MODELING FOREST STAND VOLUME AND LIVE ABOVEGROUND WOODY BIOMASS USING REMOTE SENSING AND GIS: A CASE STUDY IN CHANCHO *EUCALYPTUS GLOBULUS* PLANTATION FOREST, OROMIA REGIONAL STATE, ETHIOPIA

By
Tariku Geda

A Thesis Submitted to
School of Earth Sciences

Presented in Partial Fulfillment of the Requirements for the
Degree of Master of Science
(Remote Sensing and Geographic Information Systems)

Addis Ababa University
Addis Ababa, Ethiopia
May 2014

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Under the guidance of

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May 2014

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This is to certify that the thesis prepared by Tariku Geda, entitled: *Modeling Forest Stand Volume and Live Aboveground Woody Biomass Using Remote Sensing and GIS: A Case Study in Chancho Eucalyptus globulus Plantation Forest, Oromia Regional State, Ethiopia* and submitted in the partial fulfillment of the requirements for the degree of Master of Science (Remote Sensing and GIS) complies with the regulation of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee

Examiner ____________________ Signature_______ Date__________

Examiner ____________________ Signature_______ Date__________

Advisor _____________________ Signature_______ Date__________

Co-Advisor __________________ Signature_______ Date__________

ABSTRACT

Modeling Forest Stand Volume and Live Aboveground Woody Biomass Using Remote Sensing and GIS: A Case Study in Chancho *Eucalyptus globulus* Plantation Forest, Oromia Regional State, Ethiopia

Tariku Geda, Addis Ababa University, 2014

This study presents the utility of Landsat 5 TM satellite imagery spectral and textural features for the estimation of stem volume and aboveground biomass (AGB) in Chancho *Eucalyptus globulus* plantation forest, Oromia Regional State, Ethiopia. Stem volume and AGB are arguably the most important variables among forest attributes since they play an important role in understanding the function of forests in the environmental and ecosystem services. Both of them can be estimated using different data and approaches, like using field observation data (classical approach), remote sensing data, and GIS data (modern approach). Even though, field-based forest surveying provides highly accurate measurements, it has limitations with regard to incurring high cost, being time consuming and having low spatial coverage and frequency. In addition to this, in some cases, destructive sampling is laborious and negatively affect environment. This makes sustaining the socio-economic and ecological benefits of forests under challenge. On the other hand, although Remote Sensing and GIS approaches overcome these limitations, they are site and species specific and are highly uncertain. In general in Ethiopian and in particular in the present study site both stem volume and AGB are estimated based on the classical approach.

Thus, the present study is conducted to improve accuracy and decrease uncertainties in the modern approach in general, and replace the classical approach in the study site in particular by developing a function that estimate both attributes (dependent variables) as a function spectral and textural features (independent variables) of Landsat 5 TM image acquisition date of January 10, 2011. Based on Pearson correlation statistics test result among dependents and independents variables , Tasseled Cap brightness, GLCM Dissimilarity and GLC Variance were found as best explanatory variables for stem volume estimation. Whereas, Landsat 5 TM Band 5, GLCM Dissimilarity and GLCM Variance found to be as best explanatory variables for AGB estimation. The modeling of the stem volume and AGB equations as a function of spectral and textural independent variables were developed using Ordinary Least Square Regression method.

The modern approach estimated almost similar mean stem volume and aboveground biomass abundance with field measurement data. The overall findings presented in this study are encouraging and show that Landsat 5 TM imagery was successful in predicting both attributes with reasonable accuracy (Adjusted R^2 is 0.50 and 0.51 for stem volume and AGB, respectively; mean residual is 0 for both stem volume and AGB). Further research is recommended to document the performance of the Landsat 5 TM satellite data under different environmental conditions and topographical changes, as well as for other species.

Keywords: Aboveground biomass, GIS, OLS, Remote Sensing, Stem volume

ACKNOWLEDGMENT

First and foremost I praise the Almighty God, who cares my life,and favors me to begin and bring this study to an end.

I am very grateful and have lots of appreciation to my advisers Dr. Getachew Berhan and Mr. Binyam Tesfaw for their unreserved support, constructive comments and editing from start to end of the research activities.

I gratefully acknowledge the financial support of the Addis Ababa University (AAU) for this study. I would also like to express my appreciation to AAU; all Earth Science Department staffs for their unreserved help during my study at Addis Ababa University. Especially would like to express my warmest thanks and gratitude to Dr. K.V. Suryabhagavan for his professional and personal support throughout my graduate studies.

My special acknowledgement is to the Oromia Forest and Wildlife Enterprise, which provided me the necessary data, and facilitation services. Particular thanks are to its staff memebers; Getachew, Guta, Befiqadu and Yheyis for their support during the secondary data collection, research problem identification, and all the discussions and valuable hints are gratefully acknowledged.

I am also deeply thankful to the Federal Democratic Republic of Ethiopian, Ministry of Environment and Forestry (MEF), which gave me permission to do this MSc. My thanks also go to its staff members for their support during the research problem identification and all the discussions and valuable hints are gratefully acknowledged.

I thank you my friends; Abiy, Nigusse, Habtamu, Tenaw, Lulu, and whom I did not mention their name here, for their support.

Finally, I would like to express my deepest appreciation to my family for their support and encouragement that convinced me to pursue this study.

(Tariku Geda)

DEDICATION

To all 2013/14 academic year Remote Sensing and GIS stream graduate students of School of Earth Sciences, Addis Ababa University.

Table of Contents

Page No.

List of Tables

List of Figures

List of Equations

List of Abbreviations

AGB	Aboveground Biomass
DBH	Diameter at Breast Height
DEM	Elevation Model
EFAP	Ethiopian Forestry Action Program
Eq.	Equation
EROSDC	Earth Resources Observation System Data Center
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organization
FCC	False Color Composite
FDREMEF	The Federal Democratic Republic of Ethiopia Ministry of Environment and Forest
Fig.	Figure
GIS	Geographic Information System
GLCM	Grey Level Co-Occurrence Matrix
L1T	Level 1Terrain corrected
LAI	Leaf Area Index
NDVI	Normalized Difference Vegetation Index
OFWE	Oromia Forest and Wildlife Enterprise
OLS	Ordinary Least Square
PCA	Principal Component1 Analysis
REDD+	Reduced Emission from Deforestation and Degradation
RMSE	Root Mean Square Error
RS	Remote Sensing
SR	Simple Ratio
SR	Simple Ratio Index
SRTM	Shuttle Radar Topography Mission
TC	Tasseled Caps
TM	Thematic Mapper
VIs	Vegetation Indices
WCRGEIPG	Woreda Climate Resilient Green Economy Investment Planning Guide

CHAPTER 1 INTRODUCTION

1.1. Background of the study and justifications

Reliable, up to date, and synoptic spatial information regarding the status, trends, and structural characteristics of natural resources are required to ensure the implementation of sustainable natural resource management practices (Roberts *et al.,* 2007).

To make this feasible, computer based modern technologies like Remote Sensing (RS) and Geographic Information Systems (GIS) play a great role. Forest resources, the concern of this study, are one segment of the natural resources, assessment and monitoring of which use these technologies (Fagan and Fries, 2009).

Remote Sensing technology is defined by Lillesand *et al.* (1994) as the science of processing and interpreting images and related data obtained by sensing systems, which utilize the use of electromagnetic energy reflected/emitted by the earth's surface without being in physical contact with the object.

Thus, the object-related interaction between electromagnetic radiation and matter like forest, soil and the atmosphere is represented. This technology recently becomes more popular as huge areas can be covered with less efforts and time (Wijaya *et al.,* 2010).

The information obtained from RS is used as an input for GIS, which is defined as an organized collection of computer hardware, software, geographical data, and personnel designed to efficiently capture, store, update, manipulate, analyze and display all forms of geographically referenced data (de Jong and van der Meer, 2005).

Since its introduction in the 1960s, GIS has been providing tools to enable natural resources managers to make informed decisions. For instance, in the case of forest data like forest stand volume and biomass, its database and spatial analysis capability is employed to facilitate the forest management planning processes to update, manipulate, and analyze data (Wallerman *et al.,* 2002).

Forest structure can be characterized by several attributes, which refer to the size, shape, and distribution of forest components in both the horizontal and vertical dimensions (Roberts *et al*., 2007). According to Ozdemir and Karnieli (2011), these variables include Diameter at Breast Height (DBH *i.e*. diameter at 1.3 m aboveground), volume, basal-area, stems per hectare, mean tree height and biomass.

Among these attributes, volume and biomass are arguably the most important variables since they play an important role in understanding the function of forests in the environmental and ecosystem services (Steininger, 2000).

According to Philip (1983), Forest Stand Volume refers to the aggregate sum of the volume of all of the trees per unit area (cubic meters per a given area) in a given forest including bark but excluding branches and stumps of each tree. From now onwards it is referred as stem volume.

Although biomass is generally defined as organic material produced by plants, ecologically speaking it has a much broader definition as the mass of all living biological organisms in a given habitat or ecosystem at a given time (Ashton, 2006).

In this study, biomass is expressed for analysis purpose in a more specific manner, which is the total amount of aboveground living organic matter in trees, expressed as oven-dry weight per unit area. This definition also refers to biomass density when expressed as mass per unit area (Brown, 1997).

The term dry weight biomass is used here to distinguish from the fresh weight biomass prior to removal of water contents. While the term live aboveground biomass (AGB) is applied to differentiate from belowground biomass that contains of all living roots over 2 mm in diameter (Ravindranath and Ostwald, 2007).

Both stem volume and AGB can be estimated using different data and approaches, like using field observation data, remote sensing data, and GIS data (Fagan and Fries, 2009).

Using field observation data both could be estimated either in destructive or non-destructive (indirect) methods. Using destructive methods, they are estimated by felling and measuring the volume and AGB of each standing tree in a given small sampling unit (Picard *et al*., 2012).

In the case of indirect methods, they are computed using either site specific or region-based allometric volume and AGB equations. Allometric equation is a statistically derived expression of the relationship between volume and AGB, and other woody plant or stand variables (Husch *et al*., 1982).

These equations are used to estimate volume and AGB from easily measured variables such as DBH, stand height and crown closure (Husch *et al*., 1982).

Recent experience with the development of generic regression equations has shown that measurements of DBH explains more than 95% of the variation in tree volume and biomass even in highly species rich tropical forests (OFWE, 2012).

Even though, field-based forest surveying provides highly accurate measurements, it has limitations with regard to incurring high cost, being time consuming and having low spatial coverage and frequency (Franklin, 2005). In addition to this, in some cases, destructive sampling is laborious and negatively affect environment. This makes sustaining the socio-economic and ecological benefits of forests under challenge (Roberts *et al*., 2007).

On the other hand, Remote Sensing and GIS studies have been recommended as cost-effective sources of gathering information and valuable tools for determining forest biophysical attributes (Kayitakire *et al.,* 2006).

Therefore, these technologies are more preferable by forest policy makers, managers, silviculturists, and ecologists in order to make sound decisions for a variety of applications (Roberts *et al*., 2007).

In general, according to Fagan and Fries (2009) using field collected data and calculated the volume and AGB as function one of the forest structural attributes through appropriate allometric equation is considered as classical approach. Whereas, using RS data and computing the volume and AGB as function of spectral and/or textural value of the forest is considered as modern approach. Remote Sensing of forests began in 1972 with the launch of Landsat satellite (Fagan and Fries, 2009).

1.2. Statement of the Problem

Different studies, conducted in forested areas using the modern approach, have indicated that, there are varying degrees of success in predicting forest structural attributes. For example, Zheng *et al.*(2004) concluded that models vary between species and that the combined use of different species in modeling does not necessarily improve estimation.

Wijaya *et al.* (2010) recommend that further study is encouraged on application of Remote Sensing data for modeling of forest properties since their relationship is site and species specific and highly uncertain.

Currently in general in Ethiopia and in particular in the study site there is no well matured and documented literature that shows the stem volume and AGB of forest calculated as a function of spectral as well as textural features value of Landsat 5 Thematic Mapper. Rather, stem volume and AGB estimation of the forest including *Eucalyptus globulus* plantation is carried out using classical approach (FDREMEF, 2014).

According to Mulye Derebe. (2012), in year 2011 for the first time in Ethiopia Mesfin Sahle attempted modeling the relation between spectral and first order textural features of remote sensing data, and ground based surveyed total carbon stock data.

For this study the remote sensing data was derived from Landsat 5 TM and Enhanced Thematic Mapper satellites, whereas the carbon stock data was derived from five carbon pool (live aboveground biomass, live belowground biomass, dead organic matter in wood, dead organic matter in litter, and soil organic matter) in Menagesha Suba mixed forest, which is nearby the study area. The overall model performance was reported as 0.43 based on adjusted R^2 value but, mean residual value was not mentioned (Mesfin Sahle, 2010 as cited in Mulye Derebe, 2011).

Thus, the researcher of this study concluded that it is important to conduct further study on this topic to document the performance of the modern approach based on a selected tree species in the study site.

Therefore, this research is expected to fill this gap and provide relevant inferences of information to the scientific community, forest policy makers, managers, and silviculturists through documenting the performance of Remote Sensing (spectral and textural) data, which was taken by Landsat 5 Thematic Mapper sensor and by correlating it with the data calculated based on classical approach. This helps to improve accuracy and decrease uncertainties in the modern approach in general, and replace the classical approach in the study site in particular.

In this study, *E. globulus* coppice in Chancho forest, Oromia Regional State, Ethiopia, was selected. According to Pohjonen and Pukkala (1990) *E. globulus* converts energy and available water into biomass more efficiently compared with exotic coniferous tree species under most conditions of the Ethiopian highlands. Since it is an out performing exotic tree species that would alleviate an ever increasing wood demand of the country (Zewdie *et al.,* 2008) it is selected for this study. The study site was selected for availability of ground based forest attribute data.

During research problem identification, in addition to the above mentioned research reviews, the current trend of estimating stem volume and AGB in general in Ethiopia and in particular in the study site is discussed in a personal communication with different officials and experts from concerned bodies like Oromia Forest and Wildlife Enterprise (OFWE) and The Federal Democratic Republic of Ethiopia Ministry of Environment and Forestry (FDREMEF).

Three of the experts from OFWE, Mr. Getachew Adugna, GIS and Cartography Expert, Mr. Yheyis Daniel, Forest Industry Expert, and Mr. Befqadu WoldeGiorigs, Forest Inventory Expert explained the current trend in which their enterprise is engaged as:

> Currently the Enterprise uses the data collected manually through field surveys and established inventory approaches in its plantation forest to calculate stem volume. This is tedious, time consuming and expensive to cover large areas. The Enterprise has been applying the GIS technology to locate the field sample plots, delineate the forest stand boundary and to develop a geodatabase and manage its data and information. Still the enterprise doesn't use the modern approach. *"If this approach is successful, we are ready and willing to implement it in the future",* said the enterprise experts and officials.

