the schematic framework of anthropogenic climate change. Philippe Rekaciwicz in 2005 has developed the framework of the climate change. In Nepal, current forest policy and legislation classify the country’s forests mainly according to their tenure or control. Based on it, the following categories of forest are recognized: government-managed, community managed, leasehold, religious, private and protected forests (Acharya 2002). Government-managed and protected forests are directly administered by government agencies while community, leasehold and religious forests are managed by local communities or user groups. Private forests are under controlled by individual households (Singh and Chapagain 2006). The community forestry programme is regarded to be successful in Nepal, not only in restoring the degraded sites, biodiversity and improving the supply of forest products to people, but also in forming local level institutions for resource management and in improving the environmental situation (Niraula et al. 2013).

Forest is the second largest natural resource of Nepal after water. Nepal is acknowledged and highly appreciated for its participatory forest management regimes. At present, approximately 39.6% of geographical area of the country is under forest cover, of which 25% is managed by local and indigenous community as Community Forestry3.4.1 Optical Remote Sensing. 2015; Niraula et al. 2013).Out of 14.7 million hectares of the total Nepal area, 1.65 million hectares are controlled by communities (DoF 2012). According to FAO (2010) country report, forest living biomass (above and below ground biomass) is 484 million metric tons (359 million metric tons by above and 126 million metric tons by below ground biomass). FAO (2010)also reporting, Nepal exist in the list of the countries where deforestation is <50,000ha/year but need more improvement). The annual rate of deforestation is highest in the Terai (1.6%), followed by the High Himalayas (0.97%), and the Siwalik Hill along the Indian border (0.87%) (Niraula et al. 2013).The country was selected as one of the four countries for promoting forest conservation by controlling deforestation and degradation as well as benefiting from forest carbon stocks.

3.2 **Biomass Concept**

A wide literature review on a definition of biomass has revealed a mention of biomass to be Comprised of living organisms and non-living organisms which include animals, plants, fossil Fuels and soils (Zhou and Hemstrom, 2009, Shelly, 2012, Wikipedia, 2015). However Bombelli et al., (2009) has defined biomass as a mass of live or dead organic matter. With regard to live organic matter in particular, live plants create biomass through a process known as photosynthesis. Photosynthesis is defined as a process occurring in plants and other organisms similar to plants, to convert the light energy captured from the sun into chemical energy that can be used to fuel organism’s activities (Wikipedia, 2015).

During the process of photosynthesis carbon dioxide and water are the raw material in which, they combine with aid of sunlight to yield complex organic compounds and oxygen. The complex organic compounds form physical parts of plants such as roots, stems, branches, and leaves. These plant parts are the store of carbon that has been absorbed from the atmosphere. The capacity of plants to store carbon is referred to as carbon sink. With regard to dead organic matter, dead plants decompose to form organic matter which is an important soil constituent. The soil acts as a reservoir because it has ability to store and release carbon and is referred to as carbon pool. Forest has the ability to store up to about 80% of all above ground and 40% of all below ground terrestrial organic carbon (IPCC, 2001). This study concentrates on above ground biomass estimation. Above ground biomass includes all the plant parts which have emerged above ground such as stem, stump, branches, seeds and foliage. The measurement units of forest biomass are either in fresh weight or in dry weight. However, with regard to estimation of forest biomass, dry weight is preferred most because 50% of the plant weight is carbon (Montagu et al., 2005). There are three methods in which biomass can be measured (Lu, 2006).

3.3 Field/In Situ Measurements

Destructive sampling is oneof the ways to measure the AGB. It requires harvesting trees, drying them and then weighing the biomass. Other sampling techniques use allometry to extrapolate biomass without the harvesting trees. These measurements of forest biomass can be aggregated for a small sample area or extrapolated to wider levels using allometric equations. In situ measurements are critical to monitor terrestrial carbon stock as they are labor-intensive, expensive and difficult to implement, especially in remote areas (Lu D 2006). Other problems related to field measurements are incomplete data, inappropriate parameter definitions, inconsistent spatial and temporal scales and sampling bias in measurements.

3.4 Remote Sensing Based Measurements

Forest biomass can be evaluated using remotesensing instruments mounted on space borne or airborne platforms, but substantial refinements are needed before routine assessments can be made at national or regional scales (Baccini et al. 2004, DeFries et al. 2007). No remote-sensing instrument can measure forest carbon stocks directly and thus require additional ground-based data collection (Drake et al. 2003). Remotely sensed data benefit, such as repetitively of data collection, a synoptic view, a digital format that allows fast processing of large quantities of data and the high correlations between spectral bands and vegetation parameters make it the primary source for large area AGB estimation, especially in areas of difficult access. Remote-sensing methodologies have been more successful at measuring carbon stocks in boreal and temperate forests and in young stands with lower forest carbon densities. Tropical forests are among the most carbon rich and structurally complex ecosystems in the world and signals from remote-sensing instruments tend to saturate quickly. This has inhibited reliable forest carbon stock estimates in these ecosystems. Remote-sensing systems relying on optical data (visible and infrared light) are further limited in the tropics due to highly cloudy weather, but newer technologies such as radar systems can penetrate clouds and provide data day and night (Asner 2001).

Thus remote sensing based AGB estimation has increasingly attracted scientific interest (Zheng et al. 2004, Lu D2005). AGB can be directly estimated from signals of remotely sensed data with different ways, such as multiple regression analysis, K nearest-neighbor and neural network (Zheng et al. 2004) .Indirectly estimated from canopy parameters, such as crown diameter that were first derived from remotely sensed data using multiple regression analysis or different canopy reflectance models (Popescu et al. 2003). A number of approaches have been developed to map carbon stocks and AGB from the satellite observations.

These approaches rely on calibrating the satellite based measurements to in situ estimates of AGB at field study plots. AGB is often determined using a combination of well documented allometric relationships between simple plot-level measurements (e.g. stem diameter, density and sometimes canopy height and/or depth) and AGB, where the latter is determined from trees that have been dissected, oven-dried and weighed (Brown 1997, Chave 2005). This type of allometry has a long history of forestry operations worldwide, although refinements are always needed and ongoing (Geotz et al. 2009). Several existing AGB estimation approaches based on satellite data are described below and limitations related to the approaches are summarize in below.

3.4.1 Optical Remote Sensing

Optical remote sensing, i.e., passive sensing of visible and near-infrared reflectance from the earth, forms the basis of current global scale mapping. Optical measurements have been widely used in studies that link AGB measurements from the field to satellite observations, based on sensitivity of the optical reflectance to variations in canopy structure.

3.4.2 Coarse Spatial Resolution Data

Common coarse spatial resolution data are NOAA Advanced Very High Resolution Radiometer (AVHRR), SPOT VEGETATION and Moderate Resolution Imaging Spectro radiometer (MODIS) freely available. They are often used at national, continental and global scales. The AVHRR data have long been the primary source in large-area surveys because they offer a good trade-off between spatial resolutions, Image coverage and frequency in data acquisition, it is likely that AVHRR data are the most extensively used datasets for studies of vegetation dynamics on a continental scale.

The close relationship between middle infrared (MIR) reflectance and AGB implies that MIR reflectance may be more sensitive to change in forest properties than the reflectance in visible and near-infrared wavelengths (Boyd et al. 1999). The AVHRR NDVI data were used to estimate biomass density and assess burned areas, burned biomass and atmospheric emissions in Africa (Barbosa et al. 1999) and to estimate boreal and temperate forest woody biomass in six countries (Canada, Finland, Norway, Russia, USA and Sweden) (Dong et al. 2003). The nonparametric K nearest-neighbour method was used to analyse relationships between Landsat TM and field data and nonlinear regression analysis was used to develop models for predicting volume and biomass for WiFS pixels. Wylie et al. (2002) tested grass biomass estimation through scaling Landsat TM to coarse spatial resolution satellite data (AVHRR) over the Great Plains of North America.

3.4.3 Medium Spatial Resolution Data

The medium spatialresolution ranges from 10 to 60 meter. The most frequently used medium spatialresolution data may be the time-series Landsat data that have become the primary source in many applications, including AGB estimation at local and regional scales (Lu 2005, Zhang et al. 2007, Barrett K 2009). Lefsky et al. (2001) evaluated the utility of several remotely sensed data for estimating stand structure attributes—age, basal area, biomass and diameter at breast height (DBH). Foody et al. (2001) found that neural networks were useful for the AGB estimation using Landsat TM data in a Bornean tropical rain forest. In Finland and Sweden, Landsat TM data were used to estimate tree volume and AGB using the K nearest-neighbour estimation method. The complex forest stand structure, the impact of shadows caused by canopy and topography and the complex environments influence AGB estimation performance (Lu D, 2005). Spectral signatures or vegetation indices are often used for AGB estimation. Many vegetation indices have been developed and applied to biophysical parameter studies.

3.4.4 High Spatial Resolution Data

Fine spatial resolution data, such as SPOT-5, IKONOS, QuickBirdGeoEye1 etc. images are frequently used for modelling tree parameters or forest canopy structures for forest biomass estimation (Leboeuf et al. 2007). De Jong et al. (2003) used digital airborne imaging spectrometer (DAIS) data to estimate biomass using stepwise linear regression analysis in southern France. Many techniques or approaches used for extraction of biophysical parameters from aerial photography can also be used in high spatial resolution satellite images. Thenkabail et al. (2004) used IKONOS data to estimate AGB of oil palm plantations in Africa. The fine spatial resolution and associated multispectral characteristics have become an important data source for AGB estimation. One important application may be its use as reference data for validation or accuracy assessment for medium and coarse spatial resolution data applications. But they are costly.

3.4.5 Synthetic Aperture Rader (SAR)

SAR is an active sensor based on the principles of radio detection and ranging (Radar, often used as a synonym for SAR) and has been widely used to map AGB (Kasischke ES 1997, Tatem AJ 2008). In many areas of the world, the frequent cloud conditions often restrain theacquisition of high-quality remotely sensed data by optical sensors. Thus, radar databecome the only feasible way of acquiring remotely sensed data within a given timeframework because the radar systems can collect Earth feature data irrespective of weather or light conditions. Due to this unique feature of radar data it has been used extensively in many fields such as forest-cover identification and mapping, discrimination of forest.

3.4.6 Light Detection and Ranging (LIDER)

Lidar is based on the concept of actively sensing the vegetation using a pulse of energy, in this case from a laser operating at optical wavelengths (rather than at radio wavelengths). Lidar does not penetrate into the clouds but has the unique capability of measuring the three-dimensional vertical structure of vegetation in great detail, sometimes with hundreds of measurements in the vertical dimension for each location on the Earth (Dubayah 2000). Lidar has only been widely used for a little more than a decade.

Lidar systems are also used for forest parameter estimation (Zimble et al. 2003). Lim et al. (2003) reviewed the application of lidar data to forest studies. In previous research, airborne laser data were used to estimate timber volume (Naesset 1997), tropical forest biomass (Nelson et al. 1997) and stand height (Naesset and Bjerknes 2001, Naesset et al. 2005). The lidar data were used to estimate biomass (Means et al. 1999,Lefsky MA 2005, Sun G 2008), temperate mixed deciduous forest biomass (Lefsky et al. 1999), tropical forest biomass (Drake et al. 2003), tree height and stand volume (Nilsson 1996, Zimble et al. 2003), stand height (Wulder and Seemann 2003), tree crown diameter (Popescu et al. 2003) and canopy structure (Lovell et al. 2003).

3.5 Object Based Image Analysis

Among different resolution satellite images VHSR is more appropriate stand parameterization and has more potential ability to provide set of information for advance forest inventory (Chubey*, et al.*, 2006). However while working with very high resolution images. Pixel mixing problem persists. Object oriented image analysis techniques overcomes pixel mixing problem and has been proved to be an alternative approach to the conventional pixel-based image analysis (Zhengrong*, et al.*, 2010). Object based image analysis provides high recognition of the diverse objects in the image making it easier to classify VHSR imagery (Benz*, et al.*, 2004). Several object–based classification or image analysis systems exist that have been successfully used to extract forest information, especially for individual tree crown extraction purposes (Hay*, et al.*, 2005). Development of automated tree crown delineation has been a growing area of interest to researchers and several algorithms have been developed.

Some of the approaches include valley following approach (Gougeon, 1995), algorithms to delineate crowns based on the optimal match of geometric shapes with local radiometric values-template matching (Culvenor*, et al.*, 1998; Pollock, 1996), convex edge segmentations, local maxima and region growing (Brandtberg*, et al.*, 1998). These methods were developed for specific site conditions and were evaluated using different accuracy assessment methods. To better understand these methods it is recommended to compare those using same images and evaluation methods. The most commonly used methods for individual tree crown delineation are valley following and region growing method (Erikson*, et al.*, 2005; Ke*, et al.*, 2008;). Valley following method is implemented in ITC suite software while region growing is implemented in eCognition software.

3.5.1 Application of Individual Tree Crown Delineation

To extracts tree parameter from the high resolution data a semi-automatic method was deployed with Individual tree crown (ITC) approach. This approach was discovered in 1995. It provides tree crown width, canopy cover, species identification, crown delineation density *etc,* which are required for sustainable management of the forest (Gougeon, 1995; Leckie*, et al.*, 2005). To delineate the individual tree crowns it assumes that the valleys of shade that exist between much brighter crowns in medium to high density forest. Instead of searching for local maxima as tree tops, the valley –following algorithm finds local minima as valley bottoms. Valley following has record of separating 4-6 coniferous species with 80% accuracy in Canadian forest (Chubey*, et al.*, 2009). It is also capable of separating deciduous tree crowns, but with a lower success rate, as their rounder shapes make the presence of significant shade between them less common (Gougeon*, et al.*, 2006).

3.6 Biomass Stock Estimation from Crown Projection Area

Tree growth and biomass stock assessment are the important parameter to understand dynamic carbon cycle (Jepsen, 2006). Different kinds of methodology and approach have been developed for assessing biomass stocks and flows, ranging from analyses of land cover maps, using land cover/land use statistics, economical models, and in situ measurement of biomass (Nelson*, et al.*, 2000). The size of the crown is one of the important parameter of forest canopy which is directly influences by carbon, water and exchanges of water and energy between forest ecosystem and atmosphere (Song, 2007). The forest competition, production and forest structure can be better understood by the crown projection area (CPA) of tress (Shimano, 1997). Individual tree competition indices are derived from crown area estimates because crown dimension is a result of past competition as well as an indicator of the current growth potential (Grote, 2002). Thus, the estimation of CPA from its tree size is important in both forest ecology and silviculture point of view.

The tree size can be estimated either from the diameter at breast height or directly from the tree height because these can be directly measured in the field. Many studies done shows so far there is certain certain relationship between crown diameter and tree height (Avsar, 2004;) and between crown diameter and tree bole diameter (diameter at breast height, 1.3 m above the ground (DBH) (Bechtold, 2004; Hemery*, et al.*, 2005). Hirata (2009) used an understanding of these relationships to estimate both DBH and height from individual tree crowns delineated from QuickBird panchromatic imagery. As concise by Grote (2002), in spite of its importance crown extension remains difficult to determine. It can only be measured by optical methods from below or from above, which both are subjected to a likely underestimation of crown width due to partial visibility of crowns. The crown projection area can be estimated from stem dimensions but has to be thoroughly parameterized for precise stand conditions, which in most cases involves a large number of direct measurements. The study carried out by Li, *et al*(Li*, et al.*, 1992) scrutinized the possibility of estimating tree crown size from optical imagery, later this method was applied by other scientist (Song, 2007) for forest inventory purposes.

3.7 Image Classifications

In remote sensing context, classification is referred to as a data processing technique that involves labeling the pixels as belonging to particular spectral classes using the spectral data available (Richard and Jia, 1999). In many other literatures in remote sensing the term classification is synonymous to categorization, allocation and labeling. Classification is divided into two broad categories which are applicable in remote sensing. These are supervised classification and unsupervised classification. For this study supervised classification technique was employed

3.8 Supervised Classification

Supervised classification refers to an essential analytical tool used for extraction of quantitative information from remote sensed data. The supervised classification is based on an assumption that each spectral class can be described by a probability distribution in multispectral space. Such a distribution describes the chances of finding a pixel belonging to that class at any given location in multispectral location. The underlying technique is that the analyst has available sufficient known pixels for each class of interest such that representative signatures can be developed from those classes. These prototype pixels are referred to as training data and collection of them identified in an image and used to generate class signatures are called training fields. Signature generated from the training data may take different form depending on the type of classifier used. Examples of classifiers are parallelepiped classifier, minimum distance classifier, maximum likelihood classifier, and neural network classifier. For parallelepiped classification, the class signature will be the upper and lower bounds of brightness in each spectral band. For minimum distance classification the signatures will be the mean vector of the training data for each class while for maximum likelihood classification, both class mean vectors and covariance matrices constitute the signature.

3.9 Assessment of Classification Accuracy

The accuracy of a classification exercise is determined by selecting a sample of pixels from the thematic map and checking their labels against classes determined from reference data. The reference data mentioned here are the data gathered during field visit and are referred to as ground truth. From checked labels, the percentage of the pixels from each class in the image labeled correctly by the classifier can be estimated, along with the proportions of pixels from each class erroneously labeled into every other class. The results are expressed in a tabular form known as a confusion or error matrix.

