

Estimation of Above Ground Biomass and Net Primary Productivity of Kumaon Himalayan Forest using Geospatial Approach

Thesis

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*Pantnagar
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(Amit Kumar Rabha)
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CERTIFICATE

This is to certify that the thesis entitled “**Estimation of Above Ground Biomass and Net Primary Productivity of Kumaon Himalayan Forest using Geospatial Approach**”, submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy with major in **Environmental Science** and minor in **Agrometeorology** of the College of Post Graduate Studies, G. B. Pant University of Agriculture and Technology, Pantnagar, is a record of *bona fide* research carried out by **Mr. Amit Kumar Rabha, Id. No. 39251**, under my supervision, and no part of the thesis has been submitted for any other degree or diploma.

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Pantnagar
February, 2019


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CERTIFICATE

We, the undersigned, member of the advisory committee of **Mr. Amit Kumar Rabha, Id. No. 39251** a candidate for the degree of **Doctor of Philosophy** with major in **Environmental Science** and minor in **Agrometeorology**, agree that the thesis entitled **“Estimation of Above Ground Biomass and Net Primary Productivity of Kumaon Himalayan Forest using Geospatial Approach”**, may be submitted in partial fulfilment of the requirements for the degree.



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Member



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LIST OF ABBREVIATIONS

AGB	Above Ground Biomass
%	Per cent
AGBC	Above Ground Biomass Carbon
ALOS	Advance Land Observing Satellite
APAR	Absorb Photosynthetically Active Radiation
ASTER	Advance Spaceborne Thermal Emission and Reflection
AVHRR	Advanced Very High Resolution Radiometer
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper
FAO	Food and Agriculture Organization
fAPAR	Fraction of Absorb Photosynthetically Active Radiation
GIS	Geographic Information System
GLAS	Geoscience Laser Altimeter System
GPP	Gross Primary Productivity
ha	Hectare
IPCC	Intergovernmental Panel on Climate Change
LAI	Leaf Area Index
LIDAR	Light Detection and Ranging
LUE	Light Use Efficiency
Mg	Mega Gram
MISR	Multangle Imaging Spectroradiometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MODPRI	MODIS derived Photochemical Reflectance Index
NDVI	Normalized Difference Vegetation Index

NDWI	Normalized Difference Water Index
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
PALSAR	Phase Array Type L-band Synthetic Aperture Radar
PCA	Principal Component Analysis
RADAR	Radio Detection and Ranging
SAR	Synthetic Aparture Radar
SRTM	Shuttle Radar Topography Mission
SWR	Shortwave Radiation
TM	Thematic Mapper
USDA	United States Department of Agriculture
WWF	World Wide Fun
USGS	United States Geological Survey



Introduction

Planet Earth is undergoing significant global environmental change. The processes linked to global change are affecting the whole climate system and impacting human civilization. Understanding the effects and causes of these processes will assist human societies in devising adaptation and mitigation strategies (**Hester and Harrison, 2002, Slaymaker *et al.*, 2009**). The United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol address the importance of reducing and monitoring greenhouse gas emissions (GHG), with CO₂ being the most significant trace gas. Changes in the amount of atmospheric CO₂ due to anthropogenic activities are altering the biogeochemical cycles that allow the recycling and reuse of carbon on Earth (global carbon cycle), and produce changes in weather patterns (**IPCC, 2014**).

Terrestrial ecosystems play a vital role in the global carbon cycle. The terrestrial carbon pool is about three times bigger than the atmospheric pool (**IPCC, 2007**), and removes 30% of anthropogenic emissions from fossil fuel combustion from the atmosphere (**Canadell *et al.*, 2007**). Terrestrial ecosystems appear to act as a net sink (**Andersson, 2009**), but there are significant uncertainties on the carbon fluxes between land and atmosphere in comparison with the other fluxes, still making terrestrial carbon pools and fluxes one of the major remaining uncertainties in climate science (**Watson *et al.*, 2000, Houghton *et al.*, 2001, Bonan, 2008**).

Forests ecosystem are dominated by trees and other woody vegetation, but there are several definitions of forest worldwide based on administrative, cover, use or ecological characteristics. These different definitions are based on different concerns and interests of people and states. More recently, the World Wildlife Fund (WWF) assembled an international team of over 1000 biogeographers, taxonomists, conservation biologists, and ecologists that develop the terrestrial ecosystems classification system (**Olson *et al.*, 2001**). This bio-geographical classification, based on such a wide consensus of experts, might better reflect the distribution of species based on biophysical features (e.g. rainfall and temperature). It also allows a finer

classification in more numerous regions than previous systems. The major biomes can also be grouped in five categories: Tropical/Subtropical, Temperate, Dry, Polar/Montane, and Aquatic. Temperate (Broadleaf, Coniferous, and Mixed forest), Mediterranean, and boreal forest biomes are located in developed countries.

Global forests play an important role in the global carbon cycle as they cover approximately 30% of the land surface and store 45% of terrestrial carbon in the form of biomass via photosynthesis, which sequesters large amounts of carbon per year (**Bonan, 2008**). Forest accumulates carbon primarily in the form of living aboveground biomass of trees (*AGB*). Forest *AGB* is living organic plant material composed of 50% carbon (**IPCC, 2003b**) as well as hydrogen and oxygen, and it is usually defined for a given area. When forests are degraded, cleared or burned, large amounts of this carbon are released into the atmosphere as carbon dioxide and other compounds. Deforestation is the second largest anthropogenic source of carbon dioxide to the atmosphere after fossil fuel combustion and the largest source of greenhouse gas emissions in most tropical countries (**Gibbs *et al.*, 2007**). Afforestation, reforestation and growth of existing forest is the major contribution to the terrestrial sink term. Monitoring *AGB* stored in the world's forests is essential in order to understand the processes related to the global carbon cycle and reducing carbon emissions originating from deforestation and forest degradation.

Mapping the spatial distribution of *AGB* is crucial in order to determine the loss of carbon stocks due to disturbances (e.g. deforestation, fires) or the gain due to new planted forest or growth (**Houghton, 2005**). However, the methods should not only estimate *AGB* but also provide information about the uncertainty of the parameter itself.

Earth Observation sensors can be used to estimate *AGB* across large areas (**Santoro *et al.*, 2011, Cartus and Santoro, 2016**), but the sensitivity of the sensor to *AGB* depends on the technology used. Each technology has its own strengths and weaknesses which are mostly related to cloud penetration and topographic effects. Most approaches also face challenges related with the absence of in-situ well distributed data samples at scales useful for remote sensing (Houghton *et al.*, 2009), the poor availability of allometric models (**Henry *et al.*, 2011**), the differences among forest definitions (**Sexton *et al.*, 2015**), and the limited sensitivity of satellite sensors to

AGB (**Patenaude *et al.*, 2005**). Additionally, *AGB* distribution is ultimately driven by variations in tree allometries as a result of different climate conditions (**Reich *et al.*, 2014, Chave *et al.*, 2005**). Methods to combine different spatial datasets to exploit the specific strengths of each sensor are therefore needed. Additionally, understanding the strengths and limitations of each sensor is key to improve these methodologies.

Forests sequester carbon through photosynthesis and store it primarily as living aboveground biomass of trees (*AGB*). *AGB* is defined as the mass of living organic material for a given area and includes woody and herbaceous vegetation above the soil, including stems, branches, bark, seeds, flowers, and foliage of live plants. *AGB* is measured in units of dry mass or carbon per unit of area (t ha⁻¹ or t C ha⁻¹, respectively). In this, the term *AGB* is used when talking about dry mass, while *AGB* is used when talking specifically about carbon. Approximately 50% of *AGB* is carbon (**IPCC, 2003a**). Therefore, *AGB* is a key parameter for monitoring carbon allocation in terrestrial ecosystems as it represents a basic unit to account for carbon.

Recent global observation systems provide measurements of horizontal and vertical vegetation structures of ecosystems, which will be critical for estimating global carbon storage and assessing ecosystem response to climate change, natural and anthropogenic disturbances. Remote sensing overcomes the limitations associated with sparse field surveys; it has been used extensively as a basis for inferring forest structure and aboveground biomass (*AGB*) over large areas. Although no sensor has been developed that is capable of providing direct measures of vegetation biomass, the radiometry is sensitive to vegetation structure (crown size, tree density height), texture, and shadow, which are correlated with *AGB*. Three types of remote sensing data are often used, which are 1. Optical remote sensing 2. Radar (radio detection and ranging, microwave) data and 3. LiDAR (light detection and ranging) data. Optical spectral reflectance is sensitive to vegetation structure (leaf area index (LAI), crown size, and tree density), texture, and shadow, which are correlated with *AGB*. Radar data are directly related to *AGB* through measuring dielectric and geometrical properties of forests (**Le Toan *et al.*, 2011**). LiDAR remote sensing is promising in characterizing vegetation vertical structure and height, which are then associated to *AGB* (**Drake *et al.*, 2002a,b, Lefsky *et al.*, 2005a,b**). Vegetation structure characteristics measured

from satellite data are linked to field-based AGB estimates, and their relationships are used to map large-scale AGB from satellite data. Recently, remote sensing has been extensively used as a robust tool in delivering forest structure and AGB because it provides a practical means of acquiring spatially distributed forest biomass from local to continental areas (**Houghton 2005, Zhang and Kondragunta 2006, Goetz and Dubayah 2011**).

Vegetation AGB is defined as the mass per unit area (Mg/ha) of live or dead plant organic matter. Forest biomass consists of AGB and below-ground biomass. AGB represents all living biomass above the soil including stem, stump, branches, bark, seeds, and foliage, while below-ground biomass consists of all living roots excluding fine roots (less than 2 mm in diameter) (**FAO 2010**). Because AGB is relatively easy to measure and it accounts for the majority of the total accumulated biomass in forest ecosystem, AGB is usually estimated in many studies as to forest biomass. At the level of individual plants and forest stand levels, aboveground and belowground biomass are different, but share strikingly similar scaling exponents (**Cheng and Niklas 2007**). Below-ground biomass is often estimated based on AGB. Consequently, in this work, 'biomass' represents only aboveground forest biomass. Biomass estimate methods range from simple to more complex methods. The biome-averaged method is to estimate the biome-averaged AGB first, and the spatial distribution of biomass is mapped based on biome type. A more complex method is to develop species- and site-specific allometric models depending on bole diameter at breast height (DBH; cm) or diameter and tree height. The plot estimates of national forest inventories are commonly aggregated to represent forest biomass at national or regional scales (**Brown et al., 1989, Jenkins 2003, Gibbs et al., 2007**).

The total biomass or Vegetation production is defined as the process by which plants use sunlight to produce organic matter from carbon dioxide through photosynthesis. Gross primary productivity (GPP), or photosynthesis, is the rate of carbon fixation or total plant organic matter produced per unit of time and over a defined area, whereas the amount of carbon fixed by plants and accumulated as biomass is known as terrestrial net primary production (**Cramer et al., 1999; Zhao and Running 2010**). Productivity forms the basis of terrestrial biosphere functioning and

carbon, energy, and water budgets. Accurate estimates of plant productivity across space and time are necessary for quantifying carbon balances at regional to global scales (**Lieth 1975; Schimel 1998**). Vegetation productivity is generally limited by the availability of spatially and temporally varying plant resources (e.g., nutrients, light, water, and temperature) (**Field *et al.*, 1995; Churkina and Running 1998; Nemani *et al.*, 2003**). Improved knowledge of the main drivers and resource constraints of plant productivity is thus needed for predictable assessments of climate change.

Measures of productivity are essential in global change studies; yet despite their importance, they are quite challenging to obtain (**Baldocchi *et al.*, 2001**). The assessment of plant production is carried out in various ways, from plot measurements and plant harvests, micrometeorological fluxes, remote sensing, and through empirical and process-based models that may involve remote sensing data inputs. In situ measures include methods that vary with biome type, for example, tree inventories, litter traps, grassland forage estimates, and agricultural harvests and market statistics. Plot-level methods measure aboveground net primary production (ANPP) that often involves destructive sampling during peak biomass periods. Established long-term experimental plots enable cross site production comparisons; however, they are also amenable to many uncertainties due to differences in site-based procedures, and in some cases, inconsistent sampling methods over time at a given site (**Sala *et al.*, 1988; Biondini *et al.*, 1991; Moran *et al.*, 2014**). GPP has traditionally been estimated from plot level ANPP measurements by correcting for respiratory losses (**Field *et al.*, 1995**). Agricultural yield statistics (USDA NASS) combined with maps of cropland areas provide large-scale NPP estimates from local to national level census statistics (**Monfreda *et al.*, 2008; Guanter *et al.*, 2014**). A global network of micrometeorological tower sites, known as FLUXNET, now provide continuous measurements of carbon, water, and energy exchanges between ecosystems and the atmosphere (**Running *et al.*, 1999**). This yields information on seasonal dynamics and interannual variations of net ecosystem exchange (NEE) of carbon dioxide between the land surface and the atmosphere (**Baldocchi *et al.*, 2001; Verma *et al.*, 2005**). This has yielded quite valuable in situ data to independently evaluate and assess uncertainties in carbon models and satellite carbon products, as they are applied to global change studies. Satellite imaging sensors offer synoptic-scale

observations of ecosystem states and landscape dynamics, and are seen as invaluable tools to help fill the large spatial gaps of in situ measurements, and constrain and improve the accuracies of models. Remote sensing complements the restrictive coverage afforded by experimental plots and eddy covariance (EC) tower flux measurements, facilitating observations of broad-scale patterns of ecosystem functioning. This renders remote sensing a powerful tool for studying vegetation productivity at local, regional, and global scales (**Gitelson *et al.*, 2006**).

The integration of independently derived tower measured carbon fluxes with satellite data is the focus of many investigations across many ecosystems from sparse shrub lands to mesic grasslands, and tropical to temperate forests. Estimates of daily GPP and annual NPP are now routinely produced operationally over the global terrestrial surface at 1 km spatial resolution through production efficiency models with near real-time satellite inputs from the moderate-resolution imaging spectroradiometer (MODIS) (**Turner *et al.*, 2006**). There are many empirical, diagnostic, and process based models that have been developed over the past decades to monitor and assess vegetation productivity, with many of these methods employing remote sensing data in conjunction with micrometeorological carbon flux measurements to varying extents.

Traditionally, national-scale carbon monitoring has been accomplished with networks of field inventory plots (**FAO 2007**), which provide direct carbon measurements of only very small areas of forest, and are further difficult to install, monitor, and maintain over time (**Chambers *et al.*, 2009**). Airborne laser technology called light detection and ranging (lidar) offers much potential for terrestrial carbon assessments. Lidar measures the physical structure of woody vegetation, from sparse shrub lands to dense forests, and can serve as a reliable replacement for inventory plots in areas lacking field data (**Lefsky *et al.*, 2002; Zolkos *et al.*, 2013**). Thus, lidar integration with field inventory plots can provide calibrated lidar estimates of aboveground carbon stocks, which can then be scaled up using satellite data on vegetation cover, topography, and rainfall from satellite data to model carbon stocks (**Asner *et al.*, 2013**). Opportunities to fuse temporally dynamic vegetation optical measurements with lidar have promising potential for better assessments of not only standing wood biomass, but also forest disturbance, biomass loss, and carbon accumulation through forest regrowth (**Lefsky *et al.*, 2002; Asner *et al.*, 2010**).

Keeping in view the above facts, present research work has been planned to achieve the following objectives: -

1. Study of dominant forest types of study area.
2. Estimation of Above Ground Biomass (AGB) of dominant forest types.
3. Determines an optimal method for estimating forest AGB using multi parameter remote sensing data.
4. Assessment of Net Primary Productivity (NPP) and their spatial and temporal variability.

*Review
of
Literature*

Forest ecosystems play an important role in global change on the earth. Deforestation and forest degradation can result in carbon emission to the atmosphere, thus affecting global climate and environmental change (**Achard *et al.*, 2004; Froliking *et al.*, 2009; Hansen *et al.*, 2013**). Current concerns for global change and ecosystem functioning require accurate biomass estimation and examination of its dynamics (**Le Toan *et al.*, 2011**). In the past three decades, substantial effort has been made to develop biomass estimation models, including empirical-based and process-based ecosystem models (**Lu *et al.*, 2012; Chen 2013**).

There is wide range of biomass estimation techniques. For example, Wang *et al.* (2009) divided estimation approaches into (1) process model-based, (2) empirical model-based, (3) biomass expansion/conversion factor or coefficient-based, and (4) integration of plot and remotely sensed data. **Goetz *et al.* (2009)** and **Gleason and Im (2011)** summarized the application of major remote sensing data such as optical multispectral and hyperspectral sensor, radar (Radio Detection and Ranging, e.g. airborne L- or P-band data), and lidar (Light Detection and Ranging, e.g. airborne lidar or space-borne ICESat GLAS) to biomass estimation. However, no studies have summarized what variables from which sensor data are suitable for biomass estimation, and which algorithms/approaches are most effective to integrate various variables into biomass estimation models.

The most accurate method to estimate forest biomass is based on field measurements, but collection of field measurements is time-consuming and labor-intensive, and it is impossible to census large geographic areas (**Segura and Kanninen 2005; Seidel *et al.*, 2011; Wang *et al.*, 2011a**). Geographic Information System (GIS)-based biomass estimation models using environmental variables cannot provide accurate biomass estimates because forest biomass often has weak relationships with environmental variables (**Lu 2006; Chen 2013**). Process-based ecosystem models employ biogeochemical processes, including photosynthesis, absorption, and carbon allocation. The models generally couple biology, soil, climate, hydrology, and anthropogenic effects (**Smyth *et al.*, 2013**). Constraints in data source (e.g. climate

data, soil, and topography), spatial resolution, and inaccuracy of models often result in high uncertainties in biomass estimates (**Rivington *et al.*, 2006; Verbeeck *et al.*, 2006; Larocque *et al.*, 2008; Zhang *et al.*, 2012**). Moreover, process-based ecosystem models assume homogeneous stands and lack the ability to provide spatial variability in forest biomass. Remote sensing has the capability to consistently capture land surface features over large areas when airplanes or satellites pass over. Its unique characteristics for data acquisition, large coverage, digital format, etc. make it the primary data source for large-scale biomass estimation (**Lu *et al.*, 2012; Chen 2013**). Techniques using empirical regression models and nonparametric algorithms based on different sensor data (e.g. Landsat, radar, and lidar) have been developed (**Muukkonen and Heiskanen 2007; Blackard *et al.*, 2008; García *et al.*, 2010; Mitchard *et al.*, 2011**). Previous research has shown that remote sensing-based models provide more accurate biomass estimation than other models (e.g. process-based ecosystem models, GIS-based empirical models (**McRoberts *et al.*, 2013**)). Although much research has explored biomass estimation using remote sensing technology in the past three decades, methods to select suitable variables from remote sensing data and develop estimation models suitable for specific studies are still poorly understood.

2.1 IN-SITU FOREST ABOVEGROUND BIOMASS:

The direct method is to harvest trees, dry, and weigh the biomass. It is the most accurate method; however, the most labor intensive. For a small area, the most direct way to measure the carbon stored in aboveground living forest biomass is to harvest all trees, dry them, and weigh the biomass. The dry biomass can be converted to carbon content by taking half of the biomass weight (carbon content $\approx 50\%$ of biomass). This method is destructive, expensive, extremely time consuming, and impractical for any large regions. No methodology can directly measure forest carbon stocks across a landscape. Different methods are used to approximate large-scale carbon stocks ranging from simple empirical to more complex physically based methods. At the national level, the Intergovernmental Panel on Climate Change (IPCC) proposed different tiers of carbon stocks quality, ranging from Tier 1 (simplest to use; globally available data) up to Tier 3 (high-resolution methods specific for each country and repeated through time) (**Gibbs *et al.*, 2007**).

The simplest one is the Biome-Average Methods where use the biomass average for each biome to approximate a nation's carbon stocks (IPCC's Tier 1) (Houghton *et al.*, 2001, Gibbs *et al.*, 2007). Biome averages are compiled based on tree harvesting measurements and analysis of forest inventory data archived by the United Nations Food and Agricultural Organization (FAO) (Gibbs *et al.*, 2007). This method has both strengths and limitations. Biomes account for major bioclimatic gradients such as temperature, precipitation, and geologic substrate; it is a quick and easy way to estimate forest carbon stocks based on biomes. Besides, biome averages are free and easily accessible to map global forest carbon systematically. It provides a starting point for a country to access their carbon emission from disturbance. However, biome averages were generally focused on mature stands and were based on a few plots that may not adequately represent the biome or region. Further, forest carbon stocks vary significantly with slope, elevation, drainage class, soil type, and land-use history within each biome; therefore, an average value cannot adequately represent the variation for an entire forest category or country. Finally, the carbon stock estimates over disturbed areas could also be biased as the carbon stocks for the new growth systematically differ from the biome-average values (Houghton *et al.*, 2001).

Estimates of the AGB of trees are most commonly obtained through the use of allometric biomass equations which relate one or more measured variables (e.g. tree diameter) to total AGB (Ciais *et al.*, 2011) and is generally used to develop species-specific allometric models based on measured attributes such as diameter at breast height (DBH), tree height, and/or wood density (Overman *et al.*, 1994; Chave *et al.*, 2014). In order to parameterize an allometric model it is usually necessary to destructively harvest and weigh a representative sample of individual trees for which these variables have been measured and is only used to collect sample data in small areas due to prohibitive time and labor required for fieldwork (Klinge *et al.*, 1975). In general, AGB for a specific tree can be expressed as a function of DBH, tree height (H), and/or wood density (S): $AGB = f(DBH, H, S)$. Regression analysis is used to obtain a predictive relationship between the measured variable (s) and total AGB. This relationship is then applied to forest inventory data in order to produce estimates of AGB at larger spatial scales (e.g. plot, regional and landscape scale). Once allometric models are available for tree species, they can be used quickly and nondestructively for

stand biomass inventories. Many models have been developed based on various combinations of the aforementioned three parameters through linear or nonlinear regression models (**Saldarriaga *et al.*, 1988; Overman *et al.*, 1994; Seidel *et al.*, 2011**). Non-destructive in-situ methods such as forest inventories make use of allometric models to predict AGB. Biophysical parameters like tree height or diameter are commonly measured in forest inventories and other studies, and used to estimate AGB through allometric equations. The use of allometric equations has been shown to be a cost-efficient technique due to the use of existing and easily-measured variables. Common examples of these variables are tree height (H), basal area (BA), wood specific gravity (WSG), or diameter at breast height (DBH) models. Allometric models are the most common approach to obtain biomass reference data when DBH and/or tree height data at the plot level are available. One critical step is to carefully select suitable allometric models for specific tree species for a study (**Chave *et al.*, 2004; Melson *et al.*, 2011**).

Two allometric based approaches are commonly used to estimate AGB which are Species-Based Allometric Method and Woody Volume—and Woody Density—Based Allometric Method. The first one is a species-based approach to estimate biomass based on a given tree DBH. It requires measuring the diameter for each individual tree and allometric equations for each individual tree species. For example, **Jenkins *et al.*, (2004)** developed a set of generalized allometric regression models to predict AGB in tree components for all tree species in the United States. It is used by the USDA Forest Service, Forest Inventory and Analysis program to estimate the U.S. national forest carbon estimates. This approach provides a nationally consistent method for the estimation of biomass and C stocks at large scales and requires only a single field-based variable tree DBH (1.37 m) as input.

The second approach is a more generalized one, using woody volume and wood density to calculate biomass (**Brown 2002, Chave *et al.*, 2005, 2014**). Developing allometric equations for each individual species can be very difficult. However, grouping all species together and using generalized allometric relationships, stratified by broad forest types or ecological zones, is highly effective, particularly for the tropics because DBH alone explains more than 95% of the variation in aboveground tropical forest carbon stocks, even in highly diverse regions(**Brown 2002**). **Chave *et al.*, (2005)**

developed generalized allometric equations for the pan-tropics based on an exceptionally large dataset of 2410 trees across a wide range of forest types. They included wood density and tree height within their models and proposed a global forest classification system that contains three climatic categories (dry, moist, and wet) to account for climatic constraints determining the AGB variation. Very recently, **Chave *et al.*, (2014)** updated their allometric equations and developed a single model using trunk diameter, total tree height, and wood specific gravity across tropical vegetation types, with no detectable effect of region or environmental factors. The new allometric models should contribute to improving the accuracy of biomass assessment protocols in tropical vegetation types and to improving accuracy of carbon stock estimates for tropical forests. Studies show that the most important parameters in estimating biomass (in decreasing order of importance) were diameter, wood density, tree height, and forest type (classified as dry, moist, or wet forest). Including tree height reduced the standard error of biomass estimates from 19.5% to 12.5% (**Chave *et al.*, 2005**). Tree biomass estimation was significantly improved by including wood density (**Brown *et al.*, 1989**) and tree height (**Brown 1997, Nogueira *et al.*, 2008**) in the allometric models in addition to tree diameter. However, measuring height (H) and wood density (q) requires additional work, increasing project time and costs. This approach is not often used as it required additional height measurements for each individual tree. Despite the difficulty, more and more studies demonstrated the importance of these parameters for biomass estimates. For example, studies by **Feldpausch *et al.*, (2011, 2012)** demonstrate that incorporating height in biomass estimates for the pan tropical region improves biomass estimates by lowering it. For tropical forests, carbon storage can be overestimated by 35 PgC if height is ignored. The study by **Domke *et al.*, (2012)** for the United States also demonstrates similar results. **Domke *et al.*, (2012)** compared estimates of carbon stocks using Jenkin's and a tree height-based approach—the component ratio method (**Woodall *et al.*, 2011**)—for the 20 most abundant tree species in the 48 states of the United States and found the method incorporating height decreased national carbon stock estimates by an average of 16% for the species. These results implicate that tree height, an important allometric factor, needs to be included in future forest biomass estimates to reduce error in the estimates of tropical carbon stocks and emissions due to deforestation and to improve accuracy of national and global forest carbon.

2.2 REMOTE SENSING DATA:

A variety of remote sensing systems have been used to estimate AGB estimates: passive optical remote sensing, radar, and LiDAR. Passive optical remote sensors measure different wavelengths of reflected solar radiation, providing two-dimensional information that can be indirectly linked to biophysical properties of vegetation and AGB and carbon stocks. Several optical satellite instruments are available for mapping AGB and carbon stocks at different spatial scales. The spatial resolutions of these satellite data range from meter to kilometer scales. Those data span from 1970s to current, and some recent satellite data are collected on a daily scale. The most popular optical remote sensing satellite data being used to map AGB are multispectral satellite data at various spatial resolutions. NOAA's advanced very-high resolution radiometer (AVHRR) and NASA's moderate-resolution imaging spectroradiometer (MODIS) data are promising in producing biomass at continental and global scales (**Dong *et al.*, 2003, Baccini *et al.*, 2004, 2008, Zhang and Kondragunta 2006, Blackard *et al.*, 2008**). AVHRR provides global observations at 1 km scale every one or two days since 1979. MODIS aboard the Aqua and Terra satellites has imaged the entire globe approximately every two days at resolutions of 250–500 m, dating as far back as 2000. These datasets are used alone or fused with other remote sensing data to provide AGB and carbon stock estimates at large scales. Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) provide biomass estimates at local and regional scales at high spatial resolution (**Muukkonen and Heiskanen 2005, Zhang and Kondragunta 2006, Pflugmacher *et al.*, 2014**). Landsat provides four decades of imagery of the entire globe at 30 m spatial resolution, the longest continuous record of space-based moderate-resolution land remote sensing data freely available to the public. With the advantages of being free and long-term data records, methods of using spectral information or more complicated methods using both spectral and temporal information and fusion with other remote sensing data have been developed to estimate AGB estimates. Landsat images are invaluable data sources to AGB and carbon stock estimates. ASTER, an imaging instrument on board Terra launched in December 1999, images the earth at 15 m resolution in visible to near-infrared spectrum, which is the most sensitive to vegetation properties. Other passive optical systems such as

multiangular data from MISR on board Terra and airborne/spaceborne hyperspectral data from AVIRIS and EO1 sensors are also used for biomass estimates (**Anderson *et al.*, 2008, Chopping *et al.*, 2009**).

Radar data physically measure biomass through the interaction of the radar waves with tree scattering elements. The widely used active radar data for biomass estimates are from spaceborne synthetic aperture radar (SAR) sensors, such as the L-band Advanced Land Observing Satellite (ALOS), Phased Array- Type L-band Synthetic Aperture Radar (PALSAR), the C-band European remote sensing satellite (ERS)/SAR, RADARSAT/SAR or Environmental Satellite (ENVISAT)/Advanced Synthetic Aperture Radar, and the X-band TerraSAR-X instrument, which transmit microwave energy at wavelengths from 3.0 (X-band) to 23.6 cm (L-band). ERS and ENVISAT operated by European Space Agency (ESA) collect C-band SAR data since 1991. Canadian RADARSAT has collected C-band data since 1995. German TerraSAR-X was in space since 2010. Those data have been used to estimate AGB with low density. The L-band PALSAR was launched by Japan Aerospace Exploration Agency. ALOS/PALSAR was operated in orbit from January 2006 until April 2011. It shows a great potential for forestry applications in the boreal regions due to high signal/noise ratio, high resolution (~20 m), provision of cross polarized data, and because data are being systematically collected across the Northern Hemisphere. ALOS2 was launched in 2014, and PALSAR-2 has updated features of PALSAR. A spaceborne P-b and SAR, which would be less affected by saturation at higher biomass levels, is planned to launch in the coming years in the frame of the Earth Explorer Program of the ESA. Many airborne L-band and P-band data were also collected for biomass estimates. The major advantage of all SAR systems is their weather and daylight independency.

LiDAR is an active remote sensing system based on laser ranging, which measures the distance between a sensor and the target surface. Vegetation LiDAR systems typically emit at wavelengths between 900 and 1064 nm and record the time during which the emitted laser pulse is reflected off an object and returns to the sensor. The time-return interval is used to calculate the range (distance) between the sensor and the object. LiDAR provides direct and indirect measurements of vegetation structure, which can be used to estimate global carbon storage. Recent advances in LiDAR

technology have made LiDAR data widely available to study vegetation structure characteristics and forest biomass. LiDAR systems are classified as small-footprint LiDAR (laser footprint less than 1 m scale) and large-footprint LiDAR (laser footprint 10 m or greater) based on the size of laser footprint or discrete-return and full-waveform recording based on how laser energy is recorded (**Dubayah and Drake 2000, Wulder *et al.*, 2012**). Discrete-return systems record single or multiple returns from a given laser pulse. As the laser signal is reflected back to the sensor, large peaks, (i.e., bright returns) represent discrete objects in the path of the laser beam and are recorded as discrete points. Most small-footprint LiDAR system record discrete energy returns. In contrast, full-waveform-recording LiDAR systems digitize the entire reflected energy from a return, resulting in complete sub-meter vertical vegetation profiles. The waveform is a function of canopy height and vertical distribution of foliage, as it is made up of the reflected energy from the surface area of canopy components such as foliage, trunks, twigs, and branches, at varying heights within the large footprint. The total waveform is therefore a measure of both the vertical distribution of vegetation surface area and the distribution of the underlying ground height. Waveform-recording instruments are mainly large-footprint LiDAR systems; however, recent advances made full-waveform instruments with increasingly smaller footprint sizes available. Small-footprint multiple return LiDAR data have been collected in many regions of the globe, and more recently small footprint scanning waveform systems have become operational. Such small-footprint airborne LiDAR systems are available on a commercial basis and are now used at the operational level in forest resource inventories (**Nasset and Gobakken 2008**). At standard level, ground-based LiDAR data, such as EVI, were collected and used for AGB estimates (**Strahler *et al.*, 2008, Ni-Meister *et al.*, 2010**). With many ground LiDAR system, complex and detailed vegetation structure data have been recorded over various study sites. The Geoscience Laser Altimeter System (GLAS) was a large footprint spaceborne full-waveform profiling LiDAR carried on the Ice, Cloud, and land Elevation Satellite (ICESat) for 2003– 2009. GLAS was the first spaceborne LiDAR, and global measurement of canopy height was one of the science objectives of the ICESat mission (**Zwally *et al.*, 2002**). The size and shape of the GLAS footprints vary from 50 to 65 m in diameter and from elliptical to circular, depending on the date of the acquisition. The pulses are spaced approximately 172 m apart. Airborne data have also been collected

using a Scanning LiDAR Imager of Canopies by Echo Recovery (SLICER) with a 15 m footprint and the Laser Vegetation and Ice Sensor (LVIS) with a 20 m/25 m footprint over several large areas for improved vegetation structure characterization since 1998 (**Blair *et al.*, 1999**). This large-footprint LiDAR system records full-waveform laser energy returns. These global, regional, and local LiDAR data can provide the detailed vegetation structure and biomass maps necessary for carbon models and ecosystem process studies. Recent advances of mapping disturbance using Landsat data lead to a new approach to map AGB dynamics using forest disturbance and recover history maps derived from Landsat (**Powell *et al.*, 2010, Pflugmacher *et al.*, 2012, 2014, Main-Knorn *et al.*, 2013**). With recently developed algorithms that characterize trends in disturbance (e.g., year of onset, duration, and magnitude) and post-disturbance regrowth, the new method improved Landsat-based mapping of current biomass across large regions. The new approach includes information on vegetation trends prior to the date to enhance Landsat's spectral relationships with biomass. The method was tested in various forests in Oregon (USA), Arizona, Minnesota, Montana, and Europe using Landsat-based disturbance and recovery metrics. They found that the new method substantially improved predictions of AGB compared to models based on only single-date reflectance. Conversely, they also found that their method performed significantly better in estimating AGB dead than LiDAR models, and single-date Landsat data failed completely. **Chopping *et al.*, (2008)** investigated the usability of Multiangle Imaging SpectroRadiometer (MISR) on board the Terra satellite to measure woody biomass and other forest parameters for large parts of Arizona and New Mexico. The advantage of MISR over active or other passive sensors is timely and extensive estimates of forest biomass and other parameters at low cost. **Gonzalez *et al.*, (2010)** used Quick Bird's panchromatic band to automatically detect tree crowns and then used regression techniques to estimate biomass from the diameter of each tree crown. They found that the Quick Bird imagery resulted in higher error and lower total biomass estimates than the LiDAR data due to the shadowing that interfered with the crown detection algorithm. The cost of acquiring the images from these sensors is prohibitive for most research purposes. While the spatial resolution offered by these sensors is excellent for crown delineation, care must be taken with shadowing and other effects of sun angle and tree height, further reducing the utility of these data for small-area forest quantification (**Gleason and Im 2011**).

2.3 REMOTE SENSING AND AGB:

Describing and quantifying forest above-ground biomass (AGB) has become of importance to many scientific and societal tasks such as sustainable forest management, timber management, forest ecosystem productivity estimation, carbon sink evaluation and studies of the role of forest in the global carbon cycle, and links between hydrology and ecology, etc. (Houghton *et al.*, 2001; Zheng *et al.*, 2004; Lu, 2006). In conventional techniques on basis of statistical assessment (i.e., tree species, vertical structure, stand height, and stand density), the forest AGB information comes from expensive and time consuming field surveys by the high sampling intensity (Schroeder *et al.*, 1997; Woodbury *et al.*, 2007). As alternative, multi-parameter remote sensing techniques have been applied, in which remotely sensed data are used as proxy for quantitative forest AGB at various scales (Nelson *et al.*, 2009; Lu *et al.*, 2012; Gonzalez *et al.*, 2010).

