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Identification of the Best Vegetation Index Model for Estimating Above Ground Biomass of *Pinus roxburghii*

By

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Science Pledge

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

Kathmandu, Nepal, 22/10/2016	
Place and Date	Signature

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Abstract

Biomass is defined as the mass of living or dead organisms in a given area at a given time. It comprises of above ground biomass (AGB) and below ground biomass, but AGB is generally used to estimate the biomass because it accounts for greatest fraction of total living biomass. *Pinus roxburghii* is one of the most widely planted tree species in Nepal and one of the source of resin and timber. Despite its large abundance and high economic values, limited studies on its AGB have been conducted in Nepal, especially using *in situ* non-destructive method. There are different methods to study the AGB. The in situ non-destructive method is time consuming and expensive and requires collection of large number of sample plots, whereas regression equation based on the correlation between Vegetation index (VI) and AGB is cost effective method, and replicable in another sites of similar environment by just acquiring satellite images. Numerous methods have been developed to calculate Vegetation indices (VIs) and each calculated VI shows different relation with AGB in different environments for same species. Therefore, there is a need to identify a most appropriate VI that has the highest correlation with AGB of *P. roxburghii*. The current study was carried out in Hattiban and Dollu community forests of Kathmandu district, using ResourceSat-2 imagery, to identify the best VI for *P. roxburghii*'s AGB estimation.

Slope based and distance based VIs were used in the study. Statistical analysis showed that slope based VIs had higher relation with AGB ($r > 0.7$ and $r^2 > 0.50$) than distance based VIs ($r < 0.7$ and $r^2 < 0.5$). Slope based VIs were significant enough to estimate AGB as the adjusted r^2 was greater than 0.5 compared to distance based VIs. Within the slope based VIs, NDVI had higher relation ($r = 0.734$, $r^2 = 0.5388$, adjusted $r^2 = 0.5248$) with AGB. Hence, NDVI was concluded to be an appropriate VI for estimating AGB of *P. roxburghii*, and the derived regression equation, $AGB = -4501 + 16199 * NDVI$, was used to estimate AGB. Based on the equation, the study area was estimated to have 133,577,495.44 kg of AGB of *P. roxburghii* with RMSE of 41.49%.

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Abbreviation

AGB	Above ground biomass
BEF	Biomass expansion factor
CART	Classification and regression tree
CTVI	Corrected transformation vegetation index
DBH	Diameter breast height
DVI	Difference vegetation index
MSAVI	Modified soil adjusted vegetation index
MSR	Modified simple ratio
NDVI	Normalized difference vegetation index
NIR	Near Infrared
P. roxbhurghii	*Pinus roxburghii*
PC1	Principal component analysis component1
Pg C year^{-1}	Petagram of carbon per year
PVI	Perpendicular Vegetation Index
RDVI	Renormalized difference vegetation index
RMSE	Root mean square error
SAVI	Soil adjusted vegetation index
Spp	Species
TTVI	Thiam’s transformation vegetation index
TVI	Transformed vegetation index
VI	Vegetation index
WDVI	Weighted difference vegetation index

Chapter 1 Introduction

This chapter gives a brief introduction of biomass and its importance, above ground biomass, vegetation indices and their relation with above ground biomass. This chapter also discusses the need of the current study.

1.1 Background

Biomass is composed of two distinct words, “bio” and “mass.” “Bio” is “connected with living things”, while “mass” denotes “large quantity of something”. Biomass is defined as “the total quantity or weight of plants and animals in a particular area or volume” (Oxford University Press, 2005). It has been variously defined in different fields and disciplines. In energy related field, it has been defined as “a general term for animal and plant resources and the wastes arising from them, which have accumulated in a certain amount (excluding fossil resources).” It encompasses a wide variety of sources “including not only agriculture, forestry and fisheries resources, but also pulp sludge, black liquor, alcohol fermentation stillage and other organic industrial waste, municipal waste such as kitchen garbage and paper waste” (Japanese Institute of Energy, 2008).

In ecology, biomass has been defined as the mass of living or dead organisms in a given area at a given time (GTOS, 2009). Similarly, FAO (2012) has defined biomass as the organic material both above and below the ground and both living and dead trees, crops, grasses, dried litter root etc. McKendry (2002) has noted that biomass is “plant material that is derived from the reaction between carbon dioxide in air, water and sunlight via photosynthesis to produce carbohydrate that forms the building blocks of biomass.” Photosynthesis converts less than 1% of available sunlight to stored chemical energy.

Larger amount of biomass remains in the plant community. In plants, the primary component of biomass are cellulose, hemicellulose and lignin. Cellulose is "a polysaccharide in which D glucose is linked uniformly by β-glucosidic bonds." Hemicellulose is "a polysachharide whose units are 5-carbon monosachharides including D-xylose and D-arabinose and 6 carbon monosaccharides including D-mannose, D-galactose and D-glucose." Lignin is "a compound whose constituent units, phenylpropane and its derivatives, are bonded 3 dimensionally" (Japanese Institute of Energy, 2008). Cellulose accounts for the greatest fraction (40-50 % of the biomass by weight), whereas hemicellulose accounts for 20-40% of the material by weight (McKendry, 2002).

Within the overall vegetation also, forest vegetation stores larger amount of biomass. EPA (2012) has noted that trees, the major component of forests, store large amount of carbon during photosynthesis in their wood in the form of biomass. However, the efficiency of trees to store carbon differs from species to species (Lorenz & Lal, 2010). It is estimated that carbon uptake varies between 0.49 and 0.7 Petagram of Carbon per year (Pg C year^{-1}) for the boreal forest, and between 0.72 and 1.3 Pg C year^{-1} for the tropical forest biome (Lorenz & Lal, 2010). Trees store carbon not only in larger amount, but also for longer time, even centuries. Based on the radiocarbon analysis, the typical mean age of organic carbon in plant detritus (exudates, leaves, roots, stems) ranges from days to centuries (Trumbore & Czimczik, 2008).

Forest provides various materials such as timber, food, fodder, medicinal ingredient etc. for sustainable livelihood of human beings for which sustainable conservation/utilization of the forest is required. In the context of global warming/climate change also, forest conservation is required as the forest is the largest reservoir of carbon (GTOS, 2009). With an objective of mitigating climate change by reducing net emission of greenhouse gases through enhanced forest management in developing countries i.e. in order to reduce the amount of carbon in the atmosphere, REDD (Reducing Emissions from Deforestation and Forest

Degradation) program was launched. REDD thus provides a mechanism, where developing countries are paid for forest conservation and sustainable management, and carbon offset (carbon sequestration). Estimating carbon sequestration potential and total carbon sink requires the information of the biomass of the forest as biomass is directly correlated with carbon (WWF, 2016). Therefore, calculating forest biomass helps not only to estimate the potential of carbon sink or sequestration of forest but also for sustainable conservation and utilization of the forest for sustainable livelihood.

In addition, calculating forest biomass supports climate change modelling studies (Houghton, 2005; Zhu & Liu, 2014; Canadell & Raupach, 2008). It is helpful to assess the species diversity and primary productivity (Zheng et al., 2004). Biomass and species diversity have a hump shape (unimodal relationship) in mature vegetation. Biomass and primary productivity also have unimodal relationship (Guo, 2006). Apart from this, biomass estimation helps to access nutrient allocation, fuel allocation in forest ecosystem (Zheng, et al., 2004) and change in forest structure and growth dynamics (FAO, 1997; Reeves et al., 2001).

Biomass comprises of above ground biomass (AGB) and below ground biomass, but AGB is generally used to estimate biomass because it accounts for greatest fraction of total living biomass and can be measured easily. AGB is defined as “the total amount of aboveground living organic matter in trees expressed as oven-dry tons per unit area (tree, hectare, region, or country)” (FAO, 1997).

Different methods are used to study the AGB of vegetation of an area. This ranges from traditional to remote sensing based methods. The traditional destructive measurement method is expensive, time consuming, laborious and destroys forest (FAO, 2012). Ground based inventory using allometric equation is accurate, but it requires a large number of sample plots and also cannot measure the spatial distribution of AGB in large area

(Anderson, 2007; Lu et al., 2004; Soenen et al., 2010). Hence, it is time consuming, labour intensive and costly. GIS based methods require information of environment variables like rainfall, canopy cover, forest age etc. to estimate AGB, but due to the weak relationship of AGB with environmental variables (Lu, 2006), this method is not ideal to estimate AGB. According to Anderson (2007), Zhu & Liu (2014) and Brewer et al (2012), integrating remote sensing data along with forest resource inventory (field data) is a cost effective method and provides a geo-statistical basis for estimating AGB of large area i.e. AGB of large area can be estimated by linking information derived from remotely sensed data to AGB values measured on the ground.

Remotely sensed data comprises information of different spectral bands. Combination of the red and near infrared (NIR) spectral bands produce vegetation indices (VIs). VIs have relationship with AGB (Brewer et al., 2011; Bajracharya, 2008, Lu et al., 2004) and are commonly used to estimate AGB using a regression equation (Dong et al., 2003; Lu et al., 2004; Zheng et al., 2004; Tucker et al., 1985, Bajracharya, 2008). Spectral radiances from red and NIR bands have distinct interaction with plants. The energy from red band is strongly absorbed by the plant pigments for photosynthesis, while energy from NIR band is strongly scattered by the internal structure of the leaves (Eastman, 1999a). This strong contrast between the amount of reflected energy in red and NIR bands helps to develop vegetation indices (VIs) (Eastman, 1999a). Using this, different types of VIs such as slope based (Ratio, NDVI etc), distance based (PVI, SAVI, MSAVI etc) have been developed (Eastman, 1999a).

Although, VIs have relationship with AGB, the strength of the relation depends upon several factors such as background surface condition, amount of standing green biomass, atmospheric condition, local environment (Anderson & Hanson, 1992). As a result, different studies have reported different results. Sader et al (1989) did not find NDVI as a reliable VI to estimate AGB. Sader et al (1989) did not find difference in biomass in young tropical forest using NDVI and concluded that NDVI was not suitable for estimating AGB in uneven and mixed broadleaved forest. Similar result was reported by Hall et al (1995). On the other hand, Anderson et al (1993) found a strong relation between NDVI and AGB in-semi arid rangelands. Likewise, Mundava et al (2014) found that VIs have strong relation with AGB in open plain land that refers to areas with periodic flooding with mostly annual grasses, while relation did not exist in Spinifex grass dominated areas. Lu et al (2004) found a positive relation between AGB and VI (principal component, component1) in Pedras of Brazil, but in Altamira and Bragantina, they found a negative relation. This variation was accounted for difference in biophysical environment of study area as the relationship depends upon plant species and their local environment (Mundava et al., 2014; Lu et al., 2004).

Since the relation between VIs and AGB for a particular species differs from one VI to another, and from one place to another (different environment), one species shows higher relation on one VI, while other on another, depending upon the local environment. Hence, a need of identifying the best VI to quantify the AGB for a particular species at a particular site is highly felt. As such, the present study has focused to identify the most appropriate VI to estimate the AGB of *Pinus roxburghii*, a widely planted tree species with economic value.

1.2 Rationale of the Study

Pinus roxburghii, a large tree reaching up to 40 - 50 meters with trunk diameter up to 2 meters (Polunin & Stainton, 1992), is one of the most widely planted species in community forests of Nepal. It is also one of the good source of resin and timber. Despite its large abundance and high economic values, limited studies on its AGB - an important indicator of carbon sequestration potential (Houghton, 2005; Anderson, 2007), productivity, nutrient allocation, fuel allocation of forest (Zheng et al., 2004)- have been conducted in Nepal, especially using *in situ* non-destructive method (Baral, et al., 2009). The method uses allometric equations to derive biomass from the sampled field data (GTOS, 2009), and needs a large number of samples to be collected for each and every site due to which it becomes expensive, time consuming and laborious (Anderson, 2007; Lu, et al., 2004).

Regardless of the above method, regression equation derived based on correlation between VIs and AGB for the species can be used to quantify the AGB for same species in another sites having similar environment just using satellite imagery data, which are now a days easily and promptly available for any site and time. This reduces the cost, time and effort significantly. But, as numerous methods have been developed to calculate VIs, and each calculated VI shows different relationship with AGB in different environment for same species, there is a need to identify the best VI that has the highest correlation with AGB of *P. roxburghii* in current study area.

Therefore, a need to identify the most appropriate VI that shows the highest correlation with AGB of *P. roxburghii* has been felt to estimate the species total AGB.

1.3 Objectives of the Study

The objectives of the study are:

- To study the correlation between slope and distance based vegetation indices (Ratio, NDVI, TVI, CTVI, TTVI, PVI, DVI, SAVI, MSAVI and WDVI), and AGB of *Pinus roxburghii.*

- To identify the Vegetation index that has the highest correlation with AGB of *Pinus roxburghii.*

- To estimate the AGB of *Pinus roxburghii* in the study area based on ideal vegetation index.

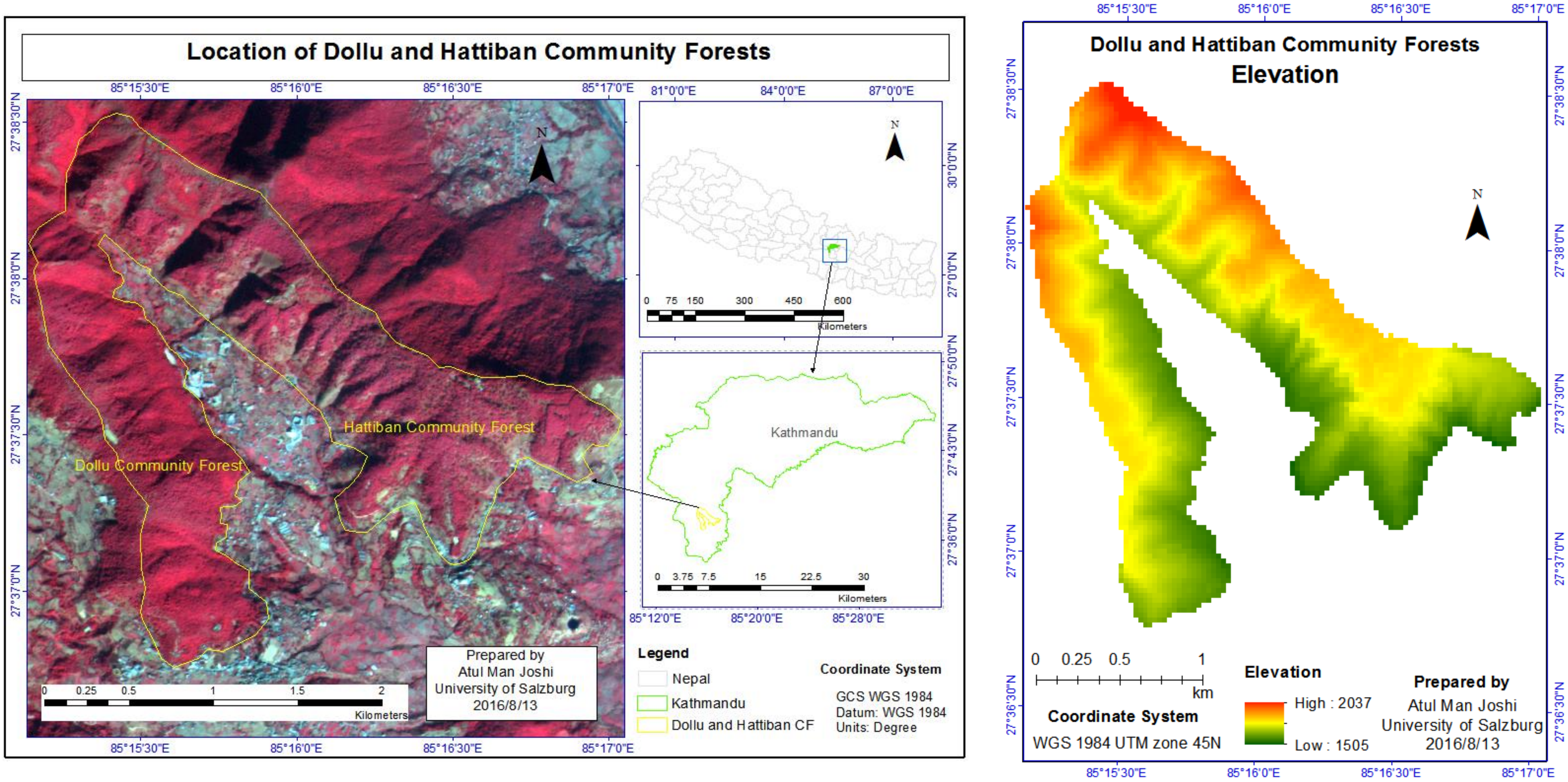
1.4 Description of Study Area

The study area is located at Hattiban and Dollu community forests in Dakshinkali Municipality of Kathmandu district. It is about 18 km south of Kathmandu city. It covers an area of 3.69 km^2 (369 hectares), and extends between latitude of 27°36’43.142” and 27°38’37.309” North and longitude of 85°14’54.041” and 85°17’13.3358” East (Map 1). The elevation of the study area ranges from 1505 m to 2037 m.

The study area falls in subtropical bio-climatic zones, with maximum temperature of about 35.6°C in April and minimum of up to –3°C in January. The annual average humidity is 75% and the average rainfall is 1400 mm per annum. Most of the rainfall occurs in the months of June to August (Pant, 2009).

The study area consists of different plant species that are not native to the area, and were planted during afforestation program. The southern aspect of the study area is dominated by *P. roxburghii*, while the northern aspect is mixed with broad leaved and *P. roxburghii. Schima wallichi, Castapnopsis indica, Rhododendron spp*. are some of the plant species present in the area (DFO, 2014).

In Dakshinkali municipality, there are 5488 households. The total population of the area is 24,297 (11,873 male, 12,424 female) (CBS, 2011). Newar, Tamang, Bahun, Chhetri, Gurung, Magar are some of the ethnic groups that reside in the area (DFO, 2014)



Map 1 Location Map (left) and Elevation Map (right) of study area (Dollu and Hattiban Community Forest)

Chapter 2 Literature Review

This chapter reviews literatures that are relevant for the study under three major headings: biomass measurement methods, relation between vegetation indices and above ground biomass and image classification.

2.1 Biomass Measurement Methods

Biomass is defined as the mass of living or dead organisms in a given area at a given time (GTOS, 2009). It helps to estimate the carbon sequestration potential, support climate change modelling studies (Houghton, 2005; Zhu & Liu, 2014; Canadell & Raupach, 2008), assess species diversity and primary productivity (Zheng et al., 2004). To measure the biomass, various methods from traditional destructive to remote sensing based have been developed, which are presented below.