The column of the confusion matrix refers to an error of omission while the row refers to error of commission. The difference between the two types of error are, the error of omission correspond to pixel belonging to the class of interest that the classifier has failed to recognize while error of commission correspond to pixels from other classes that the classifier has labeled belonging to the class of interest. Other accuracy assessment methods include the use of kappa coefficient which has been described in detail by Congalton(1991).

3.10 Forest fire Major Factor for Forest Degradation

Fire has been an integral ecological process since the arrival of vegetation on the landscape (Flannigan & Wotton, 2001). Fire and its impacts can be viewed as desirable or non-desirable, based on the compatibility with overall objectives (Wade &Lundsford, 1990). If properly used, fire can be an ecological tool of great value (Odum& Barrett, 2010) but wildfires become too destructive when uncontrolled (NHM, 2012). Forest fire is a major cause of changes in forest structure and function. However uncontrolled and misuse of fire can cause tremendous adverse impacts on the environment and the human society.

Wildfires release the sequestered carbon into the atmosphere in the form of complex mixture of particles and greenhouse gases that potentially affect climate (Amiro et al., 2001). The composition of combustion products varies with fuel types, fuel chemistry and fire behavior (Ward, 2001). Annual carbon emission (total carbon including $CO2$, $CH4$, CO and black carbon) during 1997 to 2009 from tropical deforestation and degradation fires was estimated 1.39 Giga tons $CO2$ eq which was 20% of all fire emissions (IPCC, 2014). These emissions from fires have some potential positive feedback since greenhouse gas driven climate warming may increase fire activity (Flannigan et al., 1998). Based on projected climate change impacts for mid to late 21st century, very likely and likely increased risk of wildfire was estimated by IPCC (2007) due to increased warm spells and increase in drought affected areas respectively.

Forest fire is considered as a problem in forest management systems in Nepal (Sharma, 2006). Along with the destruction of timber and non-timber products, forest fires also reduce the biological diversity of the forest to a greater extent (Bajracharya, 2002).The national institutional capacity to combat the wildfires is very weak. In Nepal, there is no systematic and complete record of occurrences of forest fires and their impacts (GoN/MFSC, 2002). Forest fire management is not practiced in Nepal. The community forest users' groups control forest fires in their own forests, although they do not have a plan for systematic prevention and control of fires (Bajracharya, 2002). During dry months fires are common in the Pinusroxburghii and Shorearobusta forests of Mid-hills and Terai region respectively (GoN/MFSC, 2002). In Nepal fire problems are acute for three to four months during the dry period between March and June every year (Bajracharya, 2002).

Once the monsoon is established, usually by the June, the fire problems disappears (Kunwar&Khaling, 2006). Forest fire has been a major agent of land cover change in the Terai (Kunwar, 2004, as cited in Kunwar&Khaling, 2006). Forest area burnt annually in Nepal is in the order of more than 400,000 hectare and the main causes of forest fires are anthropogenic due to negligence and occasionally by deliberate burning to induce succulent grass growth for domestic animals (Bajracharya, 2002). According to Sharma (1996), people set about 64 % of fire intentionally, about 32 % of fires are due to accidental/carelessness, and about 4 % by unknown causes. Recently International Centre for Integrated Mountain Development (ICIMOD) in close collaboration with the Department of Forest (DoF). Nepal has developed forest fire detection and monitoring system for Nepal based on Moderate Resolution Imaging Spectroradiometer (MODIS) data. The pilot phase was started during 2012 fire season (March to May) and United States Agency for International Development (USAID) and National Aeronautics and Space Administration (NASA) has supported the work (ICIMOD, 2012).

3.11 Application Geospatial Technology for Forest Fire

Kuntz (1995) investigated the fire risk modeling based on satellite Remote Sensing (RS) and Geographical Information System (GIS) and demonstrated that simple fire risk assessment was possible using the resultant thematic class. The GIS-based model seems to be a reasonably good approach (Jain, 1996; Roy and Panda, 2005). Integrated topographical and satellite data for the identification of fire hazard areas. Developing a GIS-based wildfire hazard modeling which aim to identify geographic locations with the highest wildfire hazards and risks. Fire hazard is defined as a fuel condition or state that may result in an undesired wildfire event. Risk is defined as the probability of an event occurring. Forest fire risk zones are locations where a fire is likely to start, and from where it can easily spread to other areas.

A precise evaluation of forest fire problems and decision on solutions can only be satisfactory when a fire risk zone mapping is available. Antoninetti*et al.* (1993) integrated topographical and satellite data for the identification of fire hazard areas. The combination of a spatial basic data (elevation, slope, aspect, precipitation, plant community types and fuel models) with remote sensing technique appeared to be a working tool for the management in North Cascades National Park (USA) (Root *et al.,* 1985). Mohammadi*et al.*, (2010) created risk map of forest fire by using GIS and (AHP) in some part of Paveh county that were derived five categories of forest fire risk, automatically. Mansouri*et al.* (2012) explained that to management program of forest fire crisis by GIS and RS technology in conflagration. Forest fire risk zones were delineated by assigning subjective weights to the classes of all the layers according to their sensitivity to fire or their fire- inducing capability (Dong *et al.,* 2005; Erten*et al.,* 2005).

CHAPTER: 4 MATERIAL AND METHODS

4.1 Material

The main material used for this research is the remote sensing data, GIS data layer, field data and software for the image and statistical analysis for composition of thesis.

4.1.1 Very High Resolution Satellite Geo-Eye Imagery

The Geo-Eye imagery with panchromatic 0.50 cm and Geo-Eye multispectral 2m images recorded 15th December, 2012 (Sources ICIMOD, Nepal). This multispectral image consisted of four bands namely blue with (450-510 nm), green (510-580 nm), red (655-690 nm) and near infrared (IR) (780-920). The image that had obtained from ICIMOD was already ortho-rectified and geo-referenced to the UTM WGS 84 System by ICIMOD Geospatial team.

Table 2 List of Image Used

Image	Spatial Resolution	Spectral Bands
Geo Eye- 1	0.5	Panchromatic
GeoEye -1 Multi spectral	2 m	4(Blue, Green, Red, NIR) Date: December 2012

4.1.2 Other Reference Data

Topographic maps at1:25000 scale, from Department of Survey, Government of Nepal, Digital Elevation Model (DEM) 90M from SRTM digital elevation data, produced by NASA**,** MODIS fire point from 2010 to 2013 from ICIMOD,Gorkha geo-database which consist with different data layer namely vegetation types , Watershed boundary, Community forest boundary, Road, Settlements, (ICIMOD, Survey Department).

4.2 Software and Equipment's

Following table shows the list of software and tools used for the research

Table 3 List of software Used for research

S.No.	Software	Purpose
1	ArcGIS version 10.2	GIS utilities and analysis
2	eCognition Developer 8.7	Object based image analysis (CPA calculation)
3	Erdas Imagine 2013	Image processing and remote sensing application
4	Microsoft Excel	Data preparation and Statistical analysis
5	Microsoft power point	Presentation of research
6	Microsoft Word	Writing thesis
7	R	Graphic representation and statistical analysis
8	End notes	Citation and reference

Table 4 List of equipment used for research

S.No	Instrument	Purpose of usage
1	Garmin GPS	Navigation
2	Diameter tape (5meters)	for measuring tree diameter
3	Meter tape (30 meters)	Length measurement
4	Clinometers	Measuring tree height
5	Plot centre marker	Marking plots
6	Chalk	Marking trees
7	Data sheet	Taking notes and recording data

4.3 Methods

The research method followed three major steps i.e. data collection and preparation, remote sensing operations, and statistical analysis. Field work was carried out to collect the data about DBH, height, spatial information and other measures whereas remote sensing operations were done to get the individual tree crown and height of each tree of the study area for fire risk Zonation, topographic map, road, settlements from department of survey government of Nepal 1:25000, forest types ,watershed and community forest delineated map from ICIMOD, DEM 90m and Garmin GPS for ground truth specially for forest species , types identification and geo-coding location. Mainly the research method of this study was divided in to three parts namely pre-field work, Field work and post field work. The sampling design was done and the images were fused prior going to the field. In the field the DBH, Height, species name, Forest types,

Spatial information like longitude, latitude, elevation, was collected and the tree were identified in the printed picture in different sampling plots. The post field comprises of data analysis and comparison between RS derived results and field measurements. For forest fire risk Zonation different data set were analysis and ranked and mapped. Finally, statistical analysis and other operation were done to find the relationship between height, CPA and biomass for estimation and mapping of above ground biomass and fire risk Zonation. A diagram of the entire methodology applied in the entire study is shown in Figure: 1

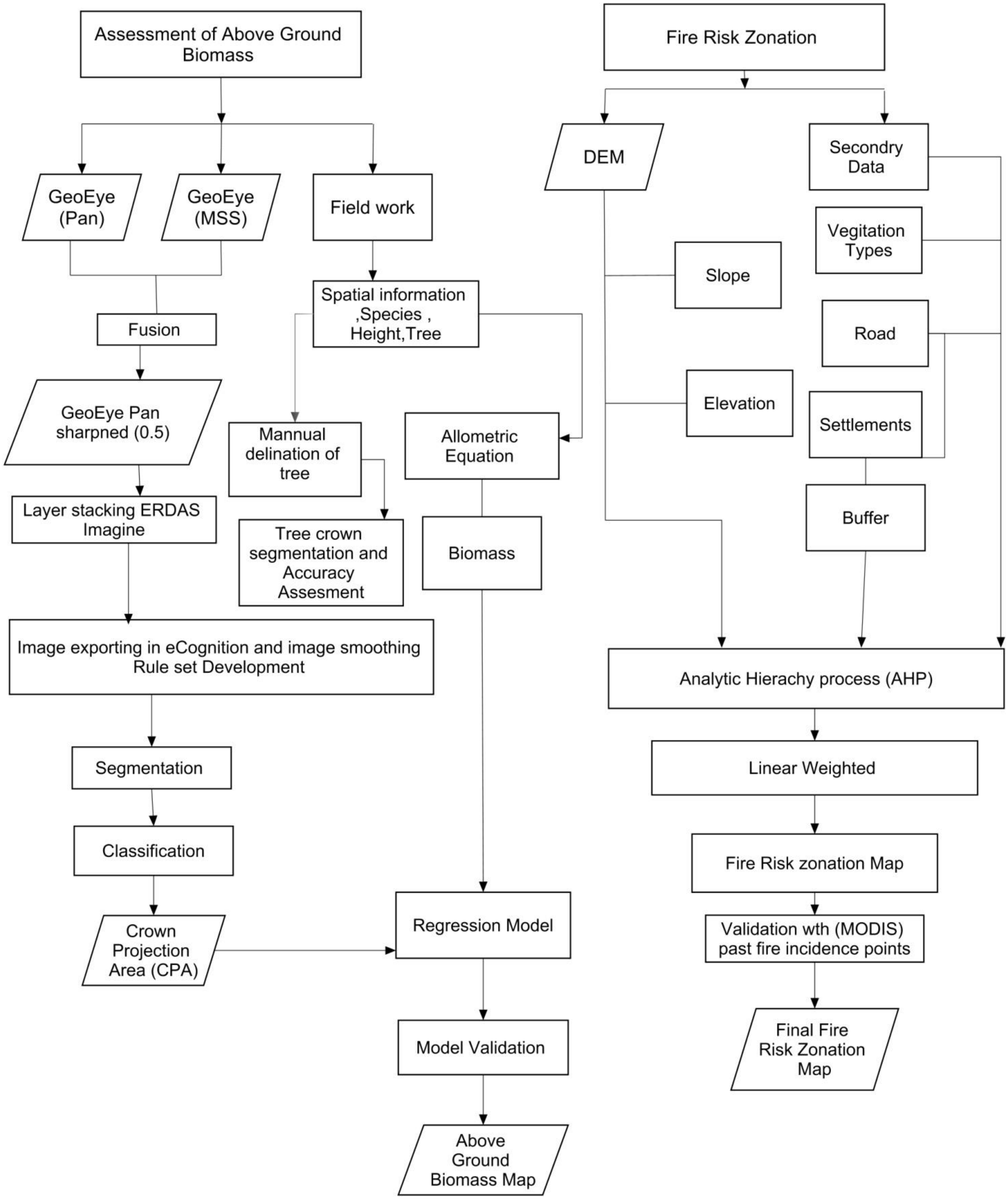


Figure 1 Methodological flow chart for study

4.4Pre- field Work

4.4.1 Image Pre-processing

Images pre-processing in any study comprise two process namely Image stacking and image fusion.

4.4.2 Image Stacking

The Geo-eye imagery was found in five separate raster file (4 multispectral bands and 1 panchromatic band) so first initial work performed was layer stack of different 4 bands to develop one composite image before performing the image fusion or Pansharpening.This work was performed in Erdas imagine 2013 was used.

4.4.3Data Fusion of Multi-spectral and Panchromatic Image

Klonus*, et al.*,(2007) define the image fusion or pan-sharpening are procedure for combining the spataily high resulation panchromatic image with spectral inofmramtion of lower resolution multispectral images to produce high resolution multispectral image. During this process GeoEye-1 multispectral satellite imagery (2 m) was merged with GeoEye pan chromatic image (0.5m) this was done to enhance the images and with the intent of obtaining quality information (Wald, 1999). The resultant image was 0.5m pan sharpened resolution of multispectral image. There are several methods that are commonly used for image fusion. For this study HPF (High pass filter) pan-sharpening method available in Erdas imagines 2013 was deployed. According to ERDAS (2013) HPF maintains the spectral properties of the original multispectral image and therefore the fuse image has higher spatial resolution with all the bands of original multispectral images.

4.5 Sampling Design

A sample is a set of data collected and/or selected from a statistical population by a defined procedure to obtain information about the population. To save resources, time and money sampling method are carried out rather than collecting census data from whole population. (de Gier, 2003). For carbon/biomass inventory, stratified random sampling generally yields more precise estimates for the other options (MacDicken, 1997). Therefore, for this study stratified random sampling was useful to design the sampling process in the field. The strata were stratified based on 5 different community forests which are distributed in total of 379.153 ha. A total of 28 plots were identified for sampling in the field, 5 in each community forest and 3 additional plots were added in field because of some scatter distribution of forest area in those forest. The sampling plots were generated with the help of the secondary data and by using the sampling equation of Husch, *et al*., (2003). Following equation was deployed to generate sample size

$$n = \frac{t^2 \times CV^2}{(E\%)} \text{ ....Equation 1}$$

Where, n= number of sampling plots, t = t-test, CV = coefficient of variance, E= allowable error

4.6 Field Work

The field work was carry out in order to measure the above ground biomass and collect ground truth data .In the beginning of the fieldwork a exploration visit was made to get an overall impression of the situation in the study area. Then, a meeting was held with the representatives of community forest user groups for further planning for data collection. During the field work a circular plots of 500m^2 and radius of 12.62m each were collected (IPCC, 2003).

These plots were selected for forest tree inventory, taking into consideration that each plot has a good representation of different tree species of various diameter. The center of the plot was located using global positioning system (GPS). DBH were measured at 1.3m above ground, the trees with DBH >10cm, height in meter, and spatial information about location was recorded in the data sheet. The field data collection form is presented in Appendix–1.

4.7 Secondary Data Collection

Secondary information such as households benefitted from REDD+ program, management activities and involvement of local people for forest management and carbon mapping was collected from the concerned agencies such as district forest office (DFO), CFUGs, ICIMOD and ANSAB. The detail information about the proper CFs was obtained from their operational plan prepared by CFUGs and local people involved in the forest management and REDD+ program.

4.8 Post Fieldwork

4.8.1 Fieldwork Data Analysis

After completing field work, the data collected in field was entered in excel and descriptive analysis of the field data was done. Box plots were made for depiction of collected field data for major tree species. Data regarding spatial information, other forest information collected during the fieldwork were converted in to shape files of plot wise using ArcGIS. The information like DBH, height, tree species were used for basal area calculation, biomass estimation, species classification, species distribution mapping and its accuracy assessment. In addition, for developing and validation of the regression models, aboveground biomass was calculated using allometric equation (Equation 5 and 6) with the field measured DBH and tree height.

In absence of species specific biomass equation of the trees, species specific volume equations developed by Sharma and Pukkala(1990) were used to estimate the AGB of forests. Total stem volume of individual trees was calculated from field measured DBH and tree height using the relationship in the following form (Sharma & Pukkala, 1990).

4.8.2 Image Classification

In ERDAS Imagine, there are several tools which are used to meet the desired analysis of the imagery data. Before all, the most important things in image analysis are the ability to identify the signatures of features in an acquired image. However, it is rare to find pixel with homogeneous signatures. In most cases, the pixel has a mixture of signatures, thus the mean, mode, standard deviation, maximum and minimum limits are used to assign signature to a feature. Also, it is useful to mention here that it is common to a downloaded image to possess some gaps. For the two images used in this study, they had gaps which were removed by using the filling procedures offered by ERDAS Imagine tools. The focal analysis tool under spatial enhancement menu in ERDAS Imagine was used to remove gaps in an image. The filling process was iterative in which it required up to six iterations to obtain a clear image for further analysis. Image classification is among the analysis which can be performed by ERDAS Imagine. For successful classification, the signatures of various features on an image must be identified. There are varieties of ways in which signatures in ERDAS Imagine can be created. However in this study, the Area of Interest (AOI) tools and the feature space image using the AOI tool and feature space tools were used to collect the signatures. The detailed step by step collections of signatures are found in ERDAS Imagine tour guide. Based on which forest and non-forest area were classified. After completing an image classification, it is important to test for how much the undertaken classification have been accurate. In ERDAS Imagine, the accuracy assessment utility compares the feature pixel in an image to a reference pixel whose class is known.