Remote sensing provides a powerful tool for fast and repeatable monitoring of land cover and above-ground carbon (i.e. AGB) dynamics at local, regional and global scales. To date a variety of remote sensing techniques have been used to produce forest classification maps, estimates of forest cover (and changes in cover through time), to map deforestation and degradation and to estimate AGB biomass (Ryan *et al.*, 2003; Saatchi *et al.*, 2011b).

However, the application of remote sensing data for the forest AGB estimation is complicated in heterogeneous forests, where the tree species, stand density, canopy closure and crown over-lap are variable. All these variables affect AGB, but it is difficult to differentiate them with remote sensing. In addition, topographic irregularities and various environmental conditions also affect the remote sensing signatures of the observed surfaces (Danson and Curran, 1993; Nelson *et al.*, 2000a; Saatchi *et al.*, 2007). Both passive and active remote sensing measurements have been used for the estimation of forest AGB, each having different advantages and disadvantages.

Some passive remote sensing techniques make use of the sensitivity of the reflectance of forests to parameters like canopy cover, crown closure, leaf area index, which are in turn correlated with AGB. Many studies have investigated the relationship

between forest AGB and satellite spectral values expressed as digital numbers, radiance, reflectance, or vegetation indices. Sensors with intermediate spatial resolution like Satellite Probatoire d'Observation de la Terre (SPOT), Landsat Thematic Mapper and Enhanced Thematic Mapper Plus data are commonly used for this purpose. Various correlations between forest AGB and the reflectance or vegetation indices were found and **reported (Roy and Ravan, 1996; Nelson *et al.*, 2000b; Zheng *et al.*, 2004; Powell *et al.*, 2008; Soenen *et al.*, 2010).**

Some active remote sensing techniques make use of the relation between Synthetic Aperture Radar (SAR) backscatter and forest AGB (**Dobson *et al.*, 1992; Yrjo, 2005**). The advantage of SAR is that the signal is less prone to saturation with AGB than optical reflectance. Not all SAR bands are equally suitable: SAR backscatter in the P and L bands has a much stronger correlation with forest AGB than the C and X bands. The L-band has proven particularly valuable for AGB estimation (Lu, 2006). Some studies (**Moghaddam *et al.*, 2002; Chen *et al.*, 2009**) found that the accuracy of forest AGB estimation improved when optical reflectance data were added to the SAR data as an additional source of information. The single most promising technique in active remote sensing is airborne laser scanning (ALS). ALS has recently led to a revolution in remote sensing of forest structure (**Salas *et al.*, 2010**), due to its unique ability to measure three-dimensional information (**Garcia *et al.*, 2010**).

There are several options for estimating forest AGB among the multi-parameter remote sensing data, differing in cost, spatial resolution, applicability and continuity. Optical remote sensing data is sensitive to the forest AGB, but the spectral signature saturates at a higher biomass level than the SAR data. SAR data are free of weather disturbance, but largely affected by topography and the quality depends on the waveform length (**Sun *et al.*, 2002**). Airborne LiDAR is the most efficient technique to estimate forest AGB. It is also the most expensive technique, which makes it unsuited for routine applications.

Two methods exist for establishing (calibrating) the relation between remote sensing data and forest AGB with ancillary data: parametric and non-parametric. The parametric method employs multiple regressions, assuming that each forest attribute affects remote sensing signals at each wavelength in a unique and uncorrelated way (**Lawrence and Ripple, 1998; Rahman *et al.*, 2008**). The method is conceptually

simple, but the success largely depends on the statistical robustness of the relationships.

With recent advancement in geospatial statistical methods and ongoing technology improvement in performing expensive statistical computations, the nonparametric method appears more prevalent in more recent studies (**Baccini *et al.*, 2004, 2008**). These methods perform recursive partitioning of datasets, make no assumptions regarding the distribution and correlation of the input data, effectively solve complex nonlinear relationships between the response and predictor variables, and show great advantages for nonlinear problems and often perform better than standard linear regression models.

The non-parametric like k-Nearest Neighbour (k-NN) method is based on more flexible assumptions than the parametric method, and does not suffer from the same limitations. In the non-parametric method the AGB of a pixel is associated with that of the k ‘nearest’ pixels in terms of remote sensing observations for which field data of AGB are available. A training set of pixels for which both field measured AGB and remote sensing data are available is established first. This training set is further used to estimate the AGB of all other pixels by linking them to pixels with similar remote sensing data in the training set.

Tree-based models (**Breiman *et al.*, 1984**), a nonparametric approach, are a fundamental tool in data mining. They perform partitioning of datasets to capture nonlinear relationships between the response and predictor variables for predicting a categorical (classification tree) or continuous (regression tree) outcome. This method has been previously used in remote sensing field to predict for classification and continuous variables (**Baccini *et al.*, 2004, 2008**). Tree-based models are known for their simplicity and efficiency when dealing with domains with large number of variables and cases. However, it can also lead to poor decision in lower levels of the tree due to the unreliability of estimates based on small samples of cases. A commonly used tree-based model in AGB estimate is random forest (**Breiman 2001, Breiman *et al.*, 1984**). Random forest constructs a multitude of decision trees at training time in which different bootstrap samples of the data are used to estimate each tree and outputting the class corresponding to the individual trees. The resulting model is more accurate and less sensitive to noise in input data relative to conventional tree-based

modelling algorithms. The use of random forest for biomass estimate demonstrates the advantages of the nonparametric statistical method. For example, **Baccini *et al.*, (2008)** compared the performance between random forest with more traditional multiple regression analysis, and they found that the traditional regression–explained variance is 71% compared to 82% from random forest of their AGB in their study region. LiDAR data, in combination with a random forest algorithm and a large number of reference sample units on the ground, often yield the lowest error for biomass predictions and become very popular in most research efforts on biomass estimates. There are, however, limitations to the random forest model in the prediction phase. The model tends to over predict low biomass values and under predict high biomass values. This trend is intrinsic of regression tree-based models whose predictions are the average of the values within the terminal node. Different methods are used in different remote sensing field for biomass estimates.

Optical remote sensing data have been extensively used to map AGB. One simple method to map AGB is to use remotely sensed land cover classification maps where each class is assigned an average value of biomass density based on literature estimates or forest inventories. The IPCC Tier 1 approach was applied to study area using their prescribed forest carbon density values combined with land cover data generated from the globally available land cover dataset, Global Land Cover 2000. Land cover data were reclassified as forest or no forest, using all forest classes of GLC2000. Aboveground carbon densities were assigned to each land cover class using IPCC values. The other more commonly used method is the determination of relationships between in situ biomass density and remote sensing characteristics/signals that can be consistently mapped over large regions (**Saatchi *et al.*, 2007**). This approach has the advantage of providing spatially consistent and continuous values of the amount of biomass present at any given location. The suite of freely available optical satellite sensors, such as Landsat, AVHRR, and MODIS, has been used extensively to map AGB based on statistical relationships between ground based measurements and satellite-observed surface reflectance, or vegetation indices or tree canopy attributes are derived from optical satellite data (**Lu 2006**). Spectral reflectance's of optical remote sensing are the simplest variables in biomass estimates. Vegetation indices are particularly useful in biomass observations because it enhances

green vegetation signals and minimizes the impacts from surface and atmospheric effects. Alternatively, tree canopy attributes such as LAI, tree cover, crown size, density, and tree shadow fraction derived from optical satellite data are considered to be effective proxies of AGB. Tree shadow fraction is an indicator of vertical vegetation structure, which can be an indicator of biomass. At continental and global scale biomass mapping, the coarse spatial resolution optical sensors, such as the NOAA AVHRR (1.1 km) and MODIS (250 m to 1 km), have been useful for forest biomass estimates due to the good trade-off between spatial resolution, image coverage, and frequency in data acquisition (**Lu 2006**). **Dong *et al.*, (2003)** used the normalized difference vegetation index (NDVI) estimate provided by the AVHRR sensor to estimate forest biomass at continental scale. A regression model was developed to relate AGB to latitude and the inverse of the AVHRR NDVI. Their results were encouraging for a study at this scale, but were ultimately unreliable for small-area, high accuracy forest inventories required by small property owners seeking to quantify their forests. Recent studies using MODIS data using random forest (**Baccini *et al.*, 2004, 2008**) found that the shortwave infrared (SWIR) bands (MODIS bands 6 [1628–1652 nm] and 7 [2105– 2155 nm]) are particularly sensitive to forest structural parameters (crown size and tree density), texture, and shadow, which are correlated with AGB. They have found a negative relationship between AGB and SWIR reflectance. They argue that SWIR signal is a strong indicator of tree shadows, which is related to stand age structure. Generally, the structure of young forests is often characterized by a single canopy layer, high density, relatively few canopy gaps, and trees of roughly the same size. Conversely, older forests are characterized by a mix of tree ages and sizes, canopy gaps, and multiple canopy layers resulting in increases in the shadow component, thus decreases in SWIR reflectance. **Baccini *et al.*, (2008)** report a high accuracy, with the map explaining 82% of the variance in AGB for 10% of field plots held back for validation, with a root mean square error (RMSE) of 50.5 Mg/ha. However, many other studies using MODIS data have various successes (**Blackard *et al.*, 2008, Anaya *et al.*, 2009**). The main limitation is that MODIS signals are not very sensitive to high biomass values (**Lu 2006, Zheng *et al.*, 2007, Anaya *et al.*, 2009**). For quantifying biomass at local to regional scales, data provided by finer spatial resolution instruments, such as Landsat TM (Lu *et al.* 2005) and ASTER (**Muukkonen and**

Heiskanen, 2005, 2007), are required. Typically, finer spatial resolution satellite data have been used as an intermediate step when relating ground reference data with coarser spatial resolution data, usually by regression techniques. For example, **Muukkonen and Heiskanen (2005, 2007)** used stand-wise forest inventory data and moderate resolution ASTER data to estimate biomass with coarse-resolution MODIS data for a large area with good accuracy. The demonstrated approach can be used as a cost-effective tool to produce preliminary biomass estimates for large areas where more accurate national or large-scale forest inventories do not exist. The Landsat series of satellites has proven to be a successful venture, providing decades of free-access moderate-resolution multispectral imagery. To estimate forest biomass, many of the studies used band combinations of the Landsat data and vegetation indices in a regression with a variety of standard field variables including mean height, Lorey's mean height (mean stand height weighted by basal area per tree), maximum height, crown width, and others. These efforts met with varying degrees of success. **Cartus *et al.*, (2014)** reported a great success of using Landsat to map biomass than radar data. Landsat data, in the form of a canopy density product, was an important predictor for the AGB of forests in Africa (**Avitabile *et al.*, 2012**) and in the Amazon (**Saatchi *et al.*, 2007**). Canopy density metrics works well on open canopies (i.e., primarily during early successional stages of forest development). Biomass differences between forests with closed canopies are not captured. **Foody *et al.*, (2003)** employed a feed-forward neural network to model forest biomass and was successful in extracting forest biomass with high levels of accuracy. **Foody *et al.*, (2003)** also note a key issue in remote sensing of biomass: the inability of models to transfer from study site to study site. Empirical models built from satellite imagery rarely transfer from one study area to another, even if the study sites are composed of similar forest species and climatic conditions. Small forest plots are not represented well by image pixels larger than their spatial extent (**Lu, 2006**), and complex biophysical environments are not well represented at the scale of Landsat data.

Radar signals are sensitive to dielectric and geometric properties of forests and are thus directly related to measurements of AGB. The ability of radar sensors to measure biomass mainly depends on how deep the radar signals can penetrate into the canopy. The longer the wavelength is, the deeper the penetration is. The L- and P-band

backscatter, particularly HV- and HH-polarized backscatter, is strongly dependent on biomass amount (**Le Toan *et al.*, 1992, Ranson and Sun 1994, Saatchi *et al.*, 2012**). P-band backscatter shows stronger dependence on biomass than L-band backscatter. The radar backscatter increases approximately linearly with increasing biomass until it is saturated at a certain biomass level that varies with the radar wavelength (**Imhoff 1995**). The biomass level for backscatter saturation is about 200 tons/ha at P-band, 100 tons/ha at L-band, and 30–50 tons/ha at X- and C-bands (**Le Toan *et al.*, 2011**). The observed relationship between radar backscatter and biomass can be physically illustrated using electromagnetic scattering models (**Sun and Ranson 1995**). HV backscatter is dominated by volume scattering from the woody elements in the trees, so that HV is strongly related to AGB. For the HH and VV polarizations, ground conditions can affect the biomass–backscatter relationship, because HH backscatter comes mainly from trunk-ground scattering, while VV backscatter results from both volume and ground scattering. Application of the radar biomass estimation at continental or globe scale is best at 1.0 ha scale (100 m × 100 m pixel size). At this scale, the distribution of AGB over the landscape is both stationary and normal, and the radar resolution is large enough to reduce the speckle noise and the geo-location error between radar pixel and the plot location. Errors associated with the biomass estimation from radar backscatter or height measurements at this scale can be reduced to acceptable levels (10%–20%) for mapping the AGB globally (**Saatchi *et al.*, 2011, 2012**). SAR sensors on board several satellites (ERS-1, JERS-1, ENVISAT, and RADARSAT) with C- and X-bands were used to quantify forest carbon stocks in relatively homogeneous or young forests, but the signal tends to saturate at fairly low biomass levels (~50–100 tons C/ha) (**Le Toan *et al.*, 2004**). Mountainous or hilly conditions also increase errors. Several studies have used the phased array-type L-band SAR (PALSAR) on board the Japanese ALOS launched in 2005 to estimate biomass and carbon stocks in sparse canopies from African savanna woodlands to boreal forests (**Carreiras *et al.*, 2012, Peregon and Yamagata 2013, Mermoz *et al.*, 2014**). Those studies found that ALOS/PALSAR data can successfully map AGB in sparse canopies when aggregating the ALOS biomass maps at large scale (county scale or hectare scale). Synergistic use of L- and X-band SAR can provide large-scale AGB (**Englhart *et al.*, 2011**). They combined multi temporal Terra SAR-X x-band and ALOS PALSAR L-band to estimate large-scale biomass for tropical forests with $r^2 = 0.53$ with an

RMSE of 79 tons/ha. Many studies have demonstrated that radar backscattering works best only to estimate biomass for sparse canopy. As an alternative to SAR backscatter intensity, recent advancement in interferometric radar analysis techniques such as polarimetric and interferometric radar (PolInSAR) has shown great potential to predict biomass (**Askne and Santoro 2005**). These interferometric techniques allow for a characterization of the vertical forest structure and thus a more immediate estimation of forest biophysical attributes. Coherence saturation levels are generally higher than those reported for backscatter intensity. Under favorable conditions, correlations exist for values of upto 250–300 tons/ha (**Santoro *et al.*, 2007, Chowdhury *et al.*, 2014**). The backscattering intensity for C- and X-bands is not very good for forest biomass estimation. But the InSAR coherence and the phase center height of X-band InSAR can be used for the purpose. However, the potential to implement such experimental techniques across large areas depends on suitable configurations of future spaceborne SAR missions. With the advancement in interferometric radar analysis techniques, radar data have a great potential for global biomass estimates due to its independence from clouds and therefore the possibility to obtain continuous global coverage.

Use of LiDAR to estimate forest biomass has accelerated rapidly in recent years. Observation from both discrete and full-return LiDAR can be translated into various forest structure metrics such as maximum canopy height and multistrata heights aboveground as well as characteristic height at which different proportions of the total reflected energy are returned to the sensor. The various derived metrics can be related to AGB, typically via correlative model with associated field measurements (**Goetz and Dubayah 2011, Wulder *et al.*, 2012**). Many studies have demonstrated the strong relationship between AGB and LiDAR-measured height metrics, ranging from boreal conifers to equatorial rain forests. LiDAR has been widely used to map AGB using different LiDAR system. LiDAR is recognized as the state-of-the-art remote sensing technology for mapping AGB because it is much less sensitive to the saturation problem, compared to conventional remote sensing optical and radar data.

2.4 REMOTE SENSING OF NET PRIMARY PRODUCTIVITY (NPP):

Remote sensing approaches to estimate productivity generally employ spectral measures of vegetation, which are used for estimating their capacity to absorb photosynthetically active radiation (APAR). Vegetation productivity is directly related

to the interaction of solar radiation with the plant canopy, based on the original logic of **Monteith (1972)**, who suggested that productivity of stress-free annual crops was linearly related to vegetation absorbed PAR. Spectral vegetation indices (VIs) such as the normalized difference vegetation index (NDVI) (**Tucker 1979**), the perpendicular vegetation index (PVI) (**Richardson and Wiegand 1977**), and the tasseled cap green vegetation index (TC-GVI) (**Kauth and Thomas 1976**) were consequently developed over croplands and grasslands. **Asrar et al.**, (1984) showed the NDVI was linearly related with vegetation absorption of light energy (APAR) or fraction of APAR (fAPAR), and thereby related to productivity through the potential capacity of vegetation to absorb light for photosynthesis. The linear relationship between NDVI and fAPAR has been documented through field measurements (**Ruimy et al., 1994; Fensholt et al., 2004**) and theoretical analyses (**Sellers 1985; Goward and Huemmrich 1992; Myneni and Williams 1994**).

In studies of ecosystem processes and environmental management, accurate net primary productivity (NPP) measurements are crucial as NPP represents an important energy flux in ecosystems. Traditionally, NPP has been measured using biometric measurements, i.e., sample surveys and field measurements (**Tao et al., 2003**). Although these traditional field based measurements have been used successfully with accurate NPP output for small scale observations (**Ogawa, 1977; Li et al., 2005**), they are often time consuming and laborious (**Lu, 2006**). The methods are also hard to extend to larger spatial scales because of the sparse measurements network. In addition, the felling of sample trees at target research sites may lead to loss of habitat and biodiversity as well as carbon sequestration potential (**Wang et al., 2007**). Therefore, it is necessary to apply alternative methods of NPP estimation to replace or complement traditional methods. The development of remote sensing has enhanced the ability to study and understand ecosystems with improved accuracy (**Lu, 2006**). Remote sensing provides an invaluable opportunity to improving the estimation of NPP at landscape and regional scales in a cost effective, efficient and accurate manner (**Running et al., 1999; Running, 2000**) at high temporal and spatial scales (**Myneni et al., 1997; Zhou et al., 2001; Lu, 2006**). Early applications of remote sensing have seen the use of the normalized difference vegetation index (NDVI), as a surrogate measure for NPP (Townshend and Justice, 1986). NDVI has been proven to provide an effective measure

of photo-synthetically active biomass and has been correlated to NPP at extensive spatial scales (**Box *et al.*, 1989; Prince, 1991; Oindo and Skidmore, 2002**). Recent developments in remote sensing are now focusing on estimating NPP quantities usually in grams of carbon per square metre per year ($\text{gC m}^{-2} \text{ yr}^{-1}$) or tones of carbon per hectare per year ($\text{ton C ha}^{-1} \text{ yr}^{-1}$). As a result, various NPP models that use remote sensing data have been developed (**Goetz *et al.*, 2000**). Recently, the moderate resolution imaging spectro-radiometer (MODIS) NPP model, based on a micrometeorological approach was developed by **Rahman *et al.*, (2004)** to provide a consistent, continuous estimate of NPP (**Heinsh *et al.*, 2006**) hereinafter referred to as the MODNPP model. This model is derived from the Monteith Model (**Monteith, 1977**) which estimates NPP as a product of light-use efficiency (LUE) and absorbed photo-synthetically active radiation (APAR).

Several studies suggest that annual vegetation productivity status can be captured with the annual NDVI integral, used as surrogate measures of fAPAR. **Goward *et al.*, (1985)** used integrated NDVI values derived from the advanced-very-high-resolution radiometer (AVHRR) and found good relationships between NPP and integrated NDVI over annual growing periods of North American biomes. **Wang *et al.*, (2004)** found that the NDVI integral over the early growing season was strongly correlated to in situ forest measurements of diameter increase and tree ring width in the U.S. central Great Plains. They also found the previous year integrated NDVI was well correlated with current year increases in tree height growth.

The annual integrated VI offers a robust approximation of vegetation productivity, because, in general, VIs provide both a measure of the capacity to absorb light energy, as well as reflect recent environmental stress acting on the canopy, with stress forcing showing up as reductions in NDVI expressed as either less chlorophyll and/or less foliage (**Running *et al.*, 2004**). Photosynthesis or primary production is essentially integrator of resource availability, and according to the resource optimization theory (**Field *et al.*, 1995**), ecological processes tend to adjust plant characteristics over time periods of weeks or months to match the capacity of the environment to support photosynthesis and maximize growth. **Ponce-Campos *et al.*, (2013)** compiled in situ field measures of ANPP across 10 sites in the United States, ranging from arid grassland to forest and directly compared annual integrated values of

the MODIS enhanced vegetation index (EVI, or iEVI). Using a log–log relation to account for the uneven distribution of ANPP estimates over time, the iEVI was found to be an effective surrogate to estimate ANPP and quantify vegetation dynamics.

Moran *et al.*, (2014) found plot-scale measurements of ANPP at arid and mesic grassland sites were significantly related to MODIS iEVI over a decadal time period in a log–log relation. **Zhang *et al.*, (2013)** studied the ecological impacts of rainfall intensification on vegetation productivity through the use of iEVI as a surrogate measure of ANPP. They found extreme precipitation patterns, associated with heavy rainfall events followed by longer dry periods, caused higher stress conditions that resulted in strong negative influences on ANPP across biomes and reduced rainfall use efficiencies. Remote sensing estimates of GPP and net primary production (NPP) have been implemented at global scales, based on the light-use efficiency (LUE/ ϵ) equation that defines the amount of carbon fixed through photosynthesis as proportional to the solar energy absorbed by green vegetation multiplied by the efficiency with which the absorbed light is used in carbon fixation (**Monteith 1972; Monteith and Unsworth 1990**).

The LUE concept has been widely adopted by the remote sensing community to assess and extrapolate carbon processes through knowledge of two conversion coefficients: the fAPAR and ϵ . Although fAPAR is readily estimated using remotely sensed “greenness” measures, ϵ is very difficult to measure as it dynamically varies with plant functional type, vegetation phenophase, and different environmental stress conditions (**Ruimy *et al.*, 1995; Turner *et al.*, 2003; Jenkins *et al.*, 2007**). As a result, there are scarce measurements of ϵ available, particularly at the landscape scale, and potential or maximum LUE values have only been specified for a limited set of biome types, with these values down regulated by environmental stress scalars derived from meteorological inputs (**Zhao *et al.*, 2005; Heinsch *et al.*, 2006**).

2.5 Variations of NPP by land use and land cover:

Several studies have identified biophysical factors (i.e., soil conditions, vegetation types and climate) (**Lieth and Whittaker, 1975; Burke *et al.*, 1997a; Burke *et al.*, 1997b; Tao *et al.*, 2003; Piao *et al.*, 2006**) as key in explaining spatial and temporal NPP variations particularly at global scales. Thus, biophysical factors

have become the most common way of explaining NPP distribution with climate being considered the best predictor of NPP variations across different biomes (**Turner *et al.*, 2006**). The result of such a focus is the advancement in our understanding of potential NPP over the surface of the Earth at large spatial scales, i.e., among different biomes. While knowledge on potential NPP distribution is vital at large spatial scales, it is also important to understand factors influencing NPP at small spatial scales. In addition, it is at the local scale that human activities particularly agricultural practices are evident. Thus, understanding factors affecting NPP variations at the local scale, in addition to larger scale biophysical factors is critical for the sustainable management of ecosystems. To this end, land use/land tenure is hypothesized to be the most important local factor affecting the spatial and temporal variation of NPP (**Vitousek, 1992; Burke, 2000; Guersehman *et al.*, 2003; Haberl *et al.*, 2004**). In fact, land use change has emerged as one of the most important factors driving global environmental change (**Turner *et al.*, 1996; Zhiqiang *et al.*, 2004**). Protected areas have been to a large extent a result of the efforts to maintain ecosystem productivity in the face of human induced land use changes (**Brandon, 1995; DeFries *et al.*, 2007; Schmidt-Soltau and Brockington, 2007**). In addition, there has been a long held view that protected areas contribute towards high NPP (**Bruner *et al.*, 2001**) relative to other land-use/land tenure types. Work in temperate systems suggests that land ownership patterns create significant spatial and temporal variations in NPP (**Crow *et al.*, 1999; Fang *et al.*, 2002**). While variations of NPP in relation to land use/land tenure have been tested in the temperate regions, such work has barely been done in the tropical savannas such as those found in Africa. This focus raises the need to test the effect of human induced factors on NPP in tropical savannas particularly in a complex landscape dominated by humans. In this thesis, the small spatial scale refers to the local or landscape scale which according to **Ahern and Cole (2012)** is an area resulting from the complex interaction of natural factors (e.g. biodiversity, soils), cultural factors (e.g. land-use/land tenure, settlement) and aesthetic qualities.



*Materials
and
Methods*



This chapter deals with the details of the study area, remote sensing and GIS applications for the investigation of land use land cover, vegetation type, altitudinal gradient, slope, aspect through DEM (Digital Elevation Model); forest above ground biomass; net primary productivity. The study area was classified into two major classes viz. non forest area and forest area. Again forest area was sub classes based on dominant tree species along altitudinal gradient. All the classification, estimation of forest above ground biomass and net primary productivity done through using satellite imagery using image processing software viz. Erdas Imagine and Arc GIS.

The following sections contain the details of materials, survey, analysis procedures and techniques adopted for determination and estimation AGB and NPP of the study area.

3.1 Location and climate:

The study area comes under the Kumaon region of Uttarakhand state in north India. It has an area of 12,178 km² and lies approximately between 28° 41' 35" to 30° 21' 10" north latitudes and 78° 40' 50" to 80° 15' 30" east longitudes as shown in Figure 1. It has an annual precipitation of 1221 mm with an annual average temperature of around 20.4 °C and the mean maximum and minimum temperatures were found to be 28.2 and -1.2 °C respectively. The maximum and minimum humidity ranged are from 98 to 66 per cent and 67 to 25 per cent respectively. The warmest month is June with an average temperature of 27.3 °C. The coolest month is January, with an average temperature of 11 °C. The climate of the region has three distinct seasons i.e. summer, monsoon (rainy season) and winter. The rainy season starts from the middle of June and continue up to the end of September. It is followed by the winter season, which starts from the end of October and goes up to February. The winter rains are generally experienced in late December or early January, which brings down the temperature. The climate of the entire study area is influenced by monsoon pattern of rainfall. The study area occupies altitudes ranges from 148 to 6797 m MSL. The climate typically comes under the sub-tropical types in low altitudes and the moist temperate types in high altitudes. The temperate region of higher altitudes receives moderate to high snowfall in the month of December to February.

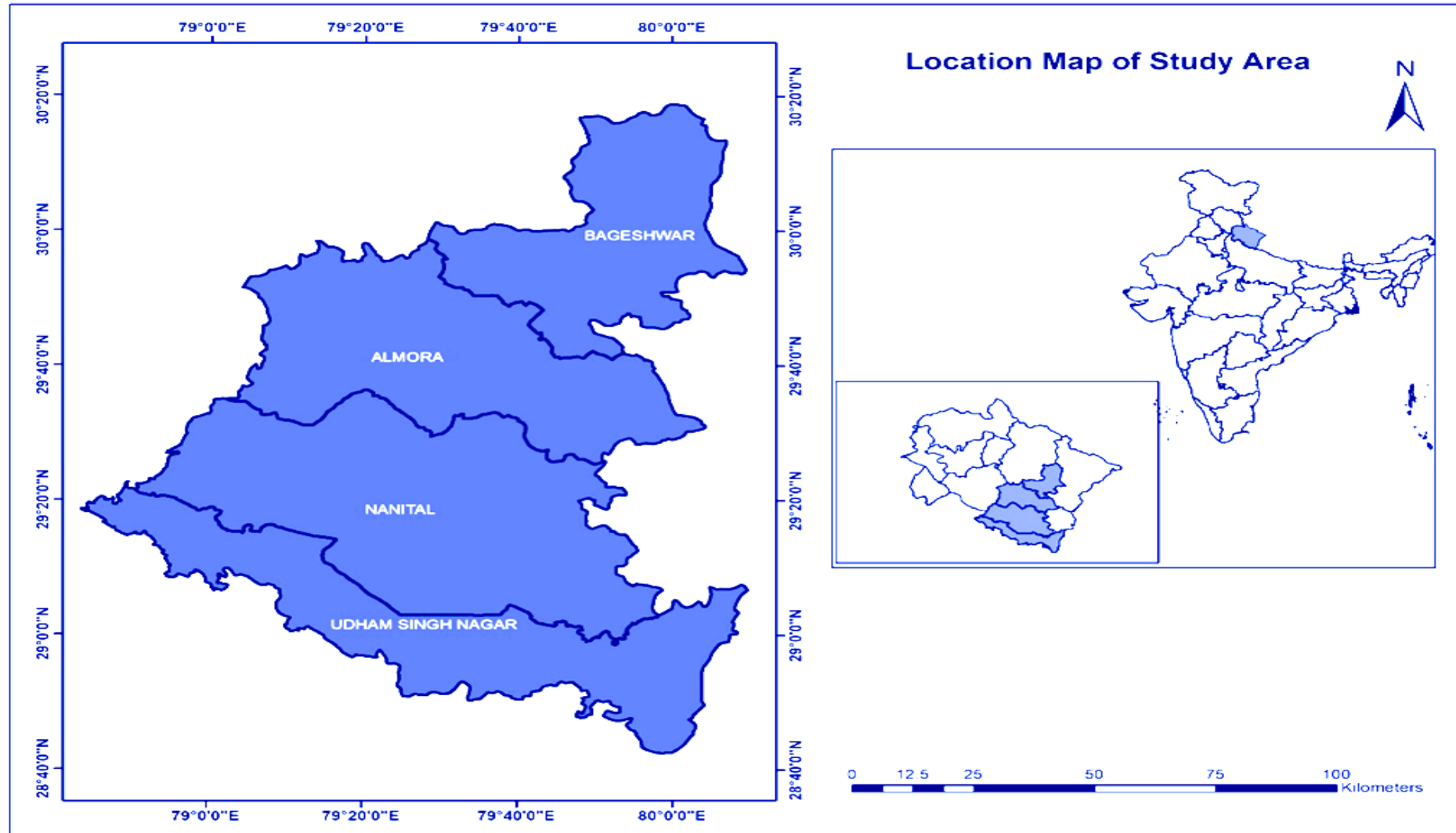


Figure 1: Location map of study area

3.2 Topography:

In the study area, most of the region falls under undulating topography as shown in SRTM DEM generated Figures 2 and 3. Based on its topography, it is divided into three zones, namely the Himalaya, the Shivaliks and the Tarai region. The state is located in subtropical latitudes but on account of elevation in mountainous terrain exhibit temperate climate at the elevations above 1500 m. Valleys below this elevation are hot and show subtropical climate. Shivalik and Tarai areas also exhibit subtropical climate.

3.3 Natural Vegetation:

As natural vegetation and biodiversity are the prime natural resources in Uttarakhand, the current study was carried out in four districts of Kumaon region viz. Bageshwar, Almora, Nainital and Udham Singh Nagar of Uttarakhand states. A variety of forests exist in study area owing to its diverse topography and climatic regions. These forests sustain rich floral and faunal diversity. The human and livestock populations in the villages are largely dependent on forests due to agrarian economy and old age pastoralism leading to heavy pressure on forests that causes degradation of ecology and environment of the area. Although the state of Uttarakhand is well endowed with biological resources, the past decades have seen an increase in pressure on the state's natural ecosystems.

The total forest cover under various classes of the study area is 6463Km² and 7% study area is under permanent snow cover, glacier and steep slopes where tree growth is not possible due to physical limitations. As per India State of Forest Report 2017, forest cover of four districts of study area is mentioned in Table 1.

Table 3.1: Total geographical and forest cover of study area

District	Geographical Area (Km ²)	2017 Assessment			
		Very Dense Forest	Moderately Dense Forest	Open Forest	Total
Almora	3144	199	837	682	1718
Bageshwar	2241	162	762	337	1261
Nainital	4251	765	1742	541	3048
Udham Singh Nagar	2542	150	193	93	436
Total	12178	1276	3534	1653	6463

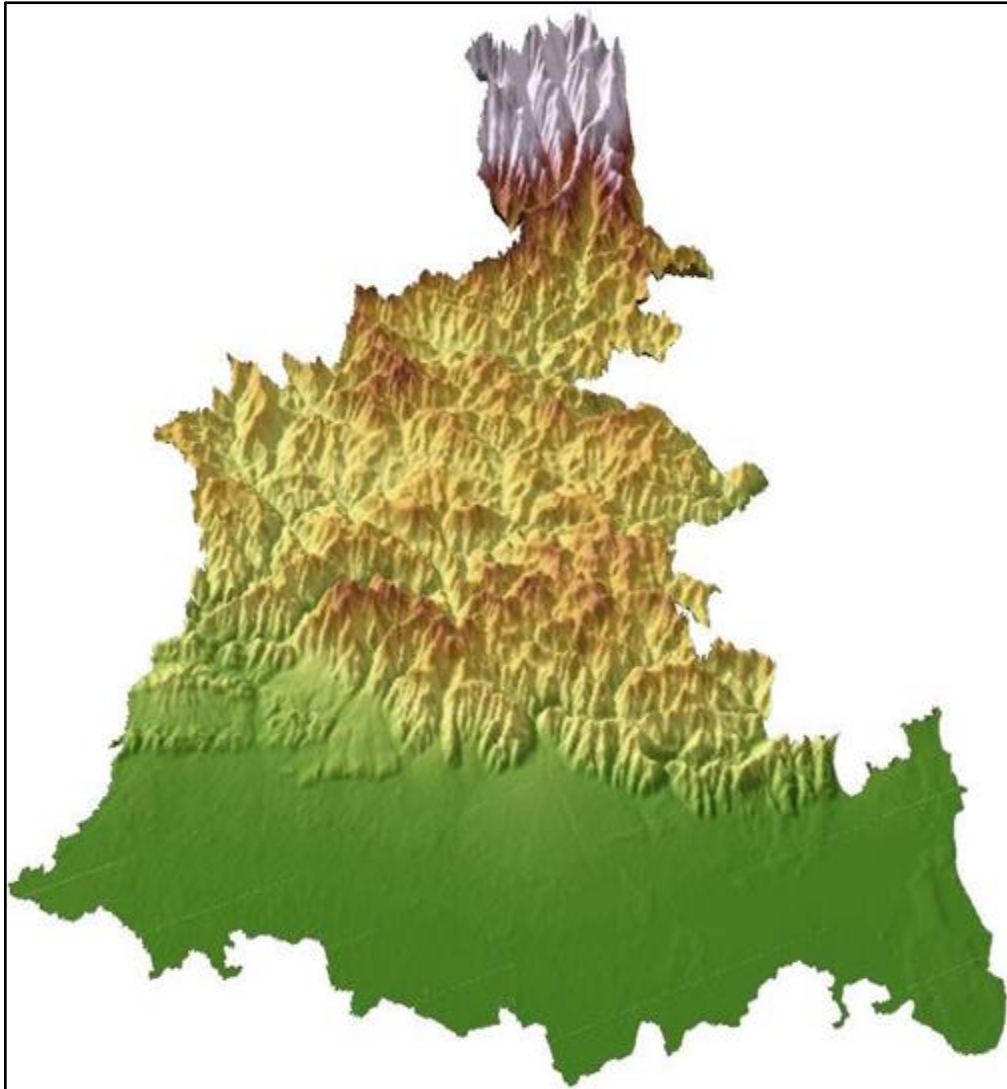


Figure 2: 3D View Map of Study Area.

