Assessment of Above-Ground Biomass and Carbon Sequestration Potential in the Moist Temperate Forests of Abbottabad District. A Geospatial Modeling Approach Using Satellite Imagery and Forest Inventory Data

By

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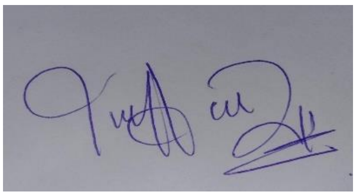
Signed: 

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DEDICATION

Dedicated to my parents for their unwavering love and prayers, and to my siblings who have been a steadfast source of support and encouragement throughout this research

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First and foremost, I'd like to bow my head in gratitude to Allah Almighty, for enabling me to have completed this research with His blessings.

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LIST OF ABBREVIATIONS

ROI	Region of Interest
AGB	Above Ground Biomass
AGC	Above Ground Carbon
NDVI	Normalized Difference Vegetation Index
EVI	Enhanced Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
MSAVI	Modified Soil-Adjusted Vegetation Index
NDWI	Normalized Difference Water Index
NDMI	Normalized Difference Moisture Index
GNDVI	Green Normalized Difference Vegetation Index
LT 5 TM	Landsat 5 Thematic Mapper
LT 8 OLI	Landsat 8 Operational Land Imager
LULC	Land Use Land Cover
EF	Emissions Factor
CE	Carbon Emissions
AD	Activity Data

ABSTRACT

Forest plays a vital role in regulating carbon and oxygen in ecosystem. Study aims to map the above-ground biomass (AGB), carbon pool, and carbon sequestration potential of the Abbottabad Forest area, while also analyzing the impact of climate indicators on carbon stock through sensitivity analysis. Using remote sensing techniques and geospatial analysis, we quantified the biomass and carbon content in different forest strata. The results indicate significant variations in AGB, ranging from 93.35 to 265.02 t/ha, with a mean of 178.6 t/ha, and corresponding above-ground carbon (AGC) values ranging from 43.87 to 124.56 t/ha, averaging 83.94 t/ha. Total carbon sequestration potential was also evaluated, showing a mean of 105.76 t/ha and a maximum of 156.94 t/ha, while the total CO_2 equivalent sequestration ranged from 202.32 to 574.41 t/ha. Additionally, the sensitivity analysis identified regions within the forest that are more susceptible to climatic changes, with some areas demonstrating high sensitivity to fluctuations in temperature and precipitation. Land use and land cover (LULC) changes were assessed, revealing significant shifts over study period, including a decrease in agricultural (-13.3%) and bare land (-0.5%) areas, and an increase in forest cover (9%). The urban and water bodies also showed slight expansions. The findings underscore the importance of targeted climate adaptation strategies to enhance carbon sequestration and improve forest resilience. Study concludes that by integrating biomass mapping with sensitivity analysis of climatic parameters, this research presents a comprehensive approach to understanding the interplay between forest dynamics and climate change, which is essential for informed decision-making and policy formulation. Study recommends to expand the application of geospatial modeling across other forest types in Pakistan to develop a comprehensive carbon inventory. Additionally, integrating these findings into local and national climate policies can enhance carbon sequestration and forest conservation efforts.

Chapter 1

INTRODUCTION

1.1. Background Information

Enormous ecosystems that blanket substantial portions of our world. Forests are a priceless natural resource providing many means of sustenance for life. Forests are essential to preserving the harmony of our planet's ecosystem because of their thick undergrowth, tall trees, and variety of flora and fauna. As the planet's lungs, they take in carbon dioxide and the world's forest cover, endangering human societies' well-being, biodiversity, and climate stability. For the well being of current and future generations, we must acknowledge the vital value of forests and move quickly to save, protect, and restore these priceless ecosystems, which release oxygen, serve as habitat for innumerable species, and control regional climates.

Forests are critical to the earth's ecological balance, serving as home to a large proportion of the world's biodiversity. They cover about 31% of the land area globally, with the maximum forested areas found in Russia, Canada, China, United States and Brazil. These ecosystems play a vital role in carbon sequestration, acting as significant carbon sinks that absorb and store CO_2 thus mitigating climate change.

Global assessments have shown that future climate change will be significantly impacted by forest ecosystems. Climate change refers to changes in global climate due to anthropogenic activities. Since industrial revolution, combustion of fossil fuels for energy and transportation has dramatically increased CO_2 emissions. Deforestation further contributes to rising CO_2 levels as trees that function as carbon sinks are removed. Environmental changes refer to any alterations in the biophysical environment, with ecosystems continuously undergoing both positive and negative transformations (Jackson et al., 2001). Urbanization, industrial growth, and deforestation are key drivers that impact the physical, chemical and biological aspects of the environment leading to the emission of gases in atmosphere and elevating health risks for humans. Climate variability can stem from natural processes in climate systems or from shifts in external forces, whether natural or human-induced. In recent decades, the planet has faced an unprecedented warming trend, with temperatures increasing at an average rate of 0.128 ± 0.026 °C annually over the past 59 years (Solomon et al., 2007).

Pakistan is situated between 23° 45’ and 36° 75’ north latitude and between 61° and 75° 50’ east longitude. As a subtropical country, Pakistan exhibits climatic variability that significantly influences its ecological diversity, supporting a wide range of forest types. To west of Pakistan is Iran on the east is India to north-west side is Afghanistan, on the north is China and on south is Arabian Sea. It vary due to the variation in altitude from south to north and geographically, extends from snowcapped mountains in north to deserts and the Arabian Sea in south. Indus River flows in country about 2500 kilometers and starts from Karakorum and Himalaya to Arabian Sea therefore Pakistan is known as a land of Indus River. Pakistan has three major regions. Arid plateau of Baloc histan in southwest, mountains in north and lowlands along indus in south. The most pleasant months are April through September in the northern part of country, while mid-day temperatures can exceed 40 OC in low-lying plains of the Indus Valley.Coldest months are January and February , with temperatures dropping between 10 and 25 degrees Celsius. The region receives an average annual rainfall of 76mm. In the northern areas of the lower Indus plains, rainfall varies from 13 cm in the plains to 89 cm in the Himalayan region. The monsoon typically occurs in the southern regions during late summer, while precipitation remains low in areas such as Baluchistan and the northern regions, including Gilgit-Baltistan and the northern parts of Khyber Pakhtunkhwa.

Pakistan's landscape is highly diverse, particularly in the northern regions where the Karakoram, Hindu Kush, and Himalaya ranges converge, forming some of the most varied high-altitude terrains. This area is part of one of the coldest regions on Earth, with elevations reaching 5175 meters above sea level in Himalayas (Ali et al., 2015). Despite its rich landscapes, According to estimates from the Pakistan Bureau of Statistics and the Food and Agriculture Organization of the United Nations, Pakistan has a minimal amount of forest cover; just 2.2%, or 4.55 million hectares under forests. Between 1990 and 2010, Pakistan's forested areas experienced significant changes, with an annual loss of 42,000 hectares, or 1.66%, leading to an overall 33.2% decline in forest cover during that period (WCMC, 2018). The forestry sector currently contributes 0.39% to the national GDP and saw a growth of 7.17% in 2018, following a decline of -2.37% in 2017, largely due to increased timber production reported in Khyber Pakhtunkhwa (Government of Pakistan, 2018; National Forest Monitoring System Annual Report, 2022).

1.2. Status of Forest Cover at the National Level

Globally, forests currently cover up 31% of the terrestrial area (UN Global Forest Goals Report 2021). According to the definition of forest as per Pakistan Forest Institute, Pakistan forest cover vary between 5.1 and 5.45 percent, with an uncertainty of ± 0.8%, are the mean national forest cover estimates. In the Western Himalaya, the province of Khyber Pakhtunkhwa (1.49 million ha), the administrative region of Gilgit-Baltistan (0.66 million ha), and the state of Azad Jammu and Kashmir (0.26 million ha) have around 67% of the world's forest area. Between 2013 and 2019, the afforestation area officially reported was around 123,500 hectares. Furthermore, Qamer et al. (2016) reported that the Provincial and State Forest Departments controlled approximately 57,912 km of linear plantations.

Pakistan has diverse ecological zones, divided into various forest types based on altitude and species composition. Mangrove, tropical thorn/scrub, tropical dry deciduous, sub-tropical broad-leaved evergreen, sub-tropical chirpine, moist temperate, dry temperate, sub-alpine, and alpine scrub forests are among these woods. According to forest type, riverine (4%), irrigated plantation (4%), thorn (3%), mangrove (3%) and sub-alpine forests (2%), followed by sub-tropical broadleaved scrub (19%), moist temperate (15%), Chirr Pine (13%), and dry temperate forests (36%) have the highest proportionate coverage. Between 2004 and 2012, the mean forest carbon store was calculated to be 192 million tonnes. (MOCC Pakistan, National Forest Monitoring System). Additionally, forests are crucial for sequestering carbon.

NFMS has defined forest on the national level as ‘a minimum of 0.5 hectares of land with a tree crown cover percentage of above 10% that is made up of trees with a minimum height potential of two metres. This would also encompass regions that are now under irrigation and areas that have previously been classified as forests in the corresponding legal documents, provided they match the standards outlined in Pakistan's national forest definition'. National Forest Monitoring System (NFMS) aims to collect accurate and consistent data across various forested landscapes in Pakistan. This definition aligns with international standards, providing a clear framework for monitoring forest resources and guiding sustainable forest management practices. It also serves as a critical reference point for assessing deforestation, afforestation, and reforestation efforts, helping to track progress toward national and global environmental goals. The inclusion of irrigated plantations and legally defined forest areas underscores the system's comprehensive approach to encompass diverse forest types within the country.

1.3. Types of Forest in Pakistan

Forest type is defined as unit of vegetation which possess characteristics in physiognomy and structure. (Champion, 1968). These characteristics can include factors such as species composition, canopy structure, density, and the ecological functions they support. A variety of environmental factors, including climate, soil type, altitude, and disturbance regimes influence forest types. This classification is essential for forest management, conservation, and biodiversity assessments, as it identifies and differentiates forest ecosystems based on their distinct features.

Following are the forest types found in Pakistan. Alpine pastures are in the northern region of country, Hazara and Malakand division, Gilgit and Diamir districts of Gilgit Baltistan. Species include Salix, Lonicera, Berberis, Junipers and Ephedra.

Sub-alpine forests are topmost tree formation in Himalayas from 3350 m to the timber limit with open canopy and are in transition zone between temperate forests and alpine meadows. This type of forests is found in AJK, Upper Dir, Swat, Chitral, Hazara and Gilgit. Main tree species are Abies pindrow and Betula utilis with undergrowth of Viburnum and Salix etc.

Dry Temperate Forests elevation range is about 1525 m to 3350 m and in upper reaches of Kaghan Valley, Swat, Dir, Chitral, Diamir and Gilgit; Hindu Kush Range, North and South Waziristan Agencies and Zhob district of Baluchistan, monsoons doesn't occur in these forests. Main tree species are; Deodar, Chilgoza, Quercus, Kail, Juniper and Spruce. Oak forests falls in temperate zone and confined to lower reaches. The trees exceed 10 m in height. The soil in dry temperate forests are bare (except where extra edaphic supplies of moisture). Xerophytic vegetation occurs, small leaved and greyish foliage is found, predominated by aromatic shrubs such as.Artemisia, and having extensive root system. The grass is mostly small and forbs have thick taproot with a few climbers.

1.4. Rationale

Forests play a crucial role in absorbing carbon dioxide through photosynthesis, thus mitigating climate change. Deforestation and forest degradation, driven by human activities, significantly increase atmospheric CO_2 levels. Without forests, CO_2 accumulation would be 43% higher (Menon et al., 2007). Sustainable forest management, conservation, restoration, and afforestation can help reduce greenhouse gas emissions, while deforestation, forest fires, and fossil fuel burning contribute significantly to these emissions. Forests sequester carbon and offer various ecological, economic, and social benefits. Land use changes, including the conversion of forests to croplands, contribute about 10% of anthropogenic CO_2 emissions and have exacerbated climate change over the past two hundred years (Dube and Stolpe, 2016; Zhang et al., 2017). As the trees grow in the forest, they absorb carbon dioxide from the atmosphere and hence reduce the concentration of carbon dioxide in atmosphere and in soil, wood, leaves it is accumulated. Carbon will be left in the forest deposited and will be discharged into environment with the destruction of forest (Justine et al., 2015).

Climate change is caused by this global warming and as a result, natural disasters such as modification in food production, stress on water resources, and harm to human health, floods, drought, wildfires, high temperatures etc. occurs (NASA, 2016). To mitigate climate change we need to control the emissions of greenhouse gasses. One of the major roles is played by forests in lessening the emission of greenhouse gases as they store atmospheric carbon dioxide when they grow. Day to day carbon dioxide CO_2 mean accumulation reached 400 ppm in "Manua Loa Station in May 2013".

Between 1990 and 2015, Pakistan lost almost a million hectares of forest (FAO, 2014), or around 25% of its natural forests. The average annual rate of deforestation is projected to be 42,200 hectares (World Bank, 2015). Deforestation reduces biomass above and below ground at a rate of 2.2 percent per year, amounting to 100 million tons of CO_2 e; from 330 million tons in 1990 to 213 million tons in 2010 (World Bank, 2015).

The primary causes of deforestation are population growth, grazing, changing land uses, illegal harvesting, and an increase in demand for forest products such as fuel wood, fodder, and lumber that exceeds availability (FCPF, 2013). Owing to sparse forest density, flooding, irrigation failure, soil erosion from watershed areas, Pakistan annually incurs a loss of PKR 2.3 billion (GOP and UNEP, 2019). Because conifer timber has such a high value, coniferous forest acreage has quickly shrunk. In recent decades, government forests have been moved to non-forestry and commercial uses like infrastructure, agriculture, tourism, and defense (World Bank, 2015). Because of their large carbon stock, peatlands, and prolonged maturity age, coniferous forests in Pakistan are thought to be the most significant areas for preservation (Khan et al. 2019).

Quantifying above-ground biomass (AGB) and carbon sequestration potential in the moist temperate forests of Abbottabad District is critical for climate change mitigation and sustainable forest management. This study employs a sophisticated approach by integrating remote sensing data from satellite imagery with detailed forest inventory data. The use of geospatial modeling techniques enhances the precision of biomass and carbon stock estimates by capturing spatial and temporal variations in forest structure and health. The application of the Analytic Hierarchy Process (AHP) to evaluate different parameters affecting biomass estimation such as forest type, canopy density, and topographic features is made possible by the integration of multiple data sources. The multi-criteria decision-making method enhances the reliability of the models used to forecast carbon sequestration capability across diverse forest landscapes. The outcomes will inform sustainable practices that optimize the forests' carbon sequestration capacity, contributing to global efforts to mitigate climate change while ensuring the conservation of critical ecosystems in the Abbottabad District.

1.5. REDD+

International interest in REDD+ has increased to achieve sustainable forest management and offset carbon release at a lower cost. The main goal of REDD+ is to create incentives for improving forest management forest management. According to the United Nation Framework Convention on Climate Change (UNFCCC), satisfaction can be quantified in relation to national performance; however, there are concerns about how these motivators will be communicated in non-specified nations and how the benefits of REDD+ will be divided among different participants.

FRELs are the emissions that will be used to measure emission reduction under REDD+ program. United Nation Framework Convention on Climate Change has defined FREL as a benchmark for aceesing country performance in implementing REDD+ activities.

As per the most recent United Nation Framework Convention on Climate Change Conference of Parties, suggested a universal administration structure for "Reducing Emissions From Deforestation and Degradation (REDD+)" and part of Sustainable forest management (SFM), conservation and increasing the carbon stock of forest in the developing countries the REDD+ eventually appear as execution based system that will give economic remuneration to deliberately taking an interest creating nations (Loft et al., 2015). The REDD+ has ability as a component for decreasing forest degradation, moderate ozone harming substance (GHG) discharges and conserve biodiversity in numerous nations (Sein et al., 2016).

Pakistan is UN-REDD partner country that started REDD+ operations in 2010. Worldwide Fund for Nature Pakistan (WWF-Pakistan), the International Centre for Integrated Mountain Development (ICIMOD), and the Climate Change Ministry launched the REDD+ Preparedness Phase for Pakistan in 2012.It has recommended REDD+ guidelines that uses ground-based carbon measurement and RS for carbon, biomass estimation, GHG emissions, and changes in forest area owing to degradation and deforestation. Forests contribute in reducing the atmospheric concentration of carbon dioxide (Alkama and Cescatti, 2016). Despite the significant contribution of forests to the global carbon cycle, they are destroyed at an accelerated rate, accounting for 12–20% of all anthropogenic carbon dioxide emissions (Collins, 2015).

Khyber Pakhtunkhwa has 66% of the nation's coniferous forests, which offer enormous potential to store carbon and lower emissions as part of the REDD+ Programme. Khyber Pakhtunkhwa has completed a thorough inventory of forest carbon and produced a sub-national REDD+ policy. The Khyber Pakhtunkhwa government has effectively finished planting one billion trees as part of a massive afforestation project, which would massively increase the province's carbon store.

Degradation and deforestation are the major cause of carbon dioxide discharge into the atmosphere. Out of the total greenhouse gasses emission due to the anthropogenic activities from degradation and deforestation, carbon emission contributes about 12%-20%. The goal of REDD+ is to mitigate climate change by reducing carbon emissions caused by degradation and deforestation in developing countries through a variety of actions.

An estimated 4.123 million tonnes of CO2 were released annually between 1992 and 2012 as a result of deforestation and forest degradation, or 2.128 million tonnes from deforestation and 1,995 million tonnes from degradation. Prior to 1992, 6.458 million tonnes of CO2 were emitted annually overall. However, it is predicted that in 2012, the annual carbon sequestered by the trees was 5.968 million tonnes.

1.6. Carbon Storage Dynamics

The processes and mechanisms by which carbon is taken in, held, and released in different ecosystems are referred to as carbon storage dynamics. Carbon Pool is a reservoir or storage area where carbon is accumulated within an ecosystem, including biomass, soil organic matter, and the atmosphere. Carbon Stock refers to the total amount of carbon stored within a specific ecosystem or ecosystem compartment. The process of absorbing and storing carbon dioxide from the atmosphere in carbon pools is known as carbon sequestration. This process is mostly carried out by plants through photosynthesis.

In 1990, the carbon stock in this Pakistan's forests was approximately 309 tons per square kilometers, but it saw a decline to 261 tons per square kilometers by 2009 due to deforestation and land-use changes. However, by 2020, the carbon stock had increased significantly to 409 tons per square kilometers because of reforestation and better forest management practices (Goheer et al. 2023)

The total amount of greenhouse gases (mostly carbon dioxide) released into the atmosphere either directly or indirectly because of human activity; this amount is typically expressed in carbon dioxide equivalents (CO2e). Since different greenhouse gases have different warming effects on the Earth's atmosphere over time, CO_2e allows for a standardized comparison. To express emissions of different greenhouse gases in a common unit, their emissions are converted to CO_2e using conversion factors.