There are various techniques in which the comparison can be made. The use of ground truth data is among the technique, while the other techniques include the use of previously tested maps and aerial photos. For the case of this study the ground truth data were used in accuracy assessment. In erdas Imagine, to add random point utility was used to generate random points on the classified image. These random points had class values which were originally generated from the classified image. To confirm the classes on the generated random points, the ground truth points were imported on the image and were used as reference points. Thereafter, the report of the assessed classes was produced through the accuracy assessment tool. To evaluate the accuracy of the classification, an error matrix is a standard accuracy assessment procedure for image classification. An error matrix was generated and the producers and users accuracies were calculated for each class from the error matrix.

4.9 CPA Detection& delineation Using Very High Resolution Image.

To detect and delineate crown projection area (CPA) by applying region growing technique following methodological steps were deployed for the process.

a) Loading image in eCognition Developer

b) Loading and executing rule sets

c) Image filter (Convolution filter)

d) Segmentation (Multi resolution segmentation)

e) Find segments local Extrema

f) Region grow

g) Assign class and Saving CPA as a shape file.

The region growing algorithm based on homogeneity is programmed finding a local radiometric maxima (peaks) and minima (valleys) which are the fundamental image features used for the delineation of crowns (Culvenor, 2002).

After the masking of river and shadow, the unclassified pixels were defined to class tree. Thus, local minima and local maxima were identified in the tree class of segmented image. Local minima are used to define the likely crown boundaries. Local maxima filter were used as “seed” points to build up a meaningful objects. In the local maxima method the assumption is that the peak of the tree-crown reflectance is located at or very close to the treetop (Wang, *et al.*, 2004). The algorithms assume that the center of the crown is brighter compared to the edges. Applying this method requires careful selection of the filter size window. If the window size is small the trees with large crown may be assigned as more than one treetop, similarly if the window size is large then there are chances that the trees with crown radii shorter than the specified radius will not be assigned as a single treetop.

To avoid this, a filter size of 3x3 was chosen. This kernel was considered appropriate as the average crown width of the trees measured in the area was approximately 5m. After the identification of tree top with the help of local maxima the next step is to grow the tree top to give it a shape of an individual crown. The region growing algorithm was used to grow the tree tops in relation with neighboring objects. It is an iterative process for delineation of crown. The region of the tree was grown in several loops and series of cycles were repeated until it forms the shape of an individual crown. The maximum crown width (5m) criterion was set to limit the growth of the tree. In each iteration the new neighbouring pixels are merged to form a tree crown provided that the tree crowns keep a circular geometric shape. The procedure carried out is shown below (figure: 2)

Figure 2 Applied Rule Set in eCoginitation

4.10 Manual Delineation of Tree Crowns

During the field visit around six hundreds of trees were measured, only one third of them could be recognized in the image for manual digitization/delineation due to the difficulties in identifying actual tree crown. The delineation of the recognized tree crowns was done for assessing the segmentation accuracy and validating the model. For this purpose, both panchromatic and 5*5 filtered pan-sharpen image were used in such a way that tree crown can relatively easy to be recognized. Both images were visualized in ArcGIS at several scales for the better view of tree crown using appropriate band combinations. Pan-sharpened and panchromatic images were checked and unchecked alternatively during the crown delineation for a better result. About 40% trees measured from field were delineated for accuracy assessment.

4.11 Accuracy Assessment of Tree Crown Delineation

Accuracy assessment of tree crown delineation is associated to the alike of reference and automatic segmented objects (Zhan et al., 2005). Reference objects means manually delineated polygons. There are several methods available for segmentation validation (. However, for this study two segmentation accuracy measures were applied i.e. 1:1 correspondence (Zhan et al., 2005) and Relative Area measures developed by Clinton et al. (2010). These schemes are applied when manually delineated and automatic segments are available. Clinton et al. (2010) reviewed several segmentation accuracy measures and modified Relative Area measures developed by Moller et al. (2007). Over segmentation and under segmentation defined by Clinton et al. (2010) are given in equation x and y.

$$\mathrm{Oversegmentation_{ij}} = 1 - \frac{\mathrm{area}\ (\mathrm{x_i} \cap \mathrm{y_j})}{\mathrm{area}\ (\mathrm{x_i})} \text{Equation 2}$$

$$\mathrm{Undersegmentation_{ij}} = 1 - \frac{\mathrm{area}\ (\mathrm{x_i} \cap \mathrm{y_j})}{\mathrm{area}\ (\mathrm{y_j})} \text{Equation 3}$$

Where $x_i$the reference is object and y_j is the corresponding segmented object

The value of over segmentation and under segmentation lies within the range of 0 to 1 (Clinton et al., 2010). When the value for both over and under segmentation is 0, then it is considered as perfect segmentation. It means segments matched exactly with the reference objects. Using over segmentation and under segmentation values, segmentation goodness (D) can be calculated. D (equation 3) is interpreted as the 'closeness' to an ideal segmentation result, in relation to a predefined reference objects (Clinton et al., 2010). D value ranges from 0 to 1. D value equals to 0 means perfect.

$$D = \sqrt{\frac{\text{oversegmentation}^2 + \text{undersegmentation}^2}{2}}$$ Equation 4

1:1 correspondence was done by matching manually delineated tree crowns with automated segments. Corresponding was considered if manually delineated and automatic segments overlap by at least 50% (Zhan et al., 2005) (Clinton et al., 2010). Moller et al. (2007) proposed methods was used for the accuracy assessment of tree crown segmentation . These accuracy measures were calculated for entire study area. A higher percentage of 1:1 correspondence indicates higher accuracy.

4.12 Biomass Stock Mapping and Modeling

4.12.1 Biomass Stock Calculation

During field visit all together 21 different species (Appendix) were recorded in Study area. Among them *Shorea robusta*, *Schima wallichii and Semecarpu s*anacardium, Bassia butyraceae were the dominated species followed by others. The use of allometric equations is a crucial step in estimating above ground biomass (AGB) which can be used to estimate carbon stock of forests. In general AGB is estimated from volumetric and structural dimension of the trees for which DBH and height are considered as major parameters. In absence of species specific biomass equation of the trees, species specific volume equations developed by Sharma and Pukkala (1990) were used to estimate the AGB of forests. Total stem volume of individual trees was calculated from field measured DBH and tree height using the relationship in the following form (Sharma & Pukkala, 1990).

$\ln(V) = a + b * \ln(DBH) + c * \ln(Ht)$ Equation 5Allometric volume equation

Where, ln is natural logarithm to the base 2.71828

V is the total stem volume with bark in m^3, to obtain the volume in cubic meters the prediction is to be divided by 1000

DBH is the diameter at breast height in cm

Ht is the tree height in m and a, b and c are model parameters.

The estimated parameter value of a, b and c for different species and wood density of the major tree species is given in Table: 4

Table 5 Model parameters and wood density of major tree

Species	a	b	c	Wood densityKg/m^3)
Shorea robusta	-2.4554	1.9026	0.8352	880
Adina cordifolia	-2.5626	1.8598	0.8783	670
Schima wallichii	-2.7385	1.8155	1.0072	689
Syzizium cumini	-2.5693	1.8816	0.8498	770
Others	-2.3993	1.7836	0.9546	720

The obtained volume was multiplied with dry wood density (specific gravity) of the species to get air dry weight of stem biomass (Chaturvedi & Khanna, 1982) using the following formula (Equation 5). Species found in the study area other than mentioned above was categorized as Miscellaneous in Terai and volume was calculated accordingly (see Equation 5).

Stem biomass = Stem volume * Wood density… Equation6 Calculation of stem biomass

Due to absence of established biomass relationship of different tree components of individual tree species of sample forest types, this study used the relationship developed by Sharma (2011) for a single species of similar forest types of Nepal which was later adopted by Shrestha& Singh (2008).

The biomasses of branches and leaves (foliage's) were estimated to be 42% and 8% of the stem biomass respectively (Sharma, 2011) to calculate the total biomass of trees. However, in case of *Shorearobusta* branch to stem and foliage to stem ratio was applied as suggested by Sharma &Pukkala (1990).

Thus, the AGB of different tree species of the study area was calculated by sum of stem, branch and foliage biomass of the tree as shown in Equation so

Total AGB = Stem biomass + Branch biomass + Foliage biomass….Equation 7 AGB

4.13 Feature Extraction

Feature extraction could be guided by visual image interpretation, semiautomatic by using different filtering algorithms and techniques. In this study, mainlycanopy projection area (CPA) were extracted using multi-resolution segmentation in eCognition software. The rule set for image segmentation was developed for individual crown delineation. Feature extraction was only received after the complete process of segmentation and object based classification of the image in eCognition. The mandatory object features were exported as a vector and raster format to ArcGIS 10.2.

4.14 Statistical Analysis

Statistical analysis is vital for any scientific research so, it was carried out for both types of data either collected in the field or extracted from remote sensing technique. The major statistical analysis includes correlation and regression analysis of two variables *i.e.* response and explanatory, model development and its validation based on the regression results.

4.15 Correlation Analysis

A scatter diagram of related two variables was depicted in order to see the relationship between them for instance image CPA and Biomass.

Correlation coefficients and coefficient of determination (R^2) was calculated which showed the percentage of variation in one variable which associated to other variables and can be explained by the given regression. Analysis of variance (ANOVA) test was also used to calculate the mean difference of different variables.

4.16 Regression Modelling

Regression modelling is normally used for biomass estimation analyse. The multiple regression analysis is the most common come close for development of AGB estimation models (Lu, 2006). It is used to model the relationship between a dependent variable and one or more independent variables. In this study Crown projection Area and field calculated biomass were used to develop the regression models. The relationship between the dependent variable (aboveground biomass) as obtained from the allometric equation and the two independent variables (tree height obtained from field and the plot level CPA from the segmented tree crowns) were explored through log transformed regression models. Two most widely used methods for model validation are co-efficient of determination (R^2) for the models developed and the root mean square error (RMSE) (Lu, 2006).Co-efficient of determination (R^2) shows the percentage of variation in one variable that is associated with other variables. The strength and the significance of the models were validated using the partitioned 30% validation dataset. The following equation (v) was used to calculate the RMSE.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{O\,i} - X_{p\,i}\right)^2}$$ .... Equation 8 RMSE

Where,

X_O = Observed biomass,

X_p= Predicted biomass, n = number of observations

4.17 Variables Used for Forest Fire Risk Zonation

4.17.1 Elevation:

Elevation is an important physiographic factor that is related to wind behavior and hence affects fire proneness (Rothermel, 1983). Fire travels most rapidly up slope and least rapidly down slope. Rathaur (2006) also reported more fire incidents in middle elevations (600-800 m). Increase in humidity and decrease in temperature do not favor fire incidences in higher elevations (Orozco *et al*., 2009 as cited in Sibanda, 2011). Elevation of this study area varies from 200 meter to greater than 600 meter as shown in Map 2. Northern part of study area having the higher elevation while southern part is less elevation.

4.17.2 Slope:

It is an indicator of rate of change of elevation (degrees). Slope affects both the rate and direction of the fire spread. Fires usually move faster uphill than downhill (Rothermel, 1983; Kushla and Ripple, 1997,). Higher slope increases the risk of upward fire spreading by convective preheating due to hot smokes released from down slope fires and contact ignition of upslope fuels. In this study slope varies from 10 degree to greater than 30 degree as shown in map 3. Most of the lower southern part of the study area have the slope greater 30 degree while middle part of study area have slope less than 10 degree.

4.17.4 Vegetation Types

Forest area is covered with different tree spices, shrub, herb and other components. Based on the density of vegetation and their occurrences they are classified in different categories. Vegetation must be considered because some vegetation types are more flammable than theirs, thereby increasing the fire hazard. In forest vegetation type grassland and open to closed dry deciduous forest is more vulnerable to forest fire than the moist open deciduous forest.

Which may the cause of sufficient open spaces for long light duration and easy accessible in such area for human grazing and other activities they catch fire easily and they have more content of dry litter during dry season. So shrub land and open dry deciduous forest are more vulnerable to forest fire than moist (Closed to open deciduous) (Sharma et al; 2006). The major vegetation types found in study area are shrub land, broadleaved open closed forest and broadleaved closed forest as shown in Map 4. Most of the area is covered with open broadleaved forest in study area while some pockets closed broadleaved forest is distributed in middle part of study area and most of shrub land is found near by the boundary community forest area.

4.17.5 Settlements and Road

Road networks proximity map and settlement area proximity map, previous studies showed that closeness to roads, settlements and agriculture lands increase the risk of fire (Jaiswal*et al*., 2002, Sibanda, 2011, Uriarte*etal*., 2012).. Nearer distance from the settlements considered as easily accessible area from the settlements (adopted from Jaiswal et al., 2002). The practice of invading into the community forest area in search of timber, fire wood, Non Timber Forest Products (NTFPs) and grasses are common practices by local people living around. Five classes of buffer distances were classified by equal interval classification. Nearer distances were assigned higher index values while farthest distance was assigned lowest. Equal interval classification was used to create buffer distance classes of all three types of road. To create road buffer distances, the maximum impact distance for each kind of road was adopted from Rathaur (2006). Passers-by on these roads were taken as potential ignition sources for fire. Sharma (1996) reported that Intentions fire for various causes of about 22 % human induced forest fires in Nepal. The different distance from Road and settlements to different part of forest area is shown in Map 5 and Map 6 and they are measured in meter from its original position.

4.18 Map Development forFire risk Criteria

Different data set were used for forest hazard Zonation i.e. the forest types, Topographic map, road, settlements from department of survey government of Nepal 1:25000, watershed and community forest delineated map from ICIMOD, DEM 90m ,topographic, vegetation, and accessibility parameters were used. These data were set in raster-based maps for more analysis. The hierarchical structure for quantifying fire risk has been intended following the Analytical Hierarchy model. The different causative factors that are affecting forest fire are topographic parameters, vegetation parameters and accessibility parameters. For the generation of elevation 20m contour lines which were used for this study. The study area stretch from 200 m elevation to 865 m as observed from prepared DEM. The area was classified into three classes by natural breaks classification with 200, 200-400 and greater than 600 m.

Similarly the slope within study area ranges from 10 to 30 degree as observed from prepared DEM.The total area of the study area was classified into five classes by equal interval classification. For Aspect different four aspect class were derived based on major land facing in different directionsouth, north, west and east. While for the land cover major land cover in study area were taken like different forest type like closed broadleaved forest, open broadleaved forest and shrub land. Likewise Road and settlement are another important parameter used for this study. They were classified in to different 5 classes nearer to far distance and converted in to raster format for further analysis like less than 50 m, 100m, 200, 300 and 400m. All these values were used for the Analytic Hierarchy Process (AHP). Detail procedure are describe in section (4.5 and 4.6)