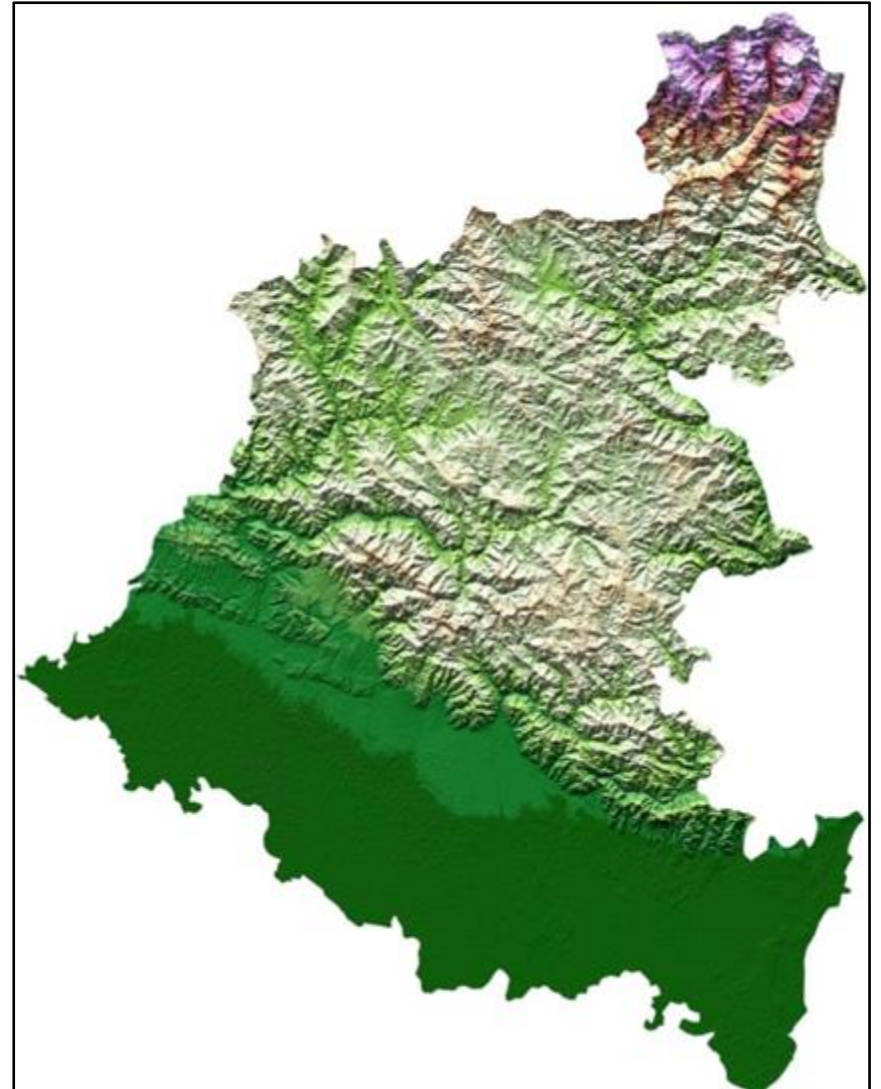


Figure 3: Relief Map of Study Area

3.4 Data used and Processing:

3.4.1 Remote Sensing Data used:

- **Sentinel -2A:** In this research made use of Sentinel -2A satellite imagery from USGS Earth Explorer portal at free of cost (<https://earthexplorer.usgs.gov/>). Sentinel -2A provides Earth observation images of spatial resolution of 10, 20 and 60 meters in 13 spectral bands.
- **SRTM DEM (Shuttle Radar Topography Mission Digital Elevation Model):** The Shuttle Radar Topography Mission (SRTM) is an international research effort that obtained digital elevation models on a near-global scale from 56°S to 60°N,^[2] to generate the most complete high-resolution digital topographic database of Earth prior to the release of the ASTER GDEM in 2009. It is available at USGS Earth Explorer portal free of cost (<https://earthexplorer.usgs.gov/>)
- **MODIS (Moderate Resolution Imaging Spectroradiometer):** The MOD021km Level-1B data set contains calibrated and geo-located at-aperture radiances for 36 discrete bands located in the 0.4 μm to 14.4 μm region of the electromagnetic spectrum. It is available at NASA Earth Data portal free of cost. (<https://ladsweb.modaps.eosdis.nasa.gov/>)

3.4.2 Analysis of Remote Sensing Data:

3.4.2.1 LULC Classification:

Sentinel-2A satellite data was used for Land Use Land Cover classification. It offers a specifically spatial resolution of 10 m and temporal resolution of 10 days and is very well suited for identifying vegetation covers because of its use of a near-infrared band for detecting chlorophyll concentrations. Remote sensing data was processed by image processing software (Erdas Imagine). Sentinel -2A satellite data was used for land cover classification of the study area which provides a statistical basis for clustering pixels and classifying the image into different vegetation structural types. The main vegetation structural types that are generally used in these classifications are five different forest classes and all other as non-forest class.

This classification was done using supervised and unsupervised algorithms in Erdas Imagine software. Subsequently, forest class types were matched with ground truth field data from field survey data.

3.4.2.2 Normalized Difference Vegetation Index (NDVI):

To determine the density of green on a patch of land, researchers must observe the distinct colours (wavelengths) of visible and near-infrared sunlight reflected by the plants. As can be seen through a prism, many different wavelengths make up the spectrum of sunlight. When sunlight strikes objects, certain wavelengths of this spectrum are absorbed and other wavelengths are reflected. The pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 μm) for use in photosynthesis. The cell structure of the leaves, on the other hand, strongly reflects near-infrared light (from 0.7 to 1.1 μm). The more leaves a plant has, the more these wavelengths of light are affected, respectively. NDVI is calculated from the visible and near-infrared light reflected by vegetation. Healthy vegetation absorbs most of the visible light that hits it and reflects a large portion of the near-infrared light (NIR). Unhealthy or sparse vegetation reflects more visible light and less near-infrared light.

Nearly all satellite Vegetation Indices employ this difference formula to quantify the density of plant growth on the Earth- near-infrared radiation minus red radiation divided by near-infrared radiation plus red radiation. The result of this formula is called the Normalized Difference Vegetation Index (NDVI). Written mathematically, the formula is:

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$$

In this study, Sentinel-2A satellite data was used to calculate NDVI of study area. Sentinel-2A satellite data has 13 bands, out of which band 4 (Red Band) and band 8 (NIR) were used according to formula mentioned above as:

$$\text{NDVI} = (\text{Band 8} - \text{Band 4}) / (\text{Band 8} + \text{Band 4})$$

Its values ranges from minus one (-1) to plus one (+1). Values towards the plus one, indicate more vegetation and vice versa. Generally, NDVI values of forest cover ranges from + 0.35 to + 0.75. But it is not fixed, the range of minimum and maximum values may slightly vary from sensor to sensor of satellite data.

3.4.2.3 Normalized Difference Water Index (NDWI):

The Normalized Difference Water Index (NDWI) is a satellite-derived index from the Near-Infrared (NIR) and Short Wave Infrared (SWIR) channels. NDWI introduced for the first time in 1996 in Gao (Gao), reflects moisture content in plants and soil and is determined by analogy with NDVI as:

$$\text{NDWI} = (\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR})$$

The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content (**Ceccato *et al.*, 2001**). The amount of water available in the internal leaf structure largely controls the spectral reflectance in the SWIR interval of the electromagnetic spectrum. SWIR reflectance is therefore negatively related to leaf water content (**Tucker 1980**).

In this study, Sentinel-2A satellite data was used to calculate NDWI of study area. Sentinel-2A satellite data has 13 bands, out of which band 12 (SWIR Band) and band 8 (NIR) were used according to formula mentioned above as:

$$\text{NDWI} = (\text{Band 8} - \text{Band 12}) / (\text{Band 8} + \text{Band 12})$$

3.4.2.4 Vegetation Texture:

Texture is a description of the homogeneity of images using the texel as the fundamental unit, which has a certain scale, regularity and directionality. Texture analysis based on the local spatial variation of intensity or colour brightness serves an important role in many applications of remote sensing images (**Kitada and Fukuyama 2012**). Texture analysis is extensively employed in image segmentation, classification, and pattern recognition. Moreover, texture feature extraction is an important content of texture analysis, which is an effective method for solving the problems of spectral heterogeneity and complex spatial distribution in the same category (**Myint *et al.*, 2004**).

Texture is an important element for pattern recognition and interpretation in the human visual system. In a digital image, it represents the visual impression of

smoothness or coarseness produced by the uniformity or variability of image colour or tone (Myint, 2001). Without universally accepted mathematical definition of texture, traditional approaches use symbolic descriptions, such as coarse and fine, rough and smooth, linear and nonlinear, low and high density, and orientation and directionality, etc., to represent texture in images (Maillard, 2003). However, descriptive terms for texture patterns presented in remote sensing imagery, usually generated by multispectral or hyperspectral sensors with various resolution. Texture analysis tools have been developed to extract features from remote sensing images with different criteria. The most frequently used pattern recognition techniques are built on statistical methods, such as spatial co-occurrence matrix and variogram. For instance, texture features are identified with a moving window to show the connection between a pixel and its neighbour according to a grey-level co-occurrence matrix (GLCM) (Franklin *et al.*, 2000). Measure the level and type of texture within a moving window passed over a continuous raster image. For example, forest areas generally have high texture while grassland has low texture. Sentinel-2A satellite data was used for analysis of texture of all total 13 number bands and only band 4 and band 8 were used for regression analysis as red band (Band 4) and NIR band (Band 8) sensitive to vegetation covered.

3.4.2.5 Principal Component Analysis:

Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still contains most of the information in the large set. PCA is a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. Principal Components Analysis (PCA) is often used as a method of data compression. It allows redundant data to be compacted into fewer bands--that is, the dimensionality of the data is reduced. The bands of PCA data are non-correlated and independent, and are often more interpretable than the source data. In this study, Sentinel-2A satellite data was used for analysis of PCA of all total 13 number bands to total 6 number bands principal components. Out of 6 number bands, band 5 and band 6 found to more correlation with forest biomass. Thus band 5 alone and band ratio of band 5 and band 6 were used for correlation with biomass. Bands rationing was done by according to formula given below as:

$$\text{PCA Band Ratio} = (\text{Band 5} - \text{Band 6}) / (\text{Band 5} + \text{Band 6})$$

3.4.2.6 Elevation Analysis:

Elevation analysis can perform certain analytical tasks quickly and easily, without having to collect or update an authoritative set of base data. Elevation analysis is essential for many GIS applications such as for natural resource management, conservation, agriculture, transportation, risk management, watershed management etc. In this study, spatial altitudinal variation was analyzed with SRTM DEM (Shuttle Radar Topography Mission Digital Elevation Model) data which help identification and distribution pattern of different forest classes along altitudinal gradient as shown in Figure 4.

3.4.2.7 Slope Analysis:

Slope is the steepness or the degree of incline of a surface. Topography is a measurement of elevation and slope is the percent change in that elevation over a certain distance. Topography may be measured with lines that connect points representing the same elevation; these are called topographic contours. Slope is measured by calculating the difference in the elevation from one point to another divided by the lateral distance between those points. Consideration of the slope of the land is important to reduce construction costs, minimize risks from natural hazards such as flooding and landslides, and to minimize the impacts of proposed development on natural resources such as soils, vegetation, and water systems. Slope can be expressed either in degrees or as a percentage as shown in Figure 5.

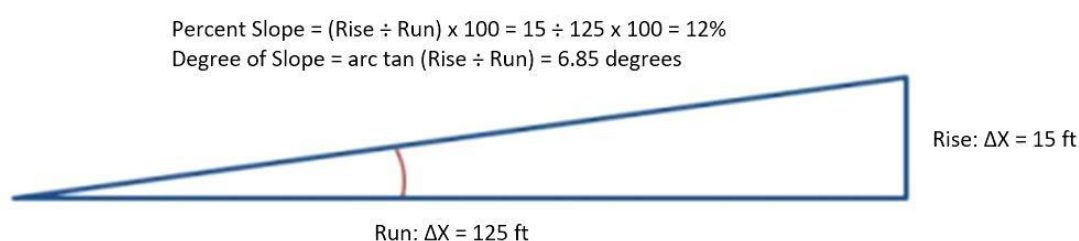


Figure 5: Showing slope calculation in percentage or degrees.

In this study, SRTM DEM data was used for to classify the slope category of the study area according to class defines by National Bureau of Soil Survey (NBSS) as shown in Figure 6.

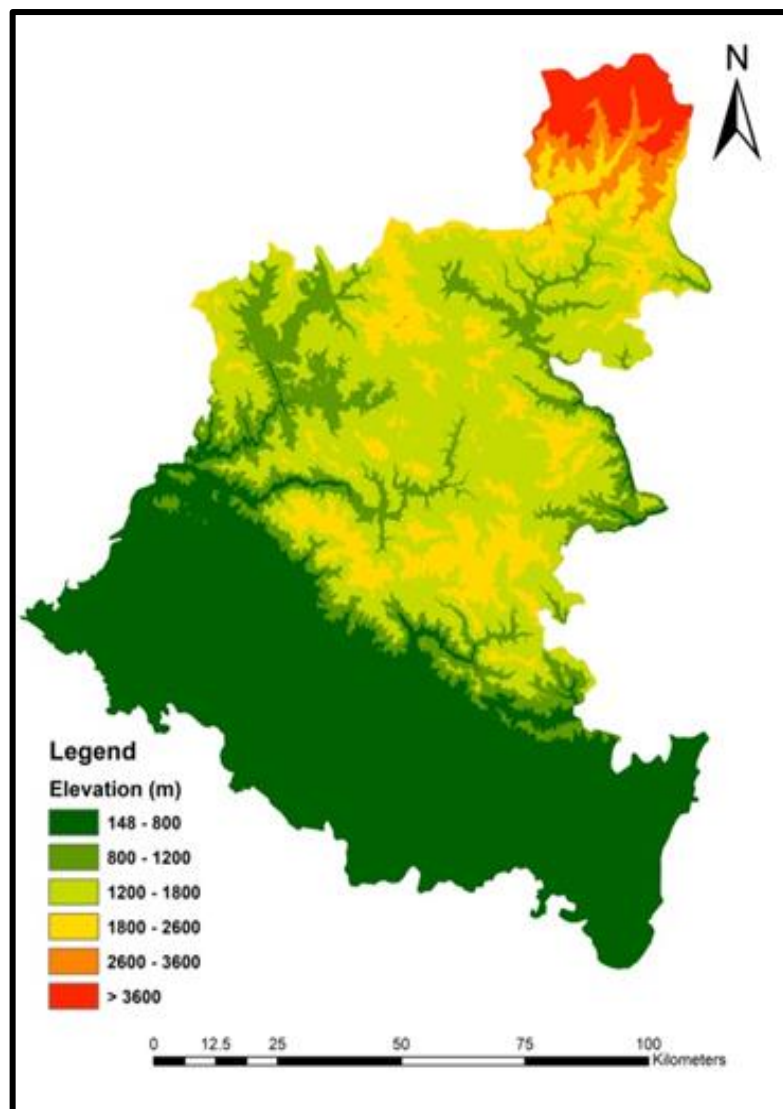


Figure 4: Elevation Map of Study Area.

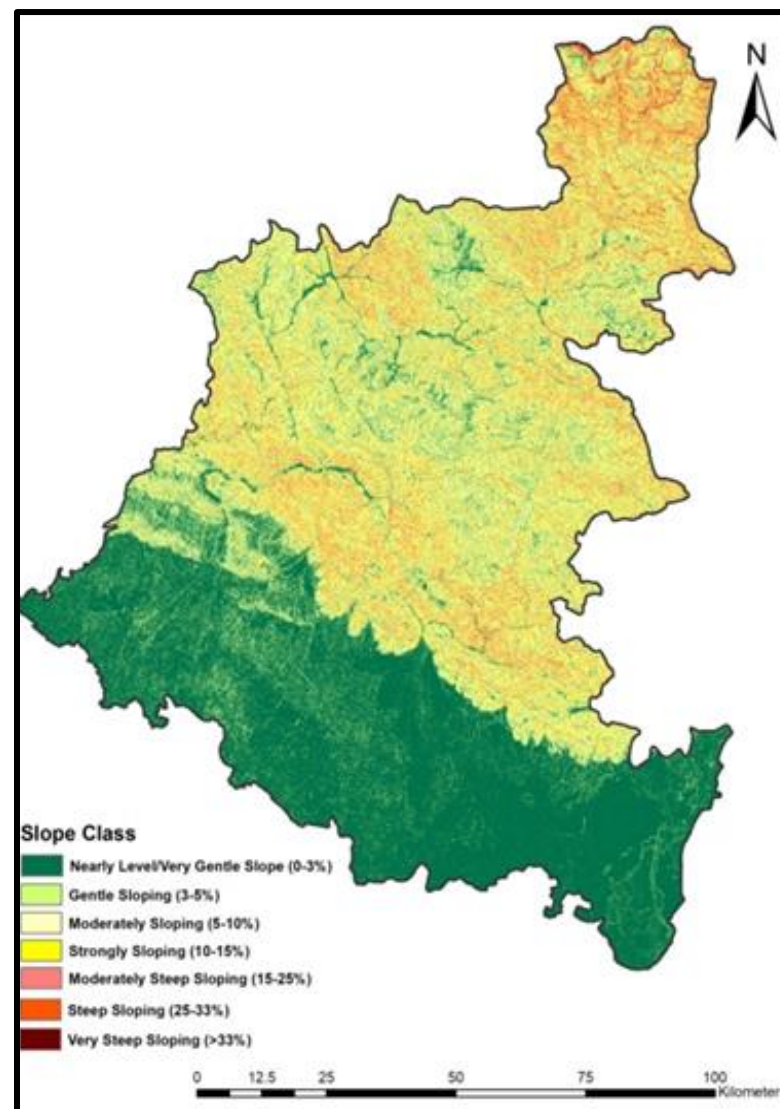


Figure 6: Slope Map of Study Area.

3.4.2.8 Aspect Analysis:

Aspect is the orientation of slope, measured clockwise in degrees from 0 to 360, where 0 is north-facing, 90 is east-facing, 180 is south-facing, and 270 is west-facing that is direction of slope gradient towards particular point target position. For example, “northern aspect” represents the slope gradient towards the north direction and “southern aspect” represent slope gradient towards the south direction. In this study, SRTM DEM data was used classify the slope gradient into four different aspects that is Northern, Eastern, Southern and Western aspect as shown in Figure7.

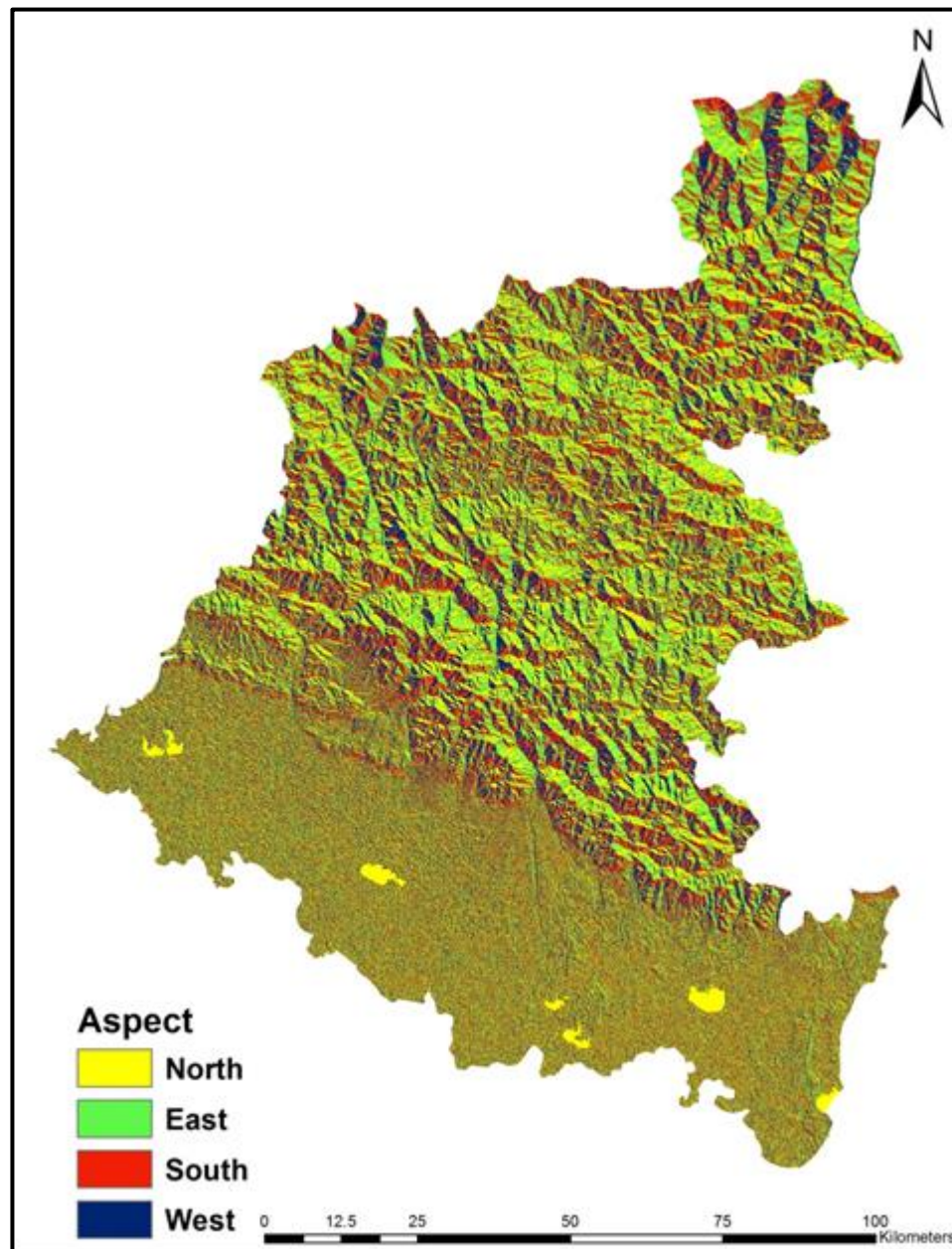


Figure 7: Aspect map of study area

3.5 Ground Data Collection and Analysis:

3.5.1 Rainfall Data:

The amount, intensity and spatial distribution of precipitation are important inputs in most climatic studies. The total amount of precipitation which reaches the ground in a stated period is expressed as the depth to which it would cover a horizontal projection of the earth's surface. In this study, at least 15 years' rainfall data was used to calculate the mean annual rainfall (mm) collected from educational institutions, research station, KVKs and IMD. All these collected rainfall data from particular location were used to create point feature rainfall data. Then this point feature rainfall data used to interpolate to get continuous rainfall data of study area by interpolation technique "Inverse Distance Weighting (IDW)" in GIS software and generate mean rainfall map as shown in Figure 8.

3.5.2 Temperature Data:

The spatial variations of temperature are important inputs in most climatic studies. In this study, at least 10 to 30 years' temperature data was used to calculate the mean annual temperature ($^{\circ}\text{C}$) collected from educational institutions, research station, KVKs and IMD. All these collected temperature data from particular location were used to create point feature temperature. Then this point feature temperature data used to interpolate to get continuous temperature data of study area by interpolation technique "Inverse Distance Weighting (IDW)" in GIS software and generate mean temperature map as shown in Figure 9.

3.5.3 Field Data and Analysis:

During the survey of the study area, the ground truth verification of non-forest class and five dominant forest types according to elevation, tree species composition and their distribution were identified and verified. All the land use land cover class sampling point's data and physiographic factors (i.e. altitude, aspect) were recorded with coordinates using handheld GPS. During the field visit, species specific tree height and Diameter at breast height (DBH) were measured and recorded for all the dominant forest class for estimation of ground base Above Ground Biomass (AGB) by allometric method. For each dominant forest class, 8 to 10 sampling point were sampled at different location of study area for allometric AGB estimation. During the sampling,

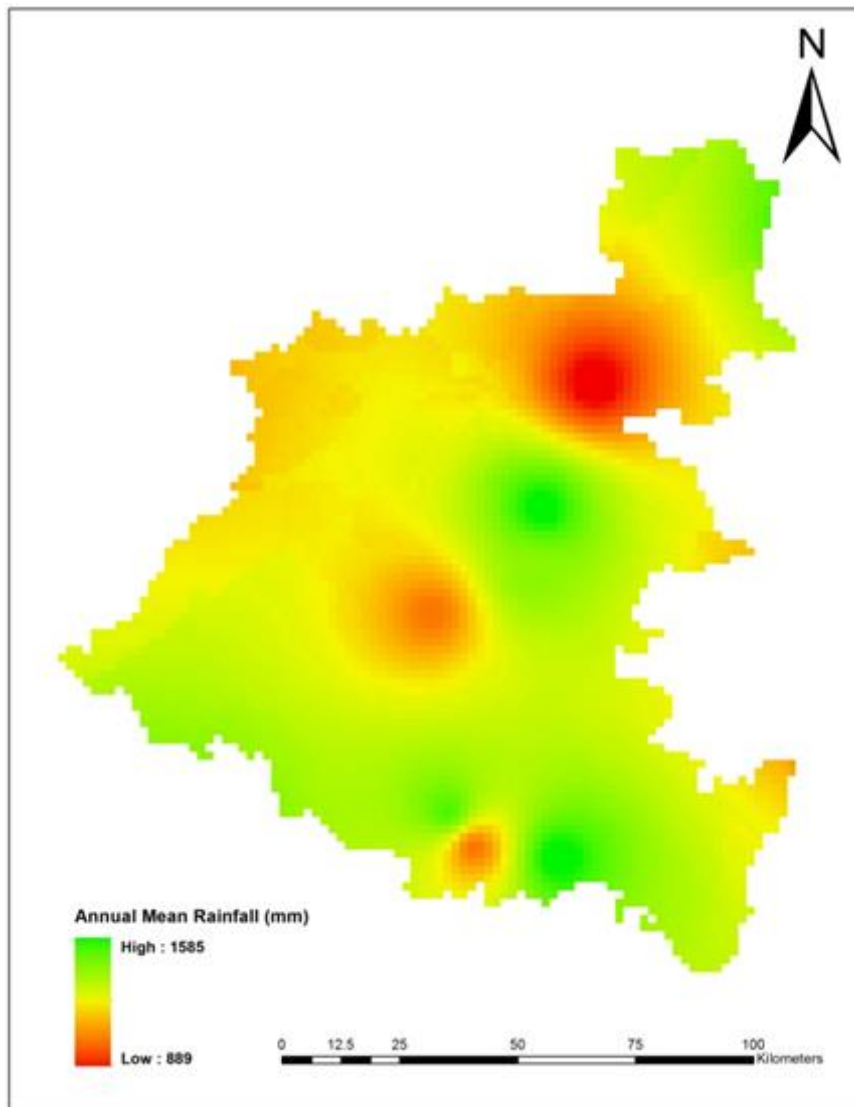


Figure 8: Mean annual rainfall of study area.

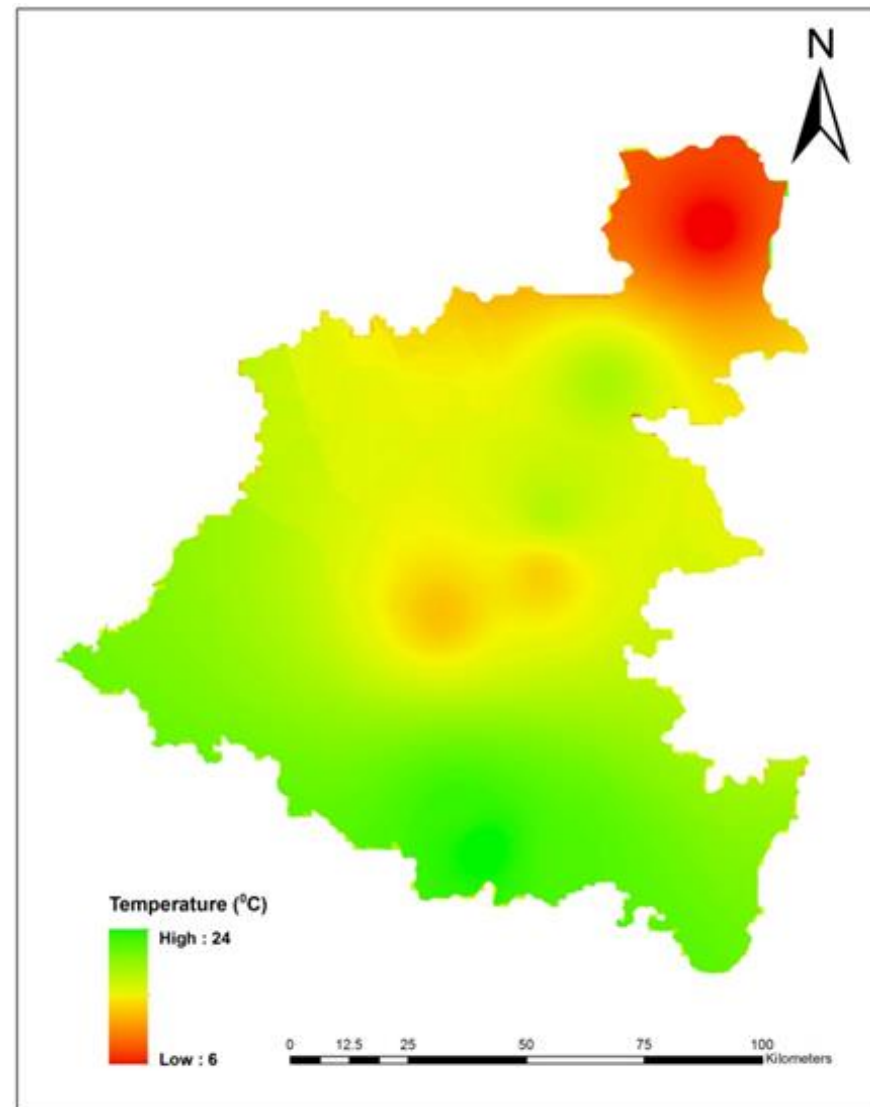


Figure 9: Mean annual temperature of study area.

tree height was measured with the help of clinometer and diameter at breast height (DBH) measured with measuring tape at 1.3 m above from the ground. The size of sample point was 100 square meter and number of tree per sample point also counted. Wood density (ρ) was extracted from a global wood density database and from literature. For better representation of a sampling point, sampling was done in five repetitive points nearby areas.

3.6 Allometric Biomass Estimation:

To estimate forest biomass, allometric method given by **Chave *et al.*, (2014)** have been used for biomass calculation. The methodology used was the non-destructive technic and easy to used. Total aboveground biomass (AGB) of each tree in the plots has been estimated using the following allometric model:

$$AGB = 0.0559 \times (WD D^2 H)$$

WD = wood density ($\text{g} \cdot \text{cm}^{-3}$),

D = diameter at breast height (cm)

H = height of tree (m)

AGB = aboveground biomass ($\text{Mg} \cdot \text{ha}^{-1}$)

3.7 Estimating aboveground biomass from Remote Sensing:

Assessment of aboveground biomass using remote sensing generally uses two approaches (1) empirical models that use a statistical relationship between ground locations of aboveground biomass matched with the spectral bands (or some combination of bands) in pixels of remote sensing images; and (2) process models that use remote sensing data as inputs to predict aboveground biomass. Empirical approaches (parametric method) generally involve using a regression relationship between the remote sensing imagery and biomass data collected from field measurements (**Dungan, 1998**).

In this study, estimation of aboveground biomass from Remote Sensing was done by parametric method. Parametric algorithms assume that the relationships between dependent (i.e. biomass) and independent (derived from remote sensing data)

variables have explicit model structures that can be specified a priori by parameters. Examples are simple or multiple linear regression models. The independent variables may be the vegetation indices like Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Principal Component Analysis (PCA), Vegetation Texture analysis etc. At present study, used a regression relationship between the field base allometrically calculated biomass and sentinel-A2 NDVI data for calculation of AGB of whole study area in each dominant forest class individually. For each forest class, regression relationship was established individually because NDVI value range varies among dominant forest class. The aboveground biomass calculated by linear regression analysis between allometric biomass estimate and NDVI data, again developed and predicted with multiple linear regression models. For this, used the Artificial Neural Network (ANN) back propagation model by taking eight independent variables (remote sensing and ground based variables) and one dependent variable. The independent variables used for ANN as input were NDVI, NDWI, PCA band 6, ratio of PCA band 5 and 6, vegetation texture ratio of band 4 and 8, annual mean rainfall, annual mean temperature and elevation. The dependent variable considered as output in ANN was biomass.

3.8 Artificial Neural Network (ANN):

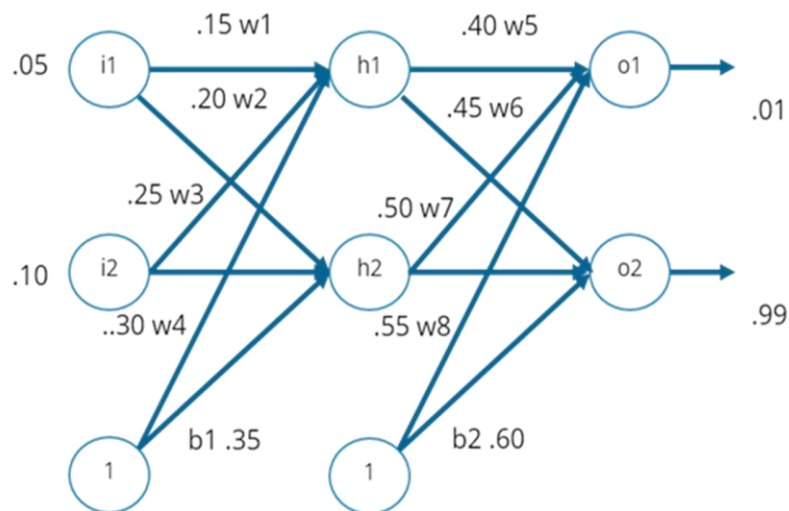
An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output.

3.8.1 Back Propagation Algorithm

It is the training or learning algorithm. It learns by example. If you submit to the algorithm the example of what you want the network to do, it changes the network's weights so that it can produce desired output for a particular input on finishing the training.

Working of Back Propagation Algorithm:

Consider the below Neural Network:



The above network contains the following:

- two inputs
- two hidden neurons
- two output neurons
- two biases

Below are the steps involved in Back propagation:

- Step – 1: Forward Propagation
- Step – 2: Backward Propagation
- Step – 3: Putting all the values together and calculating the updated weight value

Step – 1: Forward Propagation

We will start by propagating forward.