1.7. Vegetation Indices

Indices quantify various vegetation properties, such as biomass, greenness, health, and photosynthetic activity. Unlike narrowband vegetation indices, which utilize specific narrow wavelength bands, broadband vegetation indices integrate reflectance information across wider spectral regions. Canopy Water Vegetation Indices (CWVI) are vegetation indices specifically designed to quantify the water content within plant canopies. These indices utilize spectral bands sensitive to water absorption features in the electromagnetic spectrum, typically in the shortwave infrared (SWIR) region. Water absorption features occur around wavelengths of approximately 1.4 micrometers (µm) and 1.9 µm due to the presence of water molecules in plant tissues.

Khyber Pakhtunkhwa province has more than half of the nation's coniferous forests, which makes it significant for sequestering carbon. All throughout the world, three different methods—destructive, non-destructive, and remote sensing—are utilised to estimate carbon stocks. Of all the existing techniques for measuring biomass, the destructive method is the most straightforward for determining above-ground biomass and the carbon stocks present in forest ecosystems (Gibbs et al. 2007).

Non-destructive approach of estimating biomass is suitable for ecosystems containing rare or protected tree species, where it is not practical or viable to harvest those species. Allometric equations relate easily measurable plant attributes to biomass, such as tree diameter at breast height (DBH) and height. These equations are species-specific and are derived from statistical relationships between the measured attributes and actual biomass (Nelson et al. 1999).

1.8. Impact of Climatic parameters on carbon sequestration potential

The impact of minimum and maximum temperatures on a forest's carbon sequestration potential and carbon stock is significant and can vary depending on the specific ecosystem, forest type, and regional climate conditions. Higher temperatures can enhance the rate of photosynthesis up to an optimal point. Beyond this point, extreme temperatures may reduce photosynthetic efficiency due to thermal stress, reducing carbon uptake by trees.

Both minimum and maximum temperatures influence plant respiration rates. Higher temperatures increase respiration, which can lead to a net loss of carbon if respiration exceeds photosynthetic carbon gain. Warmer nights (higher minimum temperatures) can particularly increase nighttime respiration, reducing the overall carbon sequestration potential. Also, optimal temperatures promote tree growth, enhancing biomass accumulation and carbon stock. However, extreme temperatures, especially prolonged elevated temperatures, can cause heat stress, reducing growth rates and, consequently, the carbon stored in the biomass.

In cooler climates, lower minimum temperatures can slow down soil microbial activity, allowing more organic carbon to be stored in the soil. However, this stored carbon may be released more rapidly if temperatures rise. Forests with species adapted to cooler temperatures may struggle in warmer conditions, potentially leading to species composition shifts and overall forest carbon dynamics.

1.9. Climate Feedback Loops

Changes in forest carbon sequestration due to temperature variations can feed back into the climate system. Reduced carbon sequestration capacity can contribute to higher atmospheric CO_2 levels, further driving climate change and creating a cycle of warming and reduced carbon storage. Historically, the forests in the Abbottabad district have played a vital role in carbon sequestration, acting as significant carbon sinks due to their dense vegetation and diverse ecosystems. These moist temperate forests have traditionally stored substantial amounts of carbon, helping to regulate the regional climate. However, with the recent shifts in climate patterns, including temperature increases, the capacity of these forests to sequester carbon is being challenged.

In climate feedback loops, changes in the carbon sequestration capacity of these forests due to temperature variations can significantly impact the broader climate system. As temperatures rise, ability of forests and store carbon diminishes, leading to increased atmospheric CO_2 levels. This further exacerbates global warming, creating a self-reinforcing warming cycle and reducing carbon storage. In the Abbottabad region, where forests have historically been resilient, the rising temperatures may begin to disrupt this balance. While temperate forests are generally more resilient to moderate temperature changes than tropical forests, continued warming could still reduce biomass and carbon storage capacity. Understanding and mitigating these impacts is crucial for sustaining the region's forest ecosystems and their role in global climate regulation.

1.10. Analytical Hierarchy Process

The Analytic Hierarchy Process (AHP) is used to analyze the impact of various climate indicators on Above-Ground Biomass (AGB) by structuring the problem into a hierarchy of criteria. Experts perform pairwise comparisons between climate factors like temperature and precipitation, assigning weights based on their influence on AGB. These weights are calculated through a comparison matrix, ensuring consistency in judgments. Pairwise comparisons are performed between the indicators, where experts assign weights based on their relative importance in influencing AGB. These comparisons are used to construct a pairwise comparison matrix, and the weights are derived from this matrix, reflecting the significance of each indicator. The consistency ratio is calculated to ensure the reliability of the judgments. The final weighted scores reveal the relative impact of each climate indicator on AGB, providing a clear, systematic way to prioritize and understand how climate variables affect biomass, aiding in effective forest management decisions.

By performing a **pairwise comparison** of these indicators, we aim to assign relative importance to each and develop a clear understanding of how they contribute to the overall carbon sequestration potential of the forest. This process is critical for identifying the most sensitive areas of the forest that are vulnerable to climatic changes and may require targeted management interventions.

Additionally, AHP offers a mechanism for integrating geospatial analysis with decision-making processes, ensuring that the spatial variability of forest conditions is considered. This allows policymakers and resource managers to prioritize regions for conservation efforts based on a combination of environmental sensitivity and carbon storage capacity. By providing a structured, quantitative framework for decision-making, AHP enhances the accuracy and effectiveness of forest management strategies in response to climate change.

1.11. Objectives of the study

O map above ground biomass, carbon pool and carbon sequestration potential of Abbottabad Forest area.

- To analyze the impact of climate indicators on the carbon stock of forest via sensitivity analysis.

1.12. Scope of Study

The study aims to assess the biomass and carbon sequestration potential of moist temperate forests in Abbottabad. The study employs geospatial modeling techniques to estimate AGB and carbon stock across different forests and regions within district. Additionally, it examines the impact of climate variables, particularly temperature and precipitation, on carbon sequestration.

Chapter 2

LITERATURE REVIEW

Forests in Pakistan harbors approximately 213 million tons of carbon within their living biomass. Between 2012 and 2013, the forest growth rate showed a robust increase of 6.8%. However, this growth slowed notably in 2014–2015, with a decrease of −12.45%. Subsequently, there was a significant expansion in 2015–2016, marked by a rapid growth rate of 14.31%. Despite a slight decrease to 2.37% in 2016–2017, efforts such as the Billion Tree Tsunami initiative have propelled forest growth, with the growth rate rising to 7.17% in 2017–2018. These initiatives play a crucial role in combating deforestation and fostering a healthier forest ecosystem (FFCI 2018; WCMC 2018).

Bruce et al. (1999) conducted a study on allometric regressions to improve estimates of secondary forest biomass in central Amazon. They developed regression equations for eight abundant tree species using DBH as the primary input variable. Models using DBH, height and SD inputs showed better accuracy and lower error rates.

Brown et al. (1989) estimated the above ground biomass of tropical forest via regression equations. They applied these regressions to 5300 trees in 43 sample plots from forest inventories. Forest stands with smaller trees had higher expansion factors, which decreased to a constant value as QSD increased. For undisturbed forests, the expansion factors were 1.74, 1.95 and 1.5 for moist, moist to dry and dry life zones respectively. With FAO data, it increased previous volume-derived biomass estimates by 28% to 47%. However destructive based samples remained higher compared to volume data-based estimates.

Fakuda et al. (2003) analyzed forest inventory data to assess carbon budgets in hinoki and sugi forests in Japan. They converted wood volume data to biomass carbon values for accurate carbon stock estimates. Their research sought to assess carbon stocks in all sugi and hinoki plantations using forestry information. Enabling carbon stock calculations and mapping. Volume calculations for approximately 1000 trees were conducted using Smalian's formula. Bivariate regression equations were then developed based on the calculated volume, girth at breast height (GBH), and height for various girth classes. Hinoki forests showed lower volume accumulation than sugi forests until maturity. Biomass allocation varied by forest type, with hinoki forests exhibiting higher branch biomass proportions in younger stands. Total biomass to bole biomass ratios decreased with age, stabilizing after 30 years. The average expansion factor for both forest types was 1.72 Mg per hectare. Results indicated sugi and hinoki plantations in Japan collectively stored 346 and 139 x 106 Mg of carbon, respectively. Significant carbon stocks were observed in the southwestern region of Japan in both sugi and hinoki forests.

Ullah et al. (2012) analyzed carbon reserves in Bangladesh's Tankawati natural hill forest. To quantify biomass and soil carbon stocks, they used wet oxidation and loss on ignition techniques along with a systematic sampling approach and GPS to locate sampling spots. The forest's total carbon stock was 283.80 $t \cdot ha^{-1}$, with 110.94 tons from trees, 0.50 tons from undergrowth (grass, shrubs, and herbs), 4.21 tons from litter fall, and 168.15 tons from soil (down to 1 m). This suggests that the forest has the capacity to sequester carbon dioxide by acting as a substantial carbon reservoir. The total soil organic carbon measured in the study area at five different soil depths was 168.15 tons per hectare, which is very similar to the national average for India. Research recommends combining carbon sequestration with the Kyoto Protocol CDM carbon trading scheme to maximize the potential of Bangladesh's forest sector.

Mani et al. (2007) carried out research aimed at determining the distribution of AGB in 10 one hectare plots situated in forests india. There were two linear regression equations used. Using basal area (BA, Method 1) in one case, and height and BA in another (Method 2). AGB from Method 1 ranged from 39.69 to 170.02 Mg ha^{-1}, whereas Method 2 produced results from 73.06 to 173.10 Mg ha^{-1}. In both inland and coastal locations, positive associations between BA and AGB were found. 42 different tree species' basic wood-specific gravities ranged from 0.47 to 0.89 g cm^{-3} for coastal locations and from 0.46 to 0.92 g cm^{-3} for inland areas based on oven-dry weight by volume. This study's AGB estimation provides a more accurate representation of biomass in tropical dry evergreen forests due to the extensive sampling conducted.

Ghosh et al. (2021) estimated above-ground biomass (AGB) in an Indian mangrove forest that is rich in carbon using multi-temporal factors gathered from Sentinel 1 and Sentinel 2 data. They used RF, XGBoost, GBM models for prediction. Data find the best technique. Based on individual date data values, analysis showed that modeling AGB produced estimates with root mean square errors (RMSE) ranging from 149.242 t/ha for XGB to 151.149 t/ha for RF. On the other hand, prediction accuracy was improved by AGB modeling using the multi-temporal picture stack's average and percentile metrics, 81.8 t/ha for XGB to 74 t/ha for RF. Additional accuracy improvement.

Ali et al. (2020) assessed the subnational carbon stock in detail, taking into account every species of forest in the province. Data were obtained from 449 sample plots using a stratified cluster sampling technique. A total of 144.71 million tons of quantified carbon stock were found, with an average of 127.66 ± 9.32 tons per hectare. Out of this, 68.15 million tons (48 percent of the total) of above-ground carbon stock were estimated, with 10% coming from below-ground biomass and 1% from litter. The study highlighted that hold the highest carbon stock at 99.41 tons per hectare, followed by moist temperate forests at 85.04 tons per hectare. Sub Alpine forests were found to have above-ground carbon stocks of 34 tons per hectare. Subtropical forest demonstrated an above-ground carbon stock of 24.77 tons per hectare. In comparison, sub tropical forest have lower above-ground carbon stocks, with values of 4.52 and 4.48 tons per hectare, respectively.

Ghaffor et al. (2019) conducted the work Assessment of tree carbon biomass in Soan valley Scrub Forest, Pakistan 2019. The researchers compared the reliability of current generic pantropical models with local counterparts. 47 plots were measured for tree biomass as part of the study carried out in the Hayat-ul-Mir Forest, and estimations produced using allometric equations. No obvious differences were observed in biomass carbon estimates between the local and pantropical models for Acacia modesta, nor among the three models for Olea ferruginea. While all models exhibited a strong fit to the data, the pantropical model incorporating biophysical variables emerged as the most robust, offering accurate biomass predictions for subtropical species. This finding underscores the potential of pantropical models in the absence of locally developed equations, ensuring reliable reporting of carbon stock in subtropical forests.

Ahmad et al. (2014) assessed carbon stock in Chir forest of Dir district, Kpk. Study utilized data on growing stock obtained from the forest inventory conducted by the respective forest departments. Stem biomass was determined based on the respective tree species volume (m3) and wood density. The total above-ground biomass for individual trees varied depending on diameter classes.20.59 kg/tree for diameters up to 10 cm, 58.041 kg/tree for diameters between 11 and 20 cm, and 197.214 kg/tree for diameters above 20 cm. Similarly, trees total biomass within the respective diameter classes was 24.71 kg, 69.649 and 236 kg. Coniferous forest in Dir exhibited carbon stock valued 129 Mg/ha with a carbon content of 8.06 Tg.

Munawar et al. (2015) undertook a study focusing on implementing measures to reduce emission in forest degradation in northern Pakistan. They developed time series analyses to track the temporal changes in CO_2 emissions across the Dir District. Carbon stock data considered only aboveground emissions and sequestrations. The research aimed to identify potential REDD implementation sites in forest rich districts using SPOT and MODIS data. Analysis covered forest cover changes from 2000 to 2012 and associated with CO_2 emissions trends. Results showed increases in NDVI of 9.7 and 11.16%, respectively. However, emission inventories like EDGAR and REAS indicated a general upward trend in CO_2 emissions, mainly due to human activities.

Imran et al. (2020) employed remote sensing to quantify biomass a nd carbon content of Siran Forest Division. The research was mostly carried out between 2015 and 2020. Carbon stock estimation predominantly relies on non-destructive methods, with remote sensing being a commonly adopted approach. Destructive methods are utilized solely to develop allometric equations. Recorded values for aboveground and below-ground biomass varied, with the highest recorded at 246 and 64 t/ha and lowest at 55 and 14 t/ha. Above and below ground carbon stock ranged between 116 to 26 tons per hectare and from 30 t/ha to 6.7 tons per hectare.

Ali et al. (2018) conducted a study to estimate carbon stocks within the subtropical forest of Khanpur range Haripur. They employed satellite imagery and forest inventory data to quantify both biomass and carbon stocks. NDVI emerged as the preferred model for mapping biomass distribution, while Landsat-8 imagery served for comparative analysis. The highest recorded aboveground biomass reached 246 t/ha, with below-ground biomass ranging between 14 and 64 t/ha. Above-ground carbon stocks ranged from 26 to 116 t/ha, while below-ground carbon stocks varied from 6.7 to 30 t/ha. Total carbon stock assessed amounted to 43,570.9 t. On average, biomass was 104.6 and carbon stock was 49.7 t/ha. Garanthum exhibited highest biomass at 187.3 t/ha and carbon stock 87 t/ha, Choi Forest has 148 t/ha.

Ahmad eta l.(2018) used forest inventory techniques to examine the carbon sink of Deodar forest in Kumrat Valley located in Pakistan's Hindu Kush Himalaya region. categorized forest in 3 elevation classes (2300 - 2400 m, 2400 - 2500 m, and 2500 - 2700 m above sea level). They established nine sample plots (33*33 m2) in each elevation class to measure carbon values in living tree biomass. Understory vegetation biomass was assessed by destructive sampling of vegetation in each subplot. The study aimed to assess carbon in different biomass components. Overall, the results revealed that the Deodar Forest stored an average of 716 t/ha. The results highlight the Kumrat valley's impressive deodar forests' capacity to store carbon.

As per Ashraf et al. (2022), the most recent national forest cover study from 2012 indicates that Pakistan's forest cover ranges from 5.45 to 5.67 percent, with an uncertainty of ±0.8%. KPK province has the highest forest density in the country. TBTTP aims to bring additional 25% of the provincial area under forest cover technical profiling of the areas to be forested pose a severe challenge in afforestation efforts because of lack of proper scientific research and its potential impacts regarding plantation drive.

Dang et al.(2019) used a machine learning regression approach to quantify aboveground biomass of forest in Yok Don National Park, Vietnam.. The study estimated aboveground biomass (AGB) and ultimately 5 carbon stocks by combining field-measured biomass with Sentinel2 satellite imagery with Random

Forest. The number of regression trees created using a bootstrap sample of observations (Ntree) the number of variables provided to prediction tree (Mtry) were the two input parameters that were optimized in RF. The trees were trained using two thirds of the data, and the remaining third were utilized to estimate the error using an internal cross-validation method. AGB was predicted by 132 spectral and texture factors, with an R2 value of 0.94. Utilized are remote sensing data combined with forest inventories.

Yagsi et al. (2021) carried out a GIS-based site suitability analysis for Konya, Turkey's afforestation. The criteria for analysis included land use capability (LUC), rainfall, slope, aspect, erosion. The paired comparison matrices generated were used to determine the weights of each criterion. The comparison matrix came first in the calculation of the parameter weights. All weighted layers were gathered and the resulting weights were used to create the research area map. The study's 15% most appropriate area and 25.52% suitable area were determined by the results, 28.95% was medium, 12.76% was low and 17.7 was found very low for the afforestation. After determining the areas to be afforested, 10 mostsuitable sites were displayed on website.

Natsagdorj et al. (2022) geospatial information system and a multicriteria decision-making process were used to evaluate the appropriateness of the forests in the province of Khuvsgul. MCDM of the Geographic Information System and 14 carefully chosen natural and socioeconomic characteristics were combined in the study's strategy to assess prospective forest suitability in Khuvsgul province. The findings showed that, of the Khuvsgul province's total area, roughly 24.5 percent is highly suitable, around 74.4 percent is suitable, and 1.1 percent is moderately appropriate for forest restoration. Three multicriteria decision-making techniques were compared by Rashidi et al. 2022 in order to determine which area would be best for afforestation in Iran's Ardabil province. Three layers of criteria (primary criterion and two sets of sub-criteria) were identified for the suitability. The research indicates that the utilisation of TOPSIS in conjunction with the fuzzy AHP method yields more dependable results than the AHP method alone. Making more educated decisions about afforestation in the area may be aided by the findings.

Chapter 3

MATERIALS AND METHODS

3.1. Stusy Area

Area of interest (Figure 3.1) is Abbottabad district located at 34°14'45.77"N, 73°19'1.78"E in Hazara Division at an average elevation of 1256 m. With a population of 1.3 million, it covers an area of 1967 km^2. Between 1998 and 2017, growth rates were 2.5% and 4.34% for urban and rural areas (Pakistan Bureau of Statistics 2017). The average temperature is 18°C. From May to September, the hot season has an average daily hot temperature exceeding 28°C, lasting 4.4 months. June is the warmest month of the year, with an elevated temperature of 31° C and low temperature of 18°C. The cold season, which spans 2.9 months from December to March, is characterized by daily average highs below 15°C. January is the coldest month of the year in Abbottabad, with temperature between 11°C and -1°C (Weather Atlas, 2023).

3.2. Climate and Topography

According to the Pakistan Meteorological Department (2023), the average annual precipitation in Abbottabad is approximately 1262mm. The driest month is November with 28mm of precipitation and wettest month is July having 229mm of average precipitation. Elevation and moon-soon winds influence the pattern of rainfall in the region. The average rainfall reaches 1366.16mm. Average monthly rainfall varies significantly throughout the year, with the monsoon season from July to September accounting for much of the precipitation. Wettest month is usually July, with an average rainfall of over 200 mm.

Topography includes ridges, valleys, and hill shadows with erratic slopes and rugged surface configuration. The region is covered with a humid temperate forest prevalent in areas with deep soil and gentle slopes, particularly in the cool northern aspect. Situated at the foot of the Himalayas, the terrain is mountainous with an average height of 2300 m, providing a temperate environment year-round (IUCN, 2004).