2.1.1 Traditional Destructive Measurement

Traditional destructive measurement is the process of measuring biomass by harvesting trees. It is the most accurate approach for measuring biomass, however, it destroys forest and is time consuming, labor intensive and suitable for only small areas (Lu et al., 2014). It is thus called as destructive measurement method. FAO (2012) has provided procedures for measuring biomass using destructive measurement techniques. As per the technique, a sample plot is laid down based on standard plot sampling method. In each sample plot, a person stands at a start point and uses a GPS or compass to indicate the direction for the sides of the plot. Then, a square plot is created. General information such as location, coordinates at plot center are recorded. Within each plot, all live trees with DBH equal to and above 5 cm are measured. Once DBH is measured, the DBH data are grouped into classes at interval of 10 cm. Then, sample trees are selected randomly in each class. At least five sample trees from each class are cut down at their base following logging procedures. Once the sample tree is cut down, information of diameter at stump, DBH at 1.3 m, tree height, length of tree bole from the stump to the first main branch and from the stump to the point where diameter becomes 10 cm is noted. Then the cut tree is separated into different parts (e.g. bole, branches and leaves) and weights of stem, branches, and leaves are measured. Then, dry mass analysis is performed to calculate biomass.

2.1.2 Measurement using DBH and Height

This method uses allometric equation using diameter at breast height (DBH) and height of tree species to measure biomass of the species (Lu et al., 2014). Different researchers have proposed different equation for measuring AGB.

Dong et al. (2003) proposed following equation to calculate AGB of conifer and broad leaved forest.

$AGB = (N_{cf}\ (C)\ WV_n(P) + Bcf\ (C)\ WV_b\ (P)\ )\ /\ (FA\ (P))$

Where, AGB = above ground biomass, N_{cf} = conversion factor for conifer, B_{cf} = conversion factor for broad leaved, WV_n = wood volume of conifer forest, WV_b is wood volume of broad leaf forest and FA is forest area.

IPCC (2003) proposed following equation to calculate AGB of pine species in tropical and temperate pine forests.

$AGB = 0.887 + [(10486 \bullet (DBH)^{2.84}) / ((DBH^{2.84}) + 376907)]$

Where, DBH = diameter at breast height in cm

Jenkins et al. (2003) proposed following equation to estimate AGB of tree species.

AGB = Exp (b0 + b1 ln DBH)

Where, Exp = exponential; b0, b1 = specific coefficients for given species; DBH = Diameter at breast height; Ln = log base e

Bajracharya (2008) used following equation to calculate AGB of tree species.

$Ln\ W = a + b\ Ln\ DBH$

Where, W = AGB in Kg; DBH = over bark breast height (measured 1.3 meter above ground) in cm, a and b are regression coefficients of the biomass model that vary according to different species types and their climate, management and disturbances.

ICIMOD, ANSAB and FECOFUN (2010) used following equation as proposed by Brown et al (1989) to calculate AGB of tree species in moist climate with annual rainfall between 1500-4000 m.

AGB =38.4908-11.7883DBH+ 1.1926 DBH2

Where AGB = above ground biomass, and DBH is diameter at breast height.

Shrestha (2011) used following equation proposed by Chave et al. (2005) to calculate AGB of broad leaved forest.

$AGB=0.0509 * pD^2H$

Where, AGB is aboveground tree biomass, p is wood specific gravity, D is tree diameter at breast height and H is tree height.

Ahmad et al (2014) used following equation to calculate the AGB of tree species.

Stem biomass = Volume (m^3) ∗ Basic wood density (kg/m^3)

Total AGB = Stem biomass ∗ Biomass Expansion Factors (BEF)

Lu et al (2014) proposed following equation to calculate AGB of tree species.

AGB = Volume * VEF * WD * BEF + Ɛ

Where VEF = Volume expansion factor; WD = Wood density; BEF = Biomass expansion factor.

Ostadhashemi et al (2014) proposed following equation to calculate AGB of tree species.

V = Ba * h * f

Where, V = stem volume; Ba = basal area at DBH, h = height, f= form factor

AGB = V * R

Where, V = stem volume; R = basic wood density,

DFRS (2014) proposed following equation to calculate AGB of tree species in the REDD project. Karna (2012), Pokhrel (2015) also used the equation proposed by DFRS (2014) to calculate AGB.

AGB = Stem biomass + Branch biomass + Foliage biomass

2.1.3 Measurement using Indirect Attributes

This method is used for measuring biomass of trees and shrubs and is non-destructive. University of Arizona (2016) reviewed the biomass measurement method using indirect attributes and presented in website “Indirect Methods to Determine Biomass.” According to the review, this method measures biomass using the relationship between plant weight and indirect attributes such as plant height, rainfall or canopy cover. In this method, first a preliminary sampling is conducted for establishing a relationship using regression analysis with biomass as the dependent variable. Then, a rapid assessment of indirect attribute is made. Finally, the collected data is converted into biomass values using previously established regression equation. However, following demerits have been observed in this method:

1. The relationship between indirect variables and biomass is generally restricted in their applicability to the time and place where the preliminary data was collected i.e the relationship is site specific and cannot be replicated to other sites.

2. Another drawback is in order to establish relationship between biomass and indirect variables such as rainfall, data of biomass and rainfall should be concurrently gathered for a number of years (University of Arizona, 2016)

2.1.4 Remote Sensing based Measurements

Remote sensing “is the study and activity of collecting and interpreting information about features from a distance location”, and is the cost effective source for obtaining continuous data of large area (Brewer et al., 2012). Various remote sensing based systems have been developed which range from space borne to air borne systems. Selection of the system requires the understanding about their properties such as spatial resolution, number of spectral bands, temporal frequency and cost for acquiring it (Brewer et al., 2012).

Although different remote sensing systems have been developed, no systems can directly measure biomass. They simply record the energy reflected from ground. Therefore, to estimate biomass, additional ground based data is needed. Based on the relation between spectral response and ground based data (biomass), biomass of large area is calculated (Brewer et al., 2012).

Remote sensing systems have comparative advantages over other systems for measuring biomass as it provides data of any site and of any time. The digital format of the data helps for faster processing of voluminous data of large area. Further, there is a high correlation between spectral bands and vegetation parameters. This makes remote sensing an effective means to calculate biomass, especially in areas of difficult terrain (Pokhrel, 2015).

Different remote sensing systems are discussed as follows.

2.1.4.1 Optical Sensor based System

Optical sensors are passive sensors (Pokhrel, 2015). According to Yeung & Lo (2002), passive sensors “sample emitted and reflected radiation from ground surfaces when the energy source is independent of the recording instruments”. Optical sensor data are widely used to link AGB measurement from field and estimate AGB of large area (Pokhrel, 2015). Lu et al (2004), Heiskanen (2006), Jin et al (2004), Bajrachary (2008) and Zhu & Liu (2014) used different optical sensor data such as LANDSAT, SPOT, ASTER, MODIS, AVHRR to estimate biomass.

Different methods have been developed for estimating AGB using optical sensor data. Lu et al (2014) reviewed different literatures and concluded that VIs, texture measures and spectral mixture analysis (SMA) are used to estimate AGB. Lu et al (2014), Bajrachary (2008) and Zheng et al (2004) found that AGB can be estimated using the regression equation between VIs and AGB obtained from the field. Although different VIs have been developed, Anderson & Hanson (1992), Lu et al (2004), Sader et al (1989) and Mundava et al (2014) found that the relation between VIs and AGB depends on various factors, including local environment. The relation between different VIs and AGB have been discussed in sub-chapter 2.2.

2.1.4.2 Active Microwave Sensor based System

Active microwave sensors are active sensors. Active sensors broadcast a directed pattern of energy to illuminate a portion of the Earth's surface, then receive the portion scattered back to the instrument (Campbell & Wynne, 2011). Active microwave sensors are radar devices that transmit repetitive pulses of microwave energy at a given frequency and then receive reflected signals to form image (Campbell & Wynne, 2011). Sinha et al (2015) found that active microwave sensors have comparative advantages over optical sensor, especially in areas where there is frequent cloud cover. Optical sensor cannot penetrate the cloud, but active microwave sensor can penetrate the cloud and produce images of ground. According to Campbell & Wynne (2011), active microwave sensor data are not affected by solar illumination as they generate their own energy. There are different types of microwave sensors such as Side looking airborne radar (SLAR), Synthetic aperture radar (SAR), Polarimetric SAR Interferomtery (Pol-InSAR) etc, which emit energy of different wavelength.

SAR data is very useful in extracting information of forest stand parameters. Ghasemi et al (2011) studied how SAR data are used to study forest stand parameters. They found that SAR data are acquired in X, C, L and P bands, and each of these band has their own characteristics in relation to forest stand parameters. X band is useful to extract information of trees canopy as X band is scattered by leaves and canopy surface. C band is scattered by small branches, but penetrates through the leaves. L band is scattered by the trunk and main braches. P band has the highest penetration capacity. It is scattered by trunk and trunk ground reflectance. Therefore, P and L bands are most related to biophysical parameters of the trees. Generally, C, L and P bands are used for AGB estimation, but P and L bands that have higher wavelength and HV (emitted signal has horizontal polarization and backscattering signal has vertical polarization) polarization are the most sensitive to AGB.

Although SAR data is sensitive to forest stand parameters (AGB), Mette et al (2003) found that SAR data does not allow biomass inventory of forests with higher biomass level. It is suitable to estimate biomass below 150 tons/ha.

Mette et al (2003) studied how Pol-InSAR is used to calculate AGB of forest. They found that Pol-InSAR is very sensitive to forest parameters, and is based on the combination of radar polarimetry and SAR interferometry. It helps to estimate AGB based on height estimates obtained from single frequency Pol-InSAR data as height has a significant relation with AGB.

Lu et al (2014) reviewed different literatures on microwave sensor data and found that it is difficult for microwave sensor to distinguish vegetation types as radar data reflects the roughness of land cover surfaces instead of difference between vegetation types. The sensor further suffers from speckle problems which affect accurate AGB estimation (Lu et al., 2014).

2.1.4.3 Light Detection and Ranging Sensor based System

Light Detection and Ranging (LIDAR) is an active sensor that provides precise 3D information of terrain and vegetation (Gautam & Joshi, 2014). LIDAR imagery is acquired in parallel strips that match to form a continuous image of a region. LIDAR instrument uses pulse lasers to generate pulse. By measuring the time delay (travel time) for emitted and received pulses, information is generated (Campbell & Wynne, 2011).

Karna (2012) and Gautam & Joshi (2014) used LIDAR to study vegetation characteristics and concluded that it can be used to study the vegetation characteristics, including AGB.

Popescu (2007) found that LIDAR can directly measure height and precise geo location of trees, which helps it to access vegetation characteristics and AGB. Lu et al (2014), Karna (2012) and Jochem et al (2010) reviewed methods to estimate AGB using LIDAR. They found that generally, "Single tree based approach and Area based approach" are used to estimate AGB. Both of these approaches use a regression model, based on relationship between LIDAR derived individual tree parameter such as height and field based AGB, to estimate AGB. The difference between them is the requirement of number of point densities. Single tree based approach requires LIDAR data with high point densities (above 5 points per square meter), whereas Area based approach requires less point densities, but requires extensive set of reference data.

Although LIDAR can be used to measure AGB, Lu et al (2014), Nga (2010) and Garcia et al (2012) concluded that LIDAR has several constraints because of the cost and data availability. LIDAR data of specific area of different time period might not be available and taking data of different time period is comparatively expensive than other remote sensing data. Due to the high cost of LIDAR data, it is restricted to small area to estimate AGB. ICESAT GLAS, a space borne LIDAR, was available from 2003 to 2009 to estimate AGB at regional and global level, but it could map the AGB when combined with optical satellite imagery only.

2.1.4.4 Videography: Plot Level Estimation

Videography was used to estimate biomass in closed tropical forest, tropical pine savannah in Belize and homogenous temperate forest in Mississipi. Videography measures biomass using data from video and ground data. For this, airborne video camera tied with GPS and IMU data for positional information is used. Data from video system along with navigational information such as location, altitude and heading is used to create fine scale imagery. Special hardware and software is used to view the image in stereo and AGB measurement can be estimated. For this, reference data on AGB is necessary. However, this is applicable in very small areas (few square kilometer), and requires trained analyst (Brewer et al., 2012).

Brown (2005) studied the cost effectiveness of videography using multispectral three dimensional aerial digital imagery system, M3DADI, in estimating AGB and carbon of pine savannah in Belize. They found that videography was more cost effective than conventional field approach for estimating AGB and carbon. The field approach took three times more person hours than the videography approach. However, Brewet et al (2012) found that this method requires trained manpower to analyze the data, which makes it costly than field approach for estimating AGB and carbon.

2.2 Relation between VIs and AGB

Anderson & Hanson (1992) studied the relation between VIs (Ratio and NDVI) and AGB in different months for two consecutive years. They found that the relation between VIs and biomass depends on season. Ratio had the highest relation with AGB among all VIs. In the month of July, Ratio had the highest relation with AGB ($r^2 = 0.44$), while the relation was insignificant in the month of October. NDVI also had similar results. NDVI had the highest relation with AGB ($r^2 = 0.36$) in the month of June, while the relation was insignificant in the month of October. In July, r^2 for NDVI was 0.29. They accounted various reasons for the change in relationship. Amount of greenness, background soil condition, background vegetation, atmospheric condition were some of the reasons that cause the relation to fluctuate.

Richardson & Everitt (1992) studied the relation between distance based VIs and biomass in rangeland ecosystem. Honey mesquite (*Prosopis glandulosa Torr*.), fringed signal grass [*Brachiaria ciliatissima (Buckl*.) Chase], fringeleaf paspalum (*Paspalum setaceum Michx*.), hooded windmillgrass (*Chloris ucullata Bisch.),* knotgrass *[Setaria firmula (Hitchc. & Chase)* Pilger were some of the plant species present in the areas. They found a significant relation between VIs and biomass, with all the VIs having similar relation with biomass (r of PVI = 0.8, r of SAVI = 0.805, r of $SAVI_2$ = 0.8).

Roy and Rayan (1996) studied the relation between VIs and AGB using Landsat TM in the months of November and January. They found that relationship is depended upon season. The relation between Middle Infrared Index and AGB in January was significant ($R^2 > 0.59$), but the correlation decreased to less than 0.29 in the month of November. The significant relation in January was due to variation in canopy moisture level and more pronounced influence of MIR values due to woody biomass. The poor relation in the month of November was attributed to the presence of foliage in the canopy. The relation between NDVI and AGB also differed in both seasons, however, NDVI did not show a significant relation with AGB (r^2= 0.21 to 0.46).

Kryvobok (2000) studied the relation between VIs, Ratio and NDVI, and biomass of wheat using ResourceSat satellite imagery. He found that Ratio and NDVI had positive relation with biomass i.e when the VI values increased, the biomass also increased. However, Ratio had higher relation with biomass (r = 0.79) compared to NDVI (r = 0.61).

Araujo et al (2000) studied the relation between VI, SAVI, and AGB of forest and savanna in Brazil Amazonia using Landsat TM. They found that SAVI had significant relation with AGB of forest ($r^2 = 0.800$), whereas it did not have significant relation with AGB of Savanna vegetation ($r^2 = 0.1622$). The low relation in Savanna vegetation was due to the presence of low foliage cover, leaf material with higher percent of non-photosynthetic capacity in Savanna vegetation. Forests had higher relation because forest had homogenous canopy cover, with pioneer species that were photosynthetically active.

Dong et al (2003) studied the relation between NDVI and biomass, and ability of regression models to represent the relation between the two variables using Advanced Very High Resolution Radiometers (AVHRR). They found that NDVI and biomass had a statistically meaningful relation, and the regression models can be used to estimate biomass across spatial, temporal and ecological scales for relatively long time scales. Biomass estimated using the relation were statistically significant when compared with biomass generated from field data.

Lu et al (2004) studied therelation between different VIs and AGB in Bragantina, Altamira and Pedras using Landsat TM. They found that biophysical environment of the study area significantly affects the relation between AGB and VIs. The relation between VIs and AGB was highest in Bragantina and Pedras, compared to Altamira. Highest positive correlation (r = 0.815) was found between VI (Principal Component1- PC1) and AGB at Pedras. In Altamira and Bragantina, the relation between PC1 and AGB was found to be negative (r = -0.815). VI, Ratio had the highest relation with AGB in Bragatina (r = 0.505), whereas it had the lowest relation in Altamira (r = 0.124). VI, NDVI, had the highest relation with AGB inBragatina (r = 0.459), and lowest relation in Altamira (r = 0.157). VI, SAVI, had the highest relation with AGB in Bragatina (r = 0.434), and lowest relation in Pedras (r = 0.166). VI, MSAVI, had the highest relation with AGB in Bragatina (r = 0.435), and lowest relation in Altamira (r = 0.157).

Zheng et al (2004) studied the AGB of hardwood and pine forests in Northern Wisconsin, USA, using Landsat ETM+. The study incorporated six individuals bands (Blue to middle infrared bands), and five vegetation indices (ratio of blue and red, NDVI, Ratio, MSAVI and corrected NDVI (NDVIc)). They estimated the AGB by developing a regression equation incorporating different bands, vegetation parameters and VIs. The study found that AGB for hard wood forest was strongly related to stand age and NIR band with r^2 of 0.95, while AGB for pine was strongly related to NDVIc (r^2 = 0.86).

Heiskanen (2006) studied the relation between VIs and AGB in mountain birch forest, Finland, using ASTER satellite imagery. They found that all the VIs had significant relation with AGB. Ratio had the highest relation with AGB ($r = 0.902$, $r^2 = 0.81$), while MSI had the least and negative relation with AGB ($r = -0.805$, $r^2 = 0.65$). NDVI, DVI, RDVI, SAVI had correlation coefficient values of 0.817, 0.834, 0.831, 0.832 respectively and coefficient of determination values of 0.67, 0.70, 0.69, 0.69 respectively.

Liu et al (2006) studied the relation between biomass and VIs in Oasis ecosystem in Fukangm, China, using MODIS satellite imagery. The vegetation of the oasis ecosystem consists of farmland and wilderness. From south to north, the region is covered by Pipa firewood wilderness, juiciness salt firewood class wilderness, fan reason Chinese tamarisk clump, sand dune’s Sacsaoul, and white sacsaoul wilderness. They found a significant relation between VIs and biomass. NDVI had the highest relation ($r = 0.862$, $r^2 = 0.743$) with biomass, while Difference vegetation index (DVI) had the lowest relation with biomass ($r = 0.807$, $r^2 = 0.651$). MSAVI had correlation coefficient values of 0.852 and coefficient of determination value of 0.726.

Maynard et al (2006) studied the relation between VI and AGB using Landsat TM. They found that tasseled cap had higher relation to AGB ($r^2 = 0.51$) than NDVI and SAVI. SAVI had r^2 of 0.51, while NDVI had r^2 of 0.41 with AGB.

Bajracharya (2008) studied the relation between different VIs and AGB in *Schima-Castanopsis* dominant forest using ASTER imagery. When sample plot data and satellite imagery of different years (four years difference, ASTER of 2004, and sample plot data of 2007) were used, a weak relation was obtained between VIs and AGB. The r^2 values for NDVI and Ratio was 0.028 and 0.0175 respectively. Similar was the result with other VIs. Season and change in vegetation density between the periods were accounted for the low relation. When sample plot data of 2004, 2005 and 2006 were used, the relation improved significantly. The r^2 values ranged from 0.3 to 0.59. Ratio had higher relation with AGB compared to NDVI and other VIs in all the three years. Table 1 summarizes relation (r^2) between VIs and AGB in different years.

