ETHIOPIAN CIVIL SERVICE UNIVERSITY

DEPARTMENT OF URBAN LAND DEVELOPMENT AND MANAGEMENT

ENVIRONMENTAL MONITORING AND CONSERVATION OF URBAN GREEN SPACES USING LIDAR: APPLICATIONS IN FOREST MANAGEMENT, AND CARBON ASSESSMENT ADDIS ABABA THE CASE OF ENTOTO

BY
BIRUK SINTAYEHU BEKELE

A RESEARCH SUBMITTED TO THE DEPARTMENT OF URBAN LAND DEVELOPMENT AND MANAGEMENT, COLLEGE OF URBAN DEVELOPMENT AND ENGINEERING IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN LAND DEVELOPMENT AND MANAGEMENT

THESIS ADVISOR:

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MAY 2025

ADDIS ABABA, ETHIOPIA



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DECLARATION

This is to declare that the thesis entitled ‘‘Environmental Monitoring and Conservation Of Urban Green Spaces Using Lidar: Applications In Forest Management, And Carbon Assessment Addis Ababa The Case Of Entoto’’ submitted in partial fulfillment of the requirements for the degree of Master of Science in the college of Urban land development and engineering of, Ethiopian Civil Service University, is a record of original work carried out by me and has never been submitted to any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been duly acknowledged.

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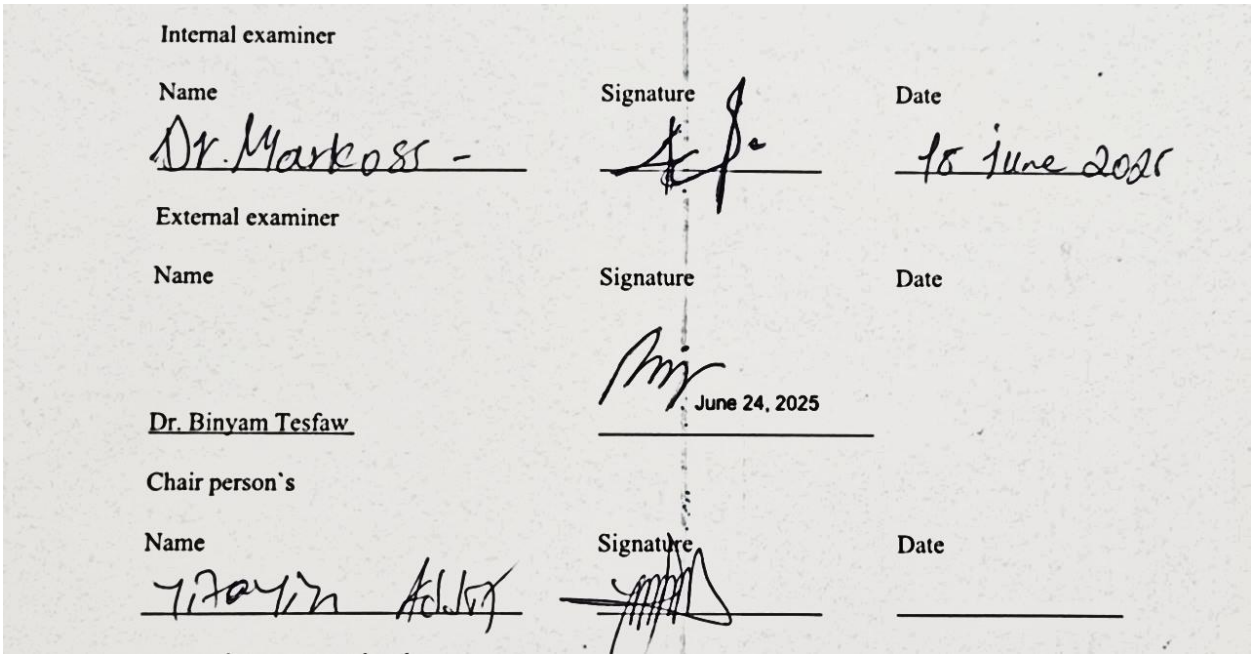
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List of Acronyms

3D	=	three-dimensional
2D	=	two- dimensional
ASPRS	=	American Society for Photogrammetry and Remote Sensing
CHM	=	Canopy Height Models
CO_2	=	Carbon Dioxide
DBH	=	Diameter at Breast Height
DEM	=	Digital Elevation Model
DSM	=	Digital Surface Model
DTM	=	Digital Terrain Model
FAO	=	Food and Agriculture Organization
GHG	=	Greenhouse Gas
GIS	=	Geographic Information System
GPS	=	Global Positioning System
GNSS	=	Global Navigation Satellite System
IMU	=	Inertial Measurement Unit
IPCC	=	Intergovernmental Panel on Climate Change
LIDAR	=	Light Detection and ranging
Mg C/ha	=	Megagram of Carbon per hectare
UGS	=	Urban Green Space
UHI	=	Urban Heat Index

Abstract

Urban forests play a vital role in climate change mitigation by serving as significant carbon sinks. This study focuses on estimating Above Ground Biomass (AGB) and carbon stock in Entoto Natural Park, located in Addis Ababa, using Light Detection and Ranging (LiDAR) technology. Field observations were collected from 471 systematically distributed sample plots, and LiDAR-derived Canopy Height Model (CHM) was utilized to build empirical models for biomass estimation.

The study found that the total AGB obtained from field observations was 609.46 Mg/ha, while the AGB estimated from LiDAR point cloud analysis was 605.99 Mg/ha, resulting in a minimal deviation of 3.47 Mg/ha (0.57% difference). The Root Mean Square Error (RMSE) for AGB estimation was calculated at 1.80 Mg/ha, indicating a high level of accuracy in LiDAR-derived estimates. Additionally, the carbon stock calculated from field measurements was 286.45 Mg C/ha, compared to 284.82 Mg C/ha from LiDAR data, with an RMSE of 0.85 Mg C/ha, further confirming the reliability of LiDAR technology for carbon stock assessments.

Results demonstrated a close agreement between LiDAR estimates and field data, indicating the potential of remote sensing in forest carbon monitoring. The findings underscore the effectiveness of LiDAR as a non-destructive, scalable, and accurate method for estimating biomass and carbon stock in urban forest settings. This approach can aid policymakers, environmental planners, and urban managers in implementing data-driven strategies for sustainable land use and climate resilience. Furthermore, the study contributes valuable insights into integrating geospatial technologies in environmental conservation, especially in developing countries like Ethiopia, where access to ground data and technological infrastructure can be limited.

Key words: LiDAR, Above Ground Biomass (AGB), Carbon Stock, Canopy Height Model (CHM), Urban Forests, Environmental Monitoring, Climate Change Mitigation.

CHAPTER ONE
1. INTRODUCTION

1.1 Background of the study

Climate is one of the most complex systems that we only partially understand, as it is characterized by significant spatial and temporal variability. Climate change is a natural aspect of the earth's variability, influenced by the interactions between the atmosphere, ocean, and land, along with fluctuations in solar radiation reaching the planet (National Environment Commission, 2011). The geological record provides substantial evidence of major climate shifts throughout the earth's history.

Environmental Monitoring is the practice of measuring and monitoring different aspects of an area's environment to determine the potential risks and impact it could have on various objects and material types. In addition to pests, different factors that are monitored include temperature, relative humidity, and light levels. (Harvard University, 2024) It is based mainly on the scientific, methodical observations of changes within our environment (J.F. Artiola, The Role of Environmental Monitoring in Pollution Science, 2019). In order to realize the interactions between natural phenomena and anthropogenic influences, researcher needs to observe the changes.

In the urban context, the term "green space" comprises parks, gardens, sports fields, children's playgrounds, forested areas, and other natural environments, and should include grassy areas as well as community gardens (Paoin & Pharino, 2024). Indeed, green space should also include the presence of green corridors, composed of paths, rivers, and canals.

Urban green spaces offer a multitude of ecosystem services that can address various urban challenges and enhance the quality of life for residents, particularly in terms of health (Michelle C. etal., 2018). Green spaces contribute to both physical and psychological health benefits by promoting physical activity, reducing stress, and advancing overall well-being. These areas, moreover, contribute to mental health by increasing opportunities for social interaction, strengthening community bonds, and fostering a sense of security (Lee & Mashewaran, 2011) coupled with a higher standard of living.

A fundamental work by Demuzere et al. 2014 exemplified the rapid accumulation of greenhouse gases in the Earth's atmosphere has led to quickly changing patterns of global

temperature and climatic conditions. Apart from causing disturbances in everyday activities and economic losses, these changes are expected to bring grave risks to safety, security, and public health (Demuzere et al., 2014)

Numerous definitions exist regarding what defines a forest. This discussion was prompted by a 1998 request from the United Nations Framework Convention on Climate Change (UNFCCC) Secretariat, facilitated by the Subsidiary Body for Scientific and Technological Advice (SBSTA) and the International Union of Forest Research Organizations (IUFRO) (Lund, 2014).

A forest is defined to be a land area dominated by tree vegetation. The widely accepted definition, at an international level, defines a forest as an area larger than 0.5 hectares, with trees taller than 5 meters and having a canopy cover of more than 10%, or trees that can reach these sizes in their natural range. In Nepal, the forested areas extend over an estimated 6,661,000 hectares, accounting for 44.74% of the country's total land area (Dr. Ananta Ram Bhandari, et al, 2020). Of the 118 natural ecosystems identified in Nepal, 112 (or 95%) are largely made up of forest. In addition, these forests also support a great number of organisms, with a total of 30,167 species, comprising 13,067 plant species and 17,097 animal species.

Ethiopia, has a very low level of urbanization 21.2% in 2019, is among the least urbanized but fast urbanizing countries in sub-Saharan Africa (Tsega, 2021). Addis Abeba is one of the rapidly urbanizing cities in Africa. However, empirical evidences on the impact of urbanization of the city on its peri-urban environment and livelihoods are scanty (Leulsegged Kasa, et al., 2016). In addition, in a coprehensive analysis by Woldemichael, and Teshome (2021), It is projected that by the year 2050, the worldwide urban populace will increase by 67.2%. The rampant proliferation of both population and urban landscapes significantly impacts the environment. Developing countries have experienced significant growth fueled by the movement of individuals from rural regions to urban centers, leading to the transformation of agricultural land into urban space. Recently, the challenges linked to uncontrolled urban development have become increasingly urgent (Woldemichael, Seifu & Teshome, Getinet, 2021).

In Addis Ababa, 68% of urban green spaces (UGS) are found in residential areas. These residential areas are further categorized into high-density mixed residence (16.7%), medium-density mixed residence (8.7%), and low-density mixed residence (42.6%) (Woldesemayat, 2021). As the city have higher population density (World Population Review, 2024); Higher population

densities often correlate with reduced UGS composition and increased fragmentation. This relationship is influenced by various factors, including urban planning, socio-economic conditions, and historical development patterns (Woldesemayat, 2021).

There is an increasing need for accurate information on carbon stocks in forests and trees at both national and global scales. This calls for the monitoring of the status and changes in carbon pools in forest ecosystems. (Barbara K. Haya, et al, 2023) Consequently, the measurement and estimation of carbon stocks, together with the changes that occur in these pools under various classes, become vital to activities involving carbon trading and marketing. This can be achieved only if clear and verifiable methodologies are applied, if uncertainties can be measured and if monitoring systems for carbon reserves can be developed in an efficient way. Carbon stock assessment is one of the critical initial phases in sustainable land use planning for reducing carbon emissions. Changes in carbon stock, driven by changes in land use, can either lead to emissions or sequestration of carbon (GeneneAssefa, 2013).

Remote sensing for environmental monitoring involves the analysis of data and images collected by sensors mounted on satellites and various platforms to gather information about specific targets on the Earth's surface or to observe relevant processes over time. It is crucial to note that remote sensing may not be suitable for every scenario, particularly in highly intricate monitoring situations (Curtarelli, 2020). In certain instances, this technique serves to enhance traditional monitoring approaches, while in others; it can entirely replace the necessity for field visits and associated laboratory or office analyses.

Some of Articles has pointed out that one of the most beneficial aspects of environmental monitoring by remote sensing is that many active satellite missions provide public and commercial data, as well as images with different spatial, spectral, and temporal resolutions (Trace X, 2024). The most notable of these missions include Landsat, operated by NASA; Sentinel, by the European Space Agency (ESA); and CBERS, a joint effort between Brazil and China. All these missions, altogether, provide historical series of images as standardized products in georeferenced archives, easily accessible to end users (Curtarelli, 2020).

The use of remotely sensed data in environmental monitoring has several advantages over the traditional approaches followed until recently. In contrast to point measurements taken at specific locations and usually characterized by a low frequency, remote sensing technology makes

possible continuous monitoring and mapping with both spatial and temporal perspectives. The overall process of environmental decision-making, therefore, where the monitoring of environmental changes and impacts is regularly carried out, can considerably be improved and enhanced by effective use of remote sensing data and techniques.

LiDAR, which stands for Light Detection and Ranging, has become a very important technology in the area of remote sensing and three-dimensional imaging. This technology measures distances using laser pulses and enables the creation of accurate models of the real world (Waykar, 2022). The beginnings of LiDAR technology date back to the early 1960s, coinciding with advancements in laser technology. Over the years, LiDAR has undergone significant development and has been widely adopted across various industries and fields of science (Wang et al., 2020).

Scholars has highlighted the significant advancements in LiDAR technology and its diverse applications in environmental monitoring, space-based observations, greenhouse gas sensing, and novel techniques for improved data acquisition and analysi (Singh, 2008). LiDAR data provides a much-improved level of accuracy and resolution compared to conventional sources of elevation data, including the National Elevation Dataset. Its unique capability to measure the elevation in the densely forested areas sets it apart from other techniques; this makes LiDAR extremely useful in terrains that have been difficult or expensive to assess (National Oceanic and Atmospheric Administration., 2012). This development is a substantial advance on previous sources of elevation data, bringing improved accuracy, higher resolution, and a more complete representation of topography in complex landscapes.

The study aims to consider the role of LiDAR technology in the oversight and preservation of urban green areas. This study will be carried out through an experimental methodology that includes data from the Entoto area in Addis Ababa. The work will commence by developing a 3D model of the area using LiDAR data, followed by analysis to appraise if it is an effective tool in showing the spatial relationship among diverse objects.

1.2 Statement Of The Problem

Urban growth of Addis Ababa has expanded more than sixfold in size between 2000 and 2020, sprawling into agricultural areas in all directions. Projections show that this will double in size again by 2050, both in urban and peri-urban areas within the basin (Hirpa, 2023). This rapid growth in urban areas mostly comes with a serious environmental impact, like the loss of green spaces (Birhane et al., 2020). In Addis Ababa, Ethiopia's capital city, urbanization has encroached into natural habitats and put pressure on urban green areas due to human activities (Hirpa et al., 2023). These green areas are important for ecological balance since they act as a home to different species and a carbon sink from the atmosphere to reduce the impacts of climate change.

In the realm of environmental monitoring and analysis, the accurate assessment of vegetation plays a crucial role in understanding ecosystems (Viera, 2023). Within this area of environmental management, numerous sources of geospatial data exist, each serving the specific objectives, scale, and scope of a project (Satapathy et al, 2008). A leading-edge method in this regard is remote sensing, which involves gathering information using any platform that can capture images, measurements, or signals from the Earth's surface or atmosphere. It gives tremendous insight into land cover, vegetation types, soil characteristics, water resources, climatic trends, pollution metrics, and many other critical environmental variables (Ghauri B.M, 2011).

Hyperspectral sensors capture a wide range of wavelengths across the electromagnetic spectrum, which is useful for identifying materials and detecting changes in vegetation health. However, they do not typically provide the precise elevation data that LiDAR does (Smith, 2024). LiDAR technology stands out for its ability to provide high-resolution spatial data critical for environmental research and monitoring. Its integration with other remote sensing technologies can enhance the overall quality and scope of data collected, making it an indispensable tool in addressing environmental challenges such as climate change, pollution, and natural resource management (Kolios, 2024).

1.3 Objectives

1.3.1 General Objectives

The main objective of the study is to use LiDAR technology for environmental monitoring and conservation of urban green areas, focusing on forest management, and carbon assessment in the Entoto area of Addis Ababa.

1.3.2 Specific objectives

1. To map the spatial distribution of urban green spaces in the area using LiDAR technology.
2. To assess the structural characteristics of vegetation, including canopy height and density, to support forest management.
3. To quantify the carbon sequestration capacity; by estimating above-ground biomass and canopy cover.
4. To analyze the correlation between vegetation structure—such as canopy height and density—captured through LiDAR data and its implications for biodiversity and ecosystem services in urban green spaces.

1.3.3 Research Questions

a) How can LiDAR technology be used to accurately map the spatial distribution of urban green spaces in the study area?
b) What are the structural characteristics of urban vegetation (such as canopy height and density) as derived from LiDAR data, and how can this information support sustainable forest management practices?
c) What is the estimated above-ground biomass (AGB) and canopy cover in the study area, and what do these values reveal about the carbon sequestration capacity of the urban green spaces?
d) How does vegetation structure, as captured by LiDAR, correlate with biodiversity and ecosystem services in urban green spaces?