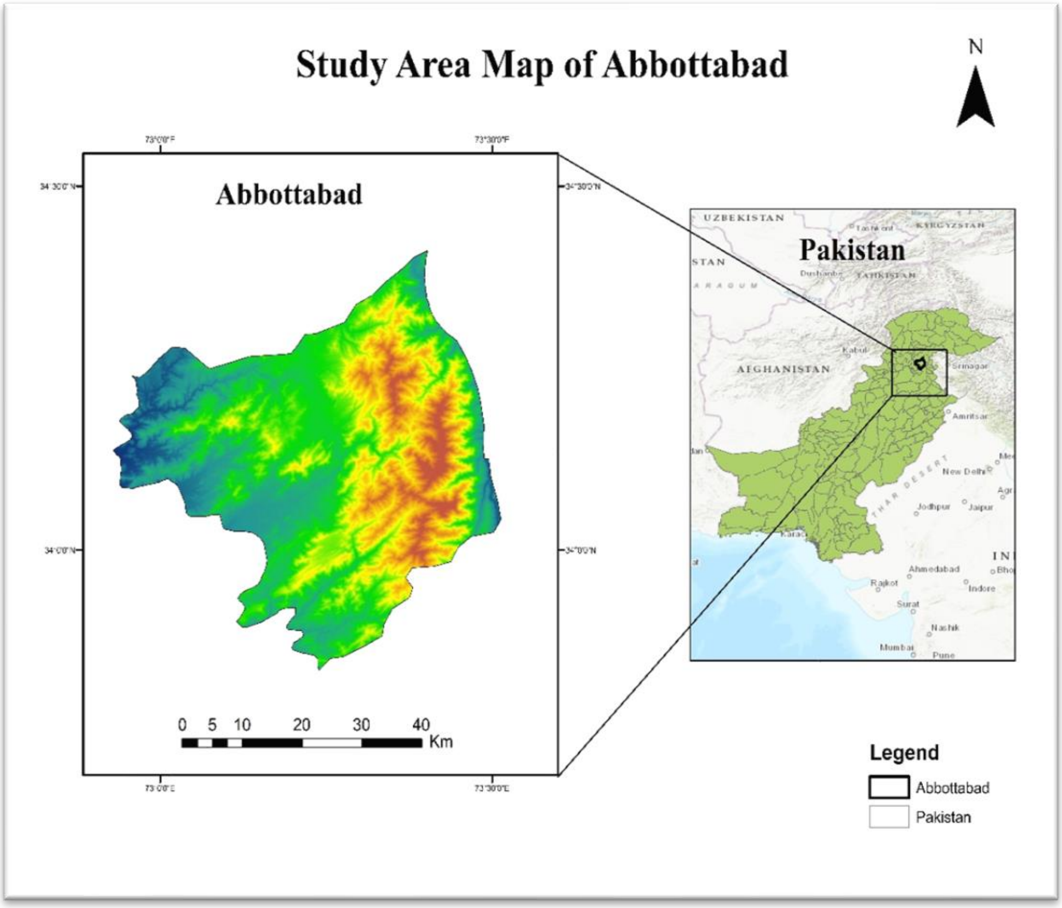

Figure 3.1. Study area map of Abbottabad.

3.3. Forest Types and Vegetation

Khyber Pakhtunkhwa (KPK) province is home to 40% of Pakistan's total forested land (Bukhari et al., 2012). The forested area ranges in elevation 1000 to 4000 meters in Abbottabad (Ahmad et al. 2012). Forest are vital to rural livelihoods in KPK. Most local population meets their needs for fuelwood, sawn timber, and fodder(Sajjad et al. 2015); nevertheless, since 1992, coniferous forests have been losing ground at a pace of 1.3% annually (Ahmad et al., 2012).

Abbottabad has 0.054 million hectares of forest covering 30% of the district's total area (Mahmood, 2011). The KPK Forests Department "Gallies Forest Division (GFD)" oversees the Abbottabad forests, which are referred as "Gallies Forests" (KP-FD). Most forests comprise of coniferous forests protected under two different management schemes: community forests and reserved forests. Reserved woods are governed by a forestry selection system, and certain sections within them are granted certain rights to the local populace (Khan et al., 2019). Residents own the community woods, and their ownership rights over them are comparatively more expansive than those over reserved forests (Hasan, 2007).

Most of the Abbottabad's forest cover is found in the Gilliat region; nevertheless, during the past century, changes in Galliyat's land use have resulted in a 50% loss in the territory's forest cover (Irshad and Khan, 2012). The tree density in community forests has decreased because of the severe forest clearing that has occurred in Ayyubia National Park (ANP) in Galliyat (Aumeeruddy et al., 2004). The three most common species in the study area are deodar, fir and blue pine. At the highest altitudes, fir is present, followed by deodar and kail at intermediate heights, and chir in lower altitudes (Khan, 2002).

3.4. Materials

Multiple fields measuring equipment's were used to collect forest inventory data on the field. Table 2.1 shows us various instruments used for field inventory of Above Ground Biomass estimation.

3.4.1. Tools and Software

For the analysis and processing of data the tools and software's used are listed in Table 2.2

3.4.2. Dataset

Research was conducted by integrating following datasets. Satellite imagery from landsat 8 and 5 were downloaded from USGS.The Pakistan Meteorological Department (PMD) in Islamabad provided climate data, which included temperature, precipitation, and humidity levels. Administrative boundaries at levels 1 and 2 were represented by shapefiles (PAK_adm1.shp and PAK_adm2.shp), which were downloaded from GADM website (http://www.gadm.org/). Additionally, forest inventory data; DBH, tree density, tree species distribution, and terrain parameters, was accessed and downloaded the Ministry of Climate Change National Forest Monitoring (NFMS) portal. Datasets used in the research along with the sources are mentioned in Table 3.3.

3.5. Analytical Framework

3.5.1. Methods

Study is divided into four major sections:

Step 1. Field Data Collection

This step includes field data collection. Forest inventory data was collected, including Diameter and Height data of the trees in sample plots, which was then processed via allometric equations for biomass estimation.

Step 2. Geospatial analysis of Hyperspectral Imagery

In this step preprocessing of satellite imagery is done. Then, the computation of vegetation indices is done to analyze their relationship with forest inventory data. Finally, biomass mapping is done from spectral indices of Landsat 8- OLI imagery.

Step 3. Quantifying Carbon pool and Forest Emissions

In the third step estimation of carbon stock, carbon Sequestration potential and CO_2e emissions and carbon emissions are calculated.

Step 4. Analyzing the impact of climate indicators via Analytical Hierarchy Process

Sensitivity to climate indicators was analyzed using the Analytic Hierarchy Process (AHP), where pairwise comparisons were conducted to assign weights to each indicator, revealing their relative impact on Above-Ground Biomass (AGB). The resulting weighted scores provided a systematic evaluation of the influence of each climate factor. Step-wise procedure is explained below, and methodology of the study is displayed in Figure 2.2.

3.5.2. Field Data Collection

3.5.2.1 Forest Inventory

Field materials were prepared, and training on the field equipment was done in pre-field work, followed by field data sheet preparation to collect data. Field data was obtained from 36 sample plots for ROI in 2022 to estimate biomass and carbon stocks.

3.5.2.2. Win rock sampling method

The Win rock sampling method developed by Win rock International was a systematic approach employed for forest carbon measurement. The method used stratified cluster sampling to represent different forest types and conditions adequately. The forest area was divided into strata based on factors such as forest type, management practices and age. This stratification helped improve the precision of carbon stock estimates. The Win rock plot calculator helps to construct carbon stock measurement field campaigns by predicting the number of sample plots required to estimate terrestrial carbon stocks. It aimed to provide accurate and consistent estimates of forests.

Table 3.1 List of Field Equipment used in the study

Sr. No	Equipment	Utility
1	Haga Altimeter	Height measurement
2	Sunnto Clinometer	Slope and height measurement
3	DBH tape	Diameter Measurement (DBH)
4	GPS device	Navigation
5	Ranging Rods	Plot Centre and Location

Table 3.2 Tools and Software used in study for analysis

Sr.No	Software and Tools	Utility
1	ERDAS 2014, QGIS 2.8.9, ENVI	Classification, Preprocessing of Sentinel-2 Imagery
2	Arc Map 10.8.2	Vegetation Indices and Biomass mapping, AHP
3	SPSS, Microsoft Excel	Statistical Analysis
4	Win rock Sample Plot Calculator	Forest Inventory Sampling Design
5	Microsoft Word	Project Report Writing
6	Satellite Land Monitoring Systems	Design of systematic sampling

Table 3.3 Datasets, variables and their sources used in the study.

Sr. No	Data	Variables	Source
1	Satellite imagery	Landsat 5 and 8.	USGS
2	Climate Data	Temperature, Precipitation, Humidity.	PMD, Islamabad
3	Administrative Boundaries	(PAK_adm1.shp) (Pak_adm2.shp)	Global Administrative Areas http://www.gadm.org/
4	Forest Inventory Data	DBH, Tree Density, Tree Species Distribution, terrain parameters.	Ministry of Climate Change (NFMS portal)

3.5.2.3. Stratified cluster sampling

Figure 3.2 depicts the initial sampling, which consisted of 10'x 10' grid plots. To collect forest inventory data, sample plots were put out in the research region using the stratified cluster sampling technique. In June 2022, tree diameter and height characteristics were collected for the forest inventory. Sampling design employs a stratified two-phase sampling approach, integrating the SLMS process. In the first phase, a systematic grid of 10’x10’ was generated for visual interpretation of land use and forest cover analysis. During the second phase, the 10’x10’ grid was adjusted to smaller sizes of 5’x5’, 2.5’x2.5’, and 1.25’x1.25’ to determine the number of sample plots and accessibility criteria. Stratification was based on forest types using the forest mask from 2012, and forest type boundaries developed during the pilot NFI 2018 were utilized.

The cluster sample plot as shown in Fig 3.3 comprises five sub-plots. The Primary Sub-unit (PSU) is situated at the center of the cluster, while the four Secondary Subunits (SSUs) are located at the four corners, each 200 meters apart. Each sub-plot comprises three concentric circular plots. The first sub-plot has a radius of 17.84 meters and is used for measuring all living trees and standing deadwood stems with diameter breast height (DBH) above 5 cm. Second subplot with the radius of 5.64 meters, is designated for counting seedlings and measuring shrubs. Third subplot with the radius of 0.56 meters is used for measuring above-ground non-tree biomass, litter, and soil samples. This design was adopted to maintain consistency with the previous inventory conducted by MOCC in 2020 (NFMS-MRV Report, MOCC 2020) (Nizami, 2012). Figures 3.2 and Figure 3.3 below shows the location of sample points in Abbottabad.

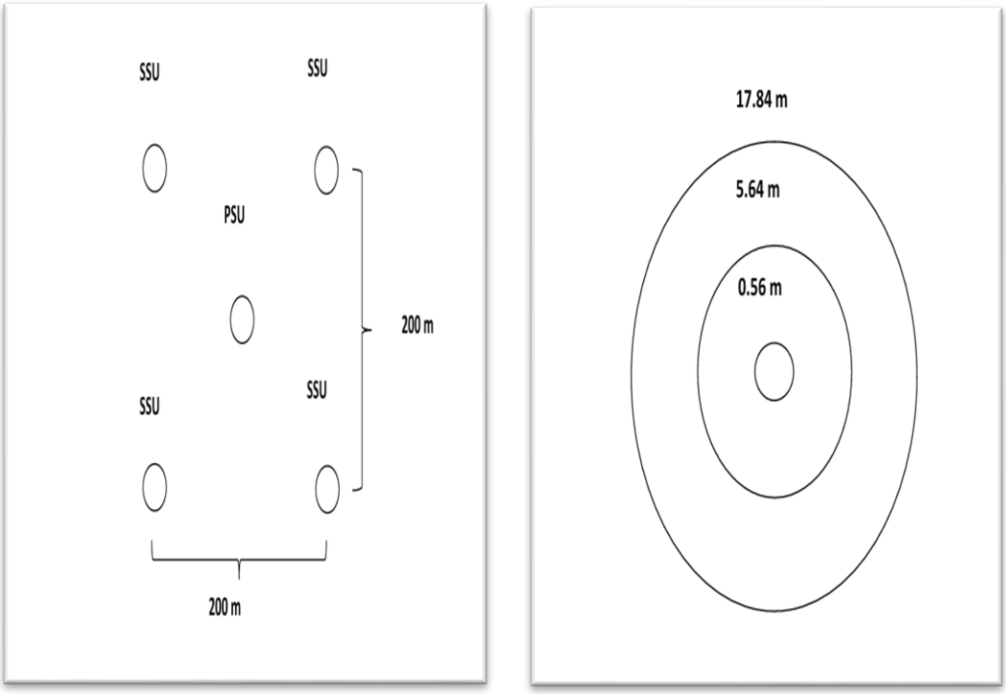

Figure 3.2.10’x 10’ grid plots using stratified cluster sampling technique

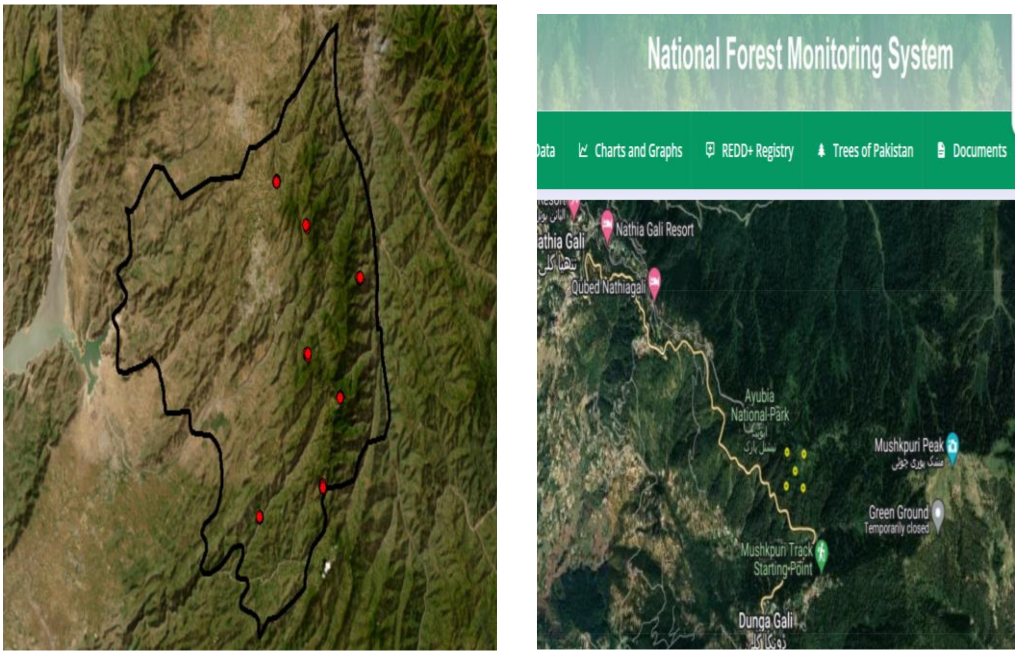

Fig 3.3.Cluster sample plot comprised of five sub-plots

3.5.2.4. National Forest Inventory Protocol

The National Forest Inventory Protocol were mainly adopted from the National Forest Inventory Manual developed during phases. All carbon pools were measured during the current MRV campaign. Measurement of sample trees was carried out by following protocol. All trees with DBH-1 above 5 cm are measured from the17.84c meter radius sample plots. Species and DBH-1 (at 1.3 meters). In case of anomaly at 1.3 m the DBH was measured slightly above that point. In the case of forked tree below DBH, two trees were considered, broken top or not. Broken top trees were not selected as sample trees.

3.5.3 Calculation of biomass from Allometric Equations

Using data from the forest inventory, allometric equations are statistical regression models created to estimate biomass; some are specie specific (Basuki et al., 2009). The accuracy of allometric equations' biomass predictions is dependent on field-collected forest inventory data; any errors in field measurement will be reflected in the equation (Picard et al., 2012). Using allometric equations, tree volume can be calculated by putting forest inventory parameters. The data from the forest inventory is entered into the allometric formulas to determine carbon stock and biomass. According to Brown et al., (1989), an equation can be created for multiple species or for a single species, allowing biomass to be approximated globally or for a particular region. Allometric equations are different for different species, meaning they are specie specific. Table 3.4 shows the allometric equations for the species identified in the forest region taken from Pakistan Forest Institute, Peshawar.

During the fieldwork, the treelevel field data and GNSS coordinates were appro priately entered into the pre-designed field forms and tally sheets. In the event where differential devices were utilized, the GNSS coordinates were post-processed using a differential correction method. All PSU and SSU center coordinates were adjusted using base station data in this procedure. This process corrected all PSU and SSU center coordinates with base station data, which was located at a known location. For the National Forest Inventory (NFI) in Pakistan, data processing and storage encompassed the entry of data into a database system using customized applications developed on Open Foris Collect. Validated data was uploaded into the NFMS National Forest Inventory Database. Finally, the data was exported in csv format, which was suitable for the spreadsheet software used for inventory calculation. Finally, the data was exported in csv format, which was suitable for the spreadsheet software used for inventory calculation. Finally, the data was exported in csv format, which was suitable for the spreadsheet software used for inventory calculation.

3.5.4 Image Acquisition

For a temporal evaluation of changes in land cover and use for 2011 Landsat 5 data was downloaded for September. The title used was of Landsat 5, Scene No. 150-036, which had 7 bands. For year 2022, Scene No. 150-036, Landsat-8 satellite data was downloaded for April because of more cloud cover in the month of September. Images of those months were downloaded in which the vegetation with less snow and cloud cover. The United States Geological Survey Earth Explorer website (Earthexplorer.usgs.gov) provided the remotely sensed data that was downloaded. Landsat 8 data has 11 bands and was of 30 m resolution. Details are mentioned in the table 3.5.

Table 3.4 Allometric equations used to calculate above ground biomass for tree species in Abbottabad

S.No.	Species	Allometric Equation	References
1	Olea ferruginea (Kahu)	$AGB=7.8863+0.0556(D^2H)$	Ali 2020 (KP)
2	Pinus wallichiana (Kial)	$AGB=0.0631\times(D^2H)^{0.8798}$	Ali et al. 2017
3	Abies pindrow (Fir)	$AGB=0.0954\times(D^2H)^{0.8114}$	Ali 2020 (KP)
4	Cedrus deodara (Deodar)	$AGB=0.0458(D^2H)^{0.92}$	Ali 2020 (KP)
5	Picea smithiana (Spruce)	$AGB=0.0843(D^2H)^{0.8472}$	Ali 2020 (KP)
6	Pinus roxburghii (Chir Pine)	$AGB= 0.0224(D^2H)^{0.9767}$	RFEL/NFMS, 2020

Table 3.5.Data sources used for Satellite Image Acquisition

S.No.	Satellite	Scene No.	No. of Bands	Acquisition Date
1	Landsat 5	150-036	7	25-09-2011
2	Landsat 8 OLI	150-036	11	16-04-2022

3.5.4.1 Landsat 5 Thematic Mapper (TM)

The Landsat 5 Thematic Mapper (TM) has seven spectral bands in total. These bands include:

- Blue (44.52-0.52 µm)
- Red (0.63-0.69 µm)
- Green (0.52-0.60 µm)
- Near Infrared (NIR) (0.76-0.90 µm)
- Shortwave Infrared 1 (SWIR 1) (1.55-1.75 µm)
- Thermal Infrared (10.40-12.50 µm)
- Shortwave Infrared 2 (SWIR 2) (2.08-2.35 µm)

Thermal band was acquired at 120 meter resolution while all other bands had a resolution of 30 meters.