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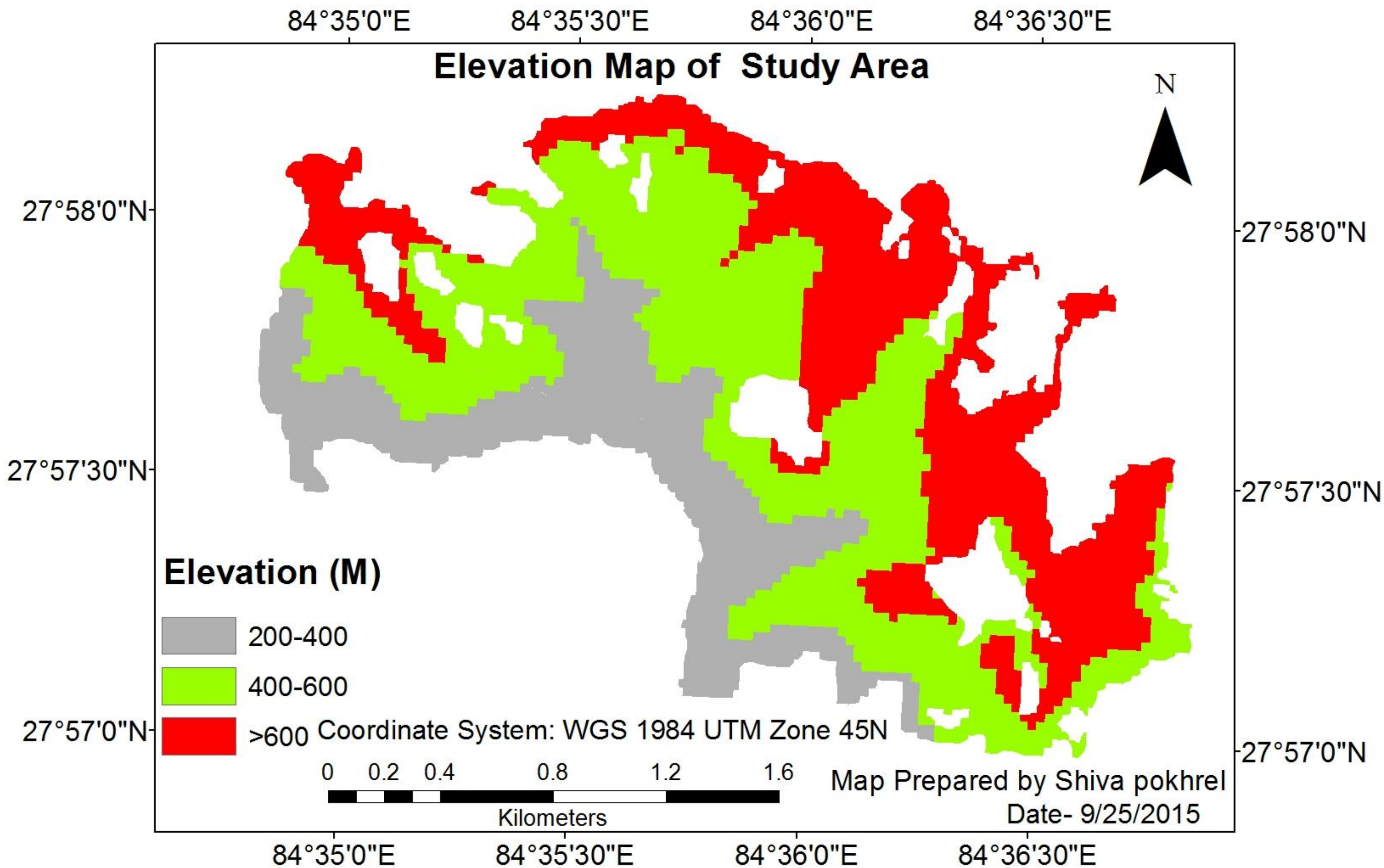
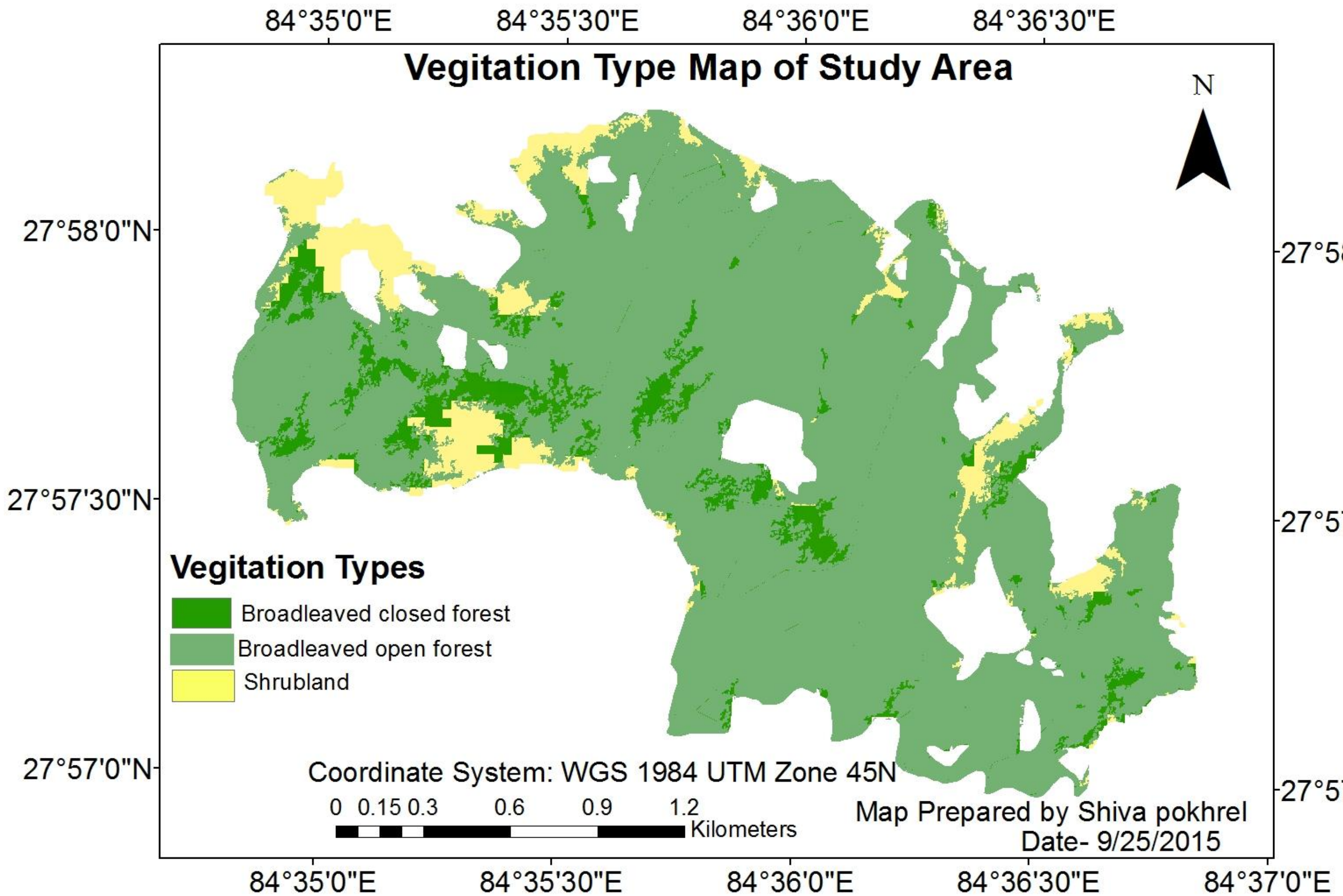
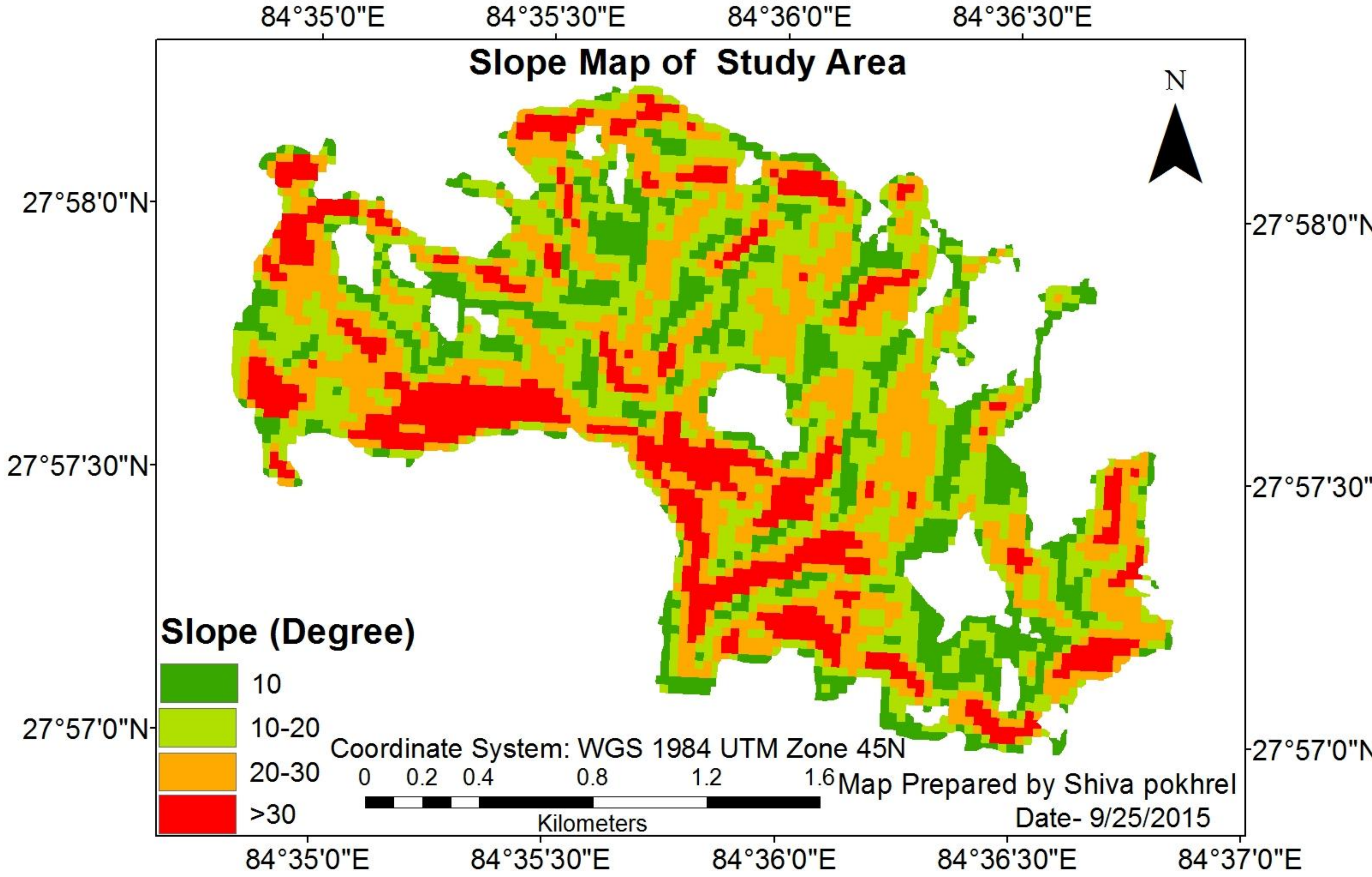


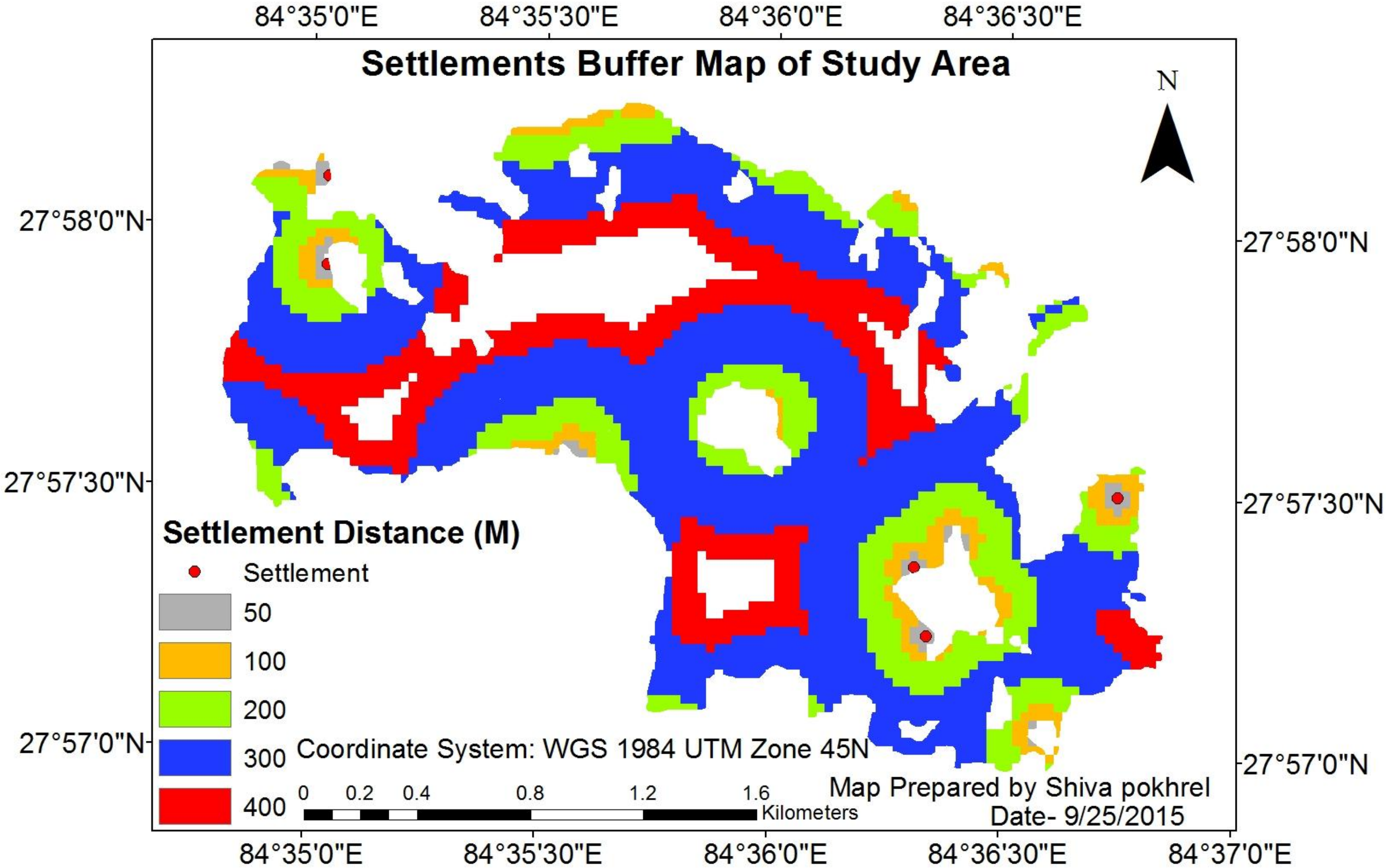
Map2: Elevation Map of study area



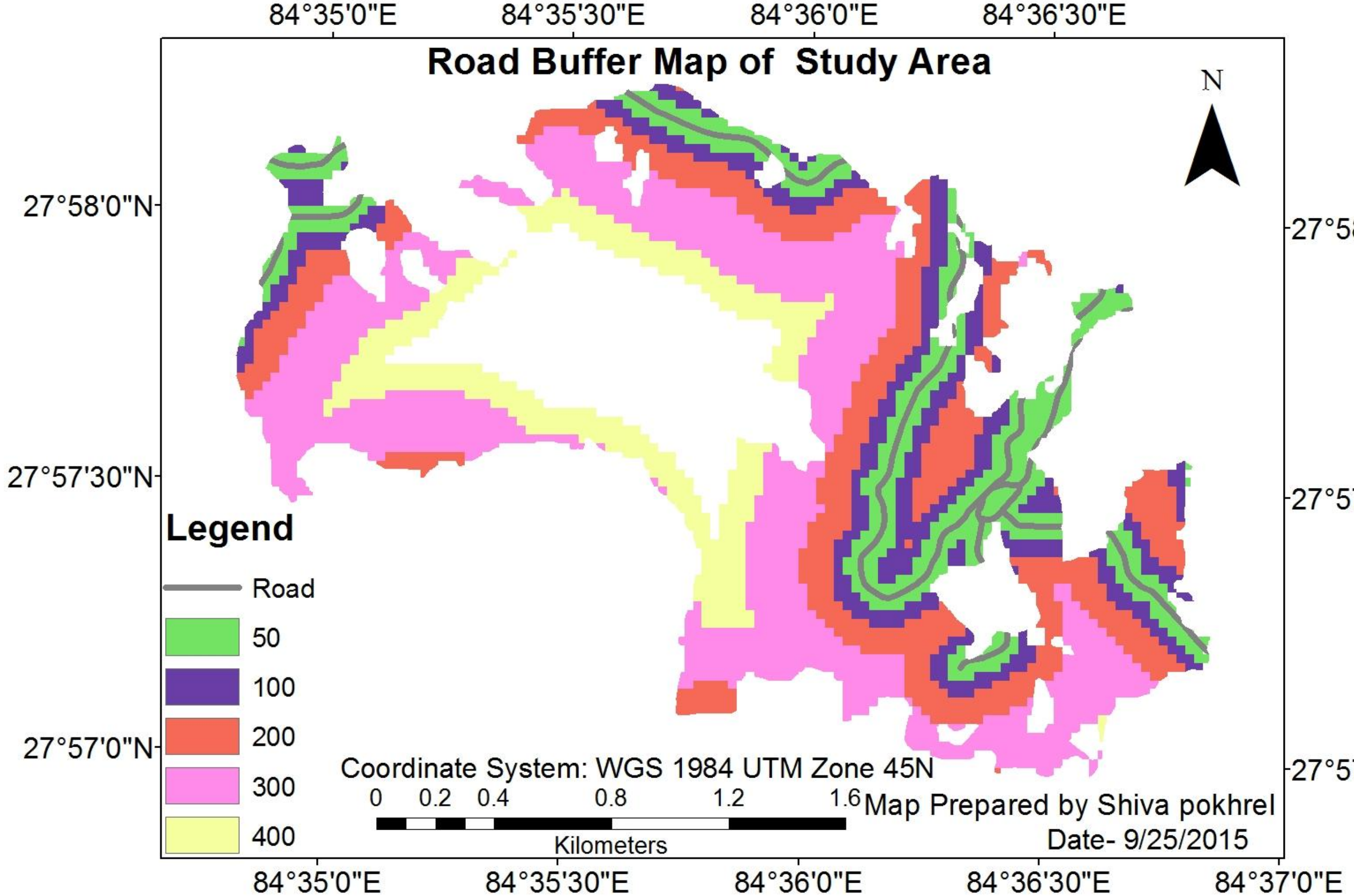
Map3: Vegetation Type Map of Study Area



Map 4: Slope Map of Study Area



Map 5: Settlement buffer Map of Study Area



Map 6: Road buffer Map of Study Area

4.19 Analytic Hierarchy Process (AHP)

The AHP, introduced by Thomas Saaty (Saaty et al; 1980) is a mathematical method which analyses complex decision problems under multiple criteria, and helps the decision makers to set priorities and make the best decision. In the AHP, the complex decisions are reduced to a series of pair-wise comparisons, and then produce the results. Moreover, the AHP incorporates a useful technique for checking the consistency of the decision maker's evaluations, which in turn help in reducing the bias in the decision making process.

AHP has been applied in many and diverse areas of decision-support in environmental management such as wildfire risk map, forest fire risk map, urban fire risk map, landslide susceptibility mapping, landfill site selection, land use pattern selection. Saatyet al; 1980)developed the following steps for applying the AHP:

1. Define the problem and determine its objective.

2. Structure the hierarchy from the top (the objectives from a decision maker's viewpoint) through the intermediate levels (criteria on which sub-sequent levels depend) to the lowest level which usually contains the list of alternatives.