Mr. Zerihun Adinew, Forest Section Coordinator and Mr. Abate Getnet Senior Environmental Project Monitoring and Evaluation Expert, both from DREMEF addressed the current trend as:

> Currently the forest resources data at the country level is collected manually, with some modern assistance, through field surveys and established inventory approaches. Although assisted with Remote Sensing and GIS technology, they are not able to implement the modern technology in its full potential. To replace the classical approach, Ethiopia has planned Remote Sensing data acquisition and analysis approach as alternative means for national forest management, monitoring, reporting and verification. This has been started as a pilot project where the country considers it as a lesson learning opportunity to implement the adopted Reduced Emission from Deforestation and Degradation (REDD+) schemes. This is aimed at generating internationally accepted, nationally adopted and Woreda specific data. According to the participants, the present study area is not included in this pilot project.

1.3. Objective

1.3.1. General objective

The overall objective of this research is to evaluate the potential of Landsat 5 TM satellite imagery for the estimation of *E. globulus* stem volume and AGB as compared to the classical approach.

1.3.2. Specific objectives

- To develop a model for the estimation of stem volume and AGB as a function of spectral and textural features.
- To compare the stem volume and AGB derived from the developed model and classical model.

1.4. Research question

In order to achieve the above mentioned objectives, the question considered for this study was: How accurately can the spectral and textural features data extracted from Landsat 5 TM satellite imagery predict *E.globulus* plantation forest stem volume and AGB in the Chancho forest plantation site?

In this study the following assumptions were made:

1. The study area is covered with forest.
2. The vegetation cover in the study area is identified from Landsat 5 TM imagery.

1.5 Structure of the thesis

The thesis report is structured in the following way:

Chapter 1 provides the background justification of the study, Chapter 2 provides with a literature review of the concept, properties and application of Remote Sensing for the estimation of stem volume and aboveground biomass. Chapter 3 describes the study area, and details of the data sets and methodology used in the study. Chapter 4 presents the result obtained and discusses on them, while Chapter 5 discusses the overall findings of this study. The last chapter of this thesis report concludes the study and give some recommendations for furthers studies in the field.

CHAPTER 2 LITERATURE REVIEW

2.1. The role of plantation forests to reduce burden on the natural forests in Ethiopia

Forest type is classified as natural and plantation forest based on their origin. As their names indicate, natural forest means a forest that includes any naturally grown trees, whereas plantation forest or man-made forest is developed by man by planting of seedlings or any other means (FAO, 2010).

Plantation forest, which is arranged in stand, refers to a contiguous community of trees sufficiently uniform in composition, structure, age and size class distribution, spatial arrangement, site quality, condition, or location to distinguish it from adjacent communities, so forming a silvicultural or management entity (Philip, 1983).

In Ethiopia, the natural forest that once covered over 40 million ha (c. 35%) of the land area has been declining both in size and quality (Zewdie *et al.,* 2008). Best estimates made by Food and Agricultural Organization (FAO) in year 2000 and Earth Trends in year 2003 indicate that in 1997 the total area of natural forest was 5.8 million ha and later reduced to 4.4 million ha in 2000 with an annual loss of 375,000 ha (FAO,2000 and Earth Trend ,2003 as cited in Zewdie *et al.*, 2008).

It has been projected that if the rate of deforestation continues, the area covered by natural forests in 2015 will be reduced to scattered minor stands of heavily disturbed forests in remote parts of the country. This shows that, despite their economic and environmental values, the remaining forests in Ethiopia are under threat. On the other hand, the importance of the plantation sector is increasing as the demand for raw materials is rising and the supply from the natural forests is decreasing (Stiles *et al.,* 1991).

Therefore, timber harvesting and fuel wood collection is shifting from natural forests to plantations and trees outside forests. They are expected to be increasingly important sources of industrial wood in the future (AFF, 2010).

In Ethiopia, including *Eucalyptus spp.*, plantations are mainly made up of exotic tree species with few indigenous trees in some of the National Forest Priority Areas. *Eucalyptus spp.* covers (56%) and *Cupressus lusitanica* covers (32 %) of the total area of plantation, followed by *Juniperus procera* (2%), *Pinus patula* (2%), and other species (8 %) (AFF, 2010).

The major regional states that account for the majority of the total forest plantation area are Oromia, Amhara, the Southern Nations, Nationalities and Peoples Regional State, and Tigray. These are also the regions with major commercial forest plantations (AFF, 2010).

In the Ethiopian highlands including Chancho plantation forest, *Eucalyptus spp.* is the prominent tree in government and community estate plantations because of its readily propagation through coppicing, resistance to browsing by livestock, and rapid growth rate (Zewdie, 2008).

The most common and widespread *Eucalyptus* species include: *Eucalyptus globulus Labill*., *Eucalyptus camaldulensis Dehnn*., *Eucalyptus saligna Sm*., *Eucalyptus grandis W. Hill ex Maid* and *Eucalyptus tereticornis Sm*. Planting Eucalyptus is expanding from state owned forestry enterprises and projects to community woodlots, household and farm field boundaries. They usually store large amount of carbohydrates, which help to sustain rapid re-growth rates (Steinbeck, 1981 as cited in Zewdie, 2008).

E.globulus, the concern of this study, grows well at elevations ranging from 1400 – 3200 meters above sea level and it is usually harvested at an age of 5 – 7 years for pole and construction materials in Ethiopia. However, the maximum wood production is commonly attained at 18 years (Steinbeck, 1981 as cited in Zewdie, 2008).

After the original seedling establishment, it is mainly managed by short rotation coppice system in 5 – 7 years harvest age over consecutive cutting cycles (Pohjonen and Pukkala, 1990). Lower cost to regenerate succeeding stands from stump sprout under subsequent rotations has made an appealing coppice management profitable (Greyer *et al.,* 1985).

2.2. Ground based forest sampling and inventory design

Husch *et al*., (1982) clearly stated that in forest inventory work, sampling consists of measuring portions of a population, i.e., the forest and its characteristics, and from the measured sampling units, obtaining estimates that are considered representative of the parent population. The author further described the sampling units may be stands, compartments, and administrative units, fixed area plots or strips or sampling points.

According to Husch *et al*., (1982), there are many forest inventory designs. As such there is not a specific pattern of design, which can be used in all inventories as each forest area varies. Nevertheless, basic inventory designs generally fall into either probability sampling or non-random sampling (Husch *et al*., 1982).

Probability sampling includes simple random sampling, stratified random sampling, multistage sampling and sampling with varying probabilities (Desta Hamito, 2001). On the other hand, non-random sampling includes selective sampling and systematic sampling (Philip, 1983).

According to de Vries (1986), all sampling methods have their roots in simple random sampling. They are modification of simple random sampling method designed to achieve greater economy or precision.

The fundamental idea of simple random sampling is that in choosing a sample of "n" units, every possible combination of "n" units should have an equal chance of being selected (Picard *et al*., 2012).

The selection of a particular unit should be completely independent of the selection of all other units. The best way to do this is to assign every unit in the population a number and then draw "n" number from a table of random digits (de Vries, 1986).

In practice, a random sample is selected unit by unit. Two methods of random selection for simple random sampling without replacement are lottery method and selection based on random number tables. Selection based on random number table's method is recommended to get precise result in forest resources assessment. In this method Random Number Generator is used to create a list of random numbers, based on the specifications. The numbers generated appear in the Random Number Table (http://www.acronymfinder.com/Roundnose-Grenadier-(FAO-species-name-code)-(RNG).html).

According to Husch *et al*. (1982), the precision of a forest inventory and its analysis result is based on sampling error and intensity. Sampling error results from the fact that the sample is only a portion of the population and may not produce estimates identical to the population parameters

The sampling error is commonly first defined in terms of percentage, instead of the real value (m^3/ha or ton/ ha). For the stand level forest inventory type ±80% precision, ±20 sampling error, 95% level of probability, and based on this a minimum 0.1% sampling intensity are recommendable, which measures the representatives of the sample for the whole population (Parent, 2000).

2.3. Properties of optical Remote Sensing and spectral reflectance of vegetation

Satellite sensor systems may operate passively (radiation reflected from the surface of the earth) or others may be active systems that emit signals of microwave energy (like RADAR). Optical Remote Sensing, which uses passive sensor, can be defined as using reflected sunlight energy from the visible to shortwave infrared spectral domains (400 – 2500 nm wavelengths) (Sabins, 1977).

Landsat is the first civilian optical Remote Sensing satellite system, which was first launched in 1972. The Landsat 5 TM is the fifth series of Landsat. Its data with suitable spectral and medium spatial resolution and relatively long history of data availability has made it a primary data source for volume and biomass estimation. It has approximate scene size of 185 kilometers × 185 kilometers (3,422,500 hectares) and seven spectral bands, viz. blue (Band 1 = TM1), green (Band 2 = TM2), red (Band 3 = TM3), near-infrared (Band 4 = TM4), and two mid-infrared as, Band 5 = TM5 and Band 7 = TM7, respectively (Lillesand *et al*., 1994). Table 2.1 presented list of these bands along with brief summary of its applications.

The dataset of this satellite, which can be freely download from Earth Resources Observation System Data Center (EROSDC) is Level 1Terrain corrected ("*L1T*") data type. Terrain correction is the correction of variations in surface reflectance due to the orientation of the terrain surface with respect to the angle of incidence of the sun's rays. It is corrected both radiometrically and geometrically. But it has been formatted to fit in an 8-bit number (ranges from 0 – 255); therefore, before using this data to calculate band rationing, vegetation indices and textural feature extraction, the data must be converted to reflectance (http://obs.comu.edu.tr/dosyalar/DersMateryal/landsat7.pdf).

Table 2.1. List of the seven spectral bands of the Landsat 5 TM along with brief summary of its applications.

	Band	Spectral resolution (µm)	Nominal Spectral Location	Spatial Resolution (meters)	Principal Application
Spectral bands	1	0.45 – 0.52	Blue	30	Designed for water body penetration, making it useful for coastal water mapping. Also useful for soil/vegetation discrimination, forest type mapping, and cultural feature identification.
	2	0.52–0.60	Green	30	Design to measure green reflectance peak of vegetation for vegetation discrimination and vigor assessment. Also useful for cultural feature identification.
	3	0.63 – 0.69	Red	30	Designed to sense in chlorophyll absorption region aiding in plant species identification. Also useful in cultural feature identification.
	4	0.76 – 0.90	Near IR	30	Useful for discriminating vegetation types, vigor and biomass content, for delineating water bodies, and for soil moisture discrimination.
	5	1.55 – 1.75	Mid IR	30	Indicative of vegetation moisture content and soil moisture. Also useful for differentiation of snow from clouds.
	6	10.4 – 12.5	Thermal	120	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping application
	7	2.08 – 2.35	Mid IR	30	Useful for discrimination of mineral and rock types. Also sensitive to vegetation moisture content.

(Source: Lillesand *et al*., 1994)

Reflectance, which is the interaction between the solar radiation and the Earth's surface, in this case vegetation canopy, is a compound of absorption and scattering processes occurring at the leaf level, combined with structural influences operating at the canopy level (Fig. 2.1 and Fig. 2.2). According to Schowengerdt (2007), the amount of reflected radiation varies as a function of five optical domains: spectral, spatial, temporal, angular, and polarization.

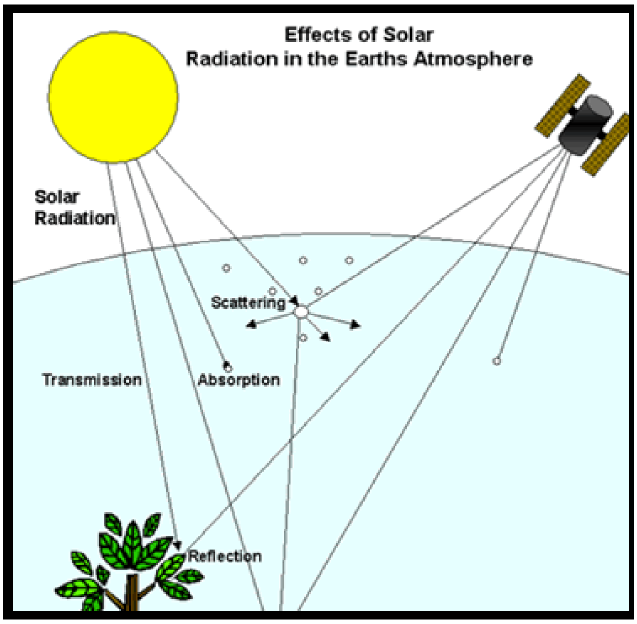

Fig. 2.1 Effects of Solar Radiation in the Earth Atmosphere.

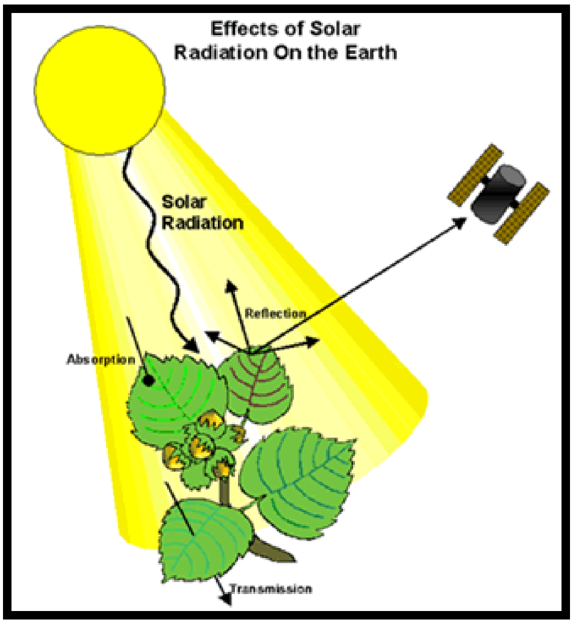

Fig. 2.2. Effects of Solar Radiation On the Earth.

(Source: www.PANCROMA.com)

After a detailed discussion made of the problems of spatial resolution and level of plant recognition in forest application by Wulder (1998), Tomppo *et al.* (2002) and Roberts *et al.* (2007), all concluded that spatial resolution is a fundamental concept in Remote Sensing and by and large, spatial resolution plays an important role in determining the type and quality of information that can be extracted from an image. The spectral resolution, which refers to the number and width of discrete wavelength ranges sampled by a sensor, are also of fundamental importance following spatial resolution, (Lillesand *et al.,* 1994).