3.5.4.2 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)/Landsat 8

It consists of 11 spectral bands:

1. Ultra Blue (Band 1)
2. Blue (Band 2)
3. Green (Band 3)
4. Red (Band 4)
5. Near Infrared (NIR) (Band 5)
6. Shortwave Infrared 1 (SWIR 1) (Band 6)
7. Shortwave Infrared 2 (SWIR 2) (Band 7)
8. Panchromatic (Band 8)
9. Cirrus (Band 9)
10. Thermal Infrared Sensor 1 (TIRS 1) (Band 10)
11. Thermal Infrared Sensor 2 (TIRS 2) (Band 11)

Bands 1 and 9 are used for coastal and aerosol studies, while band 10 and 11 are thermal bands. All bands were resampled to 30m resolution.

3.5.5 Preprocessing

3.5.5.1 Radiometric Correction

Using ENVI software, radiometric correction of the optical images from Landsat 5 and 8 was carried out to enhance the image quality. Reducing the impacts of sun angle and atmosphere was the primary goal of radiometric correction (Baillarin et al., 2012). Dark Object Subtraction (DOS) was applied to convert imagery from radiance to surface reflectance using a semi-automated classification plugin the QGIS software. This approach has the benefit of being simple to use. Moreover, because it is image-based, ground truth data is not necessary (Chavez, 1996).

3.5.5.2 Layer stacking and Image sub-setting

Layer stacking refers to the process of combining multiple raster layers or bands from different images into a single composite image. This technique is commonly used in remote sensing and GIS to create images with merged data from different sensors or sources. Using ERDAS Imagine, layer stacking of the Landsat 5 and 8 bands was done. After that image sub-setting was done to extract region of interest from both tiles via extract by mask tool in ArcMap 10.8.2. This allows for the generation of composite images that combine data from both Landsat 5 and Landsat 8, enhancing the analysis and interpretation of the selected area.

3.5.5.3 Derivation of LULC map

Using a supervised imagery classification approach, satellite images were classified into six LULC classes- forest, water, bare land, vegetation, built-up area and agriculture land. The area= under study was analyzed using Maximum Likelihood Classification to determine the patterns of land use and landcover for the years 2011 and 2022. Using seed pixels, it created signature files and combined them to create a single signature for each class. In order to reduce classification anomalies that may result from similar spectral responses of objects, the maximum likelihood classification algorithm takes into account the vector average of signatures for each land cover category (Yuan et al., 2005). Training samples collected for each class by digitizing polygons on the basis of their spectral profiles and background information. More than signature files were compiled for each land cover type. Rate of change of LULC categories per year according to LULC maps of 2011and 2022 analyzed via statistical analysis. Land use and Landcover maps for the year 2011 and 2022 were generated.

3.5.6 Deriving Vegetation Indices

Vegetation indices are numerical indicators that describe various vegetation properties based on the reflectance of different wavelengths of light. In order to improve the contribution of vegetation characteristics and enable accurate geographical and temporal inter-comparisons, the spectral image transformation of two or more bands is considered. Rectified images of Landsat 8 were used to derive spectral indices by using raster calculator in arcmap. Optical images of Landsat 8 were used in this work to estimate biomass by correlating field data with biomass. Saturation and low spatial resolution issues are major challenges in estimation of above ground biomass(Lu, 2005).

For plot-wise vegetation indices derivation, coordinates of each plot was laid upon vegetation indices and values were extracted in ArcGIS software. After that linear regression analysis was applied by step-wise multi-linear regression to analyze the relationship between vegetation indices and AGB followed by extraction of pixel values for each plot. Sixteen vegetation indices were calculated for this study and in these indices only eight were selected based on their R-square and P-value performance, Root Men Square error and Standard error. VIs with high r and R^2, low p value and standard error indicated the best fit for AGB modeling. From each land-use type, 75% of AGB data were randomly selected for the AGB modeling equation, whereas the remaining 25% of AGB data for validation of the mode. Two categories considered in selecting the VIs include Broadband and Canopy Water Content Indices.

3.5.6.1 Broadband Vegetation Indices

Broadband vegetation indices are numerical values calculated from the spectral reflectance measurements acquired by satellite or airborne sensors over broad wavelength ranges spanning visible and near infrared part of electromagnetic spectrum. These indices are used to quantify various vegetation properties as biomass, greenness, health, and photosynthetic activity. They are sensitive to canopy leaf area so they are used for monitoring. Unlike narrowband vegetation indices which utilize specific narrow wavelength bands, broadband vegetation indices integrate reflectance information across wider spectral regions. Following broadband vegetation indices are used in this study:

3.5.6.1.1 Normalized Difference Vegetation Index (NDVI)

NDVI is calculated as the normalized difference between NIR and red spectral bands that measure vegetation greenness and vigour. It is the normalized ration between NIR and red bands. Equation to calculate NDVI is as below:

$$NDVI = (NIR + Red)/(NIR - Red) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.1$$

where band 5 of Landsat 8 OLI is NIR with wavelength of 0.85 - 0.88 µm, and red is band 4 with a wavelength of 0.64 - 0.67 µm. Since a normalization process is used to generate the index, the range of values is 0 to 1, with even low vegetation-covered areas exhibiting a sensitive sensitivity to green vegetation.

3.5.6.1.2 Green Normalized Difference Vegetation Index (GNDVI)

The green band, sensitive to variations in the amount of chlorophyll in vegetation but less susceptible to the effects of soil background, is used in the modified NDVI (Green and Dielson et al., 1996). The formula used to calculate GNDVI is:

$$\boldsymbol{GNDVI = (NIR - Green)/(NIR + Green)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.2$$

Where NIR is band 5 of Landsat 8 OLI with wavelength range 0.85 - 0.88 µm whereas band 3 is green with wavelength range of 0.53 - 0.59 µm.

3.5.6.1.3 Soil Adjusted Vegetation Index (SAVI)

SAVI is an NDVI modification intended to reduce the impact of fluctuations in soil brightness in places with little or no plant cover. This is accomplished by adding a soil adjustment factor L. The formula used to get SAVI is:

$$SAVI = (NIR - Red)/(NIR + Red + L)(1 + L) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.3$$

Where L is correction factor ranging from 0 to 1. A common value for L 0.5, which is typically used in areas with intermediate vegetation cover.

3.5.6.1.4 Enhanced Vegetation Index (EVI)

EVI is an improved version of NDVI providing a more accurate representation of vegetation canopy characteristics by doing atmospheric corrections. It is particularly used for its sensitivity to changes in vegetation cover. It is developed to address some limitations of other vegetation indices regarding saturation in dense vegetation and sensitivity to atmospheric conditions in areas with dense canopies. The formula for the Enhanced Vegetation Index is:

$$EVI = G \times (NIR - RED)/(NIR + 2.4Red\ + 1) \ldots\ldots\ldots\ldots 2.4$$

Where NIR and Red are the the reflectance in band 5 and band 4 of Landsat 8 OLI with wavelength range of 0.85 - 0.88 µm and 0.64 - 0.67 µm. G is the gain factor set to 2.5 and value 1 is the soil adjustment factor, used to reduce soil background effects.

3.5.6.1.5 Moisture Soil Index (MSI)

It is a measurement of reflectance that changes in response to rising leaf water content. The degree of absorption at 1599nm increases with the amount of water that leaves in vegetation canopies contain. Since absorption at 819nm is essentially unaffected by variations in water content, it serves as the standard. Formula for MSI is.

$$MSI = (SWIR/NIR) \ldots\ldots\ldots\ldots 2.5$$

This index has a value between 0 and greater than 3. Green vegetation typically ranges from 0.4 to 2.

3.5.6.1.6 Square Root Simple Ratio (SQSR)

It is square root of simple ratio (Itkonen, 2012). Formula of SQSR is

$$SQSR = \sqrt{(NIR/Red)} \ldots\ldots\ldots\ldots 2.6$$

where NIR is spectral band 5 0.85 - 0.88 µm and Red is spectral band 4 of wavelength 0.64 - 0.67 µm of Landsat 8 OLI satellite imagery.

3.5.6.2 Canopy Water Vegetation Indices

Canopy Water Vegetation Indices (CWVI) are vegetation indices specifically designed to quantify the water content within plant canopies. If water content in canopy foliage is high, the carbon contents will also be high. These indices utilize spectral bands sensitive to water absorption features in the electromagnetic spectrum, typically in the shortwave infrared (SWIR) region. Water absorption features occur around wavelengths of approximately 1.4 micrometers (µm) and 1.9 µm due to the presence of water molecules in plant tissues. The following two indices were selected in this category:

3.5.6.2.1 Normalized Difference Water Index (NDWI)

NDWI is commonly used to estimate canopy water content in remote sensing imagery. It is calculated using the following formula.

$$NDWI = (NIR - SWIR)/\ (NIR + SWIR)\text{………....……….……}2.7$$

For Landsat 8 satellite data, NIR is usually around the range of 0.08 to 0.90 micrometers, while SWIR is around 1.55 to 1.75 micrometers.

The NDWI values themselves can range -1 to 1, where negative values generally indicate features like vegetation while positive indicate water. A higher positive value typically suggests a higher concentration of water.

3.5.6.2.2 Normalize Difference Infrared Index (NDII)

It is used to estimate water content or water stress in vegetation canopies. NDII is sensitive to canopy water whose value increase with increase in canopy water (Hunt et al., 2012). Following formula is used to calculate NDII:

$$NDII = (NIR - SWIR)/(NIR + SWIR) \quad \text{...………..……..}2.8$$

Where SWIR is the band 6 and NIR is band 5 and of OLI. For Landsat 8 satellite data, NIR is usually around the range of 0.08 to 0.90 micrometers, while SWIR is around 1.55 to 1.75 micrometers.

3.5.7 Statistical Analysis

A linear regression model was employed to evaluate each VI's relationship to the AGB. SPSS and Microsoft Excel were utilized for statistical analysis. Goodness of fit was assessed using P-value, standard error, R^2 (coefficient of determination), and RMSE wherein the lowest RMSE, highest r2, and P value less than 0.01 were used to identify the optimal model. Since R^2 has a value ranging from -1 to +1 so it was preferred. Consequently, it is simple to comprehend how independent and dependent variables relate to one another (Ji and Peters, 2007). Indices were significant, having p-value less than 0.01. We can see that the correlation of indices with biomass is good hence we can simply say that relationship exists between biomass and spectral indices. Indices were significant, having p-value less than 0.01. We can see that the correlation of indices with biomass is good hence we can simply say that relationship exists between biomass and spectral indices.All the vegetation indices along with their formulas are mentioned in the table 3.6.

3.5.8 Biomass Map

After selecting one vegetation index with the best performance that is NDVI, it was used to map above ground biomass via linear regression model. Two methods of biomass estimation are used. The **non-destructive method** was primarily used to estimate AGB, which is crucial for accurate carbon stock assessment without causing harm to the forest ecosystem. Remote sensing techniques, combined with field data, offer a reliable way to quantify biomass across large areas, especially when direct measurements are impractical. On the other hand, the **destructive method** was applied selectively to develop allometric equations and biomass expansion factors (BEFs), which are essential for refining biomass estimates. These allometric equations relate easily measurable variables like tree diameter and height to total biomass, providing an empirical basis for AGB calculations.The Intergovernmental Panel on Climate Change (IPCC) explains how to calculate changes in carbon stocks, greenhouse gas emissions, and biomass content in forest areas using various methodologies. Typically, carbon accounts for around half of the dry biomass (Malhi et al. 2004).

Table 3.6 Vegetation indices and their formulas

Index Name	Formula	Landsat 8	References
NDVI	(NIR – Red) / (NIR + Red)	(B5 – B4) / (B5 + B4)	(GU, 2019)
GNDVI	(NIR-Green)/(NIR+ Green)	(B5-B3)/(B5+B3)	(Gabri, 2019)
EVI	G×(NIR−RED)/(NIR+2.4Red +1)	2.5(B5 – B4) / (B5 + 2.4 B4* B4+1)	(USGS, 2019)
NDWI	(NIR – $SWIR_2$) / (NIR + $SWIR_2$)	(B3 – B5) / (B3 + B5)	(Ceccato et al., 2001)
NDII	(NIR+$SWIR_1$)/(NIR−$SWIR_1$)	(B5-b7)/(B5+B7)	(Gao et al. 2015)
SAVI	((NIR – R) / (NIR + R + L)) * (1 + L)	((B5 – B4) / (B5+ B4 + 0.5)) * (1.5)	(USGS, 2019)
MSI	(SWIR / NIR)	(B6 / B5)	(Welikhe et al., 2017)
SQSR	√(NIR /Red)	√(B5/B4)	(Kashif et a., 2019)

3.5.9 Validation of Biomass Map

Validating a biomass map from ground truth data typically involves comparing the biomass estimates derived from remote sensing or other modelling techniques with actual biomass measurements collected on the ground. An accurate assessment is done by interpreting the statistical metrics RMSE, P value, and Mean Absolute Error. Factors such as measurement errors, sampling bias, spatial resolution, and temporal differences between data sources can influence the validation results. Mean Absolute Error is the average of absolute differences between ground truth and estimated biomass whereas Root Mean Square error is square root of average squared differences between ground truth and estimated biomass values. Pearson correlation coefficient measures the linear relationship between ground truth and estimated biomass values.

3.5.10 Above Ground Carbon (AGC)

To convert above ground biomass (AGB) to above ground carbon (AGC), carbon content within the biomass is considered. According to IPCC guidelines, the typical carbon content of above-ground biomass for forests and woody vegetation uses a default carbon conversion factor of 50% for above-ground biomass.

The formula to convert AGB to AGC is:

$$AGC = 0.47 \times AGB$$

where:

- 0.47 = IPCC conversion factor

This formula assumes that half the dry weight of the above-ground biomass is carbon. It is an ideal condition; actual carbon content however can vary depending on factors such as plant species and growth conditions.

3.5.11 Below Ground Biomass

For assessment of BGB (Below Ground Biomass), the AGB (Above Ground Biomass) is multiplied with conversion factor of 0.26 (IPCC, 2006; Ravindranath and Ostwald, 2008; Khan and Iqbal, 2019).

The formula to convert AGB to BGB is:

$$BGB = AGB \times 0.26$$

Where:

- 0.26 = IPCC conversion factor
- AGB= Above Ground Biomass
- BGB= Below Ground Biomass

3.5.12 Below Ground Carbon

Similarly, BGC (Below Ground Carbon Stocks) is obtained by multiplying AGC (Above Ground Carbon) with conversion factor of 0.26 (IPCC, 2006; Ravindranath and Ostwald, 2008; Khan and Iqbal, 2019).

The formula to convert AGC to BGC is:

$$BGC = AGC \times 0.26$$

Where:

- 0.26 = IPCC conversion factor
- AGC= Above Ground Carbon
- BGC= Below Ground Carbon

Conversion factor 0.26 is according to the method mentioned by Ostwald and Ravindranath in the Handbook for Greenhouse Gas Inventory; book named Carbon Inventory methods as per guidelines mentioned by IPCC on BGC conversion factors.

3.5.13 Total Biomass and Total Carbon

Total biomass is calculated by the sum of AGB (Above Ground Biomass) and BGB (Below Ground Biomass) whereas total carbon is calculated by the sum of AGC (Above Ground Carbon) and BGC (Below Ground Carbon).

3.5.14 Carbon Stock

Calculating carbon sequestration in a forest from above ground biomass involves estimating the amount of carbon stored in the trees based on their biomass. The formula for calculating carbon stock stored in AGB is

$$C = AGB \times CF$$

Where,

- C = Carbon Stock
- AGB = Above Ground Biomass
- CF = Conversion Fraction of Above Ground Biomass (0.47)

The carbon fraction represents the portion of biomass that is carbon. This fraction is typically around 0.5 for most tree species, meaning that approximately half of the biomass is carbon. Unit is metric tons.

3.5.15 Carbon dioxide Equivalent

Since different greenhouse gases have different warming effects on the Earth's atmosphere over time, CO_2e allows for a standardized comparison. To express emissions of different greenhouse gases in a common unit, their emissions are converted to CO_2e using conversion factors.

Here Carbon is converted to CO_2e by multiplying total carbon stock (biomass) with 3.66 while the 3.66 is ratio of molecular mass to atomic mass of carbon.

$CO_2\ e = C \times 3.66$

Where,

- CO_2e = Carbon dioxide equivalent
- C = Carbon Stock
- 3.66 = Conversion factor for CO_2 e by IPCC

3.5.16 Impact of Climate Indicators on Above Ground Biomass via Analytical Hierarchy process

3.5.16.1 Data Collection and Data Cleaning

The temperature (minimum and maximum) and precipitation data for the Abbottabad district were obtained from the Pakistan Meteorological Department (PMD). These data sets included historical records necessary for analyzing the impact of climate indicators on the carbon stock of the forest area. The acquired climate data were thoroughly cleaned to remove any anomalies, such as missing values or outliers. This process involved cross-referencing the data with other sources to ensure accuracy and consistency, as well as applying statistical techniques to address any gaps or inconsistencies in the dataset.

3.5.16.2 Data Interpolation and generation of criterion map layers

To generate continuous surface data for the entire Abbottabad region, the collected temperature and precipitation data were interpolated using the Inverse Distance Weighting (IDW) method. This technique allowed for the estimation of climate variables at unsampled locations, providing a comprehensive spatial representation of the climate indicators. It assumes that points closer to each other are more similar than those farther apart. IDW operates on the principle that the interpolated value at any unsampled location is a weighted average of the values at surrounding known points. The weights assigned to each known point are inversely proportional to the distance from the unsampled point. This means that closer points will have a higher influence on the estimated value than farther points. After interpolation, the resulting raster layers were extracted using a mask that delineated the boundaries of the Abbottabad Forest area. This step ensured that all analyses were confined to the specific study area, facilitating a more accurate assessment of the impact of climate indicators on carbon stock.

3.5.16.3 Sensitivity Analysis via AHP

Finally, a sensitivity analysis was conducted using the Analytic Hierarchy Process (AHP) to evaluate the relative impact of each climate indicator on the carbon stock. The AHP methodology involved structuring the problem into a hierarchy, performing pairwise comparisons, and calculating the weights of each climate indicator based on their influence on carbon sequestration and above-ground biomass in the Abbottabad Forest area.

To assign weights to precipitation, maximum temperature, minimum temperature, and biomass in the AHP analysis, criteria were defined as Precipitation, Maximum Temperature, Minimum Temperature, and Biomass. A pairwise comparison matrix (Table 3.7) was constructed with the following values: Precipitation was assigned a weight of 3 compared to both Maximum and Minimum Temperature, and a weight of 5 compared to Biomass, indicating its higher importance. Maximum Temperature was assigned a weight of 1 compared to Minimum Temperature and a weight of 2 compared to Biomass. Minimum Temperature was assigned a weight of 1/2 compared to Biomass. Biomass was considered the least important relative to the other criteria. The normalized matrix was used to calculate the final weights for each criterion. Precipitation received the highest weight, followed by Maximum Temperature, Minimum Temperature, and Biomass. The consistency ratio was computed to ensure the judgments were reliable, with a CR below 0.02 indicating acceptable consistency. The results indicated that Precipitation had the highest influence on biomass, followed by Maximum Temperature, Minimum Temperature, and Biomass.