Net Input For h1:

$$\text{net h1} = w1*i1 + w2*i2 + b1*1$$

$$\text{net h1} = 0.15*0.05 + 0.2*0.1 + 0.35*1 = 0.3775$$

Output Of h1:

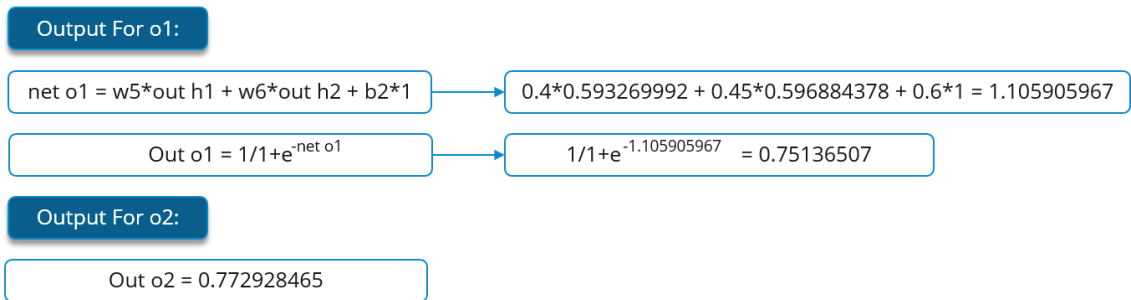
$$\text{out h1} = 1/1+e^{-\text{net h1}}$$

$$1/1+e^{-.3775} = 0.593269992$$

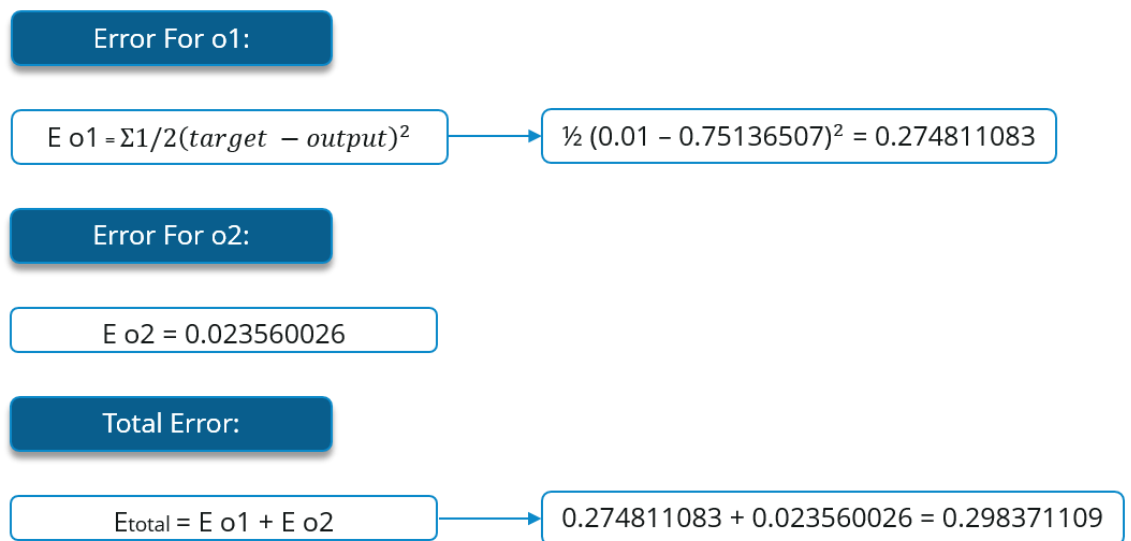
Output Of h2:

$$\text{out h2} = 0.596884378$$

We will repeat this process for the output layer neurons, using the output from the hidden layer neurons as inputs.



Now, let's see what is the value of the error:



Step – 2: Backward Propagation

Now, we will propagate backwards. This way we will try to reduce the error by changing the values of weights and biases.

Consider W5, we will calculate the rate of change of error w.r.t change in weight W5.



Since we are propagating backwards, first thing we need to do is, calculate the change in total errors w.r.t the output O1 and O2.

$$E_{total} = 1/2(target\ o1 - out\ o1)^2 + 1/2(target\ o2 - out\ o2)^2$$

$$\frac{\delta E_{total}}{\delta out\ o1} = -(target\ o1 - out\ o1) = -(0.01 - 0.75136507) = 0.74136507$$

Now, we will propagate further backwards and calculate the change in output O1 w.r.t to its total net input.

$$out\ o1 = 1/1 + e^{-net\ o1}$$

$$\frac{\delta out\ o1}{\delta net\ o1} = out\ o1 (1 - out\ o1) = 0.75136507 (1 - 0.75136507) = 0.186815602$$

Let's see now how much does the total net input of O1 changes w.r.t W5?

$$net\ o1 = w5 * out\ h1 + w6 * out\ h2 + b2 * 1$$

$$\frac{\delta net\ o1}{\delta w5} = 1 * out\ h1 * w5^{(1-1)} + 0 + 0 = 0.593269992$$

Step – 3: Putting all the values together and calculating the updated weight value

Now, let's put all the values together:

$$\frac{\delta E_{total}}{\delta w5} = \frac{\delta E_{total}}{\delta out\ o1} * \frac{\delta out\ o1}{\delta net\ o1} * \frac{\delta net\ o1}{\delta w5}$$

0.082167041

Let's calculate the updated value of W5:

$$w5^+ = w5 - \eta \frac{\delta E_{total}}{\delta w5}$$

$$w5^+ = 0.4 - 0.5 * 0.082167041$$

Updated w5

0.35891648

- Similarly, we can calculate the other weight values as well.
- After that we will again propagate forward and calculate the output. Again, we will calculate the error.
- If the error is minimum we will stop right there, else we will again propagate backwards and update the weight values.
- This process will keep on repeating until error becomes minimum.

In this study, Artificial Neural Network (ANN) back propagation algorithm was carried out in open source "R" statistical software (RStudio). The independent variables used for ANN as input were NDVI, NDWI, PCA band 6 (PCA), ratio of PCA band 5 and 6 (RPCA), vegetation texture ratio of band 4 and 8 (TEX), annual mean rainfall (RF), annual mean temperature (TEMP) and elevation (ALT). The dependent variable considered as output in ANN was biomass (BIO). The relationship formula between independent variables and dependent variable was given below:

$$BIO \approx ALT + NDVI + NDWI + PCA + RPCA + RF + TEMP + TEX$$

To execute the ANN in R, created a sample data base of all input and output variables. For this, randomly collected 160 samples of each input and output variables for each dominant forest class. That is, each forest class contains randomly collected 160 samples of BIO, ALT, NDVI, NDWI, PCA, RPCA, RF, TEMP and TEX respectively. This makes a sample data for one forest class. Thus for all five dominant forest class samples size was: $160 \times 5 = 800$. When dataset is ready, import the dataset in R environment in csv format and normalized data using following formula because value range of all variables were different and called it scaled dataset.

$$Z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

where $x = (x_1, \dots, x_n)$ and z_i is the i^{th} normalized data.

Once the dataset was scaled, out of 800 samples data, 70% (560) randomly selected samples data (Train data) was used for training the AAN. Once the AAN training is completed, the equation developed from train dataset was used for 30% remaining dataset (Test data) to calculate the biomass (Predicted biomass). The diagrammatic representation of ANN executed in R for predicting the study area biomass is shown in Figure10.

3.9 Estimating NPP from remote sensing:

In this work, MODIS level 1B Terra 1km (MOD021KM) satellite data product was used. The MOD021KM data are freely available on daily basis with a spatial resolution of 1 kilometer at nadir. By visual inspection, we selected the days that were cloud-free over the study region. Cloud-free images were considered since clouds compromise the accuracy of the indices used in the NPP model used in this study.

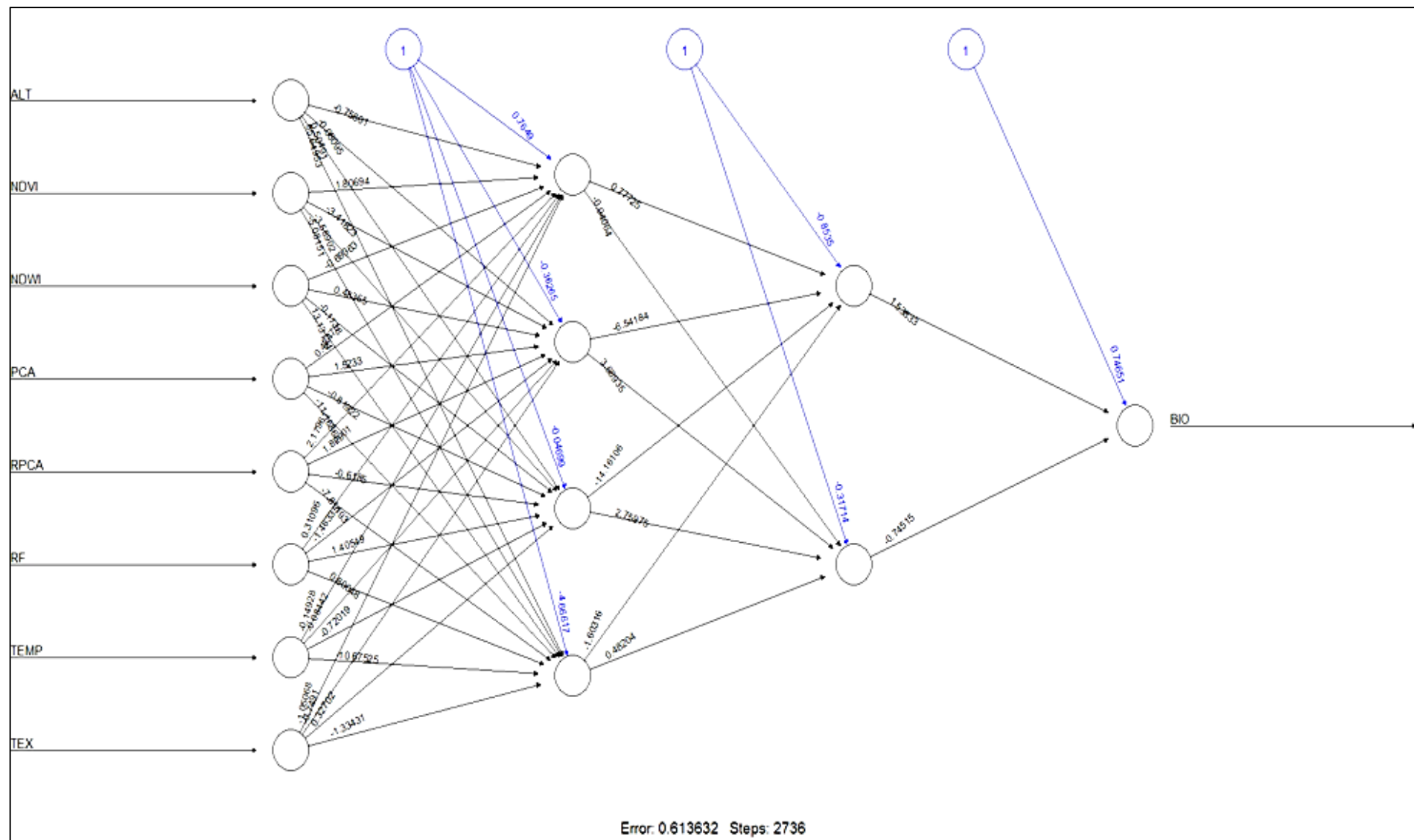


Figure 10: Artificial Neural Network (ANN) in R statistical Software.

The multiple cloud-free ten years' (2007 to 16) images were obtained and averaged them for each month. The downloaded images were already geometrically and radiometrically corrected thus we only re-projected them from the native Sinusoidal projection to universal transverse mercator (UTM) Zone 44 North based on the WGS84 global spheroid. These MOD021KM products were of land reflectance bands 1 (620-670 nm) and 2 (841-876 nm) and ocean bands 11 (526-536 nm) and 12 (546- 556 nm). The stated bands 1 and 2 as well as 11 and 12 were necessary for the estimation of two important vegetation indices used in NPP modeling in this thesis namely; the normalized difference vegetation index (NDVI) and the photochemical reflectance index (PRI).

3.9.1 The NPP estimation Model:

In this work, used a modified remote sensing micrometeorological model for estimating NPP after **Rahman *et al.*, (2004)**. The model refer to as the MODNPP utilizes the visible (band 1: 620-670 nm) and the near infra-red (band 2: 841-876 nm) as well as the “ocean” bands (band 11: 526-536 nm and band 12: 546-556 nm) for estimating carbon dioxide (CO₂) flux from terrestrial vegetation.

The MODNPP model (Equation 2) is derived from the Monteith equation (Equation 1) which is given as follows:

$$NPP = LUE \times APAR \quad 1$$

Where, APAR refers to absorbed photosynthetically active radiation and LUE is the light use efficiency.

$$MODNPP = 0.5139 \times MODPRI \times APAR - 1.9818 \quad 2$$

Where, MOD PRI is MODIS-derived photochemical reflectance index which is used as proxy for LUE and 0.5139 and 1.9818 are constants.

Inorder to estimate APAR there is need to estimate the incoming solar radiation (shortwave radiation (SWR)) and the fraction of photosynthetically active radiation (fPAR). The fPAR is the fraction of the SWR in the photosynthetically active radiation spectral region that is absorbed by vegetation. This biophysical variable is directly related to photosynthesis and some models use it to estimate the assimilation of carbon dioxide in vegetation. Thus the daily APAR (Equation 3) is given by the relationship:

$$APAR = fPAR \times \sum_{\text{sunrise}}^{\text{sunset}} PAR \quad 3$$

Where, PAR is photosynthetically active radiation estimated from sunrise to sunset and is given by the formula (Equation 4):

$$\text{PAR} = 0.5 \times \text{SWR}$$

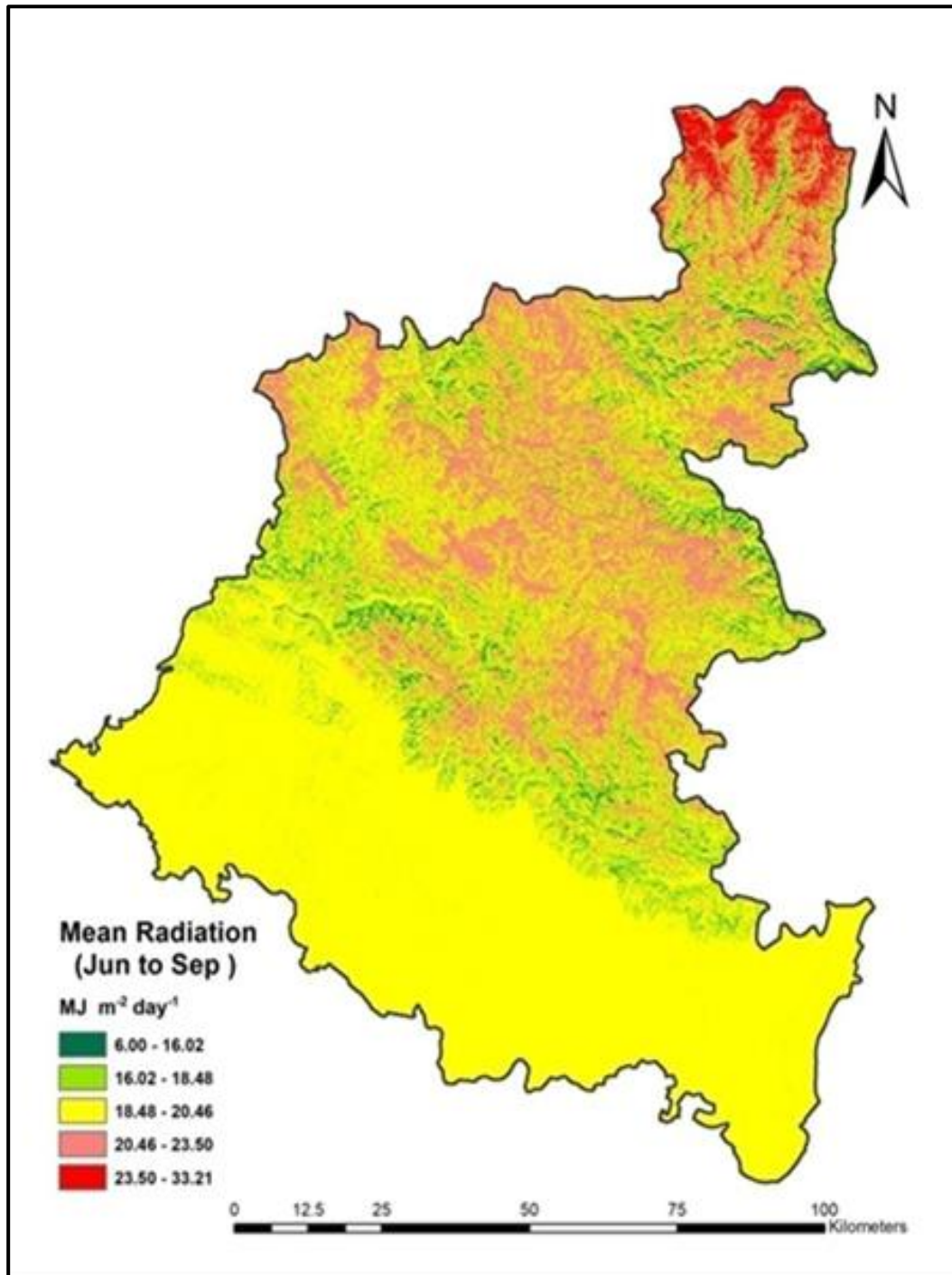


Figure 11: Mean solar radiation (MJ m⁻²day⁻¹) map of study area

In this study, a modified approach of measuring SWR was used. SWR was modelled using a GIS and DEM based SWR model after **Kumar *et al.*, (1997)** as opposed to weather station SWR data. This model uses solar altitude angle (α), solar azimuth angle (θ), angle of latitude (L), and solar declination angle (δ_s), as well as hour angle (ϕ_h) to calculate the amount of radiation received at a given surface per month given the location's slope and aspect (**Kumar *et al.*, 1997**) as shown in Figure 11. The ability of the model to integrate radiation over long time periods in inexpensive manner enables it to be used for modelling radiation by itself, or input into other ecological, hydrological, or climatological models.

To calculate fPAR, NDVI values are needed (Equation 5). MODIS bands 1 and 2 were used to calculate NDVI as follows:

$$\text{NDVI} = (\text{rNIR} - \text{rR}) / (\text{rNIR} + \text{rR}) \quad 5$$

where, rNIR is reflectance in the Near Infrared and rR is reflectance in the visible Red of MODIS data and NDVI values range from -1 for water up to 1 for healthy vegetation. fPAR was then calculated as:

$$\text{fPAR} = (1.24 \times \text{NDVI}) - 0.168 \quad 6$$

To estimate MOD PRI, MODIS ocean bands 11 and 12 were used. MOD PRI is a recently developed remote sensing spectral index used as surrogate for LUE values (**Rahman *et al.*, 2004**). The concept of light-use efficiency (LUE) is the underlying basis for estimating carbon exchange in ecosystem models, especially in models that utilize remote sensing to constrain estimates of canopy photosynthesis. MOD PRI is sensitive to changes in carotenoid pigments (e.g. xanthophyll pigments) in live foliage. Carotenoid pigments are indicative of photosynthetic LUE, or the rate of carbon dioxide (CO₂) uptake by foliage per unit energy absorbed. This MODIS satellite-based PRI is able to track changes in landscape-level photosynthesis activity (**Rahman *et al.*, 2004**). Thus, in this study, we used a scaled MODIS derived PRI (MOD PRI) calculated as:

$$\text{MODPRI} = \left\{ \left[\frac{(\text{pband 11} - \text{pband 12})}{(\text{pband 11} + \text{pband 12})} \right] + 1 \right\} \div 27$$

where, rband11 and rband12 represent reflectance in the band 11 (531nm) and band 12 (570nm) of MODIS, respectively. The values of MOD PRI range from 0 to 1.

Finally, in the MODNPP model, NPP was estimated using the regression equation developed by **Rahman *et al.*, (2004)** (Equation 2). The units of our MODNPP have been converted from grams of carbon per square metre per month ($\text{g C m}^{-2} \text{mon}^{-1}$) to tonnes of carbon per hectare per year ($\text{ton C ha}^{-1} \text{year}^{-1}$) in this study.



Results and Discussion



4.1 LULC Classification:

The present study area classified into seven land use land cover classes by digital image classification. Among them, five are classes under major forest class. These classified major forest classes are mixed deciduous forest, mixed pine forest, pine forest, mixed oak forest and high altitude mixed forest; and other two classes are non-forest and water body as shown in Figure 12. In the study area, the total forest and non-forest area are about 7258 Sq. Km. (60%) comes under forest area and 4919 Sq. Km. (40%) comes under non forest area as shown in Figure 13 and Figure 14.

4.2 Dominant Forest Classes:

Out of total forest cover, major forest class was the mixed deciduous forest which occupied about 54% of total forest area followed by mixed pine forest, pine forest, high altitude mixed forest and mixed oak forest which occupied about 19%, 17%, 6% and 4% of total forest area respectively as shown in Figure 15. The dominance of mixed deciduous forest in the study area may be due to transition zone occupied by this forest between plane and mountain region which support maximum number of vegetation diversity. Mixed pine forest also act as a transition forest class between the deciduous forest and temperate forest. This forest class consists of tree species of growing at deciduous forest and temperate forest class as it links between deciduous forest and temperate forest.

4.3 Tree species composition and distribution:

At present study site, elevation of mixed deciduous forest ranges from 148 m to 1300 m MSL and occupies about area of 3891 km² out of total studied geographical area of 12277 km² and total forest area of 7258 km² which contribute about 32% of total studied geographical area and 54% of total classified forest area. Its contributes major forest area among other forest classes. The identified dominant tree species in this class were *Mallotus philippensis*, *Toona aliata*, *Holoptelea integrifolia*, *Macaranga pustulata* and *Anogeissus latifolia* and *Shorea robusta*. The diversity and richness of shrubs also noticed more as compared to other forest.

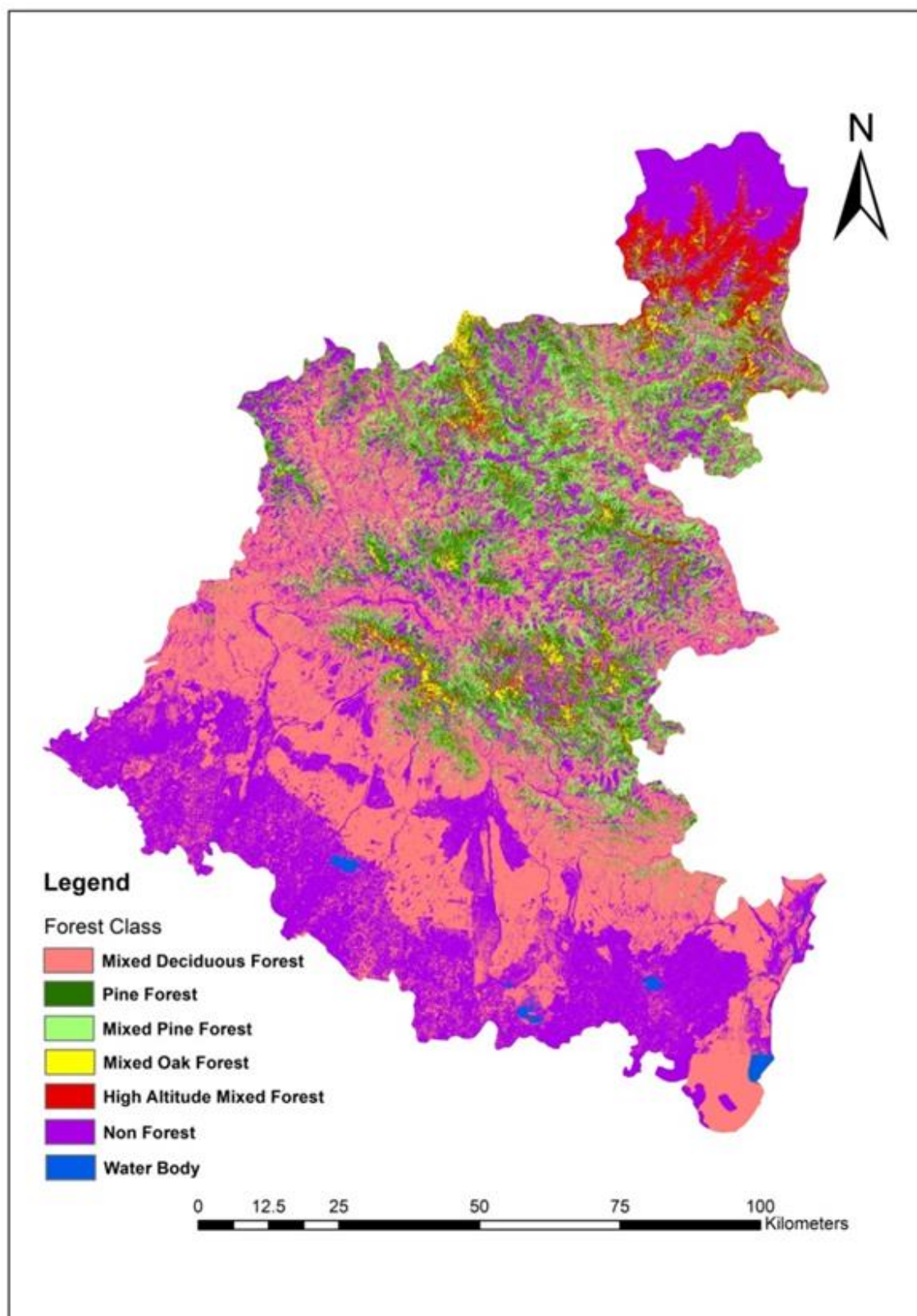


Figure 12: Land Use Land Cover classification map of study area.

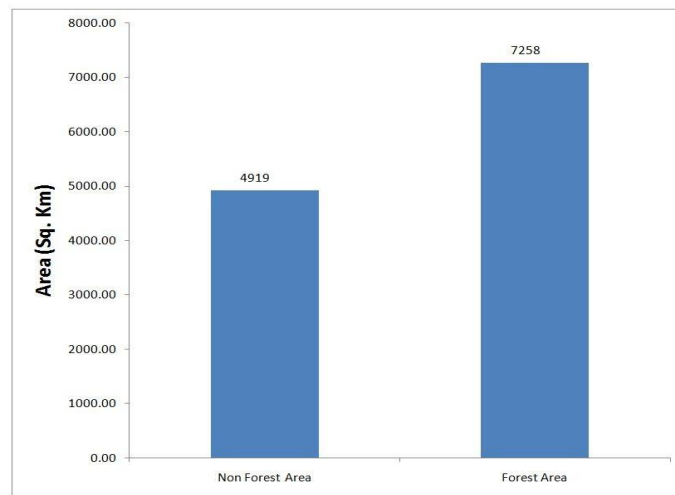


Figure 13: Total forest and non-forest class of study area (Sq. Km.)

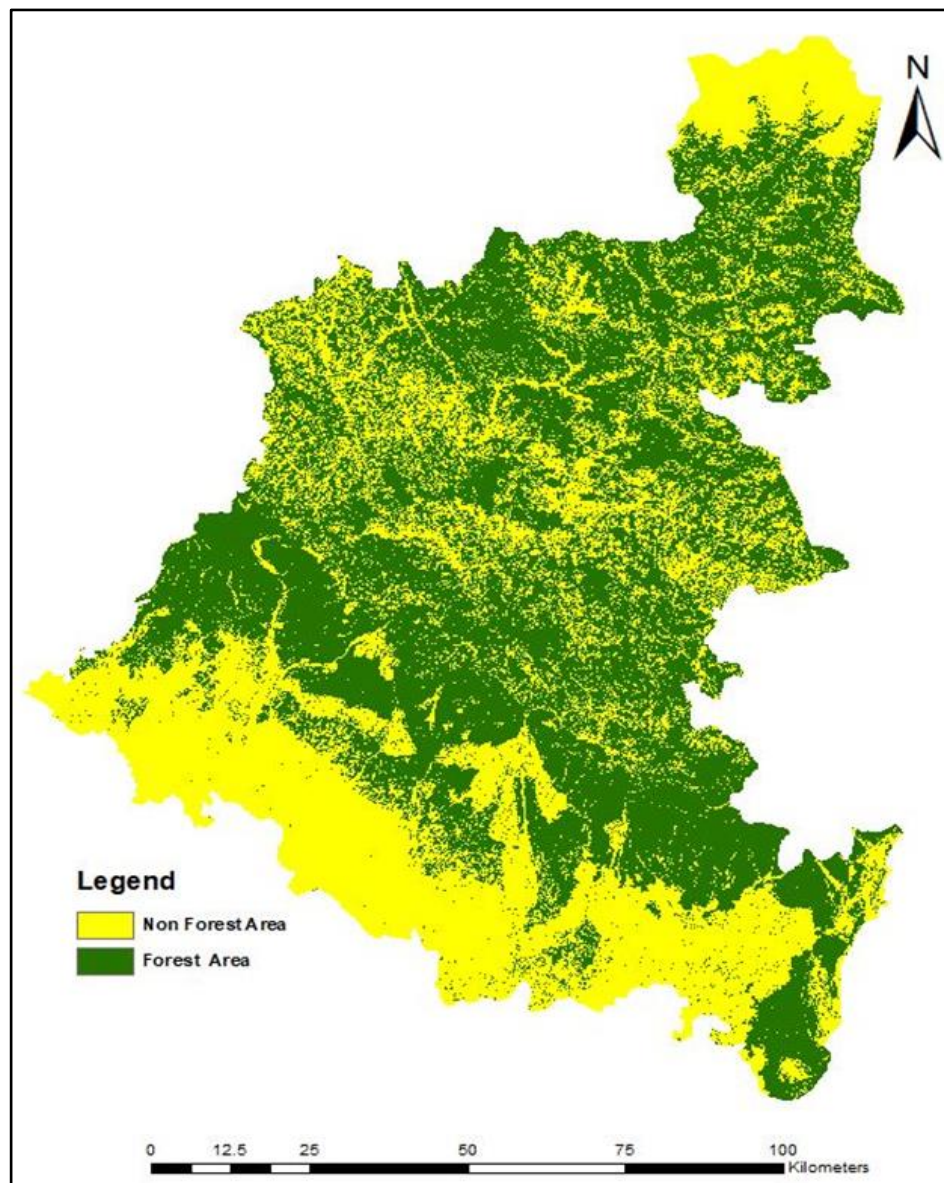


Figure 14: Total forest and non-forest class of study area.

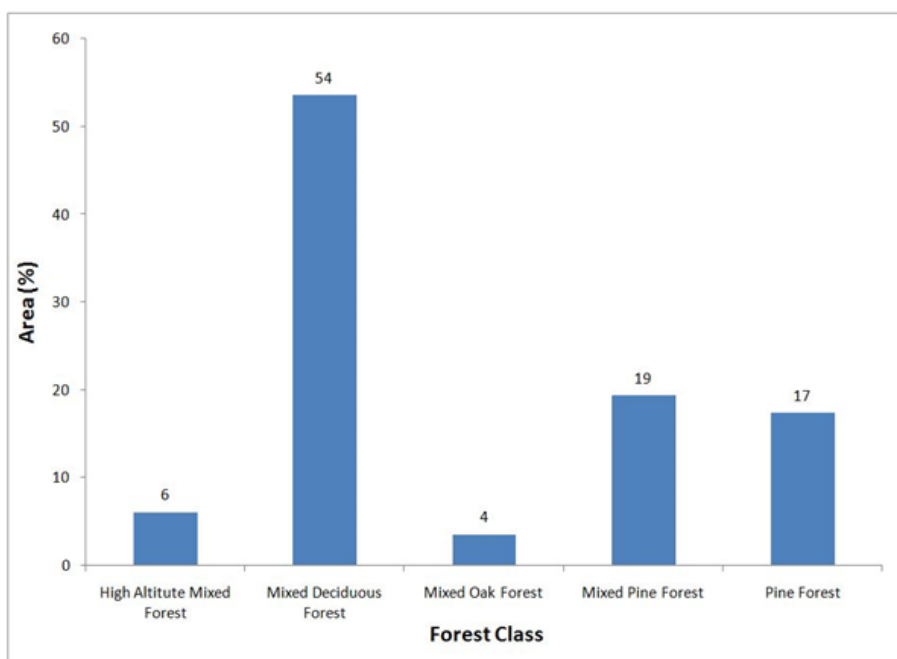


Figure 15: Forest area (%) occupied by major forest class of study area.

The mixed pine forest, altitude ranges from 1300 m to 2400 m MSL which occupies area of 1406 km². It contributes about 11% of total studied geographical area and 19% of total classified forest area. At altitude of 1200 m to 1400 m MSL, is the transition zone between mixed deciduous forest and pine forest/mixed pine forest from where pine belt start and extended up to altitude of 2300 m MSL. The dominant tree species found in this class were *Pinus roxburghii*, *Quercus Leucotrichophora*, *Quercus floribunda*, *Betula alnoides*, *Cedrus deodara*, *Acer caesium* and *Aesculus indica*. It has also more shrub diversity and richness as compared to pine forest, mixed oak forest and high altitude mixed forest and richness gradually decreases with increase in elevation.

The pine forest here represents pure pine forest i. e. *Pinus roxburghii*. It extends from altitude of 1300 m to 2300 m MSL and occupies area of 1262 km² which contributes 10% of total studied geographical area and 17% of total classified forest area. It was the third dominant forest class. Pine forest exhibited absolute dominance in terms of basal cover as compared to other classified forest classes which support least diversity of shrubs species. *Lantana camara* was the dominant shrub in this forest. Mixed oak forest represents here 80% oak species mixed with other tree species. Oak forest hardly found as pure oak forest and occupied only certain patches. Thus area

occupied by pure oak forest was very less as compared to other forest class. The dominant tree species of mixed oak forest were *Quercus spp.*, *Pinus roxburghii*, *Abies pindrow* and *Cedrus deodara*. It extends from altitude of 1600 m to 3000 m MSL and occupies area of 259 km² which contributes 2% of total geographical area and 4% of total classified forest area.

The high altitude mixed forest is the fourth dominant classified forest class and elevation ranges from 2400 m to 3600 m MSL. It occupies area of 442 km² which contributes about 3.6% of total studied geographical area and 6% of total classified forest area. It has less shrubs diversity and richness as compared to mixed deciduous forest and mixed pine forest. The diversity of shrubs sharply decreases in higher elevation. In this class, the dominant tree species were *Quercus semecarpifolia*, *Abies pindrow*, *Abies spectabilis*, *Betula utilis*, *Rhododendron arboretum*, *Rhododendron barbatum* and *Acer cappadocium*. According to the classification, different types of forests classes with elevation and dominant tree species are given in table 4.1.

Table 4.1: Different forest classes with elevation and dominant tree species.