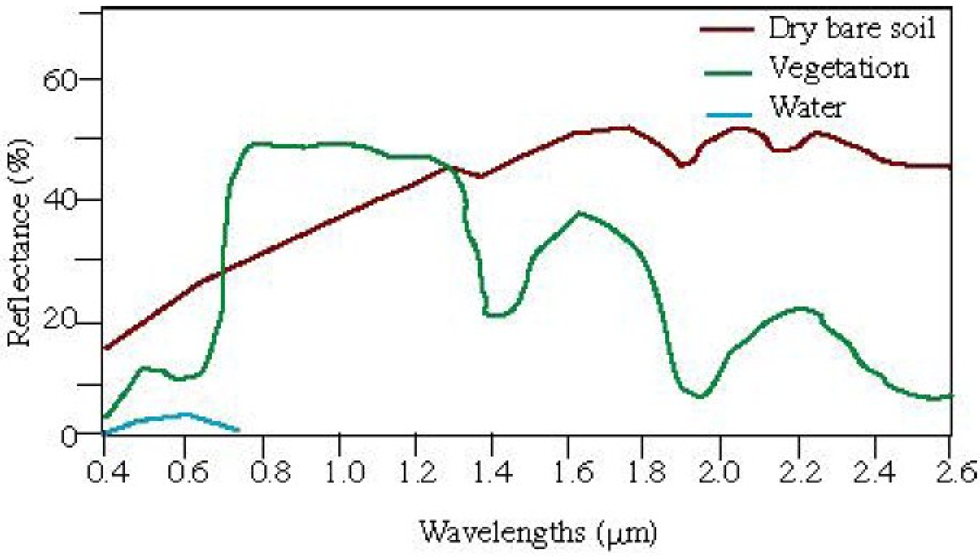

Fig. 2.3. Typical spectral reflectance curve for vegetation, soil, and water.

(Source: Lillesand *et al*.,1994).

Spectral variability of reflectance is probably the most applied source of information in the Remote Sensing of vegetation studies (Sabins, 1997). Vegetation typically shows a low reflectance in the visible range of the spectrum, mainly in the blue and red bands. The main factors are absorption by chlorophylls and carotenoid photosynthetic pigments, which absorb light in the visible spectrum (Lillesand *et al.,* 1994).

As we move from the visible to the near-infrared of the spectrum around 0.7 µm (red edge), the reflectance of healthy vegetation increases dramatically and high reflectance occurs in the near-infrared range of the spectrometer (de Jong and van der Meer, 2005). In the range from about 0.7 to 1.3 µm, a plant leaf typically reflects 40 to 50 percent of the energy incident upon it. Most of the energy is transmitted, since absorption in this spectral region is minimal (less than 5 percent). The internal structure of the leaf mainly determines the high levels of reflectance in this range (Schowengerdt, 2007).

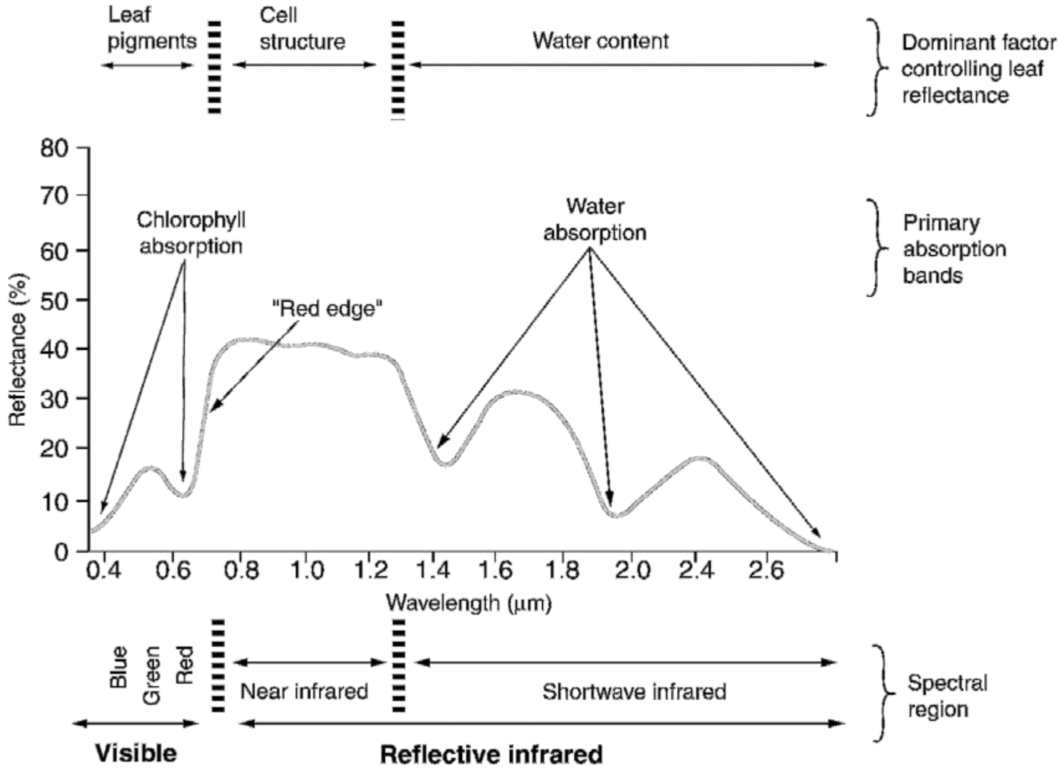

Fig. 2.4. Spectral reflectance curve of green vegetation.

(Source: Sabins, 1997)

Beyond 1.3 μm, energy incident upon vegetation is essentially absorbed or reflected, with little, to no transmittance of energy. Dips in reflectance occur at 1.4, 1.9 and 2.7 μm because of water in the leaf absorbs strongly at theses wave length. Accordingly, wavelengths in these spectral regions are referred to as water absorption bands. Reflectance peak occurs at about 1.6 and 2.2 μm between the absorption bands. Throughout the range beyond 1.3 μm leaf reflectance is approximately inversely related to the total water present in the leave. This total is a function of both the moisture content and the thickness of the leaf. As with vegetation, the presence of moisture in soil will decrease its reflectance in the water absorption bands. In short water absorbs energy in these wavelengths whether we are talking about water features such as lakes and stem or water contained in vegetation or soil (Schott, 2007).

In general, vegetation discrimination is enhanced through the incorporation of data from one of the mid-infrared bands (Table 2.2). Combinations of any one visible (band 1 to band 3), with band 4 and one mid-infrared bands are also very useful. Layer stacking is used to build a new multiband file from selected single images (Lillesand *et al*., 1994).

Each single image is combined by superimposing the transmission through blue, green and red filters, respectively. The result image is called true color composite. Other possible combination of color filters and spectral band images are known as standard False Color Composite (FCC) (Jensen, 1996).

For Landsat 5 TM imagery the standard FCC achieved by assigning blue, green and red color to observation green, red and near-infrared spectral bands, respectively. The vegetation normally reflects predominantly in near-infrared regions as compared to green or red spectral bands. Hence, the vegetation imagery obtained from Landsat TM satellite appears in red in standard FCC due to assignment of red color to infrared band (Schowengerdt, 2007).

Table 2.2. TM Band-Color Combinations Shown in different alternatives.

	Blue	Green	Red
a	1	2	3
b	2	3	4
c	3	4	5
d	3	4	7
e	3	5	7
f	4	5	7

(Source: Lillesand *et al*., 1994)

2.4. Application of Remote Sensing in Forest Inventory

Local forest inventory require approaches different from regional, national, or multi-national assessments (Boyd *et al*., 2005).

Franklin (2005) has stated general steps for prediction or estimation of forest parameters as: Establish a number of field observation sites in a forest area, collect forest condition information at those sites, acquire imagery of the sites, locate the sites on the image, extract the Remote Sensing data from these sites, develop a model relating the field and spectral data, and finally use the model to predict forest parameters for all forest pixels based on the spectral data.

Some studies indicate that medium-resolution satellite data provide adequate information that may be useful to a forest manager. The resolution of the sensors does not allow for intra-stand analysis, but forest wide data regarding stem volume, biomass and leaf area index can be derived, provided the statistical models are robust and transferable between study areas (Jaakkola, 1989).

Moreover, Hyyppä *et al.* (2000) showed that the accuracy of these models for the prediction of the parameters was greatly influenced by spatial resolution of the Remote Sensing data used and by the size of the forest stand being studied. When these variables are derived from medium spatial resolution satellite imagery, it should be at the stand and forest scale, because the spatial resolution of the sensor is not fine enough to discriminate between tree canopies.

Gebreslasie *et al*. (2008) reviewed an overview of some of the significant publications in this area of research. According to him, low spatial resolution satellite sensors were found to be insufficient for measuring spatial variation at homogenous and relatively small forest stands. A review paper by Holmgren and Thuresson (1998) concluded that results from low spatial resolution multispectral sensors can best be considered to be insignificant for forest management planning.

Trotter *et al*. (1997) concluded that Landsat TM only provides an acceptable data source for estimating wood volumes in plantation forests for areas of about 40 ha and larger.

According to Horler and Ahern (1986), among the Landsat 5 TM bands, band 3, band 4 and band 5 were the most useful bands for general forest-cover-type discrimination. Especially the mid-infrared region of the spectrum was identified to be the most sensitive to changes in stem volume, since the spectral response in this range is strongly related to canopy closure.

Lu *et al.* (2004) analyzed forest structural attributes and Landsat 5 TM data in Brazilian Amazon basin. Single band 5 and linear transformed indices such as 1st principal component (PC1), brightness of the tasseled Caps transforms, and albedo was strongly correlated with forest structural attributes.

Freitas *et al,* (2005), on the other hand, found a significant relationship between moisture vegetation index using band 5 and band 7 of Landsat 5 TM with forest structure attributes using linear regression methods in Atlantic rainforests.

Hall *et al.* (2006) explored the empirical relationships between forest structural attributes and Landsat Enhanced Thematic Mapper plus data in west-central Alberta, Canada. The study concluded that bands 3, 4, 5, and 7 returned the strongest relationships with forest structural attributes prediction. Sivanpillai *et al.* (2006), in turn, used multivariate regression techniques to generate relationships between Landsat Enhanced Thematic Mapper reflectance values and commercially managed loblolly pine stand characteristics in east Texas, USA.

Another study in mountain birch forests northernmost Finland conducted by Heiskanen (2006) indicated that Normalized Difference Vegetation Index, Modified Soils Adjusted Vegetation Index and Simple Ratio of ASTER data showed a significant relationship with biomass and leaf area index.

2.5. Image Preprocessing

To assist the visual interpretation of the RS data application of different image enhancement techniques are required based on the data and objective of application. Image enhancement is the process of making an image more interpretable for a particular application (Faust, 1989). Enhancement can make important features of raw, remotely sensed data and aerial photographs more interpretable to the human eye. Enhancement techniques are often used instead of classification for extracting useful information from images (LGGI, 2005).

There are many enhancement techniques available. They range in complexity from a simple Contrast stretch, where the original data file values are stretched to fit the range of the display device, to principal components analysis, where the number of image file bands can be reduced and new bands created to account for the most variance in the data (Jensen, 1996).

Generally, there are two types of data correction: radiometric and geometric. Radiometric correction addresses variations in the pixel intensities (DNs) that are not caused by the object or scene being scanned. These variations include: differing sensitivities or malfunctioning of the detectors, topographic effects and atmospheric effects (LGGI, 2005).

On the other hand geometric correction addresses errors in the relative positions of pixels. These errors are induced by sensor viewing geometry and/or terrain variations. Based on the data and objective of application, different image enhancement techniques such as radiometric, spectral and spatial enhancement techniques can be utilized (de Jong and van der Meer, 2005).

Radiometric enhancement technique enhances images based on the values of individual pixels; whereas spatial enhancement enhances images based on the values of individual and neighboring pixels (Schowengerdt, 2007).

In the case of spectral enhancement techniques, it enhances images by transforming the values of each pixel on a multiband basis. This enhancement technique requires more than one band of data. It can be used to: compress bands of data that are similar, extract new bands of data that are more interpretable to the eye, apply mathematical transforms and algorithms, and display a wider variety of information in the three available color guns (Red, Green and Blue) (Schott, 2007).

Radiometric Normalization- is one of the radiometric enhancement techniques. It is a prerequisite for creating high-quality satellite data; and consequently, higher level downstream products. In an ideal situation, the radiance measured by a satellite would equal the energy reflected from the Earth's surface. This is not the case, therefore, top of atmospheric reflectance with a correction for the sun angle need to be processed (Schowengerdt, 2007).

It is possible to convert from DNs to radiances using the band gain and bias parameters in the Landsat metadata file. If someone is working with Landsat data from the USGS in the "USGS GeoTIFF with Metadata" format, ENVI software version 4.7 can easily convert these data in two step process (http://www.yale.edu/ceo/Documentation/Landsat DN to Reflectance.pdf).

First, DN's should be converted to radiance values. Then it needs to convert these radiance values to reflectance values. For each scene, it needs to know the distance between the sun and earth in astronomical units, the day of the year (Julian date), and solar zenith angle. These parameters are supplied with the imagery and available in the image metadata file (http://obs.comu.edu.tr/dosyalar/DersMateryal/landsat7.pdf).

There are two formulas that can be used to convert DNs to radiance; the method one use depends on the scene calibration data available in the header file(s). One method uses the gain and bias (or Offset) values from the header file. The other, which is longer method, uses the LMin and LMax spectral radiance scaling factors. Finally radiance can be converted to reflectance (http://www.yale.edu/ceo/Documentation/Landsat DN_to_Reflectance.pdf).

In the Gain and Bias method, the formula to convert DN to radiance using gain and bias values is:

$$L_{\lambda} = gain \times DN + bias \quad \text{(Eq. 2.1)}$$

Where:

L_{λ} is the cell value as radiance.

DN is the cell value digital number.

gain is the gain value for a specific band

bias is the bias value for a specific band.

In Spectral Radiance Scaling Method, the spectral radiance (Lλ) is calculated using the following equation:

$$L_\lambda = LMIN_\lambda + \left(\frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX - QCALMIN} \right) (QCAL - QCALMIN) \text{ .... (Eq. 2.2)}$$

Where:

QCAL is the calibrated and quantized scaled radiance in units of digital numbers.

$LMIN_\lambda$ is the spectral radiance at QCAL = 0.

$LMAX_\lambda$ is the spectral radiance at QCAL = QCALMAX

QCALMIN is the minimum quantized calibrated pixel value (corresponding to $LMIN_\lambda$) in DN.

QCALMAX is the maximum quantized calibrated pixel value.

The resulting radiance (L_λ) is in units of watts per square meter per steradian per micrometer (W/(m^2×sr×µm). The exoatmospheric reflectance (ρ_p) is calculated using the following equation:

$$\rho_p = \frac{\pi . L_\lambda . d^2}{ESUN_\lambda . COS\ \theta_S} \text{ .... (Eq. 2.3)}$$

Where:

L_λ is the spectral radiance.

d is the Earth-Sun distance in astronomical units.

θ_s is the solar zenith angle in degrees.

$ESUN_\lambda$ is the mean solar exoatmospheric irradiance.

Table 2.3. TM Band-Color Combinations Shown in different alternatives.

Alternatives	**TM Band-Color Assignment in Composite**		
	Blue	Green	Red
a	1	2	3
b	2	3	4
c	3	4	5
d	3	4	7
e	3	5	7
f	4	5	7

(Source: Lillesand *et al*., 1994)

2.6. Image processing and data extraction

Beyond visual interpretation of the preprocessed data it is useful to calculate fundamental univariate descriptive statistics of multispectral remote sensor data. This normally involves computing the minimum, maximum, range, mean and standard deviation of brightness value in each band. Such statistics provide valuable information for displaying and analyzing Remote Sensing data (Jensen, 1996).