3. Construct a set of pair-wise comparison matrices (size $n \times n$) for each of the lower levels with one matrix for each element in the level immediately above by using the relative scale measurement shown in Table :13 The pair-wise comparisons are done in terms of which element dominates the other.

4. There are $n (n - 1) =$ judgments required to develop the set of matrices in step 3. Reciprocals are automatically assigned in each pair-wise comparison.

5. Calculate the normalized principal eigen vectors, maximum eigen value, consistency index and consistency ratio for each criteria.

Table 6 Scale of preference between two parameters in (APH)

(Adapted from Saaty et al; 1977)

Preference Factor	**Degree of preference**	***Explanation***
1	Equally	Two factors contribute equally to the objectives
3	Moderately	Experience and judgment slightly to moderately favor one factor over another
5	Strongly	Experience and judgment strongly or essentially favor one factor over another
7	Very Strongly	A factor is strongly favored over another and its dominance is showed in practice
9	Extremely	The evidence of favoring one factor over another is of the highest degree possible of an affirmation
2,4,6,8	Intermediate	Used to represent compromises between the preferences in weight 1,3,5,7,and 9
Reciprocals	Opposites	Used for inverse comparison

The consistency is determined by using the maximum eigen value (λmax) to calculate the consistency index (CI) as given in Equation (9).

Consistency Index (CI) $= \frac{\mu_{MAX} - n}{n-1}$........Equation 9 Consistency Index

Where n is the size of matrix.

Judgment consistency can be checked by taking the consistency ratio (CR) of CI with the appropriate value of random consistency index (RI) given in Table: 6 (Saaty, 2000). If CR does not exceed 0.10, then the comparison matrix is consistent. If CR is greater than 0.1, the comparison matrix is inconsistent. If inconsistencies in the decision process exist, the process should be repeated till a consensus is reached.

Table 7 Random Consistency Index (RI) adopted from (Saaty, 1977, 2000).

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

6. Perform steps 3–5 for all levels in the hierarchy. Integrate weight values (normalized principal eigen vectors) to reach an optimum decision.

7. Analytic Hierarchy Process provides an easy applicable decision making methodology which helps the decision maker to precisely decide the judgments.

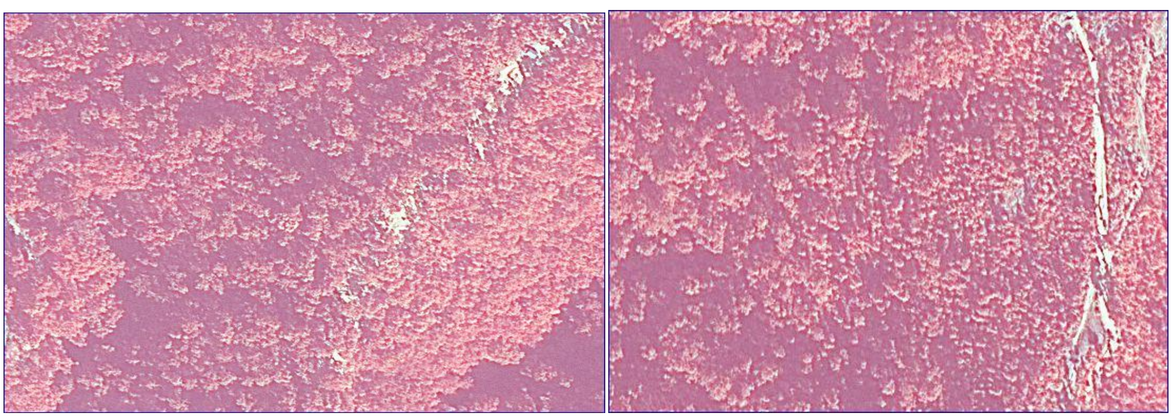
The main advantages of Analytic Hierarchy Process over other multi criteria methods are its flexibility, perceptive appeal to the decision makers and its ability to check inconsistencies (Ramanathan, 2001).However, the main demerit of AHP is that it has a subjective nature of the modeling process which may differ from one expert to another. Hence, methodology cannot guarantee the decisions as definitely true (Long et al; 2012)

4.20 Results

4.20. 1 Pre-processing of Images

The pan sharpened, image was pre- processed using 3x3 low pass filters which worked better for the region growing algorithm and 5x5 low pass filter image was used for valley following algorithm in eCognition. The processed filtered images are shown below in the Figure: 3.

(a)



(b) (c)

Figure 3GeoEye image (a) IHS pan sharpened image (b) smoothed image using 3x3 low pass filter (c) smoothed image using a 5x5 low pass filter (images are at 1:700)

4.20.2 Individual Tree Crown Delineation

4.20.2.1 Valley Following Algorithm

The segmentation in ITC suite follows mainly the three processes before delineating an individual tree crown. To delineate the individual tree crown the thresholds for upper limit (700 - 900) and lower limit (300) both the thresholds were used in NIR band. A total number of.... Trees identified in the field which were manually delineated were overlapped with the segment crowns to see one to one relation. Figure: 4 shows the results generated from the process mentioned in Chapter 4 in section 9.4

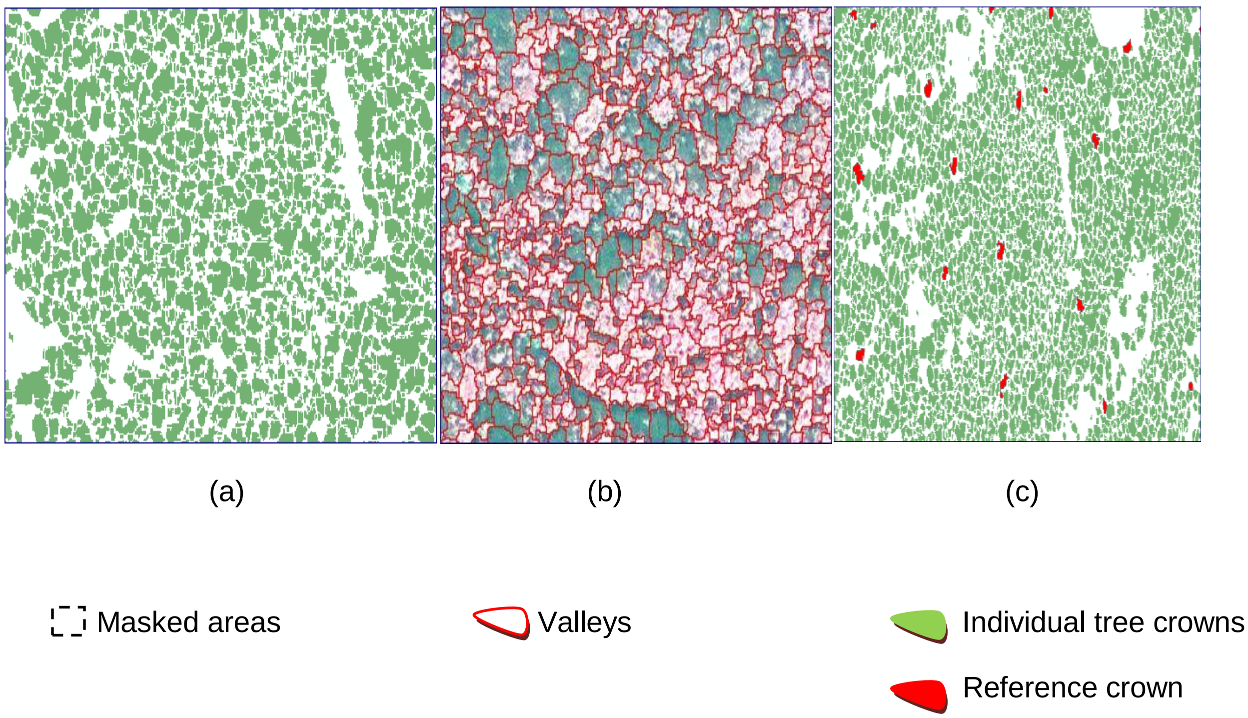


Figure 4 Valley following algorithm (a) white area masked as non-vegetated area (b) valley following algorithm (c) Individual tree crown overlaid with manually digitized trees.

4.20.2.2 Region Growing Algorithm

Pan-sharpened images were used as a distinctive layer for segmentation. 2x2 pixels Chessboard segmentation algorithm was applied to the stacked layers of pan-sharpened MSS GeoEyeimage (0.5m spatial resolution) .The reason of the chessboard segmentation was for separation of the image into homogenous objects for individual tree crown delineation to build similar homogeneity conditions. Figure 5shows a process of chessboard segmentation and pan-sharpened image

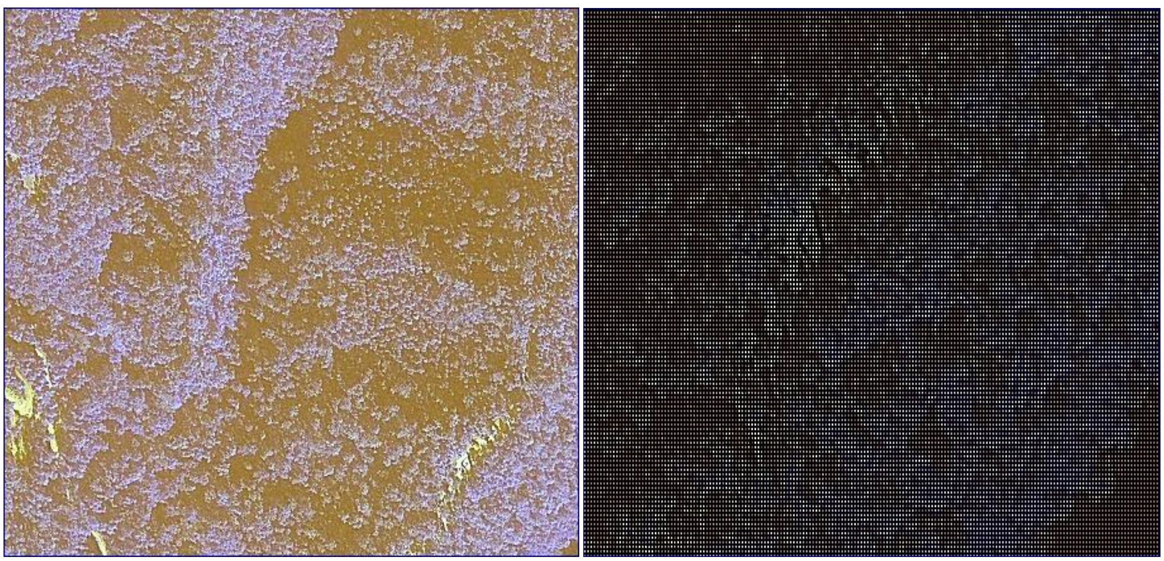
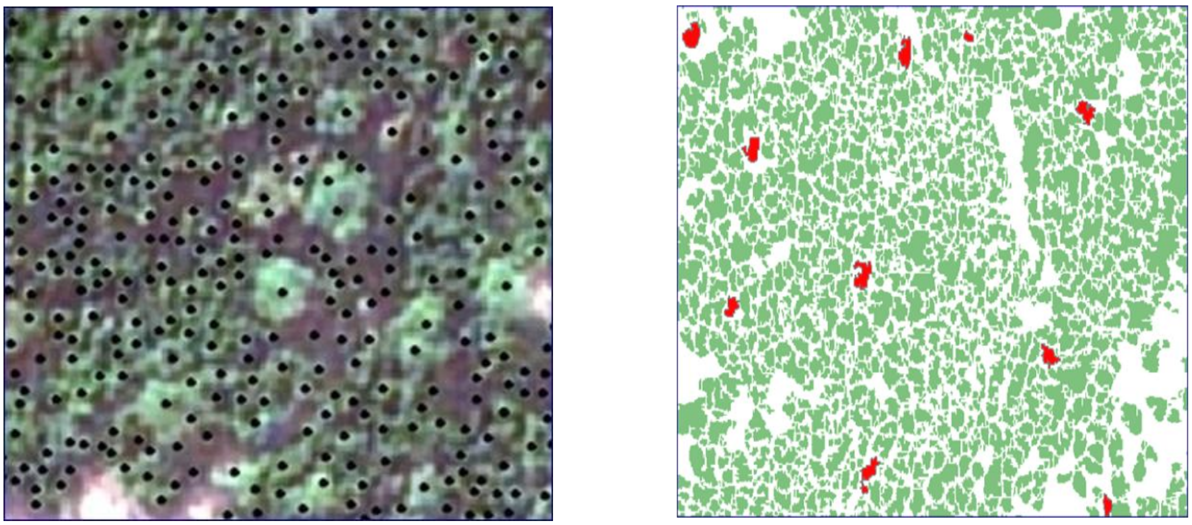


Figure 5 (a) Panchromatic image (b) Chessboard segmentation of thepanchromatic Image using tile size of two pixels

Further the individual tree crown was delineated by locating the local maxima and minima of the tree tops. Figure 4.4 shows the identified tree top using local maxima. Tree tops are the brightest point of the crown shown as a black cross in the image. The region growing algorithm is then applied to grow the tree tops in an individual tree crowns. Since it is an iterative process the region growing continues until it reaches the local minima as in shown in the Figure 4 (b) as a red mark.

In figure 4 (b) the green colour shows individual tree crowns obtained using region growing. The region growing algorithm is then applied to grow the tree tops in an individual tree crowns. Since it is an iterative process the region growing continues until it reaches the local minima as in shown in the Figure 6 (b) as a red mark. In figure 6 (b) the green colour shows individual tree crowns obtained using region growing.



(a) (b)

▪ Tree top Local minima Individual tree crown

Figure 6 Illustrate (a) Black cross corresponds to tree top identified by the local maxima (b) Fully delineated individual

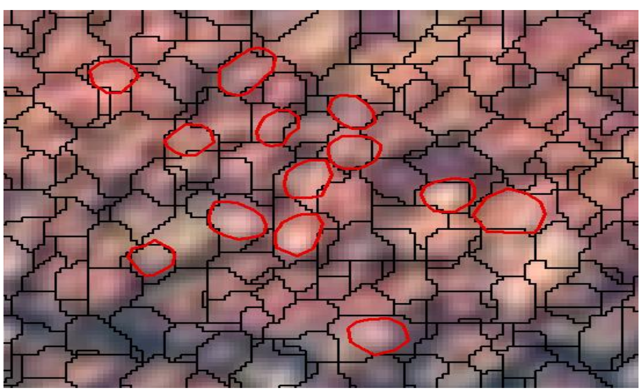


Figure 7 Manual delineated tree crowns (red colour) superimposed on the automatic segments (black colour)

4.20.2.3 Accuracy assessment of Valley Following and Region Growing Algorithm

Assessment using Goodness Measure Approach

Intersector tool was used for the accuracy measurement of two algorithms namely region growing and valley following. As per the formula given in chapter four section 4.11. To calculate the D value this gives overall result of over segmentation and under segmentation. As mentioned in the method closer the D index towards 0 higher will be the accuracy. The segmentation accuracy explains that using valley following algorithm the D value = 0.43 so this explains it delineated only 68% of the crown correctly whereas using region growing algorithm the D value =0.29 which explains 71 % of the trees were correctly delineated and using the same reference crown for accuracy assessment. The result is given in Table: 7

Table 8 Segmentation accuracy of valley following and region growing algorithms

Segmentation	Valley following	Region growing
D value	0.43	0.29
Over Segmentation	0.38	0.17
Under Segmentation	0.42	0.39
Over all Segmentation accuracy	57%	71%

The 1to1 matching was done to check the positive identification of the trees. The reference crown and segmented crown were overlapped and only those trees which overlapped 50% or more were considered as correctly delineated. Table: 8 shows that out of 155 identified trees valley following were able to detect 85 trees only whereas region growing were able to detect 92 trees correctly. Remaining trees were missed by an algorithm.