Table 1 Relation between VIs and AGB in different years

Year	NDVI	Ratio
2004	0.327	0.445
2005	0.506	0.598
2006	0.3303	0.3772

Source: Bajracharya (2008)

Edirishnghe et al (2011) also studied the relation between VI, NDVI, and AGB in pasture of Australia using Landsat satellite imageries. They found that AGB of pasture has significant relation ($r^2 = 0.84$) with NDVI.

Das & Singh (2012) studied the relation between VI and AGB in the forests of Maharashtra, India, using Landsat TM. They found that all the VIs had significant relation with AGB, and Ratio had the highest relation with AGB ($r^2 =0.785$) and was most suitable for estimating AGB. MSAVI had the lowest relation with AGB ($r^2 = 0.676$), while NDVI had r^2 of 0.75 with AGB. They found that the study area had large amount of photosythetically active vegetation and Ratio was more sensitive to contrast between Red and NIR reflectance. Due to this, Ratio showed highest relation with AGB compared to other VIs.

Jin et al (2014) studied the relation between VIs and biomass in grassland of Xilinolleague, China, using MODIS satellite imagery. In the region, there were nine types of grassland, but for simplicity, the grassland was categorized into three types, Meadow steppe region, typical steppe region and desert steppe region. The study showed that VIs and biomass had a significant relation in all the regions. Highest relation was obtained between biomass and NDVI ($r = 0.791$) in typical steppe region, and lowest relation was obtained between biomass and NDVI in desert steppe region ($r = 0.686$). In meadow steppe region, correlation coefficient of 0.731 was obtained for NDVI. SAVI and MSAVI also had similar pattern of relation with biomass. In meadow steppe, typical steppe and desert steppe regions, SAVI had correlation coefficient values of 0.711, 0.743 and 0.702 respectively, and MSAVI had correlation coefficient values of 0.708, 0.728 and 0.702 respectively.

Zhu & Liu (2014) studied the relation between VI, NDVI, and AGB in different seasons in Ohio, and found a positive relation throughout the year, except on April. The relation was significant ($r^2 = 0.63$) during the months of September and October, which are the senescing periods for the vegetation. The correlation in the senescing period was high compared to peak season, June, where vegetation attains its maximum leaves or greenness. The weaker correlation in peak season was due to saturation of NDVI values in dense canopy. When vegetation is dense and there is maximum greenness, red reflectance remains almost constant, but NIR reflectance increases continuously, which causes the NDVI values to saturate.

Mundava et al (2014) studied the relation between VIs and AGB using Landsat ETM+ in open plains, bunch grasses and spinifix in Western Australia. Open plains are areas with periodic flooding dominated by annual grasses, bunch grasses are dominated with perennial grasses, and spinifex sites are dominated by hard of soft spinifex (*Triodia spp.).* They found the relation is site specific and relation depends upon biophysical environment of the study area. In open plains area, the relation between AGB and VIs (SAVI and NDVI) were high (r^2= 0.6). Bunch grasses had a relation of 0.4 (SAVI and NDVI), while Spinifex had very low relation with VIs (0 for SAVI and 0.1 for NDVI).

Goswani et al (2015) studied the relation between VI, NDVI, and AGB in six different plant species,*Arctophila fulva, Carex aquatilis, Dupontia fisheri, Eriophorum angustifolium, Eriophorum scheuchzeri and Petasitesfrigidu*, in Barrow, Alaska. They found that NDVI had a significant relation with AGB of all the plant species. AGB of *Dupontia fisheri* had the highest relation with NDVI ($r^2 = 0.87$), followed by *Arctophila fulva* (0.82) and *Petasites frigidus* (0.77). AGB of *Eriophorum scheuchzeri* had the lowest relation with NDVI (0.50).

Gunlu et al (2014) studied the relation between VIs and AGB in Anatolian pine forest of Turkey using Landsat TM. They found that VI derived from Landsat TM bands were more successful for AGB prediction than from individual Landsat TM band reflectance as VIs can maximize the sensitivity for recording green vegetation situation. Enhanced vegetation index (EVI) and Normalized difference between band 5 and 7 (ND57), had significant relation with AGB (Adjusted $R^2 = 0.606$). Band 1 had a negative relation with AGB, while Band 2 had a positive relation.

2.3 Image Classification

Lilesand et al (2008) defined image classification as the process of automatically categorizing pixels of an image into land cover classes or themes. Traditionally, classification was performed by visual interpretation of features and manual digitization of boundaries. However, with advancement in technologies, classification focused on computer assisted interpretation (Eastman, 1999a). Generally, multispectral data are used for classification and the spectral pattern of each pixel is used as the numerical basis for categorization. Spectral pattern refers to the set of radiance measurements obtained in various wavelength (different bands) for each pixel of the band. Spectral pattern recognition utilizes pixel by pixel spectral information as the basis for automated land cover classification. In case of spatial pattern recognition, image pixel are categorized on the basis of their spatial relationship with their pixel surrounding them. Image texture, pixel proximity, feature size, shape etc. are taken into consideration for classifying image (Lilesand et al., 2008). Different methods of classification have been developed for image classification. Unsupervised, supervised and object based classification are commonly used for classification.

Unsupervised classification uses spectral pattern for classification. In unsupervised classification, a clustering algorithm automatically finds and defines a number of clusters in the feature space. The algorithm searches for pixels with similar reflectance characteristics or pixels are grouped based on reflectance characteristics (ITC, 2004).

In supervised classification, user defines the spectral characteristics of the class by identifying sample areas (training sites). Then the algorithm uses the training sites to identify classes in the image (ITC, 2004).

Object based classification involves segmenting an image into objects. Apart from imageries, image derivatives like PCA, VI, ancillary data like DEM can be used for classification in object based classification (Lawrence & Wright, 2001). It uses both spectral and spatial pattern for classification (Lilesand et al., 2008).

Choosing the correct classification method is a complicated task. Various studies have been made for choosing the correct classification method. Weih and Riggan (2010) compared the object based classification method with supervised and unsupervised pixel based classification methods, and found that object based classification had the highest accuracy. Two multi temporal (leaf on and leaf off) medium spatial resolution SPOT-5 satellite images and a high spatial resolution color infrared digital orthophoto was used for the study. "Leaf on" refers to image taken on winter, while "leaf off" refers to image taken on spring. The images were merged to evaluate the relative importance of multi temporal and multi spatial imagery for classification accuracy. Three different combinations were created. First combination included the combination of high spatial resolution image and SPOT 5 image (leaf on and leaf off). Second combination included high spatial resolution image and SPOT 5 image (leaf off). Third combination included SPOT 5 image with leaf on and leaf off. The object based classification obtained the highest overall accuracy of 82% when first combination was used. When second combination and third combination was used, accuracy of 78.2% and 66.1% was obtained respectively. Supervised classification obtained an accuracy of 66.9% when first combination was used. When second combination and third combination was used, accuracy of 71.8% and 64.4% was obtained respectively. Unsupervised classification produced the least overall accuracy among all classification methods. When first combination was used, the overall accuracy obtained was 64.4%. When second and third combination was used, accuracy of 41.5% and 60.1% was obtained respectively.

Dehvari & Heck (2009) compared the accuracy of object based classification and pixel based classification. They found that land cover classes obtained from pixel based classification showed salt and pepper effect and produced lower accuracy of 59.5%. In contrast to this, the object based classification produced accuracy from 80 to 90%.

Whiteside & Ahmad (2005) compared the accuracy of object based classification and pixel based classification. They found that land cover classes obtained from object based classification had higher accuracy of 78% compared to pixel based classification that had an accuracy of 69%.

Chapter 3 Methodology

This chapter discusses the materials and methods used for the study.

3.1 Materials

3.1.1 Data

3.1.1.1 Satellite Imagery

Satellite imagery of 5 m resolution (ResourceSat-2, Scene ID: RS2-LISS4-24-Jan-2015-104-52, acquired on January 24, 2015) was obtained from India Space Research Organization through GEOID consult. ResourceSat-2 is a “data continuity mission of ISRO (Indian Space Research Organization) with improved spectral bands of the IRS-P6/ResourceSat-1” (ESA, 2016).The metadata of the satellite imagery is presented in Table 2.

Table 2 Metadata of ResourceSat-2 image

Specification	
Acquired date	January 24, 2015
Spectral bands (µm)	B2:0.52-0.59,(green) B3:0.62-0.68,(red) B4: 0.77-0.86 (NIR)
Resolution (m)	5

3.1.1.2 Digital Elevation Model

Digital elevation model (DEM) of 30 m resolution (ID: SRTM1N27E085V3), acquired on February 11, 2000, was obtained from Shuttle Radar Topography Mission (SRTM) for ortho-rectification, and was obtained from USGS (USGS, 2016). DEM from SRTM was used as it is freely available, and it produces better topographic data than ASTER data, another freely available DEM (Wilson et al., 2014).

SRTM uses single pass interferometry, which acquires two signals at the same time by using two different radar antennas. One data set is collected by an antenna on board space shuttle, while the other data set is collected by antenna located at the end of a 60 meter mast extended from the shuttle. Based on difference between the two data or signal, surface elevation is calculated (USGS, 2015). The metadata of downloaded SRTM DEM is provided in Table 3.

Table 3 Metadata of SRTM DEM

Projection	Geographic
Acquired Date	February 11, 2000
Horizontal Datum	WGS84
Vertical Datum	EGM96 (Earth Gravitational Model 1996) ellipsoid
Vertical Units	Meters
Spatial Resolution	1 arc-second for global coverage (~30 meters)
Raster Size	1 degree tiles
C-band Wavelength	5.6 cm

Source: (USGS, 2016)

3.1.2 Equipments

Different equipment's were used to collect data in the field. The list of equipment's are provided in Table 4.

Table 4 List of field instruments used in the field

S.N	Equipments	Purpose
1	Garmin GPS (Etrex summit HC)	Geo-Positioning
2	Diameter tape	Measure DBH of tree
3	Clinometer	Measure Height of tree

3.1.3 Software

Following software's (Table 5) were used for performing spatial and statistical analysis.

Table 5 Software's used for completion of the study

S.N	Software	Purpose
2	E-cognition	Image segmentation and classification
3	ArcGIS	Cartography, spatial analysis
4	R	Statistical analysis

3.2 Methods

3.2.1 Pre-Field Work

3.2.1.1 Sampling Design

Sampling is a means of selecting a subset of units from a target population for the purpose of collecting information from the entire population (Statistics Canada, 2015). The accuracy of the result depends on sampling, therefore sampling design was done prior to sampling. Sampling design is "the protocol for selecting the subset of spatial units that will form the basis of accuracy assessment" (Olofsson et al., 2014).

a. Sampling Type

There are different types of sampling methods, however, stratified random sampling was followed for this study because the southern aspect of the study area was homogenously covered by *P. roxburghii.* A stratified random sample is "a random sample in which members of the population are first divided into strata, then are randomly selected to be a part of the sample" (Study.com, 2016). It is generally used when one can divide study area into separate and relatively homogeneous sections (Oregon State University, 2007), or when one is interested in particular strata of a population (Lund Research, 2012).

b. Sample Size

Identifying correct sample size is very important for representing a population. Soerianegara and Indrawan (1978) reviewed different quadrant size to sample vegetation based on the type of vegetation. Table 6 shows the different quadrant size proposed by different researchers.

Table 6 Quadrant size for sampling

Vegetation	Size of quadrant	Authors
Trees	100 m^2 (10 * 10)	Oosting 1942
Shrubs and seedlings <3m	16 m^2	Oosting 1942
Herbs	1 m^2	Oosting 1942
Trees	2000 m^2	Gates 1949
Shrubs and samplings	200 m^2	Gates 1949
Herbs and seedlings	40 m^2	Gates 1949
Trees	400 m^2	Wyatt-Smith 1959
Young trees with trunk diamtere < 4 inch	100 m^2	Wyatt-Smith 1959
Trees	1000 m^2	Soeriangara 1967
Shrubs and saplings	100 m^2	Soeriangara 1967
Herbs and seedlings	10 m^2	Soeriangara 1967

Source: (Soerianegara and Indrawan, 1978)

In this study, quadrant size of 10 * 10 m^2 as proposed by Oosting (1942) was used for sampling. Taking sample plots greater than 10 * 10 m^2 was not possible in the study area as there were steep slopes. Within the sample plot, diameter at breast height (DBH) and height of *P. roxburghii* was taken because AGB calculation requires the data of DBH and height of the tree. Sample plots were laid only in areas where *P. roxburghii* is homogenously present.

c. Number of Sample Plots

The minimum number of sample plots were determined using Equation 1 proposed by Husch et al (2003).

$$N = t^2 * CV^2 * (1/E)^2 \qquad \text{Equation 1}$$

Where,

N = Minimum number of sample plots

t^2 = Value of student's t distribution for N plots at desired probability

CV^2 = Coefficient of variation (in percent) of DBH of trees

E = estimated allowable error (in percent)

Based on Equation 1, it was determined that a minimum of 34 sample plots were required at 95 % Confidence interval (CI).

3.2.2 Field Work

Field visit was conducted in the month of January, 2016. 10 * 10 m^2 quadrants (sample plots) were laid on the strata consisting of *P. roxburghii,* and DBH and height of trees within the quadrant were measured. GPS point of each quadrant was taken in center of the quadrant.

3.2.3 Data Analysis

The data collected in the field were analyzed to calculate AGB of *P. roxburghii.* Following equations were used to calculate the AGB.

3.2.3.1 AGB Calculation

AGB is calculated from the volumetric and structural dimension of the trees. DBH and height are the major parameters for measuring AGB (Pokhrel, 2015). AGB of *P. roxburghii* of sample plots was calculated using Equation 2 proposed by DFRS (2014).

$$AGB = \text{Stem biomass} + \text{Branch biomass} + \text{Foliage biomass} \qquad \text{Equation 2}$$

Stem biomass is the product of stem volume and air dried wood density of tree species, and was calculated using Equation 3 proposed by Sharma & Pukkala (1990).

$$\text{Stem biomass} = \text{Volume} * \text{Density} \qquad \text{Equation 3}$$

Where,

Volume = stem volume in cubic meters

Density = Air dried wood density.

The air dried wood density suggested by (DFRS, 2014) was used. The air dried wood density of *P. roxburghii* is 650 kg/m^3

Stem volume is a “function of a tree's height, basal area, shape, and depending on definition, bark thickness” (Australian National University, 1999). Stem volume was calculated using Equation 4 (Sharma & Pukkala, 1990; DFRS, 2014; Pokhrel, 2015).

$$\ln(V) = a + b \ln(D) + c \ln(H) \qquad \textit{Equation 4}$$

where,

ln = Natural logarithm to the base 2.71828

V = Stem volume

D = DBH in cm

H = Tree height

a, b, and c are coefficients, where a = -2.977, b = 1.9235 and c = 1.0019 for *P. roxburghii.* The obtained volume was divided by 1000 to convert it into cubic meter (DFRS, 2014; Pokharel, 2015).

Branch and foliage biomass were calculated using branch to stem biomass ratio and foliage to stem biomass ratio as proposed by MoFSC (1988). The ratio depends on the DBH of tree species. The branch to stem and foliage to stem ratio for *P. roxburghii* computed by MoFSC (1988) is presented in Table 7.

Table 7 Branch to stem and Foliage to stem ratio

Branch to stem ratio			Foliage to stem ratio		
DBH < 28 cm	DBH = 28-53 cm	DBH > 53 cm	DBH < 28 cm	DBH = 28-53 cm	DBH > 53 cm
0.189	0.256	0.3000	0.101	0.046	0.033

Source: (MoFSC, 1988)

3.2.4 Image Processing

3.2.4.1 Image Ortho-rectification

The topographic variation on the earth surface and the tilt of satellite or aerial sensor affects the distance with which features on the satellite are displayed. When the sensor is not pointing directly at nadir of the sensor, image data acquired are affected by systematic sensor and platform induced geometry that results in terrain distortion. The distortion can be from a meter to hundreds of meters. Flat land has less distortion compared to areas with diverse topographic landscape (Satellite Imaging Corporation, 2015). To remove such distortion, ortho-rectification is done.

Ortho-rectification is the process of removing distortion due to terrain relief and off vertical imaging geometry. It creates an ortho-image that has features positioned as they would be in planimetric map (Smith, 2015).

ResourceSat-2 image was ortho-rectified using Rational polynomial coefficient (RPC) supplied by image vendor, ground control points and DEM. RPC is “one of type of replacement sensor model, which replaces the rigorous sensor with an approximation of the ground to image relationship.” They relate pixels locations in an image to the corresponding latitude, longitude and elevation (Harris Geospatial Solution, 2016). The accuracy of the ortho-rectified image was 1.2019 m (less than 1 pixel). The image before and after ortho-rectification is presented in Figure 1.

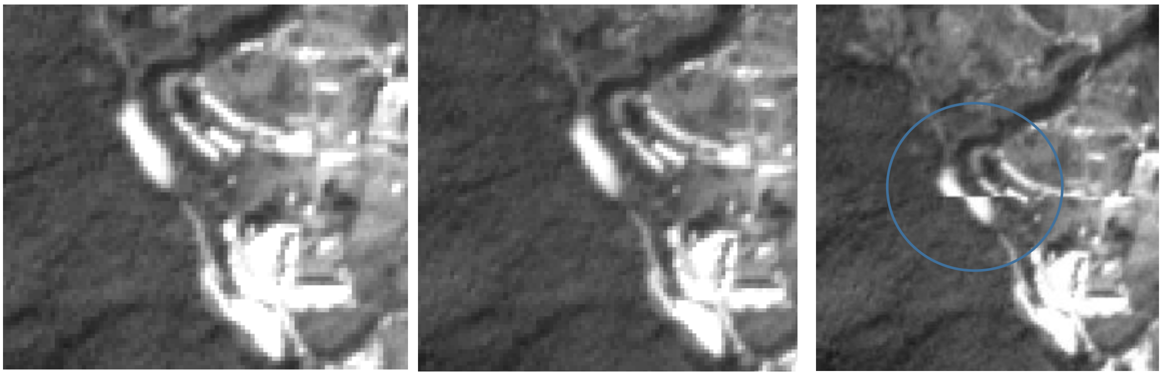


Figure 1 Image ortho-rectification

Image before ortho-rectification (left), Image after ortho-rectification (middle), Image showing displacement of image before and after rectification using Swipe tool (right).

3.2.4.2 Atmospheric Correction

Atmosphere consists of water vapour, aerosols and gases that disturb the signal or radiation reaching the sensor from the ground. The atmospheric particles effect the radiance received at the satellite by scattering, absorbing and refracting process. This changes the actual radiance value, which subsequently affects the extraction of information from the image (Chavez, 1996; Mahlny & Turner, 2007). Therefore, atmospheric correction is an important step in preprocessing remotely sensed data, especially for visible bands of shorter wavelength (Mustak, 2013). Atmospheric correction can be defined as the process of removing the distortion, due to atmospheric particles, from the radiation received by the sensor from the ground (Chavez, 1996; Mahlny & Turner, 2007).