1.4 Significance of The study

1.4.1 Policy

As a study on public health shows the existence of urban green space is crucial for enhancing biodiversity, improving air quality, and mitigating urban heat effects (Kondo et al., 2018). However, despite Addis Ababa having a green coverage of 37% of its total area, these spaces have not been adequately protected. Green space in urban areas is fading as a result to large-scale violation, including those committed by public sector entities (AACPPO, 2017). The final findings of this research can provide reliable facts that could be use full to support policies that give priority to preservation and expansion of urban green spaces.

1.4.2 Community

Public engagement in protecting and maintaining green areas is essential to ensuring their sustainability. However, violations of green spaces in Addis Ababa indicate a lack of awareness and enforcement (Eshetu et al., 2021). This study aims to highlight the potential of urban forestry in social wellbeing by giving thorough insight on its climate change impact, enhancing recreational spaces, and promoting environmental efficiency.

1.4.3 Academic

The study will contribute to urban ecology and forestry research by providing empirical data on the spatial distribution and structural characteristics of green spaces in Addis Ababa. LiDAR technology enables precise assessment of forest density, biomass, and overall vegetation health (Çakir et al., 2021). These findings can serve as a valuable academic resource for future studies on sustainable urban forestry, biodiversity conservation, and carbon sequestration in urban environments.

1.4.4 Local Government

By using LiDAR data, the research will help local government agencies with accurate information on forest, assisting in effective decision making regarding environmental conservation, resource allocation, and sustainable urban forest management. Also, the study's assessment of carbon sequestration capabilities in Entoto's forests can guide local and national efforts to reduce greenhouse gas emissions through improved urban forestry strategies.

1.5 Scope of The study

This study tries to explore the distribution, structure, and ecological role of urban green spaces in Addis Ababa, with a special focus on the Entoto area. Using LiDAR technology and GIS-based analysis, it aims to offer valuable insights into the health of urban forests, their biomass potential, and their contribution to carbon sequestration. By considering both spatial and thematic aspects, the research takes a comprehensive approach to understanding and evaluating these vital green spaces.

1.5.1 Spatial

The study is geographically limited to the city of Addis Ababa, specifically focusing on the Entoto area. Because Entoto have a higher ecological significance and extensive vegetation cover. Entoto is one of the city's largest urban forest reserves, making it a model case study for evaluating green space sustainability and biomass estimation. The spatial analysis will be done using the mapping of tree cover, variation of canopy height, and overall vegetation distribution using high-resolution LiDAR data. This localized focus will be best to produce new insights applicable not only to Addis Ababa but also to other urban environments with similar challenges.

1.5.2 Thematic

This study has a thematic scope of exploring urban green space management and conservation focusing on their structure, sustainability and policy implications. A major part of the research examines vegetation structure by mapping tree distribution, analyzing canopy height differences, and assessing vegetation density. These helps to have a clearer picture of the overall health and composition of urban forests.

Using high-resolution LiDAR data, the study aims to capture detailed structural characteristics of these green spaces with high accuracy. Another key focus is estimating above-ground biomass (AGB), which involves using LiDAR-derived measurements to calculate tree biomass. This is crucial for understanding the carbon storage capacity of urban forests, highlighting their role in mitigating climate change.

1.6 Limitations of the study

While the results of This study offer valuable insights into the potential of remote sensing in urban ecosystem monitoring, the research faced several limitations that are important to acknowledge. The most significant of these is the temporal mismatch between LiDAR data acquisition (2021) and field measurements (2025). Although an adjustment using average monthly growth estimates was applied, the potential variation in growth rates among different tree species and environmental factors introduces uncertainty in the final biomass and carbon calculations.

A primary limitation of the study was the variability in LiDAR data resolution and spatial coverage across the selected plots. Although LiDAR is known for its high precision in capturing three-dimensional vegetation structure, some areas experienced inconsistent point cloud densities due to factors such as terrain shadowing, sensor configuration, or minor gaps during data acquisition. Another limitation lies in the exclusive focus on above-ground biomass. While AGB constitutes a major portion of carbon stocks, other components such as below-ground biomass, soil carbon, and deadwood were not assessed due to data and methodological constraints. This narrows the scope of carbon stock estimation and may result in a conservative representation of the forest's total carbon sequestration potential.

Due to constraints in time, manpower, and resources, fieldwork was conducted on a limited number of plots. While these plots were carefully chosen to capture a range of urban green space types, a more extensive sampling strategy would have enhanced the robustness of the empirical models. The study also focused exclusively on above-ground biomass, excluding other significant carbon pools such as below-ground biomass (roots), soil organic carbon, and deadwood. This focus was primarily due to methodological limitations and the scope defined for this particular study. As a result, the total carbon sequestration capacity of the urban green spaces may have been underestimated, and the full carbon accounting potential remains unexplored.

Lastly, while LiDAR excels in structural mapping, it inherently lacks the ability to capture species-specific information or directly measure biodiversity. Consequently, the study was unable to explore ecological attributes such as species composition, functional diversity, or habitat quality, which are crucial for understanding the broader ecosystem services provided by urban green spaces.

CHAPTER TWO
2. LITERATURE REVIEW

2.1 conceptual definition

2.1.1 Environmental Challenges in Urban Areas

The rapid growth and concentration of human activities in urban areas have led to a growing recognition of these areas as critical sites for environmental challenges. Both local ecosystems and the health of the environment worldwide are greatly impacted by the land-use change, pollution, and climate change that cities greatly contribute to as they grow (Assefa, 2024). The interaction of these elements produces a complicated web of obstacles that policymakers and urban planners must overcome in order to support sustainable urban growth.

Air pollution is one of the most urgent problems in urban settings. Roughly 75% of greenhouse gas emissions worldwide are caused by cities (United Nations Environment Programme, 2024). High concentrations of automobiles and industrial operations lead to increased concentrations of pollutants like particulate matter and nitrogen oxides, which are extremely harmful to human health. Around 9% of deaths globally are attributed to air pollution, highlighting its importance as a public health emergency (Roser, 2024). Furthermore, 90% of city dwellers breathe polluted air, and urban areas frequently fall short of WHO air quality standards (United Nations Environment Programme, 2024).

Waste management is still a major problem in cities. Significant waste is produced as a result of the quick rise in population density, frequently surpassing the capacity of current disposal systems. Addis Ababa is one of many developing cities where solid waste is routinely neglected or disposed of incorrectly, resulting in unsightly litter and health risks from vector-borne illnesses (IJSRD, 2019).

These environmental issues are made more difficult by the phenomenon of urban sprawl. Cities' outward growth results in the destruction of natural habitats and agricultural land, which fragments habitats and reduces biodiversity (Birtukan Abebe et al., 2023). Urban areas' ability to lessen the effects of climate change is diminished as a result of landscape change, which also disturbs ecosystems. Additionally, urban sprawl makes people more dependent on their cars, which raises greenhouse gas emissions and makes traffic worse (Birtukan Abebe et al., 2023). The

Ethiopian Urban Green Space is at risk as a result of hap hazard urban expansion of major Ethiopian cities (Berhanu Keno Terfa, 2019).

2.1.2 What is Urban Green Space

Urban land use is a primary driver of environmental impacts on both local and global levels (Assefa, 2024). Defining urban green space is challenging because its meaning varies depending on the context. Broadly, urban green spaces include parks, gardens, street trees, wetlands, and other natural features within urban settings. These areas provide crucial ecosystem services such as air purification, climate regulation, and habitats for biodiversity (Frontiers in Public Health, 2022). According to the definition of European Environment Agency; urban green space refers to areas of vegetation within urban environments primarily designed for recreational purposes. It may also encompass suburban natural areas managed as urban parks. These spaces can vary in scale, ranging from green roofs and small pocket gardens to expansive urban parks. (European Environmental Agency, 2022).

Urban green spaces can range from areas with "natural surfaces" or "natural settings" to particular kinds of urban greenery, like street trees, and "blue space," which symbolizes water features like ponds and coastal areas. Urban green spaces typically include public parks, but they can also include private gardens, woodlands, children's play areas, non-amenity areas (like roadside verges), riverbank walkways, beaches, and more (Oliveira, 2016). There are numbers of Characteristics in order to Interpret UGS pointed out in a research done at Kuala Lumpur Malaysia; I.e. spatial arrangement (proximity to residences), ecological attributes (biodiversity), and social features (community engagement) and so on (Najihah, 2019).

2.1.3 Benefits of Urban Green Space

The many advantages that urban green spaces (UGS) offer to social cohesion, environmental sustainability, and public health are becoming more widely acknowledged. The advantages of UGS vary and are influenced by regional and local climate, management practices, and the types of vegetation present (M.F. Aronson et al., 2017). Numerous studies have established a strong link between access to urban green spaces and improved health outcomes. A comprehensive review highlighted that urban green spaces can enhance mental health by reducing stress, anxiety, and depression while promoting physical activity and social interaction.

❖ Mental Health

Numerous studies have documented the positive effects of UGS on mental health. Access to green spaces is associated with reduced levels of stress, anxiety, and depression. A study have highlighted that exposure to nature can increase psychological well-being through mechanisms such as relaxation and stress relief (Oliveira, 2016). UGS offers a natural setting that aids in stress reduction and emotional stability. According to research, being in green spaces can help people relax and maintain emotional stability by lowering cortisol levels, a hormone linked to stress (Chen, et al., 2021). Nature's soothing influence is especially helpful in urban areas where environmental stressors like pollution and noise are common.

Another crucial element of UGS's contribution to mental health is the idea of cognitive restoration. Natural settings help restore cognitive resources that have been depleted, claims the Attention Restoration Theory. Spending time in green areas improves cognitive function and attention span, which helps people recover from mental exhaustion (Chen, 2021). The negative effects of urban living on cognitive health are lessened by UGS, which offers a place for people to relax and mentally recharge. Maintaining mental health requires this cognitive restoration, particularly in high-stress urban settings (Oliveira, 2016) (Chen, 2021).

Exposure to small doses of greenery can provide micro-rejuvenating experiences that aid in mental recovery. To illustrate, individuals who are fortunate enough to have window views of perfect natural landscapes frequently demonstrate reduced stress and elevated moods, as compared to their counterparts without such views (Muhammad Mainuddin Patwary, et al., 2024). These short-lived restorative intervals are essential for safeguarding mental health in bustling metropolitan areas, where residents often confront daily pressures.

❖ Physical Health Outcomes

Urban green spaces (UGS) are essential for improving physical health because they encourage active lifestyles, enhance the environment, and offer social interaction opportunities. Among UGS's most important advantages is its capacity to promote physical activity. Studies consistently demonstrate that people who have access to parks, gardens, and other green spaces engage in more physical activity (Sreenivas, 2023). According to studies; walking, jogging, cycling, and sports are among the more common activities that take place in these natural

environments, and they can greatly reduce the risk of obesity and associated health problems (Oliveira, 2016). Living close to green spaces, has been linked to increased physical activity, which is associated with better cardiovascular health and a decreased risk of developing chronic diseases like diabetes and hypertension.

It also enhances the quality of the environment and thereby promote better health overall. The urban heat island effect is a common problem in urban areas, where heat is absorbed and retained by asphalt and concrete, raising temperatures. Because they provide shade and cool the surrounding areas, green spaces help lessen this effect. In addition to improving the enjoyment of outdoor activities, this temperature drop lowers the chance of heat-related illnesses during hot weather (Sreenivas, 2023). By removing carbon dioxide and filtering pollutants, UGS can also enhance air quality and lessen respiratory issues linked to poor air quality (Lee AC, 2015). Research has indicated that communities with easily accessible green areas typically have more cohesive social bonds among their inhabitants, potentially contributing to enhanced mental health and a feeling of inclusion (Michelle C. Kondo et al., 2018).

❖ **Environmental Outcomes**

The complex role that urban green spaces (UGS) play in fostering ecological balance, enhancing air quality, controlling temperatures, and managing storm water makes them essential for maximizing environmental benefits in urban settings (Kumar et al,. 2023). The incorporation of UGS is becoming more and more necessary as cities keep growing in order to lessen the negative consequences of urbanization. By releasing oxygen and absorbing carbon dioxide and other pollutants through the natural process of photosynthesis, plants serve as an efficient filter for urban environments (James Mulligan, 2023).

Apart from enhancing air quality, UGS are essential for controlling urban temperatures and reducing the impact of the urban heat island (UHI). Because of the abundance of heat-absorbing materials like concrete and asphalt as well as human activity, urban areas frequently experience higher temperatures (Marzieh Mokarram, 2023). In order to counteract this phenomenon, UGS offer shade and evapotranspiration, which can considerably reduce surface temperatures. It has been demonstrated that carefully positioned trees and other vegetation can lower the surrounding temperature by a number of degrees, improving the quality of life for locals (James Mulligan, 2023).

2.1.4 Principles of LiDAR technology

Light Detection and Ranging, or LiDAR for short, is a state-of-the-art remote sensing technology that, since its introduction in the 1960s, has greatly improved the field of gathering and analyzing spatial data (Wang et al,. 2020). Emitting laser pulses in the direction of a target and timing how long it takes for the reflected light to return to the sensor is the fundamental idea behind LiDAR. By precisely calculating distances, this time-of-flight measurement makes it possible to create intricate three-dimensional representations of the surveyed environment (Pyroistech, 2021). This process is governed by the following basic equation:

$$D = \frac{c.\Delta T}{2}$$

Where D is the distance to the object, c is the speed of light (roughly 300,000 km/s), and ΔT is the time it takes for light to reach the target and return. When it comes to mapping features within a specific area, this method offers greater precision and resolution than conventional remote sensing technologies like radar and sonar (Pyroistech, 2021).

A LiDAR system emits laser light in quick bursts, frequently at speeds of over 100,000 pulses per second. These pulses move in the direction of the target surface from the LiDAR sensor (Pyroistech, 2021). Different wavelengths of light can be released, but for terrestrial applications, the near-infrared spectrum is usually used.

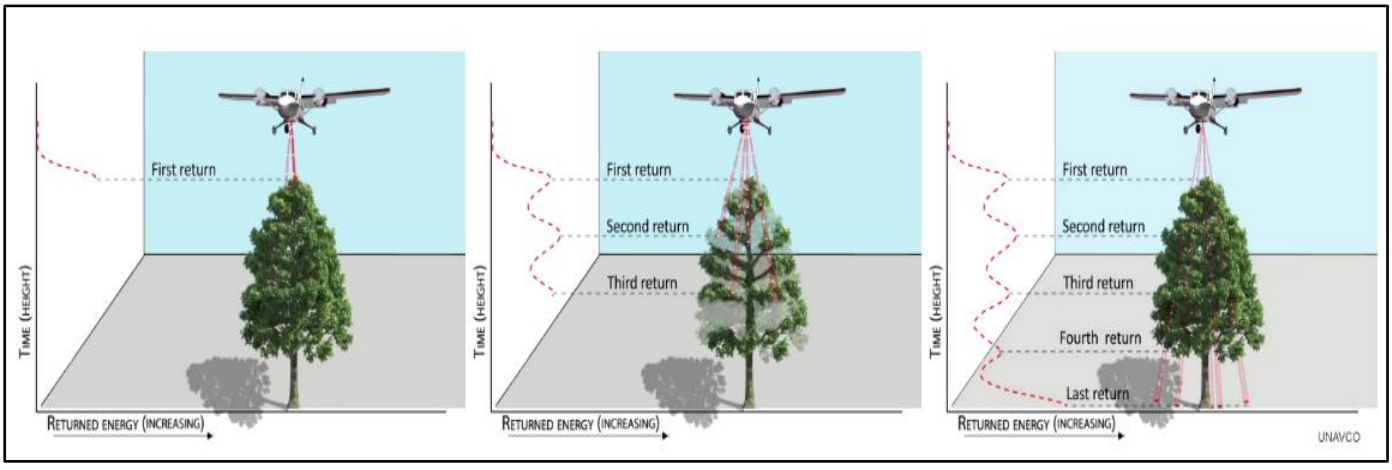


Figure 1: LiDAR scanning operating principle (UNAVCO, n.d.)

When compared to conventional techniques, LiDAR technology greatly improves remote sensing precision due to its sophisticated data acquisition capabilities, accuracy, and adaptability

in a variety of environments (Langhorst, 2024). Ground-based measurements, which are frequently used in traditional surveying methods, can be laborious and constrained by accessibility concerns, especially in rocky or heavily vegetated areas. By using laser pulses to record precise three-dimensional data about the Earth's surface, LiDAR, on the other hand, enables quick data collection over wide regions (LJA, 2024). With LiDAR's ability to achieve centimeter-level accuracy, this capability is especially helpful in applications like topographic mapping, which may find it difficult to accurately depict terrain features using more conventional techniques (He, 2020).

Because of its adaptability, LiDAR can be used in a variety of settings and landscapes, including dangerous areas where human surveyors could be in danger. Drones and other remote-controlled platforms with LiDAR sensors allow surveying teams to safely gather data from hard-to-reach locations without sacrificing security (STV Inc, 2023). This improved safety factor helps to increase the overall efficiency of the project by reducing interruptions and enabling work to continue without being delayed by dangerous situations.