Table 9 Showing 1 to 1 matching of individual tree crown

	Valley following	Region growing
Total reference tree	155	
Positive identification of trees	85	92
Detection rate (%)	54.83%	59.35%

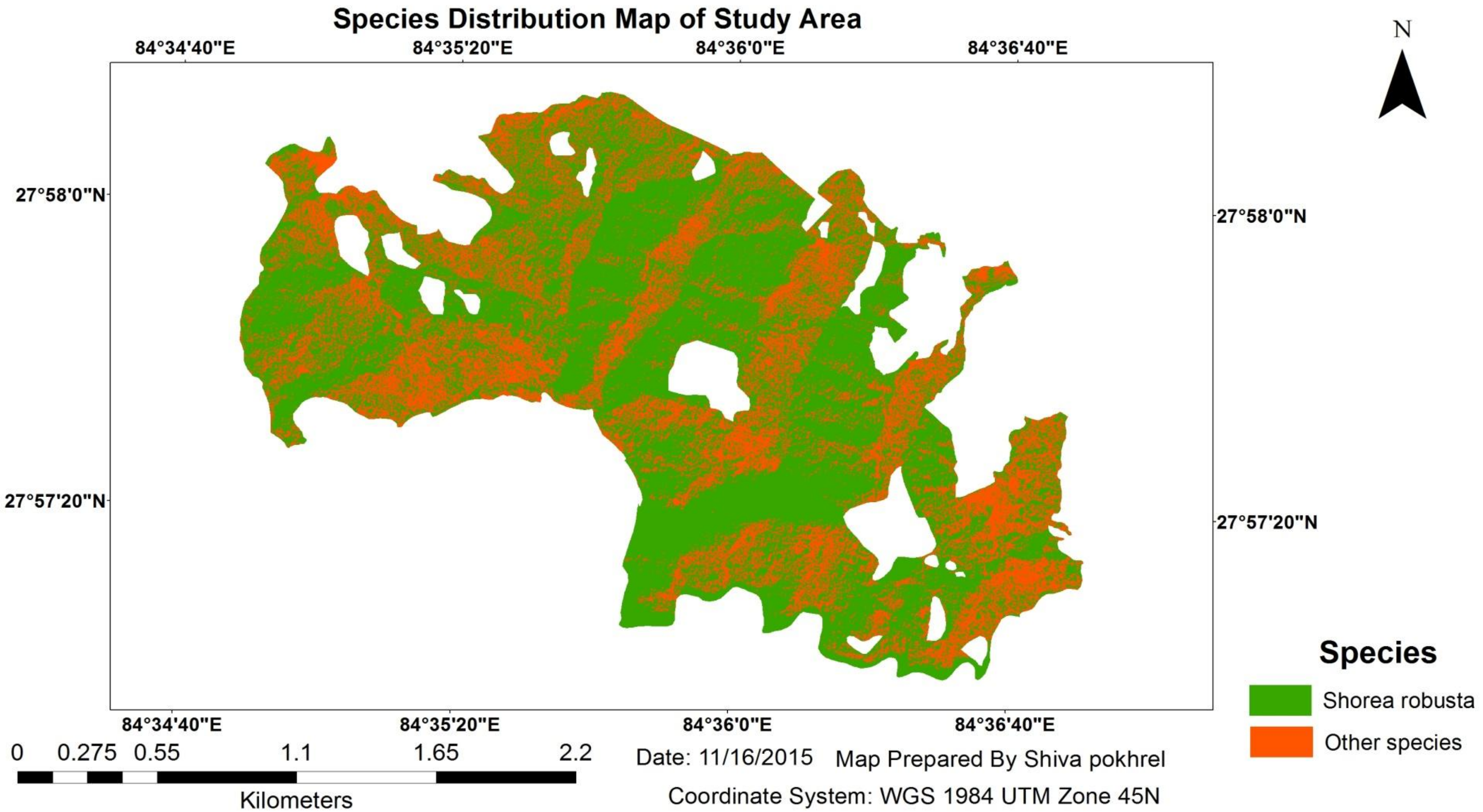
4.21 Image Classification of Species

The segmented image obtained from region growing algorithm was further used to classify according to the species. HPF pan sharpened image was classified applying nearest neighbour classification. Than Individual tree segments were classified into two main classes namely *Shorea robusta* and other tree species this was done mainly because of mixed forest with shorea dominancy as shown in Map 7. A total of 155 trees were used for training the classifier and a total of 135 trees were used for assessing the classification accuracy. Accuracy assessment was conceded using the standard accuracy assessment procedure of an error matrix. Users and Producers accuracy were computed form the error matrix. The Users accuracy gives an indication on the reliability of the classified image as a predictive device relative to what species are on the ground. The Producers accuracy describes the accuracy by class; of the classification by the classification program. The accuracy matrix is given in below Table10.

Table 10 Accuracy of classification

	Reference Data			
Class name	*Shorea robusta*	Other tree species	Total Classified	Users' accuracy (%)
Shorearobusta	77	29	106	72.9
Other tree species	13	12	29	41.0
Total	90	31	135	
Producers' accuracy (%)	85.55	29.26		
	Overall Accuracy = 85.8%			

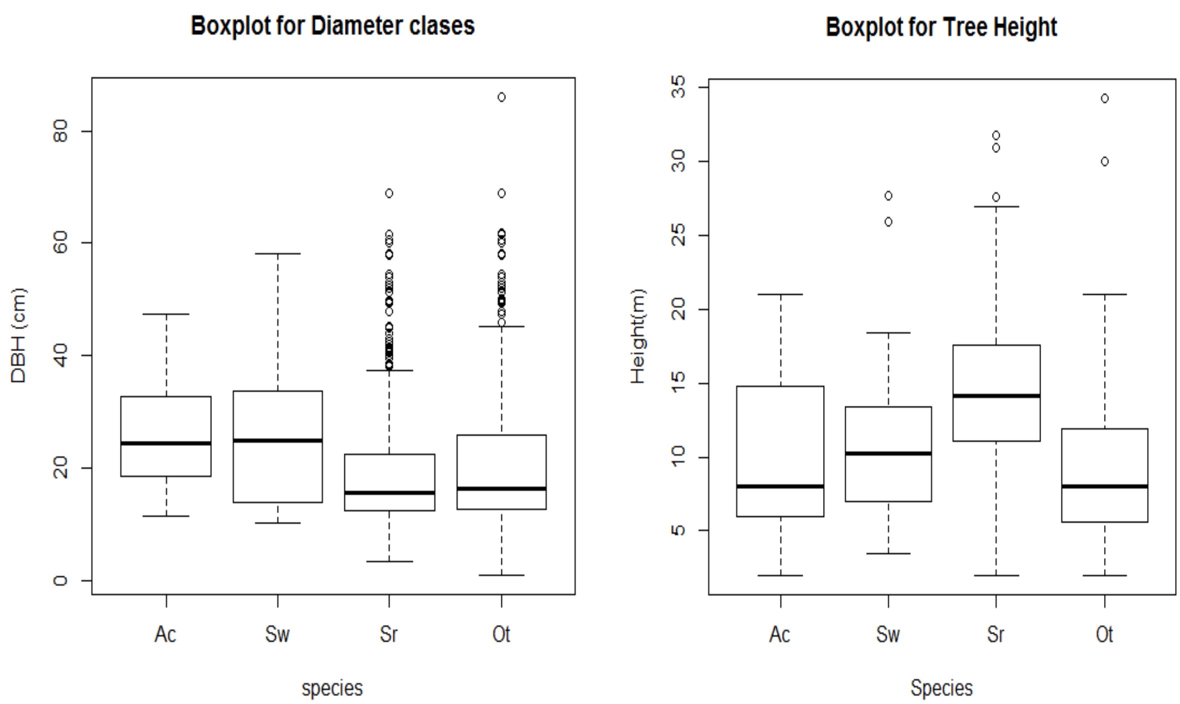
The image was classified into 2 classes as mentioned above



Map: 7 Map showing species distribution in Study Area

4.22 Descriptive Statistics of the Field Data

Data collected from the field inventory Consisted of Diameter at Breast Height DBH (1.3 m) above 10 cm and tree height were recorded for 647 trees in 28 plots of some selected community forest of Ludhikhola watershed, Gorkha, Nepal. The descriptive statistics of the DBH and height for *Shorea robusta*, *Adina cardifolia,* and other tree species is presented in by box-plots in figure 8. The mean DBH of *Shorearobusta*andother tree species range from 10cm to 25 cm respectively. *Shorearobusta* and other tree species have a mean height ranges from 8 m to 15m respectively.



(Sr = *Shorea robusta*, Ac =*Adina cordifolia* Sw = *Schima wallichii*, Ot=Others

Figure 8 Average DBH and tree height for species

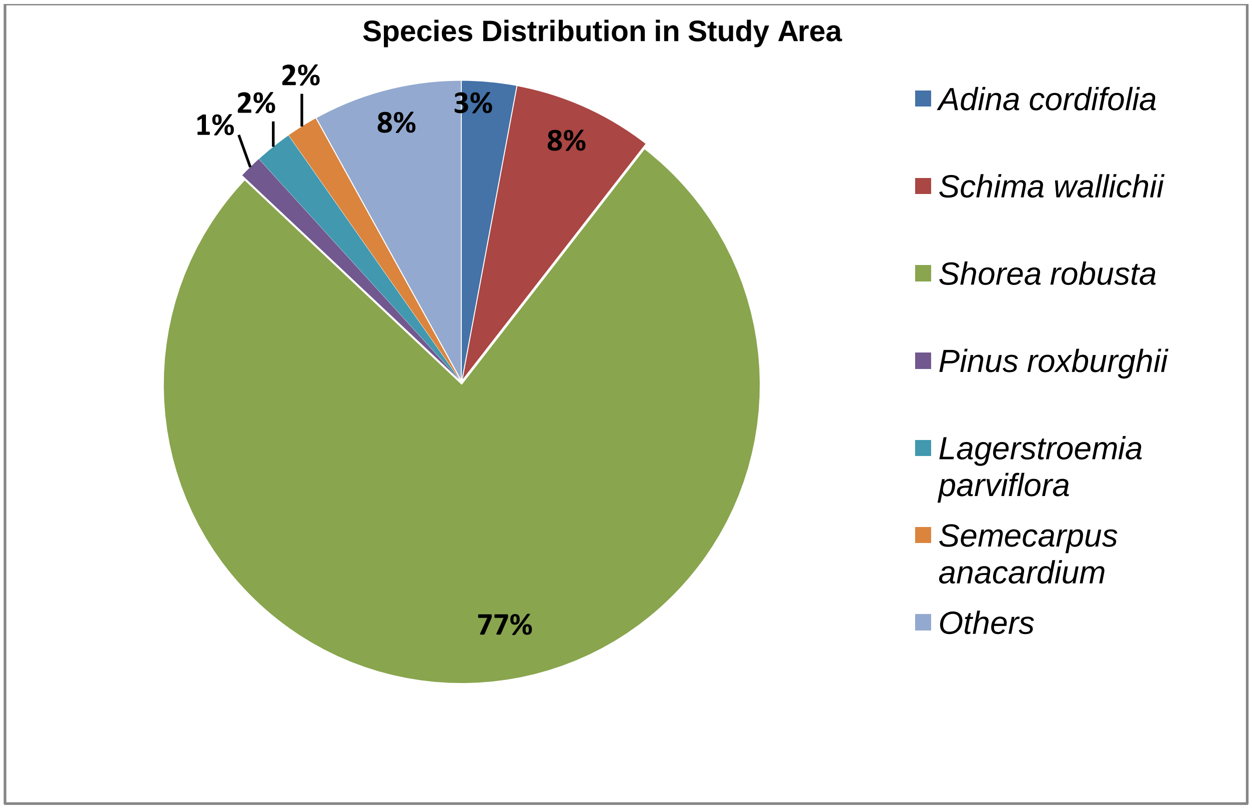


Figure 9 Species composition of study area

Study area has different tree species diversity with 16 species were encountered during the field inventory. However Shorea *robusta is the most dominated species with 77%* followed by *Schimawallichi* 8% and *Adina cordifolia* 3% *pinus roxburghii* 3% and Similarly, *Semecarpus anacardium* contributes 2%, *Lagerstroemia parviflora 2%* in species composition. Miscellaneous with 8% as shown in Figure 9.

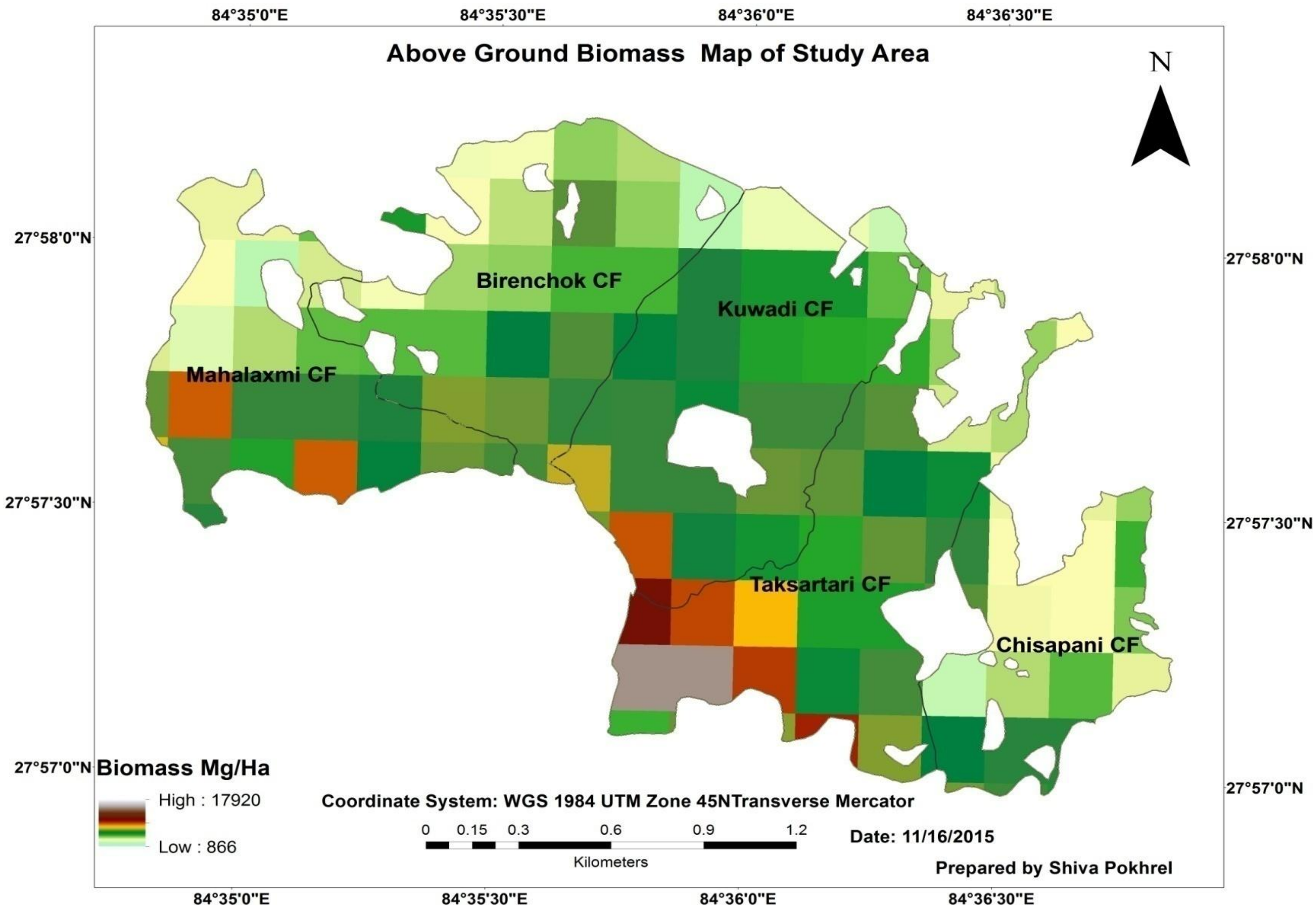
4.23 Biomass Stock Calculation from Field Data

Above ground biomass stock was accessed from field measured DBH and height by using species specific allometric equation as described in Section 4.11 for whole study area. Biomass stock of individual trees was calculated species wise then total carbon of trees measured in the sampling plots were calculated and averaged (i.e. per plot) for each community forest.

After that, biomass stock per ha was calculated by extrapolating the biomass stock from plot (500 m^2) to ha.A total 35822.85 Mg biomass was calculated in the study area, Taksartari community forest has highest amount of biomass stock of 17920.56 Mg biomass, with12890.56 Mg biomass ha^{-1} which is followed by Kuwadi community forest with 14029 Mg biomass and 17.31 Mg biomass ha^{-1} and least is observed in Chisapani Community forest with 866.10 Mg biomass and 50.04 Mg biomass ha^{-1}.The accessed biomass stock (Mg biomass ha^{-1}) for each CF is shown in Table 11. Similarly biomass calculated per ha. In study area is shown in Map 8.

Table 11 Table Showing Above ground Biomass in different Community Forest

Name of Community Forest	No of plots	Biomass in all plots	Average Biomass per plot Kg	Biomass per ha in Kg	Biomass per ha (Mg biomass ha-1)	Area of CF	Total Biomass in CF (Mg /h)
Birenchok	5	43051.57	86010.33	20559.91	20.56	83.57	1718.10
Chisapani	4	34657.25	8664.31	17307.15	17.31	50.04	866.10
Kuwadi	7	53275.61	7610.81	152048.77	152.05	92.27	14029
Mahalaxmi	5	70110.39	14022.10.	280133.52	280.14	63.97	12890.56
Takasartari	7	50648.05	7235.44	14452.89	14.45	89.21	17920.09
Total	28					379.16	35822.85



Map: 8 Map Showing Above ground Biomass per Hectare in different Community Forest

4.24 Regression Analysis

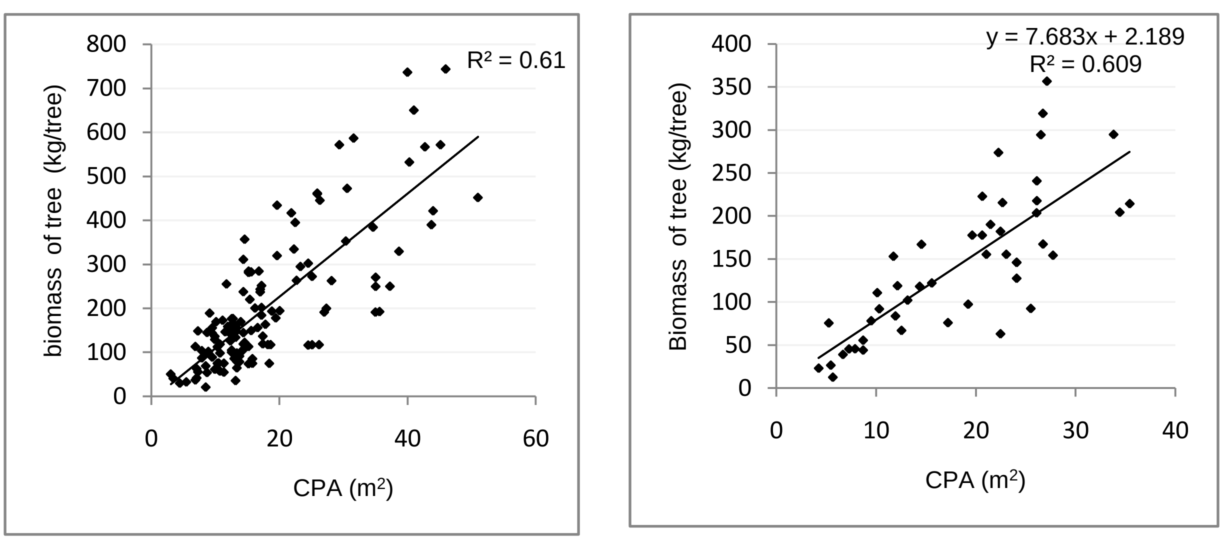
4.24.1 Relationship Between CPA, and Aboveground Biomass

Linear regression models were developed to derive the relationship between CPA and biomass for both *Shorearobusta* and other species. A total of 155 measurements were used for model development in case of *Shorearobusta* where as a total of 80 measurements were used in case of the other species. The coefficient of determination (R^2) for *Shorea robusta* and other species were 0.61 and 0.60 respectively (Figure 10 and 11). The regression analysis showed good correlation between CPA and biomass for both the classes with the correlation coefficient varying from 79% (*Shorea robusta*) to 78% (others). The models developed for biomass stock estimation of *Shorea robusta* and other species are.