2.6.1. Vegetation Indices (VI's)

De Jong and van der Meer (2005) are recommended that from Landsat imagery data the integration of the shortwave infrared bands in Vegetation Indices (VI's) could unify different cover types and reduces the background effects.

The application of both of traditional and complex VI's as well as ratios is wide, ranging from soil moisture, vegetation monitoring to mineral deposits mapping (Jensen, 1996).

These vegetation indices were proposed for different applications, such as soil moisture, vegetation monitoring, mineral deposits mapping, etc. A variety of vegetation indices have been developed using broad-band remotely sensed data based on the spectral features of green vegetation (Jensen, 1996).

These indices are combinations of surface reflectance at two or more wavelengths designed to highlight a particular property of vegetation. Each of the VIs is designed to accentuate a particular vegetation property. In general VI's are used for image enhancement and data extraction from satellite data. More than 150 VIs have been published in scientific literature, but only a small subset have substantial biophysical basis or have been systematically tested (RS, 2005).

The most common indices are the Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), and Enhanced Vegetation Index (EVI). These indices enhance the spectral contribution of vegetation, while minimizing that of the background (de Jong and van der Meer, 2005).

NDVI is defined by the following equation.

$$NDVI = \frac{(TM4 - TM3)}{(TM4 + TM3)} \quad \text{(Eq. 2.4)}$$

The combination of its normalized difference formulation and use of the highest absorption and reflectance regions of chlorophyll make it robust over a wide range of conditions. It can, however, saturate in dense vegetation conditions when LAI becomes high (RS, 2005).

Major advantage of ratio images, like Simple Ratio Index (SR), is that they convey the spectral and color characteristics of image features, regardless of variations in scene illumination conditions. In addition to this, they are often useful for discriminating subtle spectral variations in images from individual spectral bands or in standard color composites (Lillesand *et al*., 1994).

The SR is the ratio of the highest reflectance; absorption bands of chlorophyll makes it both easy to understand and effective over a wide range of conditions. As with the NDVI, it can saturate in dense vegetation when LAI becomes very high. SR is defined by the following equation (de Jong and van der Meer, 2005).

$$SR = \frac{TM4}{TM3} \quad \text{(Eq. 2.5)}$$

Enhanced Vegetation Index (EVI) was developed to improve the NDVI by optimizing the vegetation signal in Leaf Area Index (LAI) regions by using the blue reflectance to correct for soil background signals and reduce atmospheric influences, including aerosol scattering. This VI is, therefore, most useful in LAI regions, where the NDVI may saturate. EVI is defined by the following equation (RS, 2005).

$$EVI = \frac{2.5 \times (NIR - RED)}{(NIR - 6RED - 7.5BLUE + 1)} \quad \text{(Eq. 2.6)}$$

In addition to these VIs, a number of image processing techniques have been employed to extract image information. Among the most common of these, Principal Component and Tasseled Caps transform are described below.

2.6.2. Principal Components Analysis

In most cases, spectral bands will yield a better classifier when processing multispectral data. But both spatial (texture) and spectral data tend to be highly correlated. Adding another band of data that is highly correlated with previous bands may add little new data and only increase the noise and the processing time, possibly even reducing the effectiveness of the algorithm(LGGI, 2005).

Image transforms can be used to overcome some of these limitations. The most common transform is the Principal Component (PC) transform that is specifically designed to decorrelate the data and maximize the variability in a reduced number of features. Therefore, fewer features can carry the information needed for processing algorithms such as multispectral classifiers (RS, 2005).

2.6.3. Tasseled Caps Transformation (TCT)

There are several factors that influence the reflectance quality of vegetation on satellite and Remote Sensing imagery. These include brightness, greenness and moisture (http://landcover.usgs.gov/pdf/tasseled.pdf).

Simplistically, the TCT is a guided and scaled principal components analysis, which transforms the 6 Landsat TM bands into 3 bands of known characteristics; soil brightness, vegetation greenness, and soil/vegetation wetness (Franklin, 2005).

Brightness is the result of a weighted sum of all bands, defined in the direction of the principal variation in soil reflectance i.e., non-vegetated signature. Greenness is orthogonal to brightness, a contrast between the near-infrared and visible bands. It is strongly related to the amount of green vegetation in the scene. And wetness relates to canopy and soil moisture (http://landcover.usgs.gov/pdf/tasseled.pdf).

2.6.4. Gray Level Co-occurrence Matrix (GLCM)

The use of vegetation indices or single band approaches may not be amenable for extraction of more detailed structural information provided by medium spatial resolution image data. A combination of spectral and spatial information extraction techniques shows promise for improving estimation performance of forest stand parameters (Haralick *et al.,* 1973 as cited in Roberts *et al.,* 2007).

A special emphasis; therefore, has been placed on feature extraction and structural image analysis methods in the case of such imagery. There are four types of textural measures viz. statistical, geometrical, model-based, and signal processing identified. Statistical texture analysis, which is the most frequently, cited method for image texture analysis, takes into consideration the distribution and variation of spectral/tonal variability in a given local area (Trimble, 2012).

It uses filters combined with first and second order measures of variance to determine the grey level differences within a predefined region. They inform on the general variation or structure of the image which in turn reflects the variation of forest canopies (Haralick *et al.,* 1973 as cited in Roberts *et al.,* 2007). Appendix II provides a summary of second order various texture measures.

2.7. Applications of models in forestry and Remote Sensing

Physical or empirical model is used to establish the relationship among in situ forest volume, biomass, and remotely sensing data like wavelength bands and vegetation indices. The relationship between forest stand attributes and Remote Sensing data is then used to derive spatially explicit map of these attributes, which in turn are used for planning purposes (Fagan and Fries, 2009).

According to Field (2009), regression analysis has become one of the most widely used statistical tools for analyzing multi-variables. It is appealing because it provides a conceptually simple method for investigating functional relationships among variables. The standard approach in regression analysis is to take data, fit the model and then evaluate the fit using statistics such as t, F and R^2.

Ordinary Least Squares (OLS) is the best known of all regression techniques. It is concerned with the development of graphs, or mathematical expressions corresponding to graphs, showing the relationship between a dependent variable of interest and one or more other independent variables (http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=Regression_analysis_basics).

In a regression model, a response variable Y is expressed as a function of one or more independent variables X, plus noise or random error (ε). Regression model can be single or multiple (Field, 2009).

Simple regression is given as:

$$Y = a + bX + \varepsilon \quad \text{(Eq. 2.7)}$$

Multiple regressions are given as:

$$Y = a + b_1 X_1 + b_2 X_2 + \ldots + b_n X_n + \varepsilon \quad \text{(Eq. 2.8)}$$

The accuracy of these methods is tested using reference areas of known volume and biomass.

CHAPTER 3 METHODS AND MATERIALS

3.1. Description of the Study area

3.1.1. Location

Chancho plantation is one of more than 9 of the plantation sites managed by Oromia Forest and Wildlife Enterprise (OFWE). It is found about 60 km northwest of the Capital city of Ethiopia, Addis Ababa, in the Finfine Surrounding Oromia Special Zone of Sululta Woreda, Central Ethiopia. This study area is located at latitudes 9°15'43" – 9°16'17" North and longitudes 38°46'57"–38°47'44" East (Fig. 3.1). The whole plantation covers an area of 3418 hectares; while 168 hectares seven years aged coppice stand was utilized for this study. A single topo sheet with number 0938D4, at the scale of 1:50,000 and published in 1973 by the Ethiopian Mapping Agency can cover the study area.

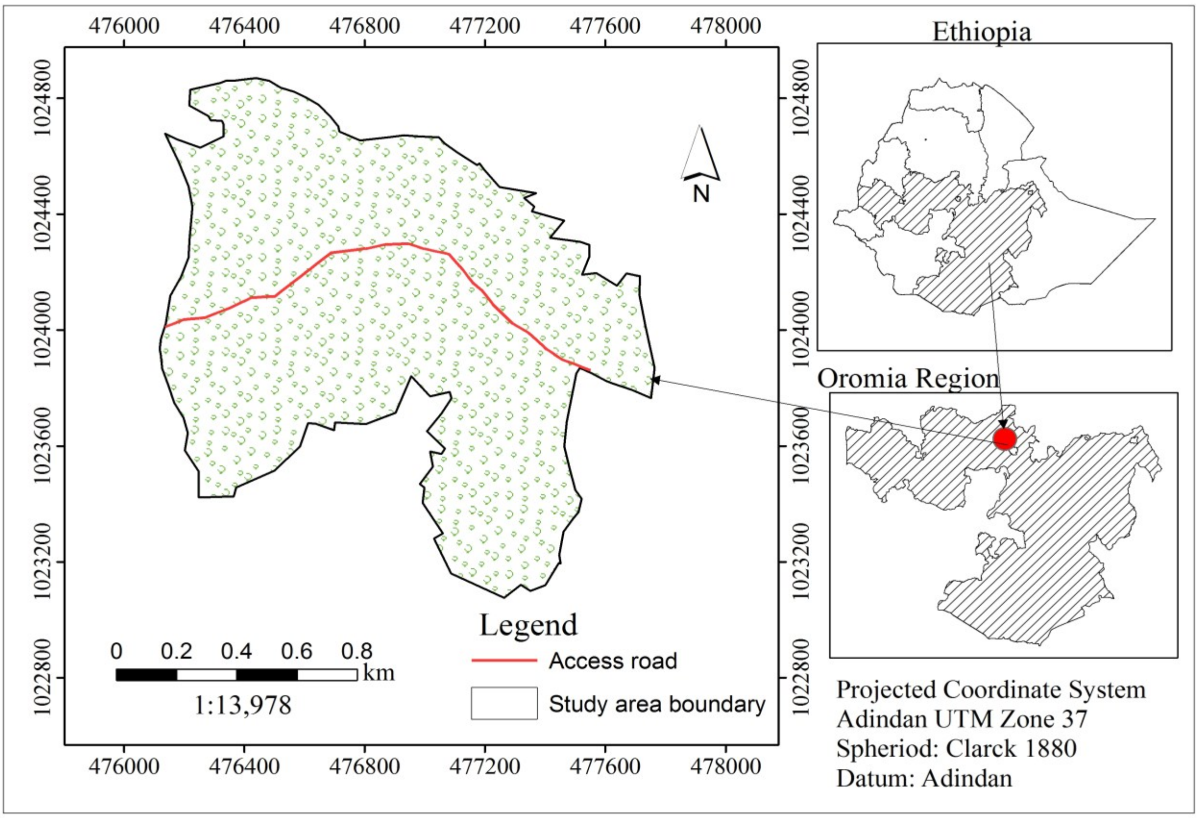

Fig. 3.1. Location map of the study area.

3.1.2. Topography and Soil

The study area is found in altitude ranges from 2680 m - 2907 m above mean sea level (Fig. 3.2). Its slope ranges from 0.46^{o} - 46.82^{o} as is shown in figure 3.3. These values were extracted from Digital Elevation Model (DEM) of Shuttle Radar Topography Mission (SRTM) 30 m spatial resolution (http://edcsns17.cr.usgs.gov/EarthExplorer/).

According to the World Resource Base Classification Systems, the soil types are represented with Andosols, Vertisols, Nitisols, Solonchaks as well as Solonetzs followed by Cambisols. However, the dominant soil type in the study area is characterized by Haplic Nitisols (Zewdie *et al.,* 2008)

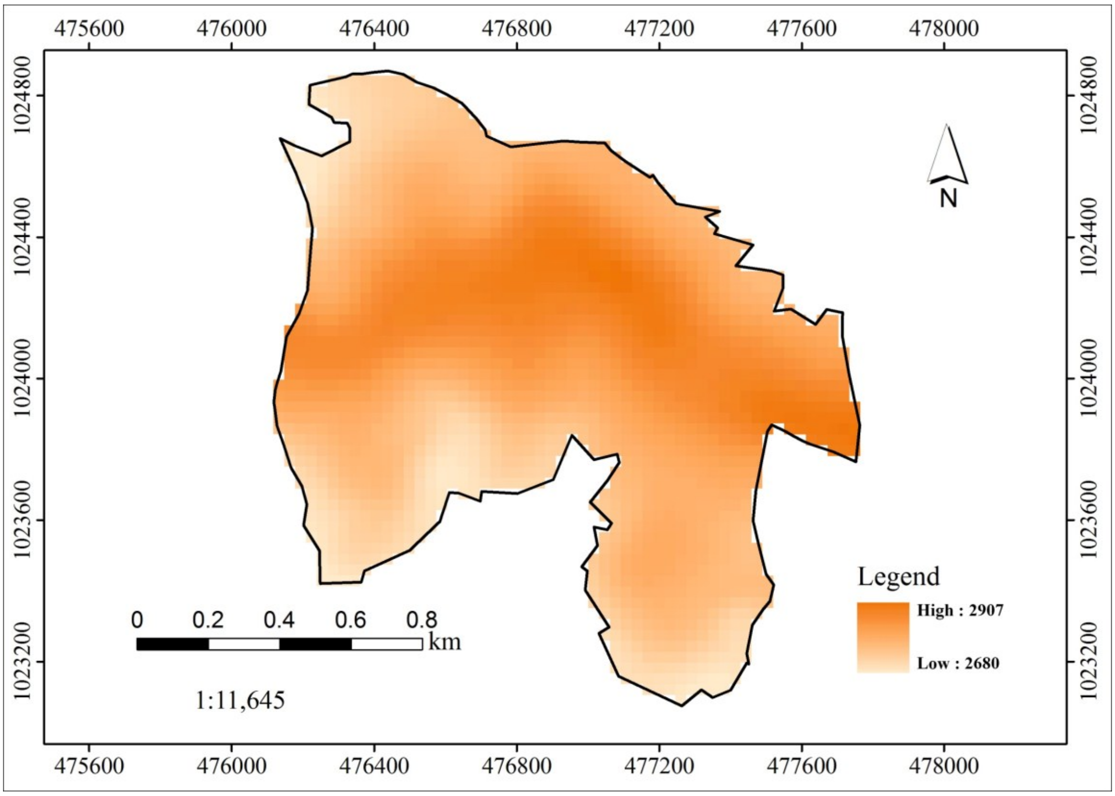

Fig. 3.2 Elevation map of the study area.