Atmospheric correction was done using COST model developed by Chavez (1996). The model uses cosine of sun zenith as an acceptable parameter for approximating the effects of absorption by atmospheric gases and Rayleigh scattering. The model first converts DN of the images to radiance using Equation 5.

$L_{sat}= (L_{min}+ (L_{max}- L_{min})/DN_{max})\ DN$ Equation 5

Where,L_{sat} = the spectral radiance at the sensor

L_{min} = Minimum spectral radiance for a given band

L_{max}= Maximum spectral radiance for a given band,

DN_{max} = Maximum digital number of the image range.

The radiance is then converted to surface reflectance by correcting solar (includes corrections for sun elevation angle, amount of solar irradiance for the individual spectral bands and earth sun distance) and atmospheric effects. The image after correction is presented in Figure 2.

$Ref = л * D^2 * (L_{sat} - L_{haze}) / (E_0 * cos\ TZ * TAUZ)$ Equation 6

Where,

Ref = Spectral reflectance of the surface that we want

Л = Constant equal to 3.141593

D = Earth-sun distance

L_{sat} = the spectral radiance at the sensor

$L_{haze =}$ Atmospheric scattering for given spectral band (i.e, path radiance) and is determined by dark object minimum DN values extracted from the image

E_0=Solar irradiance for given spectral band (equal to the total amount of radiance coming in for the given band)

TZ = Solar zenith angle

TAUZ = Atmospheric transmittance along the path from the sun to the ground surface (atmospheric absorption) (Chavez, 1996; Mahlny & Turner, 2007; Chavez, 2014).

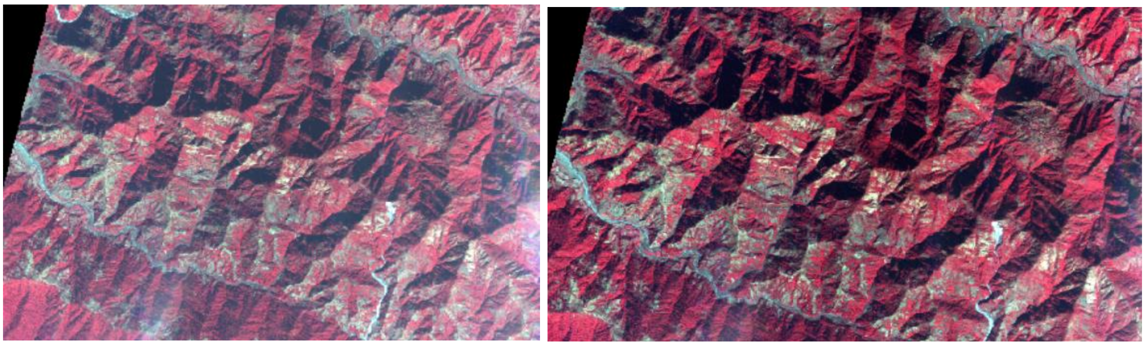


Figure 2 Image before (left) and after (right) using COST Model

3.2.4.3 Vegetation Indices

Plant canopies have distinctive interaction with the energy in visible and NIR regions. In the visible region, plant chlorophyll strongly absorbs energy for the purpose of photosynthesis. The absorption is high in red region of visible spectrum. In the NIR region, the energy is not used for photosynthesis, but is strongly scattered by the internal structure of leaves. This leads to high apparent reflectance in the NIR. This strong contrast between amount of energy reflected in red and NIR region has helped to develop vegetation indices (Eastman, 1999a).

Vegetation indices (VIs) are the combination of different spectral bands, usually red and NIR, of satellite data that produce a single image representing the amount of vegetation present. Low index value represents little healthy vegetation, while high value represents higher healthy vegetation. VIs are used to estimate AGB, monitor environmental changes and land degradation (Kogan, 1990; Kogan & Liu, 1996; Tripathy et al., 1996). Jackson & Huete (1991) classified VIs into two groups: (1) slope-based and (2) distance-based VIs. Sloped based VI and distance based VI have been used in the study.

a. Slope based Vegetation Indices

Slope based VI is the simple linear combination that uses the reflectance of red and NIR spectral bands and focuses on the contrast between the spectral response pattern in the red and NIR portion of electromagnetic spectrum. The term “Slope based” was coined because any value of the index can be produced by a set of red and NIR reflectance values that form a line emanating from the origin of a bi-spectral plot.” It is used to study the status and abundance of vegetation cover and AGB. (Eastman, 1999a). Ratio Vegetation Index, Normalized Difference Vegetation Index, Transformed Vegetation Index, Corrected Transformed Vegetation Index and Thiams Transformed Vegetation Index are some of the slope based vegetation indices that have been used in the study.

Ratio Vegetation Index

Ratio Vegetation Index (RATIO) was proposed by Rouse et al (1974) to separate green vegetation from soil background. It is the ratio of NIR and Red bands (Equation 7).

$$RATIO = NIR / Red \qquad \text{Equation 7}$$

The result clearly captures the contrast between the read and NIR bands vegetation pixel, with higher index values being produced by combination of low red (because of absorption by chlorophyll) and high NIR (as a result of leaf structure) reflectance. The index is susceptible to division by zero.

Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) was proposed by Rouse et al (1974) to produce a VI that differentiates green vegetation from soil. It is the difference between NIR and red bands normalized by the sum of those bands (Equation 8).

$$NDVI = (NIR - Red) / (NIR + Red) \qquad \text{Equation 8}$$

The index value ranges from -1 to 1, where negative values represent non vegetated surface. Division by zero error is significantly reduced in the index.

Transformed Vegetation Index

Transformed Vegetation Index (TVI), proposed by Deering et al (1975), modifies NDVI by adding a constant of 0.50 to all its values and taking the square root of the results. The constant is used to remove the negative NDVI values, while the square root is used to transform NDVI histogram into a normal distribution (Equation 9).

$$\mathrm{TVI} = \sqrt{\mathrm{NDVI} + 0.5} \qquad \text{Equation 9}$$

Corrected Transformed Vegetation Index

Corrected Transformed Vegetation Index (CTVI) was proposed by Perry & Lautenschlager (1984), which aims to correct the TVI. Adding a constant 0.50 to NDVI does not always remove negative values, therefore to remove the negative values, the (NDVI + 0.5) is divided by its absolute value ABS(NDVI + 0.5) and the result is multiplied by the square root of the absolute value (Equation 10).

$$\mathrm{CTVI} = \frac{(\mathrm{NDVI}+0.5)}{\left|(\mathrm{NDVI}+0.5)\right|} \cdot \sqrt{\left|(\mathrm{NDVI}+0.5)\right|}$$

Equation 10

Thiam's Transformed Vegetation Index

Thiams (1997) found that resulting image from CTVI can be noisy due to over estimation of greenness, therefore he suggested using Thiams's Transformed Vegetation Index (TTVI) that ignores first term of CTVI equation and uses ABS(NDVI + 0.5) (Equation 11).

$$\mathrm{TTVI} = \sqrt{\left|(\mathrm{NDVI}+0.5)\right|}$$

Equation 11

b. Distance based Vegetation Indices

Distance based vegetation index "measures the degree of vegetation present by gauging the difference of any pixels reflectance from the reflectance of bare soil." This VI helps to cancel the effect of soil brightness where vegetation is sparse and pixels contains mixture of green vegetation and soil background (Eastman, 1999a). This VI is based on soil line. Soil line represents the description of typical signatures of soils in red/NIR bispectral plot. It is obtained through linear regression of the NIR band against the red band for sample of bare soil pixel. Pixels that fall near the soil line are assumed to be soils, whereas pixels that fall far away from soil line are assumed to be vegetation indices (Eastman, 1999a). Perpendicular Vegetation Index, Vegetation Index, Difference Vegetation Index, Weighted Difference Vegetation Index, Soil Adjusted Vegetation Index and Modified Soil Adjusted are some of the distance based vegetation indices that have been used in the study.

Perpendicular Vegetation Index

Perpendicular Vegetation Index, proposed by Richardson and Weigand (1977), is the parent index from which entire distance based VIs is derived. It is effective in detecting dry and green vegetation. It uses the perpendicular distance from each pixel coordinate to the soil line (Eastman, 1999a). The perpendicular distance is derived based on following steps.

2. Determine the equation of the soil line by regressing bare soil reflectance values for red versus NIR. The equation will be in following form:

$Rg5 = a_0 + a_1 Rg7$ Equation 12

Where Rg5 is Y position on the soil line,

Rg7 is the corresponding X coordinate

a_1 is the slope of soil line

a_0 is the Y intercept of the soil line

3. Determine the equation of the line that is perpendicular to the soil line. The equation will be as follow.

$Rp5 = b_0 + b_1 Rp7$ Equation 13

Where, $b_0 = Rp5 – b_1Rp7$

Rp5 is red reflectance

Rp7 is NIR reflectance

$b_1 = -1/a_1$

where, a_1 is the slope of the soil line.

4. Find the intersection of these two lines (i.e the coordinate Rgg5, Rgg7)

   Where $Rgg5 = (b_1a_0 - b_0a_1)/(b_1 - a_1)$

   $Rgg7 = (a_0 - b_0)/(b_1 - a_1)$

5. Find the distance between the intersection (Rgg5, Rgg7) and the pixel coordinate (Rp5, Rp7) using equation 14.

   $PVI = \sqrt{((Rgg5 - Rp5)^2 + (Rgg7 - Rp7)^2)}$ *Equation 14*

Difference Vegetation Index

Difference Vegetation Index (DVI), proposed by Richardson and Wiegand (1977), weights the NIR band by slope of the soil line (Eastman, 1999a). It is based on equation 15.

$DVI = g\ MSS7 - MSS5$ *Equation 15*

Where, g is slope of the soil line

MSS7 is the reflectance in the NIR band

MSS5 is the reflectance in the visible red band

Weighted Difference Vegetation Index

Weighted Difference Vegetation Index (WDVI) was proposed by Richardson and Weigand (1997). The effect of weighting the red band with the slope of the soil line is the maximization of vegetation signal in the NIR band and the minimization of the effect of soil brightness. The equation of WDVI is as follows (Equation 16)

$WDVI = NIR - y\ Red$ *Equation 16*

Where, NIR = reflectance of NIR band

Red = reflectance of red band

Y = slope of soil line

Soil Adjusted Vegetation Index

Soil Adjusted Vegetation Index (SAVI), proposed by Huete (1998), is intended to minimize the effects of soil background on vegetation by incorporating soil adjustment factor L into the denominator of NDVI equation. The value of L varies with the reflectance characteristics of soil. The value of L depends on the density of the vegetation. For very low vegetation, its value is 1. For intermediate vegetation, its value is 0.5, and for dense vegetation, its value is 0.25 (Eastman, 1999a). The equation of SAVI is as follow (Equation 17):

$SAVI = (NIR - Red) * (1 + L) / (NIR + Red)$ *Equation 17*

Where, NIR is reflectance in NIR band

Red is reflectance in Red band

L is soil adjustment factor

Modified Soil Adjusted Vegetation Index

Modified Soil Adjusted Vegetation Index (MSAVI), proposed by Qi et al. (1999), is based on a modification of the L factor of SAVI. Here L is selected as an empirical function due to the fact that L decreases with decreasing vegetation cover. In order to cancel or minimize the effect of the soil brightness, L is set to be the product of NDVI and WDVI (Eastman, 1999a). The equation of MSAVI is as follow (Equation 18):

$$MSAVI = (NIR - Red) * (1 + L) / ((NIR + Red + L) \qquad \text{Equation 18}$$

Where, NIR = reflectance in NIR band

Red = reflectance in Red band

$L = 1- 2y\ NDVI * WDVI$

Where, NDVI is Normalized Difference Vegetation Index

WDVI is Weighted Difference Vegetation Index

Y is slope of background soil line

3.2.4.4 Image Classification

Image classification is the “process of developing interpreted maps from remotely sensed imagery.” The objective of image classification is to categorize pixels of image into different land use land cover classes (Lilesand et al., 2008). There are different methods to classify image. Unsupervised, supervised and object based classification are some of the methods for classifying image (Weih & Riggan, 2010). In this study, object based classification was used to classify image as it has the highest accuracy (above 80%) compared to supervised and unsupervised classification (Weih & Riggan, 2010; Dehvari & Heck, 2009) Further, it involves segmenting an image into objects, and uses both spectral and spatial pattern for classification (Lilesand et al., 2008). Apart from imageries, image derivatives like PCA, VI, ancillary data like DEM can be used for classification in object based classification (Lawrence & Wright, 2001).

Land Use Land Cover classes- Agriculture, Barren land, Built up, Forest and Water bodies- were present in the area. However, the current study focused on *P. roxburghii* only, therefore, Forest class was subdivided into *P. roxbhurgii* and Broad leaved classes, and all other remaining classes were grouped into other class.

Green, Red and NIR bands, and their derivatives, Principal Component Analysis Component1 (PC1), Ratio and Normalized Vegetation Index (NDVI), were used for image classification. Image bands and their derivatives provide useful information for distinguishing spectrally inseparable vegetation classes and help to increase the accuracy of vegetation classification (Yu, et al., 2006) (Lawrence & Wright, 2001). Multi-resolution segmentation and Classifier algorithm were used for classifying the image.

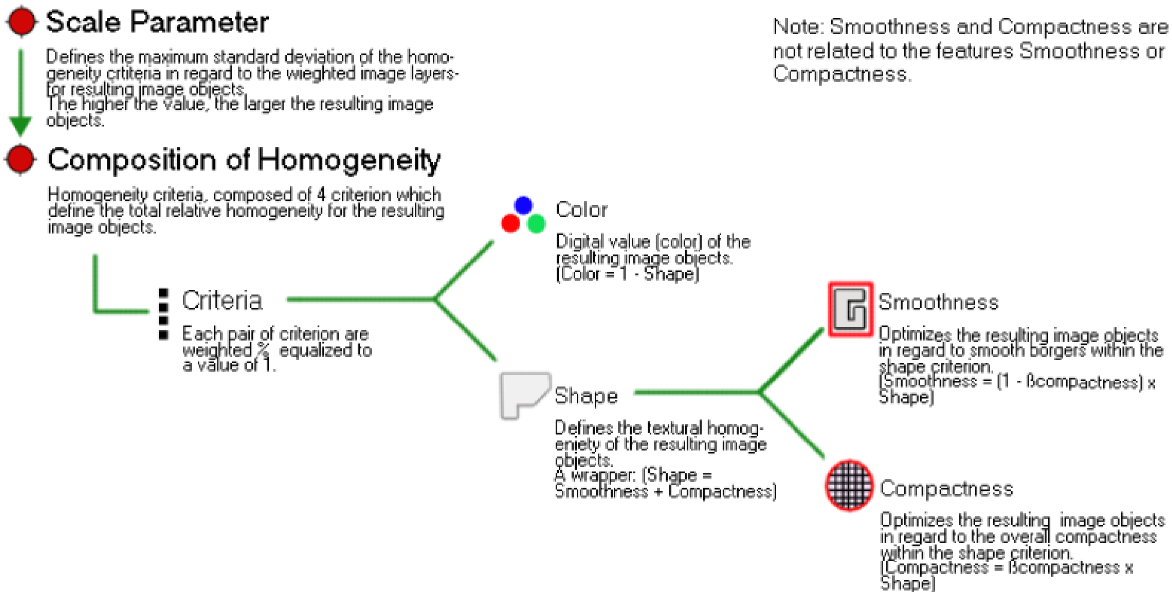
a. Multi-resolution Segmentation Algorithm

Multi-resolution segmentation algorithm is used to minimize the heterogeneity of image objects and maximize the homogeneity by merging pixels or existing image objects. The procedure "starts with single image objects of one pixel and repeatedly merges them in several loops in pairs to larger units as long as an upper threshold of homogeneity is not exceeded locally." The homogeneity is affected by scale and homogeneity criterion (Trimble, 2011).

The scale criterion determines the maximum allowed heterogeneity, and size of image object. Higher values result in larger image objects, while smaller values result in smaller image objects. Homogeneity criterion measures how homogenous or heterogeneous an image object is within itself, and is calculated as a combination of color and shape properties. Color homogeneity is based on standard deviation of the spectral colors, while shape homogeneity is based on deviation of a compact or smooth shape (Trimble, 2014). The concept flow diagram of multi-resolution segmentation is presented in Figure 3.

b. Classifier Algorithm

The Classifier algorithm was used to classify the image using Classification and Regression Tree (CART) statistical classification algorithm which provides higher accuracy compared to other statistical classification algorithms (Fried & Brodley, 1997). Classifier algorithm applies machine-learning functions to the analysis. It is a two-step process, where in step 1, the classifier is trained using the classified objects of image object domain as training samples. In step 2, the trained classifier is applied to the domain, and the image is classified based on the trained parameters (Trimble, 2011).



Source: (Trimble, 2011)

Figure 3 Multi-resolution concept flow diagram

Classification and Regression Tree (CART) Algorithm

CART algorithm is generally “used in data mining, where a series of decisions are made to segment the data into homogenous subgroups” (Trimble, 2011). It is a recursive and iterative process that partitions feature space into smaller parts within which the class distribution becomes homogenous (Yu et al., 2006). It selects useful spectral and ancillary data from the data supplied and predicts the class of the unknown variable forming a tree like structure with several branches (Lawrence & Wright, 2001). The tree consists of a root node that has all the data, a set of internal nodes (splits) and a set of terminal nodes (leaves). The data are recursively splitted until end points or terminal nodes are achieved or until homogenous terminal nodes are reached (Lawrence & Wright, 2001). All variables are analyzed and the binary divisions of single variable that best reduces deviance in the response variable is determined. At each node, binary decisions separate a class or a bundle of classes from remaining classes. Features carrying maximum information are selected in class division at each node and the remaining features are rejected. The process is a top down approach that starts with the first node to the final one (Hanoi & Joensuu, 2012).

In the present study, 78 random sample points collected in the field were used to create training set to train the classifier. To increase the accuracy of classification, features, border index, brightness, maximum difference, asymmetry, compactness, shape index, mean and standard deviation of NDVI, SR, PC1, Green, Red and NIR bands, were used.

Where,

Border index = It describes how jagged an image object is. The more jagged, the higher is the border index (Trimble, 2011)

Brightness = It is the sum of mean values in all bands divided by the number of bands (Hellesen & Matikainen, 2013).

Maximum difference = It is the minimum mean value of an object subtracted from its maximum value. The means of all bands belonging to an object are compared with each other. Subsequently, the result is divided by the brightness. (Trimble, 2011).

Asymmetry = It describes the relative length of an image object compared to a regular polygon (Trimble, 2011).

Compactness = It describes how compact an image object is. The more compact an image object is, the smaller its border appears. The compactness of an image object is the product of the length and the width, divided by the number of pixels (Trimble, 2011)

Shape index = It describes the smoothness of an image object border. The smoother the border of an image object is, the lower its shape index. It is calculated from the Border Length feature of the image object divided by four times the square root of its area (Trimble, 2011).

Standard deviation = It is calculated from the image layer intensity values of all pixel/voxels forming an image object (Trimble, 2011).

Mean = It refers to the mean layer intensity value of an image object (Trimble, 2011).