$\text{Biomass stock (Shorea robusta)} = -7.99 + 11.72 \times \text{CPA} \ldots$ ....Equation 10

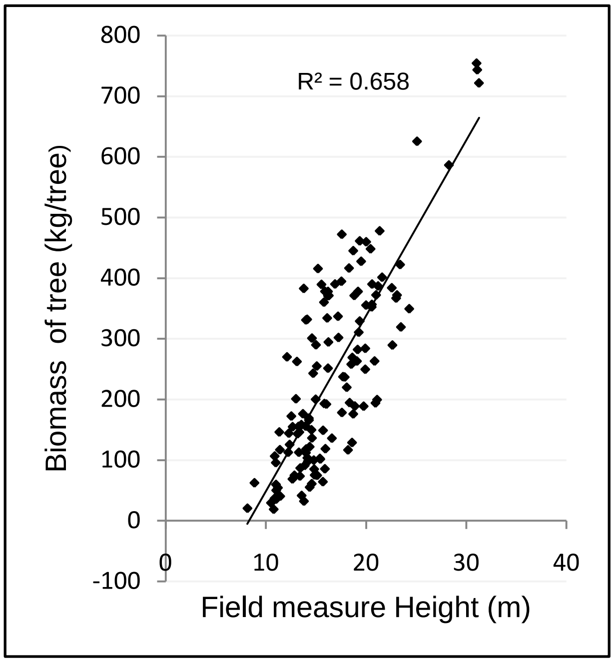
$\text{Biomass stock (Others)} = 2.19 + 7.68 \times \text{CPA} \ldots \ldots \ldots \ldots \ldots \ldots .$ ....Equation 11

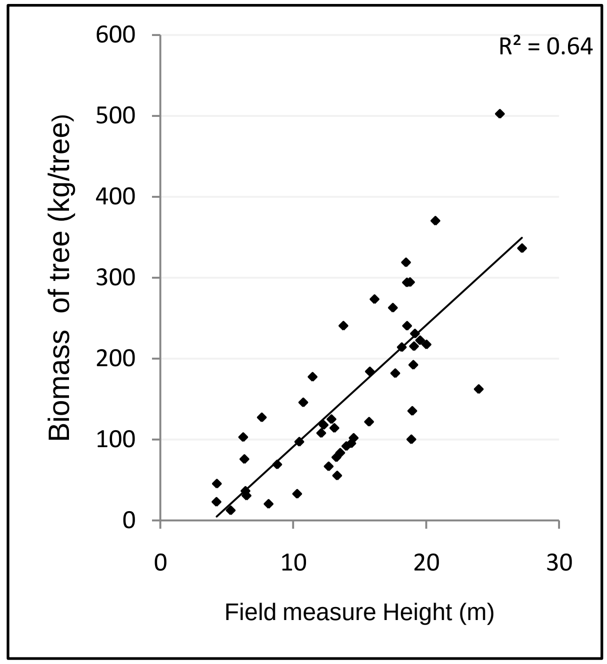
One way Analysis of Variance (ANOVA) test at 95% confidence level showed the significant relationship between biomass and CPA.



(a) *Shorea robusta* (b) Others

Figure 10 Relationships between CPA and Biomass





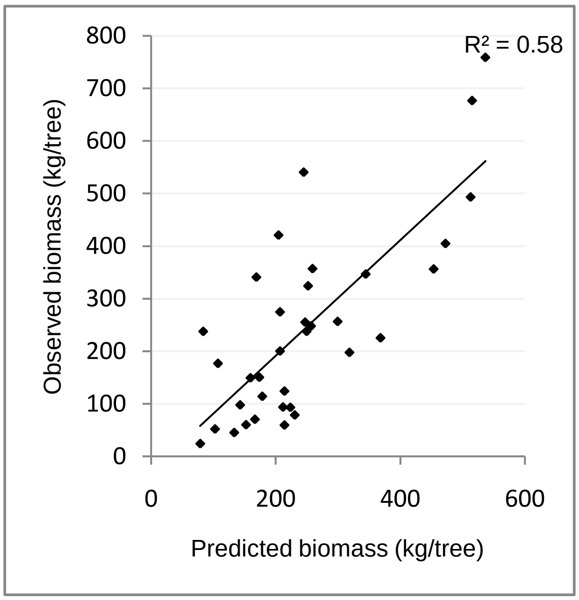
a. *Shorea robusta* b. Others

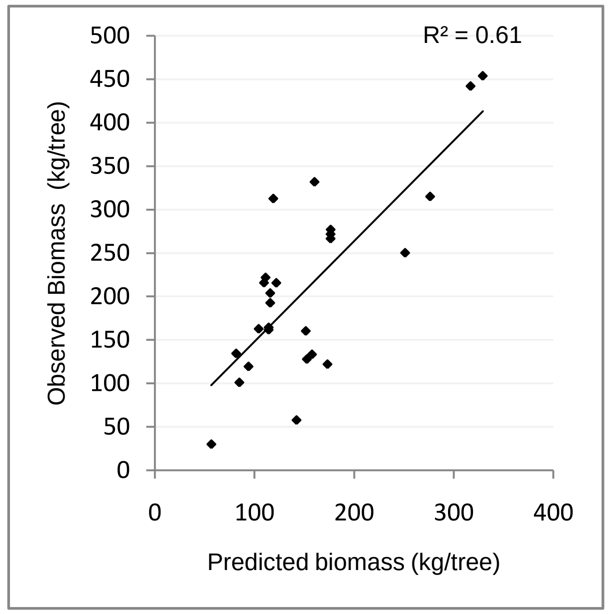
Figure 11 Relationship between height and Biomass

4.24.2 Model Validation

Developed model were validated against the field observed datasets (n=40, *Shorea robusta*; n=20, others). The results of the modelling corresponded well with the observed values as shown in Figure: 12commonly all models were explaining the relationship of biomass with CPA. Comparing all models, multiple linear regression models had the lowest RMSE% i.e. 37.61% and 33.33% for both *Shorea robusta* and other species respectively. This means there is 37.61% average error in the prediction of biomass for *Shorea robusta* and 33.33% average error in the prediction of biomass for other species.

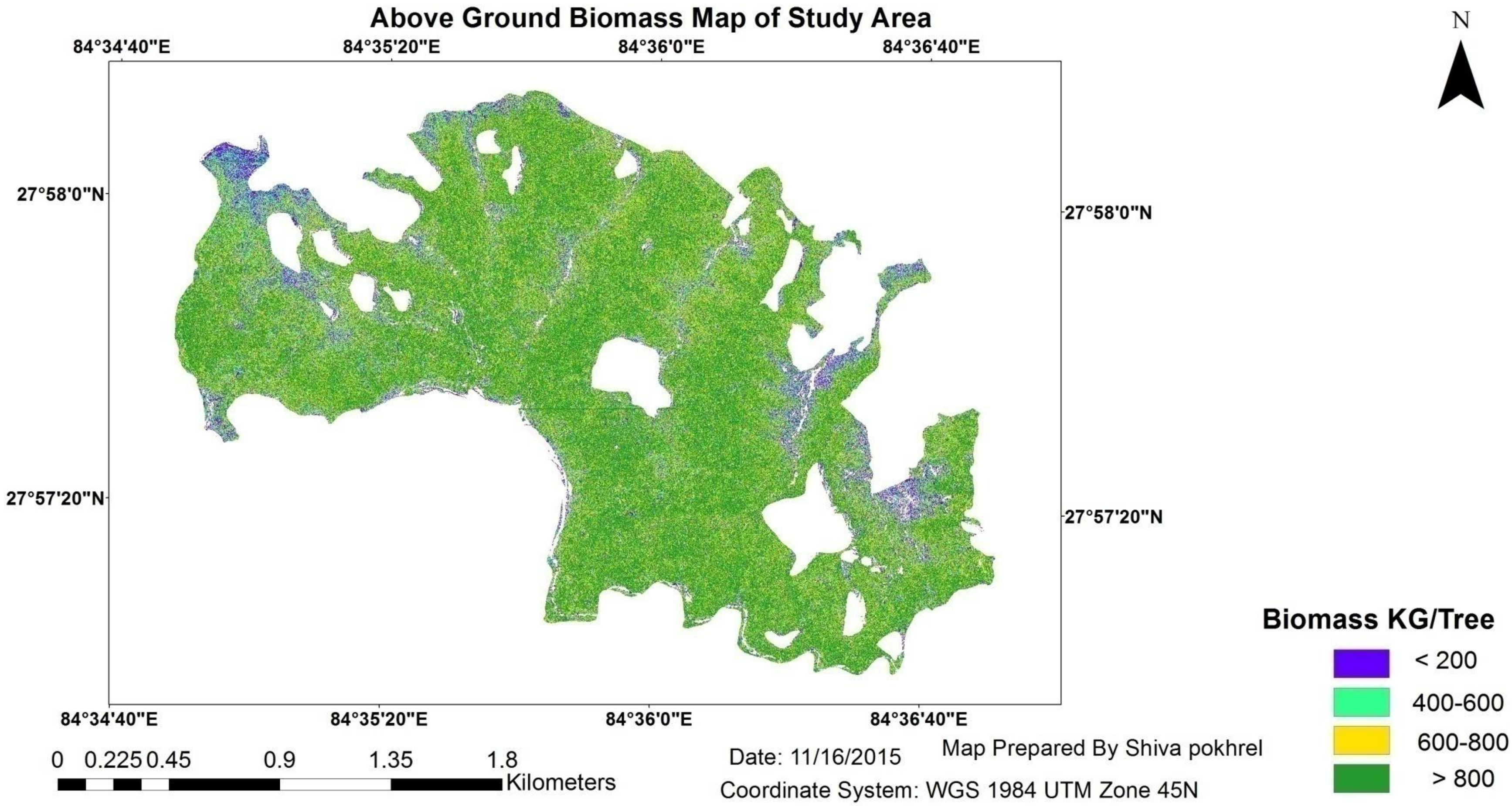
The relationship between CPA and biomass for both classes of trees resulted in higher RMSE% i.e. 47.1% for *Shorea robusta* and 41.5% for other species. RMSE% of the model developed for height and carbon were 40.3% and 35.3% for *Shorea robusta* and other species respectively. This means multiple regression models improve accuracy of biomass estimation than other models and finally biomass per tree in study area were extrapolated to entire area as shown in map 9. .





a. *Shorea robusta* b. Others

Figure 12 Relationship predicated and observed biomass



Map: 9 Map Showing Estimated Above Ground Biomass in Study Area

4.25 Result of AHP Analysis for Fire Hazard Zonation

Table 12 Sample of comparison of each classes of parameter fire Risk Zonation

Question 1.	**With respect to fire Hazard Zonation mapping**
Given that the distance from the settlements is <50 m which criteria is important? Classes 50–100 m 100–200 m 200–500m >500 m	Weight value
Question 2	With respect to fire Hazard Zonation mapping
Given that the distance from the settlements is 50 m-100 which criteria is important? Classes <50 m 100–200 m 200–500m >500 m	Weight value
Question 3	With respect to fire Hazard Zonation mapping
Given that the distance from the settlements is 100 m-200m which criteria is important? Classes <50 m 100–200 m 200–500m >500 m	Weight value
Question 4	With respect to fire Hazard Zonation mapping
Given that the distance from the settlements is 200 m-500m which criteria is important? Classes <50 m 100–200 m 200–500m >500 m	Weight value
Question 5	With respect to fire Hazard Zonation mapping
Given that the distance from the settlements is 500m which criteria is important? Classes <50 m 100–200 m 200–500m >500 m	Weight value

Table 13 Pair-wise comparison matrix and normalized principal eigenvector for the classes within each causative factor of fire potential, as required for applying the AHP method

Causative Factors and Classeswithineach Factor	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	Normalized Principal Eigen Vector
	Distance from settlements									
[1] <50 m	1	2	4	6	9					0.456
[2] 100 m	1/2	1	2	3	6					0.347
[3] 200 m	1/4	1/2	1	5	7					0.105
[4] 300 m	1/6	1/3	1/5	1	2					0.073
[5] 400 m	1/9	1/6	1/7	1/2	1					0.019
Vegetation types										
[1] Shrub land veg.	1	5	7							0.687
[2] Closed forest	1/5	1	5							0.234
[3] Open forest	1/7	1/5	1							0.079
	Distance from Road									
[1] <50 m	1	2	4	7	9					0.423
[2] 100 m	1/2	1	2	3	9					0.255
[3] 200 m	1/4	1/2	1	5	7					0.190
[4] 300m	1/7	1/3	1/5	1	2					0.080
[5] 400 m	1/9	1/9	1/7	1/2	1					0.052
	Slope in degree									
[1] <10	1	1/2	1/3	1/4						0.26
[2] 10- 20	2	1	1/2	1/3						0.25
[3] 20-30	3	2	1	1						0.26
[4] >30	4	3	2	1						0.43
	Elevation									
[1] 200-400 m	1	1/2	1/3							0.104
[2] 400–600 m	2	1/3	1/3							0.399
[3] >600	3	2	1							0.497

4.26 Application of AHP in Fire Potential Hazard Mapping

In this study, evaluation of criteria are made using a scale from 1 to 9 if the factors have a direct relationship and a scale from 1/2 to 1/9 if the factors have an inverse relationship as shown in Table : 13. Elements of the matrix in each level are compared in pairs with respect to their importance to the element in the next higher level. Starting at the top of the hierarchy and working down from there, the pair-wise comparison square matrixes are formed such that all the elements in the matrix are positive (Habibi et al; 2008) as given in Equation 12.

$$A = [A_{ij}] = \begin{bmatrix} A_{11} & A_{12} \cdots & A_{1n} \\ \underset{\cdots}{A_{21}} & \underset{\cdots}{A_{22}} \cdots & A_{2n \ldots} \\ A_{n1} & A_{n2} \cdots & A_{nn} \end{bmatrix} \ldots \ldots \ldots \text{Equation 12}$$

Such that aij> 0

Table 12 shows the sample of comparison of each classes of causative factor, *i.e*., distance from settlements, the relative weight values for each class of different causative factors, Shows the calculation of normalized principal eigen vector for causative factors distance from settlements, forest type, distance from road, and topographic factors for assessing fire potential zone map. Table: 14shows the test result for consistency of the rating values for each criteria of fire hazard zone, Since the CR of the each class of causative factors namely, distances from road, different forest type and topographic factors are less than 0.10, the rating values for these causative factors are consistent. In order to generate fire potential hazard map, the linear weighted combination is used for different causative factor maps as given in Equation

Fire Hazard Zonation = Weight map of (distance from settlements + Forest cover + distance from road + Slope + Elevation) …………..Equation 13

Table 14 Number of order of matrix n, largest eigen value λmax of the preference matrix, consistency index (CI), random consistency index (RI), and consistency ratio (CR), for the fire potential causative factors

Causative Factors	n	λmax	CI	RI	CR
Distance from Settlements	5	5.01	0.002	1.12	0.003
Distance from road	5	5.25	0.06	1.12	0.056
Land Cover	3	3.06	0.02	0.58	0.025
Slope	4	4.29	0.07	0.90	0.081
Elevation	3	5.02	0.005	1.12	0.005

Settlement, accessibility and forest types had played an important role in fire risk Zonation. The other variables elevation and slope have comparatively less impacting estimation of fire risk zonation. The area under different fire risk zones is summarized in Table 15.