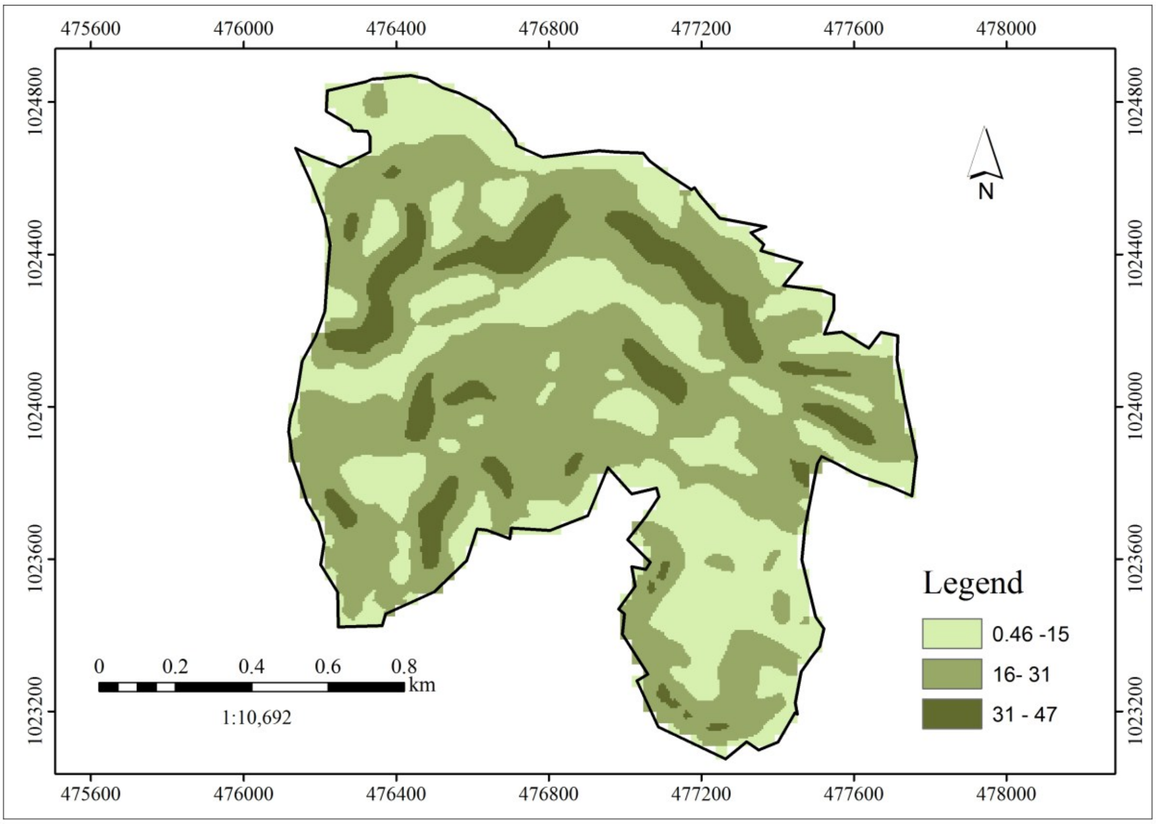

Fig. 3.3. Slope map of the study area.

3.1.3. Climate

The mean annual rainfall over the last 10 years (2003- 2013) was 920 mm. The small rains occur from March to May and the heavy rains from June to September, with the higher concentration in July to August. August to October comprises the wet season and November to March is the dry season. Around January the season is most dry and has cloud free conditions. The mean maximum and minimum annual temperature are 24^{o}C and 12^{o}C, respectively (http://www.ethiometmaprooms.gov.et:8082/maproom/).

3.2. Data and Methodology

This study used 37 temporarily and randomly distributed ground based sample plots data over 168 ha forest stand (Appendix I) , and the Landsat 5 TM sensor on board image scene with path 168 and row 054 (Fig. 5.1). In order to brings both data to a temporal coincidence and cloud free imagery of the site, it was used the ground based data, which was collected in January, 2011 and an image acquisition date of January 10, 2011.

The field inventory data and study area boundary were obtained from Oromia Forest and Wildlife Enterprise. The remote sensing data was freely downloaded from the Landsat data archive at the EROSDC (http://edcsns17.cr.usgs.gov/EarthExplorer/). Different software packages were used to process the data as shown in Table 3.1.

Table 3.1. Software packages used in the present study.

Type	Name	Utility
Software	ENVI version 4.7	Image processing and data analysis
	ArcGIS version 9.3	Personal database creation, model development, map preparation, and preparation
	MS Office 2010	Documentation, Statistical analysis and presentation
	SPSS version 20	Statistical analysis
Hardware	Computer	For storage, software installation, internet support, writing, and editing of the whole document

3.2.1. Field inventory data and sampling design summary

In order to select an appropriate forest stand, discussions were made with Oromia Forest and Wildlife Enterprise officials and experts. The spatial location and extent of each stand, planting dates (age), coppice status, management regimes, and cloud free months attributes were used in the selection procedure of an appropriate forest stand.

To check that the 37 plots were representative of the population the sampling intensity of the inventory was calculated using equation (3.1) and was found 0.22%, that is acceptable as compared with minimum required value 0.1% (Parent, 2000).

$$I(\%) = \frac{Number\ of\ \ plots\ \times Unitary\ \ plot\ \ area(ha) \times 100}{Total\ \ area(ha)} \quad \text{.................................... (Eq. 3.1)}$$

$$= \frac{37 \times 0.01ha \times 100}{168ha} = 0.22\%$$

The ground based data were collected using tape meter in a circular sample plots which were laid out with a radius of 5.64 m (area = 100 m^2). This plot size is recommendable for homogeneous and even aged plantation forest resources assessment (FFDME, 2005 and Yohannes, 2002). Each plot has a spatial location and data that represents the specific area of the forest.

The coordinates of each sample plot are recorded in the center of each plot using Global Positioning System (GPS) (with accuracy ≤ 10 m). All trees in the plot were measured for DBH.

The DBH values of individual trees in the 37 sampled plots were employed to calculate individual tree stem volume and AGB using equation (3.2) and equation (3.3) allometric functions, respectively.

These functions were generated by destructively means 40 sampling of *E. globulus* trees for Addis Ababa *E. globulus* coppice forest, which is nearby the study area (Yohannes, 2002). According to this author for the stem volume and AGB inventory of the plantation of *E.globulus* coppice trees these functions are recommendable since it is more cost efficient than the function involving other forest attributes.

$$V = b_{0_v} DBH^{b1v} \qquad \text{(Eq. 3.2)}$$

$$AGB = b_0 DBH^{b1} \qquad \text{(Eq. 3.3)}$$

Where,

V = Single tree stem volume

AGB = Single tree aboveground biomass

b_{0v} = Coefficient (0.0001) for V

b_{1v} = Coefficient (2.603) for V

b_0 = Coefficient (0.3478) for AGB

b_1 = Coefficient (2.2024) for AGB

DBH = Diameter at Breast Height of individual trees

Then plot level stem volume and AGB were calculated as the sum of individual tree stem volume and AGB in each plot. These plot levels were converted to hectare level by using equation (3.4) and equation (3.5) for stem volume and AGB, respectively (Husch *et al*., 1982).

$$V = \frac{\sum^{n}\left(\sum V_{ij}\right)}{na} \text{ .... (Eq. 3.4)}$$

Where:

V = Average stem volume per hectare (m^3/ha) estimated from 37 samples

a = Size of sample plot (100 m^2)

V_{ij} = Volume of an individual standing tree (m^3/tree) measured on the i^{th} plot

n = Number of plots (37)

$$AGB = \frac{\sum^{n}\left(\sum AGB_{ij}\right)}{na} \text{ .... (Eq. 3.5)}$$

Where:

AGB = Average aboveground biomass per hectare in (kg/ha) estimated from 37 samples

AGB_{ij} = Aboveground biomass of an individual standing tree (kg/tree) measured on the i^{th} plot

Finally, both stem volume and AGB were converted from hectare base to stand base by multiplying the average value of each of them by the total area of the forest (Husch *et al*., 1982).

3.2.2. Image Pre-processing

All the input datasets were projected to Projected Coordinate System in UTM Zone 37, Clark 1880 Spheroid and Adindan Datum.

Image pre-processing like visual examination of the imagery was conducted to assess contamination by in-scene components such as clouds, smoke, haze, line dropouts and striping. There was no such contamination observed. The images were radiometrically and geometrically corrected; therefore, there was no need of radiometric and geometric correction for the images of the study area.

With regard to atmospheric correction, it was processed only relative atmospheric correction but not absolute atmospheric correction. This due to absolute atmospheric correction is not essential for the current study for two reasons. Firstly, the scene is free of haze and cloud over the study area and contains no shadows cast by topographic effects because it is terrain corrected. Secondly, since the area of interest is fairly small, it contained no visible variations in atmospheric conditions, and since the methods applied do not require absolute reflectance measurements (Wallerman *et al.,* 2002).

Then raw satellite data in each Landsat 5 TM band (except thermal) were converted to reflectance using ENVI software in two-step process. First DN's were converted to radiance values. Then these radiance values were converted to reflectance values. During this process the parameters required as an input for the software were referred form the image metadata file as well as from Landsat 7 handbooks (http://obs.comu.edu.tr/dosyalar/DersMateryal/landsat7.pdf).

Then, to build a new multiband file except thermal, all six bands were layer stacked using ENVI software in the order of band 1, band 2, band 3, band 4, band 5 and band 7.

From this stacked band, different band combinations were explored among these six bands. Finally by assigning blue, green and red color gun to observation green, red and near-infrared spectral bands, respectively, Landsat 5 TM standard False Color Composite image was produced (Fig.5.1).

After these pre-processing techniques were carried out, spectral and textural extractions features were done. The general work flow of the methodology is illustrated in figure 3.4.

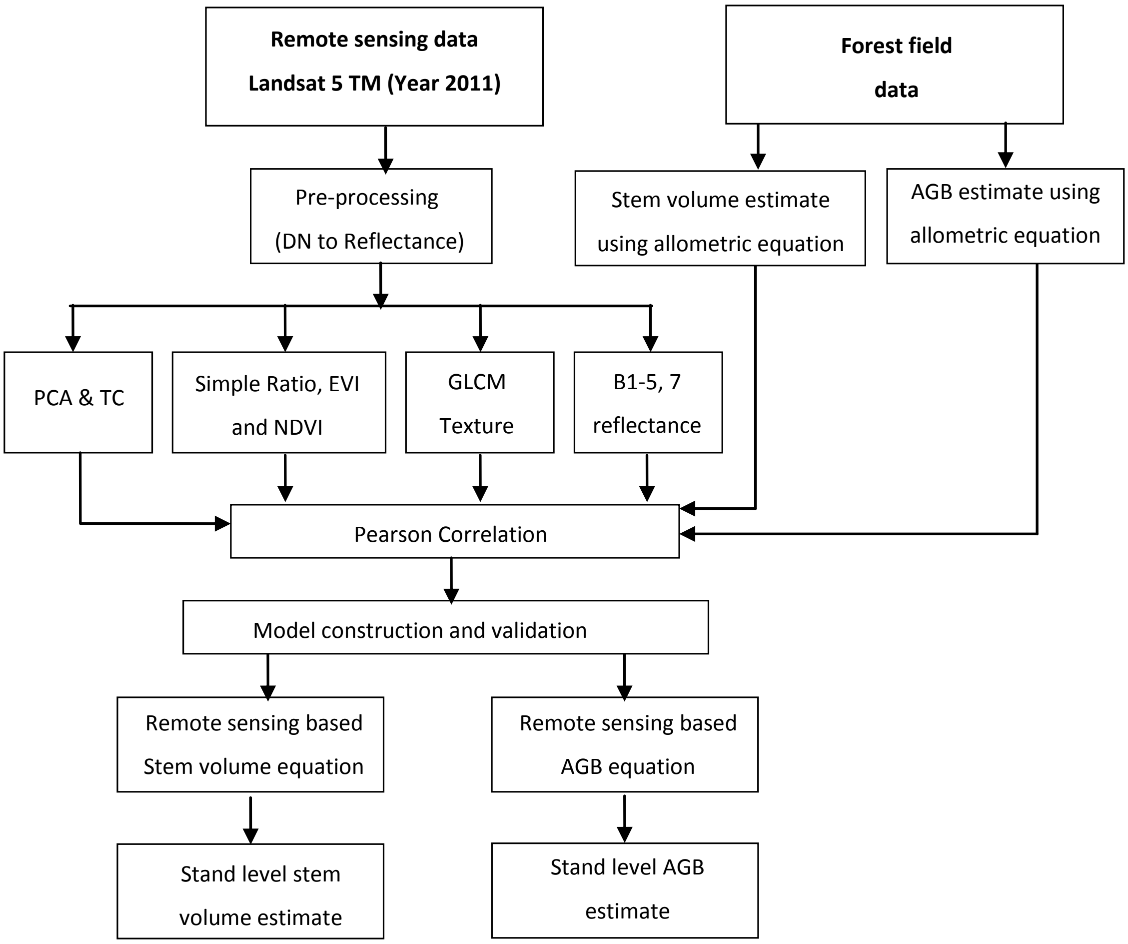

Fig. 3.4. Diagram of the processing and analysis work flow.

3.2.3. Image Post-processing, data extraction and model construction

Using ENVI software, univariate descriptive images statistics was computed from Landsat 5 TM images of the study area and illustrated in Table 5.1.

By integration of these 6 individual bands, the following 17 images were generated and used as independent variables during model development processes.

- Simple Ratio Index (TM4/TM3)
- Normalized Difference Vegetation Index (NDVI)
- Enhanced Vegetation Index (EVI)
- Three bands of principal component analysis (PCA) i.e. Principal Component1 (PC1), Principal Component2 (PC2) and Principal Component3 (PC3)
- Three Tasseled Caps (TC) bands, i.e. brightness (TC1), greenness (TC2) and wetness (TC3).

- Eight texture features based on the Grey Level Co-Occurrence Matrix (GLCM) from TM4: GLCM Mean, GLCM Variance, GLCM Homogeneity, GLCM Contrast, GLCM Dissimilarity, GLCM Entropy, GLCM Second moment, and GLCM Correlation.

But prior to the computation of the texture features, a variance matrix calculated from each Landsat 5 TM were computed and it was found TM4 representing the highest variance of the forest stand (Table 5.1). This band was ultimately selected for the texture features generation using a 5×5 moving window (Jensen, 1996). The 5 × 5 window sizes were chosen to cover a range of sizes corresponding roughly to the space between the homogenous patches of trees in the plantation forest (Jensen, 1996). The texture layers were calculated in each direction with single shifting pixel and were quantified into a 64 gray levels (de Jong and van der Meer, 2005). The description of the selected statistical texture models is given in Appendix III.

After these data sets were processed, the outputs were exported to ArcGIS software. Then, the 37 sampled plots were overlaid on each dataset and their corresponding values were extracted using Extracted value by point's tools.

Once extraction process from these 21 independent variables completed, they were exported to SPSS software in order to identify how they are related to each other as well as with dependent variables (Table 5.2). Next, based on Pearson's product moment correlation coefficients results, those statically significant independent variables were exported to ArcGIS software to develop a model using Ordinary Least Square regression (OLS) method.

Then, through iteration process, the stem volume and AGB equations as a function of spectral and textural variables were developed. Using these equations and Raster Calculator (Spatial Analyst tool) in ArcGIS software, the stem volume and AGB biomass at stand level were calculated from the hectare basis. The model performance assessment and validation were carried out based Ordinary Least Square regression null hypothesis assumptions (http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=Regressionanalysis_basics).

CHAPTER 4 RESULTS

This chapter presents the result obtained from all the processes involved to develop the models for the estimation of stem volume and AGB as a function of spectral and textural features. It also present a general comparison of the stem volume and AGB derived from the developed model and classical approach.