Sl. No	Forest Class	Elevation Range (m)	Dominant Tree Species
1	Mixed Deciduous Forest	148-1300	<i>Mallotus philippensis</i> , <i>Toona aliata</i> , <i>Holoptelea integrifolia</i> , <i>Macaranga pustulata</i> , <i>Anogeissus latifolia</i> , <i>Shorea robusta</i>
2	Mixed Pine Forest	1300-2400	<i>Pinus roxburghii</i> , <i>Quercus Leucotrichophora</i> , <i>Quercus floribunda</i> , <i>Betula alnoides</i> , <i>Cedrus deodara</i> , <i>Acer caesium</i> , <i>Aesculus indica</i> ,
3	Pine Forest	1300-2300	<i>Pinus roxburghii</i>
4	Mixed Oak Forest	1600-3000	<i>Quercus spp.</i> , <i>Pinus roxburghii</i> , <i>Abies pindrow</i> , <i>Cedrus deodara</i> ,
5	High Altitude Mixed Forest	2400-3600	<i>Quercus semecarpifolia</i> , <i>Abies pindrow</i> , <i>Abies spectabilis</i> , <i>Betula utilis</i> , <i>Rhododendron arboretum</i> , <i>Rhododendron barbatum</i> , <i>Acer cappadocium</i> , <i>Cedrus deodara</i>

The classification of forest class on the basis of spectral reflectance of vegetation cover in satellite imagery gives very good information of distribution of vegetation cover along altitudinal gradient. The variations in spectral reflectance of vegetation cover on satellite image help in digital image classification through image processing software. In the past, authors have analyzed and documented the forest cover on the basis of species composition, distribution and community structure by plot sampling techniques along altitudinal gradient (**Saxena *et al.*, 1985, Adhikari *et al.*, 1992, Rawal and Pangtey 1994, Dhar *et al.*, 1997, Hussain *et al.*, 2008**). In this study, classification of forest covers types mainly done by analysis of variation in vegetation's spectral reflectance along altitudinal gradient through digital image classification as mentioned in results. Earlier, some authors classified and documented forest types on the basis of dominant tree species by surveying and sampling along altitudinal gradient (**Saxena and Singh 1982, Ram *et al.*, 2004, Kharkwal and Rawat 2010**). The composition of dominant tree species in classified forest types of the study area along altitudinal gradient found to be similar with earlier reported (**Singh and Singh 1987, Dhar *et al.*, 1997**).

In the study area, *Pinus roxburghii* and *Quercus spp.* found to be dominant tree species of forest covered. The occurrence of *Pinus roxburghii* (chir pine) starts from altitude of 1300 m MSL up to 2300m MSL (**Ralhan *et al.*, 1982 and 1985**). However, in some areas, it is recorded at altitude of 1000 m MSL. The pine forest mainly occurred as pure pine forest with absolute dominant basal cover and *Lantana camara* as a dominant shrub in the forest (**Saxena and Singh 1982**). *Quercus* species represent the climax species of the study area whose altitudinal distribution varies place to place. Generally, its distribution starts from altitude of 1400 m MSL to 3300 m MSL. Some authors documented that, *Quercus* species distributed between 1000 m MSL to 3500 m MSL and the dominance of particular *Quercus* species depends on altitudes (**Singh *et al.*, 2016**). Among the *Quercus* species, *Quercus leucotrichophora* found to be distributed from altitude of 1300 m MSL to 2200 m MSL, with high abundance between 1800 m to 2000 m elevation. In the past studies (**Singh and Singh 1986; Rana *et al.*, 1989; Zobel and Singh 1997; Singh and Rawat 2012**) have reported and documented the occurrence of *Quercus leucotrichophora* between 1000 to 2500 m elevations, with high abundance around 2000 m elevation. At the elevation between

2000 m to 2400 m, *Quercus leucotrichophora* also associated with *Quercus floribunda* and *Quercus lanuginosa* and disappeared gradually with dominant of *Quercus semicarpifolia* beyond 2400 m elevation which is distributed up to 3000 m MSL. In the past studies, (Singh *et al.*, 1994, Singh and Singh 1986) also reported that *Quercus semicarpifolia* present between 2366- 3000 m and 2400- 3600 m respectively. The classified forest type viz. mixed pine forest between elevation 1300 m to 2300 m was dominant with tree species of *Pinus roxburghii*, *Quercus leucotrichophora*, and *Quercus floribunda* which were also associated with other tree species such as *Persea odoratissima*, *Bauhinia retusa*, *Betula alnoides*, *Cedrus deodara*, and *Acer caesium* (Saxena and Singh, 1982).

In high altitude mixed forest, the identified dominant tree species were *Quercus semecarpifolia*, *Abies pindrow*, *Aesculus indica*, *Rhododendron arboreum*, *Betula utilis*, *A. caesium*, *Rhododendron barbatum*, *R. campanulatum* and *Acer cappadocium* which were similar as reported by Rawal *et al.*, (1994). In the past studies, similar tree composition and distribution also reported at elevation ranges between 2400 m to 3600 m MSL (Adhikari *et al.*, 1991, Rawal and Pangtey 1994, Gairola *et al.*, 2008). This classified forest types also support good basal cover of shrubs species like *Thamnocalamus spathiflora*, *Arundinaria falcata*, *Berberis umbellata* and *Chimonabambusa jaunsarensis* (Rawal and Pangtey 1994).

4.4 Distribution of forest class at different aspects:

The analysis of distribution of different forest classes at different aspects revealed that, all classified forest types were found to be variation in distribution pattern. Saxena and Singh (1982) reported the variation of distribution of forest type on different aspects on the basis of dominant tree species. In the present study area, the distribution of all the five classified forest types in four different aspects viz northern, eastern, southern and western aspects shown that the mixed deciduous forest distribution of tree species were more or less equal in all four aspects. This may be due the facts that mixed deciduous forest found to be dominant at plane and lower altitude region. Again due to lower slope area, sunlight distributed equally in all aspects which does not impact much in distribution pattern.

In mixed pine forest, distribution pattern at northern and western aspects more or less the same and higher as compared to eastern and southern aspects. This may be due to the facts that mixed pine forest act as a starting zone of temperate forest which support cold loving vegetation at cooler aspects that is northern and western aspects. In the case of pine forest, although it has the characteristic to grow in low and direct sunlight condition and depends on favorable soil condition, *Pinus roxburghii* prefers relatively cooler aspects for better growth and development. Thus pine forest shows highest distribution in northern aspects. **Dwivedi and Mathur (1978)** also reported that the growth of *Pinus roxburghii* was poor on warmer slopes. The distribution pattern of mixed oak forest found to be equal in both northern and eastern aspects and both southern and western aspects respectively. The high altitude mixed forest shows similar distribution pattern with mixed pine forest that is highest at cooler slope (northern and western aspects). The distribution area of all major forest class at different aspects are shown in Figure 15.

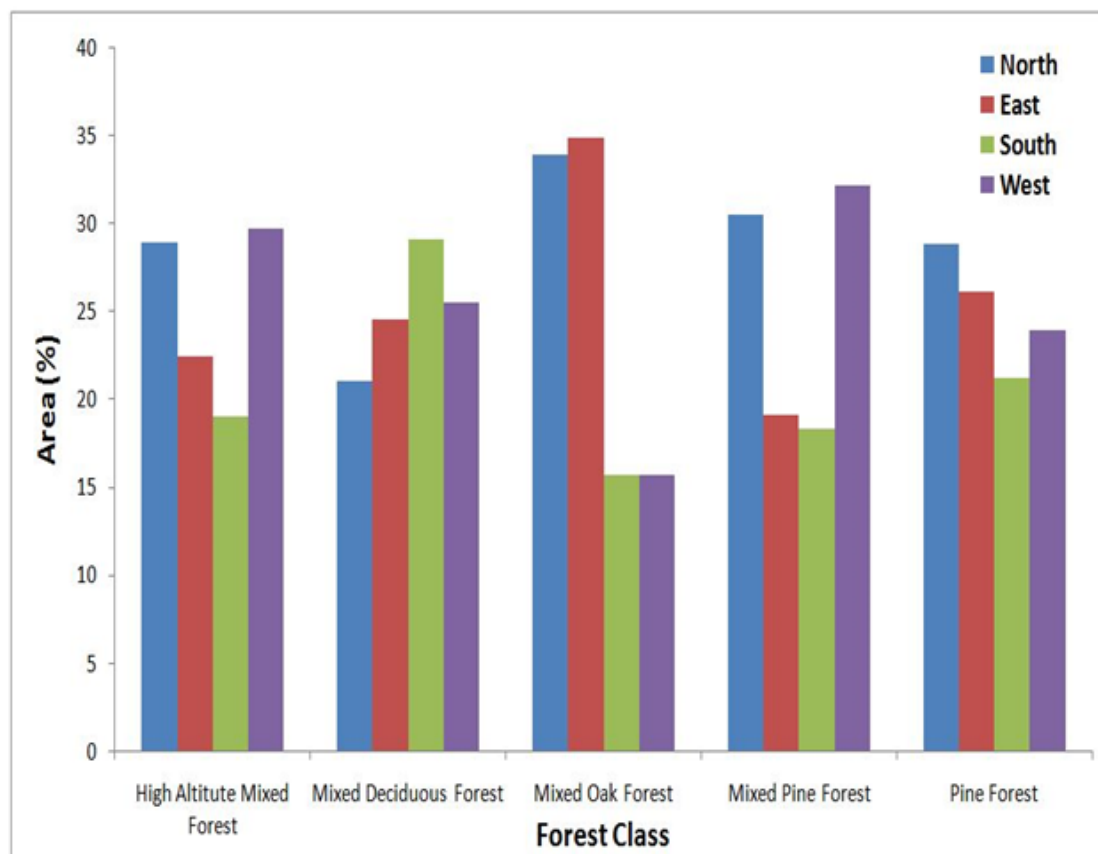


Figure 15: Distribution area (%) of major forest classes at different aspects.

4.5 Estimation of biomass:

4.5.1 Mixed Deciduous Forest:

In the mixed deciduous forest, the estimated biomass ranges from 184 Mg ha⁻¹ to 436 Mg ha⁻¹. This is the forest which gives highest estimate of biomass among all other forest types (Figure 16). Majority of this forest found to be under lower region of Nainital district followed by Udham Singh Nagar, Almora and Bageshwar district respectively. As altitudinal gradient increases, there was decrease in biomass production and area under the forest also decreases. Maximum estimate of biomass was in lower region of Nainital district. The biomass calculated for mixed deciduous forest is shown in Figure 16 and the altitudinal distribution are shown in Figure 17. The dark green colour code indicate the highest biomass production of the forest. The earlier study carried out by **Ghasemi, et al., (2013)**, estimate the AGB of temperate deciduous forest using wavelet analysis found to similar result whose estimated biomass ranges from 150 Mg ha⁻¹ to 350 Mg ha⁻¹.

It is also observed that the basal cover, crown cover, density and tree height found to more as compared to other forest types. This may be the main reason for high biomass production in this forest class. But DBH show variation as other forest types depending on the age of the tree. As move towards the high elevation, the tree density, tree height, crown cover and DBH were recorded decreasing which shows the reduction in biomass production in along altitudinal gradient. In the case of Udham Singh Nagar district, less biomass production was observed in lower elevation region. This may due the fact that, majority of forest are under plantation forest and some are natural forest which are also under human disturbances.

When we consider the distribution pattern of estimated biomass of mixed deciduous forest of whole area as shown in Figure 18, where whole mixed deciduous forest area were plotted in horizontal line with biomass and vertical line with area covered. Thus, from histogram it depicts that biomass range from 400 Mg ha⁻¹ to 436 Mg ha⁻¹ covered an area of 2.63 Sq. km, 300 Mg ha⁻¹ to 400 Mg ha⁻¹ covered an area of 755 Sq. km, 200 Mg ha⁻¹ to 300 Mg ha⁻¹ covered an area of 1073 Sq. km, 100 Mg ha⁻¹ to 200 Mg ha⁻¹ covered an area of 781 Sq. km and 2 Mg ha⁻¹ to 100 Mg ha⁻¹ covered an area of 1277 Sq. km.

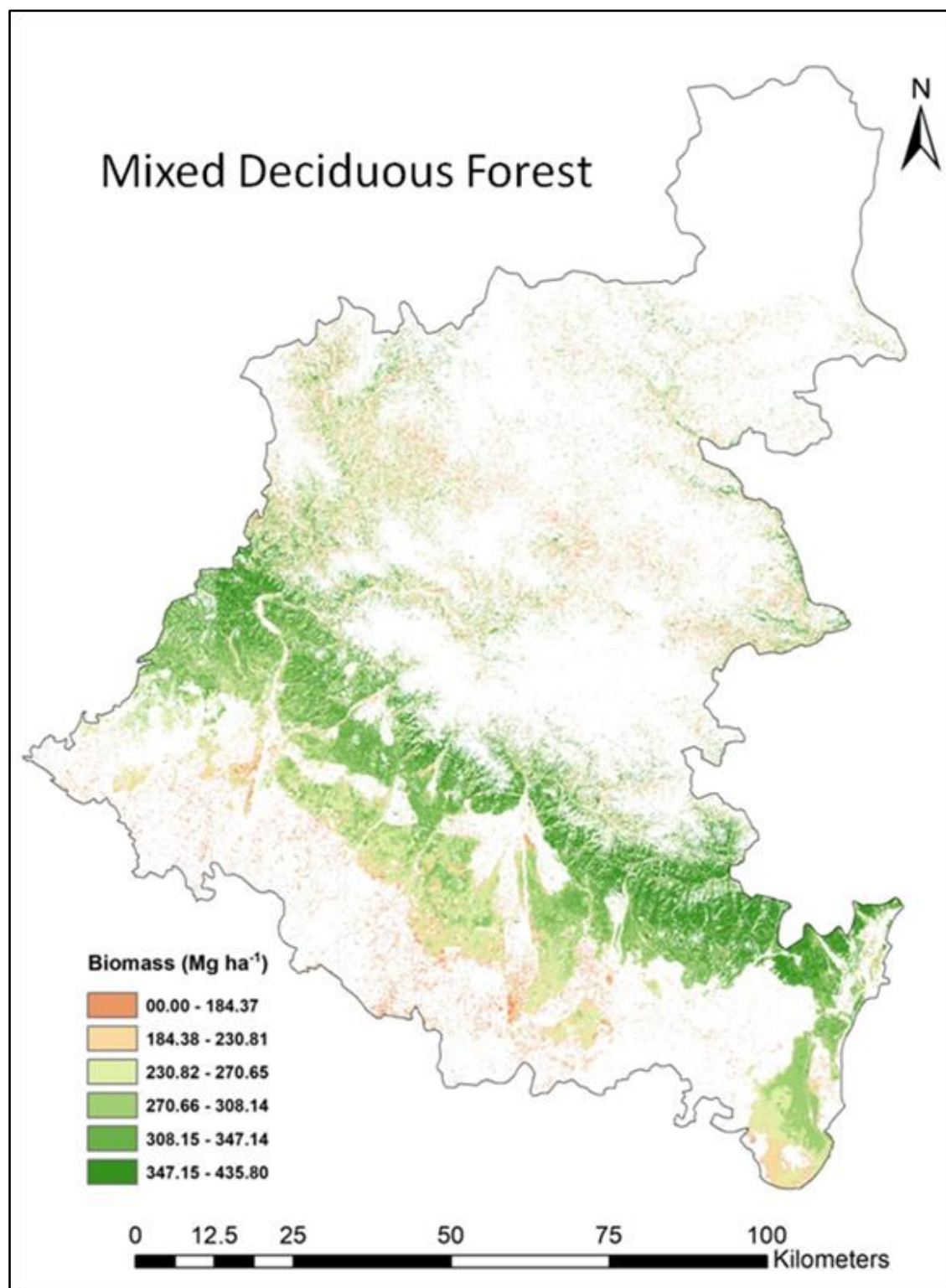


Figure 16: AGB of Mixed deciduous Forest of study area

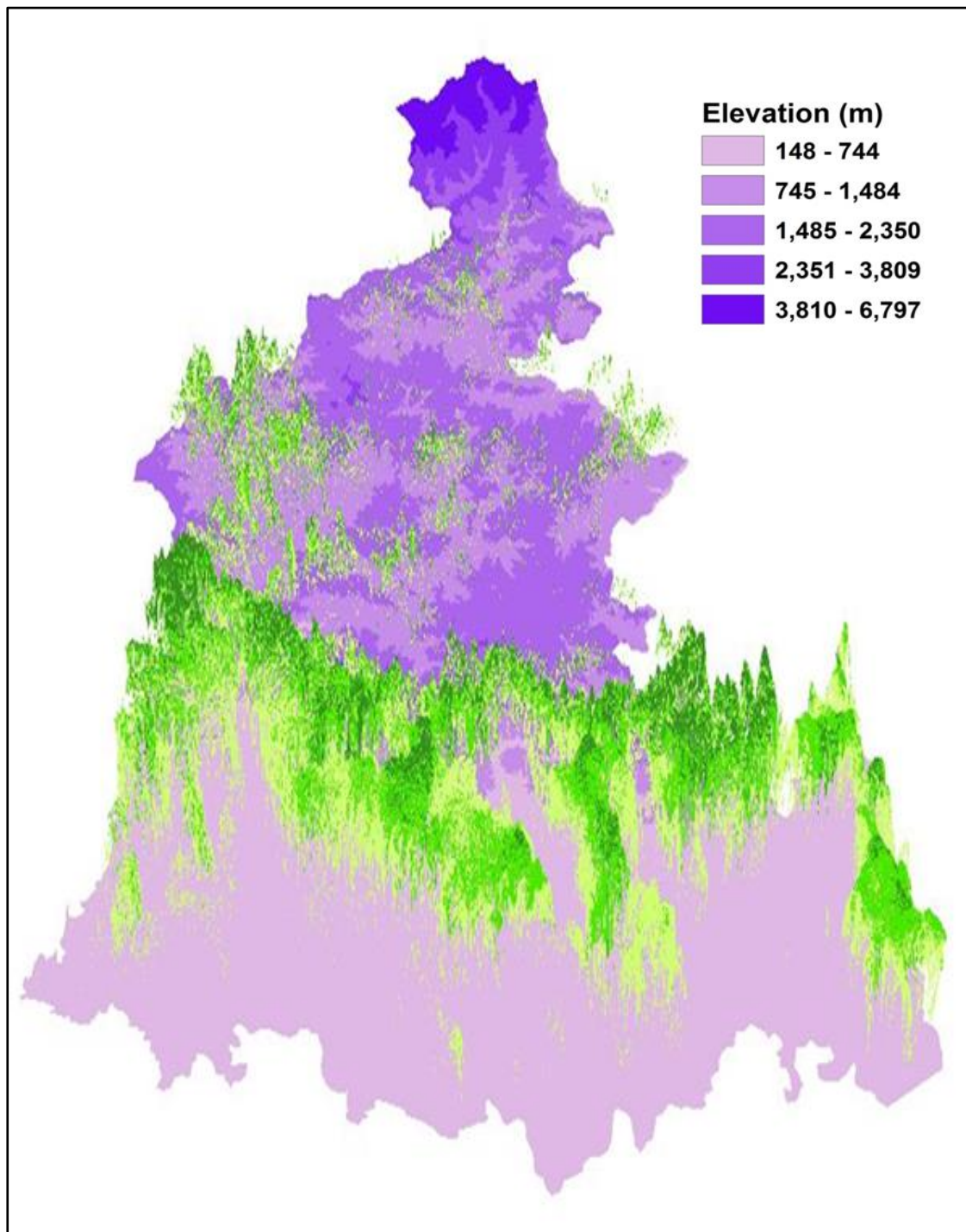


Figure 17: Altitudinal distribution of AGB of mixed deciduous forest of study area

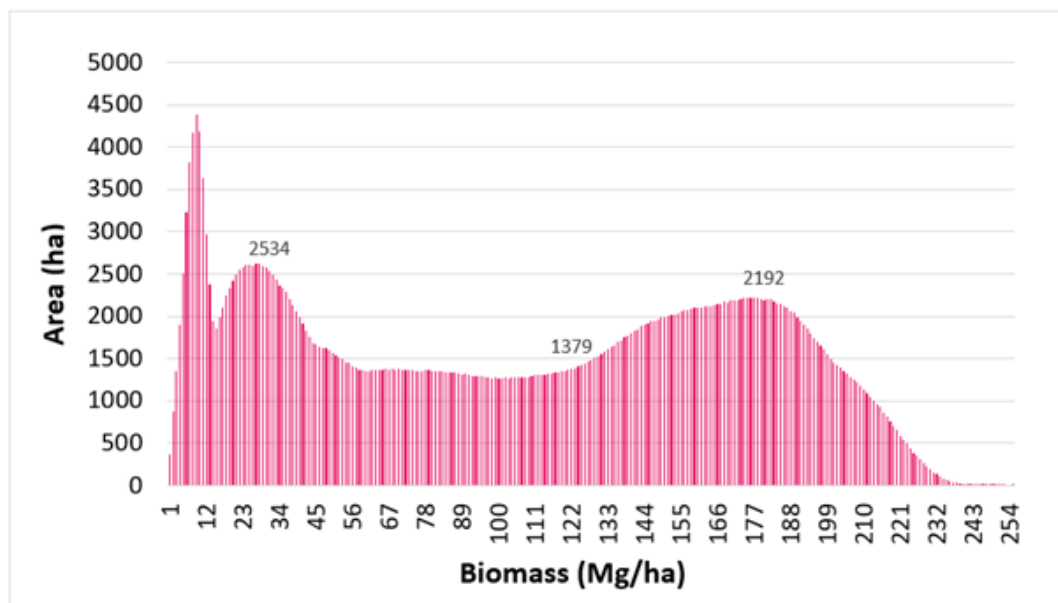


Figure 18: Histogram of biomass distribution area of mixed deciduous forest.

4.5.2 Mixed Pine Forest:

In the mixed Pine forest, the estimated biomass ranges from 62 Mg ha⁻¹ to 252 Mg ha⁻¹. This is the forest which sparsely distributed among all other forest types and occupied most the study area. As the distribution of this forest starts from elevation 1300 m to 2400 m, it occurs along altitudinal height from Nainital to Bageshwar district. This was the only forest class where there was no direct relationship between elevation gradient and estimated biomass that changes in estimated biomass irrespective of elevation. This may be due to the transition zone between deciduous forest and temperate forest which allowed the growth of both temperate deciduous forest and temperate forest. The estimated biomass shows high and low biomass content only because of the number of trees per unit area. The estimated biomass of mixed pine forest is shown in Figure 19 and the altitudinal distribution is shown in Figure 20. The dark green colour code indicates the highest biomass production of the forest.

When we consider the distribution pattern of estimated biomass of mixed pine forest of whole area as shown in Figure 21, where whole mixed pine forest area was plotted in horizontal line with biomass and vertical line with area covered. Thus, from histogram it depicts that biomass range from 1 Mg ha⁻¹ to 50 Mg ha⁻¹ covered an area of 570 Sq. km, 51 Mg ha⁻¹ to 100 Mg ha⁻¹ covered an area of 313 Sq. km, 101 Mg ha⁻¹ to 150 Mg ha⁻¹ covered an area of 310 Sq. km, 151 Mg ha⁻¹ to 200 Mg ha⁻¹ covered an area of 203 Sq. km and 201 Mg ha⁻¹ to 251 Mg ha⁻¹ covered an area of 10 Sq. km.

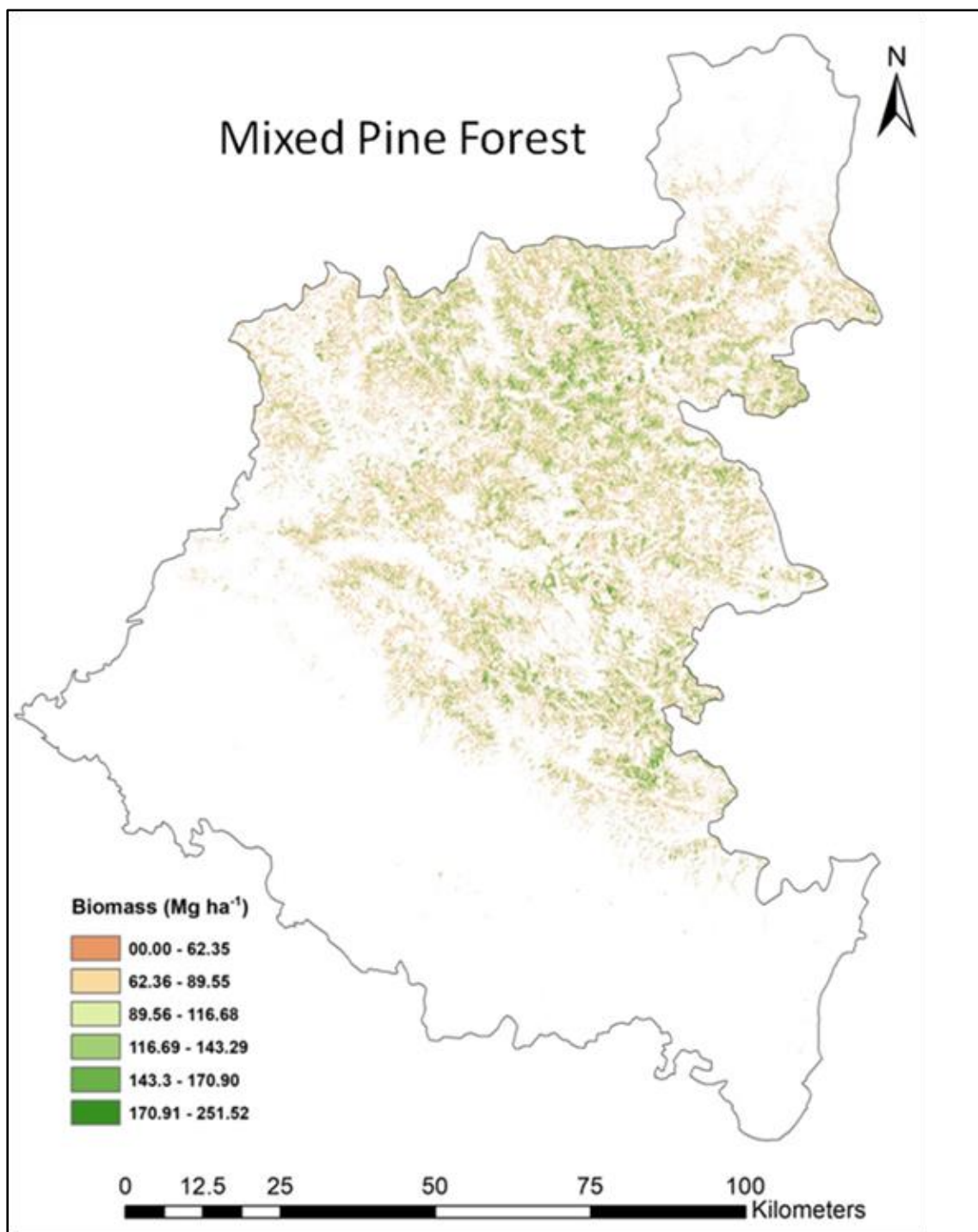


Figure 19: AGB of mixed pine forest of study area

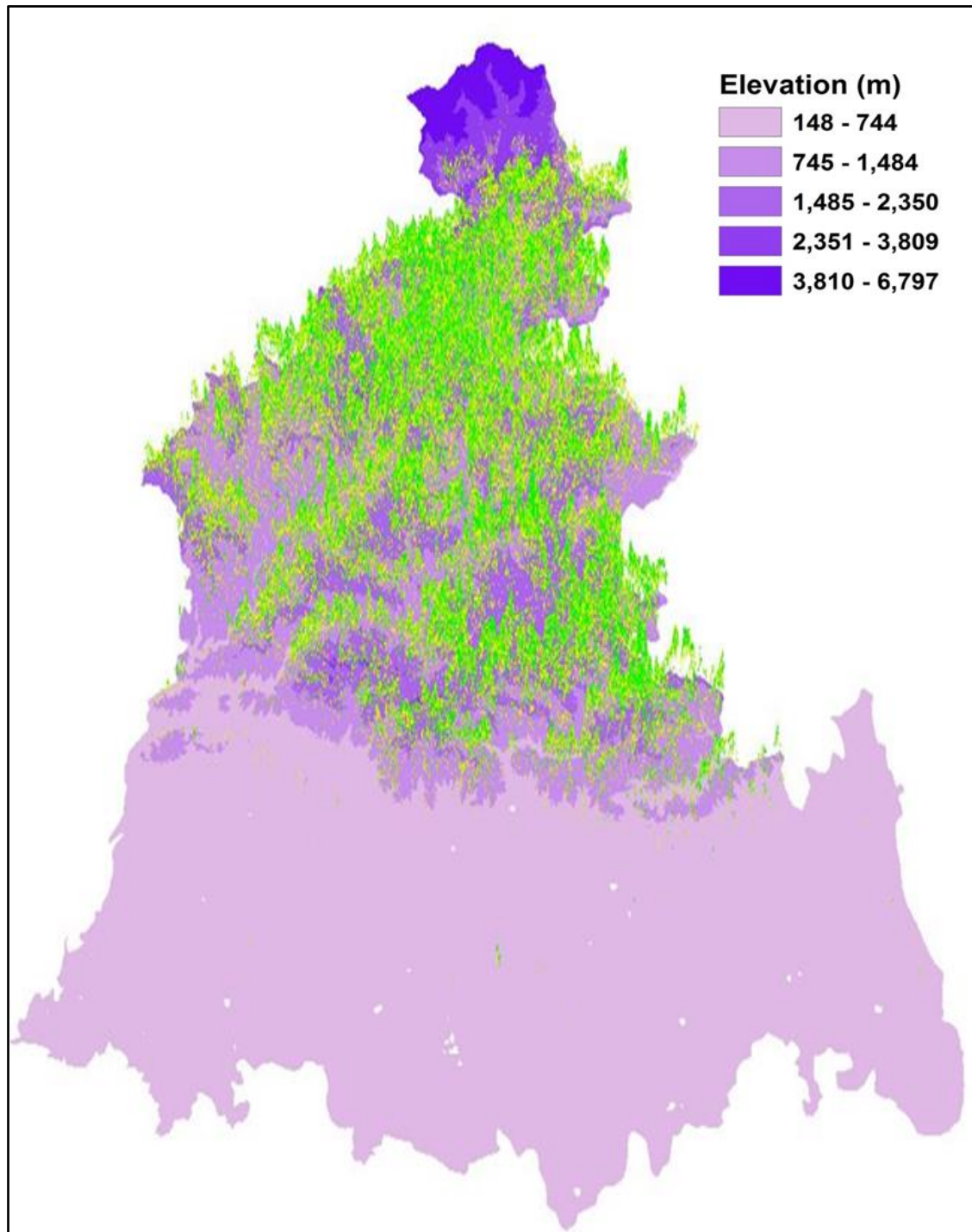


Figure 20: Altitudinal distribution of AGB of mixed pine forest of study area

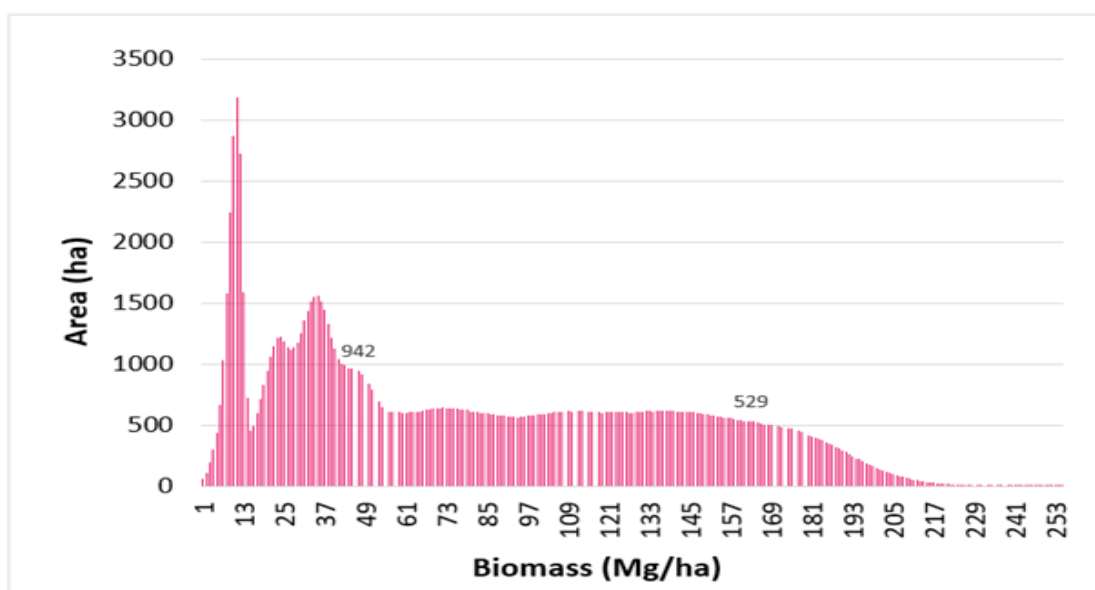


Figure 21: Histogram of biomass distribution area of mixed pine forest.

4.5.3 Pine Forest:

In Pine forest the estimated biomass ranges from 80 Mg ha⁻¹ to 302 Mg ha⁻¹. The estimated biomass more or less found to be in similar range with previous study. Some authors also reported that AGB of pine forest also varies from 150 Mg ha⁻¹ to 320 Mg ha⁻¹ (Rana *et al.*, 1988).

The pine is forest which clustery distributed among all other forest types and also mixed with other forest types. Although the distribution of this forest starts from elevation 1300 m to 2300 m, it may also occur beyond this elevation. This forest dominant is also reported at elevation from 1600 m to 1900 m (Ralhan *et al.*, 1982 and 1985). Pine tree was one of the dominant tree species in the study area. Most of the study area, the estimated biomass of pine forest ranges from 116 Mg ha⁻¹ to 223 Mg ha⁻¹ as shown in Figure 22 and their altitudinal distribution is shown in Figure 23.