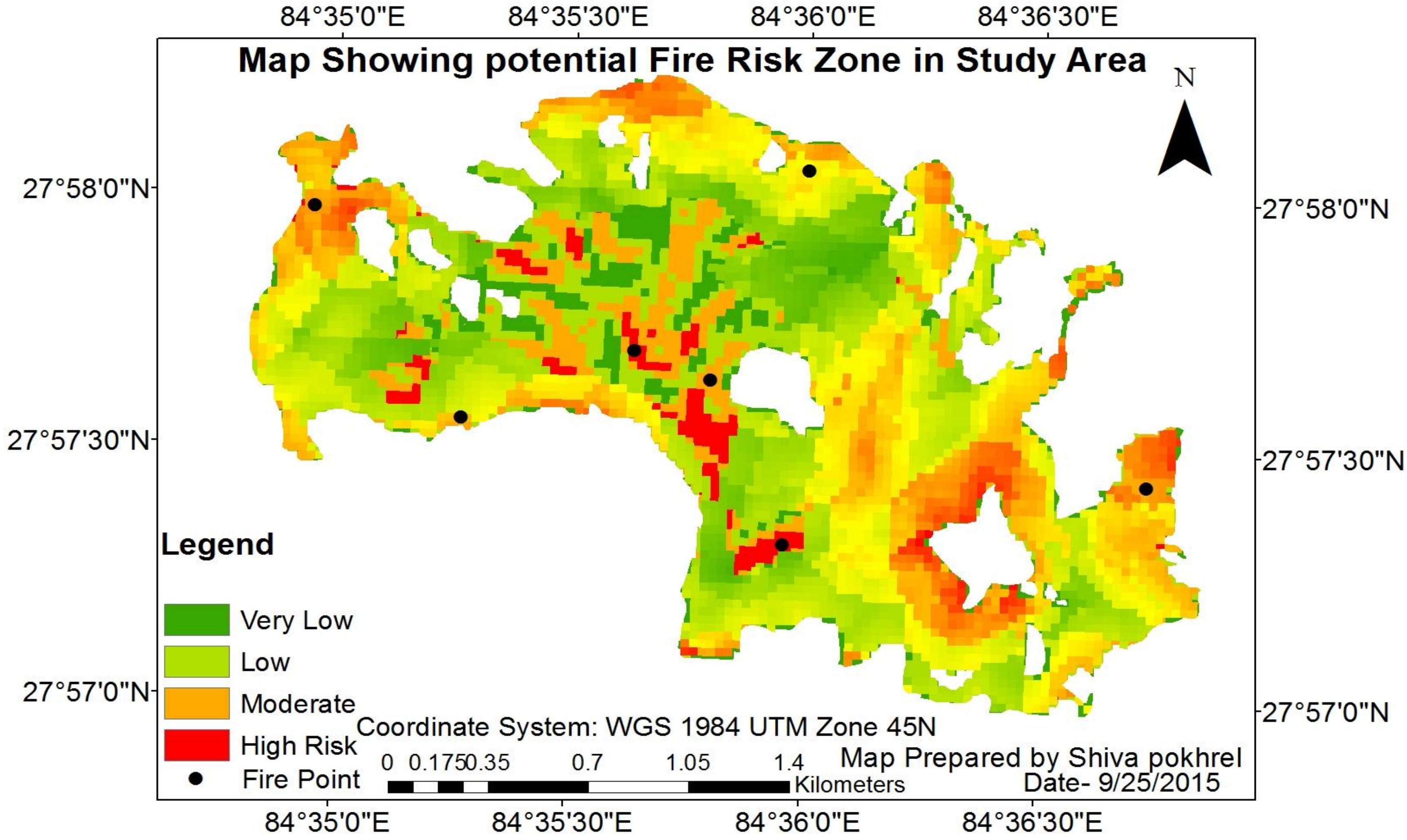
Table 15 Table Showing Fire Risk Percentage

Fire Risk	Percentage	Area in hectare
Very Low	11%	41.71
Low	55%	208.54
Moderate	30%	113.75
High	4%	15.17

A further study of fire risk Zonation map (Map: 10) showed that Shrub land and open broadleaveddeciduous and degraded forest types having high fuel content were falling on very high and high risk areas where closed broadleaved were falling on low and very low fire risk areas which is the causes of shade and keeping forest moist and creating unsuitable condition in below ground surface. Very high and high fire risk areas were mostly lying in southern and western aspect having warmer and dry conditions, whereas northern and eastern slopes were falling on low and very low fire risk areas. This may be attributed to the fact that southern and western aspects receive high amount of sun insulation for the major part of the day and accordingly are warmer than other aspects. Fire could thus certainly be averted by taking precautionary measures. Hence, despite the fact that no fire prone areas can be demarcated where fire occurs due to natural or intentional human causes, it is advantageous to have a fire risk map to avert possible disasters caused by fire due to human activities. It should prove to be helpful to the community forest user group, Forest Department. As this type of fire risk zone map would enable the department to set up an appropriate fire-fighting infrastructure for the areas more prone to fire damage. Such a map would help in planning the main roads, subsidiary roads, inspection paths, etc. and may lead to a reliable communication and transport system to efficiently fight small and large forest fires.

4.27 Validation of Forest Fire Risk Model

The final forest fire risk model was validated with past fire incidences data that was collected from ICIMOD MODIS fire alert system. The results of the study showed that out of 7 incidence of fire from 2010 to 2013 almost all of them were located in the moderate to high risk area zone in the Map.



Map: 10 Map showing fire risk zone in study area

CHAPTER 5 DISCUSSION

5.1 Tree Crown Delineation

eCognition software offers a range of tree crown delineation looms (i.e. segmentation) such as watershed, multi-resolution and region growing. For this study the individual tree crown delineation techniques was carried out by region growing method using the local maxima approach and valley following. The valley following and region growing algorithms applied for the individual tree crown delineation are based on similar underlying principles, the identification of trees through the local maxima filter and the delineation of crowns using local minima or darker radiometric valleys in the image. This research shows that yet they performed differently with different segmentation accuracy which was 71% and 68% for region growing algorithm and valley following algorithm respectively. The segmentation accuracy was assessed by D goodness of measure approach and the 1:1 correspondence method. Accuracy assessment of the individual tree crown delineation resulted in an overall accuracy of 71% (D value 0.29) using the D goodness of measure approach and 59.35% with the 1:1 correspondence method.

While for valley following 57% (D value 0.43), the segmentation accuracy of this study is within the range published in other studies using the region growing approach. Many studies have been carried out in pure and mixed forest stands using the local maxima approach of the region growing method (Bunting & Lucas, 2006; Erikson, 2003;Tsendbazar, 2011). For example, Erikson (2003) segmenting individual trees in a mixed forest stand reported an accuracy of 73% with the manual delineated reference tree crowns using colour infrared aerial images. Similarly, Bunting & Lucas (2006) obtained a tree crown delineation accuracy of 72% in a diverse mixed species forest stand and Tsendbazar (2011) reported a tree crown segmentation accuracy of 75% in a heterogeneous mixed forests in Nepal.

The over-segmentation and under-segmentation of individual tree crowns obtained in this study valley following was o.38 for over segmentation and 0.42.For the under segmentation similarly for region growing 0.17 and 0.39 respectively. A reference object is over-segmented if the area of overlap is less than 100 % and under-segmented if the area of overlap is more than 100% (Clinton, et al., 2010). In other words, over-segmentation represents smaller crown delineation compared to the reference crowns and under-segmentation represents bigger crown delineation compared to the reference crowns. The under segmentation was higher than over segmentation because of intermingling tree canopies, irregular tree crown shapes and peculiar branches of broadleaved tree species.

5.2 Classification of Species and Accuracy Assessment

Only two classes were considered for tree species classification because *Shorearobusta* constitutes about 77% of the total tree grouped as other tree species class for the classification purpose. Moreover, earlier study in the same area has indicated that the class separability between different species was poor (Shah, 2011). Overall classification accuracy achieved in this study was 85.8%. The user accuracy for *Shorea robusta* was 72.9% whereas for other species it was 41%. The user accuracy for *Shorea robusta* was higher because of more the trees recognized in the field were *Shorea robusta*. The user accuracy in classifying other species is lower. This could be due to the smaller number of samples for training and validation. Moreover, all other species except *Shorea robusta* were grouped into one class as 'others'. Different species have their own spectral characteristics due to which there would be confusion in spectral response from the class 'others'. Classification accuracy is also affected by segmentation quality (Ke et al., 2010). The higher classification accuracy will be obtained if the tree crown delineation is more precise. In this study, the classification could be influenced by the segmentation quality particularly omission and commission errors might create confusion in the classification as brightness value of those segments would be affected.

5.3 Modeling the Relationship of CPA, Biomass, Heightand Validation

Linear relationship was found between CPA, biomass stock and height of the trees for both *Shorearobusta* and other species. The linear relationship was observed as most of the trees in the study area were young with mean DBH of 20 ± 7.5 cm and mean height of 13. ± 6.2 m. Mean DBH could be smaller than above mentioned if trees with DBH less than 10 cm had been measured in the field. Field observation showed that there was not competition between tree crowns in most of the cases because most of trees were young. During young age, DBH and crown increases linearly and later crown growth decreases as crown start touching each other (Shimano, 1997).

Coefficient of determination R^2 obtained for the relationship between CPA and biomass in the study were 0.61 for *Shorearobusta*and 0.60 for other species. In this study, R^2 for the relationship between height and biomass were 0.65 and 0.64 for *Shorea robusta.* All models were explaining the relationship of biomass with CPA. Comparing all models, multiple linear regression models had the lowest RMSE% i.e. 37.61% and 33.33% for both *Shorea robusta* and other species respectively. This means there is 37.61% average error in the prediction of biomass for *Shorea robusta* and 33.33% average error in the prediction of biomass for other species. The relationship between CPA and biomass for both classes of trees resulted in higher RMSE% i.e. 47.1% for *Shorea robusta* and 41.5% for other species. RMSE% of the model developed for height and biomass were 40.3% and 35.3% for *Shorea robusta* and other species respectively.

5.4 Biomass Stock Estimation

Biomass stock per ha was calculated by extrapolating the biomass stock from plot (500 m^2) to ha. A total 35822.85 Mg biomass was calculated in the study area, Taksartari community forest has highest amount of biomass stock of 17920.56 Mg biomass, with 12520.56 Mg biomass ha^{-1}.Which is followed by Kuwadi community forest with 14029 Mg biomass and 17.31 Mg biomass ha^{-1} and least is observed in Chisapani Community forest with 866.10 Mg biomass and 50.04 Mg biomass ha^{-1} In this study, approximately 94.7 $MgCha^{-1}$ of carbon stock was estimated for the study area which is lower compared to results of Baral et al. (2010) who found 99.43 $MgCha^{-1}$ Similarly sajana (2012) found 89.45 $MgCha^{-1}$ which is less than this study,Jamarkattel (2011) obtained 70 $MgCha^{-1}$ in a study done in CFs where *Shorea robusta* is the dominant species.

5.5 Fire Risk Zonation

The AHP method is one of the most widely used multi-criteria decision analysis approaches, Moreover, pair-wise comparisons between parameters are appealing to users as in this method pair-wise comparisons (A is more important than B) can be converted into a set of numbers representing the relative priority of each of the criteria. Fire risk modeling using multi criteria analysis and integrating different layers resulted in developing fire risk hazard Zonation of study area. Fire risk index map can be used to prioritize for taking forest fire prevention initiatives at management level. From Table 4, it can be seen that fire hazard is directly proportional to the distance from road, settlement as a closer distance nearer to road, settlement has higher weight values and a farther distance has lower weight value. For elevation the area was classified into three classes by natural breaks classification. Highest index value was calculated assigned to elevation class 500 m - 600 m, where greater fire incidences were observed by earlier study as well as according to local people.

Rathaur (2006) also reported more fire incidents in middle elevations (600-800 m). Increase in humidity and decrease in temperature do not favor fire incidences in higher elevations. In case of slope similarly the total area of the study area was classified into five slope classes by equal interval classification. Lower index value was assigned for classes having less slope and higher index value for greater slope classes. Higher slope increases the risk of upward fire spreading by convective preheating due to hot smokes released from down slope fires and contact ignition of upslope fuels. In same way for aspect Due to geographic location of Nepal, south facing slopes have more sunshine hours than those of north facing slopes. This difference creates drier southern slopes, so here fuels remain warm and dry while fuel of northern and eastern slopes have more humidity and cooler conditions. Hence south and west facing slopes were assigned higher index values than for north and east facing slopes. The aspect classes and their respective index values, in forest vegetation type grassland and open to closed dry deciduous forest is more vulnerable to forest fire than the moist open deciduous forest.

Which may the cause of sufficient open spaces for long light duration and easy accessible in such area for human grazing and other activities they catch fire easily and they have more content of dry litter during dry season. So shrub land and open dry deciduous forest are more vulnerable to forest fire than moist, the precision in the modeling could be increased by adding more number of variables in the analysis. In this research test result for consistency of the rating values for each criteria of fire hazard zone, Since the CR of the each class of causative factors namely, distances from road, different forest type and topographic factors, Slope, Aspect and elevation are less than 0.10, the rating values for these causative factors are consistent. In order to generate fire potential hazard map. However, the selection of variables should be based on knowledge base of the area. The areas shown under very high, high and moderate 'fire risk' zones are those areas where fire can be unintentionally caused by human activities.

5.7 Sources of Uncertainties

5.7.1 Allometric Equation

The accuracy of allometric equation influence the accuracy of the model (García et al., 2010). The allometric equation developed for one area may introduce error when it is used for a different area. Site specific and species specific allometric equations are essential to accurately estimate biomass of the forest. The major sources of uncertainty are the coefficient parameters ‘a’ and ‘b’ in allometric equation when they are not calibrated for a specific site (Ketterings et al., 2001).

5.7.2 Other Uncertainty

According to (Wang et al., 2005) Errors and uncertainties can be introduced at any step from data and operations which are then accumulated and propagated to the maps. There were mainly four major operations in this study and in each operation; error could be introduced. The segmentation accuracy showed there were errors. Commission and omission errors were observed due to overlapping trees and branches of big trees which can reach far in different directions and grow into irregular shape. The next operation was classification of tree species. When classification is not correct, accurate estimation of biomass is not possible. Error in classification may lead to selection of wrong wood specific gravity for a tree. Error in classification could be due to spectral characteristic of vegetation, shadows, distortion of the image and misidentification of tree. Selection of appropriate model is required. Data used for the model should be good representative of population (trees) in the study area. Otherwise, this might affect the model. Beside these, errors from allometric equation would affect the model. For fire risk hazard Zonation The main demerit of AHP method is that it has a subjective nature of the modeling process which may differ from one to another. Hence, methodology cannot guarantee the decisions as definitely true.

5.8 Recommendations

In general, the results of this research demonstrated the usefulness remote sensing and geospatial technique for accessing forest above ground biomass with integrating field data, and Spatial mapping of forest fire risk Zonation. Forest fire is considered one of the important factors leading to loss of huge amount of forest biomass and creating negative impacts on forest ecosystem. The research was carried out successfully and there are some recommendations

- ✓ An accurate field validation technique is strongly recommended. For instance differential GPS (DGPS) should be used to minimize the field based location error and recognizing the individual trees on image.
- ✓ The allometric equation are the major problem for biomass estimation in Nepal so more allometric equation for site and species specific need to be develop for the accurate biomass estimation.
- ✓ Sufficient sample size and a range of forest types *i.e.* according to elevation gradient or climatic zone should be preferred to generalize the relationship between biomass and other tree parameter.
- ✓ For developing a fair benefit sharing mechanism to community and better management of forest resources, zoning of the landscape according to dominant species and canopy cover, Fir risk hazard zonecould be helpful.
- ✓ Forest area near by the settlements, open area (Shrub land) and road are more vulnerable to forest fire so awareness and fire control preparedness training should be given to local community.

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Appendix 1: Sample of data collection sheet

Data Collection Sheet

Name of recorder: **Date:**

CF Name		**Coordinates**	**X:**
Sample plot ID			**Y:**

Slope (%): **Aspect:** **Altitude:**

Reference Points: **Bearing:** **Distance:**

Undergrowth:

S.N.	Species	D B H (cm)	Height (m)	Elevation	Latitude	Longitude	Rem.
1.							
2.							
3.							
4.							
5.							
6.							
7.							
8.							
9.							
10.							

***** Rem= Remark

Appendix2: Location of sample plots

Longitude (X)	Latitude(Y)	Plot no	Name of C.F	Aspect
262276	3095969	4	Mahalaxmi	SE
262209	3095942	5	Mahalaxmi	sw
264667	3095071	6	Taksatari	E
262809	3095259	7	Mahalaxmi	E
263010	3096193	8	Birinchowk	SE
264765	3094831	9	Chisapani	S
262982	3095680	10	Birinchowk	SE
264765	3094831	9	Chisapani	S
262982	3095680	10	Birinchowk	SE
263541	3094369	11	Taksatari	W
262044	3095469	12	Mahalaxmi	E
264648	3094102	13	Chisapani	SW
264058	3095753	14	Kuwadi	E
264399	3095325	15	Taksatari	E
263441	3096044	17	Birinchowk	W
263893	3095286	18	Kuwadi	SW
263427	3095925	19	Birinchowk	W
264861	3094280	20	Chisapani	E
263536	3095591	21	Birinchowk	SW
262153	3095374	22	Mahalaxmi	W
264037	3094997	24	Kuwadi	S
263533	3095090	25	Kuwadi	S
264897	3094378	26	Chisapani	W`
264164	3094470	27	Taksatari	SW
263799	3094412	28	Taksatari	W`
264336	3094202	29	Taksatari	E
264359	3094880	30	Taksatari	S
262114	3095103	31	Mahalaxmi	SW