2.1.5 LiDAR in mapping urban vegetation

LiDAR technology has become an effective tool for mapping urban vegetation, with many benefits over conventional techniques. Urban planning, environmental management, and the evaluation of ecosystem services all depend on the ability to capture high-resolution, three-dimensional data, which enables in-depth analysis of urban green spaces (Langhorst, 2024). Its capacity to swiftly and effectively gather high-resolution data; LiDAR systems are capable of producing dense point clouds that precisely depict the distribution and structure of urban vegetation by generating laser pulses and timing their return (Wang et al., 2020). Studies have shown, for example, how well LiDAR maps urban tree heights and canopy structures, which is vital information for planning and management initiatives related to urban forestry (Krzysztof Pyszny et al., 2020).

LiDAR technology allows vegetation data from several years to be compared, which makes temporal analysis easier. Changes in urban vegetation cover have been demonstrated by research using airborne LiDAR data from various time periods, highlighting trends like increases or decreases in tree populations brought on by urban development or the effects of climate change (Bladh, 2024). LiDAR data was used in one project to evaluate how urban vegetation affects heat mitigation and air quality. For urban planners hoping to improve public health through better green

space management, the study's mapping of tree cover and assessment of its distribution throughout the city offered useful information (Szostak, 2022). For urban planners and legislators to make well-informed decisions about the creation of green infrastructure and conservation measures, this capability is essential.

LiDAR mapping of urban vegetation makes a substantial contribution to the planning of green infrastructure. LiDAR assists in locating regions appropriate for the creation of new green spaces or the improvement of existing ones by offering comprehensive maps of vegetation density and distribution (Krzysztof Pyszny et al., 2020). This knowledge is essential for reducing the effects of urban heat islands, enhancing biodiversity in urban landscapes, and improving air quality. For instance, research has demonstrated that precise vegetation mapping can guide the creation of multipurpose green areas that support ecological processes and give locals access to recreational opportunities (Ramdani, 2013).

2.1.6 Applications of LiDAR in Environmental Monitoring

Light Detection and Ranging, or LiDAR, technology has become a game-changer in environmental monitoring, providing previously unheard-of capacities for gathering and analyzing data in a variety of ecosystems (STV Inc, 2023). By using laser pulses to produce incredibly detailed three-dimensional models of the Earth's surface, this remote sensing technique makes it easier to evaluate habitat quality (Darin J. McNeil, 2023), environmental changes (Unal Okyay, 2019), and conservation tactics (Tommaso Jucker et al., 2023). LiDAR has a wide range of uses in environmental monitoring (Viera, 2023), from urban planning (Smith, 2024) to forestry management (Çaki, 3D LiDAR Scanning of Urban Forest Structure Using a Consumer Tablet., 2021), and its expanding use is a reflection of the growing awareness of the need for accurate and effective data collection techniques in the face of environmental challenges.

- **forestry management**

The technology enables accurate assessments of forest structure, including tree height, canopy density, and biomass (Çakir et al., 2021). This information is crucial for understanding carbon stocks and supporting carbon sequestration efforts (GeneneAssefa, 2013). For instance, studies have demonstrated that LiDAR can effectively estimate tree volume and biomass in forested areas, which is essential for sustainable forestry practices and conservation initiative

(Bladh, 2024). By providing detailed insights into forest composition and health, LiDAR aids in making informed decisions regarding forest management and conservation strategies.

2.1.7 Role of Urban forests in carbon sequestration and climate mitigation

Urban forests are essential elements of urban ecosystems that contribute significantly to carbon sequestration and climate mitigation (GeneneAssefa, 2013). In addition to improving biodiversity, these green areas also play a major role in lowering atmospheric carbon dioxide (CO_2) levels. The process by which trees take in CO_2 from the atmosphere and store it in their biomass—trunks, branches, leaves, and roots—is known as carbon sequestration (Nowak et al., 2013). The significance of urban forests in addressing climate change is becoming clear as metropolitan areas continue to grow.

Urban forest carbon sequestration capacity depends on a number of factors, such as tree species, age, density, and health. Since they have more biomass, larger and healthier trees typically store more carbon (National Park Service, 2022). As an example, research indicates that urban trees in the US store roughly 643 million tonnes of carbon annually, with a sequestration rate of roughly 25–6 million tonnes (Nowak et al. (2013). In order to lessen the effects of climate change, this significant carbon storage is essential because it helps balance out greenhouse gas emissions from urban activities. Urban forests not only store carbon directly but also offer indirect benefits that help mitigate climate change. Because they provide shade and lessen the heat island effect, they help control urban temperatures and can reduce the amount of energy needed to cool buildings (Mejia et al., 2024). Healthy urban forests also enhance air quality by absorbing toxic gases and filtering pollutants, improving public health in general.

Urban forests' ability to mitigate climate change, however, depends on how well they are maintained. Planting native and diverse tree species that can withstand changing climate conditions is crucial, according to recent research (Mejía et al. (2024). This strategy guarantees that urban forests continue to be an efficient means of sequestering carbon in the face of climate change, while also improving biodiversity. Urban forests are indispensable assets in the fight against climate change (Nowak, 2013).

2.2 Theoretical review

2.2.1 Overview of Carbon Assessment

A crucial component of comprehending and addressing climate change is carbon assessment. It encompasses various methodologies aimed at quantifying the carbon emissions associated with different activities, products, and organizations. The importance of carbon footprint assessments, the methods used, and the consequences for sustainable development are all examined in this paper.

The carbon footprint is defined as the total greenhouse gas emissions (GHG) caused directly or indirectly by an individual, organization, event, or product, expressed as carbon dioxide equivalent (CO2e) (National Park Service, 2022). Carbon footprint analysis has become popular as a vital instrument for environmental management and policymaking. Various standards have been developed to guide organizations in measuring their carbon footprints. Notable among these are the ISO 14064 and the Greenhouse Gas Protocol for organizational assessments, as well as PAS 2050 and the Product Life Cycle Assessment (LCA) for product-related assessments. These guidelines offer methods for figuring out emissions from various sources, such as waste management, transportation, and energy use (Tao Gao, 2014).

The ability of carbon assessment to establish a baseline for tracking advancement is one of the main reasons it is essential for mitigating climate change. It becomes difficult to assess the efficacy of mitigation strategies in the absence of precise data on current carbon stocks. For example, the Intergovernmental Panel on Climate Change (IPCC) highlights that substantial CO2 emission reductions are required to keep global warming to 1 to 5°C, necessitating thorough carbon accounting procedures (IPCC, 2022). Policymakers can set reasonable goals for reducing emissions and create plans that improve carbon storage capacity by having a clear picture of how much carbon is stored in urban green spaces.

Finding possible areas for intervention is aided by an efficient carbon assessment. Knowing the carbon dynamics in green spaces can help inform conservation and restoration decisions in urban areas where land use changes frequently take place. Urban forests, for instance, are essential parts of climate mitigation strategies because research has shown that they can absorb significant amounts of CO2 (GeneneAssefa, 2013).

2.3 Empirical Literature Review

2.3.1 Case Studies of LiDAR in Urban Green Spaces

A notable example is a study conducted in Gorzów Wielkopolski, Poland, which utilized LiDAR data to map urban vegetation density. The research demonstrated LiDAR's ability to accurately capture the spatial distribution of various tree species within urban areas, enabling detailed evaluations of vegetation health and diversity (Krzysztof Pyszny et al., 2020). By examining the density and distribution of trees, urban planners identified areas where green infrastructure could be improved, enhancing ecosystem services like air quality regulation and carbon storage. This case highlights LiDAR's potential to support sustainable urban forestry by providing precise data for tree planting and maintenance strategies.

Another study in Melbourne, Australia, employed mobile laser scanning (MLS) LiDAR to assess the visibility of urban greenery. The findings revealed significant differences in greenery visibility across neighborhoods, exposing inequalities in access to green spaces (Liyu Tang et al., 2023). By combining LiDAR data with socio-economic indicators, the research offered valuable insights into how urban design impacts residents' access to nature. This approach is especially relevant for cities like Addis Ababa, where ensuring equitable access to green spaces is vital for enhancing community well-being and resilience to climate change.

LiDAR has proven effective in estimating biomass and assessing carbon emissions reductions in forestry initiatives. A recent study in Beijing employed airborne LiDAR data to compare various modeling techniques for estimating carbon emissions reductions (Qin Shize et al, 2023). The results showed that tree structural parameters derived from LiDAR data greatly enhanced the accuracy of carbon assessments compared to conventional methods. This research underscored the potential of LiDAR-based models as dependable tools for Certified Emission Reduction (CER) evaluations, showcasing their utility in large-scale afforestation efforts.

In Canada, a study examined the spatial relationships between urban vegetation and built infrastructure using LiDAR data. It found that higher tree densities correlated with improved ecosystem services, such as carbon storage and flood mitigation (Gülçin D. , 2020). These findings equipped policymakers with the tools to design green spaces that not only improve aesthetics but also play a critical role in climate adaptation strategies. This is particularly relevant for areas like

Entoto, where understanding the interplay between urban development and green spaces can inform conservation efforts to mitigate climate change impacts.

Recent research has focused on the impact of forest management practices on carbon stocks. A comparison of managed and unmanaged forests revealed that unmanaged forests had higher carbon stocks (Van Winckel et al., 2025). However, inconsistencies between field measurements and remote sensing models highlighted difficulties in accurately capturing these differences, primarily due to signal saturation issues. This underscores the importance of ongoing improvements to remote sensing techniques to better support their use in diverse management scenarios.

2.3.2 Relevant Local Studies

Identifying studies focused on urban management and carbon assessment at the local level proved to be quite challenging. The scarcity of research in this area highlighted a significant gap in the available literature. Furthermore, locating a local study that effectively integrated LiDAR technology with urban management practices and carbon assessment efforts was virtually impossible. This lack of comprehensive studies underscores the need for innovative research to bridge these knowledge gaps and advance the application of modern technologies like LiDAR in addressing urban environmental challenges.

An influential study titled "*Modeling Urban Dynamics and Carbon Sequestration in Addis Ababa, Ethiopia, Using Satellite Images*" by (Abdo, 2021), emphasizes the profound impact of land cover change (LCC) on carbon sequestration and its broader implications for global environmental change. The authors highlight that the transition of forests and grasslands into urbanized areas significantly diminishes the landscape's capacity to sequester carbon, thereby exacerbating environmental challenges. The study further asserts that advancements in GIS and remote sensing technologies have revolutionized the ability to monitor, evaluate, and analyze LCC patterns with greater precision, enabling researchers and policymakers to better understand and mitigate the environmental consequences of urban expansion (Abdo, 2021).

Another research paper explores the contribution of urban forests to carbon emission reduction in Addis Ababa, Ethiopia (Habtamu, 2022). It presents several key arguments and claims: Firstly, urban forests in Addis Ababa play a vital role in carbon sequestration and the

mitigation of climate change. The carbon sequestration potential of these urban forests is on par with, or even exceeds, that of certain natural forests and other urban forests worldwide. Furthermore, the paper highlights the importance of conserving and effectively managing urban forests to maximize their capacity for carbon sequestration and to support broader climate change mitigation efforts (Habtamu, 2022).

The Study titled "*Sustainable Forest Management and Forest Products Industry in Ethiopia*" provides a comprehensive analysis of the current state of forest management practices in the country. It examines Ethiopia's Proclamation on Forest Development, Conservation, and Utilization No. 1065/2018, which classifies forests based on ownership and management objectives (Rawat, 2021). The report highlights the importance of participatory forest management approaches that actively involve local communities in conservation initiatives. Such collaborative efforts are deemed critical for expanding forest cover and enhancing carbon sequestration capacity, particularly in urban areas like Addis Ababa. The findings underscore the potential of combining community engagement with advanced technologies, such as LiDAR, to develop more effective conservation strategies. By integrating these approaches, it is possible to address both ecological and socio-economic challenges, fostering sustainable urban forest management while promoting environmental and community well-being.

A study titled *"Monitoring Environmental Conditions for Urban Trees Plantation and Growth Using IoT"* (Wakjira, 2020) underscores the pivotal role of technology in the effective management of urban green spaces. While the research primarily delves into the applications of IoT, it highlights the importance of real-time monitoring systems as a powerful complement to LiDAR-based data collection. By integrating these technological approaches, researchers can achieve a more holistic understanding of the environmental variables that influence the growth and health of urban trees. This comprehensive perspective not only improves management practices but also strengthens efforts to maximize carbon storage capacity and foster sustainable urban forestry initiatives.

2.4 Research Gap

Analysis of green space is critical for long-term environmental protection, particularly in rapidly urbanizing regions like Addis Ababa. Existing research on urban forest management and environmental conservation is primarily based on traditional field surveys, which, while valuable, are frequently time-consuming, labor-intensive, and limited in spatial scope. The use of remote sensing techniques for mapping and analyzing green spaces is overlooked. This limitation reduces the ability to make informed decisions about conservation strategies, carbon sequestration potential, and the long-term viability of urban green spaces.

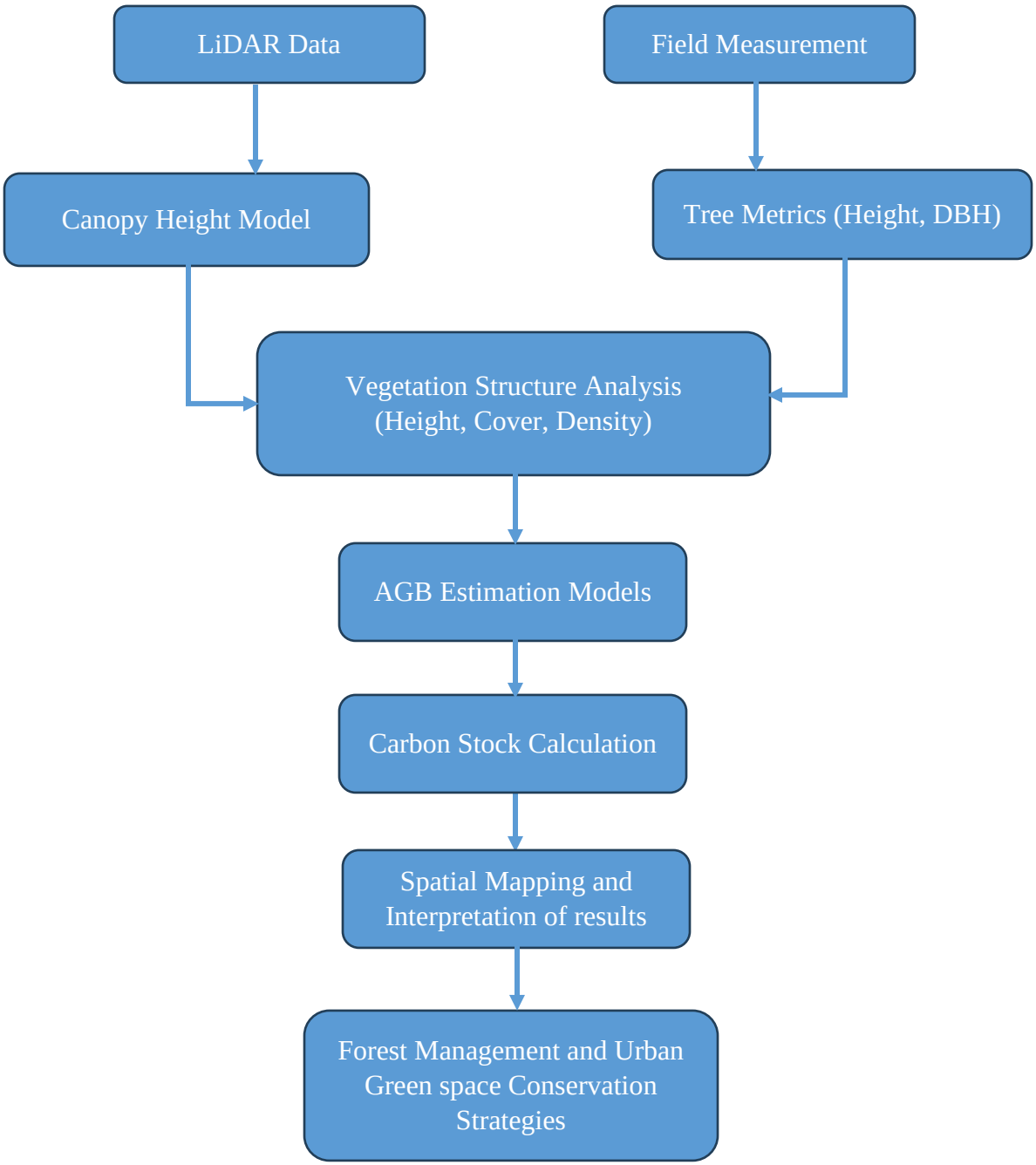
The application of LiDAR in urban forest monitoring in Ethiopia remains underexplored, with very few studies utilizing its full potential for assessing Above-Ground Biomass (AGB) and evaluating the condition of urban green spaces. Furthermore, there is limited research integrating LiDAR-based assessments with carbon sequestration analysis, which is essential for understanding the role of urban forests in mitigating climate change. Additionally, there is a lack of comprehensive methodologies that leverage machine learning models and empirical approaches to enhance biomass estimation accuracy, particularly in the context of Entoto's urban forest.