3.2.4.5 Accuracy Assessment

Accuracy assessment was done to check the quality of the classification result. This is done by generating a random set of location to visit on the ground for verification of true land use land cover type. Once the ground verified data are obtained, two images (one image contains the interpreted land use land cover map, while the second image contains the result of ground truth investigation) are compared. An error matrix is then created that tabulates the different land use land cover classes to which ground truth cells have been assigned (Eastman, 1999a). Error matrix compares on a category by category basis the relationship between known reference data and the corresponding results of an automated classification (Lilesand, Kiefer, & Chipman, 2008). The output or error matrix includes column and row marginal totals, producer and user accuracy, an overall error measure, confidence intervals for that figure, and a Kappa Index of Agreement (KIA), both for all classes and on a per category basis (Eastman, 1999a).

User accuracy is computed by “dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in the category.” User accuracy indicates the probability that a pixel is classified into a given category actually represents that category on the ground (Lilesand, Kiefer, & Chipman, 2008). Producer accuracy is computed by “dividing the number of correctly classified pixels in each category (on the major diagonal) by the number of training set pixels used for that category” (Lilesand, Kiefer, & Chipman, 2008).

The overall accuracy is calculated by “dividing the total number of correctly classified pixels in by the total number of reference pixels” (Lilesand, Kiefer, & Chipman, 2008). It reflects the probability that a randomly selected point on the map is correctly classified (Bajracharya, 2008). Kappa statistics refers to the precision agreement between observations, and gives a quantitative measure of magnitude of agreement between observers. Kappa estimate of 1 indicates perfect agreement, while estimate of 0 indicates agreement equivalent to chance (Bajracharya, 2008).

In present study, 39 random points were generated, and these points were checked on the ground. An error matrix was prepared and overall accuracy, producer accuracy, user accuracy and Kappa coefficient were calculated to check the quality of the classification result.

3.2.5 Statistical Analysis

3.2.5.1 Correlation between Vegetation Indices and AGB

Correlation between VIs and AGB of *P. roxburghii* was calculated to show the relation between the two variables. Two variables are said to be correlated if change in one variable affects the other variable. If increase in one variable increases the other variable, then these variables are considered to have positive correlation. In contrast to this, if increase in one variable decreases the other variable or vice versa, then variables are considered to have negative correlation. The degree of relationship is represented by correlation coefficient (r) (Shrestha, 1996).

In the present study, a quadrant of 10 m * 10 m was used, while the image pixel was of 5 m * 5 m, that means a quadrant comprises of 4 pixels. AGB was derived quadrant by quadrant (plot) wise. Since correlation calculation is performed pixel by pixel, AGB obtained by quadrant by quadrant requires to be transformed to pixel wise. Since the quadrat was laid on homogenous patch of *P. roxburghii*, it is assumed that the AGB of the quadrat is uniformly distributed over the plot. Hence, the AGB was divided by 4 to derive the AGB for a pixel.

3.2.5.2 Regression Analysis

Regression analysis is used to show the relationship between dependent and independent variables, as well as predict or estimate the value of one variable (dependent) based on the value of another variable (independent) (Shrestha, 1996). Multiple R square and Adjusted R square explains the extent of variability in the dependent variable explained by independent variable.

Multiple R square explains the extent of variability in the dependent variable explained by all independent variable. It assumes all independent variable affects the dependent variable. On the other hand, the adjusted R square explains the variation explained by independent variables that only affect the dependent variable (Investopedia, 2016). For a successful relation, the adjusted R square should be at least 0.5 (Mundava, et al., 2014).

Regression equation (model) was developed and used to predict the AGB (dependent variable) of the study area covered by *P. roxburghii* based on the independent variable, VIs.

3.2.6 Validation of Regression Model

The performance of a model is validated using several methods. Root mean square error (RMSE) is a widely used to validate a model, which is calculated using Equation 19 (Lu, 2006). To calculate RMSE of the model, the estimated AGB from regression model was validated with field data of 34 sample points.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x1_i - x2_i)^2}$$

Equation 19

Where,

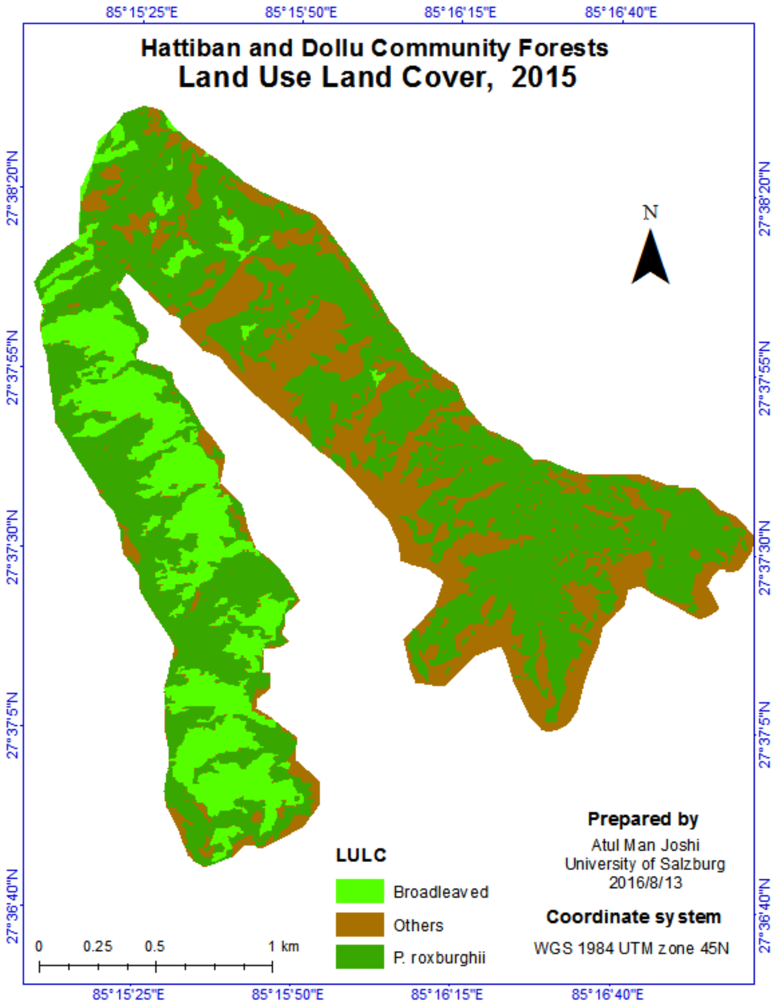
$X1_i$ = AGB measured in the field; $X2_i$ = Predicted AGB from the model; N = number of observation

Chapter 4 Result and Discussion

This chapter provides the results of image classification, AGB, and VIs and their relation with AGB. The chapter also identifies regression equation to estimate AGB.

4.1 Land Use Land Cover

Land Use Land Cover (LULC) (Map 2) of the study area showed that *P. roxburghii* occupied an area of 2.12 km^2 (57.45% of total area), broadleaved species occupied 0.63 km^2 (17.07% of total area) and other class occupied 0.94 km^2 (25.47% of total area) (Table 8).



Map 2 Land Use Land Cover (LULC) classification

Table 8 Land Use Land Cover classification

Class	km^2	Hectares	Percent Covered
P. roxburghii	2.12	212.66	57.45
Broadleaved	0.63	63.25	17.07
Others	0.94	94.80	25.47
Total	3.69	369.71	100

4.2 Accuracy Assessment

The accuracy of the classified land use land cover showed that the overall accuracy of the land use land cover was 87.18 %. This shows the probability that a randomly selected point on the map is correctly classified is 87.18%.The Kappa index was 0.7613. This shows that observed classification is 76.13% better than one resulting from chance.

The user and producer's accuracy of *P. roxburghii* cover was 84.62% and 95.65% respectively. This specifies that although 95.65% of *P. roxburghii* cover is correctly identified as *P. roxburghii,* only 84.62% of the areas identified as *P. roxburghii* within the classification are truly *P. roxburghii.* The user will find 84.62% of time he visits on ground the species is actually *P. roxburghii.* Producer accuracy is high because out of 23 points, 22 were identified correctly as *P. roxburghii.* User accuracy is low because out of 26 random points, 4 points that were supposed to be *P. roxburghii* were classified as broadleaved. The detailed error matrix is provided in Table 9.

Table 9 Accuracy assessment

		Ground truth image				Error C	User accuracy
	Class	1	2	3	Total		
Classified image	1	22	4	0	26	0.1538	84.62
	2	1	6	0	7	0.1429	85.71
	3	0	0	6	6	0	100
	Total	23	10	6	39		
Error O		0.0435	0.4	0		0.1282	
Producer accuracy		95.65	60	100			

Where, 1= *P. roxburghii,* 2 = Broadleaves species, 3 = others

Error O = Errors of omission (expressed as proportions); Error C = Errors of Commission (expressed as proportions).

4.3 Descriptive Statistics of Field Data

Analysis of field data showed that diameter at breast height (DBH) of *P. roxburghii* ranged from 11 cm to 65 cm, with mean DBH of 30.44 cm. The height of *P. roxburghii* ranged from 10 m to 33 m, with mean height of 22.68 m. The volume of *P. roxburghii* ranged from 0.05 m^3 to 5.21 m^3, with mean volume of 0.9849 m^3. The detailed statistics of DBH, height and volume of *P. roxburghii* are presented in Figure 4, 5 and 6 respectively.

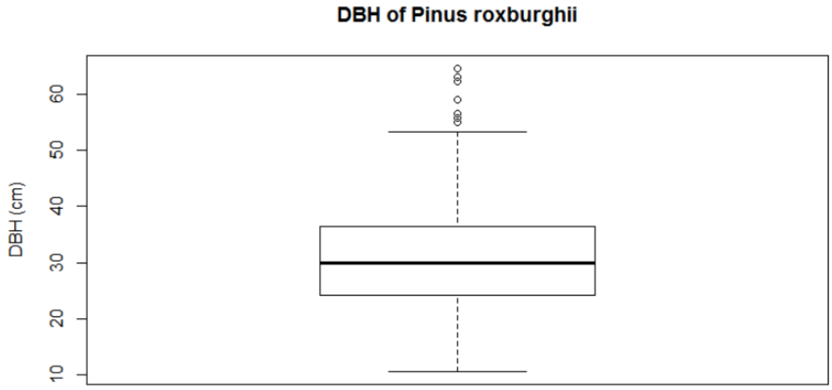


Figure 4 Statistics of DBH of Pinus roxburghii

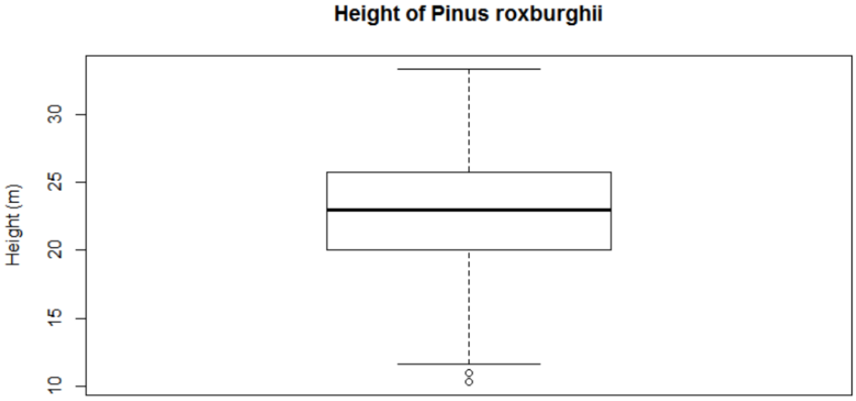


Figure 5 Statistics of Height of Pinus roxburghii

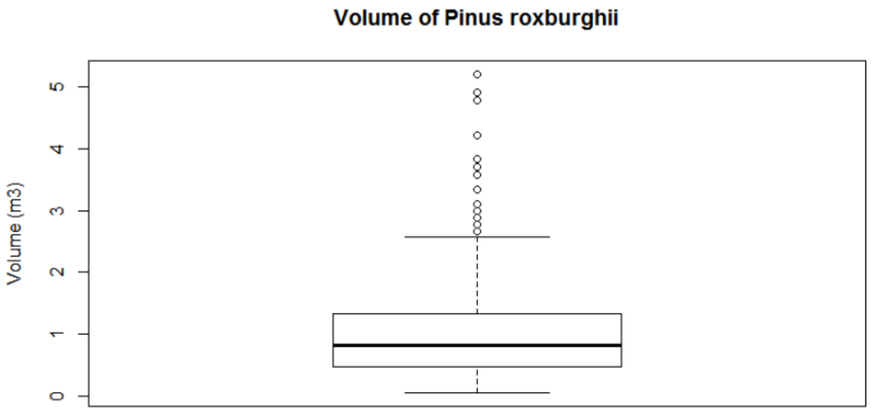


Figure 6 Statistics of Volume of Pinus roxburghii

4.4 Above Ground Biomass

Analysis of AGB in the sample plots showed a wide range of AGB ranging from 2,284.02 to 13,259.91 kg per plot. The average AGB of the sample plots was 6,482 kg per plot. Details of AGB in each plot are presented in Table 10. Detailed calculation of AGB by tree (*P. roxburghii)* is presented in Appendix 1.

4.5 Vegetation Indices

Analysis of VIs showed that VIs had different range of values. The different range was due to different formulas used to derive each VI. The range of values and their distribution pattern are presented in Map 3, 4, 5, 6 and 7. Despite of having different range of values, the spatial pattern of all VIs were similar as all the VIs used same spectral bands i.e. red and NIR.

4.5.1 Slope based Vegetation Indices

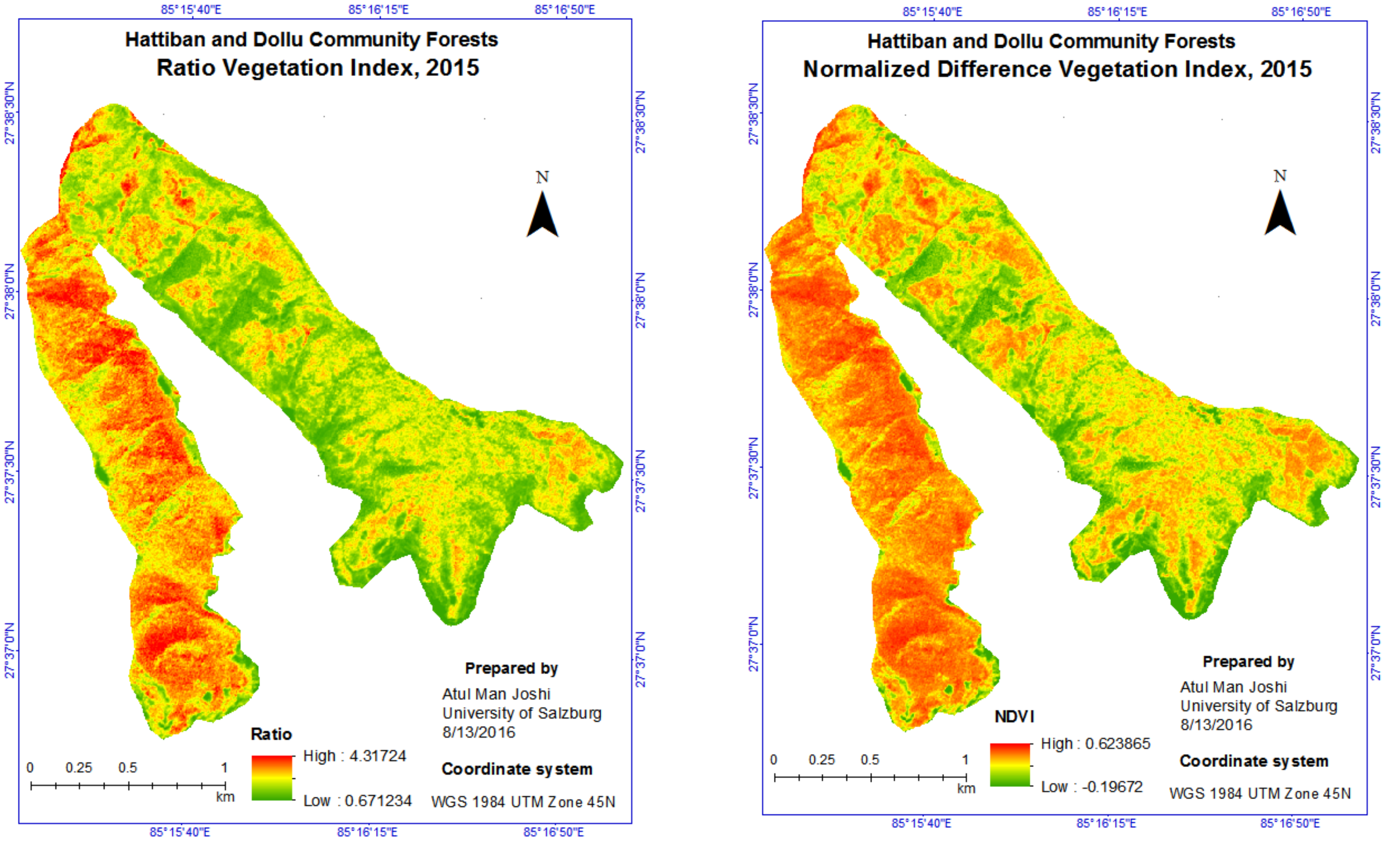
Analysis of slope based vegetation indices in the image showed that in Ratio, NDVI, TVI, CTVI and TTVI vegetation indices, *P. roxburghii* had average values of 2.23, 0.37, 0.91, 0.91 and 0.91 respectively. The detailed VI maps are presented in Map 3, 4 and 5.