Table 3.7: Pairwise comparison matrix for sensitivity analysis

Criteria	Precipitation	Max Temp	Min Temp	Biomass
Precipitation	1	5	7	9
Maximum Temperature	1/5	1	3	7
Minimum Temperature	1/7	1/3	1	5
Biomass	1/9	1/7	1/5	1

Chapter 4

RESULTS AND DISCUSSION

4.1 LULC maps

Classification of Landsat satellite images of the year 2011 (Landsat-5) and 2022 (Landsat 8) was done using method of supervised classification in Arc map 10.8.2. Classes include forest, water, barren land, settlement, vegetation, and agricultural land. Figures 4.1 and 4.2 show LULC maps for the year 2011 and 2022. In 2011, the area covered by agriculture was 25,386.82 hectares, constituting 14% of the total area. By 2022, this had decreased to 13,779.55 hectares, representing 0.7% of the total area. This indicates a reduction of 11,607.28 hectares, marking a -13.3% change. In 2011, bare land covered 16,171.82 hectares, accounting for 0.8% of the total area. By 2022, the area had decreased to 6,168.79 hectares, making up 0.3% of the total area. This reflects a decrease of 10,003.04 hectares, corresponding to a -0.5% change. Forest areas increased from 28,475.37 hectares in 2011, which was 15% of the total area, to 44,872.17 hectares in 2022, covering 24% of the total area. This represents an increase of 16,396.80 hectares, a 9% change. The urban area expanded from 6,705.03 hectares in 2011 (0.6% of the total area) to 11,226.30 hectares in 2022 (0.6% of the total area), indicating an increase of 4,521.26 hectares, which is a 0.3% change. Vegetation decreased from 99,631.81 hectares in 2011, which was 55% of the total area, to 96,626.94 hectares in 2022, representing 53% of the total area. This shows a decrease of 3,006.86 hectares, a -2% change. Water bodies expanded from 3,796.71 hectares in 2011, accounting for 0.2% of the total area, to 7,496.16 hectares in 2022, which is 0.4% of the total area. This indicates an increase of 3,699.45 hectares, a 0.2% change. Statistical interpretation of land use and land cover changes over the course of 11 years is represented by table 4.1. Negative signs in the data indicate a decreasing trend in the respective LULC classes. Comparative analysis and net change in land use change patterns is represented by the bar graphs as shown in figure 4.2. To know forest cover change and how much area has been gained by forest cover, forest area was calculated separately for both years forest cover maps were created as shown in figure 4.3

and 4.4. A gradual increase in trend after 2014 is due to the massive afforestation project of the government of Khyber Pakhtunkhwa named the Billion Tree Tsunami through planting and natural regeneration, to restore the province's depleted forests and combat the effects of climate change. Results show a continuously increasing trend in vegetation and built-up areas, whereas the category other land showed a decreasing trend. A gradual increase in trend after 2014 is due to the massive afforestation project of the government of Khyber Pakhtunkhwa named the Billion Tree Tsunami through planting and natural regeneration, to restore the province's depleted forests and combat the effects of climate change. Results show a continuously increasing trend in vegetation and built-up areas, whereas the category other land showed a decreasing trend.

The pie charts in figures 4.3 and 4.4 depict the land use and land cover (LULC) distribution for 2011 and 2022. 2011 agriculture covered 14% of the total area, while bareland accounted for 0.8%. Forests made up 15%, and urban areas constituted 3% of the land. Vegetation was the largest category, covering 55%, and water bodies represented 0.2%. By 2022, there were significant changes. The agricultural area decreased to 7%, and bareland reduced to 0.3%. Forest areas saw a notable increase, rising to 24% of the total area. Urban areas expanded to 6%. Vegetation remained stable, making up 53% of the land, while water bodies doubled their percentage to 0.4%. Table 4.2 illustrates a significant reduction in agricultural and bareland areas, substantial growth in forest and urban areas, and a slight increase in vegetation and water bodies over the 11-year period.

Table 4.2 represents change in forest cover area from year 2011 to 2022. Area increased from 28475.37 ha to 44872.17 ha with a net increase of 16396.80 ha. Forest cover covered 15% of the area of district in 2011 but with 9% increase over the span of 11 years it increased to 24% of the land cover vof the forest by year 2022 under the massive afforestation efforts by the government of Khyber Pakhtunkhawa subsequently leading to enhanced carbon stock and carbon sequestration potential of the forest region. These results are comparable those recorded by Ali *et al.* (2015) when assessing the land-use pattern in District Abbottabad using GIS and RS. Similar observations were made by Ali et al. (2017) while estimating carbon stock for the Moist temperate forest of KPK.

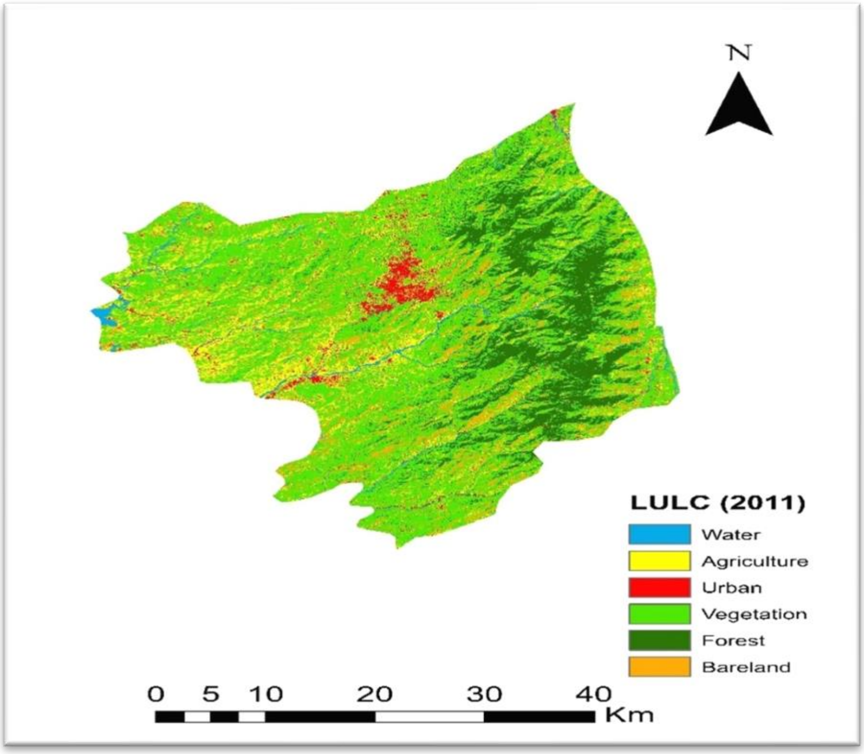

Figure 4.1. Land use and land cover map of Abbottabad district (2011)

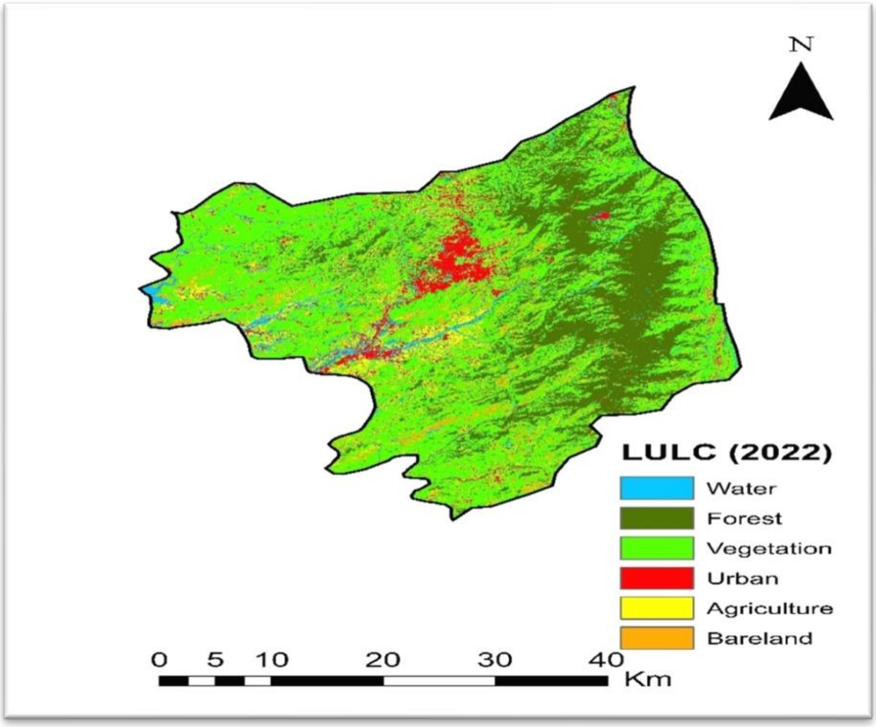

Figure 4.2.Land use and land cover map for Abbottabad (2022)

Table 4.1. Percentage and area wise distribution of Land cover and land use classes of 2011 and 2022

LULC Class	**Area (ha)-2011**	**Percentage-2011**	**Area (ha)-2022**	**Percentage-2022**
Agriculture	25386.82	14	13779.55	0.7
Bareland	16171.82	0.8	6168.79	0.3
Forest	28475.37	15	44872.17	24
Urban	6705.03	0.3	11226.30	0.6
Vegetation	99633.81	55	96626.94	53
Water	3796.71	0.2	7496.16	0.4
Total Area	180169.57		180169.91	

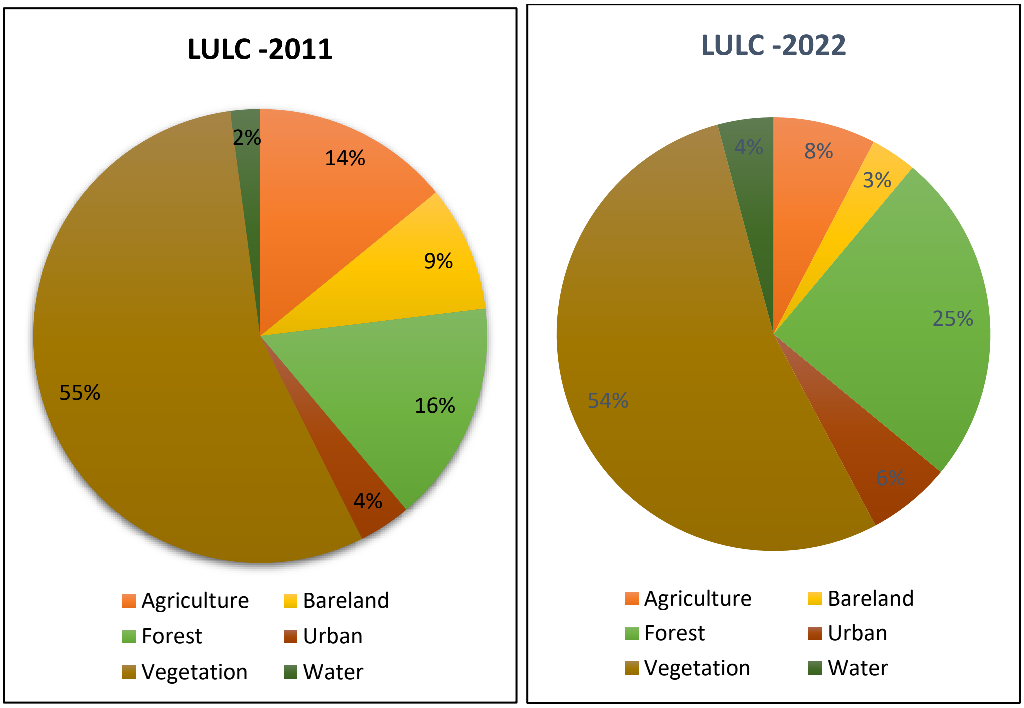

Figure 4.3. Pie chart displaying percentages of LULC for year 2011 and 2022

Table 4.2. Statistical computation of rate of change of various LULC categories per year according to LULC maps of 2000 and 2015

LULC Change	Area Change (ha)	Percentage change
Agriculture	-11607.28	-13.3
Bareland	-10003.04	-0.5
Forest	16396.80	9
Urban	4521.26	0.3
Vegetation	-3006.86	-2
Water	3699.45	0.2
Total Area	180169.91	

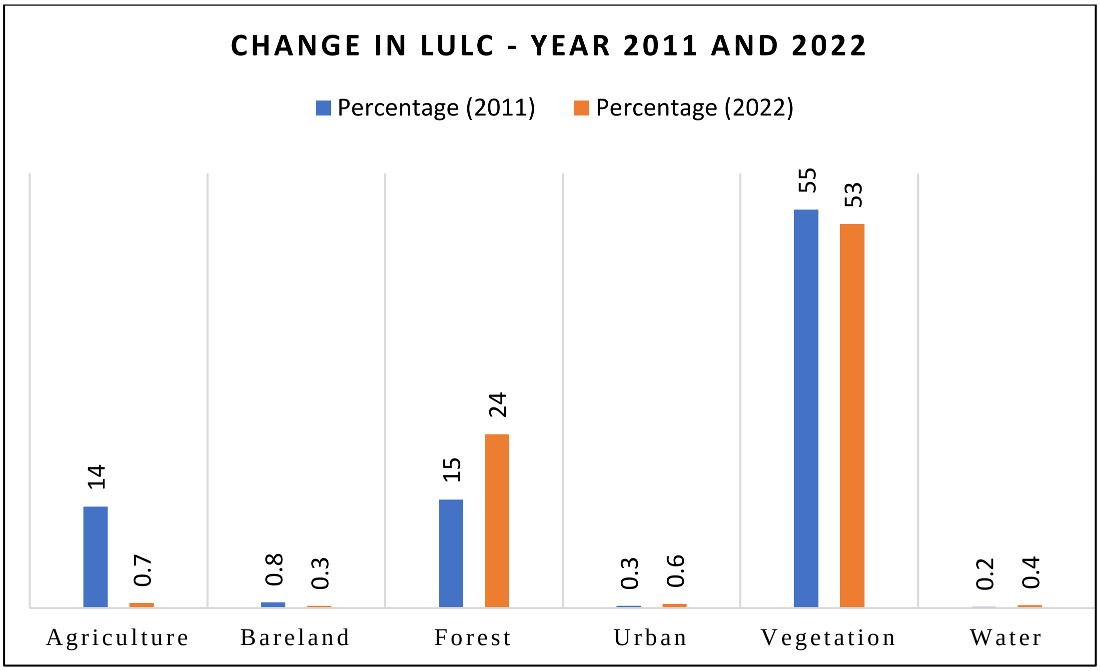

Figure 4.5.Bar Graph displaying the relative change in different Land cover and land use classes from in year 2011 and 2022 (%)

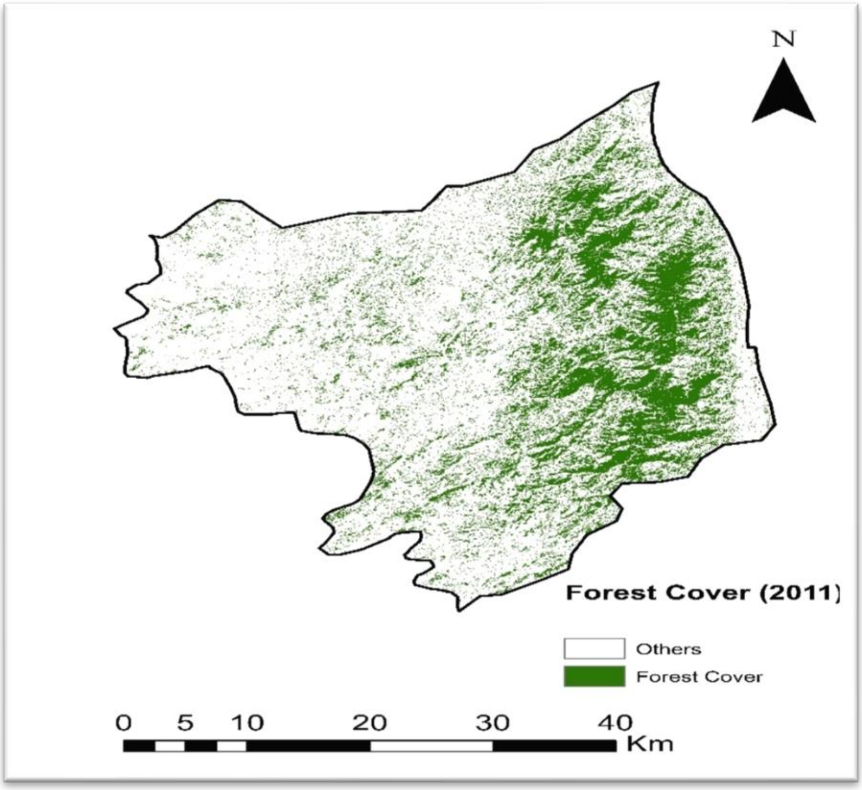

Figure 4.6.Map displaying forest cover for Abbottabad (2011)

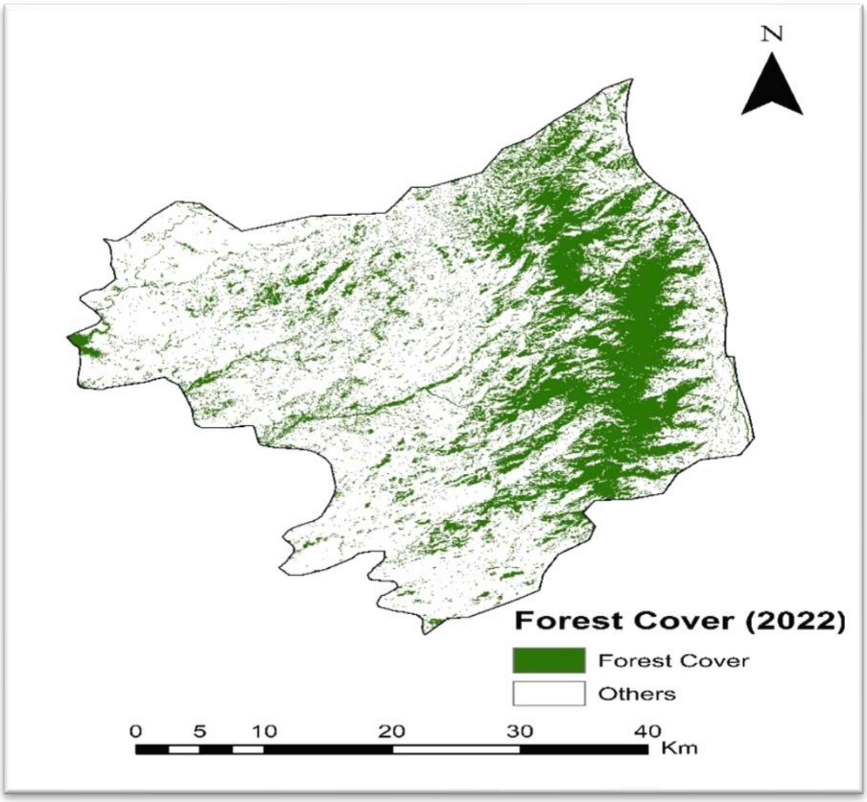

Figure4.7. Figure 4.6.Map displaying forest cover for Abbottabad (2022)