Equations (4.1) and (4.2) were developed for the estimation of stem volume and AGB, respectively. Their Standard Error, p-value and t-value is presented in Table 5.1 and 5.2.

$$stem\ volume = 14.293 - 0.093 GLCM\ Variance - 73.852 T1 + 0.826 GLCM\ Dissimilarity \quad \text{.................................. (Eq. 4.1)}$$

$$AGB = 14{,}962 - 78{,}988 TM5 - 97 GLCM\ Variance + 860 GLCM\ Dissimilarity \quad \text{.. (Eq. 4.2)}$$

From the selected independent varaibles and applying these equations, the mean stem volume and AGB were estimated at 49 m^3/ha and 48.81 ton/ha, respectively. The total stem volume and AGB over the study area were estimated at 8,253.36 m^3/ha and 8,200 ton/ha, respectively. For stem volume, the minimum and maximum values were estimated at 0.01 m^3/ha and 61.29 m^3/ha (Fig.4.1), while for AGB the minimum and maximum values were estimated at 47.11 ton/ha and 147.86 ton/ha (Fig.4.2), respectively.

Based on the field observation data and applying allometric equations (3.2) and (3.3), the mean stem volume and AGB were estimated at 48.73 m^3/ha and 48.25 ton/ha, respectively. The total stem volume and AGB over the study area were estimated at 8,186.9 m^3/ha and 8,106.7 ton/ha, respectively. For stem volume, the minimum and maximum values were estimated at 7.10 m^3/ha and 128.6 m^3/ha, respectively, while for AGB, the minimum and maximum values were estimated at 6.41 ton/ha and 132.43 ton/ha, respectively.

The results from the new developed model in both stem volume and AGB based on mean values are not considerably different the results obtained from field observation data and calculated using allometric equation.

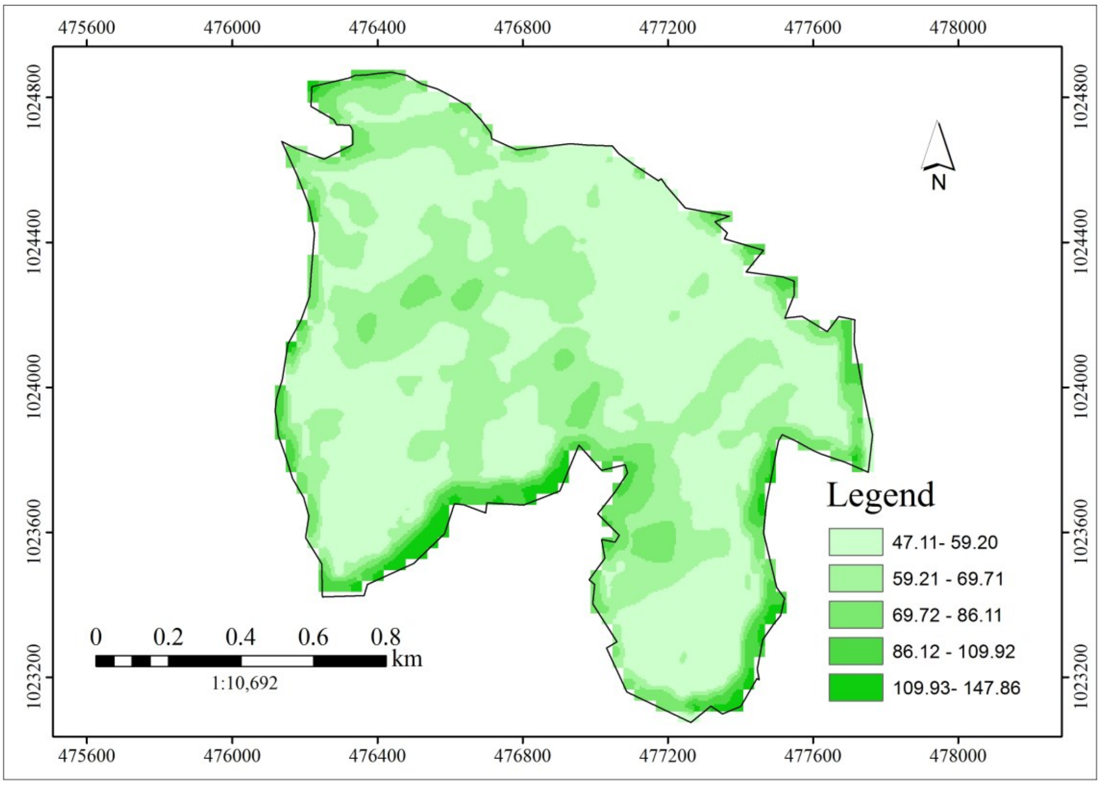

Fig. 4.1. The spatial distribution of the AGB (ton/ha) map.

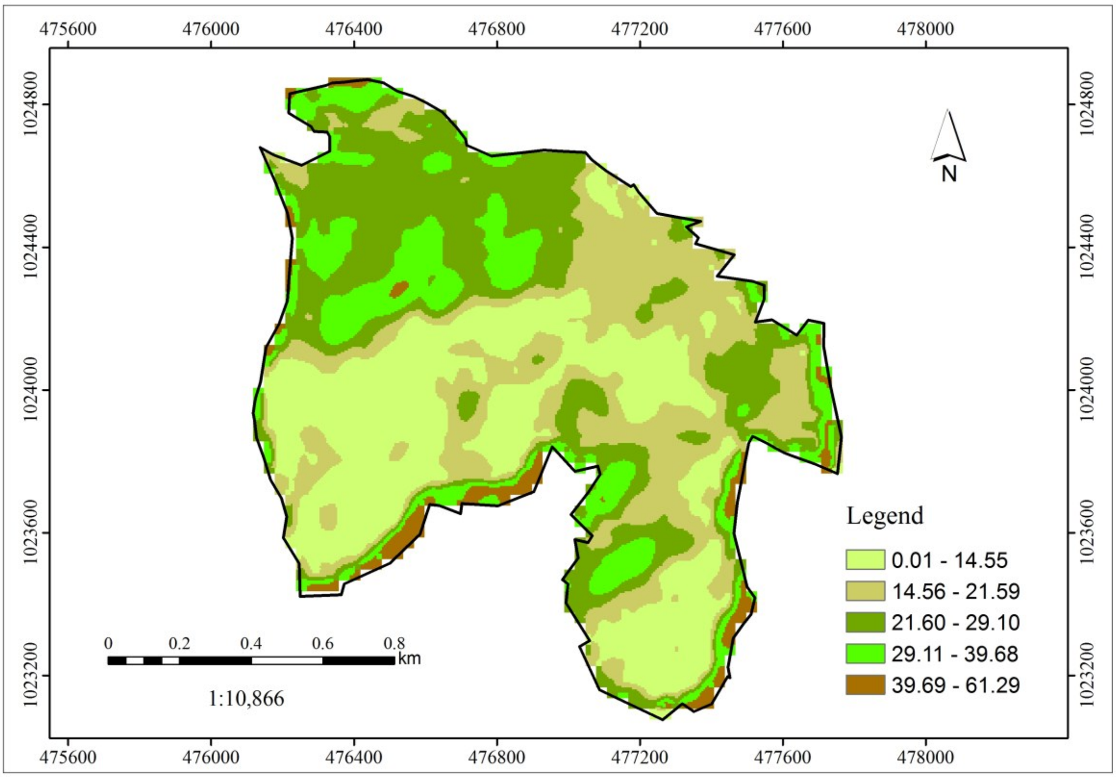

Fig. 4.2. The spatial distribution of the stem volume (m^3/ha) map.

CHAPTER 5 DISCUSSION

This chapter discusses the overall findings of this study. The first section briefly describes the comparison of stem volume and AGB estimates from the present study and results reported by different. The second section discusses the spectral reflectance response of vegetation on the study site as compared with the properties of optical Remote Sensing. The third section discusses the correlation status among the dependent and statistically significant independent variables, and the final section discusses the performance presumed and validation of the developed models under different null hypothesis assumptions.

5.1. Comparison of stem volume and aboveground biomass estimates

The stem volume and AGB findings in this study have been supported by locally executed researches on *E. globulus* coppice plantation in nearby areas of the study site at different years based on classical approach.

For instance, Yohannes (2002) reported the mean aboveground biomass is 31 tons/ha for Addis Ababa and its surroundings for 4 up to 6 years old of the same species coppice plantation and Zewdie (2008) reported that the mean aboveground biomass ranged from 11 to 153 tons/ha, from 1 up to 9 year old, respectively, at similar study sites with Yohannes. Both of these studies were estimated based on the classical approach.

The mean prediction from the present study for 7 years old of same species is more than Yohannes' finding where as it falls within the range of Zewdie's findings for both the developed model (48.81 tons/ha) and classical approach (48.25 tons/ha).

As discussed in the results section, the stem volume values range from 0.01 – 61.29 m^3/ha and 7.10 – 128 m^3/ha for the developed model and classical approach, respectively. The mean stem volumes were 49 m^3/ha and 48.73 m^3/ha, based on classical and modern approach, respectively.

These stem volume results, when compared to the report of Finfinnee Forest Development and Marketing Enterprise on *Forest Resources Development and Utilization Management Plan: For the period of July 2005 - June 2011,* where the stem volume per hectare of Chancho Plantation site was estimated to be in the range of 0.88 – 174 m^3/ha with a mean stem volume of 42.16 m^3/ha, make the numerical values obtained in this study plausible.

Since there are no documented findings based on the modern approach in the above mentioned areas, it was difficult to substantiate the outcomes of the modern approach. Similarly, since there are no documented findings based on modern approach exactly using Landsat 5 TM spectral and textural features, OLS method and for *E.globulus,* it was also difficult to substantiate the outcomes of the present study with similar finding in different place.

Therefore, however, results obtained differ between studies, depending on the sensor types, tree species and site conditions, the outcomes of the present study were compared with the general recommendation and conclusion given by different researcher.

According to Sales *et al*. (2007, as cited in Wijaya *et al.,* 2010), several attempts to estimate AGB from remote sensing data found high uncertainties. To elevate the estimate precision, the author recommended that correlation analysis between the RS data and biomass can be separately implemented for different land cover and suggested for further study.

Many researchers (e.g. Puhr and Donoghue, 2000; Kayitakire *et al.,* 2006; Sprintsin *et al.,* 2007; Wolter *et al.,* 2009, as cited in Ozdemir and Karnieli 2011) also concluded that promising results can be obtained in plantation forests consisting of pure stands dominated by one tree species.

The result of the present study confirms the importance of the above mentioned recommendation and also agreed up on the conclusions.

5.2. Spectral reflectance properties of vegetation compared with the properties of optical Remote Sensing

The standard False Color Compost (Fig. 5.1) image for the study area helped to enhance the vegetation discrimination and improve visual interpretation the details. It appeared red brown color, which indicates the study site is covered dominantly with forest (Jensen, 1996).

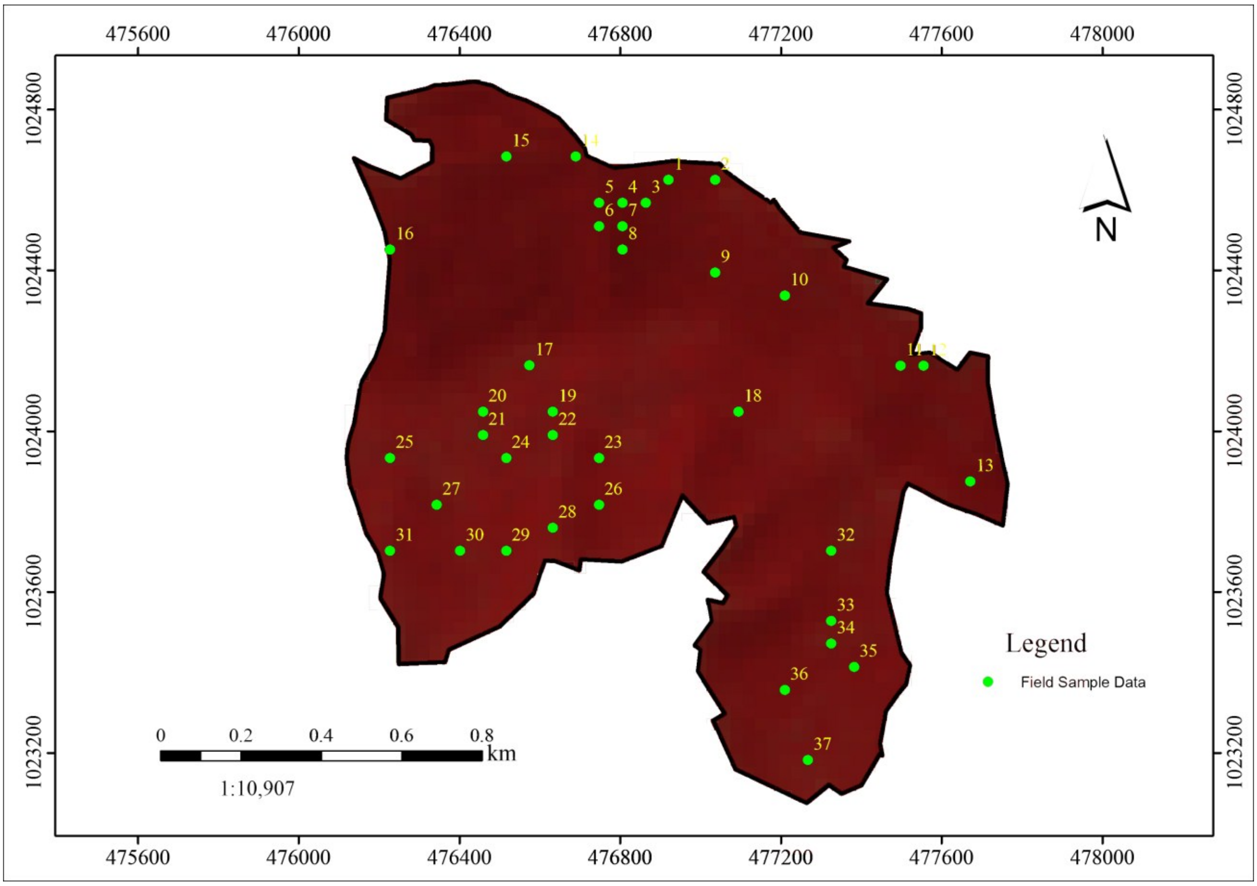

Fig. 5.1. Landsat 5 TM standard False Color Composite map.

The univariate descriptive images statistics (Table 5.1) of the image showed that from the visible region of the electromagnetic spectrum, band 2 has the highest reflectance value (16.4%), as compared to band 1 (0%) and band 3 (13.7%). But, band 4 has showed the highest reflectance (23%) value of all the seven bands of the spectrum.

In all these regard, this result is agrees with the general reflectance characteristics of vegetation (Lillesand *et al.,* 1994).

Table 5.1. Spectral reflectance of the study area (%).