4.5.2 Distance based Vegetation Indices

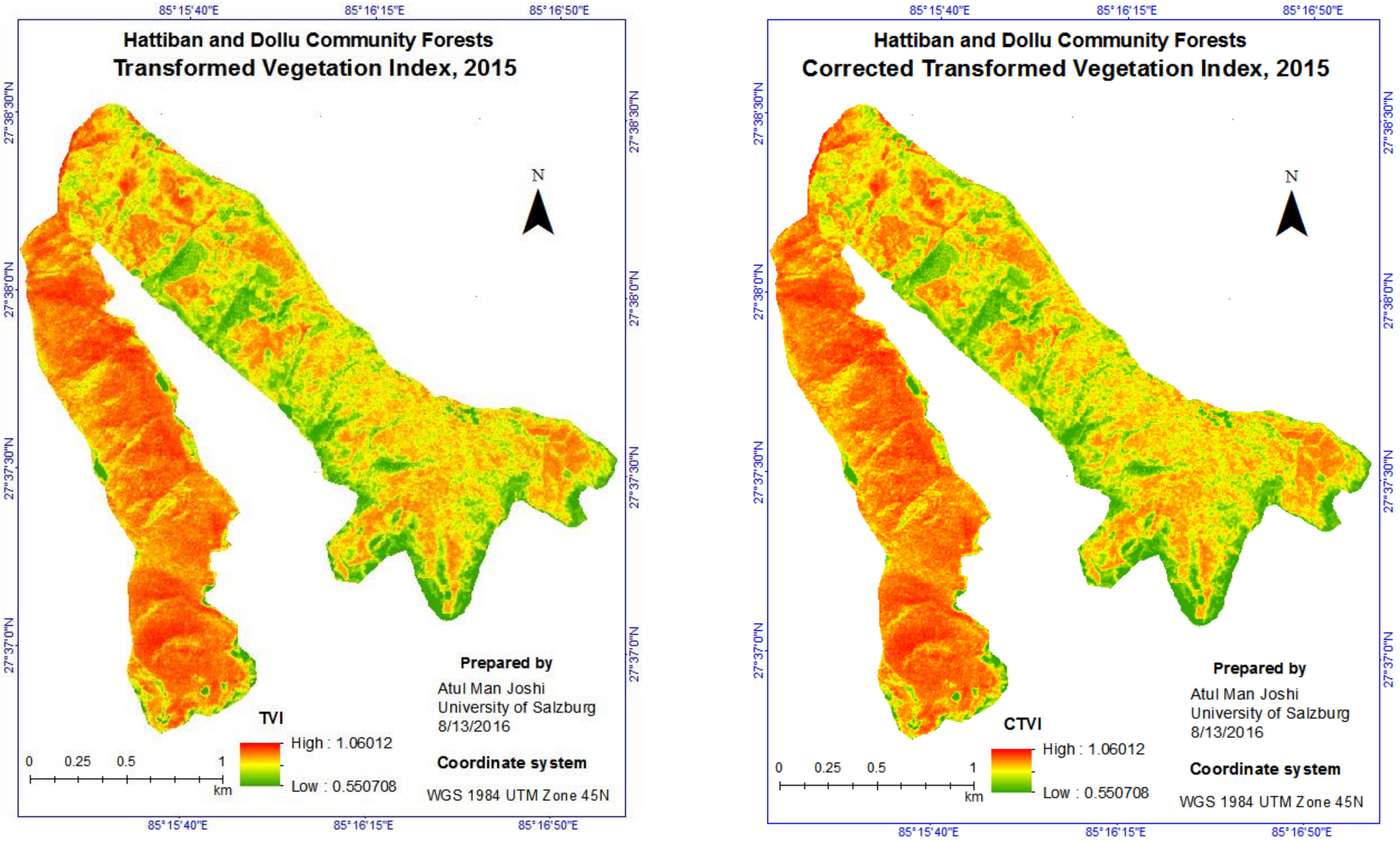
Analysis of distance based vegetation indices in the image showed that in PVI, DVI, WDVI, SAVI and MSAVI vegetation indices, *P. roxburghii* had average values of 0.03, 0.17, 0.08, 0.21 and 0.18 respectively. The detailed VI maps are presented in Map 6 and 7.

Table 10 AGB of sample plots

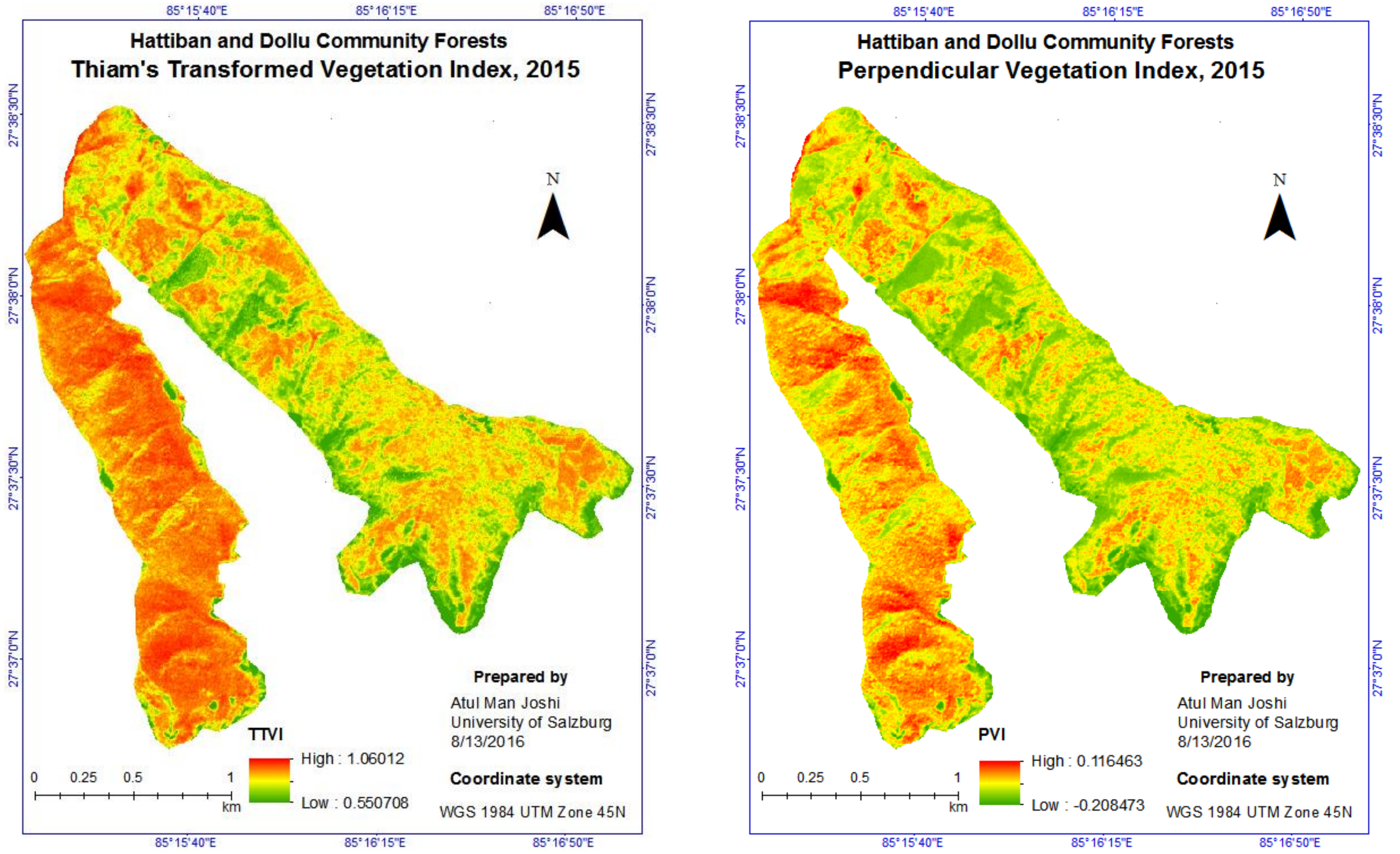
Plot	Longitude	Latitude	Total AGB (kg)	Plot	Longitude	Latitude	Total AGB (kg)
1	330631	3056897	4664.77	**19**	329622	3056991	11882.12
2	330489	3057003	8606.16	**20**	329490	3057225	10495.56
3	330389	3057078	6993.62	**21**	329852	3056959	7765.59
4	330301	3056968	11350.49	**22**	329326	3056475	6795.75
5	330305	3056793	6715.37	**23**	328609	3057946	4708.15
6	330393	3056715	4407.07	**24**	328689	3058027	4627.53
7	330519	3056813	4115.91	**25**	328857	3058120	2284.02
8	329868	3056465	3408.03	**26**	328954	3058026	3329.52
9	329818	3056580	4868.91	**27**	329031	3057806	5742.26
10	329821	3056185	5082.56	**28**	329257	3057632	13259.91
11	329717	3056359	2929.41	**29**	329419	3057466	5596.86
12	329710	3056466	6319.62	**30**	329319	3057363	7506.16
13	329696	3056655	5915.50	**31**	329581	3057329	5108.83
14	329770	3056825	8419.24	**32**	328091	3056661	4040.95
15	329878	3056795	9507.95	**33**	328241	3056529	4140.19
16	329463	3056578	3964.14	**34**	328293	3056609	5322.63
17	329502	3056750	9266.83	**35**	329748	3056994	11013.20
18	329556	3056848	8379.34				



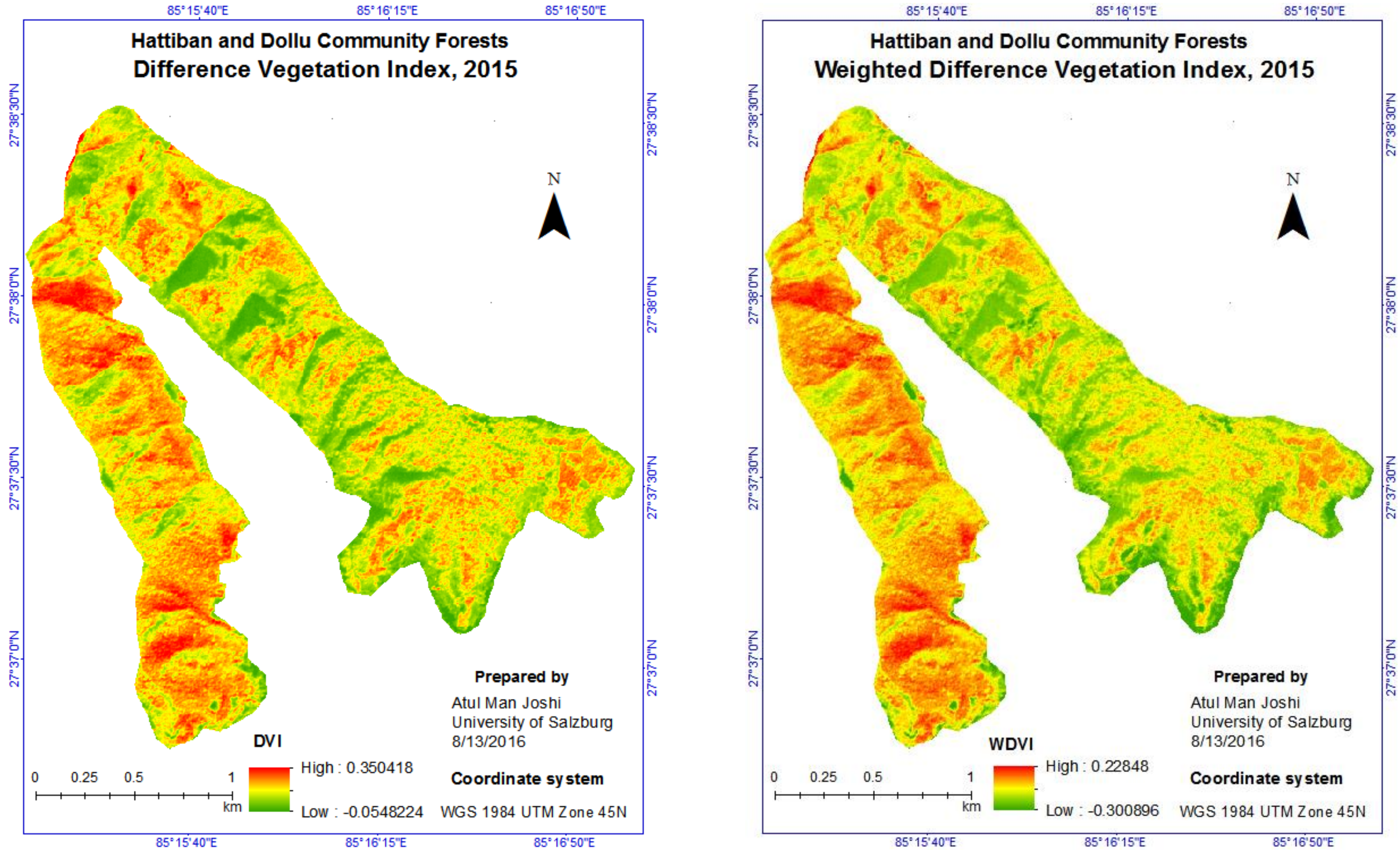
Map 3 Ratio (left), NDVI (right) vegetation indices



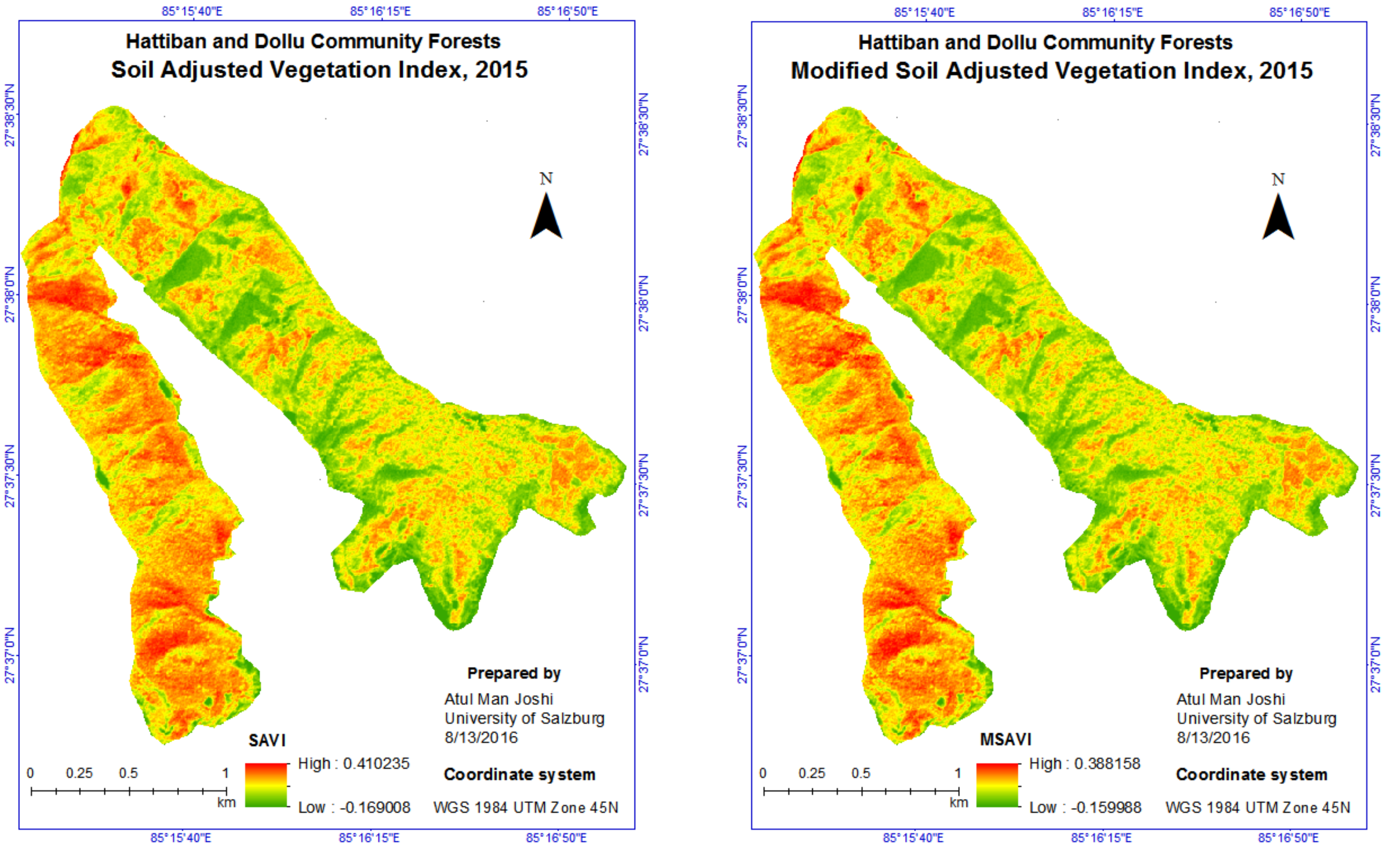
Map 4 TVI (left) and CTVI (right) Vegetation Indices



Map 5 TTVI (left) and PVI (right) vegetation indices



Map 6 DVI (left) and WDVI (right) vegetation indices



Map 7 SAVI (left) and MSAVI (right) vegetation indices

4.6 Statistical Analysis

4.6.1 Correlation between Vegetation Indices and AGB

4.6.1.1 Slope based Vegetation Indices and AGB

Correlation analysis between slope based VIs and AGB showed significant correlation with correlation coefficient (r) above 0.7. The correlation coefficient in all of the VIs were almost same having relatively higher correlation (r =0.734) in NDVI. The details are provided in Table 11.

Table 11 Correlation between sloped based VIs and AGB

Variables	Correlation coefficient (r)
Ratio and AGB	0.731
NDVI and AGB	0.734
TVI and AGB	0.733
CTVI and AGB	0.733
TTVI and AGB	0.733

4.6.1.2 Distance based Vegetation Index and AGB

Correlation analysis between distance based VIs and AGB showed that distance based VIs and AGB had correlation coefficient (r) below 0.7. SAVI had the highest correlation with AGB (r = 0.619), while DVI had the least correlation with AGB (r = 0.452). The details are provided in Table 12.

Table 12 Correlation between distance based VIs and AGB

Variables	Correlation coefficient (r)
PVI	0.608
DVI	0.452
WDVI	0.608
SAVI	0.619
MSAVI	0.588

4.6.2 Regression Analysis

4.6.2.1 Slope based Vegetation Indices and AGB

Regression analysis between slope based VIs and AGB showed that the intercept and slope values in the developed regression equations distinctly varied from one VI to another, but the statistical tests resulted more or less similar findings (Table 13). Multiple R-square values were almost similar and ranged from 0.5348 to 0.5388. Similarly, Adjusted R square (adjusted r^2) values ranged from 0.5207 to 0.5248. F-test values ranged from 37.93 to 38.55, while P values ranged from 0.000000522 to 0.000000604 and T-values ranged from 6.159 to 6.209. NDVI showed relatively high Multiple R-square and Adjusted R square values compared to other VIs. Findings of regression analysis between slope based VIs and AGB are provided in Table 13 and Figure 7.

Table 13 Statistical summary of regression analysis between slope based VIs and AGB

Regression equation and Statistics	**Slope based vegetation Indices**				
	Ratio VI	**NDVI**	**TVI**	**CTVI**	**TTVI**
Equation	AGB = -5251 +3091 * Ratio	AGB = -4501 + 16199 * NDVI	AGB = -26789 + 30325 * TVI	AGB = -26789 + 30325 * CTVI	AGB = -26789 + 30325 * TTVI
Multiple R-squared	0.5348	0.5388	0.5385	0.5385	0.5385
Adjusted R-squared	0.5207	0.5248	0.5245	0.5245	0.5245
F – Statistics on 1 and 33 DF	37.93	38.55	38.51	38.51	38.51
P value	0.000000604	0.000000522	0.000000527	0.000000527	0.000000527
T Value	6.159	6.209	6.205	6.205	6.205

Adjusted R Square

Adjusted R square values ranged from 0.5207 to 0.5248, where NDVI had the highest adjusted r^2 of 0.5248 and Ratio had the lowest (0.5207). TVI, CTVI and TTVI had adjusted r^2 value of 0.5245. Mundava et al (2014) noted that the adjusted r^2 value should be at least 0.5 for the regression equation to be significant and to predict the dependent variable. Hence, the adjusted r^2 value (0.5207 to 0.5248) showed that the relation between all VIs and AGB were significant. However, NDVI was relatively more significant for *P. roxburghii* in the study area.