Table 4.3. Change in forest cover area from 2011 to 2022

Forest	**2011**	**2022**	**Net change**
Area (ha)	28475.37	44872.17	16396.80
Percentage	15%	24%	9%

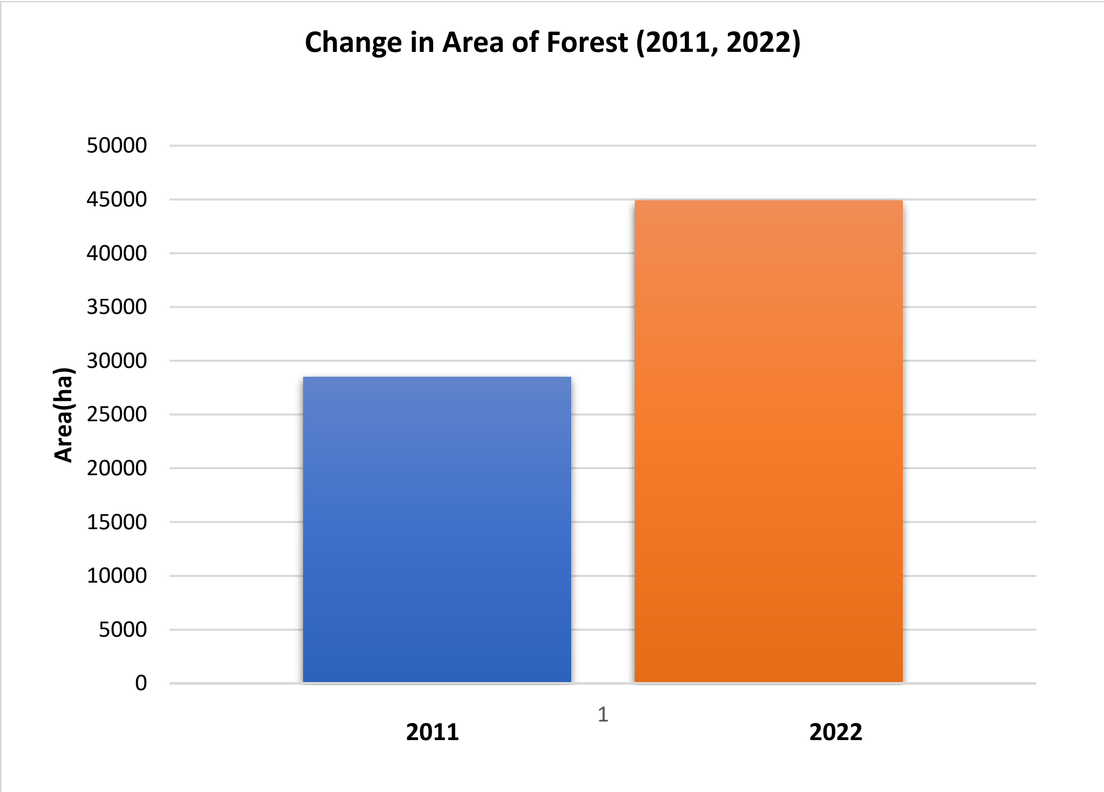

Figure4.8. Bar graph representing change in forest area

4.2 Estimation of Biomass from Vegetation Indices

Coordinates of each plot were laid upon different VI images and values were extracted by using a tool that extracts by point values in ArcGIS software to derive all eight vegetation indices. Multi-linear regression then analyzed the relationship between Above Ground Biomass and vegetation indices, followed by extraction of pixel values for each plot of different indices. Multi-linear regression then analyzed the relationship between Above Ground Biomass and vegetation indices, followed by extraction of pixel values for each plot of different indices. Multi-linear regression then analyzed the relationship between Above Ground Biomass and vegetation indices, followed by extraction of pixel values for each plot of different indices. Out of sixteen vegetation indices calculated for this study and only eight selected with high r and R^2, low p value and standard error. Figure 4 shows the vegetation index map for NDVI. The scatter plot displays the relationship between calculated AGB and NDVI. From the plot, it is observed that as the value of X increases, the value of Y also tends to increase. The upward slope of the trend line illustrates this positive correlation. The data points, while scattered, generally align with this trend, indicating a moderate to strong positive relationship between the two variables.

Two categories considered in selecting the VIs include Broadband and Canopy Water Content Indices. From the plot, it is observed that as the value of X increases, the value of Y also tends to increase. The upward slope of the trend line illustrates this positive correlation. The data points, while scattered, generally align with this trend, indicating a moderate to strong positive relationship between the two variables.

NDVI was the best fit for AGB modeling. From each land-use type, 75% of AGB data were randomly selected for the AGB modeling equation, whereas the remaining 25% of AGB data for validation of the mode. Two categories considered in selecting the VIs include Broadband and Canopy Water Content Indices.