Band name		Minimum	Maximum	Mean	Standard deviation
Visible	Band 1	0	7.7	3	2.7
	Band 2	0	16.4	4.9	4.5
	Band 3	0	13.7	3.2	3.1
Reflective infrared	Band 4	0	23	8.8	8.1
	Band 5	0	1.2	3	3
	Band 7	0	0	0	0

The main factor why band 1 and band 3 showed lower reflectance value is that light energy in these bands is absorbed by chlorophylls and carotenoid photosynthetic pigments for photosynthetic process (Fagan and Fries, 2009). The maximum reflectance value (23%) at near-infrared region was found lower than the expected range (i.e. the range from 40 to 50 percent) for healthy and green vegetation (de Jong and van der Meer, 2005).

Similarly, the maximum reflectance value at the band 5 and band 7(which are sensitive to the vegetation moisture content) were found to be is lower than expected result. This implies the forest in the study area contains high moisture content than normal.

5.3. The relationship among the dependent and statistically significant independent variables

Analysis of Pearson correlation test result showed that negative correlations between both stem volume and AGB with all bands of remote sensing data (Table 5.2). Some of them were found statistically significant and some were not-statically significant. Although some have significant relationships, they were not considered in the model since they showed multicollinearity effect with Variance Inflation Factor more than 7.5. (http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=Regression_analysis_basics).

Relatively low correlation coefficients were observed for both stem volume and AGB with their corresponding independent variables with the correlation (*r*) values less than 0.355 in absolute value term. Despite the poor correlation, a general evidence was observed on TM5 from Landsat 5 TM bands, TC1 from Tasseled Caps Transformation and GLCM Dissimilarity from texture features which performed better than other independent variables in terms of absolute value correlations when related to plantation attributes.

Table 5.2. Correlations between Remote Sensing data, stem volume and AGB.

	Stem volume		AGB
stem volume	1	AGB	1
TM1	-0.575**	TM1	-0.577**
TM2	-0.626**	TM2	-0.629**
TM3	-0.631**	TM3	-0.633**
TM4	-0.633**	TM4	-0.645**
TM5	-0.636**	TM5	-0.646**
NDVI	0.56**	NDVI	0.57**
TM4/TM3	0.250	TM4/TM3	0.241
PC1	0.672**	PC1	0.679**
PC2	0.355*	PC2	0.348*
PC3	-0.305	PC3	-0.319
TC1	-0.674**	TC1	-0.544**
TC2	-0.530**	TC2	-0.681**
TC3	-0.672**	TC3	-0.678**
EVI	0.308	EVI	0.323
GLCM Variance	-0.590**	GLCM Variance	-0.603**
GLCM Mean	-0.152	GLCM Mean	-0.144

	Stem volume		AGB
GLCM Homogeneity	0.034	GLCM Homogeneity	0.042
GLCM Contrast	-0.123	GLCM Contrast	-0.117
GLCM Dissimilarity	0.720**	GLCM Dissimilarity	0.728**
GLCM Entropy	-0.077	GLCM Entropy	-0.067
GCLM Second moment	0.039	GCLM Second moment	0.027
GCLM Correlation	0.282	GCLM Correlation	0.271

** Correlation is significant at $p<0.01$ level (2-tailed).

*Correlation is significant at $p<0.05$ level (2-tailed).

An inverse relationship was observed between stem volume and Tasseled Caps brightness. This indicates that as the forest coverage increases the soil exposure to sun light decrease. As a result the amount of stem volume increases. The result is similar with Lu *et al.* (2004), who analyzed forest structural attributes and Landsat TM data in Brazilian Amazon basin.

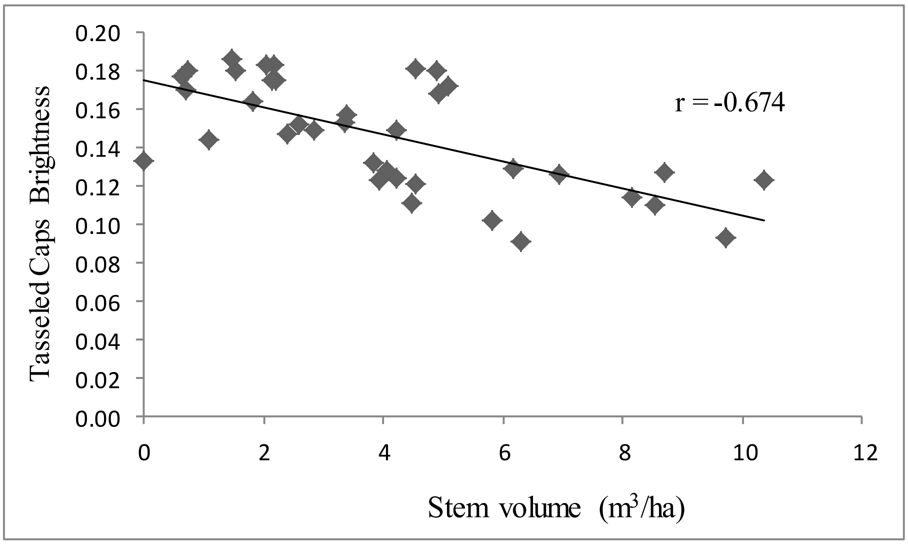

Fig. 5.2. Scatter plot of Tasseled Caps brightness versus stem volume.

The GLCM Variance and stem volume correlation analysis result indicated that negative relationship exists between them. Similarly, GLCM Variance showed inverse relationship with AGB. GLCM Variance indicate us the general variation or structure of the image (Haralick *et al.,* 1973 as cited in Roberts *et al.,* 2007). But plantation forests of similar ages often exhibit comparable levels of crown closure and could potentially have similar spectral reflectance. Therefore, as variance decrease the probability of the land covered with similar land features increases. This, in turn, indicates the study area is covered dominantly with forest. Consequently, the total amount of stem volume and AGB increase.

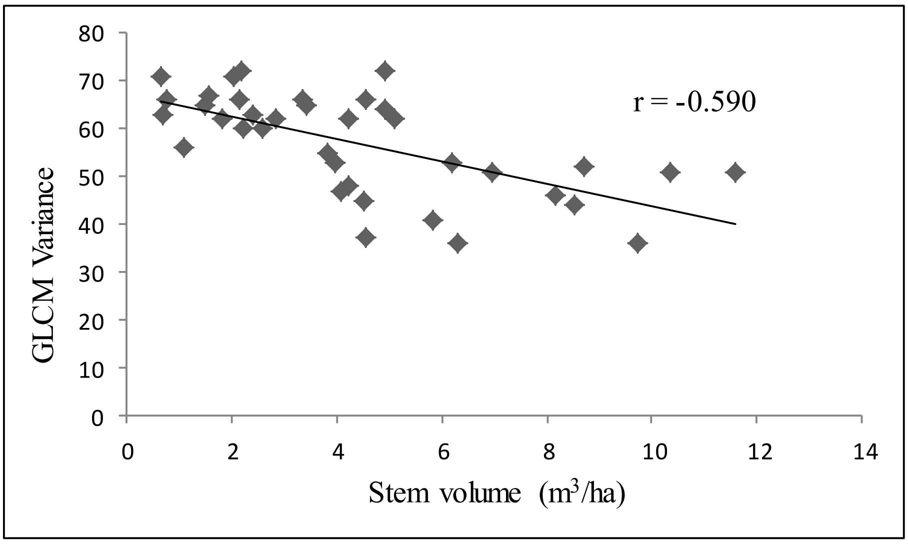

Fig. 5.3. Scatter plot of GLCM Variance versus stem volume.

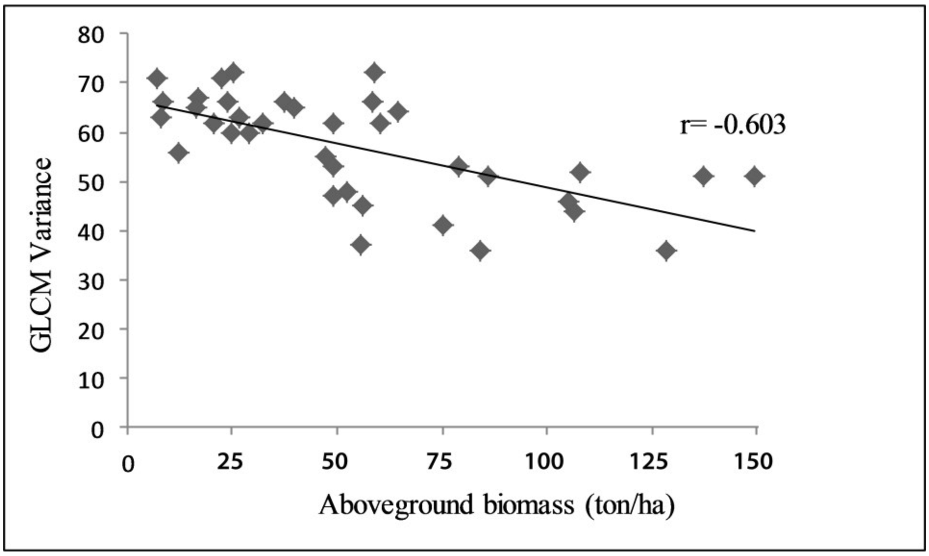

Fig. 5.4. Scatter plot of GLCM Variance versus Aboveground biomass.

A direct relationship was observed between the GLCM Dissimilarity scores of the image and stem volume. Similarly, GLCM Dissimilarity texture exhibited positive relationship with AGB. This relationship was attributed to the pattern of varying sub canopy plantation structural attributes; as result, trees tends to grow fast and become taller and bigger to compete for sun light (Haralick *et al.,* 1973 as cited in Roberts *et al.,* 2007). Consequently, the total amount of stem volume and AGB increases.

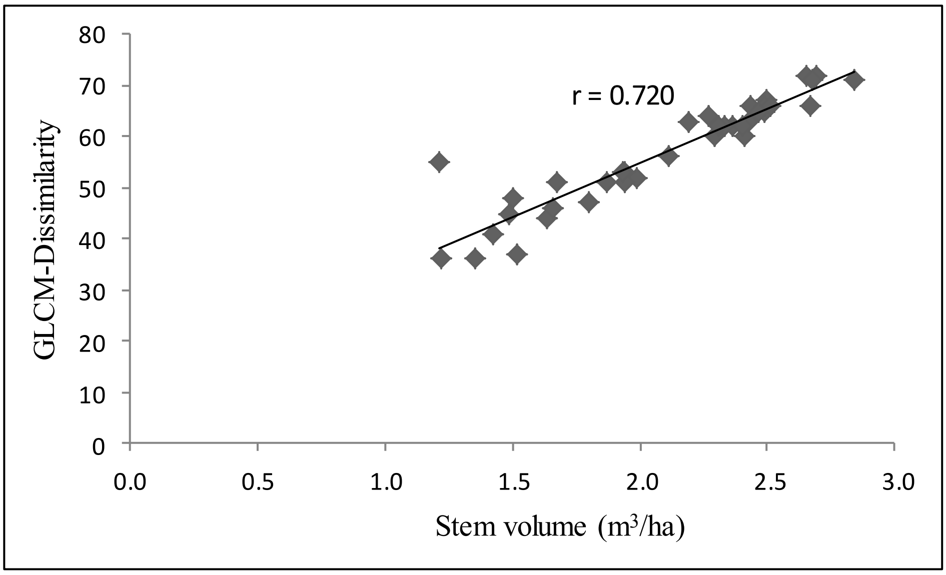

Fig. 5.5. Scatter plot of GLCM Dissimilarity versus stem volume.

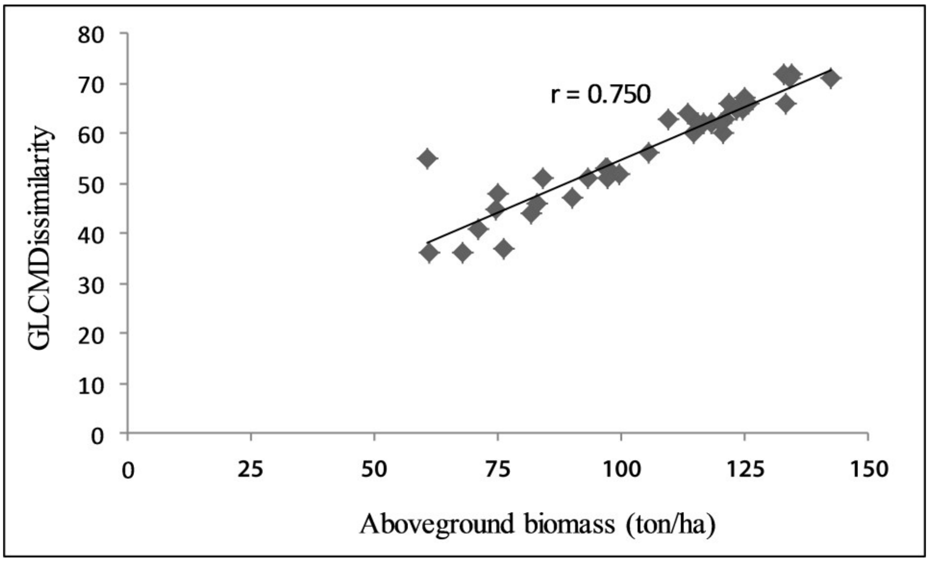

Fig. 5.6. Scatter plot of GLCM Dissimilarity versus Aboveground biomass.

An indirect relationship was observed between TM5 scores of the image and AGB. Since this band is sensitive to plant water moisture, it exhibited low reflectance value than from expected result (Jensen, 1996). This could happen in the forest when there is higher moisture content.

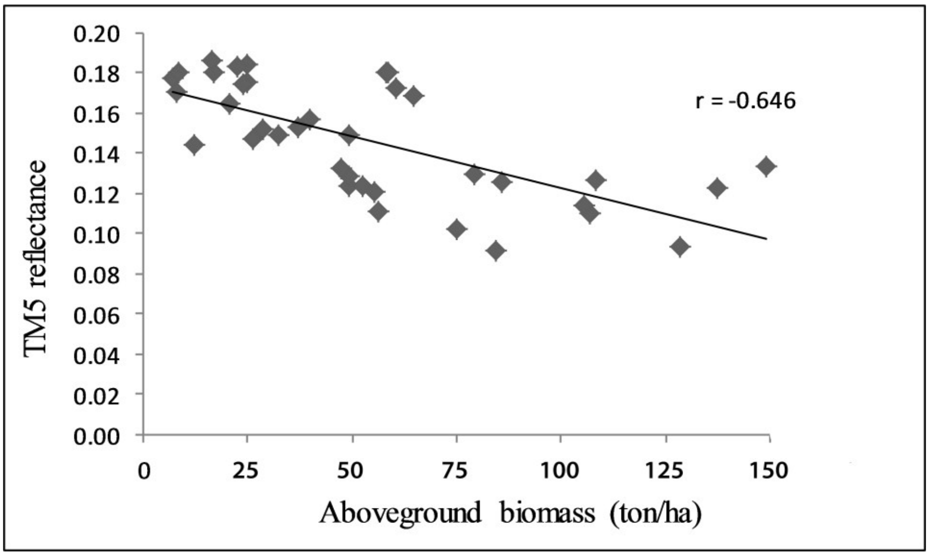

Fig. 5.7. Scatter plot of TM5 versus Aboveground biomass.