The absence of a standardized framework for LiDAR-based green space monitoring in Addis Ababa presents a critical research gap, leaving policymakers and urban planners without the necessary data to implement effective conservation and management strategies. This study seeks to address these gaps by utilizing LiDAR technology for detailed urban green space mapping, incorporating advanced analytical techniques to quantify biomass, and providing empirical data to support sustainable urban forestry initiatives.

2.5 Conceptual Framework

LiDAR technology serves as the basic data for generating high resolution Canopy Height Models (CHM), which provide critical data on the vertical structure of vegetation in urban forests. These CHMs are then used to estimate Above Ground Biomass (AGB). By applying localized allometric equations tailored to the unique species composition and canopy structure of urban green spaces. Accurate biomass estimations derived from CHMs are further utilized to asses carbon sequestration and climate change mitigation.

Conceptual Framework



CHAPTER THREE
3. RESEARCH METHODOLOGY

The study employs a research methodology that combines conventional ecological assessment techniques with cutting-edge remote sensing technology to offer a thorough framework for monitoring urban green spaces. Using Light Detection and Ranging (LiDAR) technology, this method seeks to map and examine vegetation density, carbon storage, and general ecosystem health in Addis Ababa's urban setting, with an emphasis on the Entoto neighborhood.

3.1 Discription of study area

Entoto, located in Addis Ababa, Ethiopia, serves as an important study area for the research. Entoto's geographical coordinates are approximately 9°05'31"N latitude and 38°46'08"E longitude, placing it on the southeastern slopes of the Mountains. This area covers approximately 2,300 hectares (23 km²) and has altitudes ranging from 2,600 to 3,100 meters above sea level (BirdLife International, 2025). Entoto's elevation and geographic features contribute to its distinct ecological characteristics, making it an ideal location for researching urban green spaces and their role in carbon sequestration.

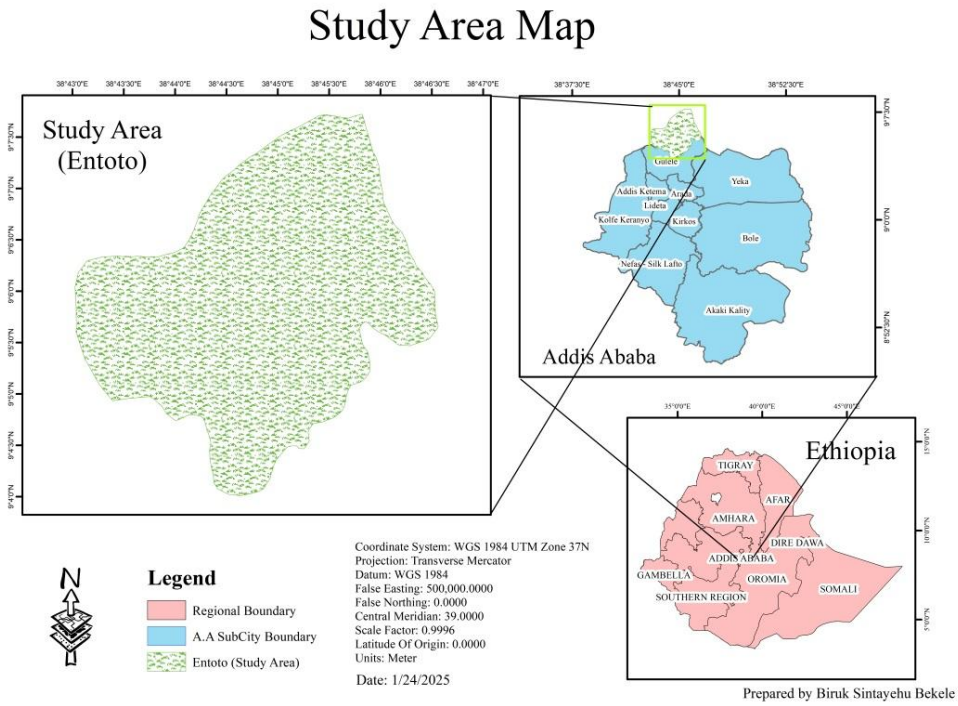


Figure 2:- Study Area Map of the Research

Entoto's climate makes it even more appropriate for carbon assessment research. The average annual temperature in the area is about 14°C, and there is about 1,200 mm of rainfall (Wikipedia, 2024). These climate variables affect carbon uptake rates by changing the vegetation growth patterns in the region. A wide variety of tree species may be found in Ethiopia's Entoto region, with Juniperus procera being the most common. This species' dominance and ecological significance in the local ecosystem are demonstrated by the fact that it makes up about 90.3% of the woody vegetation in the area (Ergua Atinafe et al., 2020). Other noteworthy species that add to the floristic diversity are Rosa abyssinica and Eucalyptus globulus, which are both non-native but have been planted extensively in the area (Ergua Atinafe et al., 2020).

Over 600,000 native trees, including Maytenus arbutifolia, and a variety of shrubs, including Bulleia polystachya, have been planted as part of the Entoto Natural Park program to restore indigenous flora in addition to the dominating species (Ethiopian Heritage Trust, 2023). Restoring water flow, halting soil erosion, and enhancing biodiversity are the three main objectives of this restoration project. The significance of indigenous species in preserving natural equilibrium and improving urban carbon sequestration capacities is underscored by the current conservation initiatives (Ethiopian Heritage Trust, 2023). Effective environmental monitoring and conservation efforts depend on an understanding of the biological roles and composition of tree species in places like Entoto, as urbanization continues to affect natural spaces.

Its close proximity to Addis Ababa makes it a key location for urban environmental monitoring. With the rapid expansion of Ethiopia's capital, preserving and managing urban green spaces, such as those in Entoto, has become increasingly important. Urbanization presents serious challenges to these areas, including habitat fragmentation and degradation (Berhanu Keno Terfa et al., 2019). As a result, leveraging advanced technologies like LiDAR in forest management can offer critical insights for policymakers and conservationists, aiding in the protection of these essential ecosystems while maximizing their role in promoting urban sustainability. The Entoto study region in Addis Ababa represents a unique fusion of historical legacy, ecological significance, and urban development issues. Using cutting-edge technology like LiDAR, this study aims to highlight the vital role of efficient environmental monitoring and conservation methods. By doing this, it hopes to advance our knowledge of the dynamics of carbon in urban forests and support larger projects for Ethiopia's sustainable urban growth.

3.2 Research paradigm and research design

❖ **Research paradigm**

The study requires a clear research design and paradigm that complements the goals of evaluating urban green spaces and their function in dealing with carbon. A pragmatic research paradigm is well-suited to the study. This paradigm is distinguished by its emphasis on workable answers to actual issues, stressing the combination of multiple approaches to tackle intricate environmental problems. In this regard, a practical strategy that blends quantitative data collection with qualitative insights from ecological management practices is demonstrated by the use of LiDAR technology for monitoring urban green spaces and evaluating carbon stocks.

The foundation of pragmatic research is the conviction that knowledge is best acquired by combining empirical observation with real-world application. This is especially important for environmental monitoring since many interconnected factors affect ecosystem dynamics. Researchers can obtain high-resolution spatial data using LiDAR technology, which provides vital details about the distribution of biomass, vegetation structure, and potential for carbon sequestration in urban environments (David B. Lindenmayer, 2010). Developing successful conservation plans that address the particular difficulties posed by urban settings requires this kind of data.

It also promotes cooperation between local communities, scientists, and policymakers, among other stakeholders. This cooperative strategy is essential for effective environmental management because it encourages active participation in conservation initiatives and a common understanding of the ecological values at risk. Participating in carbon assessment projects, for example, not only improves data accuracy but also increases public awareness of the value of urban green spaces in reducing climate change (Wang et al. (2023).

The pragmatic paradigm supports mixed-methods research. This may include combining quantitative LiDAR data with qualitative assessments from stakeholder interviews or community surveys in the context of your study. A deeper understanding of the ecological and social conditions in which urban green areas function is made possible by this approach. It provides information on how locals perceive the value of these places, which may be used to inform conservation and management policies.

In determining the results of research, the pragmatic paradigm acknowledges the importance of context. Land use change, rapid urbanization, and socioeconomic constraints provide particular issues for Addis Ababa and other urban areas (Birtukan Abebe et al., 2023). Researchers might modify their approaches to address particular issues while maintaining flexibility in response to evolving conditions by adopting a pragmatic approach. As environmental conditions change over time, this adaptability is essential to making sure conservation methods continue to be effective.

❖ Research Design

The research design for the study uses quantitative methods. This method approach will allow for a thorough examination of urban green spaces, focusing on their ecological functions, particularly in carbon sequestration and biodiversity conservation. The research will use LiDAR technology to provide high-resolution spatial data that can inform effective urban forest management practices in Addis Ababa.

It relies on LiDAR data to evaluate the structural characteristics of urban green spaces in Entoto. This method uses airborne laser scanning to create detailed three-dimensional (3D) models of vegetation, which can then be analyzed to determine tree height, canopy cover, and biomass density. Previous studies have shown that LiDAR is effective for accurately mapping urban vegetation and assessing its ecological functions (Pyszny, 2020). The collected data will be processed with specialized software to generate Digital Elevation Models (DEMs) and Canopy Height Models (CHMs), which will serve as the foundation for further carbon stock analysis in these green spaces (Wang et al., 2020).

To ensure a thorough analysis, spatial analysis techniques will be used in conjunction with Geographic Information Systems (GIS). This enables the integration of LiDAR-derived data with other spatial datasets, such as land use maps and socioeconomic indicators. By analyzing these layers together, the study can pinpoint areas where urban green spaces are most effective in providing ecosystem services and where additional interventions may be required. For example, GIS can aid in visualizing connectivity between green spaces and assessing their potential role as wildlife corridors or buffers against urban heat islands

3.3 Data type collection and analysis techniques and procedure

3.3.1 Data Collection and Data Source

The study will primarily use high-resolution LiDAR data acquired from Ethiopian Space and Geospatial Institute (SSGI) on urban vegetation in the Entoto area using the TerrainMapper-2 Sensor. This data will be supplemented with ground-based surveys to counter validate the LiDAR measurements. Using this method, the researchers hope to quantify carbon sequestration potential in Entoto's urban forests, informing conservation strategies that are consistent with climate change mitigation goals.

3.3.2 LiDAR data Acquisition

An airborne LiDAR survey was carried out over the study area in 2022 using a Leica Terrain Mapper 2 sensor mounted on a CARAVAN/Beechcraft aircraft. The Terrain Mapper 2 system collects LiDAR, imagery, and GNSS data, which are stored in mass memory (MM). To process these datasets using Leica HXmap, they must first be transferred to a workstation computer or an external hard drive. The survey was conducted under leaf-off conditions to enhance ground penetration, achieving an average point density of 8 points per square meter. Processing LiDAR data and aerial imagery requires high-performance workstations; for this research, Dell workstation equipped with a 64 GB RAM processor will be utilized, in order to handle the computational demands efficiently.

3.3.3 Ground Truthing and Validation

❖ **Height Estimation using DBH (Allometric Equation)**

These equations express tree height as a function of DBH, often using a power-law or logarithmic relationship. A commonly used model is $H=a\times DBH^{b}$, where H represents the tree height, DBH is the diameter at breast height, and a and b are species-specific coefficients obtained through regression analysis. Another widely applied model is the logarithmic equation H=a + b× ln (DBH), which accounts for the natural tendency of trees to reach a maximum height at larger diameters.

❖ **Use of GCP**

Ground truthing and validation are essential steps in the methodology to ensure the accuracy and reliability of data derived from LiDAR technology. Ground truthing entails the collection of field data, which is used to verify and calibrate the information obtained through remote sensing. This process often involves the establishment of control points using high-precision GPS devices, which contribute to improved geospatial accuracy. By providing a benchmark for comparison, ground truthing enhances the credibility of the LiDAR-derived models.

In the context of Addis Ababa, where urban green spaces are increasingly threatened by rapid urbanization, effective monitoring has become crucial for informed decision-making and the development of sustainable conservation strategies. The integration of Ground Control Points (GCPs) plays a pivotal role in this process, as it enables researchers to validate LiDAR-derived data by comparing it with actual ground measurements. This validation provides a critical benchmark for assessing the accuracy of the point clouds generated by LiDAR systems. By analyzing the locations of GCPs and their corresponding positions in the LiDAR data, researchers can identify and rectify any discrepancies, thereby enhancing the reliability and fidelity of spatial analyses conducted on urban green spaces (U.S. Geological Survey. (n.d.)).

3.3.4 Lidar Data Processing techniques and procedures

❖ **Software**

LiDAR-based 3D modeling is a process that utilizes both software and material resources to create three-dimensional models. In terms of software, LB3DM (LiDAR-based 3D Modeling) requires specialized tools for data collection, analysis, and reporting, as well as Geographic Information System (GIS) software for mapping and visualization. The software solutions used for LB3DM include licensed programs such as Esri ArcGIS, ArcScene, HxMap, Inertia Explorer, Mission Pro, and Flight Pro, which are employed for mapping, spatial analysis, and data management. Additionally, Bentley MicroStation and TerraScan software are used for 3D modeling and visualization of infrastructure.

Leica HxMap

Leica HxMap is an advanced software solution specifically developed for the processing and analysis of geospatial data, with a particular focus on data collected through airborne LiDAR and photogrammetry systems. Created by Leica Geosystems, a renowned leader in geospatial measurement and mapping technologies, this software provides powerful tools for managing, visualizing, and processing high-resolution geospatial datasets. Leica HxMap is widely utilized across various industries and applications, including urban planning, environmental monitoring, forestry, and infrastructure management. Its robust capabilities enable professionals to generate accurate and actionable insights, making it an indispensable tool for decision-making and strategic development in geospatial projects (Leica Geosystems. (n.d.)).

Its capacity to streamline the post-processing workflow, which is essential when handling large datasets commonly, associated with urban green space assessments. The software enables rapid data ingestion, quality control, and processing, significantly reducing the time needed to transform raw LiDAR data into actionable outputs such as digital surface models (DSMs), orthophotos, and 3D city models (Leica Geosystems. (n.d.)). This efficiency is particularly advantageous in a dynamic urban setting like Addis Ababa, where timely information is crucial for decision-making in forest management and carbon assessment. By facilitating quicker updates and analyses, HxMap allows researchers to respond more effectively to changes in urban green spaces and implement conservation strategies based on the most current data.

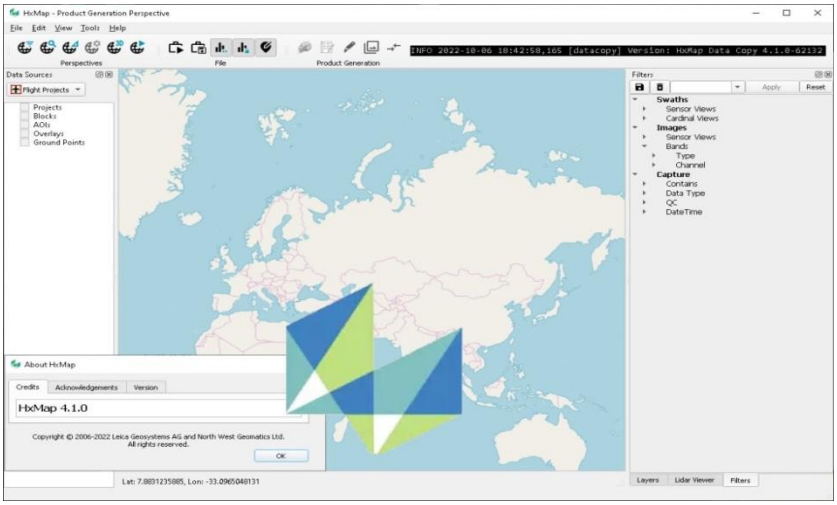


Figure 3:- HxMap 4.4 User Interface

TerraSolid

TerraSolid is a comprehensive desktop software suite developed by TerraSolid Ltd., designed primarily for processing point cloud data. It caters to the specialized needs of geospatial, engineering, operational, and environmental professionals, providing advanced tools to meet their demanding requirements. The software operates in conjunction with either Bentley Systems or the Spatix platform, which must be installed as a prerequisite for TerraSolid to function effectively. This integration ensures seamless performance and compatibility with the chosen platform, making TerraSolid a powerful solution for a wide range of applications (TerraSolid. (n.d.)).

TerraSolid offers a suite of specialized software tools designed for processing and analyzing LiDAR and photogrammetric data, widely used in industries such as surveying, forestry, urban planning, and infrastructure development. Key products include TerraScan for LiDAR point cloud classification and filtering, TerraModeler for surface modeling and volume calculations, and TerraPhoto for orthophoto production and image processing. Additional tools like TerraMatch for LiDAR data calibration and TerraSurvey for field data validation further enhance the software's capabilities. Known for their precision, efficiency, and ability to handle large datasets, TerraSolid products integrate seamlessly with CAD platforms like MicroStation, providing a comprehensive solution for geospatial data processing. (TerraSolid. (n.d.)).