Multiple R square

Multiple R-square or regression coefficient values ranged from 0.5348 to 0.5388, where NDVI had the highest multiple r^2 values of 0.5388 and Ratio had the lowest (0.5348). TVI, CTVI and TTVI had multiple r^2 value of 0.5385. This shows that NDVI explains the highest extent of variability in the dependent variable, AGB. Around 53.88% of variance in AGB is explained by NDVI.

Multiple R square finding showed that NDVI had relatively higher relation with AGB. Similar findings were obtained by Dong et al (2003), Lu et al (2004) and Liu et al (2006). Dong et al (2003) studied the relation between NDVI and biomass, and found that NDVI and biomass had statistically meaningful relation, and the regression model is applicable to estimate biomass across spatial, temporal and ecological scales for relatively long time scales. Liu et al (2006) found that NDVI had higher relation ($r = 0.862$, $r^2 = 0.743$) with biomass, compared to other VIs. Lu et al (2004) also found NDVI to have higher relation ($r = 0.247$) compared to Ratio ($r = 0.243$) in Pedras, Brazil. However, in Bragatina, NDVI had lower relation to AGB ($r= 0.459$) compared to Ratio ($r = 0.505$). This variation was attributed to different biophysical environment of the study area.

Different researches have also shown that the relation between NDVI and AGB is dependent upon biophysical environment, species and time period. Kryvobok (2000) obtained a correlation coefficient of 0.61 between NDVI and biomass in wheat plantation. Bajracharya (2008) obtained r^2 of 0.327, 0.506 and 0.3303 in 2004, 2005 and 2006 respectively in Schima-Castanopsis dominant forest. Jin et al (2014) found NDVI to have significant relation ($r = 0.791$) with AGB in typical steppe region of grassland, China, and a correlation coefficient of 0.731 and 0.686 in meadow steppe region and desert steppe region respectively. Goswani et al (2015) found the relation between NDVI and AGB to be dependent on species. As such, *Dupontia fisheri* showed significant relation with NDVI (r^2 = 0.87), followed by *Arctophila fulva* (r^2 = 0.82) and *Petasites frigidus* (r^2 = 0.77), while *Eriophorum scheuchzeri* showed lower relation with NDVI (0.50).

Anderson & Hanson (1992), Mundava et al (2014) and Lu et al (2004) also concluded that the strength of relation between VIs and AGB depends on different factors, including plant species and their environment. As such one species shows higher relation on one VI, while other on another, depending upon the local environment. Due to this, the r^2 values of the relation between VIs and AGB in our study might have differed from other studies.

F statistics

F statistics indicates the overall significance of the regression equation. If the F value from the F-table is less than the calculated F value, the regression equation is considered to be significant (Eastman, 1999; Shrestha, 1996). In this study, the F value obtained from F-table was 4.139 at 95% confidence interval, which is less than the calculated F value of 37.93 (Ratio), 38.51 (TVI), 38.51 (CTVI), 38.51 (TTVI) and 38.55 (NDVI). Therefore, at 95% confidence interval, the derived regression equation between all the VIs and AGB are significant and the independent variable, VIs, contributes significantly to the prediction of the dependent variable, AGB.

P Value

P value also indicates the significance of the regression equation. If calculated P value is less than confidence interval, the regression equation is considered to be significant (Murack, 2016) (Minitab, 2016). In this study, the calculated P value of 0.000000604 (Ratio), 0.000000527 (TVI), 0.000000527 (CTVI), 0.000000527 (TTVI) and 0.000000522 (NDVI) were less than confidence interval of 0.05, which indicates that the regression equations between all the VIs and AGB are significant

T statistics

Regression coefficient expresses the individual contribution of each independent variable to the dependent variable. T test for regression coefficient verifies the significance of the variables departure from zero (no effect) (Eastman, 1999). If calculated T value is more than the value from T-table, then the independent variable is significant. Here, the T value from T-table at 95% confidence interval was 1.684, which was less than the calculated T value of 6.159 (Ratio), 6.205 (TVI), 6.205 (CTVI), 6.205 (TTVI) and 6.209 (NDVI). This shows that at 95% confidence interval, the derived regression equations between all the VIs and AGB are significant and the independent variable, VIs, contributes significantly for the prediction of the dependent variable, AGB.

4.6.2.2 Distance based Vegetation Indices and AGB

Regression analysis between distance based VIs and AGB showed that the intercept and slope values in the developed regression equations varied from one VI to another (Table 14). Multiple R-square values ranged from 0.2052 to 0.3838. Similarly, Adjusted R square (adjusted r^2) values ranged from 0.1811 to 0.3651. F-test values ranged from 8.519 to 20.56, while P values ranged from 0.0001068 to 0.006286, and T-values ranged from 2.919 to 4.534. SAVI, showed the highest value in Multiple R-square and Adjusted R square, while DVI showed the lowest. Findings of the regression analysis between distance based VIs and AGB are presented in Figure 8 and Table 14.

Adjusted R Square

Adjusted R square values ranged from 0.1811 to 0.3651, where SAVI had the highest adjusted r^2 values of 0.3651 and DVI had the lowest (0.1811). PVI, WDVI and MSAVI had adjusted r^2 values of 0.3506, 0.3506 and 0.3263 respectively. Mundava et al (2014) noted that the adjusted r^2 values should be at least 0.5 for the regression equation to be significant and to predict the dependent variable. Hence, the relation between distance VIs and AGB is not significant to predict AGB of *P. roxburghii.*

Table 14 Statistical summary of regression analysis between distance based VIs and AGB

Regression equation and Statistics	**Distance based Vegetation Indices**				
	PVI	**DVI**	**WDVI**	**SAVI**	**MSAVI**
Equation	AGB = 423.4 + 40637 * PVI	AGB = -353.8 + 11464.8 * DVI	AGB = -543 + 24943 * WDVI	AGB = -1730 + 15832 * SAVI	AGB = -1135 + 15466 * MSAVI
Multiple R-squared	0.3697	0.2052	0.3697	0.3838	0.3461
Adjusted R-squared	0.3506	0.1811	0.3506	0.3651	0.3263
F – Statistics on 1 and 33 DF	19.36	8.519	19.36	20.56	17.46
P value	0.0001068	0.006286	0.0001068	0.00007236	0.0002019
T Value	4.400	2.919	4.400	4.534	4.179

Multiple R square

Multiple R-square or regression coefficient values ranged from 0.2052 to 0.3838, where SAVI had the highest multiple r^2 value of 0.3838 and DVI had the lowest (0.2052). PVI, WDVI and MSAVI had multiple r^2 values of 0.3697, 0.3697 and 0.3263 respectively. This shows that SAVI explains the highest extent of variability in the dependent variable, AGB, and DVI explains the least. Around 38.38% of variance in AGB is explained by SAVI, while DVI explains only 20.52%.

Multiple R square findings showed that SAVI had the highest relation with AGB. Richardson & Everitt (1992) and Jin et al (2014) also obtained similar results. Richardson & Everitt (1992) compared the relation between VIs (PVI and SAVI) and AGB in range land, and found that SAVI had higher relation with AGB (r^2 = 0.648) than PVI (r^2 = 0.64). Jin et al

(2014) compared the relation between VIs (SAVI and MSAVI) and AGB in grassland, and found that SAVI had higher relation ($r^2 = 0.518$) compared to MSAVI ($r^2 = 0.492$).

F statistics

The calculated F value of PVI, DVI, WDVI, SAVI and MSAVI were 19.36, 8.519, 19.36, 20.56 and 17.46 respectively, which are greater than F value obtained from F-table (4.139 at 95% confidence interval). Therefore, at 95% confidence interval, the derived regression equations between all the VIs and AGB are significant.

P value

The calculated P value of PVI, DVI, WDVI, SAVI and MSAVI were 0.0001068, 0.006286, 0.0001068, 0.00007236 and 0.0002019 respectively, which are less than confidence interval of 0.05. This indicates that the regression equations between all the VIs and AGB are significant.

T statistics

The calculated T value of PVI, DVI, WDVI, SAVI and MSAVI were 4.400, 2.919, 4.400, 4.534 and 4.179 respectively, which are greater than the T value obtained from T-table (1.684 at 95% confidence interval). This shows that at 95% confidence interval, the derived regression equations between all the VIs and AGB are significant.

4.6.3 Comparing Slope and Distance based Vegetation Indices

Slope based VI and distance based VI were compared to know which VI had higher relation with AGB. The analysis showed that slope based VIs had higher relation with AGB ($r > 0.7$ and $r^2 > 0.50$) than distance based VIs ($r < 0.7$ and $r^2 < 0.5$). Similar results have been reported in several studies. Lu et al (2004), Liu et al (2006), Das & Singh (2012) and Jim et al (2014) found that slope based VIs had better relation with AGB than distance based VIs.

Lu et al (2004) compared the relation between different VIs and AGB in different sites of Brazil. They found that slope based VIs had higher relation with AGB compared to distance based VIs. In Bragatina, Ratio ($r = 0.530$) and NDVI (0.459) showed higher relation with AGB compared to SAVI ($r= 0.434$) and MSAVI ($r = 0.435$). Similar was the situation in Pedras and Altamira also. Liu et al (2006) compared the relation between different VIs and biomass in Oasis ecosystem, and found that NDVI had higher relation ($r = 0.862$, $r_2 = 0.743$) with biomass compared to MSAVI ($r = 0.852$, $r^2 = 0.726$). Das & Singh (2012) studied the relation between VI and AGB in forests of Maharashtra, and found that Ratio and NDVI had higher relation than MSAVI with AGB. Ratio had the highest relation ($r^2 =0.785$), NDVI had r^2 of 0.75 and MSAVI had the lowest relation ($r^2 = 0.676$) with AGB. Jin et al. (2014) also found that NDVI ($r = 0.791$) had higher relation with AGB than SAVI ($r = 0.74$) and MSAVI ($r = 0.72$) in grassland.

However, on the other hand, Heiskanen (2006) and Mundava et al (2014) found mixed results. Heiskanen compared the relation between different VIs and AGB in mountain birch forest and found that Ratio had higher relation ($r^2 = 0.81$) with AGB compared to SAVI ($r^2 = 0.69$), but NDVI showed lower relation ($r^2 = 0.67$) compared to SAVI. Mundava et al (2014) compared the relation between NDVI and SAVI with AGB in different sites of Brazil, and found that in open plains, NDVI and SAVI showed same relation with AGB ($r^2 = 0.6$). Similar result was found by them in bunchgrass also. But in Spinifex dominated areas, SAVI showed no relation with AGB ($r^2 = 0$), while NDVI had very low relation with AGB ($r^2 = 0.1$).

The variation in relation between VIs and AGB could be attributed to the variation in biophysical environments of the study area because the strength of the relation between VIs and AGB depends on various factors, including plant species and their environment (Anderson & Hanson, 1992; Mundava et al., 2014 and Lu et al., 2004). As such, one species shows higher relation on one VI, while other on another, depending upon the local environment.

Regression analysis between slope based VIs and AGB

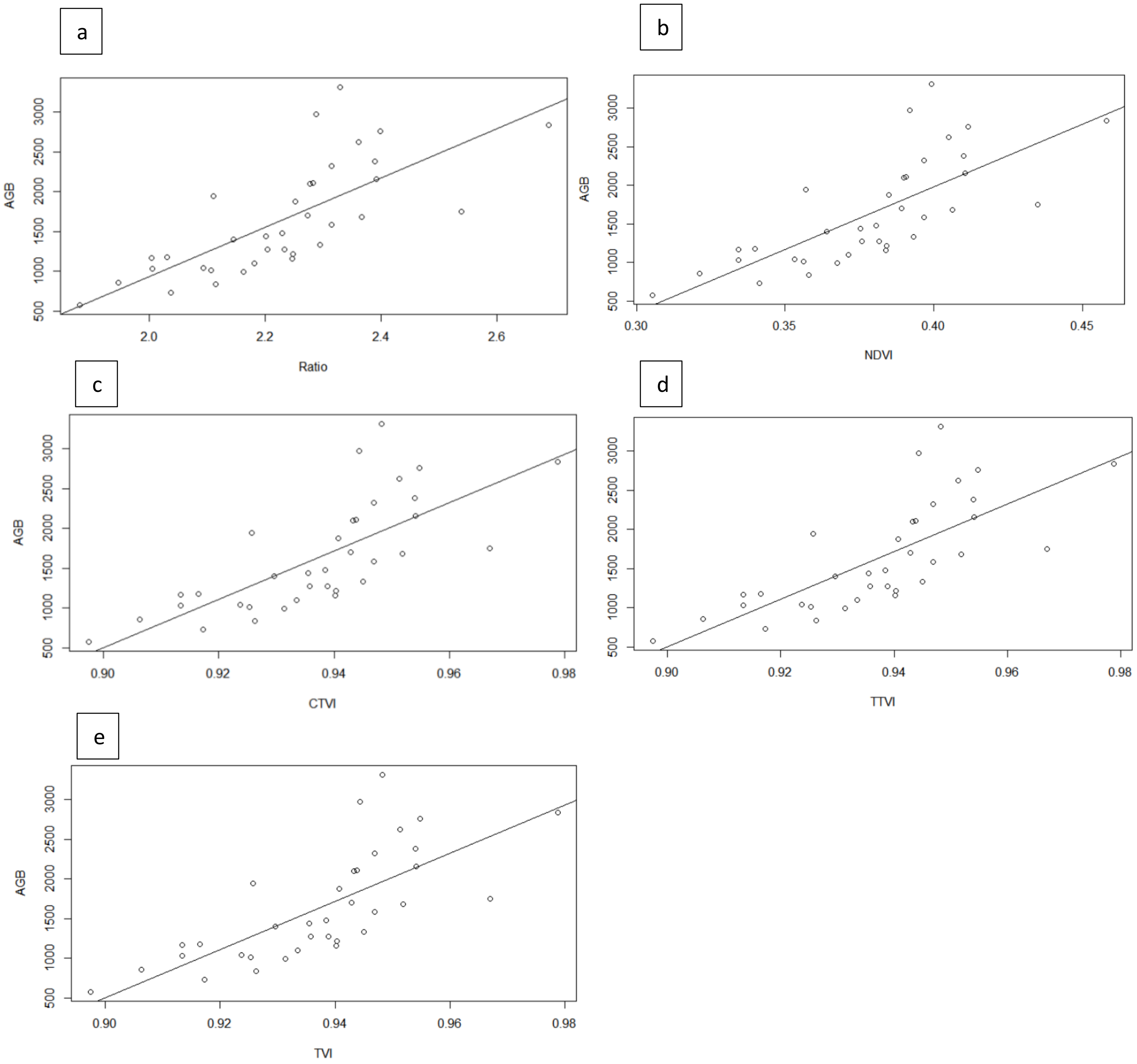


Figure 7 Regression analysis between slope based VIs and AGB

a) between Ratio and AGB, (b) between NDVI and AGB, (c) between CTVI and AGB, (d) between TTVI and AGB, (e) between TVI and AGB

Regression analysis between distance based VIs and AGB

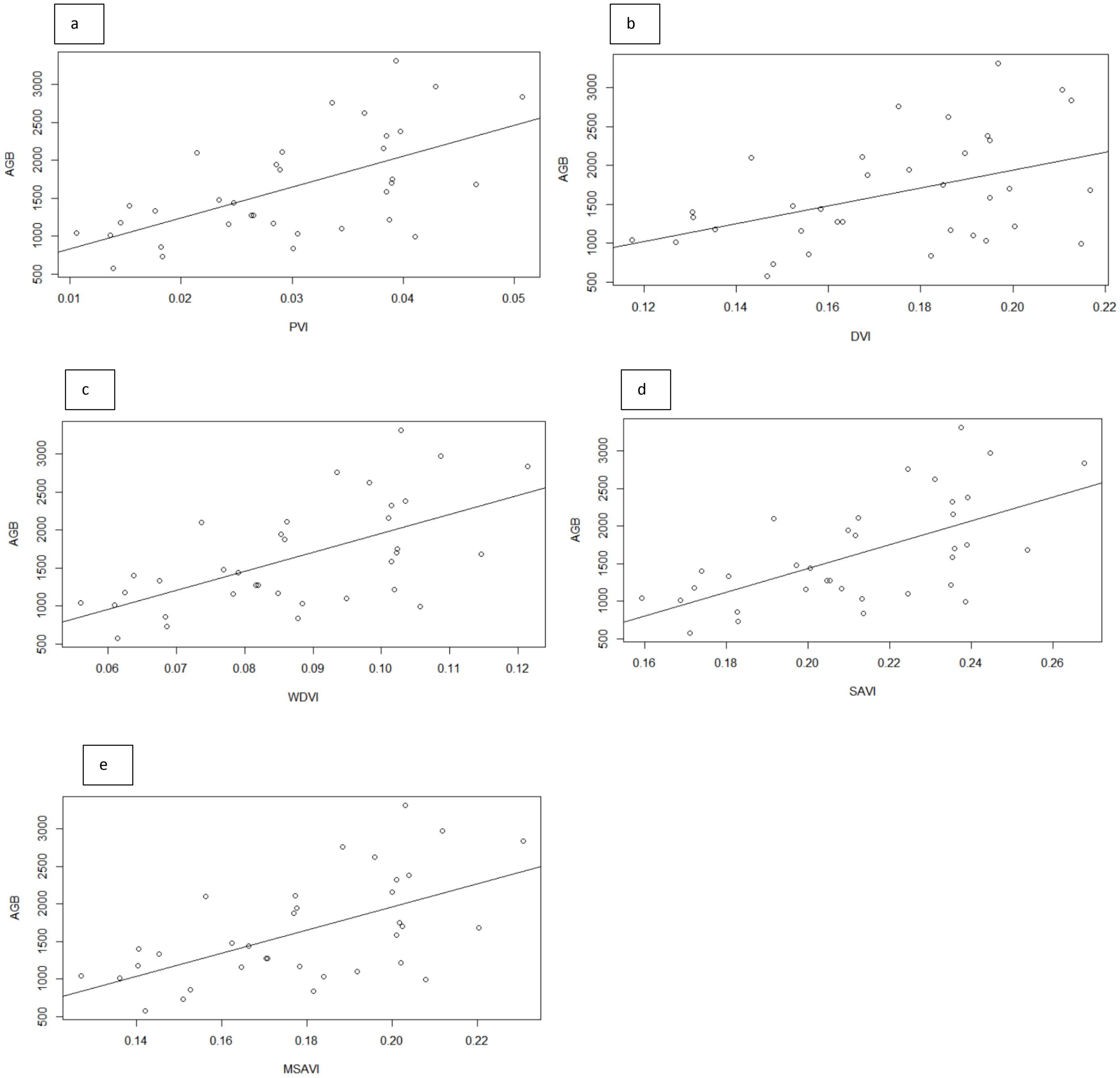


Figure 8 Regression analysis between distance based VIs and AGB

(a) between PVI and AGB, (b) between DVI and AGB, (c) between WDVI and AGB, (d) between SAVI and AGB, (e) between MSAVI and AGB

4.6.4 Best Vegetation Index

Overall statistical analysis showed that slope based VIs ($r > 0.7$, $r^2 > 0.50$ and adjusted $r^2 > 0.50$) had significant relation with AGB of *P. roxburghii* than distance based VIs ($r < 0.7$, $r^2 < 0.50$ and adjusted $r^2 < 0.5$). However, out of all VIs, NDVI had higher relation with AGB of *P. roxburghii.* Therefore, NDVI was regarded as the best VI for estimating AGB of *P. roxburghii* in the study area.