In general, it can be concluded that the ability of quantifying image texture using statistical texture analysis creates an opportunity to estimate forest structural attributes.

5.4. Model performance assessment and validation

The model performance assessment and validation were carried out through testing (accepting or rejecting) the Ordinary Least Square regression null hypothesis assumptions. This is based on a 95% confidence level and critical Probability (p) value = 0.05 set for this study. The Student's "t" test is also used to assess whether or not an independent variable is statistically significant (Table 5.3 and Table 5.4).

In both models, each independent variable was assessed based on its Coefficient sign, Probability or Robust Probability, and Variance Inflation Factor (VIF).

The Ordinary Least Square regression result showed that, for both models, all independent coefficients are different from zero, hence statistically significant at a Robust p-values smaller than 0.05. The null hypothesis for this test is that the coefficients for all intents and purposes, equal to zero (and consequently is not helping the model). Therefore, the null hypothesis is rejected and the results of both models are accepted.

Table 5.3. Coefficient table for stem volume model.

Variable	Coefficient	SE	t-value	p-value	Robust SE	Robust t-value	Robust p-value	VIF
Intercept	14.294	1.770	8.076	0.000	1.560	9.163	0.000*	
GLCM Dissimilarity	0.826	0.418	1.974	0.057	0.347	2.378	0.023*	3.43
GLCM Variance	-0.093	0.037	-2.524	0.017*	0.030	-3.092	0.004*	3.45
TC1	-73.852	12.086	-6.111	0.000*	10.745	-6.873	0.000*	1.06

*Coefficient is significant at p< 0.05 level (2-tailed).

Table 5.4. Coefficient table for AGB model.

Variable	Coefficient	SE	*t*-value	p-value	Robust SE	Robust *t* -value	Robust p-value	VIF
Intercept	14962	1869	8.0	0.00*	1616	9.3	0.00*	
TM5	-78988	12759	-6.2	0.00*	11280	-7.0	0.00*	3.43
GLCM Variance	-97	39	-2.5	0.02*	33	-2.9	0.01*	3.45
GLCM Dissimilarity	860	442	1.9	0.06	378	2.3	0.03*	1.06

*Coefficient is significant at p< 0.05 level (2-tailed).

With regard to the signs associated with the coefficients of independent variables for both models, all of them were found the same sign as their correlation coefficient values with dependent variables. Therefore, all independent variables associated with a statistically significant coefficient were found important to both regression models.

In order check model biasness due to redundancy (multicollinearity) effect among independent variables, the results were tested based on their Variance Inflation Factors value, with values less than 7.5 accepted. For TC1, GLCM Dissimilarity and GLCM Variance the VIFs were found 1.06, 3.43 and 3.45, respectively for stem volume model. Similarly, the VIFs for TM5, GLCM Dissimilarity and GLCM Variance were also found 3.43, 1.06 and 3.45, respectively for AGB model. Since these values area less than 7.5, they are not redundant independent variables in the models and do not bring biasness on the model.

The Koenker (BP) Statistic (Koenker's studentized Bruesch-Pagan statistic) is a test to determine if the independent variables in the model have a consistent relationship to the dependent variable both in geographic space and in data space. The null hypothesis for this test is that the model is stationary. For a 95% confidence level, a p-value smaller than 0.05 indicates statistically significant heteroscedasticity and/or non-stationarity. Based on this test, stationarity was assessed and found both models are free from heteroscedasticity effect. The results obtained is not statically significant, p = 0.44 and 0.42 for stem volume and AGB, respectively (Appendix III and Appendix IV).

Each model's significance was assessed based on Joint F-Statistic and Joint Wald Statistic which, are measures of the overall model significance. The null hypothesis for this test is that the independent variables in the model are not effective. For a 95% confidence level, a p-value smaller than 0.05 indicates statistical significance. Thus, for both models, the p-values were found smaller than 0.05. Therefore, the models are statistically significant and hence accepted.

In order to check whether or not a key variable is missing from the model a Spatial Autocorrelation (Moran's I) test was run on the regression residuals (Table 5.5 and 5.6). The result indicated that for both models the residuals are randomly distributed and not statistically significant since p = 0.95 and 0.91 for stem volume and AGB, respectively. Statistically significant clustering of high and/or low residuals (model under and over predictions) indicates a key variable is missing from the model. Therefore, the developed models in this study did not miss key variables.

Table 5.5. Global Moran's I summary for stem volume Model.

Global Moran's I Summary	
Moran's Index:	-0.022049
Expected Index:	-0.027778
Variance:	0.007403
Z Score:	0.066588
p-value:	0.946910

Table 5.6. Global Moran's I summary for AGB Model.

Global Moran's I Summary	
Moran's Index:	-0.017964
Expected Index:	-0.027778
Variance:	0.007397
Z Score:	0.114100
p-value:	0.909159

The overall model performance was assessed based on Adjusted R-Squared values. Possible values range from 0 to 1 (0 to 100 percent), with 0 denoting that model does not explain any variation and 1 denoting that it perfectly explains the observed variation. The models' Adjusted R-Squared values were found to be 0.51 for stem volume model and 0.50 for AGB model. These would indicate the independent variables modeled for stem volume model explains 51% of the variation in the dependent variable, whereas, the independent variables modeled for AGB model explains 50% of the variation in the dependent variable. Both values are found to be in an acceptable range of performance level.

The reason why these values were not found perfect or near to perfect could be explained as the field plots have small plot area size as compared to the Landsat 5 TM pixel size (1/9 of Landsat 5 TM pixel size). Although results could be constructed using 100 m^2 sample plots, it is still encouraging that up to 51% and 50% of stem volume and AGB variation, respectively, could be explained by spectral and textural data.

Finally, the models prediction accuracy was tested based on their residuals mean values, which are the mean value of observed values minus the estimated values. Using equation (5.1) it was found to be zero. It is also statistically tested based on the Jarque-Bera statistic, which indicates whether or not the residual are normally distributed with mean zero value and constant variance. The null hypothesis for this test is that the residuals are normally distributed. When the p-value for this test is smaller than 0.05 for a 95% confidence level, the residuals are not normally distributed, indicating that results from Ordinary Least Square regression model are not trustworthy. The Jarque-Bera statistic result of this study (Appendix II and III) indicates that there is no statistically significant, p = 0.12 and 0.10, for stem volume and AGB, respectively. Therefore, the null hypothesis is rejected and the result in this study is accepted.

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(y_i - j_i) \quad \text{(Eq. 5.1)}$$

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

The objectives of this study have been achieved and research question answered. The study illustrated that an approach, using spectral value combined with statistical texture features computed from Landsat 5 TM imagery for estimation of forest stem volume and AGB have been developed and validated. The Landsat 5 TM has significant potential to estimate the stem volume and aboveground biomass with acceptable accuracy.

The results from the new developed model in both stem volume and AGB are not considerably different from the species specific allometric equation.

The application of the developed volume and biomass function is wide for the enterprise and other concerned bodies. The classical approach can be replaced by the developed model and applied for sustainable forest management planning for the study area and its surroundings for the same species, as well as for other research purposes.

The inclusion of GLCM features improved to estimate forest structural attributes from optical Landsat 5 TM data.

Information provided by stem volume and AGB maps is useful for management of forest resources to support decision making processes for sustainable forest management.

6.2. Recommendations

Based on the findings described above the following recommendation have been forwarded.

For further studies in estimating stem volume and aboveground biomass using this approach, it is recommended to use larger field data sample plot size (up to 900 m^2), in order to increase the overall performance of the models, across other coppice rotations and seedling trees of the same species.

Further works also recommended in order to document the performance of the Landsat 5 TM satellite data under different environmental conditions and topographical changes, as well as for other species.

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APPENDICES

Appendix I: Ground Based Sample Plots Data

Plot ID	Easting	Northing	Stem volume ($m^3/100\ m^2$)	AGB (kg/ 100 m^2)
1	476838	1024419	0.95	947.95
2	476954	1024419	0.97	960.20
3	476781	1024362	0.50	499.96
4	476723	1024362	0.65	667.51
5	476665	1024362	0.91	935.24
6	476665	1024304	1.15	1218.10
7	476723	1024304	1.08	1141.53
8	476723	1024246	0.70	747.72
9	476954	1024188	0.69	703.22
10	477127	1024131	0.77	762.78
11	477415	1023957	1.29	1325.65
12	477473	1023957	0.50	492.56
13	477589	1023669	0.44	435.68
14	476607	1024477	0.47	465.06
15	476434	1024477	0.45	435.78
16	476145	1024246	0.43	419.75
17	476492	1023958	0.57	537.49
18	477012	1023842	0.55	573.53
19	476550	1023842	0.51	517.65
20	476376	1023842	0.17	148.75
21	476376	1023784	0.24	219.94
22	476550	1023784	0.24	222.43

Plot ID	Easting	Northing	Stem volume (m^3/100 m^2)	AGB (kg/ 100 m^2)
23	476665	1023727	0.37	330.17
24	476434	1023727	0.55	522.23
25	476145	1023727	0.16	143.76
26	476665	1023611	0.27	235.01
27	476261	1023611	0.29	255.54
28	476550	1023553	0.23	201.02
29	476434	1023496	0.07	64.19
30	476319	1023496	0.24	212.53
31	476145	1023496	0.08	70.76
32	477243	1023496	0.12	109.18
33	477243	1023322	0.32	285.83
34	477243	1023265	0.20	182.25
35	477300	1023207	0.38	354.48
36	477127	1023150	0.47	642.30
37	477185	1022976	0.08	73.13

(Source: OFWE, 2011)

Appendix II: Description of the Selected Statistical Texture Features

Statistical Features	Value range	Description
Mean	[0,255]	Provided the mean of the grey levels in the window.
Variance	[0,255]	Information on how spread out the distribution of grey levels is. It is expected to be large if the grey levels of the image are spread out.
Homogeneity	[0,1]	If the image is locally homogeneous, the value is high if GLCM concentrates along the diagonal. Homogeneity weights the values by the inverse of the contrast weight with weights, decreasing exponentially according to their distance to the diagonal.
Contrast	[0,65025]	Measures the local contrast of an image. It is expected to be low if the grey levels of each pixel pair are similar.
Dissimilarity	[0,255]	Similar to contrast, but increases linearly. High if the local region has a high contrast.
Entropy	[0,10404]	Measures the randomness of a grey level distribution. It is expected to be high if the grey levels are distributed randomly through the image It is low if the elements are close to either 0 or 1
Second moment	[0,1]	Measures the number of repeated pairs. It is expected to be high if the occurrence of repeated pixel pairs is high
Correlation	[0,1]	Measures the linear dependency of grey levels on those of neighboring pixels in the GLCM

(Source: Trimble, 2012)

Appendix III: Diagnostic Output Table for Stem Volume

Diagnostic Name	Diagnostic Value	Definition
AIC	160.23	Akaike's Information Criterion: A relative measure of performance used to compare models; the smaller AIC indicates the superior model.
R2	0.54	R-Squared, Coefficient of Determination: The proportion of variation in the dependent variable that is explained by the model.
AdjR2	0.50	Adjusted R-Squared: R-Squared adjusted for model complexity (number of variables) as it relates to the data.
F-Stat	13.10	Joint F-Statistic Value: Used to assess overall model significance.
F-Prob	0.00	Joint F-Statistic Probability (p-value): The probability that none of the explanatory variables have an effect on the dependent variable.
Wald	48.65	Wald Statistic: Used to assess overall robust model significance.
Wald-Prob	0.00	Wald Statistic Probability (p-value): The computed probability, using robust standard errors, that none of the explanatory variables have an effect on the dependent variable.
K(BP)	2.71	Koenker's studentized Breusch-Pagan Statistic: Used to test the reliability of standard error values when heteroskedasticity (non-constant variance) is present.
K(BP)-Prob	0.44	Koenker (BP) Statistic Probability (p-value): The probability that heteroskedasticity (non-constant variance) has not made standard errors unreliable.
JB	4.22	Jarque-Bera Statistic: Used to determine whether the residuals deviate from a normal distribution.
JB-Prob	0.12	Jarque-Bera Probability (p-value): The probability that the residuals are normally distributed.
Sigma2	4.02	Sigma-Squared: OLS estimate of the variance of the error term.

Appendix IV: Diagnostic Output Table for Aboveground biomass

Diagnostic Name	Diagnostic Value	Definition
AIC	675.42	Akaike's Information Criterion: A relative measure of performance used to compare models; the smaller AIC indicates the superior model.
R2	0.55	R-Squared, Coefficient of Determination: The proportion of variation in the dependent variable that is explained by the model.
AdjR2	0.51	Adjusted R-Squared: R-Squared adjusted for model complexity (number of variables) as it relates to the data.
F-Stat	13.36	Joint F-Statistic Value: Used to assess overall model significance.
F-Prob	0.00	Joint F-Statistic Probability (p-value): The probability that none of the explanatory variables have an effect on the dependent variable.
Wald	51.34	Wald Statistic: Used to assess overall robust model significance.
Wald-Prob	0.00	Wald Statistic Probability (p-value): The computed probability, using robust standard errors, that none of the explanatory variables have an effect on the dependent variable.
K(BP)	2.77	Koenker's studentized Breusch-Pagan Statistic: Used to test the reliability of standard error values when heteroskedasticity (non-constant variance) is present.
K(BP)-Prob	0.43	Koenker (BP) Statistic Probability (p-value): The probability that heteroskedasticity (non-constant variance) has not made standard errors unreliable.
JB	4.58	Jarque-Bera Statistic: Used to determine whether the residuals deviate from a normal distribution.
JB-Prob	0.10	Jarque-Bera Probability (p-value): The probability that the residuals are normally distributed.
Sigma2	4478965.83	Sigma-Squared: OLS estimate of the variance of the error term.

D E C L A R A T I O N

I hereby declare that the thesis entitled: *Modeling Forest Stand Volume and Live Aboveground Woody Biomass Using Remote Sensing and GIS: A Case Study in Chancho Eucalyptus globulus Plantation Forest, Oromia Regional State, Ethiopia* has been carried out by me under the supervision of Dr. Getachew Berhan and Mr. Binyam Tesfaw**,** School of Earth Sciences, Addis Ababa University, during the academic year 2013/14 as a part of my study of the Master of Science degree in Remote Sensing and GIS. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

Tariku Geda

Signature_______________

Addis Ababa University
Addis Ababa
Date _____, 2014

APPROVAL

This is to certify that the thesis entitled**:** *Modeling Forest Stand Volume and Live Aboveground Woody Biomass Using Remote Sensing and GIS: A Case Study in Chancho Eucalyptus globulus Plantation Forest, Oromia Regional State, Ethiopia* is carried out by Tariku Geda under our guidance and supervision. We know this is an actual work done by Tariku Geda for the partial fulfillment of the award of the Degree of Master of Science in Remote Sensing and GIS from Addis Ababa University.

Dr. Getachew Berhan

Signature_________________

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