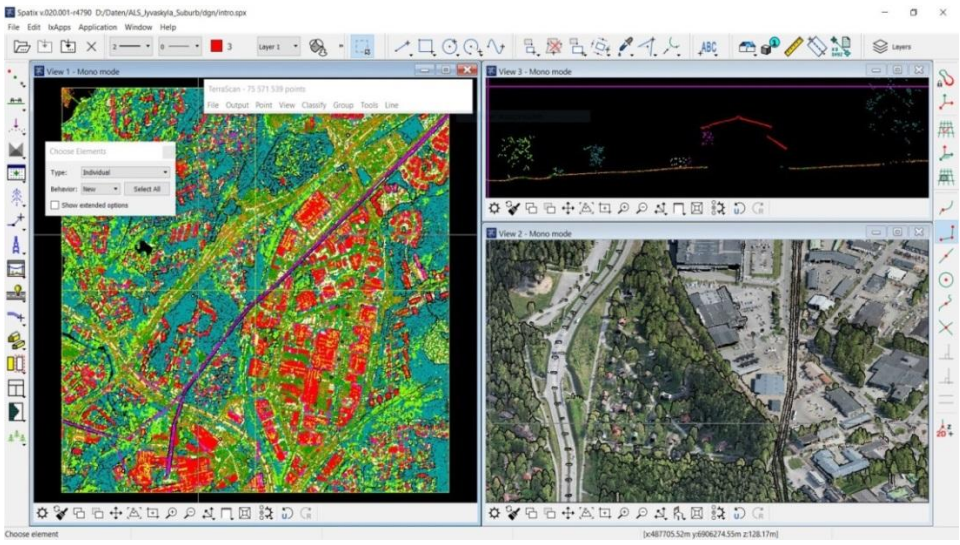


Figure 4:- Terra Solid User Interface **(TerraSolid. (n.d.))**

Cloud Compare

CloudCompare is a 3D point cloud (and triangular mesh) processing software. It has been originally designed to perform comparison between two dense 3D points clouds (such as the ones acquired with a laser scanner) or between a point cloud and a triangular mesh. It relies on a specific octree structure dedicated to this task. Afterwards, it has been extended to a more generic point cloud processing software, including many advanced algorithms (registration, resampling, color/normal/scalar fields handling, statistics computation, sensor management, interactive or automatic segmentation, display enhancement, etc.).

In this study, canopy height models (CHMs) were obtained using airborne LIDAR data to assess the urban green spaces of Entoto. CHM represents the height of the vegetation by calculating differences in digital surface models (DSMs), including differences in tree awnings and other features on the ground, as well as differences in the digital model of topography (DTM). Lidar Cloud was handled with CloudCompare, non-ground Points were classified to create DSMs, and ground points were used to retrieve DTMs. After ensuring the correct classification of CHM, it was calculated using the CHM = DSM -DTM equation. Certified CHM was exported in the appropriate format for detailed analysis with GIS and statistical software. This CHM serves as an important entry for assessing biomass and monitoring urban forests, providing valuable information on canopy structure and vegetation distribution.

3.3.5 processing workflow

Raw LiDAR data will be processed using HxMap, TerraScan, and MicroStation software to ensure accurate feature extraction and classification. The workflow includes point classification into ground and non-ground categories, digital elevation model (DEM) interpolation, and noise filtering. The classification process will effectively distinguish ground points from vegetation and building features. Manual classification will enhance precision, particularly for creating high-quality 3D models of vegetation.

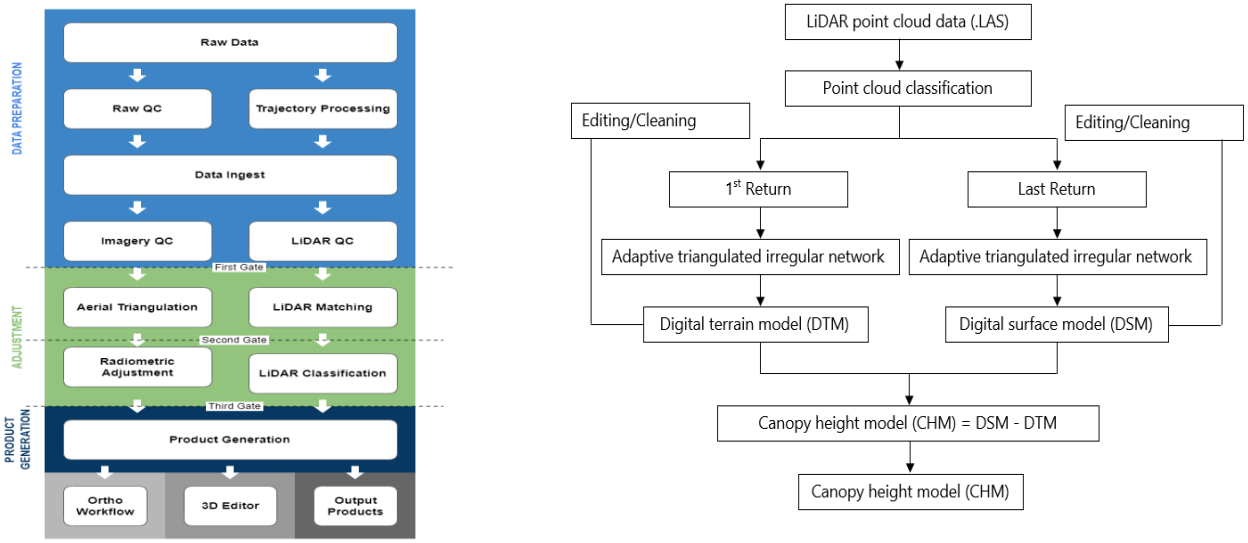


Figure 5:- Schematic display of processing flow of LiDAR system (Leica Geosystems. (n.d.)) (Omar Hamdan et al., 2015)

In leveraging LiDAR technology for environmental monitoring and the conservation of urban green spaces, a detailed and methodical approach to data processing is paramount. The process begins with validating the quality of trajectory data collected during LiDAR flight operations. This validation step is essential to guarantee the accuracy and reliability of all subsequent analyses. Following validation, the raw LiDAR data comprising Global Navigation Satellite System (GNSS) data, flight logs (including parameters such as pressure, temperature, and altitude), and Inertial Measurement Unit (IMU) data will be ingested into HxMap software. This software is specifically designed to apply necessary calibration settings for cameras or LiDAR sensors and to conduct radiometric corrections. Furthermore, it performs internal georeferencing, ensuring precise alignment of the data with geographic coordinates. The output from this phase will include processed LiDAR data in LAS format, accompanied by metadata that adheres to geospatial standards.

Following the initial processing, a project block will be created within HxMap to define the reference coordinate system and projection parameters. For this study, the WGS 84 datum and UTM Zone 37N projection will be adopted, accompanied by an ellipsoidal height system. This selection ensures accurate spatial representation of the geographical features in Entoto, as supported by (Michal Gallay et al., 2013). Subsequently, LiDAR matching will be performed to address minor offsets between flight strips or sessions. The HxMap LiDAR matching tool will be

utilized to align point clouds, ensuring data consistency and improving the overall quality of the dataset.

Advanced processing will involve leveraging additional modules within MicroStation V8, including TerraScan, TerraPhoto, and TerraModel. TerraScan serves as a comprehensive tool for effectively managing point cloud data. It supports processes such as classification, visualization, and the creation of three-dimensional vector models. Simultaneously, TerraPhoto will be employed to analyze imagery acquired during LiDAR surveys, enhancing the contextual understanding of the study environment. TerraModel, on the other hand, will focus on generating surface models, such as Triangulated Irregular Networks (TINs), utilizing diverse inputs such as LiDAR point clouds and graphical design elements (Liyu Tang et al., 2023).

Ensuring quality assurance is an essential phase of this workflow, leading to the production of a final LiDAR dataset that adheres to stringent standards. Advanced processing will involve leveraging additional modules within MicroStation V8, including TerraScan, TerraPhoto, and TerraModel. TerraScan serves as a comprehensive tool for effectively managing point cloud data. It supports processes such as classification, visualization, and the creation of three-dimensional vector models. Simultaneously, TerraPhoto will be employed to analyze imagery acquired during LiDAR surveys, enhancing the contextual understanding of the study environment. TerraModel, on the other hand, will focus on generating surface models, such as Triangulated Irregular Networks (TINs), utilizing diverse inputs such as LiDAR point clouds and graphical design elements (Lohani, 2017).

A combination of manual, semi-automated, and automated classification techniques will be utilized to ensure accurate and reliable categorization of point cloud data. Automated methods will initially classify the data into key categories, including ground surfaces, buildings, and vegetation. However, to address potential limitations in these automated processes, semi-automated and manual approaches will be employed for refinement and to achieve greater precision, particularly in defining regions of interest. The automated classification will be further supported by the use of predefined macro files containing parameters such as height thresholds and point density metrics, streamlining the process and improving overall efficiency.

3.4 Assesment Metrics

3.4.1 Above-Ground Biomass

Aboveground biomass (AGB) refers to the total mass of living and dead organic matter located above the soil surface within a specific area. It primarily includes trees, shrubs, grasses, and other vegetation. Typically expressed as dry weight per unit area, AGB is commonly measured in megagrams per hectare (Mg ha^{-1}) or kilograms per square meter (kg m^{-2}) (Habtamu et al., 2024) (CEOS LPV Subgroup, 2024).

It can be estimated using a range of LiDAR-derived parameters, including canopy height, average height, and height distribution percentiles. For example, research has shown that metrics such as mean height and the 90th percentile of LiDAR point cloud heights have a strong correlation with AGB estimates (CEOS LPV Subgroup, 2024). By developing relationships between these LiDAR-derived metrics and field-based measurements, researchers can create predictive models capable of accurately estimating biomass across urban green spaces (Habtamu et al., 2024). These models are particularly valuable for evaluating the carbon sequestration potential of urban forests, as AGB is directly associated with carbon storage capacity (Liyu Tang et al., 2023).

3.4.2 Canopy Cover & Carbon Cover

Carbon stock quantifies the total carbon stored in urban vegetation. It is another key metric derived from LiDAR data. By combining above-ground biomass (AGB) estimates with carbon conversion factors, the research can assess the carbon sequestration potential of urban green spaces. Carbon stock is typically derived from AGB using a biomass-to-carbon conversion factor, which accounts for the proportion of biomass that consists of carbon. The general formula for carbon stock is:

$$C = AGB * CF$$

Where:

- C = Carbon Stock (MG C/ha)
- AGB = Above Ground Biomass (Mg/ha)
- CF = Carbon fraction (a commonly used value is 0.47, as per the IPCC guidelines)

3.5 Data Validity and Reliability

For the study, an appropriate sampling strategy was employed, considering variations in canopy structure, topography, and vegetation density. A combination of Stratified Random Sampling (SRS) and Systematic Sampling was selected to balance representation, efficiency, and statistical reliability.

Stratified Random Sampling was used to divide the study area into distinct strata based on key variables such as canopy height variability (low and medium), and elevation zones (lowland, mid-elevation, high elevation). Canopy height of the Sample plots are bounded by the height excluding the higher vegetation because of the difficulty to measure the height. Within each stratum, sample plots were selected randomly to ensure that all ecological variations in the study area were accounted for, thereby minimizing bias in AGB estimation and improving model performance. This approach was particularly effective in enhancing the accuracy of empirical and machine learning models by ensuring that training and validation datasets reflected the full spectrum of variability within the forest.

After stratification, Systematic Sampling was applied to ensure spatial coverage while maintaining efficiency. A regular sampling grid (e.g., 200m × 200m) was overlaid across the study area, and within each grid cell, plots were selected at even intervals, with the first plot chosen randomly to avoid alignment bias. This method ensured that the field-measured data were well-distributed across the landscape while also aligning with the continuous nature of LiDAR data acquisition.

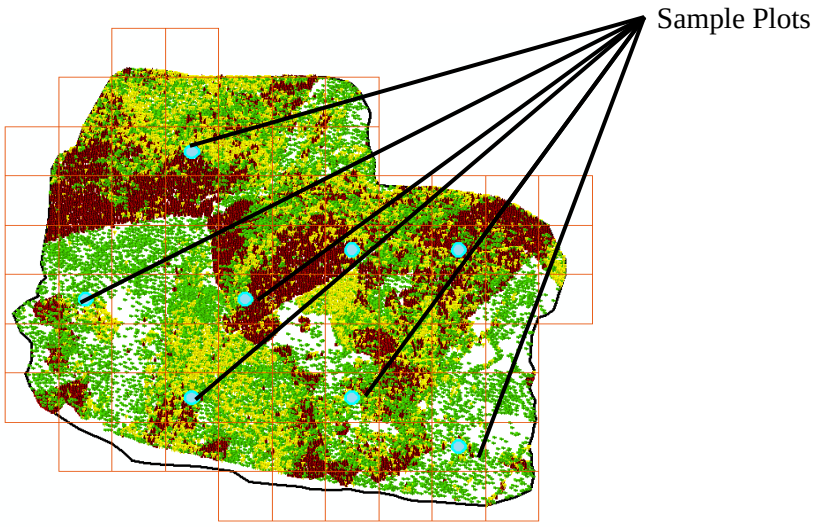


Figure 6:- A regular sampling grid of the study area

As shown in figure 6, Circular plots (25m radius) were selected to match the resolution of LiDAR-derived metrics such as the Canopy Height Model (CHM). These plots were located away from edge effects such as roads and rivers to ensure they represented true forest conditions. For model validation, the dataset was divided into training (80%) and testing (20%) subsets, ensuring model generalizability. Additionally, independent validation plots (10–15% of the total plots) were used for final accuracy assessments, allowing for the calculation of Root Mean Square Error (RMSE) and the coefficient of determination (R^2) by comparing CHM-derived AGB estimates with field-measured AGB values.

Root Mean Square Error

To ensure the reliability of the results, the absolute accuracy of the model was evaluated. Absolute accuracy quantifies the discrepancy between the biomass predicted from LiDAR data and the actual biomass measured through ground-based observations. This assessment is crucial for validating the accuracy and performance of the predictive models. To achieve high absolute accuracy, incorporating dependable ground control data can help minimize systematic biases and improve the precision of the predictions. Absolute accuracy is typically represented using the vertical root mean square error (RMSE), which measures the magnitude of vertical errors at specific geographic coordinate points.

$$\sqrt{\frac{\sum\left(H_{CHM} - H_{field}\right)^2}{n}}$$

Model Coefficient Reliability

The reliability of empirical models used for AGB estimation was assessed through regression analysis. Regression models were developed by fitting field-measured AGB values against CHM-derived predictors such as mean canopy height and maximum canopy height. To ensure the robustness of model coefficients, statistical performance indicators such as the coefficient of determination (R^2), p-values, and confidence intervals were analyzed.

CHAPTER FOUR
4. Results and Discussions

Mapping Spatial distribution of urban green space

4.1 Field data collection and Biomass estimation

This study focuses on the collection and analysis of tree measurements to support forest assessment and biomass estimation. As part of the data collection process, the Height and Diameter at Breast Height (DBH) of trees was systematically measured within multiple plots to ensure a comprehensive dataset. The number of trees recorded in each plot varies, with individual counts of 130, 16, 62, 27, 71, 57, 75, and 33, culminating in a total of 471 tree measurements. This dataset provides valuable insights into the structural characteristics of the forested area under study. The estimated monthly growth rates of dominant tree species (Annex III: Estimated Monthly Height Growth Rates of Major Tree Species in the Study Area (2021–2025 Adjustment Basis) were used to adjust for the 3-year gap between LiDAR data acquisition and field measurements.