When we consider the distribution pattern of estimated biomass of pine forest of whole area as shown in Figure 24, where whole mixed pine forest area was plotted in horizontal line with biomass and vertical line with area covered. Thus, from histogram it depicts that biomass range from 1 Mg ha⁻¹ to 50 Mg ha⁻¹ covered an area of 407 Sq. km, 51 Mg ha⁻¹ to 100 Mg ha⁻¹ covered an area of 254 Sq. km, 101 Mg ha⁻¹ to 150 Mg ha⁻¹ covered an area of 190 Sq. km, 151 Mg ha⁻¹ to 200 Mg ha⁻¹ covered an area of 202 Sq. km, 201 Mg ha⁻¹ to 250 Mg ha⁻¹ covered an area of 175 Sq. km and 250 Mg ha⁻¹ to 302 Mg ha⁻¹ covered an area of 42 Sq. km

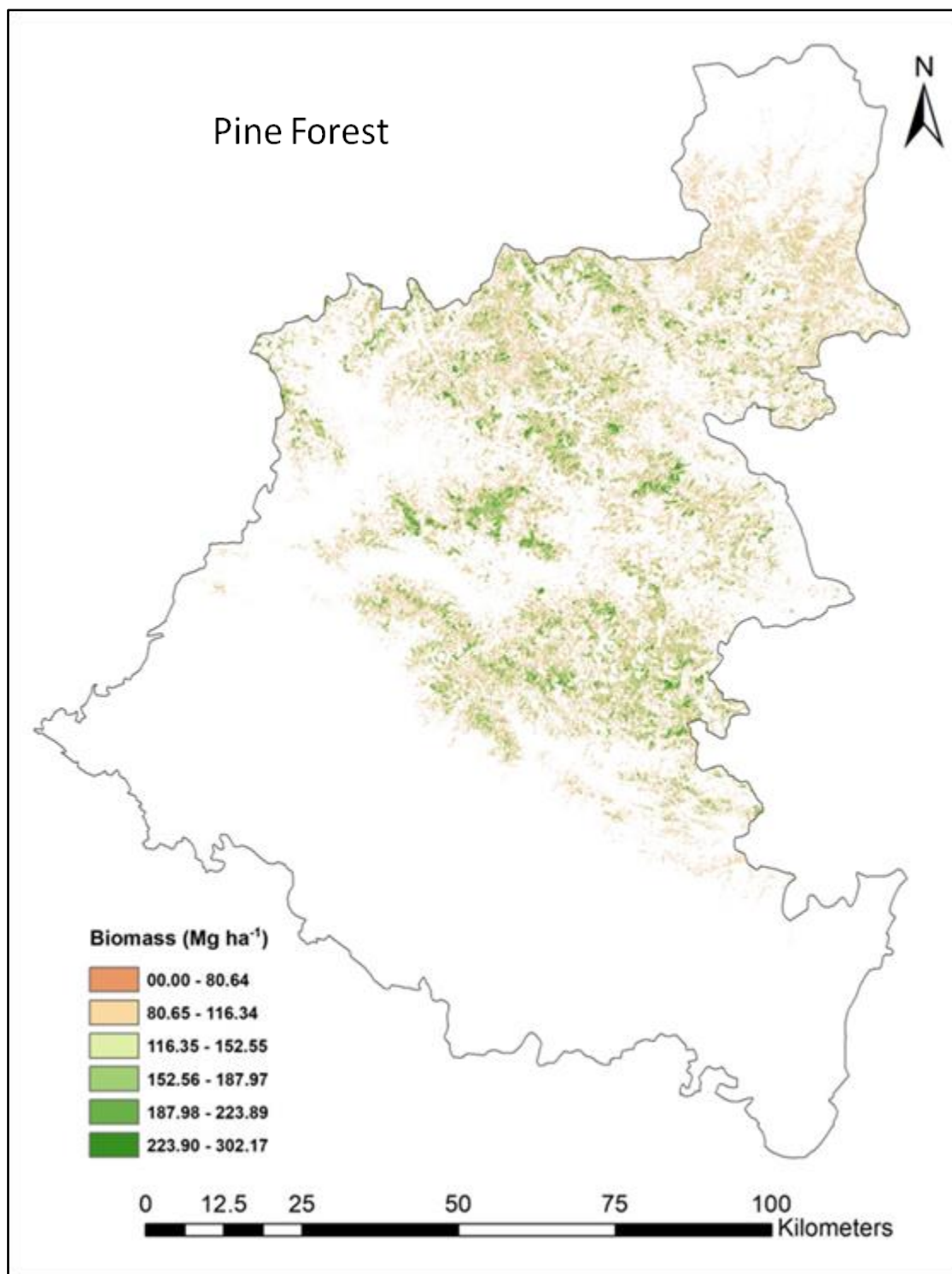


Figure 22: AGB of pine forest of study area.

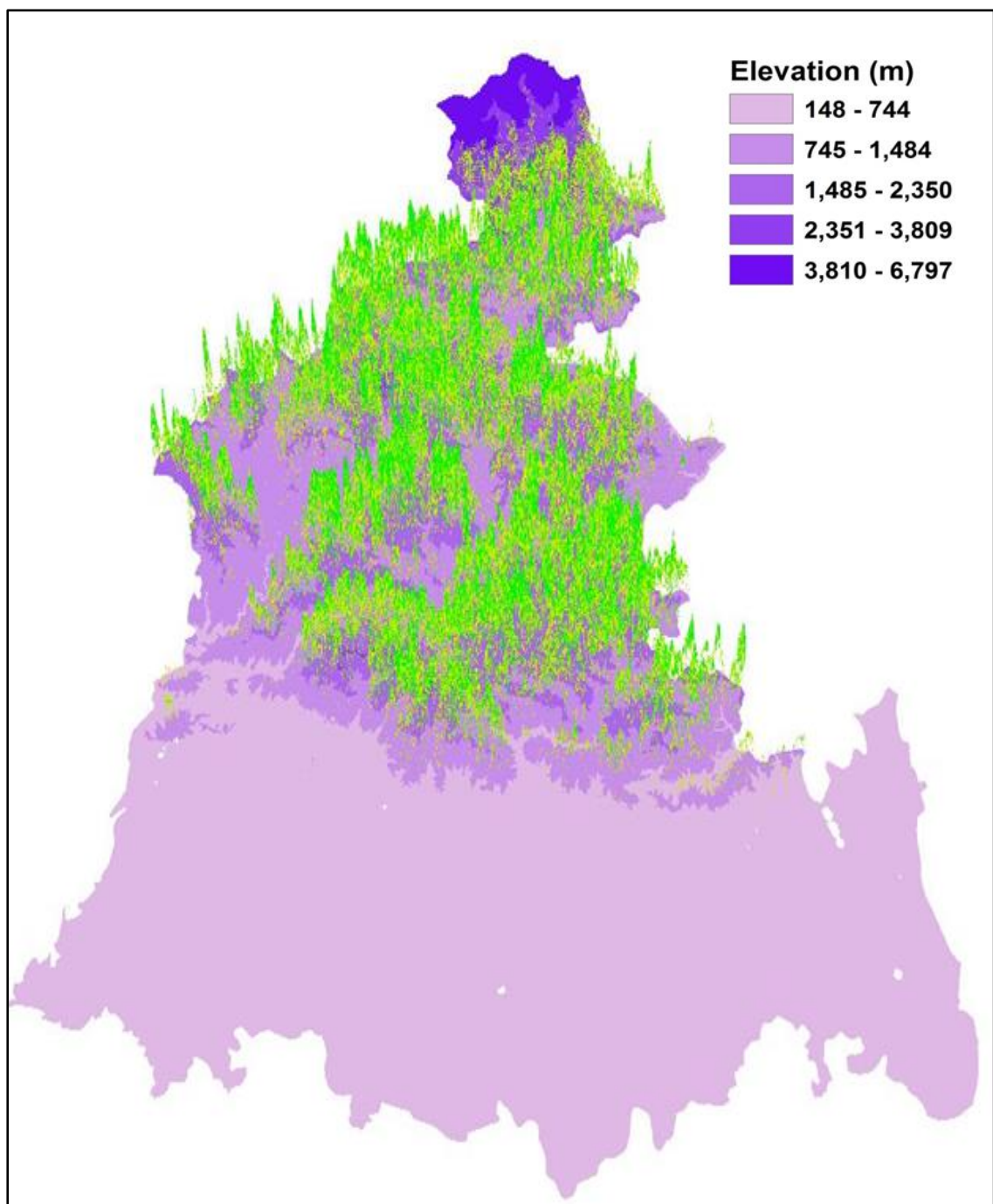


Figure 23: Altitudinal distribution of AGB of pine forest of study area.

4.5.4 Mixed Oak Forest:

In mixed oak forest, the estimated biomass ranges from 71 Mg ha⁻¹ to 265 Mg ha⁻¹. The estimated biomass more or less in similar range with previous study. Some authors also found that AGB of mixed oak forest also varies from 150 Mg ha⁻¹ to 320 Mg ha⁻¹. The estimated biomass of mixed oak forest is shown in Figure 25. However, in another study AGB was estimated three relatively protected oak forest site in the Kumaon Himalaya using allometric equations based on circumference at breast height and density, ranges from 197.2 to 322.8 Mg ha⁻¹ (Negi *et al.*, 1983).

The oak forest also clusterly distributed along altitudinal gradient and also mixed with other tree forest species. Some authors documented that, *Quercus* species distributed between 1000 m MSL to 3500 m MSL and the dominance of particular *Quercus* species depends on altitudes (Singh *et al.*, 2016). The altitudinal distribution of oak forest shown in Figure 26.

When consider the distribution pattern of estimated biomass of mixed oak forest of whole area as shown in Figure 24, where whole mixed oak forest area was plotted in horizontal line with biomass and vertical line with area covered. Thus, from histogram it depicts that biomass range from 1 Mg ha⁻¹ to 50 Mg ha⁻¹ covered an area of 92 Sq. km, 51 Mg ha⁻¹ to 100 Mg ha⁻¹ covered an area of 40 Sq. km, 101 Mg ha⁻¹ to 150 Mg ha⁻¹ covered an area of 39 Sq. km, 151 Mg ha⁻¹ to 200 Mg ha⁻¹ covered an area of 52 Sq. km and 201 Mg ha⁻¹ to 255 Mg ha⁻¹ covered an area of 35 Sq. km.

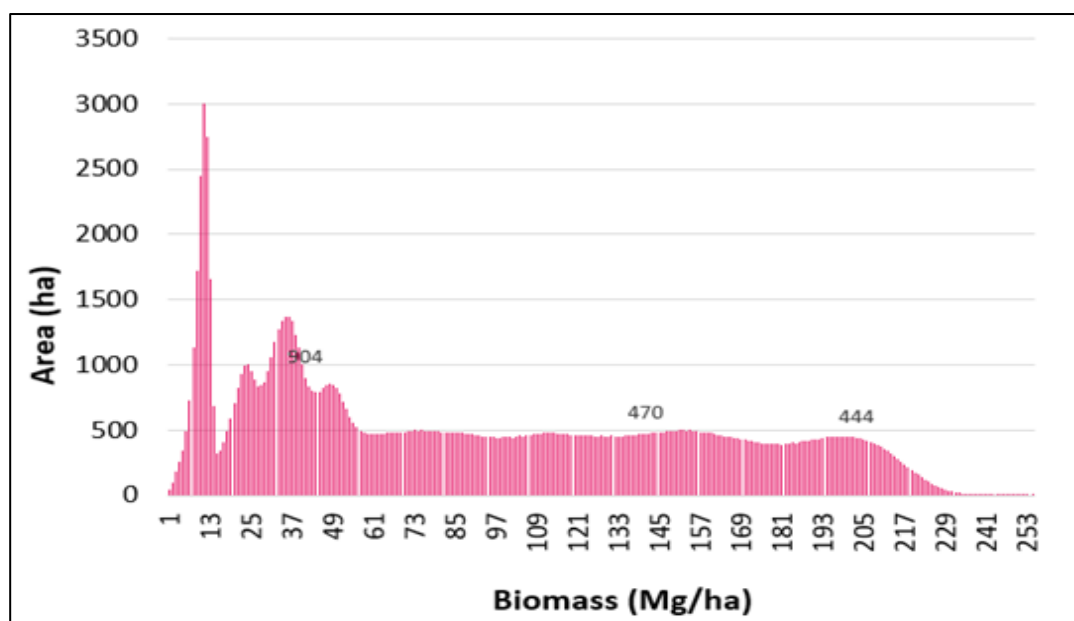


Figure 24: Histogram of biomass distribution area of pine forest.

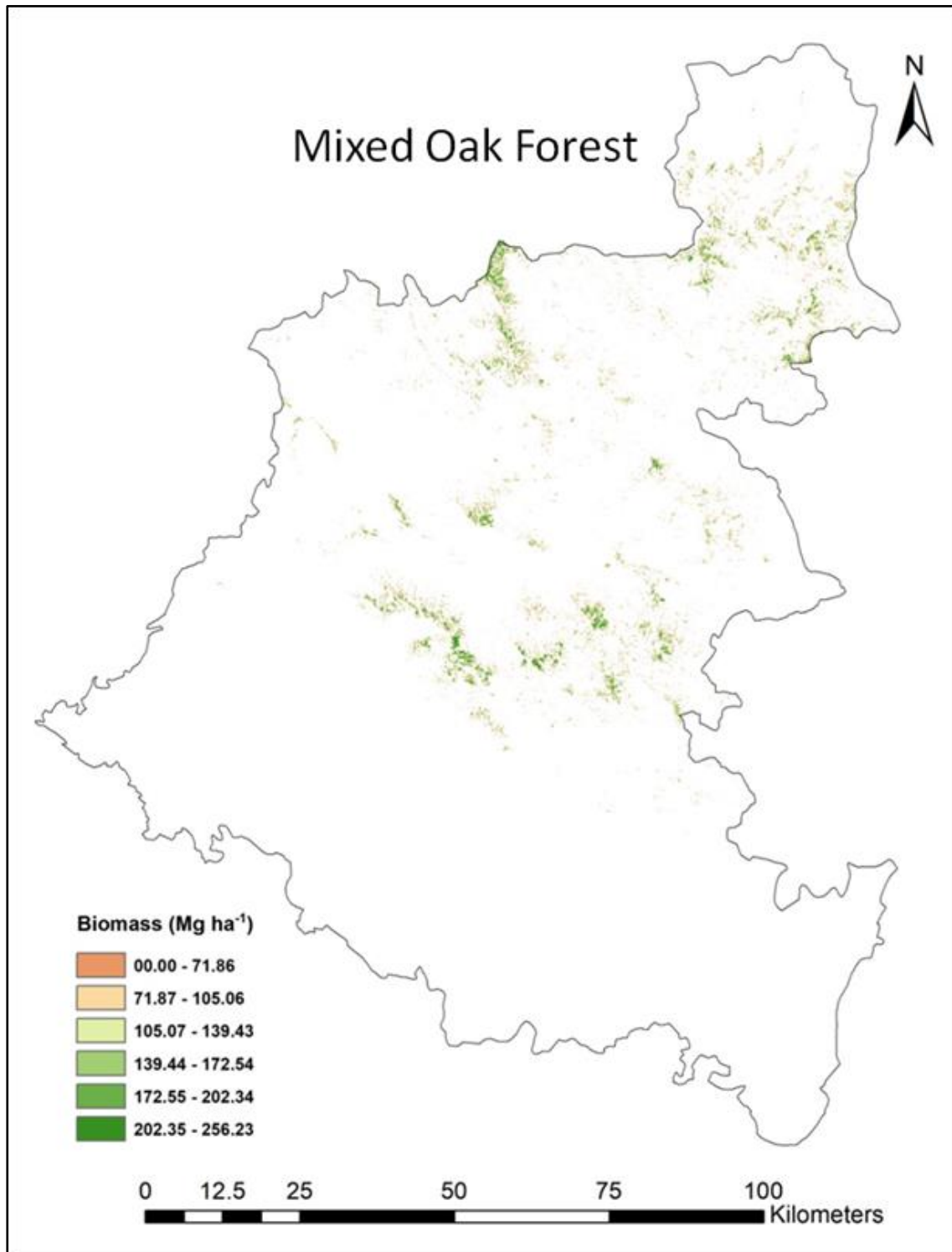


Figure 25: AGB of mixed oak forest of study area

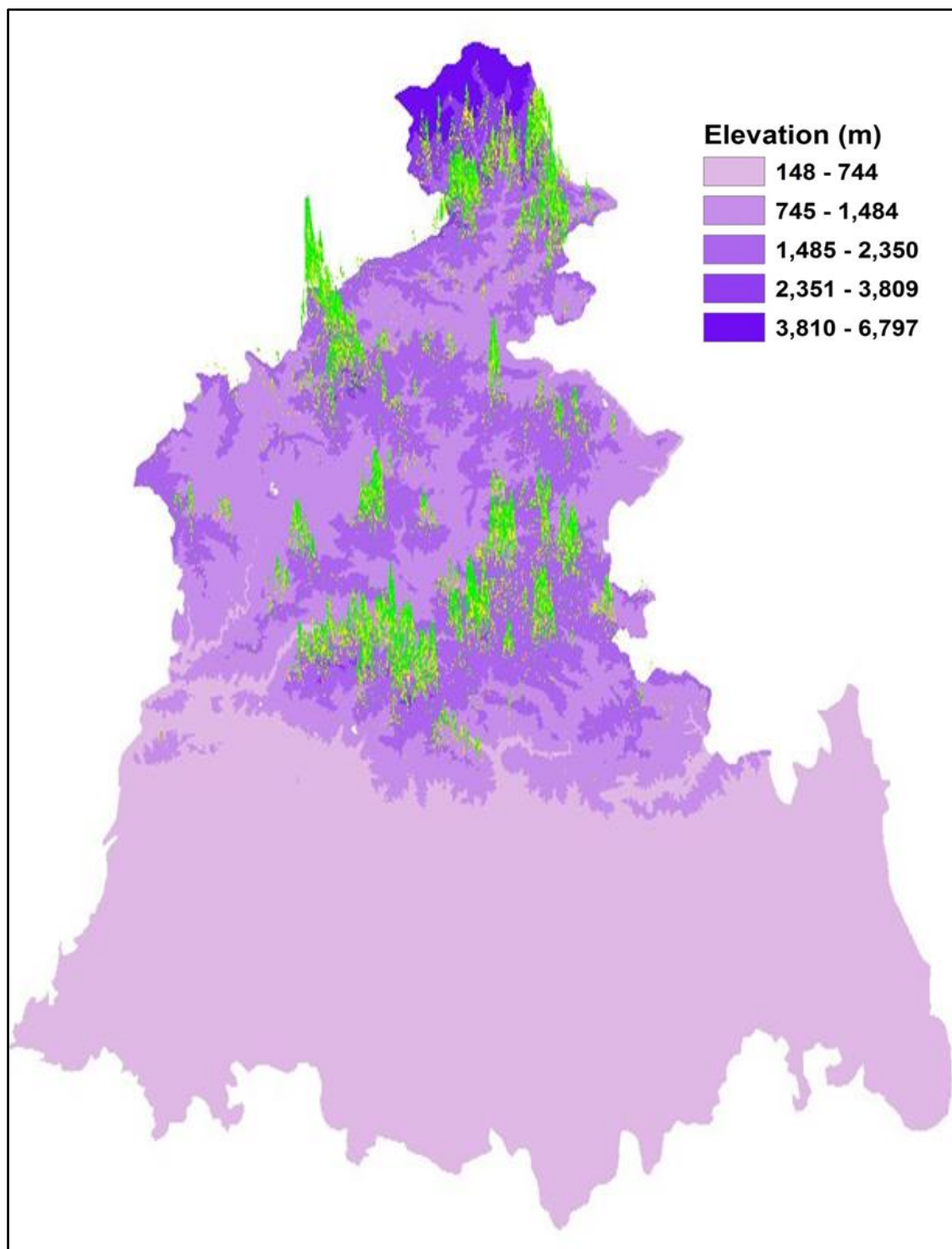


Figure 26: Altitudinal distribution of AGB of mixed oak forest of study area

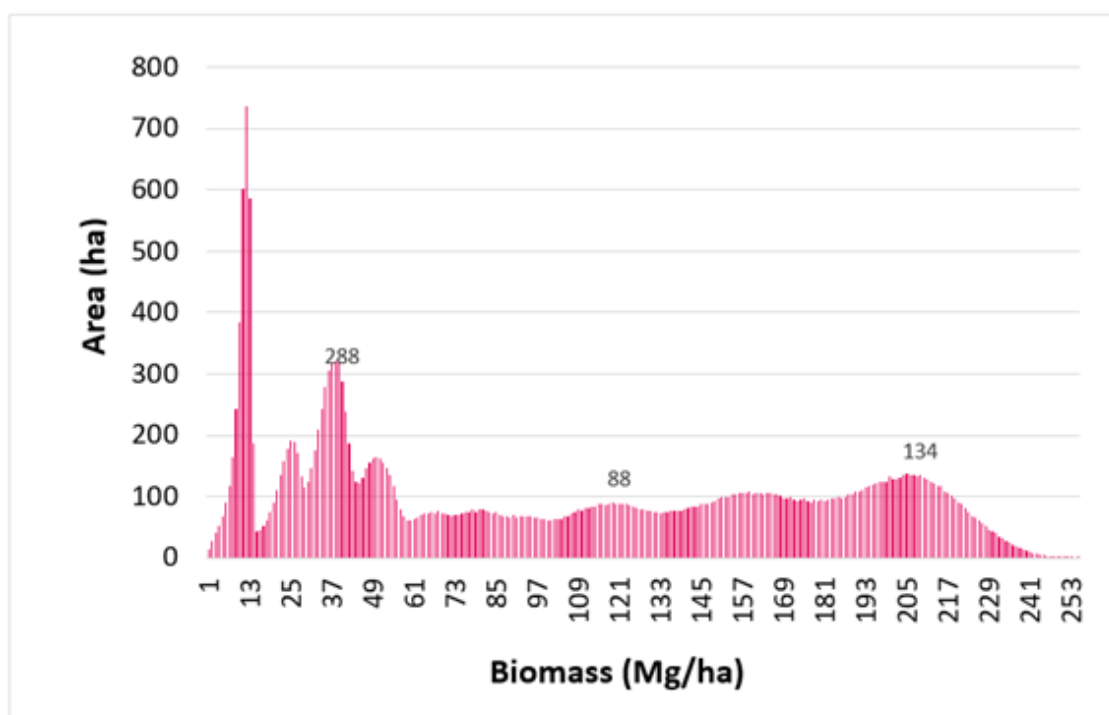


Figure 27: Histogram of biomass distribution area of mixed oak forest.

4.5.5 High Altitude Mixed Forest:

The estimated biomass of high altitude mixed forest found to be ranges from 43 Mg ha⁻¹ to 195 Mg ha⁻¹ as shown in Figure 28. This is the forest which gives lowest production of biomass. This may be due to the decrease in tree height, diameter at breast height and density along altitudinal gradient which were similar as reported by **Rawal et al., (1994)**. In high altitude mixed forest, the identified dominant tree species were *Quercus semecarpifolia*, *Abies pindrow*, *Aesculus indica*, *Rhododendron arboreum*, *Betula utilis*, *A. caesium*, *Rhododendron barbatum*, *R. campanulatum* and *Acer cappadocium*. In earlier study it is reported that the biomass production of *Rhododendron* forest ranges from 43 Mg ha⁻¹ to 70 Mg ha⁻¹ (**Garkoti and Singh, 1992**).

The altitudinal distribution of high altitude mixed forest ranges from 2400 m to 3600 m as shown in Figure 29. In the past studies, similar elevation range distribution also reported (**Adhikari et al., 1991**)

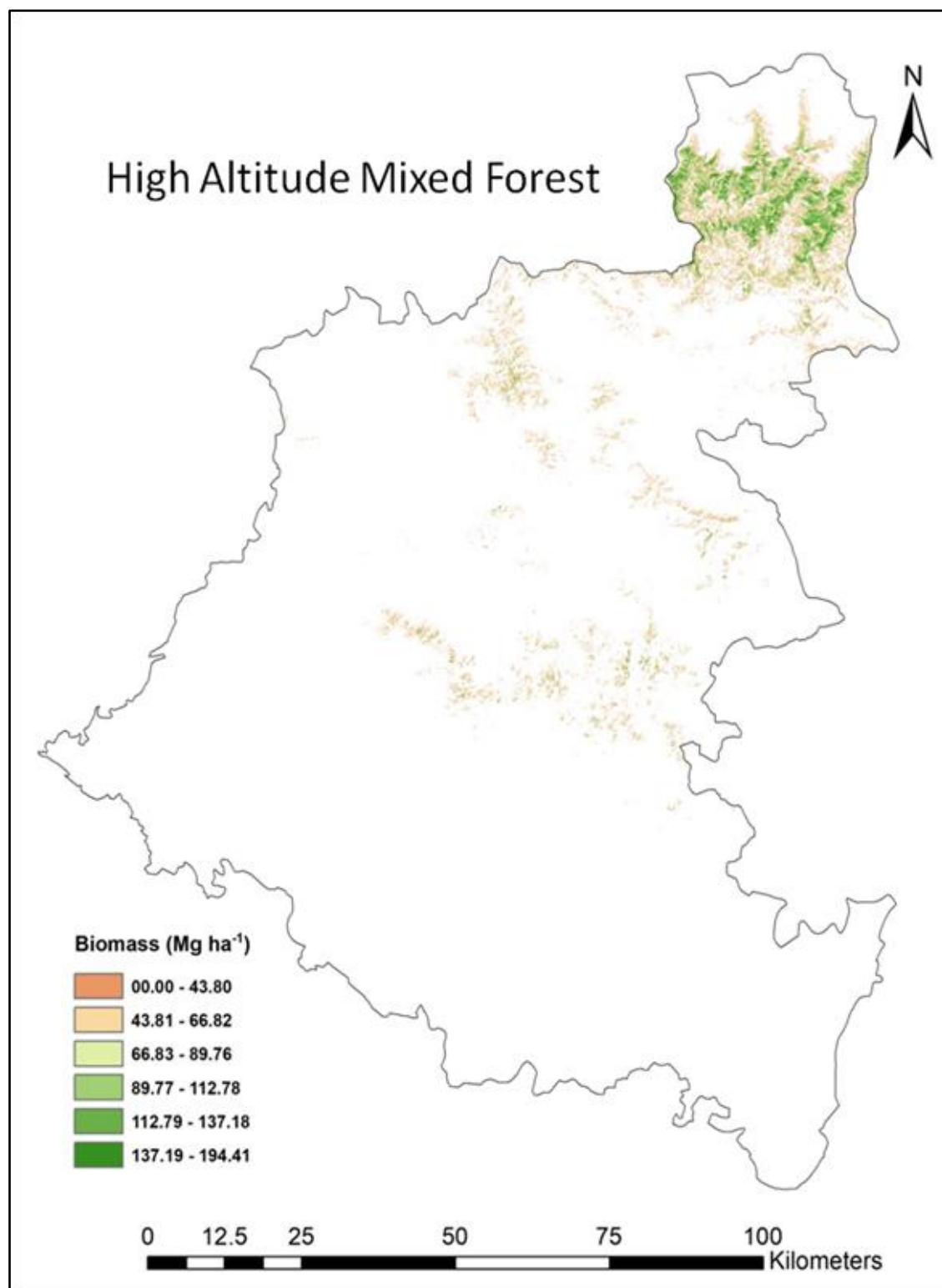


Figure 28: AGB of high altitude mixed forest of study area.

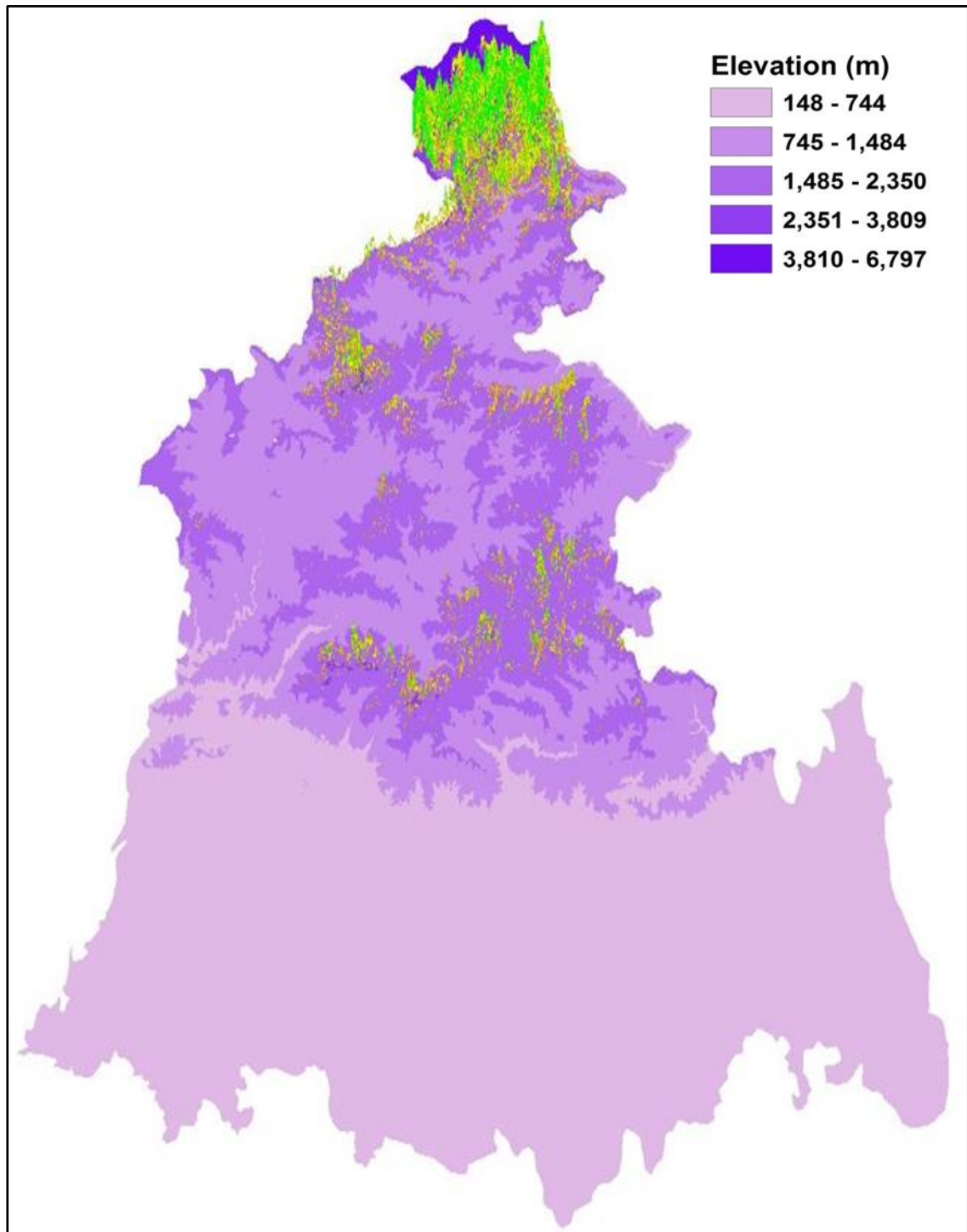


Figure 29: Altitudinal distribution of AGB of high altitude mixed forest of study area.

When we consider the distribution pattern of estimated biomass of high altitude mixed forest of whole area as shown in Figure 30, where whole mixed pine forest area was plotted in horizontal line with biomass and vertical line with area covered. Thus, from histogram it depicts that biomass range from 1 Mg ha⁻¹ to 50 Mg ha⁻¹ covered an area of 196 Sq. km, 51 Mg ha⁻¹ to 100 Mg ha⁻¹ covered an area of 125 Sq. km, 101 Mg ha⁻¹ to 150 Mg ha⁻¹ covered an area of 103 Sq. km and 151 Mg ha⁻¹ to 195 Mg ha⁻¹ covered an area of 17 Sq. km.

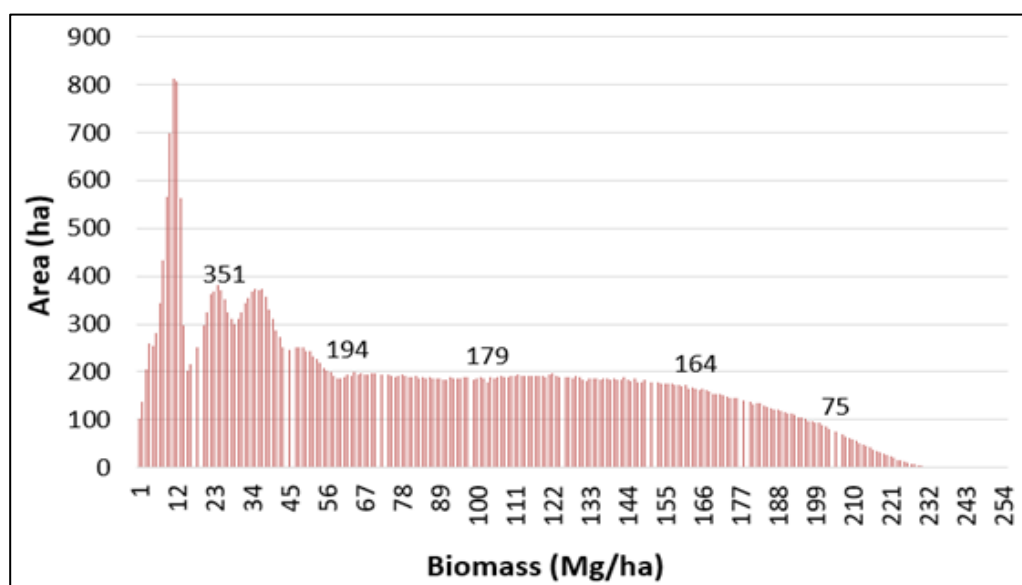


Figure 30: Histogram of biomass distribution area of high altitude mixed forest.

4.6 Prediction of AGB with artificial neural network backpropagation:

In present study, AGB estimated from regression relationship between the field base allometrically calculated biomass and sentinel-A2 NDVI value, was used to develop a prediction model through artificial neural network backpropagation. The prediction model was again tested with already estimated biomass and prediction model which show a very good result with remote sensing based estimated biomass as shown in Figure 31. When it is plotted in a scatter plot graph between remote sensing based estimated biomass and predicted biomass, it gives a R^2 of 0.896 which was a very good and acceptable R^2 value as shown in Figure 32.

Thus, the model developed from ANN backpropagation with acceptable R^2 values, can be used as prediction model with the similar input variables. However, this prediction model gives the best result if more number of data set are used to train the model before prediction.

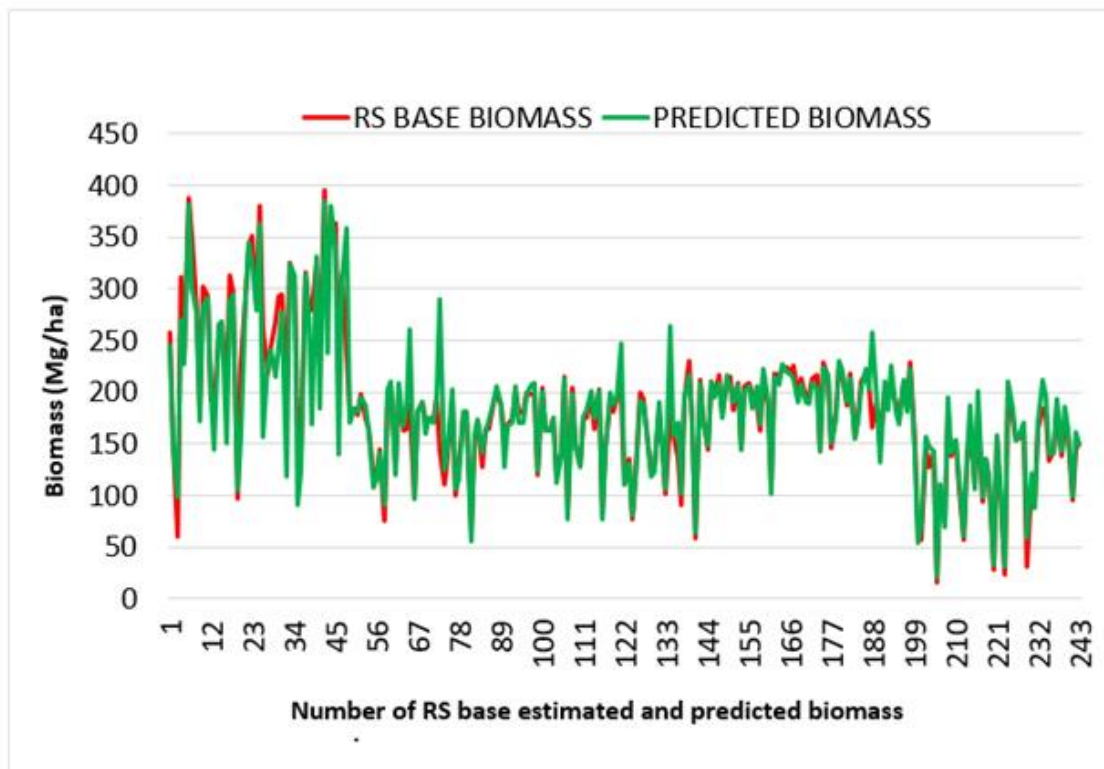


Figure 31: Line graph showing relationship between remote sensing based estimated biomass and predicted biomass.