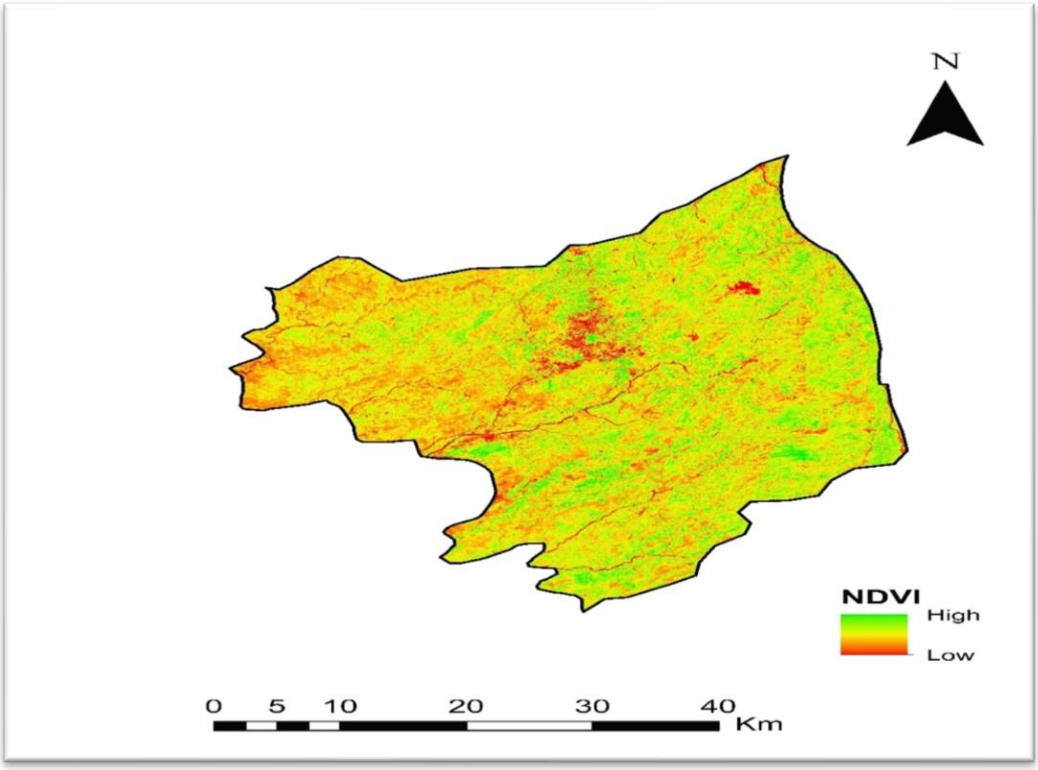

Figure 4.9.Map displaying the relationship between NDVI and calculated AGB

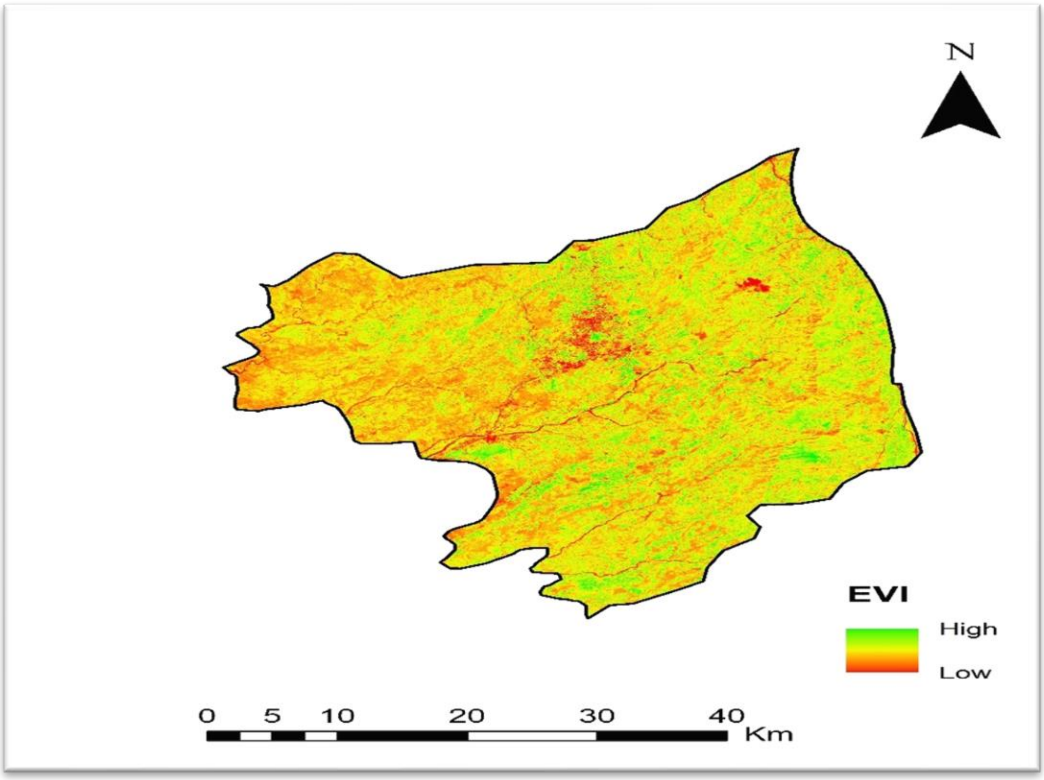

Figure 4.10.Map displaying the relationship between EVI and calculated AGB

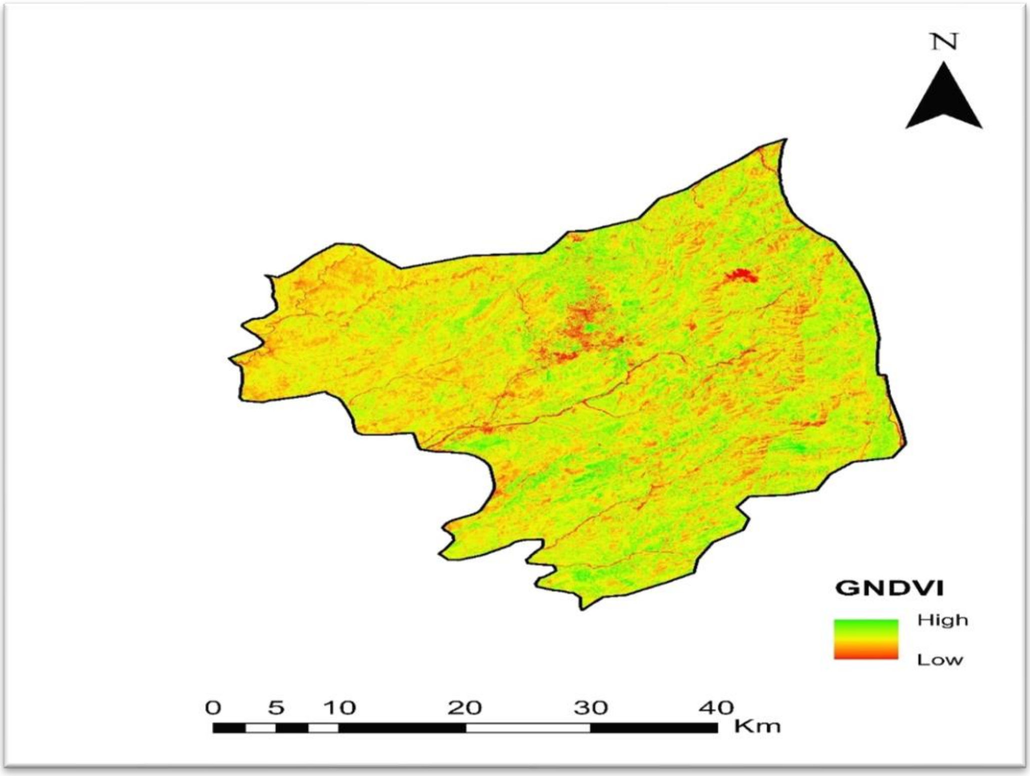

Figure 4.11.Map displaying the relationship between GNDVI and calculated AGB

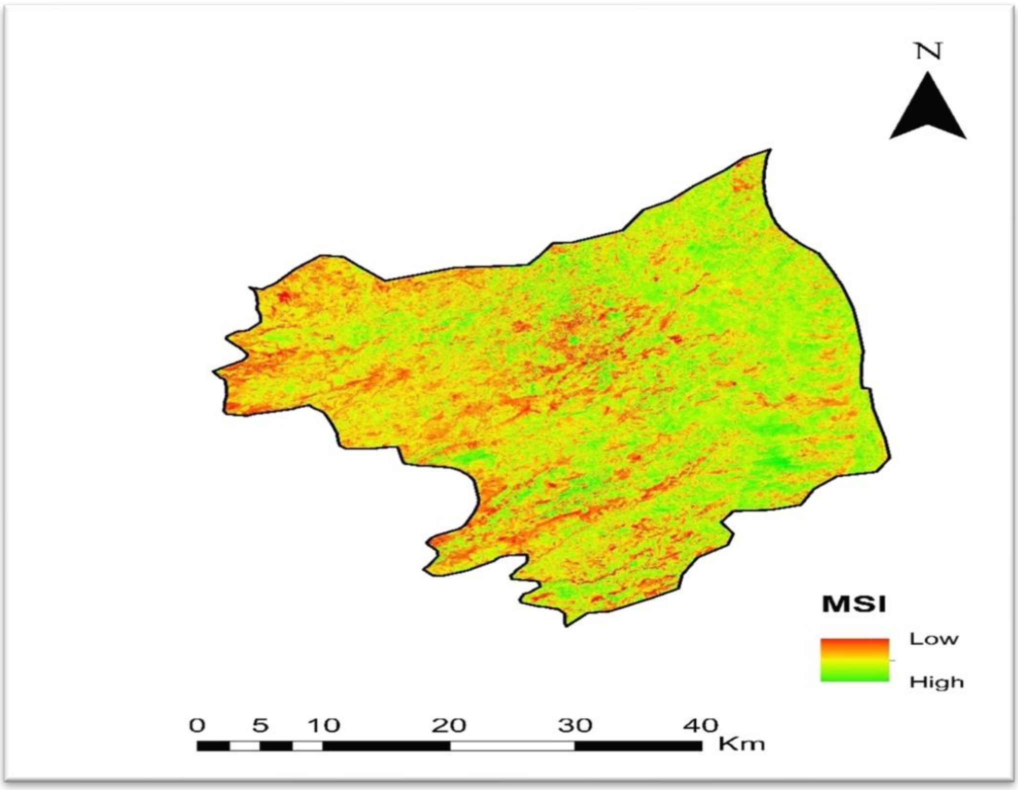

Figure 4.12. Map showing the relationship between MSI and calculated AGB

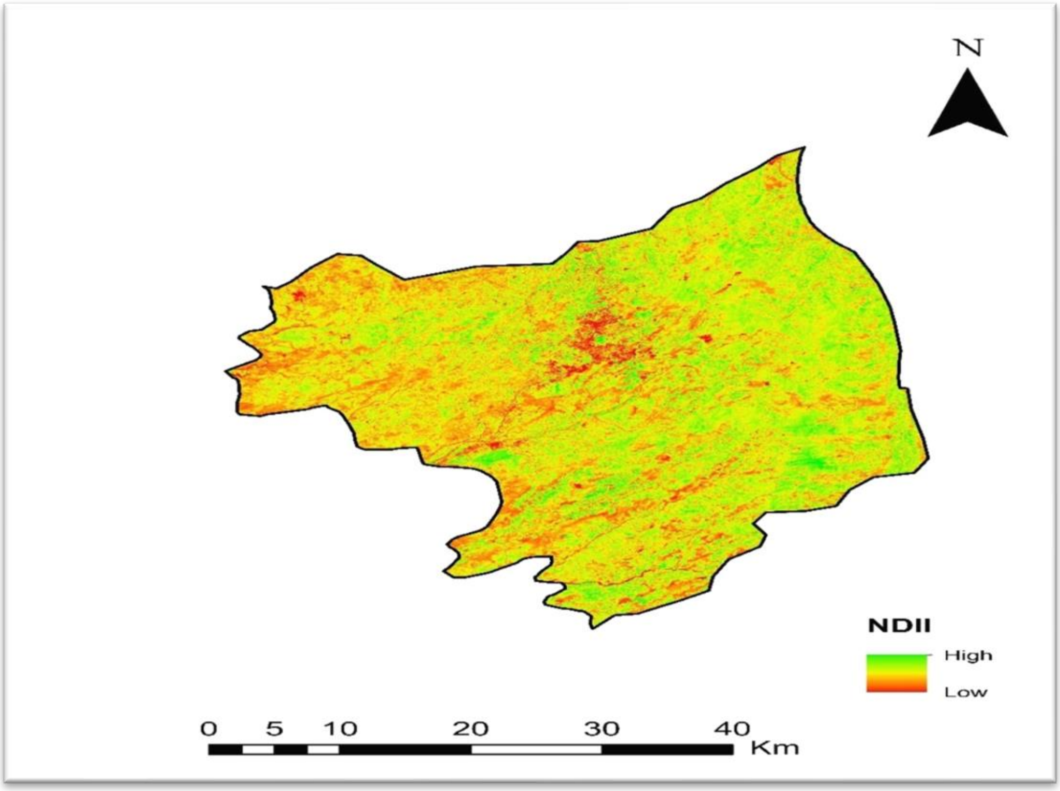

Figure 4.13. Map showing the relationship between NDII and calculated AGB

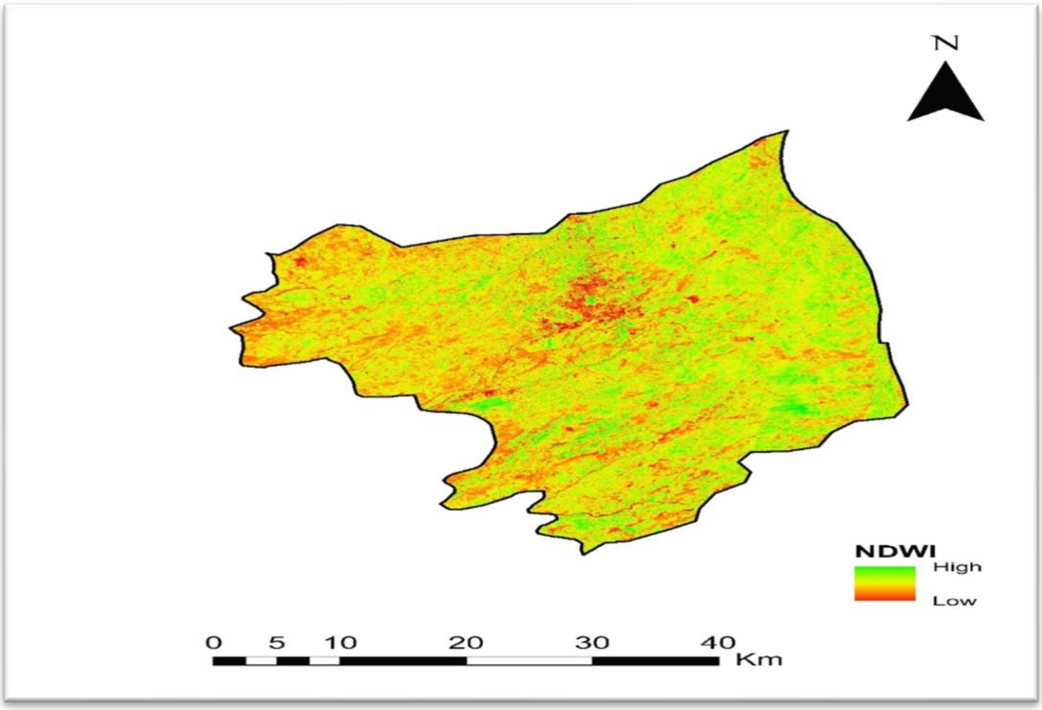

Figure 4.14. Map showing the relationship between NDWI and calculated AGB

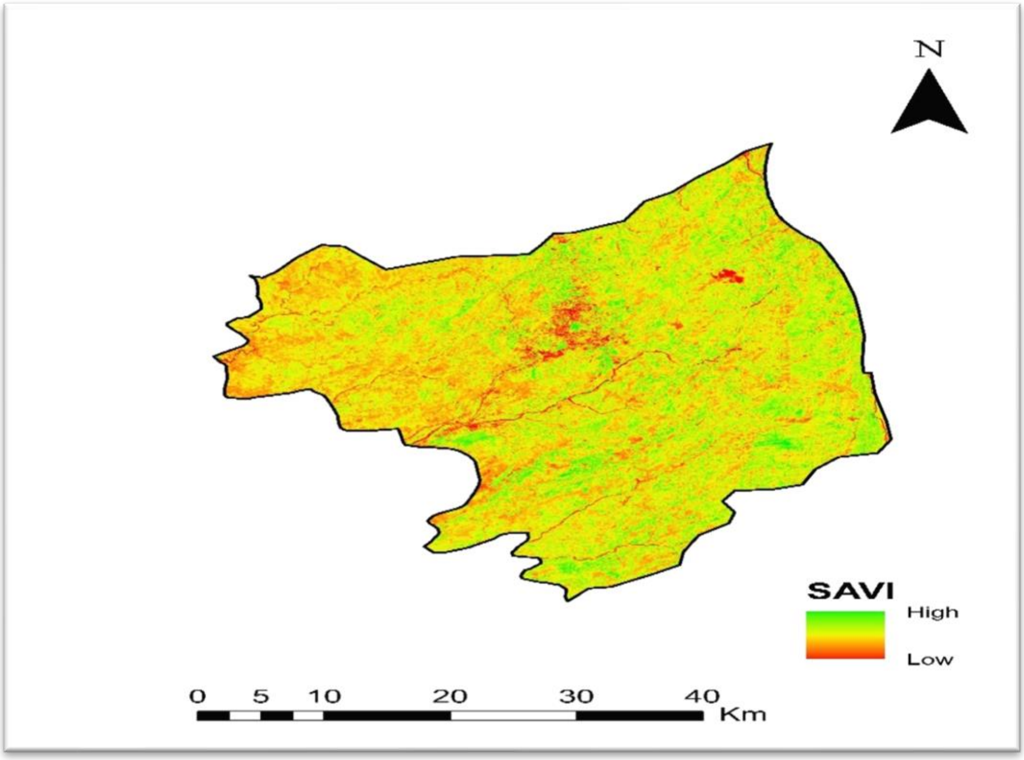

Figure 4.15. Map showing the relationship between SAVI and calculated AGB

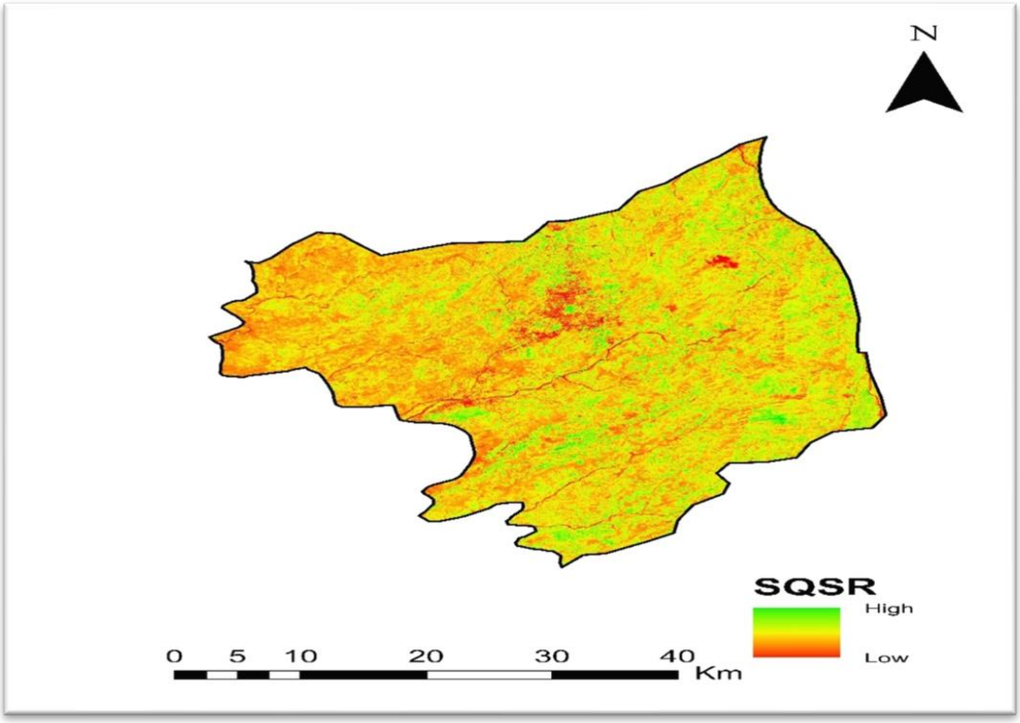

Figure 4.16. Map showing the relationship between SQSR and calculated AGB

Scatter plots displaying the relationship between Broadband VIs and AGB

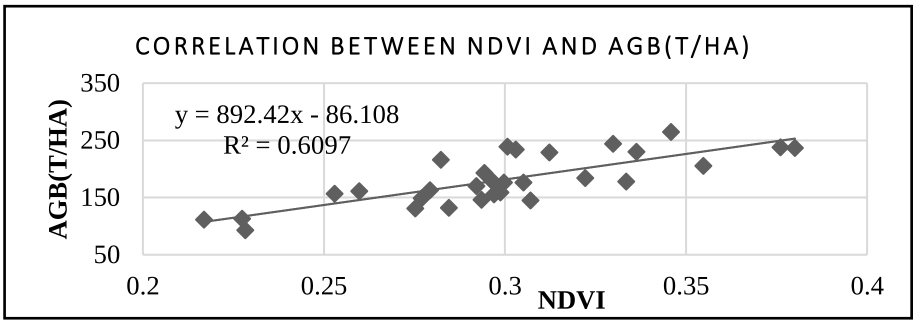

Figure 4.17: Scatter plot showing the relationship between NDVI and AGB

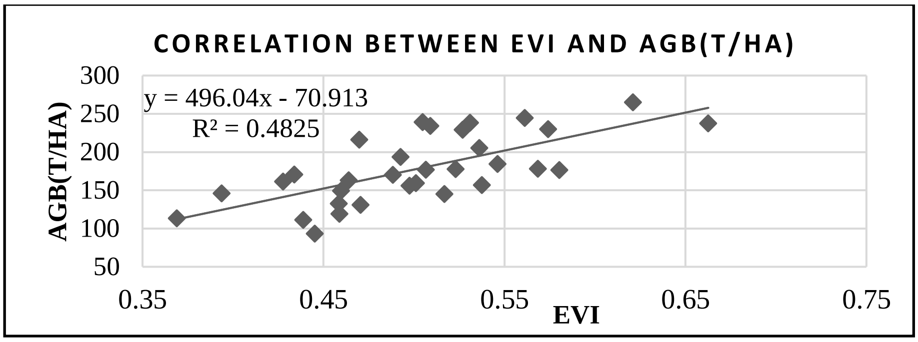

Figure 4.18.Scatter plot showing the relationship between EVI and AGB

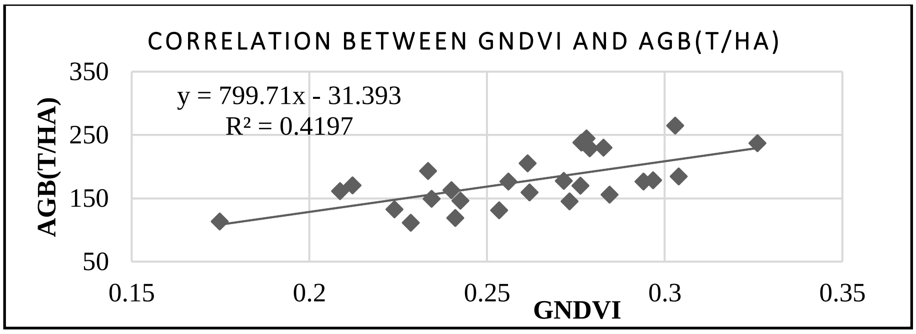

Figure 4.19.Scatter plot showing the relationship between GNDVI and AGB

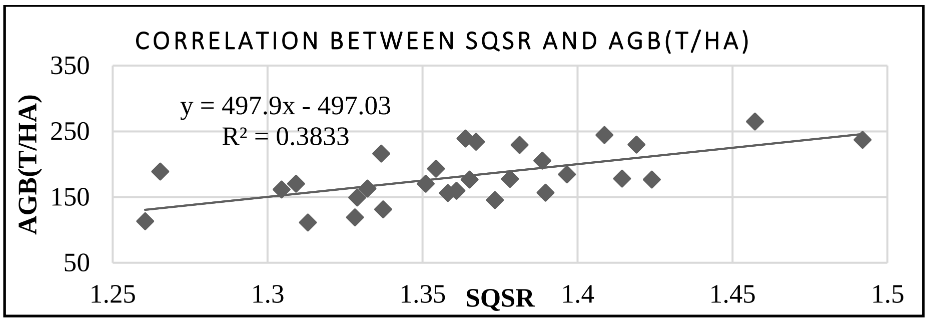

Figure 4.20.Scatter plot showing the relationship between SQSR and AGB

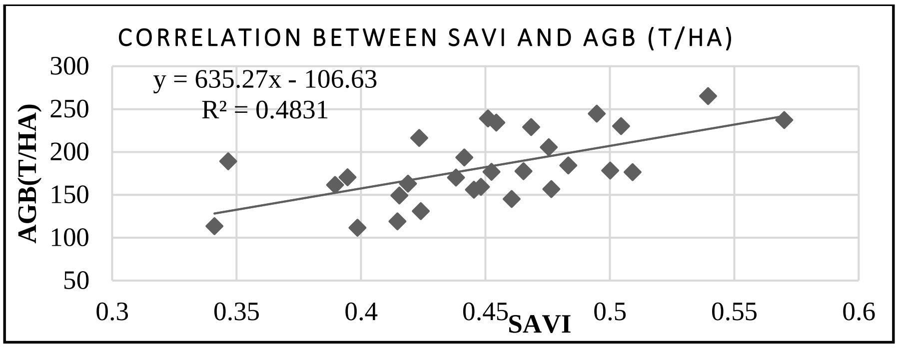

Figure 4.21.Scatter plot showing the relationship between SAVI and AGB

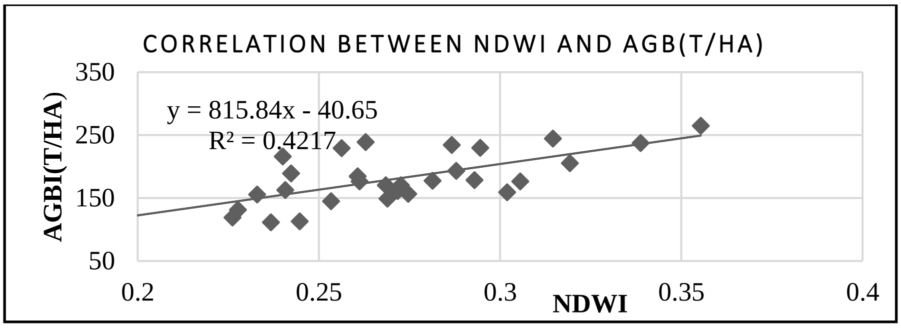

Figure 4.22.Scatter plot showing the relationship between NDVI and AGB

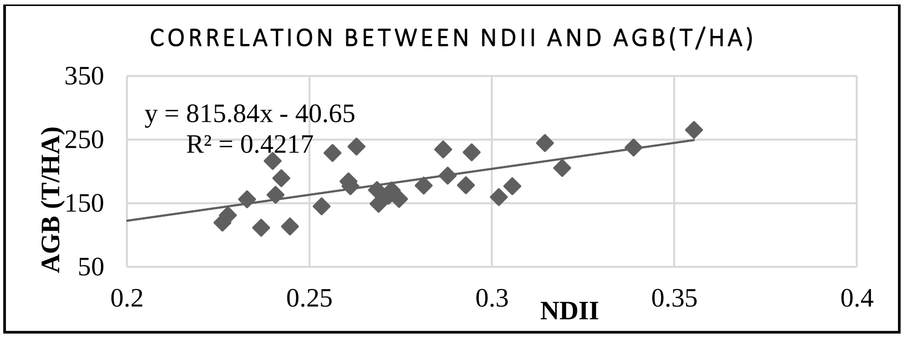

Figure 4.23.Scatter plot showing the relationship between NDII and AGB

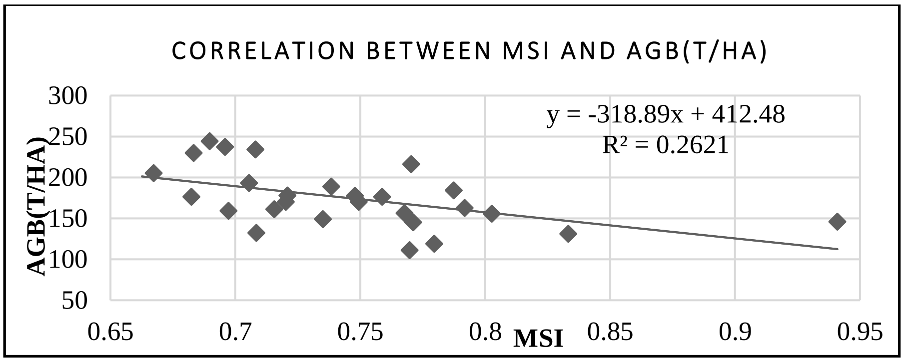

Figure 4.24.Scatter plot showing the relationship between MSI and AGB

4.3 Validation of Biomass Map

The validation of the biomass map, based on the given metrics, demonstrates strong accuracy and reliability. The Root Mean Square Error (RMSE) is 31.26, indicating a relatively low average deviation between observed and predicted values. The Mean Absolute Error (MAE) is 0.29, further confirming minimal discrepancies. The R-squared value of 0.8 signifies a near to perfect correlation between the observed and predicted data, suggesting that the model explains 100% of the variance in biomass. Additionally, the p-value is less than 0.01, highlighting that the results are statistically significant and unlikely to have occurred by chance. These metrics collectively confirm the high precision and validity of the biomass map.

4.4 Biomass and Carbon Stock Estimation Results

For Above-Ground Biomass (AGB), the minimum value recorded was 93.35 t/ha, while the maximum was 265.02 t/ha. The total AGB summed up to 5893.63 t/ha, with an average (mean) of 178.60 t/ha. The standard deviation was 44.12, indicating variability in the data, and the standard error was 7.68. Above-Ground Carbon (AGC) 's minimum value was 43.87 t/ha and the maximum was 124.56 t/ha. The total AGC was 2770.01 t/ha, with a mean value of 83.04 t/ha. The standard deviation was 20.74, and the standard error was 3.61. For Below-Ground Biomass (BGB), the minimum recorded was 24.27 t/ha and the maximum was 68.90 t/ha. The sum of BGB amounted to 1532.35 t/ha, with an average value of 46.43 t/ha. The standard deviation was 11.47, and the standard error was 2.00. Below-ground carbon (BGC) had a minimum value of 11.41 t/ha and a maximum of 32.38 t/ha. The total BGC was 720.20 t/ha, with a 21.82 t/ha mean. The standard deviation was 5.39, and the standard error was 0.94. Total Biomass's minimum value was 117.61 t/ha and the maximum was 333.92 t/ha. The sum of the total biomass was 7425.98 t/ha, with an average of 225.03 t/ha. The standard deviation was 55.59, and the standard error was 9.68. Total Carbon had a minimum of 55.28 t/ha and a maximum of 156.94 t/ha. The total carbon summed up to 3490.21 t/ha, with a mean value of 105.76 t/ha. The standard deviation was 26.13, and the standard error was 4.55. For CO_2 e, the minimum value was 202.32 t/ha and the maximum was 574.41 t/ha. The total CO_2e was 12774.18 t/ha, with an average of 387.10 t/ha. The standard deviation was 95.63, and the standard error was 16.65. All the results are summarized in Table 4.4.

Results are comparable with the estimates mentioned by Moazzam et al. 2022 study. The average biomass (t·ha−1) was 237 in Ghora gali site and 186 t·ha−1in Lehterar site. However, on average, both the forests have 114.5± 2.26 t·ha−1 of carbon stock which comprises 92% in tree biomass and only 8% in the topsoils. Brown and Lugo (1984) estimated that the tropical forests of Bangladesh hold approximately 55−90 t·ha-1 of carbon in forest ecosystems.

In a study conducted by Sharma et al. (2018) on above-ground biomass and carbon stock estimation in the temperate forests of the Western Himalayas, the researchers utilized remote sensing and field inventory data to assess biomass variability across different forest types. The results indicated an average above-ground biomass (AGB) of 190.5 tons per hectare, with corresponding carbon stock averaging 90.3 tons per hectare. They found that forests at higher elevations with cooler temperatures and moderate rainfall had higher AGB and carbon sequestration capacity. Moreover, minimal land-use change areas retained more biomass, highlighting the importance of preserving forest cover in mitigating climate change.

Similarly, Ahmed et al. (2020) evaluated the carbon sequestration potential of forests in northern Pakistan using satellite data and field surveys. The study reported an average AGB of 165.7 tons per hectare, with an associated carbon stock of 78.6 tons per hectare. The total carbon sequestration potential of the study area was estimated at 5,600 metric tons. The findings also revealed that forests in regions with stable precipitation and cooler climates had higher carbon sequestration rates, while areas with greater temperature variability showed reduced biomass accumulation. The authors emphasized the need for targeted conservation policies to enhance the carbon storage potential of these forests. he findings also revealed that forests in regions with stable precipitation and cooler climates had higher carbon sequestration rates, while areas with greater temperature variability showed reduced biomass accumulation. The authors emphasized the need for targeted conservation policies to enhance the carbon storage potential of these forests.