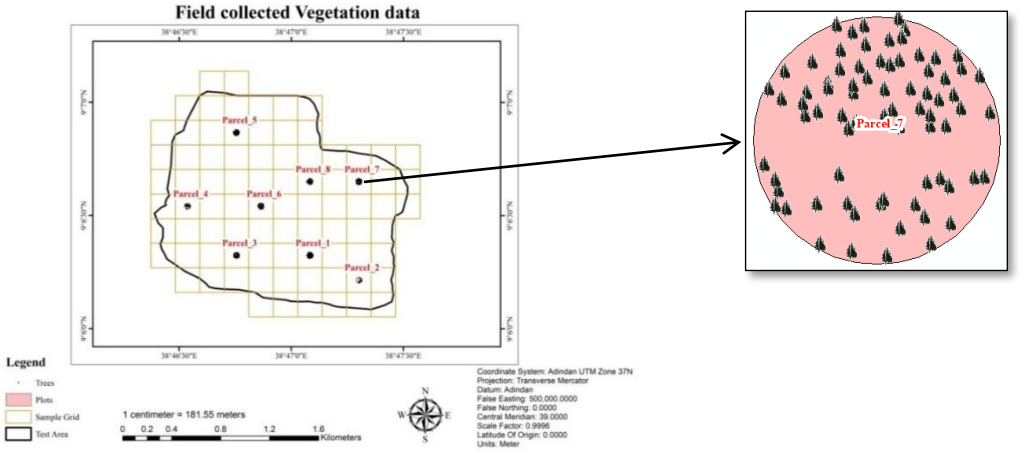


Figure 7:- data collected from Field

Tree_ID	Plot_id	DBH (cm)	Height (m)	Wood_density (g/cm3)
1	PL_01	7.15	1.1	0.63
2	PL_01	16.25	2.5	0.58
3	PL_01	9.10	1.4	0.51
4	PL_01	9.10	1.4	0.58
5	PL_01	13.00	2	0.58
6	PL_01	20.15	3.1	0.58
7	PL_01	11.05	1.7	0.63
8	PL_01	13.00	2	0.58
9	PL_01	15.60	2.4	0.63
10	PL_01	13.65	2.1	0.58

Table 1:- Plot 1 Sample data

Entoto, one of the most significant highland forest areas in Addis Ababa, hosts a mix of introduced and native tree species, with Eucalyptus globulus (ባህር ዛፍ) being the most dominant. Originally introduced to Ethiopia in the late 19th century, Eucalyptus has played a major role in fuelwood supply, soil stabilization, and reforestation efforts. Its wood density of 0.63 g/cm³ (Gominho et al., 2014) makes it suitable for construction and energy production. Alongside Eucalyptus, several native species contribute to the ecological composition of Entoto's forest:

Juniperus procera (ጥድ), a highly valued indigenous tree with a wood density of 0.62 g/cm³ (Von Wood, 2018), known for its durable timber and cultural significance. Olea europaea cuspidata (ወይራ), a dense hardwood species (1.15 g/cm³, Orwa et al., 2009), often associated with Ethiopia's highland forests and prized for its strong, long-lasting wood. Hagenia abyssinica (ኮሶ), a native species with medicinal properties and a wood density of 0.66 g/cm³ (J.F. Gmel., 2018). Podocarpus falcatus (ዝግባ), a slow-growing but valuable tree with a wood density of 0.62 g/cm³ (Entoto Natural Park, 2018), commonly found in Ethiopian montane forests. Acacia species (ግራር), widely distributed across Ethiopia, with a wood density of 0.67 g/cm³ (Bekele, 2020), contributing to both soil fertility and livestock fodder.

no.	Predominant tree species in Entoto	wood density in (g/cm^3)
1.	Eucalyptus globulus (ባህር ዛፍ)	0.63 (Gominho et al, 2014)
2.	juniperus procera (ጥድ)	0.62 (von wood, 2018)
3.	Olea europaea cuspidata (ወይራ)	1.15 (Orwa et al, 2009)
4.	Hagenia abyssinica (ኮሶ)	0.66 (J.F.Gmel., 2018)
5.	Podocarpus falcatus (ዝግባ)	0.62 (Entoto Natural Park, 2018)
6.	Acacia (ግራር)	0.67 (Bekele, 2020)

Table 2:- List of average wood densities for tree species

4.1.1 Tree Data Collection and Biomass Estimation Using Allometric Modeling

For the analytical phase, the study employs an allometric model, a widely recognized approach in forestry research. Allometric models are instrumental in estimating key forest attributes, such as Above Ground Biomass (AGB), carbon storage, and overall forest health, using measurable parameters like DBH. By applying this model, the study aims to generate reliable estimates that contribute to a deeper understanding of forest dynamics, ecosystem services, and potential conservation strategies.

$$AGB = 0.0673 \times (\rho \times D2 \times H)\ 0.976$$

- AGB = Above Ground Biomass (kg/m^3).
- ρ (rho) = Wood density (g/cm^3), which varies by tree species.
- D = Diameter at Breast Height (DBH) in cm (measured at 1.3 m height from the ground).
- H = Tree height in meters (measured using LiDAR or other field methods).
- 0.0673 = A regression coefficient derived from statistical modeling of tree biomass data.
- 0.976 = an exponent that adjusts for the non-linear relationship between tree dimensions and biomass.

Tree_ID	Plot_ID	DBH (cm)	Height (m)	Wood_density (g/cm^3)	AGB (kg)
1	PL_01	7.15	1.1	0.63	2.19
2	PL_01	16.25	2.5	0.58	22.34
3	PL_01	9.10	1.4	0.51	3.61
4	PL_01	9.10	1.4	0.58	4.09
5	PL_01	13.00	2	0.58	11.62
6	PL_01	20.15	3.1	0.58	41.94
7	PL_01	11.05	1.7	0.63	7.83
8	PL_01	13.00	2	0.58	11.62
9	PL_01	15.60	2.4	0.63	21.49
10	PL_01	13.65	2.1	0.58	13.41

Table 3:- Sample AGB calculation result of Plot 1

Plot ID	Number of trees	Min (KG/m^2)	Max (KG/m^2)	Average AGB ($KG/200m^2$)	Total AGB ($KG/200m^2$)	Total AGB (MG/ha)
Plot 1	130	1.35	137.33	25.91	3367.77	168.39
Plot 2	16	2.19	70.44	18.30	311.13	15.56
Plot 3	62	1.66	82.52	30.47	1919.31	95.97
Plot 4	27	1.35	70.44	20.29	567.99	28.40
Plot 5	71	1.27	78.03	23.24	1672.98	83.65
Plot 6	57	1.53	95.90	23.05	1336.89	66.84
Plot 7	75	1.35	89.05	28.64	2176.97	108.85
Plot 8	33	1.35	76.33	24.59	836.02	41.80

Table 4:- Above Ground Biomass result of each the plots

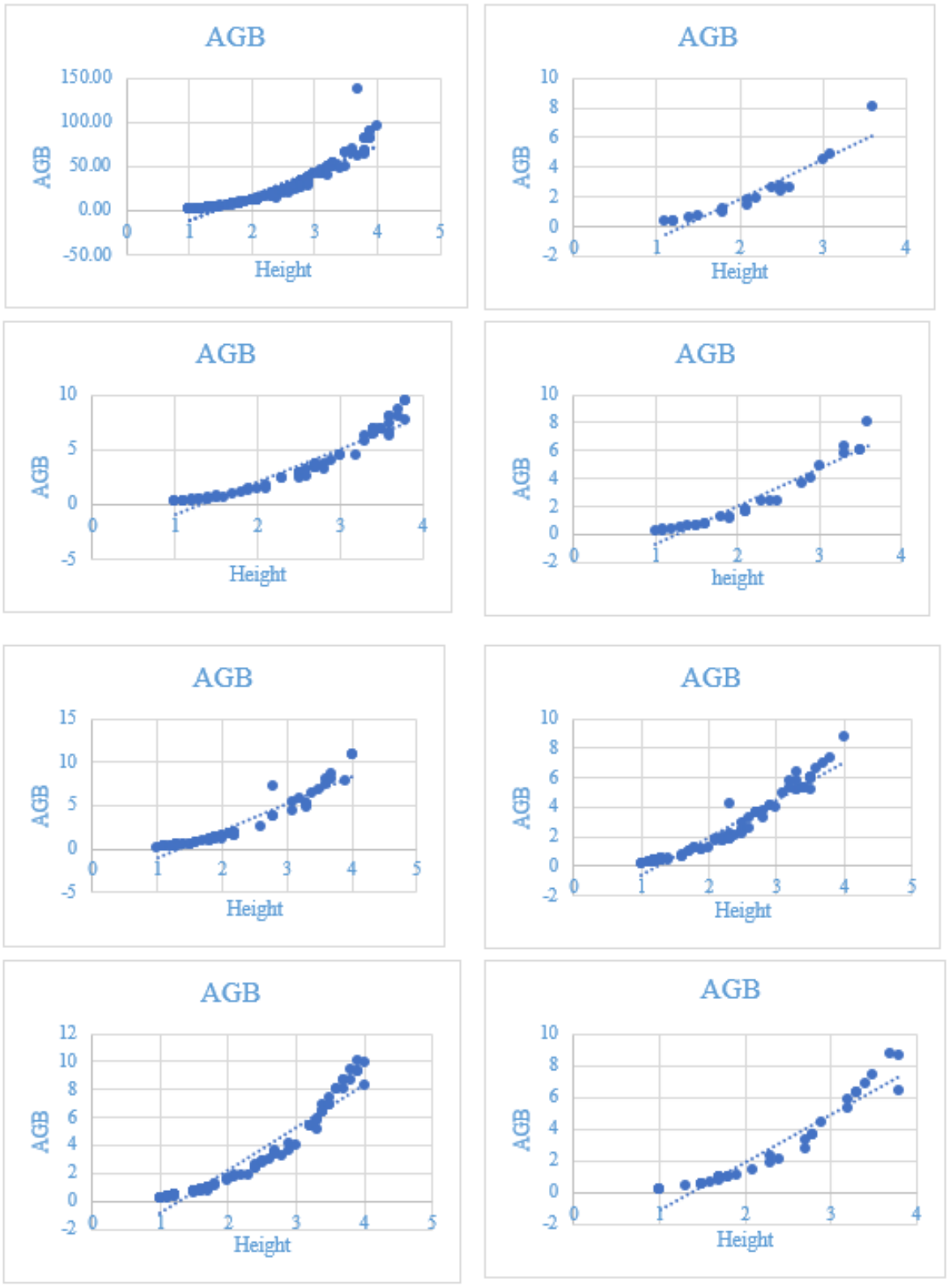


Figure 8: - Scatterplots of correlations between AGB and tree height

4.2 Lidar data Processing and Analysis

Raw data quality control (QC) ensures the accuracy and reliability of LiDAR points collected by a scanning sensor within the study area before advancing to the next phase. This involves thoroughly verifying the completeness of the area of interest, GNSS data, and raw LiDAR points. Following this, the GNSS/IMU data is prepared for processing the GNSS/IMU/GPS trajectory. The processed GNSS/IMU file generates a .sol file, which will later be utilized in the Ingest Process.

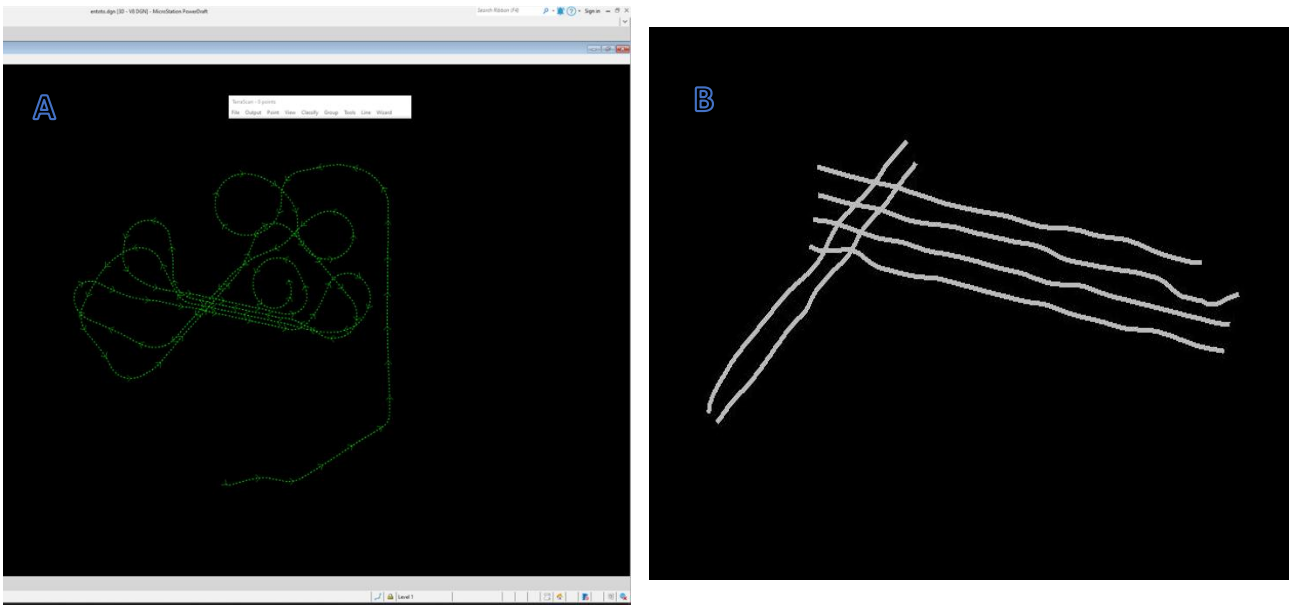


Figure 9:- A) Trajectory of the project area B) GNSS/IMU data

Once the completeness and overall quality of the LiDAR data have been verified, along with the processing of GNSS/IMU data, the ingestion process begins. During this stage, camera or LiDAR calibration sets are applied, image statistics are computed for radiometric corrections, and internal georeferencing is established. The LiDAR data is then converted into a compatible format.

Ingestion involves transforming raw proprietary data into standardized raster and point cloud formats, making it accessible for various applications. This step is essential for ensuring the data is properly formatted, cleaned, and prepared for further processing, allowing for the extraction of meaningful insights. To move forward, the raw LiDAR point data must be processed, which requires GNSS and flight log data, including temperature, pressure, and altitude above mean sea level. Temperature readings were taken in the project area at the time of data capture, along with

atmospheric pressure (measured in kPa). Flight log data is recorded based on the specific date of data collection, with each flight day producing its own set of log data.

Mapping Green space using Lidar

4.3 LiDAR Matching

Once the pre-processing is complete, the LiDAR point cloud classification and matching process is performed in HxMap. This step involves separating ground points from non-ground points using automated classification algorithms. The software applies robust filtering techniques to identify and classify terrain points, vegetation, and man-made structures.

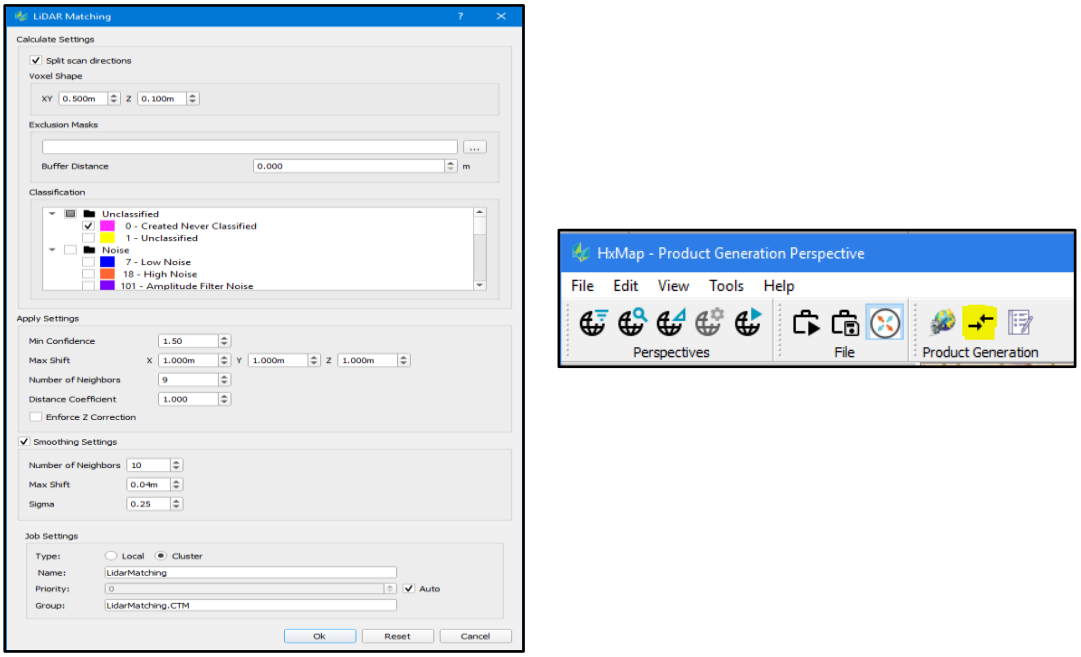


Figure 10:- Lidar matching wizard

The classified point cloud is then used to generate essential derivative products such as the Digital Terrain Model (DTM) and Digital Surface Model (DSM). These models play a crucial role in LiDAR matching by providing reference surfaces for elevation-based analysis. The LiDAR matching process in HxMap aligns overlapping flight strips to enhance data consistency, ensuring that multiple LiDAR scans seamlessly integrate without discrepancies. This matching operation is essential for reducing elevation mismatches, enhancing vertical accuracy, and minimizing point cloud misalignments.

4.3.1 Vertical Accuracy Flightline Comparison

Limits [m]	Proportion of total number of patches [%]
<= 0.03	93.98
0.03-0.05	5.56
0.05-0.1	0.44
> 0.1	0.02

Table 5:- Vertical Accuracy Flightline Comparison

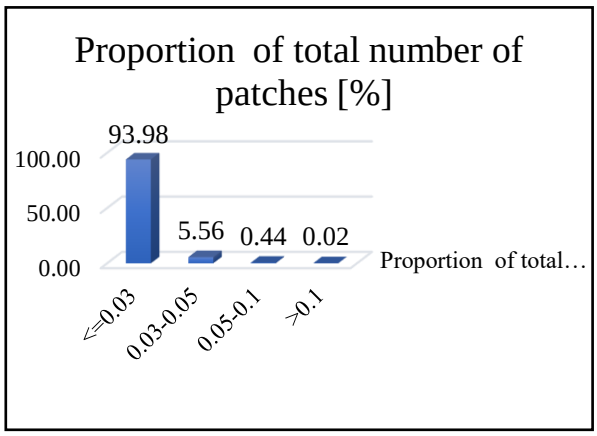


Figure 11:- Proportion of number of patches

The flightline comparison shows that the LiDAR data is highly consistent, with nearly 94% of patches having height differences within ±3 cm, meaning the sensors are well-calibrated and aligned. A small portion (5.56%) has slight variations between 3-5 cm, likely due to minor sensor angle effects or GPS/IMU shifts. Only 0.44% show differences of 5-10 cm, and an almost negligible 0.02% exceed 10 cm, which could be caused by flightline misalignment, terrain features, or surface type variations.