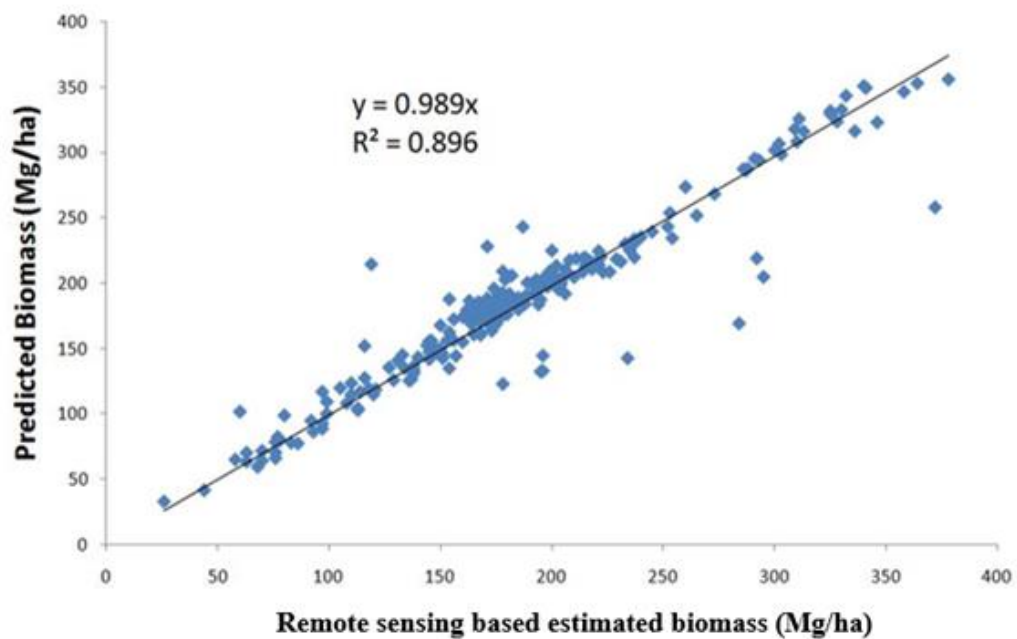


Figure 32: Scatter plot between remote sensing based estimated biomass and predicted biomass.

4.7 Estimation of Net Primary Productivity:

4.7.1 Monthly Net Primary Productivity of study area:

The estimated net primary productivity of study area shows a variation from January to December on monthly basis. The monthly estimated NPP indicate that, in the month of January, the NPP was very low and it shows gradual increase in NPP in subsequent months up to July. Then from the July, further NPP started decreasing till December. This increasing and decreasing trend of NPP from January to December may be due to the variation in temperature, precipitation and solar radiation as all these parameters changes with month. **Li and Wang, (2012)** reported that temperature and precipitation had a remarkable influence on NPP and total solar radiation has a bigger influence on NPP than the monthly precipitation. The July month shows the highest estimated NPP as compared to other months. This may be due the facts that July month received the good amount of precipitation and solar radiation for better vegetation growth along with optimum temperature for photosynthesis. The monthly estimated NPP of study area ranges from 0.28 to 2.80 ton ha⁻¹ month⁻¹ as shown in Figure 33 and 34.

4.7.2 Seasonal Net Primary Productivity of study area:

In the present seasonal NPP study included the four season of a year namely winter season (December, January and February), summer season (March, April and May), monsoon season (June, July, August and September) and autumn season (October and November). The season wise estimated biomass depicts that in the monsoon season (rainy season) NPP was the highest among the seasons followed by summer and autumn season and least in the winter season. This may be due the facts that monsoon season received the good amount of precipitation and solar radiation for better vegetation growth and also get the optimum temperature for photosynthesis. **Singh and Yadava, (1974)** also reported that the maximum net primary production is during the rainy season. The season wise estimated NPP ranges from 0.12 to 2.36 ton ha⁻¹ in winter season (Figure 35), 0.98 to 5.33 ton ha⁻¹ in summer season (Figure 36), 1.78 to 8.12 ton ha⁻¹ in monsoon season (Figure 37) and 0.26 to 2.47 ton ha⁻¹ in autumn season (Figure 38).

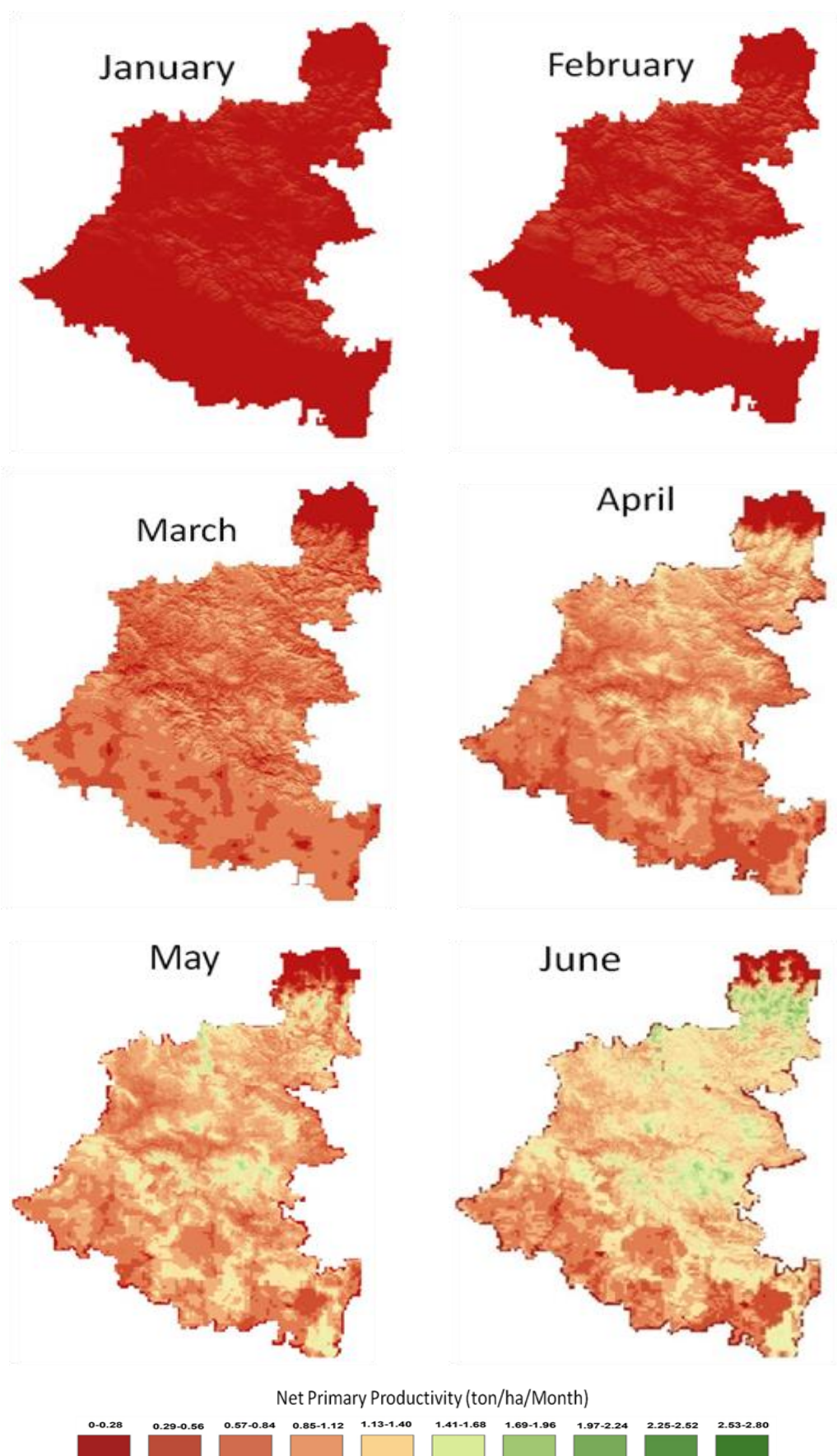


Figure 33: Monthly NPP ($\text{ton ha}^{-1}\text{month}^{-1}$) of Study Area.

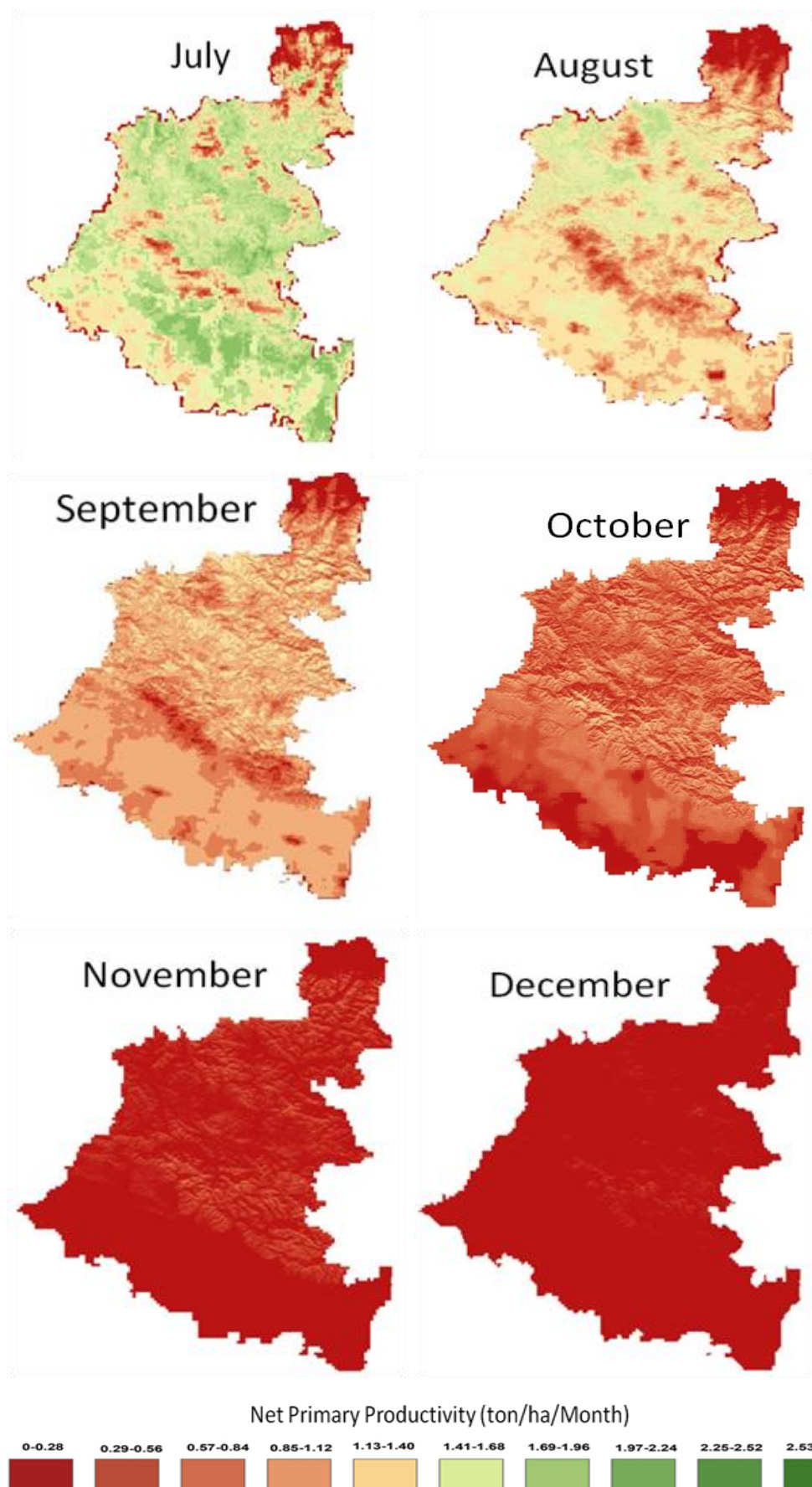


Figure 34: Monthly NPP (ton ha⁻¹month⁻¹) of Study Area.

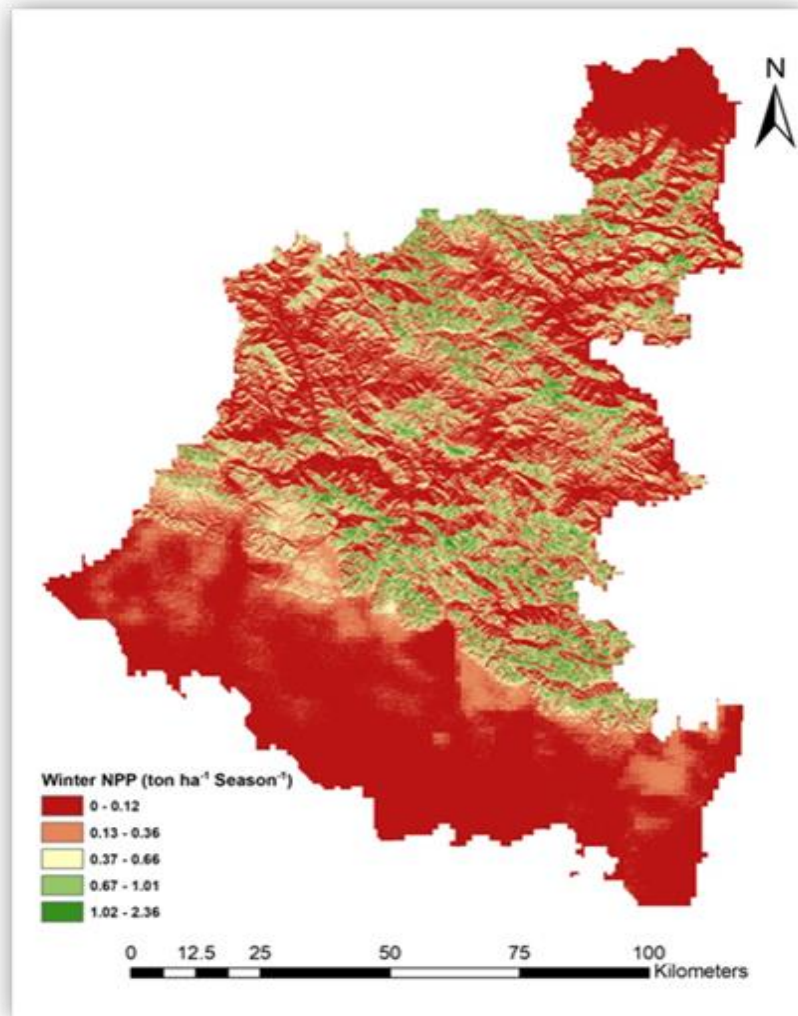


Figure 35: Winter Season Net Primary Productivity of study area

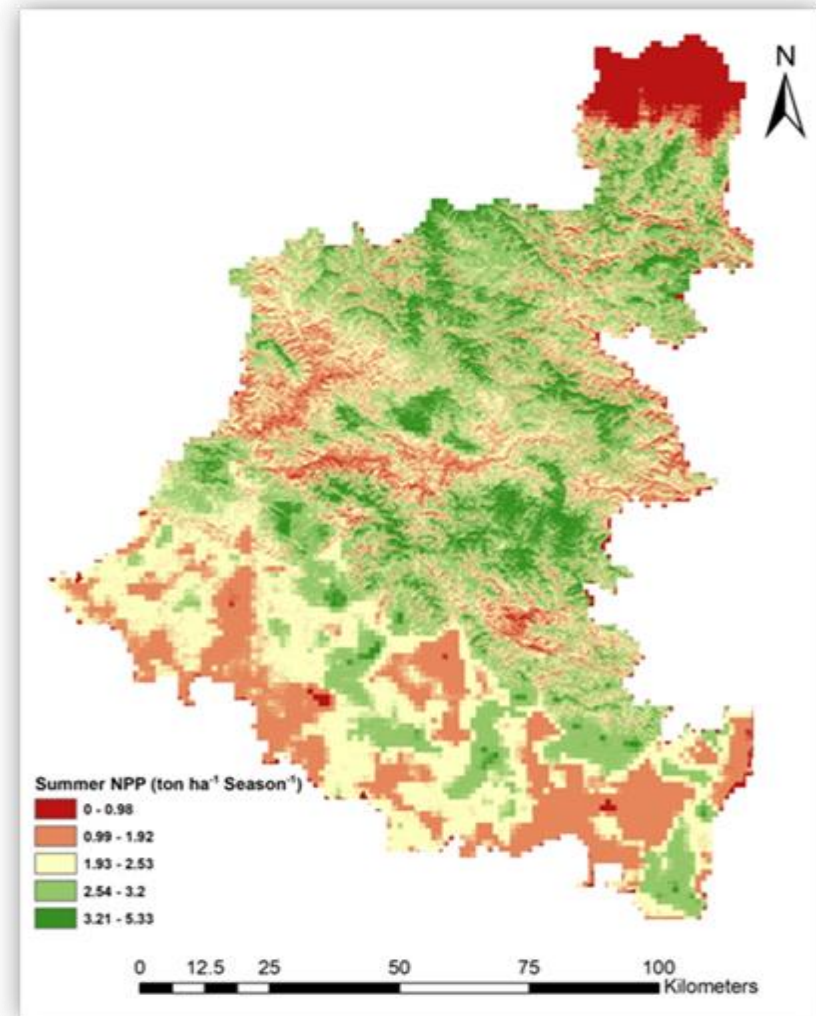


Figure 36: Summer Season Net Primary Productivity of study area

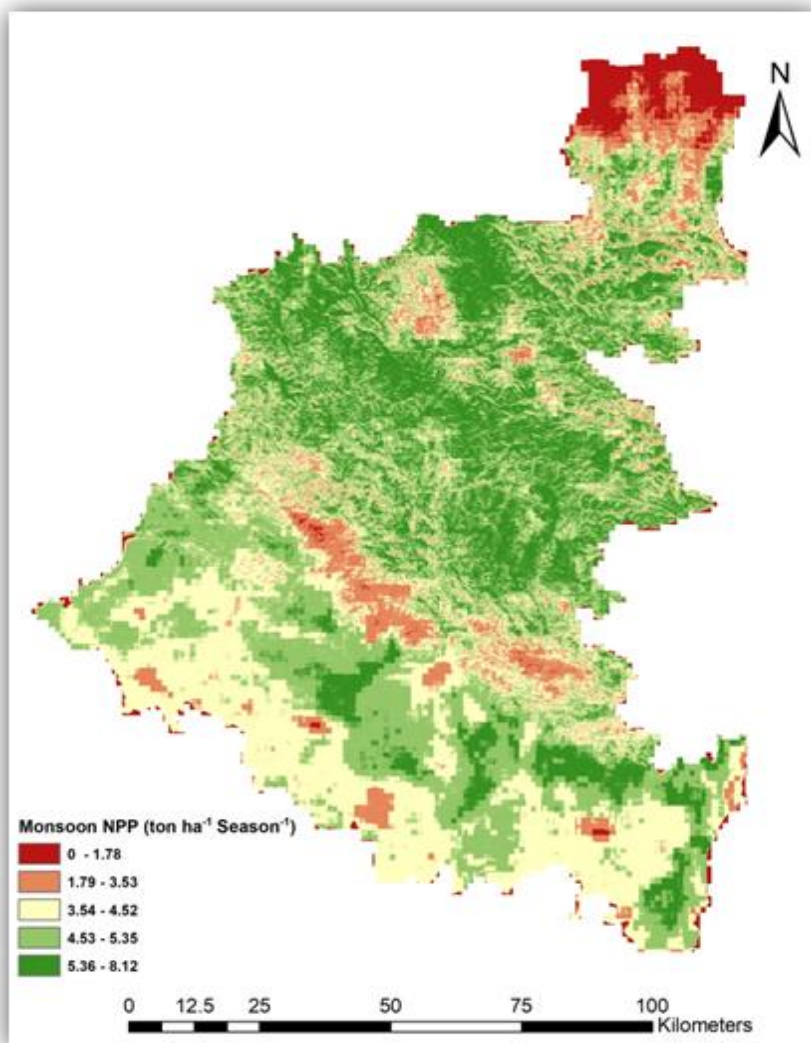


Figure 37: Monsoon Season Net Primary Productivity of study area

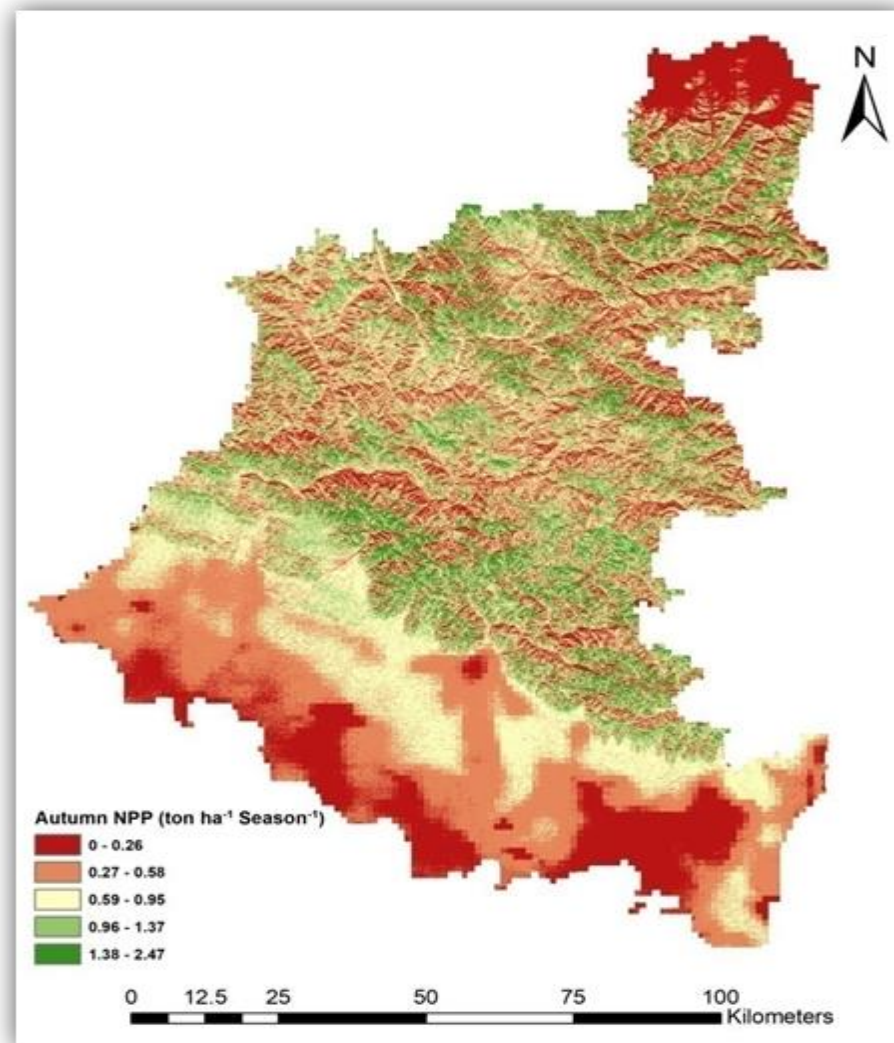


Figure38: Autumn Season Net Primary Productivity of study area

4.7.3 Annual Net Primary Productivity of study area:

The estimated Annual NPP (ANPP) of the study area ranges from 1.5 to 16.5 ton ha⁻¹ year⁻¹ as shown in Figure 39. **Rana et. al., (1988)** reported the NPP of mixed pine forest of central Himalaya shivalik region whose annual NPP was 12.4 ton ha⁻¹ year⁻¹. The higher estimate of NPP mainly located at higher altitude region. This may be the facts that the forests located at higher altitude are temperate evergreen forest. The earlier study carried out at plot scale on tropical deciduous forest for estimation of NPP observed to be in the range from 6 to 16 ton ha⁻¹ year⁻¹ (**Martinez-Yrizar et. al., 1996**). As the species composition changes region to region according to climate and relief, NNP estimate also varies. **Zhu et. al., (2017)** reported that the remotely sensed estimation of net primary productivity in the Greater Khingan Mountain region, ranges from 5.6 to 9.5 ton ha⁻¹ year⁻¹ with mean NPP value of 5.7 ton ha⁻¹ year⁻¹.

4.7.4 Annual Net Primary Productivity of Mixed Deciduous Forest:

The estimated annual NPP of mixed deciduous forest found to be ranges from 7 to 13.93 ton ha⁻¹ year⁻¹. Majority of this forest found to be under lower region of Nainital district followed by Udham Singh Nagar, Almora and Bageshwar district respectively. Most of the area, estimated annual NNP found to be ranges from 7 to 9 ton ha⁻¹ year⁻¹. Only some patches of area show NPP ranges from 9 to 13.93 ton ha⁻¹ year⁻¹ as shown in Figure 40. Some of the similar result also reported by **Lodhiyal and Lodhiyal (2002)**. The estimated NPP does not show any relation with elevation. The variation of annual NPP, may be due to the changes in density, composition and age of tree species.

4.7.5 Annual Net Primary Productivity of Mixed Pine Forest:

The estimated annual NPP of mixed pine forest found to be ranges from 3 to 14.88 ton ha⁻¹ year⁻¹. Majority of this forest fall under Almora district followed by Nainital and Bageshwar district respectively and it is absent in Udham Singh Nagar due to low elevation region. Most of the area, estimated annual NNP of this forest found to be ranges from 6 to 9 ton ha⁻¹ year⁻¹. Only some patches of area show NPP ranges from 9 to 14.88 ton ha⁻¹ year⁻¹ as shown in Figure 41. The dominant tree species that contribute Annual NNP in this class were *Pinus roxburghii*, *Quercus Leucotrichophora*, *Quercus floribunda*, *Betula alnoides*, *Cedrus deodara*, *Acer caesium* and *Aesculus indica*. In this class also, estimated NPP does not show any relation with elevation. The variation of annual NPP, may be due to the changes in density, composition and age of tree species.

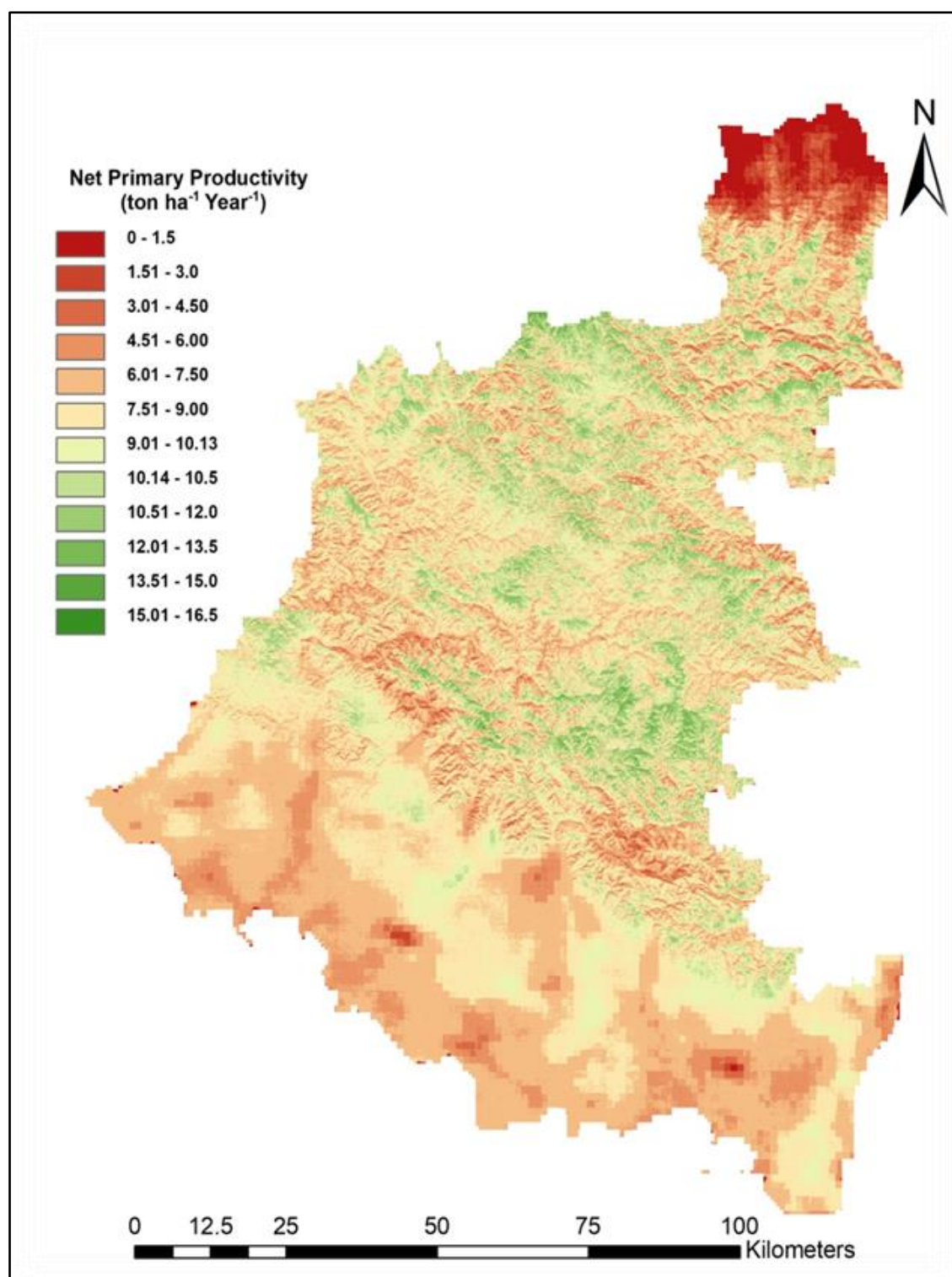


Figure 39: Annual Net Primary Productivity of study area

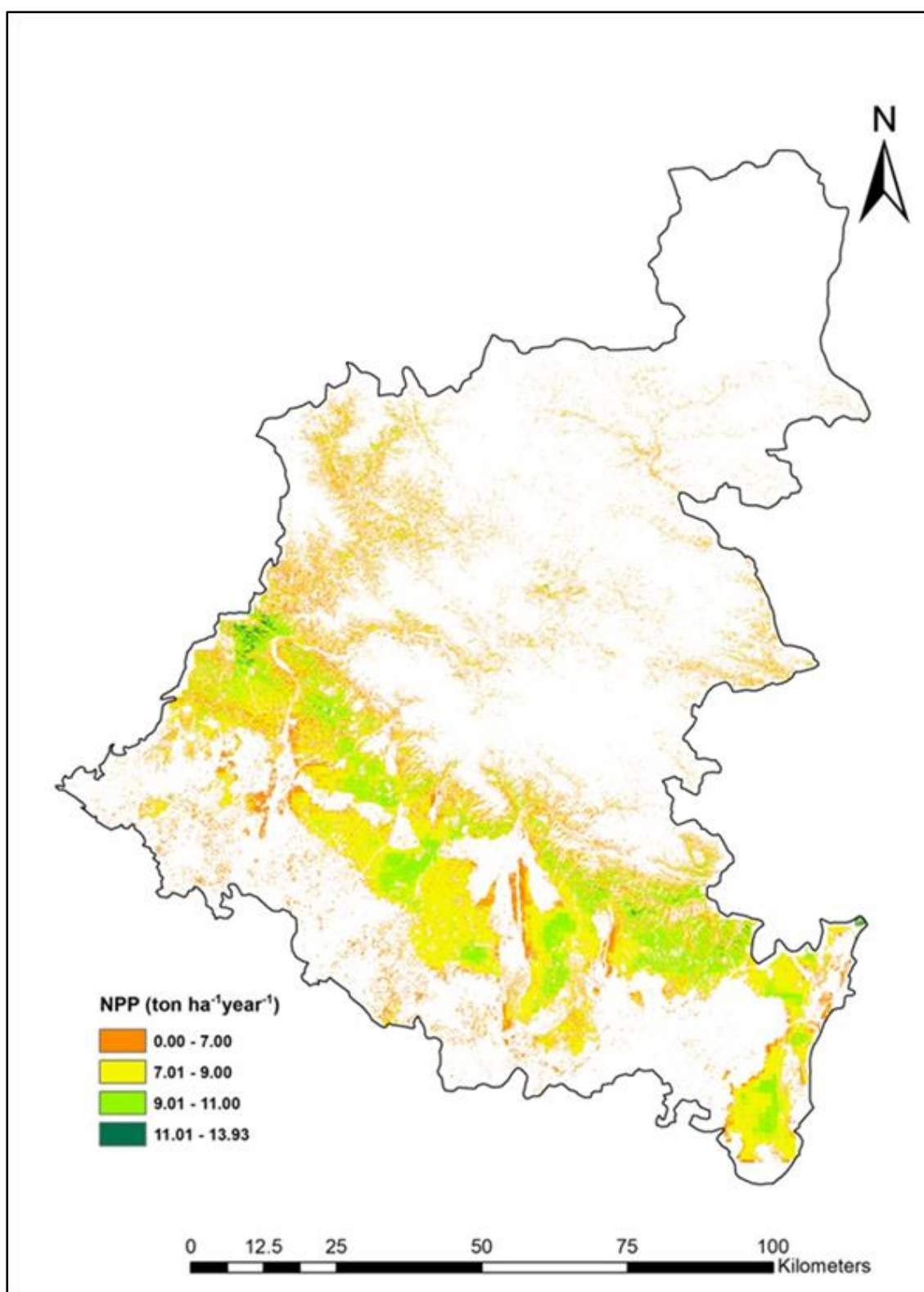


Figure 40: Annual NPP of mixed deciduous forest of study area

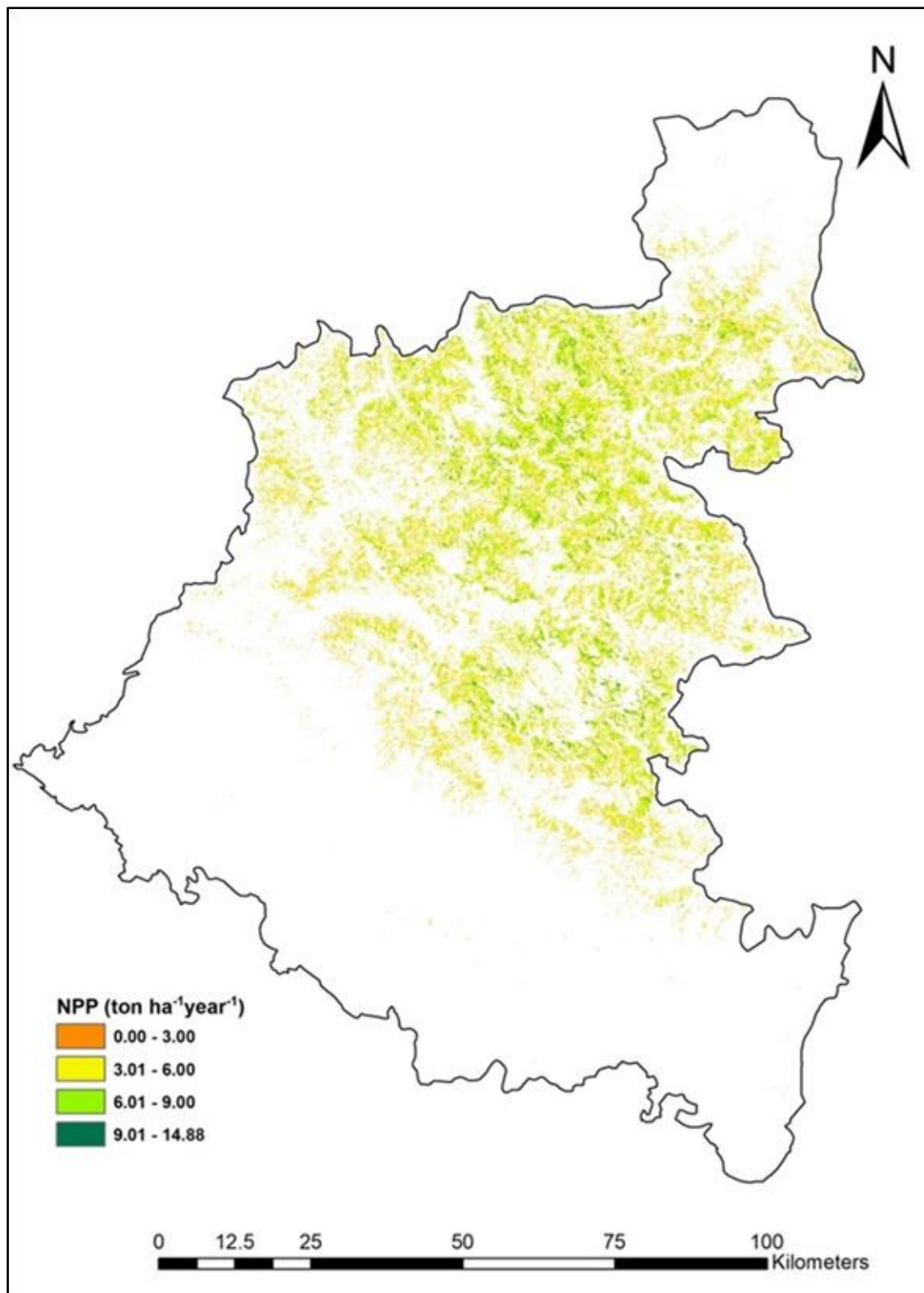


Figure 41: Annual NPP of mixed pine forest of study area

4.7.6 Annual Net Primary Productivity of Pine Forest:

The estimated annual NPP of pine forest found to be ranges from 3 to 15.2 ton ha⁻¹ year⁻¹ as shown in Figure 42. It is occupied three district of study area viz. Nainital, Alomra and Bageshwar district and absent in Udham Singh Nagar due to low elevation region. Most of the area, estimated annual NNP found to be ranges from 6 to 15.2 ton ha⁻¹year⁻¹. The variation of annual NPP, may be due to the changes in tree density and age of tree species. In india, **Rana et. al., (1989)**, reported that the annual NPP of chir-pine forest goes up to 17.3 ton ha⁻¹ year⁻¹. **Whittaker (1966)** also reported the annual NPP of pine forest is 11 ton ha⁻¹ year⁻¹. The dominant tree species of pine forest is *Pinus roxburghii*.