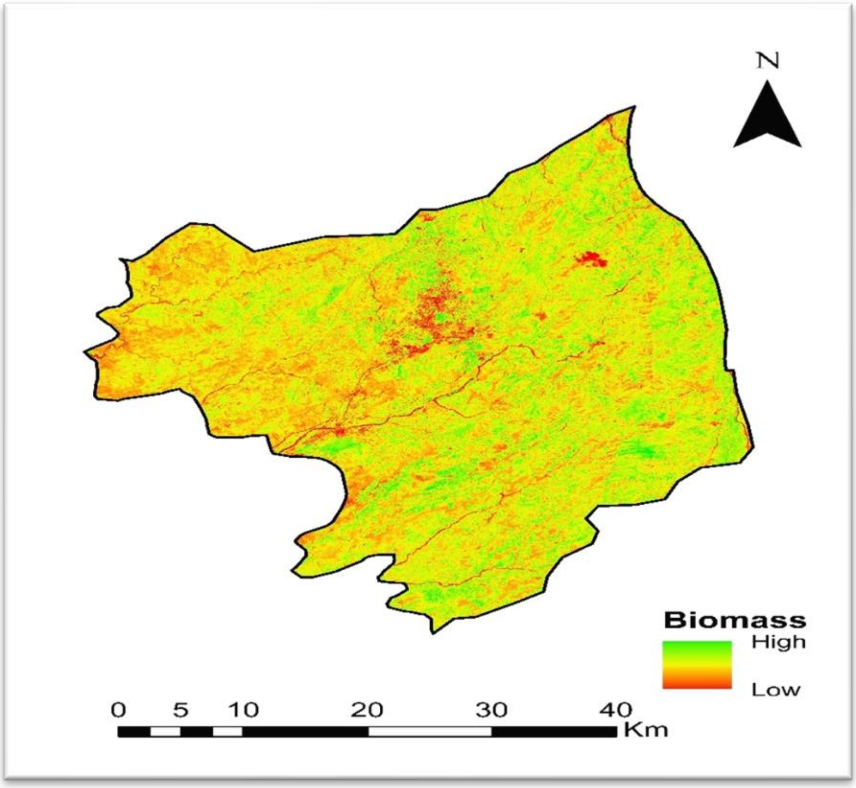

Figure 4.26: Estimated Biomass Map for Abbottabad

Table 4.4. Statistics of Biomass and Carbon Stock Estimation

Statistics	AGB(t/ha)	AGC(t/ha)	BGB(t/ha)	BGC(t/ha)	Total Biomass(t/ha)	Total Carbon(t/ha)	CO_2 e (t/ha)
Minimum	93.35	43.87	24.27	11.41	117.61	55.28	202.32
Maximum	265.02	124.56	68.9	32.38	333.92	156.94	574.41
Mean	5893.63	2770.01	1532.35	720.2	7425.98	3490.21	12774.18
Sum	178.6	83.94	46.43	21.82	225.03	105.76	387.1
St. Dev	44.12	20.74	11.47	5.39	55.59	26.13	95.63
St. Error	7.68	3.61	2	0.94	9.68	4.55	16.65

4.6 Sensitivity Analysis to analyze the impact of climate indicators on the Above Ground Biomass

The climate data layers for annual average precipitation, average minimum temperature, and average maximum temperature were prepared using the Inverse Distance Weighting (IDW) interpolation method, and corresponding maps were generated to visualize these parameters across the study area. These maps were then integrated into an Analytical Hierarchy Process (AHP) to create a sensitivity analysis map, identifying biomass areas most sensitive to climatic parameters.

The **annual average precipitation map** as shown in figure illustrates spatial variations in precipitation across the study area, ranging from 1266 mm to 1655 mm. The central region experiences moderate rainfall, while the eastern and southwestern parts receive higher amounts, as darker blue shades indicate.

The **average minimum temperature map** as shown in figure depicts the spatial distribution of minimum temperatures, which range from 7.65°C to -1.03°C. Warmer minimum temperatures (in red and orange) are predominant in the central and southern areas, while cooler temperatures (in green and blue) are confined to the northern regions, indicating potential frost risks.

The **average maximum temperature map** as shown in figure shows variations in maximum temperatures, ranging from 34°C to 41°C. The highest temperatures (in red) are recorded in the central and southern parts, whereas the northern regions have relatively lower maximum temperatures, as denoted by yellow and blue hues.

The **sensitivity analysis map** as shown in figure 4.25 offers a detailed assessment of how various regions within the study area respond to changes in key climatic parameters such as precipitation, minimum temperature, and maximum temperature. Created using the Analytical Hierarchy Process (AHP), this map integrates the three climate data layers, each contributing differently to the overall sensitivity of biomass in the region. The sensitivity levels are categorized on a scale from low (1) to high (5), represented by a gradient from green (low sensitivity) to red (high sensitivity).

Areas marked in red on the map indicate regions with high sensitivity, suggesting that biomass in these areas is more susceptible to changes in climatic conditions. These zones may face significant biomass variability due to fluctuations in temperature or precipitation, requiring more adaptive management practices. The presence of high sensitivity in the central and southern parts of the study area, as shown by red and orange colors, could be attributed to the combined effect of high maximum temperatures and moderate to high precipitation levels. These conditions may create a delicate balance where even slight climatic changes could significantly impact biomass production.

Conversely, areas in green represent regions with low sensitivity, where biomass is less affected by climatic changes. These regions, typically located in the northern and northeastern parts, may benefit from more stable climate conditions with less extreme variations in temperature and precipitation, resulting in more consistent biomass levels.

The sensitivity analysis highlights critical zones that require focused attention for climate adaptation measures. High-sensitivity areas may benefit from strategies such as improved water management, drought-resistant crop varieties, or enhanced soil conservation practices. Meanwhile, low-sensitivity areas might serve as relatively stable regions for sustainable biomass production under current climatic conditions.

By understanding these spatial variations in sensitivity, policymakers and resource managers can make more informed decisions, directing resources and interventions to the areas most at risk from climate variability and ensuring more resilient agricultural and ecological systems.

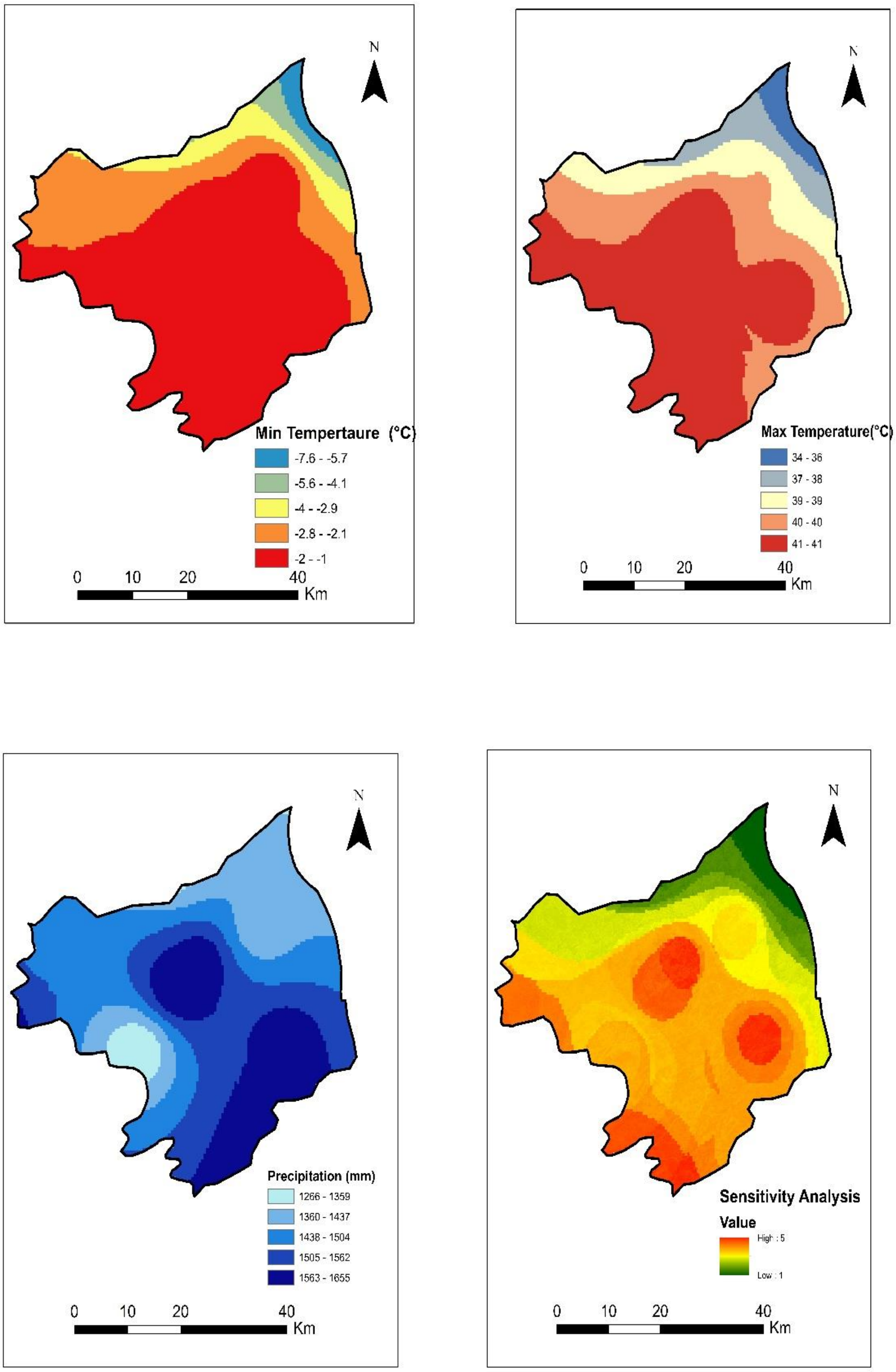

Figure 4.27. Sensitivity analysis maps showing biomass areas sensitive to climatic parameters.

Conclusion

The research on "Assessment of Above-Ground Biomass and Carbon Sequestration Potential in the Moist Temperate Forests of Abbottabad District" concludes that geospatial modeling and remote sensing techniques are effective in quantifying biomass and carbon sequestration potential. The study highlights a significant positive impact of afforestation efforts, with a 9% increase in forest cover in the study area. Analysis of carbon pools revealed an average contribution of 105.76 tons of carbon per hectare in 2022, with a total carbon stock of 4,745.68 metric tons for the region of interest. The forest in Abbottabad also demonstrated its importance in carbon dynamics, acting as a source of 2.2 metric tons/ha CO_2 equivalent over the period of 2011-2022, compared to its carbon sequestration potential of 0.6 metric tons/ha.

Additionally, sensitivity analysis showed that forests at higher altitudes, with lower temperatures and moderate rainfall, are less vulnerable to climatic changes compared to other areas. These findings emphasize the role of such forests in mitigating climate change and underscore the importance of targeted climate adaptation strategies to enhance carbon sequestration and improve forest resilience. afforestation efforts have positively impacted forest cover, with a 9% increase, and that forests in the region play a significant role in carbon dynamics. The total carbon stock was estimated at 4,745.68 metric tons, with an average contribution of 105.76 tons per hectare. The sensitivity analysis revealed that areas with high altitude, low temperature, and moderate rainfall are less vulnerable to climatic changes, while central and southern areas, marked in red, showed high sensitivity to temperature and precipitation fluctuations. These high-sensitivity zones may experience significant biomass variability, requiring adaptive management strategies such as improved water management and drought-resistant crops. Conversely, areas marked in green showed lower sensitivity, benefiting from more stable climate conditions and consistent biomass levels.The research recommends expanding the use of geospatial modeling to other forest types in Pakistan to build a comprehensive carbon inventory. Integrating these results into climate policies can further support forest conservation and carbon sequestration efforts at both local and national levels.

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Appendices

Appendix 1- Forest Inventory Data.

FID	grid_coor_x	grid_coor_y	Area	AGB (t/ha)	BGB (t/ha)
1	89.19517021	37.64450166	Abbotabad	30.74825	7.994545
2	89.18517021	37.64350166	Abbotabad	3.409615	0.8865
3	89.20517021	37.64350166	Abbotabad	2.079115	0.54057
4	89.20517021	37.64550166	Abbotabad	56.34455	23.45443
5	89.18517021	37.64550166	Abbotabad	65.24553	32.53211
6	90.40276069	37.68208978	Abbotabad	43.08017	11.20084
7	90.39276069	37.68108978	Abbotabad	12.58355	3.271723
8	90.39276069	37.68308978	Abbotabad	25.87597	6.727751
9	90.41276069	37.68308978	Abbotabad	33.01147	8.582981
10	90.41276069	37.68108978	Abbotabad	78.45335	38.53463
11	90.71669038	37.7774209	Abbotabad	156.2209	40.61743
12	90.72669038	37.7764209	Abbotabad	46.31012	12.04063
13	90.72669038	37.7784209	Abbotabad	66.54227	17.30099
14	90.70669038	3777842.09	Abbotabad	109.6117	28.49904
15	90.70669038	37.7764209	Abbotabad	53.79727	13.98729
16	90.04536915	37.81888874	Abbotabad	232.2558	60.38652
17	90.03536915	37.81788874	Abbotabad	86.1186	22.39084
18	90.03536915	37.81988874	Abbotabad	21.43035	5.571891
19	90.05536915	37.81788874	Abbotabad	134.1977	34.89139
20	90.05536915	37.81988874	Abbotabad	37.73455	9.810982
21	91.02987655	37.90313092	Abbotabad	62.79402	16.32645
22	91.01987655	37.90213092	Abbotabad	53.45059	13.89715
23	91.01987655	37.90413092	Abbotabad	54.67614	14.2158
24	91.03987655	37.90213092	Abbotabad	24.68912	6.419171
25	91.03987655	37.90413092	Abbotabad	90.345	44.75389
26	89.97211613	37.95308497	Abbotabad	68.00703	17.68183
27	89.98211613	37.95208497	Abbotabad	42.26499	10.9889
28	89.98211613	37.95408497	Abbotabad	63.92934	16.62163
29	89.96211613	37.95408497	Abbotabad	179.7804	46.74289
30	89.96211613	37.95208497	Abbotabad	212.0041	55.12106
31	89.36425213	37.99651996	Abbotabad	23.97239	6.232822
32	89.36425213	37.99851996	Abbotabad	20.05757	5.214967
33	89.38435213	37.99851996	Abbotabad	52.07169	13.53864
34	89.38425213	37.99651996	Abbotabad	37.38259	9.719474
35	89.37425213	37.99751996	Abbotabad	72.34427	18.80951

Appendix 2- Estimated AGB in Abbottabad District.

ID	Longitude	Latitude	Area	NDVI	AGB t/ha	AGC t/ha
1	891951.7021	3764450.166	Abbotabad	0.300705	239.006	112.3328
2	891851.7021	3764350.166	Abbotabad	0.275231	131.065	61.60055
3	892051.7021	3764350.166	Abbotabad	0.312257	229.123	107.6878
4	892051.7021	3764550.166	Abbotabad	0.380069	237.231	111.4986
5	891851.7021	3764550.166	Abbotabad	0.345877	265.016	124.5575
6	904027.6069	3768208.978	Abbotabad	0.307024	145.256	68.27032
7	903927.6069	3768108.978	Abbotabad	0.292094	170.145	79.96815
8	903927.6069	3768308.978	Abbotabad	0.228268	93.345	43.87215
9	904127.6069	3768308.978	Abbotabad	0.279251	163.023	76.62081
10	904127.6069	3768108.978	Abbotabad	0.293508	146.098	68.66606
11	907166.9038	3777742.09	Abbotabad	0.30513	176.594	82.99918
12	907266.9038	3777642.09	Abbotabad	0.302968	234.231	110.0886
13	907266.9038	3777842.09	Abbotabad	0.295889	119.173	56.01131
14	907066.9038	3777842.09	Abbotabad	0.336334	230.014	108.1066
15	907066.9038	3777642.09	Abbotabad	0.243924	189.356	88.99732
16	900353.6915	3781788.874	Abbotabad	0.284481	132.519	62.28393
17	900353.6915	3781988.874	Abbotabad	0.276956	149.187	70.11789
18	900553.6915	3781788.874	Abbotabad	0.217601	170.387	80.08189
19	900553.6915	3781988.874	Abbotabad	0.252902	156.786	73.68942
20	910298.7655	3790313.092	Abbotabad	0.333448	178.276	83.78972
21	910198.7655	3790213.092	Abbotabad	0.329835	244.498	114.9141
22	910198.7655	3790413.092	Abbotabad	0.354821	205.409	96.54223
23	910398.7655	3790213.092	Abbotabad	0.376049	238.167	111.9385
24	910398.7655	3790413.092	Abbotabad	0.294346	193.39	90.8933
25	899721.1613	3795308.497	Abbotabad	0.22742	113.278	53.24066
26	899821.1613	3795208.497	Abbotabad	0.299683	176.709	83.05323
27	899821.1613	3795408.497	Abbotabad	0.28227	216.247	101.6361
28	899621.1613	3795408.497	Abbotabad	0.259764	161.378	75.84766
29	893642.5213	3799651.996	Abbotabad	0.322175	184.378	86.65766
30	893642.5213	3799851.996	Abbotabad	0.296692	177.673	83.50631
31	893842.5213	3799851.996	Abbotabad	0.298774	159.382	74.90954
32	893842.5213	3799651.996	Abbotabad	0.216876	111.376	52.34672
33	893742.5213	3799751.996	Abbotabad	0.29694	155.921	73.28287

Appendix 3- Carbon Stock Estimated in ROI.

Statistics	AGB(t/ha)	AGC(t/ha)	BGB(t/ha)	BGC(t/ha)	Total Biomass(t/ha)	Total Carbon(t/ha)	CO_2 e (t/ha)
Minimum	93.35	43.87	24.27	11.41	117.61	55.28	202.32
Maximum	265.02	124.56	68.90	32.38	333.92	156.94	574.41
Sum	5893.63	2770.01	1532.35	720.20	7425.98	3490.21	12774.18
Mean	178.60	83.94	46.43	21.82	225.03	105.76	387.10
St. Dev	44.12	20.74	11.47	5.39	55.59	26.13	95.63
St. Error	7.68	3.61	2.00	0.94	9.68	4.55	16.65

Appendix 4- Land use and Land cover calculations of year 2011 and 2022.

2011			2022			
LULC	Area (ha)	Percentage	Area	Percentage	Area change	% change
Agriculture	25386.82	14	13779.55	0.7	-11607.28	-13.3
Bareland	16171.82	0.8	6168.79	0.3	-10003.04	-0.5
Forest	28475.37	15	44872.17	24	16396.80	9
Urban	6705.03	0.3	11226.30	0.6	4521.26	0.3
Vegetation	99633.81	55	96626.94	53	-3006.86	-2
Water	3796.71	0.2	7496.16	0.4	3699.45	0.2