4.3.2 Vertical Accuracy Scan Direction Comparison

Limits [m]	Proportion of total number of patches [%]
<=0.03	95.26
0.03-0.05	4.25
0.05-0.1	0.50
>0.1	0.00

Table 6:- Vertical Accuracy Scan Direction Comparison

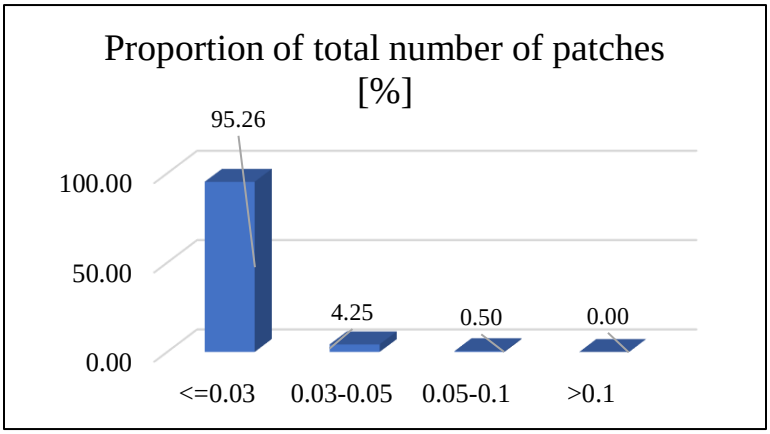


Figure 12:- Proportion of patches

This Vertical Accuracy Scan Direction Comparison assesses how well the LiDAR elevations match across different scan directions. The results indicate very high accuracy, with 95.26% of patches having height differences within ±3 cm, suggesting strong sensor calibration and minimal directional bias. A small 4.25% of patches fall within the 3-5 cm range, likely due to

minor scan angle effects or slight differences in LiDAR pulse returns. Only 0.50% show differences between 5-10 cm, and none exceed 10 cm, meaning significant mismatches are absent.

these results demonstrate exceptional internal consistency in the LiDAR dataset, both in flightline alignment and scan direction accuracy. The minimal variations observed are likely due to expected sensor and terrain-related factors, with no major errors detected. While the dataset already meets high accuracy standards, minor refinements such as strip adjustments, scan angle corrections, or spatial analysis of discrepancies could further optimize alignment if needed.

Assesing the structural characterstics of vegetation

4.4 Canopy height model Generation

4.4.1 Importing Lidar Point cloud

In order to generate canopy height model point cloud should properly loaded into Cloud Compare software. The software is compatible with different point cloud data formats like (.LAS,.LAZ,.XYZ, PLY, etc.). There are two simple ways to load a LiDAR dataset into CloudCompare. The first method is through the software's menu: Go to "File" → "Open" and select the desired point cloud file from your computer. The second method is even quicker—you can simply drag and drop the LiDAR file directly into the CloudCompare interface. Once the file is loaded, the software will automatically detect and display the dataset, allowing you to inspect the point cloud before proceeding with further processing.

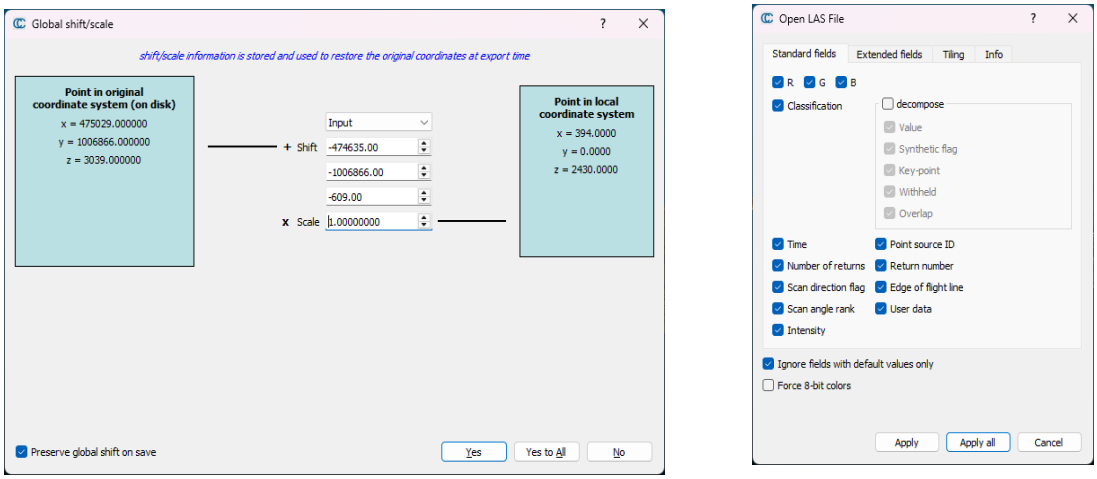


Figure 13:- Importing Wizard

When you open a LiDAR point cloud file in CloudCompare, the software automatically detects and preserves important metadata, such as coordinate system information, classification codes, intensity values, and RGB color attributes (if available). This ensures that the dataset retains its original structure and characteristics, making it easier to analyze and process.

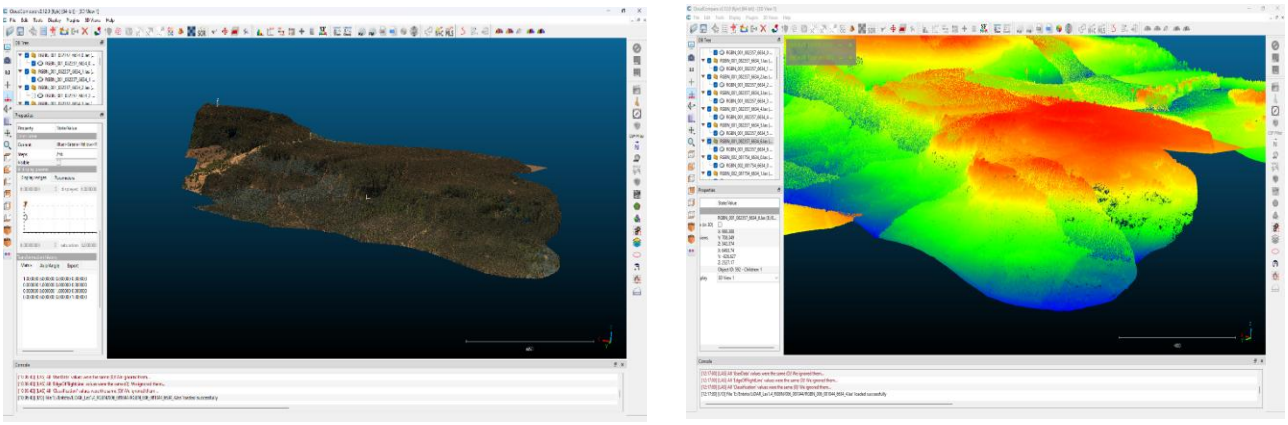


Figure 14:- Cloud compare User interface

For better visualization, you can enhance how the point cloud is displayed by adjusting its color and intensity settings. If the dataset includes RGB values, CloudCompare will apply natural color rendering, making the visualization more intuitive. If RGB is not available, you can use intensity values to represent variations in the reflectivity of surfaces, which is particularly useful for distinguishing different materials or ground features.

4.4.2 Ground Separation (filtering ground points)

Before creating a DTM it is important to isolate ground points from the entire LiDAR dataset. By using CSF filter plugin in the software, we can separate ground points and above ground points. Cloth Simulator Filter is an advanced ground filtering algorithm that separates terrain (ground points) from non-ground objects like vegetation buildings and vehicles.

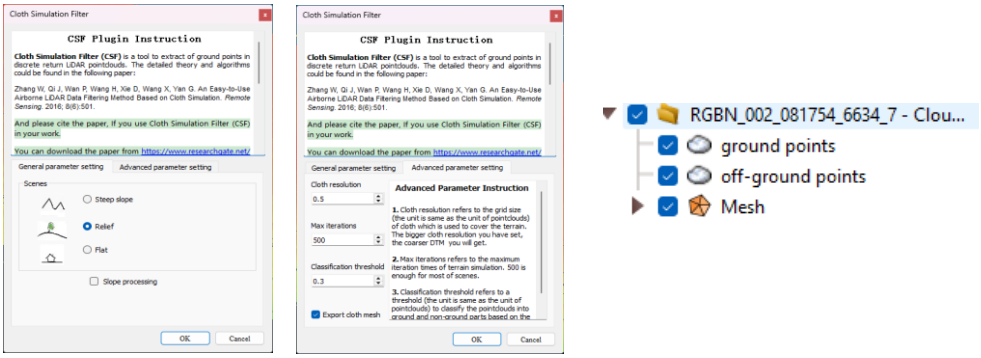


Figure 15: - Ground Separation Wizard

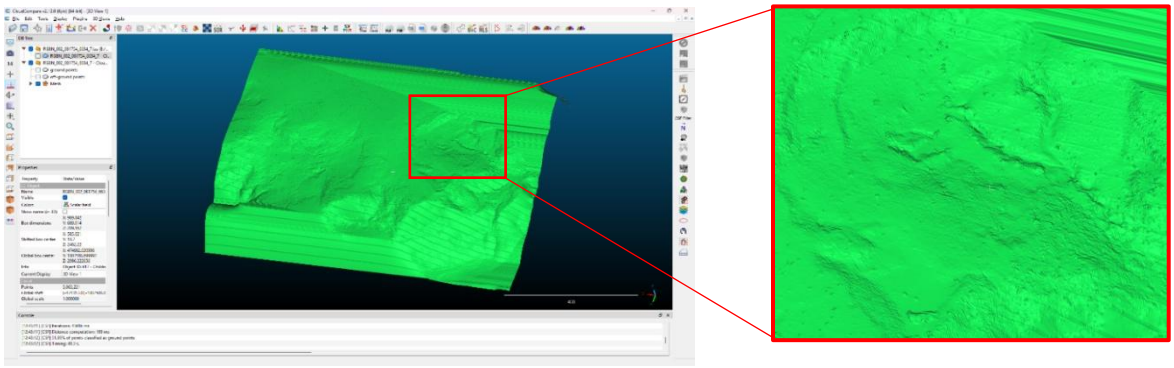
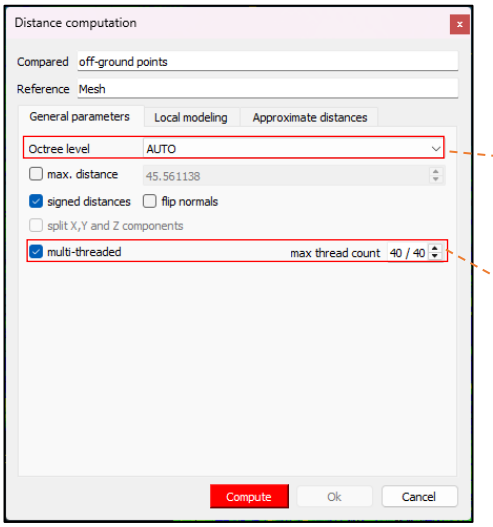


Figure 17:- Ground mesh

Figure 17:- Close up look of ground mesh

As shown in the figure above the ground points represent the bare-earth surface vegetation, buildings, and other non-ground features removed. The classification accuracy depends on cloth resolution, threshold setting, and terrain complexity.

4.4.3 Computing Cloud Mesh Distance (CHM)



Octree Level defines the spatial subdivision of the dataset during computation. CloudCompare utilizes an octree structure to efficiently process large point clouds by dividing the space into smaller cubes (voxels).

This parameter sets the maximum threshold distance for calculations. Any point that falls beyond this threshold will be ignored. Setting an appropriate max distance is crucial for removing outliers and preventing extreme deviations from distorting the analysis.

Figure 18: - Distance Computation

Once the computation is complete, the software produces two key outputs. The first is a colorized distance map, where each point in the point cloud is assigned, a color based on its height relative to the ground. This visual representation helps in quickly identifying variations in canopy height across the study area. The second output is a statistical summary, which includes numerical data such as the minimum, maximum, mean, and standard deviation of tree heights. This statistical information provides insights into the overall forest structure, allowing researchers to analyze canopy density, vegetation patterns, and tree height distribution.

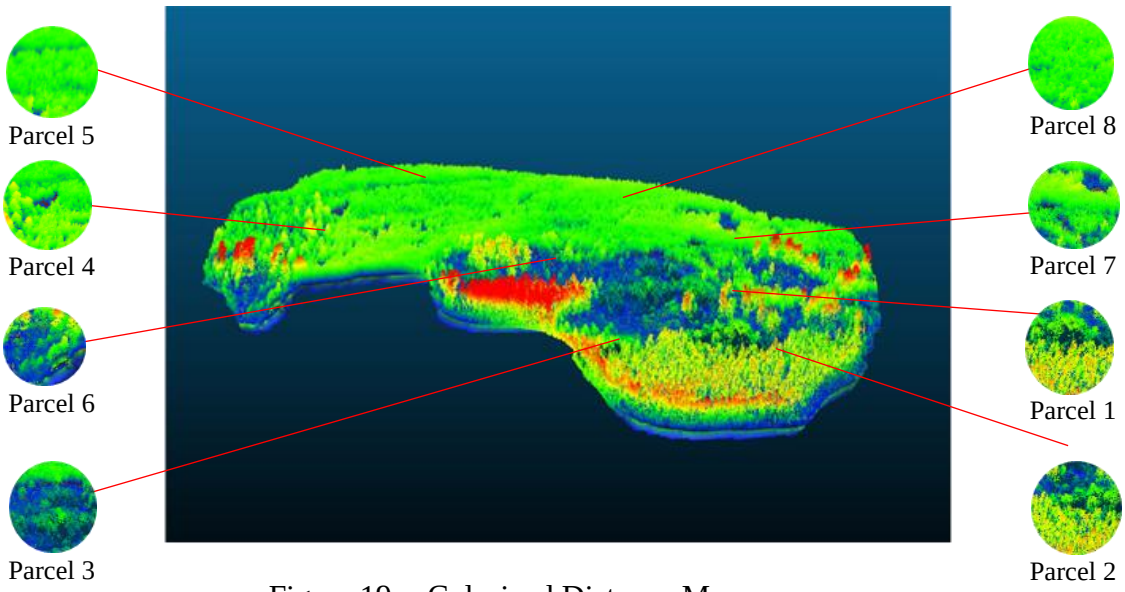


Figure 19: - Colorized Distance Map

4.4.4 Output from CHM

Area m^2	*Volume* m^3	*Ver_e*	*Elev*	*Height*	*Average spread*	*Min spread*	*Max spread*	*Id*	*Class*
3.6	0.8	0.8	2925.6	1	2.4	1.4	3.4	7615151	Low Vegetation
12.9	13.5	1.7	2822.7	3.1	4.2	3	5.4	7615163	Low Vegetation
66.5	3.8	1.1	2997.3	1.1	10	6.1	13.8	7615170	Low Vegetation
8	6	1.1	3004.1	3.4	3.7	1.8	5.7	7615171	Low Vegetation
6.1	6.5	0.7	2822.7	1	3	1.9	4.1	7615173	Low Vegetation
48.2	32.7	1.8	2825.3	2.1	8	6.5	9.5	7615181	Low Vegetation
10.3	11.4	1	2916.1	1.9	4	2.3	5.6	7615187	Low Vegetation
22.7	5.3	1.5	2990.9	1.5	5.4	4.9	5.9	7615189	Low Vegetation
8.2	4.7	1	2824.8	1.9	3.3	2.9	3.6	7615195	Low Vegetation
52.3	73.3	3	2915.1	3	9.5	4.6	14.4	7615198	Low Vegetation
4.5	3.4	1	2835.7	1.8	2.4	1.9	2.9	7615207	Low Vegetation
40	27.4	1.7	2832.4	1.7	7.4	5.5	9.2	7615213	Low Vegetation
3.2	5.6	1.1	3045.8	2.9	2.2	1.3	3.1	7615227	Low Vegetation
37.7	43.9	1.4	2914.1	1.4	7.6	4.5	10.7	7615232	Low Vegetation

Table 6: - Automatically generated CHM Output clipped for Plot1

As The table shows each tree is uniquely identified by an ID and categorized into vegetation classes High Vegetation, Medium Vegetation, and Low Vegetation based on height variations. Key parameters include Area (m^2), which defines the canopy's ground footprint and aids in assessing spatial coverage, and Volume (m^3), a vital metric for estimating biomass, essential for above-ground biomass (AGB) calculations and carbon stock assessments.