4.7.7 Annual Net Primary Productivity of Mixed Oak Forest:

The estimated annual NPP of mixed oak forest found to be ranges from 4 to 15.48 ton ha⁻¹ year⁻¹ as shown in Figure 43. It is occupied three district of study area viz. Nainital, Almora and Bageshwar district and absent in Udham Singh Nagar due to low elevation region. Most of the area, estimated annual NNP found to be ranges from 4 to 12 ton ha⁻¹year⁻¹. The variation of annual NPP, may be due to the changes in tree density and age of tree species. In india, **Rana et. al., (1989)**, reported that, the annual NPP of oak dominated forest goes up to 15.5 ton ha⁻¹ year⁻¹. The dominant tree species of mixed oak forest were *Quercus spp.*, *Pinus roxburghii*, *Abies pindrow* and *Cedrus deodara*.

4.7.8 Annual Net Primary Productivity of High Altitude Mixed Forest:

The estimated annual NPP of mixed oak forest found to be ranges from 5 to 15.17 ton ha⁻¹ year⁻¹ as shown in Figure 44. It is occupied three district of study area viz. Nainital, Almora and Bageshwar district with major area under Bageshwar district due to higher elevation. It is absent in Udham Singh Nagar due to low elevation region. Most of the area, estimated annual NNP found to be ranges from 8 to 12 ton ha⁻¹year⁻¹. In high altitude mixed forest, the dominant tree species were *Quercus semecarpifolia*, *Abies pindrow*, *Aesculus indica*, *Rhododendron arboreum*, *Betula utilis*, *A. caesium*, *Rhododendron barbatum*, *R. campanulatum* and *Acer cappadocium* which were similar as reported by **Rawal et al., (1994)**. In India, **Garkoti and Singh (1995)**, reported that, the annual NPP goes up to 19.6 ton ha⁻¹ year⁻¹ for Acer forest and 19.6 ton ha⁻¹ year⁻¹ for Rhododendron forest.

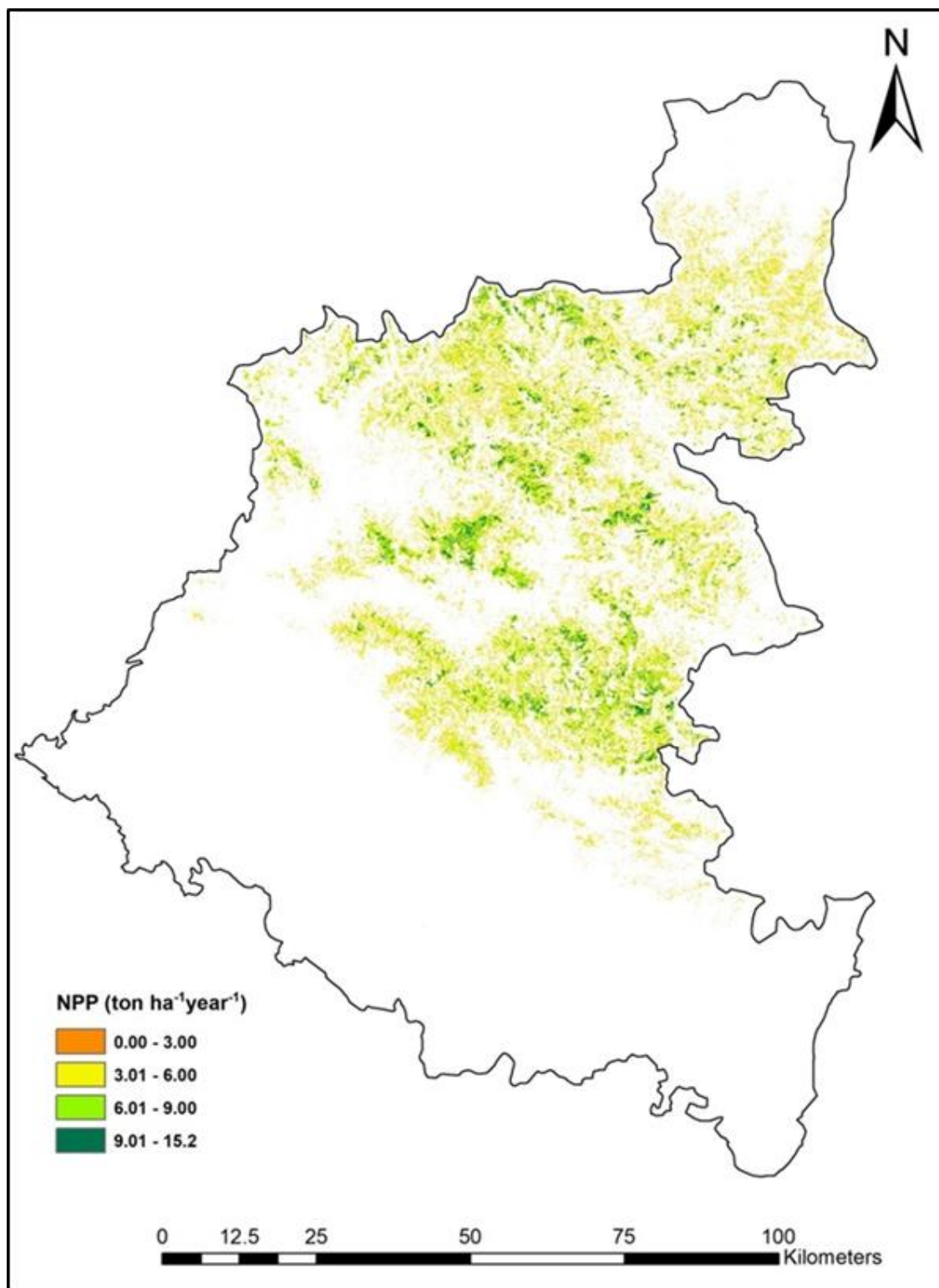


Figure 42: Annual NPP of pine forest of study area

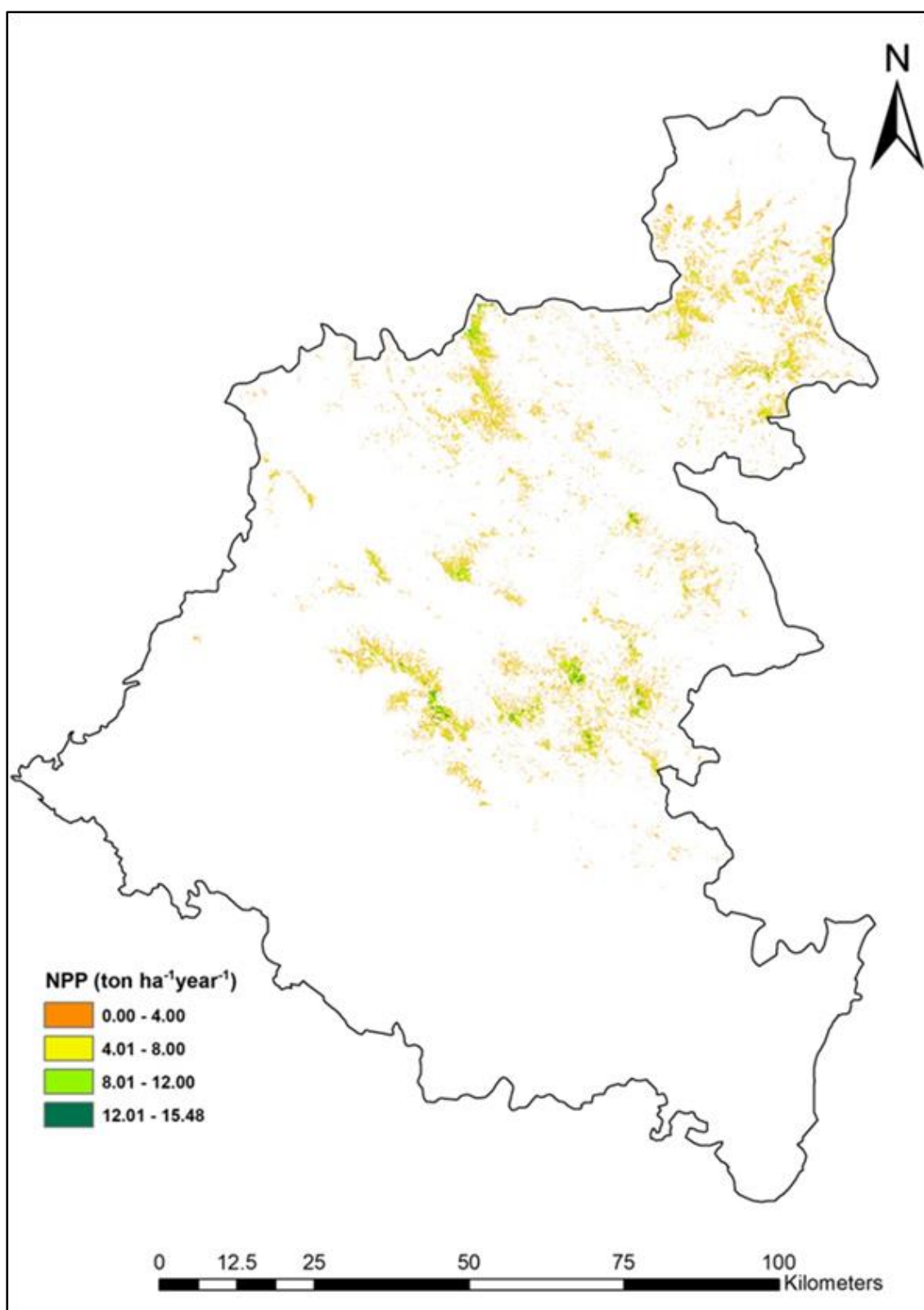


Figure 43: Annual NPP of mixed oak forest of study area

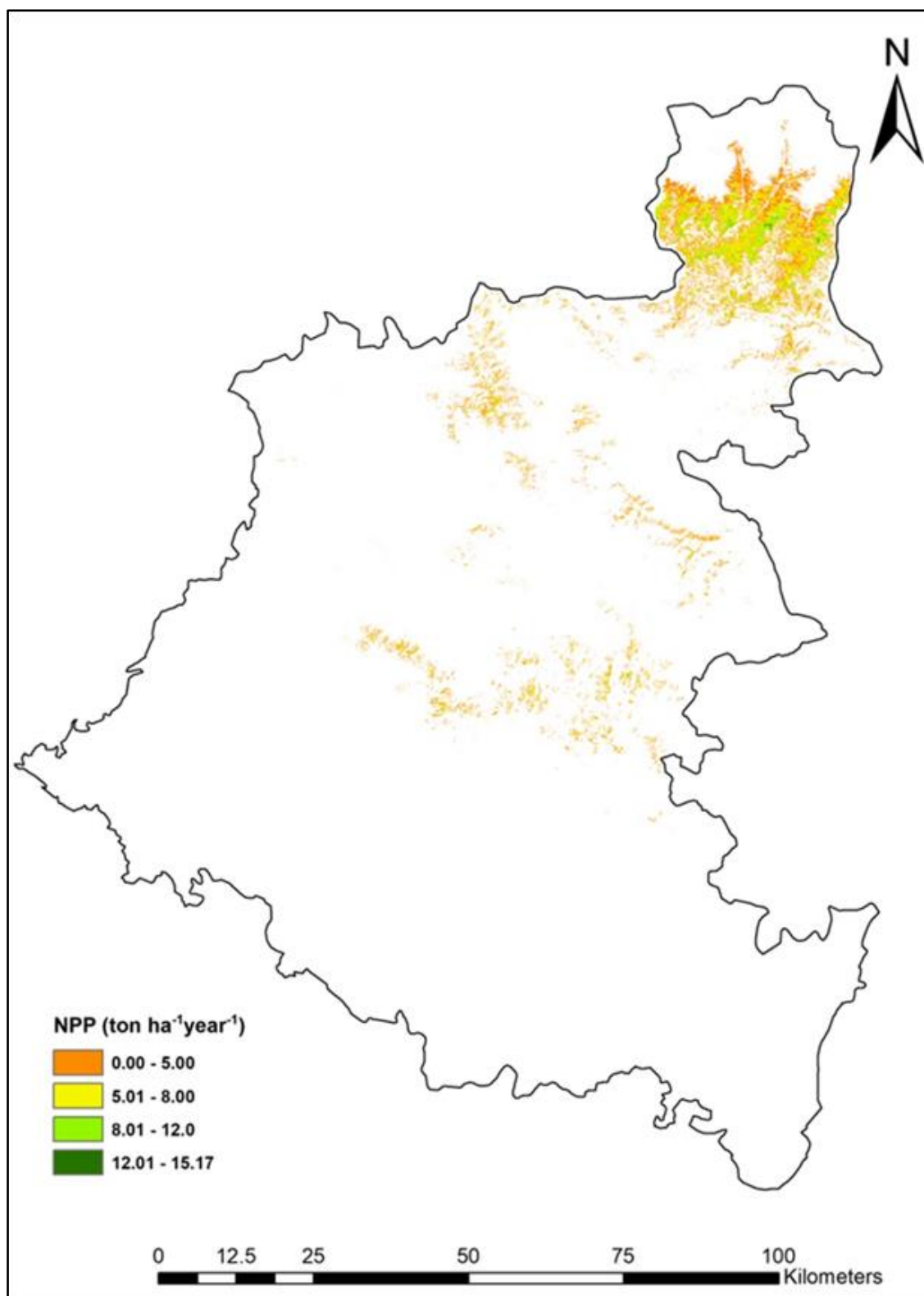


Figure 44: Annual NPP of high altitude mixed forest of study area

The current study mainly focuses on estimation of above ground biomass (AGB) and Net Primary Productivity (NPP) of forest ecosystem. The forests play an important role in the terrestrial carbon cycle and accumulate terrestrial carbon in the form of biomass via photosynthesis, which sequesters large amounts of carbon per year. Monitoring stored above ground biomass and NPP in the forests ecosystem is essential in order to understand the processes related to the carbon cycle and reducing carbon emissions originating from deforestation and forest degradation. Moreover, estimation of forest AGB and NPP of a region, can give quantitative details of available forest carbon stock and carbon accumulation rate of an area which is valuable information for better forest management strategies. Mapping of spatial distribution of AGB and NPP is also helpful to determine the loss of carbon stocks due to disturbances (e.g. deforestation, fires) or the gain due to forest growth.

Moreover, classification of dominant forest types in the study area helps in analyzing and mapping of forest cover distribution along altitudinal gradient. Traditionally, regional and national level carbon monitoring has been accomplished with networks of field inventory plots which provide direct carbon measurements in limited areas. The remote sensing based estimates can overcome this problem. Moreover, biomass production and NPP can be monitored periodically with cost effectiveness and with less man power.

*Summary
and
Conclusions*

The present study entitled “Estimation of Above Ground Biomass and Net Primary Productivity of Kumaon Himalayan Forest using Geospatial Approach” was conducted in four districts of Kumaon region namely Udham Singh Nagar, Nainital, Almora and Bageshwar districts, Uttarakhand. The study area is good representation of increasing altitudinal gradient from Udham Singh Nagar to Bageshwar district. The study area classified into five major forest classes along altitudinal gradient based on composition of dominant tree species. The major classified forest classes are mixed deciduous forest, mixed pine forest, pine forest, mixed oak forest and high altitude mixed forest. The distribution of major forest classes also analyzed along increasing elevation. In the current study, the estimation of Above Ground Biomass and Net Primary Productivity of major forest classes carried out. In the study area, the Above Ground Biomass was calculated by allometric and remote sensing based method and developed a multi parameter AGB prediction model using Artificial Neural Network Backpropagation algorithm. For estimation of NPP, used a modified remote sensing micrometeorological model refers to as MODNPP which is derived from the Monteith equation. The salient finding of the investigation are summarized as below:

1. The study area classified into two major land use land cover classes: forest and non-forest.
2. Forest area classified into five major forest classes namely mixed deciduous forest, mixed pine forest, pine forest, mixed oak forest and high altitude mixed forest.
3. About 60% area comes under forest area and 40% comes under non forest area.
4. Out of total forest cover, major forest class was the mixed deciduous forest which occupied about 54% of total forest area followed by mixed pine forest, pine forest, high altitude mixed forest and mixed oak forest which occupied about 19%, 17%, 6% and 4% of total forest area respectively.
5. The elevation of mixed deciduous forest ranges from 148 m to 1300 m MSL and occupies about 54% of total classified forest area. The identified dominant

tree species in this class were *Mallotus philippensis*, *Toona aliata*, *Holoptelea integrifolia*, *Macaranga pustulata* and *Anogeissus latifolia* and *Shorea robusta*.

6. The elevation of mixed pine forest ranges from 1300 m to 2400 m MSL and occupies about 19% of total classified forest area. The dominant tree species found in this class were *Pinus roxburghii*, *Quercus Leucotric hophora*, *Quercus floribunda*, *Betula alnoides*, *Cedrus deodara*, *Acer caesium* and *Aesculus indica*.
7. The elevation of pine forest ranges from 1300 m to 2300 m MSL and occupies about 17% of total classified forest area. The dominant tree species is *Pinus roxburghii*.
8. The elevation of mixed oak forest ranges from 1600 m to 3000 m MSL and occupies about 4% of total classified forest area. The dominant tree species of mixed oak forest were *Quercus spp.*, *Pinus roxburghii*, *Abies pindrow* and *Cedrus deodara*.
9. The elevation of high altitude mixed forest ranges from 2400 m to 3600 m MSL and occupies about 6% of total classified forest area. The dominant tree species were *Quercus semecarpifolia*, *Abies pindrow*, *Abies spectabilis*, *Betula utilis*, *Rhododendron arboretum*, *Rhododendron barbatum* and *Acer cappadocium*.

Estimation of above ground forest biomass of study area:

1. To estimate above ground forest biomass, allometric method and remote sensing based method has been used for biomass calculation and developed a biomass prediction model by using artificial neural network back propagation algorithm.
2. In the mixed deciduous forest, the estimated biomass ranges from 184 Mg ha⁻¹ to 436 Mg ha⁻¹. This is the forest which gives highest estimate of biomass as compared to other forest class. Majority of this forest found to be under lower region of Nainital district followed by Udham Singh Nagar, Almora and Bageshwar district respectively.
3. In the mixed Pine forest, the estimated biomass ranges from 62 Mg ha⁻¹ to 252 Mg ha⁻¹. This is the forest which sparsely distributed among all other forest types and occupied most the study area.

4. In Pine forest the estimated biomass ranges from 80 Mg ha⁻¹ to 302 Mg ha⁻¹. The pine is forest which clustery distributed as compared to other forest classes and also mixed with other forest classes.
5. In mixed oak forest, the estimated biomass ranges from 71 Mg ha⁻¹ to 265 Mg ha⁻¹. The oak forest also clustery distributed along altitudinal gradient and also mixed with other forest tree species.
6. The estimated biomass of high altitude mixed forest found to be rages from 43 Mg ha⁻¹ to 195 Mg ha⁻¹. This is the forest which gives lowest production of biomass.

Estimation of net primary productivity of study area:

1. For estimation of Net Primary productivity of study area, used a modified remote sensing micrometeorological model refers to as the MODNPP.
2. The NPP of study area was calculated monthly, seasonally and annually. The monthly estimated NPP of study area ranges from 0.28 to 2.80 ton ha⁻¹ month⁻¹. The monthly estimated NPP indicate that, in the month of January, the NPP was very low and it shows gradual increase in NPP in subsequent months up to July. Then from the July, further NPP started decreasing till December.
3. In the present seasonal NPP study included the four season of a year namely winter season (December, January and February), summer season (March, April and May), monsoon season (June, July, August and September) and autumn season (October and November).
4. The season wise estimated NPP ranges from 0.12 to 2.36 ton ha⁻¹ in winter season, 0.98 to 5.33 ton ha⁻¹ in summer season, 1.78 to 8.12 ton ha⁻¹ in monsoon season and 0.26 to 2.47 ton ha⁻¹ in autumn season. The estimated Annual NPP (ANPP) of the study area ranges from 1.5 to 16.5 ton ha⁻¹ year⁻¹.

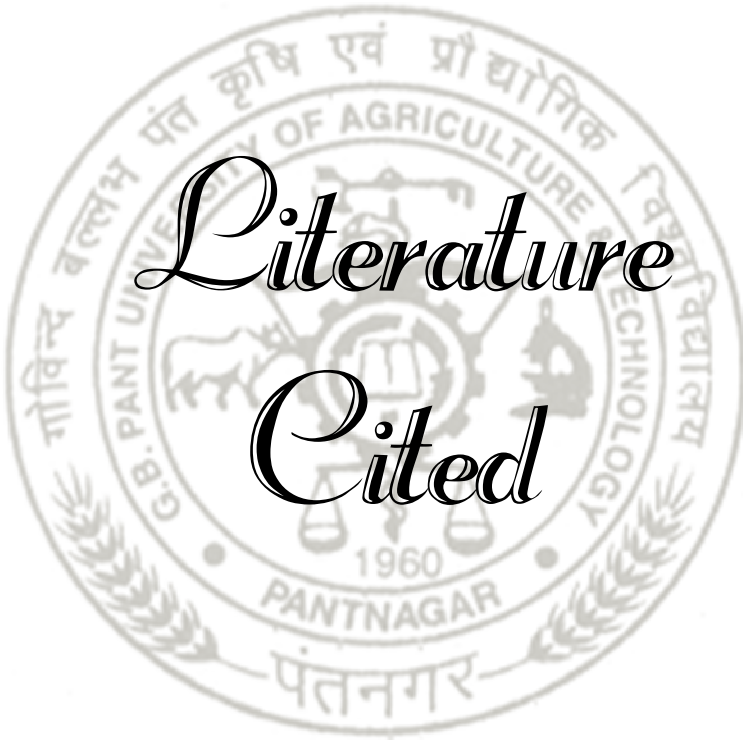
Estimation of net primary productivity of major forest class of study area:

1. The estimated annual NPP of mixed deciduous forest found to be rages from 7 to 13.93 ton ha⁻¹ year⁻¹. Most of the area, estimated annual NNP of this forest found to be ranges from 7 to 9 ton ha⁻¹ year⁻¹.

2. The estimated annual NPP of mixed pine forest found to be ranges from 3 to 14.88 ton ha⁻¹ year⁻¹. Most of the area, estimated annual NPP of this forest found to be ranges from 6 to 9 ton ha⁻¹ year⁻¹. Only some patches of area show NPP ranges from 9 to 14.88 ton ha⁻¹ year⁻¹.
3. The estimated annual NPP of pine forest found to be ranges from 3 to 15.2 ton ha⁻¹ year⁻¹ and most of the area estimated annual NPP found to be ranges from 6 to 15.2 ton ha⁻¹ year⁻¹.
4. The estimated annual NPP of mixed oak forest found to be ranges from 4 to 15.48 ton ha⁻¹ year⁻¹ and majority of area of this forest, annual NPP ranges from 4 to 12 ton ha⁻¹ year⁻¹.
5. The estimated annual NPP of mixed oak forest found to be ranges from 5 to 15.17 ton ha⁻¹ year⁻¹. Most of the area, estimated annual NPP found to be ranges from 8 to 12 ton ha⁻¹ year⁻¹.

From the present investigation, following conclusions may be drawn:

1. Sentinel-2A satellite data found to very good product for LULC study because of its high spatial resolution. Moreover, it is available free of cost.
2. The combination of both allometric and RS base biomass estimation approach found to good alternative biomass estimation method.
3. ANN back propagation prediction model is a good option for forest AGB using multi parameter remote sensing data. With quality training data set, can also further improve the prediction model.
4. Mapping the spatial distribution of AGB and NPP gives very useful information about carbon stocks of a region and natural resource management.
5. Moreover, remote sensing base estimate of biomass production and NPP can be calculated periodically with this as a very effective method.



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ABSTRACT

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The present study was conducted in four districts of Kumaon region namely Udham Singh Nagar, Nainital, Almora and Bageshwar districts, Uttarakhand considering different altitudinal gradient. The study area is good representation of increasing altitudinal gradient from Udham Singh Nagar (148 m MSL) to Bageshwar district (>4000 m MSL). The study area is classified into five major forest classes along altitudinal gradient based on composition of dominant tree species. The major classified forest classes are mixed deciduous forest, mixed pine forest, pine forest, mixed oak forest, high altitude mixed forest and occupied about 54%, 19%, 17%, 4% and 6% of studied total forest area respectively.

The distribution of major forest classes also analysed along increasing elevation. In the current study, the estimation of Above Ground Biomass (AGB) of major forest classes was calculated by allometric and remote sensing (RS) based method and developed a multi parameter AGB prediction model using Artificial Neural Network Backpropagation algorithm and the Net Primary Productivity (NPP) was calculated using a modified remote sensing micrometeorological model refers to as MODNPP for monthly, seasonal and annual basis. For seasonal NPP study, include four season namely winter, summer, monsoon and autumn season. The remote sensing based estimated biomass of mixed deciduous forest, mixed pine forest, pine forest, mixed oak forest and high altitude mixed forest was measured within ranges from 184 Mg ha⁻¹ to 436 Mg ha⁻¹, 62 Mg ha⁻¹ to 252 Mg ha⁻¹, 80 Mg ha⁻¹ to 302 Mg ha⁻¹, 71 Mg ha⁻¹ to 265 Mg ha⁻¹, and 43 Mg ha⁻¹ to 195 Mg ha⁻¹ respectively. The monthly NPP was measured in the ranges from 0.2 to 2.80 ton ha⁻¹ month⁻¹. The seasonal NPP was measured for different season between 0.12 to 2.36 ton ha⁻¹ season⁻¹ (winter), 0.98 to 5.33 ton ha⁻¹ season⁻¹ (summer), 1.78 to 8.12 ton ha⁻¹ season⁻¹ (monsoon) and 0.26 to 2.47 ton ha⁻¹ season⁻¹ (autumn). However, the annual NPP was recorded between 1.5 to 16.5 ton ha⁻¹ year⁻¹ for different location. The calculated annual NPP for different major forest types namely mixed deciduous forest, mixed pine forest, pine forest, mixed oak forest and high altitude mixed forest ranges from 7 to 13.93 ton ha⁻¹ year⁻¹, 3 to 14 ton ha⁻¹ year⁻¹, 3 to 15 ton ha⁻¹ year⁻¹, 4 to 15.48 ton ha⁻¹ year⁻¹ and 5 to 15.17 ton ha⁻¹ year⁻¹ respectively.

Therefore, this study envisaged that models used for calculation of AGB and NPP are best suited for its calculation and cost effective.


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मुख्य विषय	: पर्यावरण विज्ञान	विभाग	: पर्यावरण विज्ञान
गौढ़ विषय	: कृषि मौसम विज्ञान		
शोध विषय	: भू-स्थानिक द्रष्टिकोण के द्वारा कुमायूं हिमालयी वन के भूमि ऊपरी जैव-द्रव्यमान तथा कुल प्राथमिक उत्पादकता का आंकलन		
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प्रस्तुत शोध विभिन्न ऊंचाई प्रवणता को ध्यान में रखकर उत्तराखंड के कुमायूं क्षेत्र के चार जिलों; उधम सिंह नगर, नैनीताल, अल्मोड़ा, तथा ऋगेश्वर में किया गया। शोध क्षेत्र ऊंचाई प्रवणता; उधम सिंह नगर (148 मी.औ.स.त.) से ऋगेश्वर (>4000 मी.औ.स.त.) के बढ़ते हुए क्रम का अच्छा प्रतिनिधित्व है। शोध क्षेत्र ऊंचाई घनत्वों के साथ मुख्य वृक्ष प्रजातियों के संयोजन के आधार पर 5 मुख्य वन ऋक्सZ में वर्गीकृत किया गया है। मुख्य वर्गीकृत वन ऋक्सZ मिश्रित पतझड़ी वन, मिश्रित चीड़ वन, चीड़ वन, मिश्रित बांज वन एवं अधिक ऊंचाई वाले मिश्रित वन हैं जिनका कुल वन क्षेत्र का प्रतिशत लगभग क्रमशः 54%, 19%, 17%, 4% तथा 6% है।

मुख्य वन ऋक्सZ के वितरण का आंकलन बढ़ती हुई ऊंचाई के आधार पर भी किया गया। प्रस्तुत शोध में मुख्य वन ऋक्सZ के भूमि ऊपरी जैव-द्रव्यमान का आंकलन एलोमेट्रिक तथा रिमोट सेन्सिंग आधारित पद्धति द्वारा किया गया तथा आर्टिफिसियल न्यूरल नेटवर्क बैक प्रोपगेशन कलन विधि के उपयोग से एक बहु-प्राचल भूमि ऊपरी जैव-द्रव्यमान पूर्वकथन नमूने का विकास किया गया तथा मासिक, मौसमी तथा वार्षिक कुल प्राथमिक उत्पादकता की गढ़ना शंशोधित रिमोट सेन्सिंग शूक्ष्म-जलवायुवीय प्रारूप (MODNPP) के प्रयोग से की गयी। मौसमी कुल प्राथमिक उत्पादकता के लिए चार मौसम सर्दी, गर्मी, बरसात और पतझड़ सम्मिलित किए गए। मिश्रित पर्णपाती वन, मिश्रित चीड़ वन, चीड़ वन, मिश्रित बांज वन एवं अधिक ऊंचाई वाले मिश्रित वन का रिमोट सेन्सिंग आधारित जैव-द्रव्यमान क्रमशः 184 से 436 esxk.ग्रा. प्रति हेक्टेयर, 62 से 252 esxk.ग्रा. प्रति हेक्टेयर, 80 से 302 esxk.ग्रा. प्रति हेक्टेयर, 71 से 265 esxk.ग्रा. प्रति हेक्टेयर, और 43 से 195 esxk.ग्रा. प्रति हेक्टेयर तक मापा गया। मासिक शुद्ध प्राथमिक उत्पादकता 0.2 से 2.80 टनप्रति हेक्टेयर प्रति माह तक मापी गयी। मौसमी शुद्ध प्राथमिक उत्पादकता विभिन्न मौसमों के लिए 0.12 से 2.36 टनप्रति हेक्टेयर प्रति मौसम (सर्दी), 0.98 से 5.33 टनप्रति हेक्टेयर प्रति मौसम (गर्मी), 1.78 से 8.12 टनप्रति हेक्टेयर प्रति मौसम (बरसात) तथा 0.26 से 2.47 टनप्रति हेक्टेयर प्रति मौसम (पतझड़)। वार्षिक शुद्ध प्राथमिक उत्पादकता विभिन्न स्थानों के लिए 1.5 से 16.5 टन प्रति हेक्टेयर प्रति वर्ष पायी गयी। आंकलित वार्षिक शुद्ध प्राथमिक उत्पादकता विभिन्न मुख्य वन प्रकारों; मिश्रित पतझड़ी वन, मिश्रित चीड़ वन, चीड़ वन, मिश्रित बांज वन एवं अधिक ऊंचाई वाले मिश्रित वन के लिए क्रमशः 7 से 13.93 टन प्रति हेक्टेयर प्रति वर्ष, 3 से 14 टन प्रति हेक्टेयर प्रति वर्ष, 3 से 15 टन प्रति हेक्टेयर प्रति वर्ष, 4 से 15.48 टन प्रति हेक्टेयर प्रति वर्ष तथा 5 से 15.17 टन प्रति हेक्टेयर प्रति वर्ष पायी गयी।

अतः प्रस्तुत शोध से परिकल्पना की जाती है कि भूमि ढक ऊपरी जैव-द्रव्यमान तथा कुल प्राथमिक उत्पादकता ढह गढ़ना के लिए उपयुक्त यह प्रारूप बहुत ही उपयोगी तथा कम लागत वाला है।


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