4.7 Estimating AGB

Since NDVI had the highest relation ($r = 0.734$, $r^2 = 0.5388$ and adjusted $r^2 = 0.5248$) with AGB compared to other VIs, NDVI based regression equation (AGB = -4501 + 16199 * NDVI) was used to estimate the overall AGB of *P. roxburghii* in the study area. Based on the above regression equation, the total AGB of *P. roxburghii* in the study area was estimated to be 133,577,495.44 kg. The estimated AGB has been presented in Map 8.

4.8 Validation of Estimated AGB

The estimated AGB was cross validated with observed AGB from field using RMSE equation. The calculation resulted a RMSE of 41.49%. This shows that the estimated AGB of the species is accurate by around 59%. The relation between estimated AGB and observed AGB is presented in Figure 9.

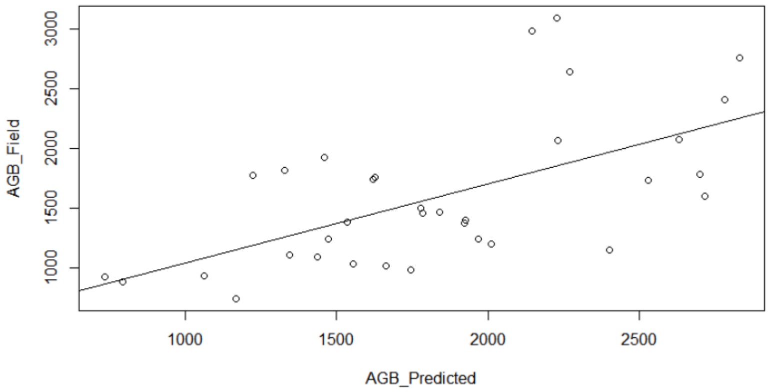
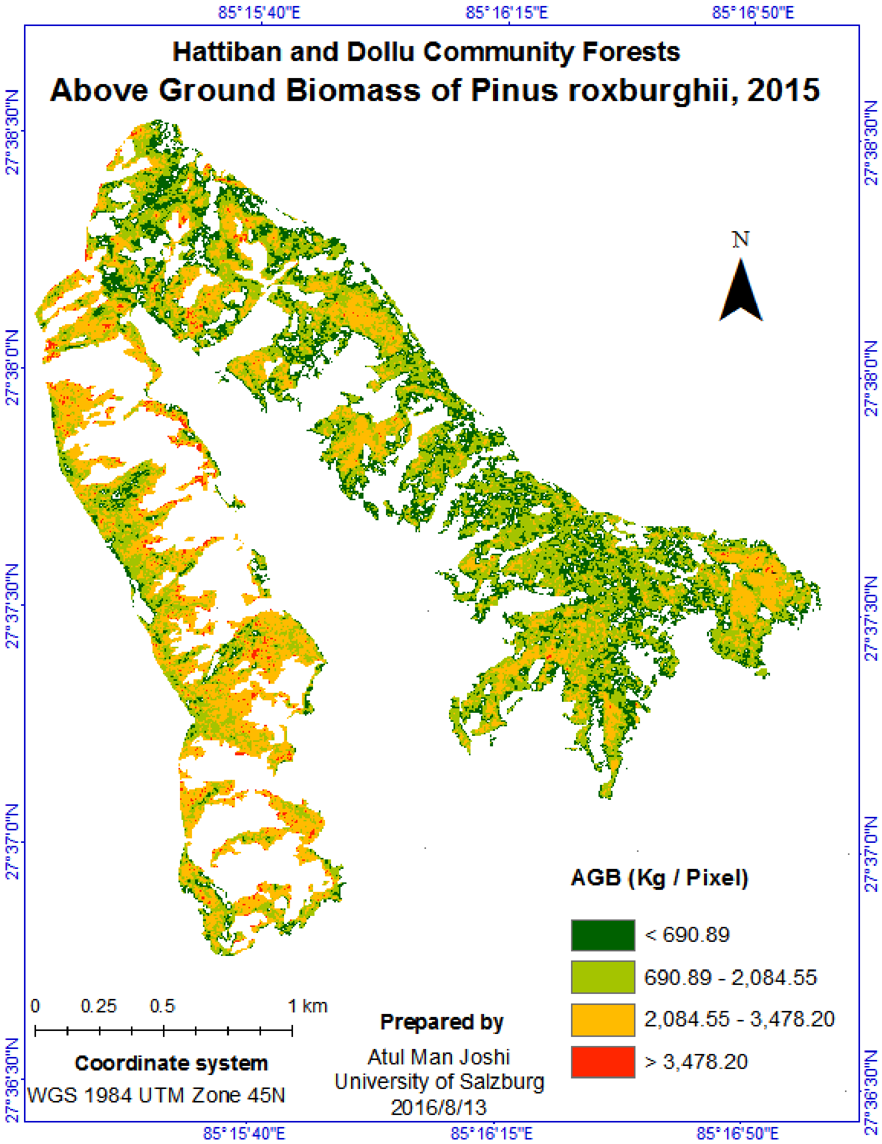


Figure 9 Relation between Observed and Predicted AGB



Map 8 AGB of Pinus roxburghii

1 pixel = 5 m* 5m

Chapter 5 Conclusion and Recommendation

This chapter concludes the result and gives recommendation.

5.1 Conclusion

Land Use Land Cover analysis of the study area showed that 57.45% of the study area is covered by *P. roxburghii*. The AGB of *P. roxburghii* cover in the sample plots ranged from 2284.02 to 13259.91 kg per plot. Various vegetation indices in the sample plots showed different values. However, they were observed to have positive relationship with AGB but the strength of the relationship varied from one to another.

Statistical analysis showed that slope based VIs had higher relation with AGB ($r > 0.7$ and $r_2 > 0.50$) than distance based VIs ($r < 0.7$ and $r^2 < 0.5$). Although statistical results from F test, P value and T test showed that the relation between both slope based and distance based Vis were significant, results of adjusted r^2 showed that only slope based VIs were significant enough to estimate AGB.

Out of all VIs, NDVI had the highest relation with AGB ($r = 0.734$, multiple $r^2 = 0.5388$, adjusted $r^2 = 0.5248$). Therefore, it was concluded that NDVI was the most appropriate VI to estimate AGB of *P. roxburghii,* and the regression equation, $AGB = -4501 + 16199 * NDVI$, was used to estimate the AGB of *P. roxburghii* in the study area. Based on the regression equation, it was found that the AGB of *P. roxburghii* in the study area was 133,577,495.44 kg. Cross validation of the estimated AGB with observed AGB from field showed RMSE of 41.49 %. In other word, the estimated AGB in the study area is accurate by around 59%.

5.2 Recommendation

- Image classification is an important component for accurate AGB estimation, therefore, image classification should be done with high accuracy.

- The relation between VIs and AGB depends upon season, therefore, the studies should be carried out throughout the year (all seasons) to estimate AGB with higher accuracy.

- Image obtained from optical based sensor are affected by cloud cover. Image acquired on cloudy days, especially in rainy season, might not be useful to estimate AGB due to cloud cover Therefore, images captured from other sensors that are not affected by cloud cover should be used, for which, Pol-InSAR is recommended as it is very sensitive to forest parameters, and is not affected by cloud cover.

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Appendix 1

Total AGB of *Pinus roxbhrughii*

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
1	330631	3056897	P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
2	330489	3057003	P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
3	330389	3057078	P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	16.99	15.42	0.18	119.27	22.54	12.05	153.86
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	10.52	10.32	0.05	31.72	5.99	3.20	40.92
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
4	330301	3056968	P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
5	330305	3056793	P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
6	330393	3056715	P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
7	330519	3056813	P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
8	329868	3056465	P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
9	329818	3056580	P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	11.32	11.01	0.06	39.02	7.37	3.94	50.33
			P.roxburghii	11.32	11.01	0.06	39.02	7.37	3.94	50.33
10	329821	3056185	P.roxburghii	16.99	15.42	0.18	119.27	22.54	12.05	153.86
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	16.99	15.42	0.18	119.27	22.54	12.05	153.86
			P.roxburghii	18.61	16.55	0.23	152.49	28.82	15.40	196.71
11	329717	3056359	P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
12	329710	3056466	P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
13	329696	3056655	P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	11.32	11.01	0.06	39.02	7.37	3.94	50.33
			P.roxburghii	13.75	12.99	0.10	66.89	12.64	6.76	86.28
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	12.13	11.69	0.07	47.29	8.94	4.78	61.00
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	14.56	13.62	0.12	78.29	14.80	7.91	100.99
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
14	329770	3056825	P.roxburghii	44.49	28.56	2.17	1409.31	360.78	64.83	1834.92
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
15	329878	3056795	P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	45.30	28.81	2.26	1471.54	376.71	67.69	1915.94
16	329463	3056578	P.roxburghii	12.94	12.34	0.09	56.56	10.69	5.71	72.97
			P.roxburghii	10.52	10.32	0.05	31.72	5.99	3.20	40.92
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	12.94	12.34	0.09	56.56	10.69	5.71	72.97
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
17	329502	3056750	P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	44.49	28.56	2.17	1409.31	360.78	64.83	1834.92
18	329556	3056848	P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
19	329622	3056991	P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	43.68	28.31	2.07	1348.49	345.21	62.03	1755.73
			P.roxburghii	44.49	28.56	2.17	1409.31	360.78	64.83	1834.92
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
20	329490	3057225	P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	46.11	29.05	2.36	1535.17	393.00	70.62	1998.80
			P.roxburghii	50.96	30.38	2.99	1946.46	498.29	89.54	2534.29
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
21	329852	3056959	P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
22	329326	3056475	P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	16.99	15.42	0.18	119.27	22.54	12.05	153.86
			P.roxburghii	17.80	15.99	0.21	135.27	25.57	13.66	174.50
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
23	328609	3057946	P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
24	328689	3058027	P.roxburghii	27.50	21.81	0.66	426.45	109.17	19.62	555.23
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
25	328857	3058120	P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
26	328954	3058026	P.roxburghii	18.61	16.55	0.23	152.49	28.82	15.40	196.71
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
27	329031	3057806	P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
28	329257	3057632	P.roxburghii	49.34	29.95	2.78	1803.75	461.76	82.97	2348.49
			P.roxburghii	50.96	30.38	2.99	1946.46	498.29	89.54	2534.29
			P.roxburghii	50.15	30.17	2.88	1874.41	479.85	86.22	2440.48
			P.roxburghii	63.10	33.05	4.91	3194.52	958.36	105.42	4258.30
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
29	329419	3057466	P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
30	329319	3057363	P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	44.49	28.56	2.17	1409.31	360.78	64.83	1834.92
			P.roxburghii	51.77	30.58	3.11	2019.91	517.10	92.92	2629.92
			P.roxburghii	45.30	28.81	2.26	1471.54	376.71	67.69	1915.94
31	329581	3057329	P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	18.61	16.55	0.23	152.49	28.82	15.40	196.71
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	44.49	28.56	2.17	1409.31	360.78	64.83	1834.92
			P.roxburghii	17.80	15.99	0.21	135.27	25.57	13.66	174.50
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
32	328091	3056661	P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
33	328241	3056529	P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
34	328293	3056609	P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	16.18	14.83	0.16	104.45	19.74	10.55	134.74
			P.roxburghii	18.61	16.55	0.23	152.49	28.82	15.40	196.71
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	17.80	15.99	0.21	135.27	25.57	13.66	174.50
35	329748	3056994	P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	59.05	32.25	4.22	2743.77	702.41	126.21	3572.39
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	55.82	31.55	3.70	2408.13	616.48	110.77	3135.38
36	330577	3056871	P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
37	330512	3056821	P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
38	330577	3056931	P.roxburghii	48.54	29.73	2.67	1734.50	444.03	79.79	2258.32
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
39	330366	3056863	P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
40	329876	3056526	P.roxburghii	12.13	11.69	0.07	47.29	8.94	4.78	61.00

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	12.13	11.69	0.07	47.29	8.94	4.78	61.00
			P.roxburghii	15.37	14.23	0.14	90.80	17.16	9.17	117.13
			P.roxburghii	51.77	30.58	3.11	2019.91	517.10	92.92	2629.92
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	10.52	10.32	0.05	31.72	5.99	3.20	40.92
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	16.18	14.83	0.16	104.45	19.74	10.55	134.74
41	329790	3056575	P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	18.61	16.55	0.23	152.49	28.82	15.40	196.71
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
42	329811	3056372	P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	27.50	21.81	0.66	426.45	109.17	19.62	555.23
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
43	329747	3056726	P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
44	329794	3056537	P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	15.37	14.23	0.14	90.80	17.16	9.17	117.13
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
45	329477	3056636	P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
46	329381	3056611	P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
47	329670	3056859	P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	46.11	29.05	2.36	1535.17	393.00	70.62	1998.80
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
48	329424	3057341	P.roxburghii	56.62	31.73	3.83	2489.95	746.99	82.17	3319.10
			P.roxburghii	48.54	29.73	2.67	1734.50	444.03	79.79	2258.32
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
49	329659	3057225	P.roxburghii	64.71	33.35	5.21	3384.49	1015.35	111.69	4511.53
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	53.39	30.98	3.34	2171.01	651.30	71.64	2893.95
			P.roxburghii	56.62	31.73	3.83	2489.95	746.99	82.17	3319.10
50	328388	3057768	P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	50.15	30.17	2.88	1874.41	479.85	86.22	2440.48
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
51	328521	3057876	P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
			P.roxburghii	43.68	28.31	2.07	1348.49	345.21	62.03	1755.73
53	329470	3057386	P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
			P.roxburghii	16.18	14.83	0.16	104.45	19.74	10.55	134.74
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	12.94	12.34	0.09	56.56	10.69	5.71	72.97
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	21.03	18.14	0.33	211.59	39.99	21.37	272.96
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	24.27	20.07	0.47	308.39	58.29	31.15	397.83

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	16.18	14.83	0.16	104.45	19.74	10.55	134.74
			P.roxburghii	17.80	15.99	0.21	135.27	25.57	13.66	174.50
54	328488	3056619	P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
55	328420	3056629	P.roxburghii	55.01	31.36	3.58	2327.69	698.31	76.81	3102.81
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	20.22	17.62	0.29	190.63	36.03	19.25	245.92
			P.roxburghii	25.89	20.96	0.56	364.72	68.93	36.84	470.49
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	27.50	21.81	0.66	426.45	80.60	43.07	550.12
			P.roxburghii	14.56	13.62	0.12	78.29	14.80	7.91	100.99
56	328294	3056572	P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	43.68	28.31	2.07	1348.49	345.21	62.03	1755.73
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	33.97	24.80	1.12	728.24	186.43	33.50	948.16
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	17.80	15.99	0.21	135.27	25.57	13.66	174.50
57	328354	3056644	P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	50.15	30.17	2.88	1874.41	479.85	86.22	2440.48

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	17.80	15.99	0.21	135.27	25.57	13.66	174.50
			P.roxburghii	13.75	12.99	0.10	66.89	12.64	6.76	86.28
			P.roxburghii	19.41	17.09	0.26	170.94	32.31	17.26	220.51
			P.roxburghii	21.84	18.64	0.36	233.84	44.20	23.62	301.65
58	328340	3056464	P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	47.73	29.51	2.56	1666.66	426.66	76.67	2169.99
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	16.99	15.42	0.18	119.27	22.54	12.05	153.86
			P.roxburghii	16.99	15.42	0.18	119.27	22.54	12.05	153.86
59	329405	3057281	P.roxburghii	46.11	29.05	2.36	1535.17	393.00	70.62	1998.80
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	43.68	28.31	2.07	1348.49	345.21	62.03	1755.73
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
60	329362	3057354	P.roxburghii	43.68	28.31	2.07	1348.49	345.21	62.03	1755.73
			P.roxburghii	46.11	29.05	2.36	1535.17	393.00	70.62	1998.80
			P.roxburghii	46.11	29.05	2.36	1535.17	393.00	70.62	1998.80
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	41.25	27.52	1.81	1174.45	300.66	54.02	1529.14
61	329333	3057321	P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	31.55	23.75	0.93	604.69	154.80	27.82	787.30
			P.roxburghii	62.29	32.90	4.77	3101.61	930.48	102.35	4134.44
			P.roxburghii	51.77	30.58	3.11	2019.91	517.10	92.92	2629.92
			P.roxburghii	51.77	30.58	3.11	2019.91	517.10	92.92	2629.92
62	329473	3057213	P.roxburghii	50.15	30.17	2.88	1874.41	479.85	86.22	2440.48

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
63	329393	3057152	P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	34.78	25.13	1.19	772.21	197.69	35.52	1005.42
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	46.92	29.28	2.46	1600.21	409.65	73.61	2083.48
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
64	329546	3057086	P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	22.65	19.13	0.40	257.38	48.64	0.10	306.12
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
65	329588	3056977	P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	32.36	24.11	0.99	644.48	164.99	29.65	839.11
			P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	25.08	20.52	0.52	335.89	63.48	33.92	433.30
66	329768	3056933	P.roxburghii	26.69	21.39	0.61	394.91	74.64	39.89	509.43
			P.roxburghii	42.06	27.79	1.89	1231.06	315.15	56.63	1602.84
			P.roxburghii	42.87	28.05	1.98	1289.07	330.00	59.30	1678.37
			P.roxburghii	40.45	27.25	1.72	1119.26	286.53	51.49	1457.27
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07

Plot	Longitude	Latitude	Species	DBH (cm)	Height (m)	Volume (m3)	Stem biomass (kg)	Branch biomass (kg)	Foliage biomass (kg)	Total AGB (kg)
			P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
67	329768	3056817	P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	29.93	23.00	0.81	529.26	135.49	24.35	689.09
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	23.46	19.60	0.43	282.23	53.34	28.50	364.07
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	29.12	22.61	0.76	493.62	126.37	22.71	642.69
68	329737	3056700	P.roxburghii	22.65	19.13	0.40	257.38	48.64	26.00	332.02
			P.roxburghii	36.40	25.77	1.33	864.35	221.27	39.76	1125.38
			P.roxburghii	38.83	26.68	1.56	1013.08	259.35	46.60	1319.03
			P.roxburghii	28.31	22.22	0.71	459.35	117.59	21.13	598.07
			P.roxburghii	35.59	25.46	1.26	817.58	209.30	37.61	1064.49
			P.roxburghii	39.64	26.97	1.64	1065.47	272.76	49.01	1387.24
			P.roxburghii	37.21	26.08	1.40	912.52	233.61	41.98	1188.10
69	329764	3056619	P.roxburghii	38.02	26.39	1.48	962.10	246.30	44.26	1252.65
			P.roxburghii	46.92	29.28	2.46	1600.21	409.65	73.61	2083.48
			P.roxburghii	33.17	24.46	1.05	685.66	175.53	31.54	892.73
			P.roxburghii	30.74	23.38	0.87	566.28	144.97	26.05	737.30