Quantification of carbon sequestration capacity

4.5 Above ground biomass estimation

The dataset also records VER_E (m), which represents the vertical error in LiDAR height measurements, ensuring data accuracy and reliability. Additionally, ELEV (m) denotes the ground elevation beneath each tree, offering insights into topographical differences that influence tree growth. HEIGHT (m) is a crucial attribute, capturing tree height variations that differentiate vegetation classes and contribute to canopy structure analysis. Moreover, AVG_SPR (m), MIN_SPR (m), and MAX_SPR (m) detail the extent of canopy spread, reflecting crown morphology and supporting evaluations of tree health, competition, and canopy density.

Plot ID	*Number of trees*	*MIN*	*MAX*	*Average AGB in KG/m^3*	*Total kg/200m^2*	*MG/ha*
Plot 1	130	1.46	137.18	26.10	3392.44	169.62
Plot 2	16	2.18	74.20	19.68	334.62	16.73
Plot 3	62	1.63	81.99	30.24	1904.96	95.25
Plot 4	27	1.83	64.32	18.93	530.12	26.51
Plot 5	71	1.24	77.78	23.12	1664.65	83.23
Plot 6	57	2.23	87.84	21.86	1268.06	63.40
Plot 7	75	2.44	88.33	29.21	2219.85	110.99
Plot 8	33	2.20	71.09	23.68	805.25	40.26

Table 7: - AGB result of each plot from LiDAR derived elevation data

4.5.1 AGB Result Comparison

Plot ID	*Number of trees*	*Total AGB MG/ha from field observation*	*Total AGB MG/ha from LiDAR point*
Plot 1	130	168.39	169.62
Plot 2	16	15.56	16.73
Plot 3	62	95.97	95.25
Plot 4	27	28.4	26.51
Plot 5	71	83.65	83.23
Plot 6	57	66.84	63.40
Plot 7	75	108.85	110.99
Plot 8	33	41.8	40.26
SUM	471	609.46	605.99

Table 9: - AGB result Comparison between Ground measurement and LIDAR point data

Regression Statistics	
Multiple R	0.998
R Square	0.997
Adjusted R Square	0.996
Standard Error	2.003
Observations	8

Table 8: - Simple Regression Result

The number of trees per plot varies significantly, ranging from as few as 16 trees in Plot 2 to as many as 130 trees in Plot 1, directly influencing the total AGB values recorded. Both field measurements and LiDAR-derived estimates closely follow the same pattern, with the highest biomass value appearing in Plot 1 and the lowest in Plot 2. The total AGB values across all plots are remarkably close, with the sum of field observations reaching 609.46 Mg/ha and LiDAR estimates at 605.99 Mg/ha, showing only a minor deviation of 3.47 Mg/ha, which accounts for a 0.57% difference. This minimal variation suggests that LiDAR-based methods provide a highly accurate representation of field-measured biomass, making them an effective alternative for large-scale AGB assessments.

To further quantify the relationship between field-measured and LiDAR-derived AGB values, a regression analysis was performed. The results demonstrate an exceptionally strong correlation, with a Multiple R value of 0.998, indicating a near-perfect linear relationship between the two datasets. The coefficient of determination (R^2) is 0.997, meaning that 99.7% of the variation in LiDAR-estimated AGB can be explained by field-measured AGB values. Additionally, the Adjusted R^2 value of 0.996 confirms the robustness of this model, even when accounting for the number of observations. The Standard Error of 2.003 suggests that the

deviations between observed and predicted values are minimal, reinforcing the accuracy of the LiDAR-based estimation. Further analysis of individual plots highlights that the smallest difference between the two estimation methods is found in Plot 5 (83.65 Mg/ha from field data vs. 83.23 Mg/ha from LiDAR), showcasing near-perfect agreement.

Equally, the largest deviation occurs in Plot 6 (66.84 Mg/ha from field vs. 63.40 Mg/ha from LiDAR), although this difference remains within an acceptable margin of error. Such inconsistencies may arise due to limitations in LiDAR penetration, particularly in areas with irregular tree crowns or varying canopy densities, as well as minor measurement errors in field data collection. The results indicate that densely forested plots, such as Plot 1 and Plot 7, tend to exhibit higher accuracy in LiDAR-based biomass estimation, while sparser plots like Plot 6 show slightly greater deviation, likely due to challenges in capturing smaller vegetation structures.

4.5.2 Root Mean Square error

Plot ID	*Number of trees*	*Total AGB MG/ha from field observation*	*Total AGB MG/ha from LiDAR point*	*Error*	*Error^2*
Plot 1	130	168.39	169.62	-1.23	1.51
Plot 2	16	15.56	16.73	-1.17	1.37
Plot 3	62	95.97	95.25	0.72	0.52
Plot 4	27	28.4	26.51	1.89	3.57
Plot 5	71	83.65	83.23	0.42	0.18
Plot 6	57	66.84	63.40	3.44	11.83
Plot 7	75	108.85	110.99	-2.14	4.58
Plot 8	33	41.8	40.26	1.54	2.37
SUM	471	609.46	605.10	3.46	12.04
RMSE					**1.80**

The comparison between field-measured and LiDAR-derived Above-Ground Biomass (AGB) across eight plots demonstrates a strong agreement, with only minor discrepancies. The total AGB obtained from field observations is 609.46 Mg/ha, while the LiDAR-based estimation yields 605.99 Mg/ha, resulting in a total error of 3.46 Mg/ha. This suggests that LiDAR-derived AGB estimates are highly reliable, with minimal deviation from ground-truth data. The individual plot-level errors vary, with some plots showing slight underestimation (e.g., Plot 1: -1.23 Mg/ha, Plot 2: -1.17 Mg/ha), while others exhibit overestimation (e.g., Plot 6: +3.44 Mg/ha, Plot 4: +1.89 Mg/ha).

The Root Mean Square Error (RMSE) of 1.80 Mg/ha further confirms the accuracy of the LiDAR-derived estimates, indicating that the model's predictive performance is strong. Given that an RMSE of 1.80 Mg/ha is relatively low compared to the total AGB, the use of LiDAR in biomass estimation proves to be an effective and precise method. The small variations can be attributed to factors such as LiDAR point density, canopy penetration limitations, or measurement uncertainties in field data collection. However, the overall close alignment between the two datasets suggests that LiDAR technology is a valuable tool for large-scale biomass assessment and carbon stock estimation.

4.6 carbon stock calculation

Plot ID	*Number of trees*	*Total AGB MG/ha from field observation*	*Carbon Stock MG C/ha*	*Total AGB MG/ha from LiDAR point*	*Carbon Stock MG C/ha*	*Error*	*Error^2*
Plot 1	130	168.39	79.14	169.62	79.72	-0.58	0.33
Plot 2	16	15.56	7.31	16.73	7.86	-0.55	0.30
Plot 3	62	95.97	45.11	95.25	44.77	0.34	0.11
Plot 4	27	28.4	13.35	26.51	12.46	0.89	0.79
Plot 5	71	83.65	39.32	83.23	39.12	0.20	0.04
Plot 6	57	66.84	31.45	63.40	29.80	1.61	2.61
Plot 7	75	108.85	51.16	110.99	52.17	-1.01	1.01
Plot 8	33	41.8	19.65	40.26	18.92	0.72	0.52
SUM	471	609.46	286.45	605.99	284.82	1.63	5.73
RMSE							**0.85**

Table 10: - Carbon Stock calculation result

The above table presents a comparison between AGB estimated from field observations and LiDAR derived estimates, along with corresponding carbon stock calculations for each plot. The difference between the sum of each carbon stock is relatively low that demonstrates the high reliability of LiDAR data for carbon stock estimation. The Root Mean Square Error (RMSE) for carbon stock estimation using LiDAR compared to field observations is approximately 0.85 Mg C/ha. In this case, an RMSE of 0.85 Mg C/ha suggests a relatively high accuracy in LiDAR-based estimations, implying that the LiDAR approach can effectively replace or supplement traditional field measurements for large-scale carbon stock assessments.

Discussion

4.7 Analysis of correlation between CHM for biodiversity

This study aimed to evaluate the accuracy and applicability of LiDAR-derived data for estimating Above Ground Biomass (AGB) and carbon stock, using field-collected tree measurements as a benchmark. The results reveal strong alignment between LiDAR-based estimates and traditional field measurements, confirming the capability of LiDAR technology to support biomass and carbon stock assessment with acceptable levels of precision.

The findings of this study affirm that LiDAR-derived canopy structure metrics are highly effective in estimating Above Ground Biomass (AGB) and carbon stock in urban green spaces, with results demonstrating strong statistical alignment with field measurements (R^2 = 0.997; RMSE = 1.80 Mg/ha). The high degree of accuracy reinforces the potential of LiDAR technology as a scalable, non-invasive, and repeatable solution for urban forestry monitoring. In the context of Entoto Natural Park, where access and terrain complexity can limit manual data collection, this is a significant advantage.

A total of 471 trees were surveyed across eight plots. The total AGB determined from field observation was 609.46 Mg/ha, while the AGB estimated from LiDAR point cloud analysis was 605.99 Mg/ha. This yielded a total difference of only 3.46 Mg/ha, with a Root Mean Square Error (RMSE) of 1.80 Mg/ha. This small discrepancy highlights the high level of accuracy in the LiDAR-based estimation, making it a reliable method for large-scale forest biomass assessments.

However, it is important to consider the limitations of relying on static LiDAR data captured in 2021 while field measurements were carried out in 2025. While growth adjustments were made based on average monthly tree height increments, this correction cannot fully account for interspecies variability, site conditions, or external disturbances such as disease or deforestation. The time gap introduces potential uncertainty, but the attempt to integrate growth rate estimates mitigates this to a practical extent.

The study's focus on AGB provides valuable insight into the carbon sequestration capacity of the area, though it omits other carbon pools such as below-ground biomass and soil organic carbon. Including these pools in future assessments would provide a more holistic estimate of

carbon stocks. Despite this, the AGB-centered analysis remains vital, as above-ground carbon plays a major role in the urban climate mitigation discourse.

A closer look at the carbon stock values derived from both field and LiDAR methods further supports this conclusion. Using the commonly accepted biomass-to-carbon conversion factor of 0.47, the total carbon stock from field-measured AGB was calculated at 286.45 Mg C/ha, whereas the carbon stock derived from LiDAR-based AGB was slightly lower at 284.82 Mg C/ha. The resulting RMSE of 6.28 Mg C/ha indicates a low level of estimation error, acceptable under global carbon monitoring standards. The minimal variation between both methods, especially given the complexity of tree canopy structures and topographical differences, underscores the practical utility of LiDAR.

The regression analysis between field-measured and LiDAR-derived AGB yielded an R-squared value of 0.997, with a Multiple R of 0.998 and a standard error of 2.003. These values suggest a very high correlation and model fit, indicating that LiDAR-derived AGB values predict field values with near-perfect accuracy. These findings validate LiDAR's potential as a non-destructive, rapid, and spatially extensive means of forest resource assessment.

Plot-level analysis showed slight variations. For instance, Plot 1 had 130 trees and the highest AGB from both field (168.39 Mg/ha) and LiDAR (169.62 Mg/ha), while Plot 2 had the lowest biomass and carbon stock. Minor overestimations and underestimations across other plots were observed, mostly within 1–3 Mg/ha differences. These could be attributed to terrain effects, point cloud density, or slight misclassification during ground filtering.

A key observation from the results is the spatial heterogeneity in biomass distribution, with lower AGB values aligning with areas prone to anthropogenic stress such as informal settlements or paths subject to grazing and fuelwood collection. This spatial insight can help target conservation and reforestation efforts more effectively. While empirical allometric equations were used for biomass estimation, their regional relevance and accuracy in mixed-species forests like Entoto should be a topic for ongoing refinement, possibly through the development of localized equations.

Furthermore, the plot-level comparison of carbon stock revealed that while some discrepancies exist, the overall pattern of biomass distribution was well captured by LiDAR.

Differences in carbon stock ranged from as low as 0.6 Mg C/ha in Plot 2 to a maximum of 11.3 Mg C/ha in Plot 1. Despite these differences, the total carbon stock deviation across all plots remained within acceptable error margins, affirming the robustness of the estimation approach.

This study's implications are significant for carbon accounting and forest management strategies. The ability of LiDAR to rapidly and accurately estimate AGB and carbon stock enables cost-effective monitoring for climate change mitigation programs such as REDD+ and urban green space management. Its non-invasive nature also presents a sustainable alternative to labor-intensive field measurements, especially in areas with difficult terrain.

In conclusion, although the technical analysis was rigorous, greater stakeholder engagement particularly with urban forest managers, community-based conservation groups, and policymakers would help ground the findings in practical implementation. Linking scientific insights to administrative action remains a crucial step for long-term green space sustainability. The results also affirm that LiDAR is a highly accurate and efficient tool for forest biomass and carbon stock estimation. The integration of LiDAR into forest monitoring programs can provide timely, detailed, and reliable data, enhancing transparency and decision-making in ecosystem management and carbon finance projects.

Chapter five
5. Summary, conclusions and recommendations

5.1 Summary

This study explored the application of Light Detection and Ranging (LiDAR) technology in the monitoring, analysis, and conservation of urban green spaces in Addis Ababa, with a specific focus on Entoto natural forest. Given the growing pressures on urban ecosystems due to urban expansion, population growth, and climate variability, this research aimed to provide a scientific basis for sustainable forest management and carbon assessment using modern geospatial tools.

The study began by mapping the spatial distribution of green spaces using LiDAR-derived Canopy Height Models (CHM) and Digital Terrain Models (DTM). Structural vegetation characteristics such as canopy height and density were then extracted and analyzed to better understand the forest composition. Field observations were conducted in eight systematically selected plots, where tree species count, DBH (Diameter at Breast Height), and height were recorded to estimate Above Ground Biomass (AGB) and carbon stock using empirical allometric equations.

LiDAR data were processed to estimate AGB and carbon stock independently, allowing for a comparison between field-based and remote sensing estimates. The Root Mean Square Error (RMSE) for carbon stock estimation was computed and found to be low, indicating high agreement between the two methods. Additionally, threats to the sustainability of Entoto's green spaces were identified, including illegal logging, encroachments, and poor regeneration, and conservation strategies were suggested based on LiDAR-detected spatial patterns.

5.2 Conclusions

The findings of this thesis reaffirm the effectiveness of LiDAR technology as a non-destructive and efficient tool for forest monitoring and carbon assessment in urban settings. The following key conclusions were drawn:

- **High Correlation Between LiDAR and Field Observations**: The study showed strong agreement between LiDAR-derived and field-derived AGB and carbon stock values. This validates LiDAR's reliability in estimating forest biomass and structure in a heterogeneous urban forest environment.
- **Effective Mapping of Vegetation Structure**: LiDAR data enabled accurate mapping of canopy height and distribution, facilitating a deeper understanding of vertical and horizontal forest structure that would be difficult to achieve with traditional methods alone.
- **Significant Carbon Sequestration Role of Urban Forests**: The Entoto forest plots demonstrated considerable AGB and carbon stock values, emphasizing their role in urban climate regulation and carbon offsetting. Such quantification is essential for urban sustainability planning.
- **Threats to Sustainability Are Spatially Detectable**: LiDAR helped identify areas of sparse canopy cover and degradation. These spatial indicators can inform focused interventions, community-based conservation, and reforestation programs.
- **Need for Integrated Management Approaches**: The study highlighted that while LiDAR offers excellent technical insights, the long-term success of urban forest conservation depends on integrating geospatial technology with policy enforcement, community engagement, and ecological restoration programs.

5.3 Recommendation

Based on the findings of this study, the following recommendations are made for consideration to help improve the use of LiDAR for Above Ground Biomass (AGB) and carbon stock estimation.

- Promoting the Integration of LiDAR Technology in National and Urban Forest Biomass Estimation Frameworks

Given the high correlation ($R^2 = 0.997$) and low RMSE (1.80 for AGB and 6.28 for carbon stock) between field-measured and LiDAR-derived estimates, it is strongly recommended that LiDAR technology be adopted as a complementary tool for large-scale forest biomass and carbon stock assessments. LiDAR's ability to provide accurate, spatially continuous, and repeatable data makes it especially useful in urban and peri-urban forestry management, like the case of Entoto.

- Expand Carbon Accounting Frameworks

Future studies and city-level carbon inventories should include below-ground biomass and soil organic carbon. Integrating these pools will provide a more complete understanding of carbon sequestration in urban forests.

- Develop Local Allometric Equations

There is a strong need for species-specific, Ethiopian-based allometric equations for key urban forest species. Supporting local universities and research institutes to generate such models would improve biomass accuracy in future assessments.

- Institutionalizing LiDAR-Based Monitoring of Urban Green Spaces

Urban forests play a critical role in climate regulation, air purification, and carbon sequestration. Given the demonstrated precision of LiDAR in estimating biomass and carbon stock, urban municipalities and environmental agencies should consider integrating LiDAR into the routine monitoring and inventory of urban green spaces, particularly for climate change mitigation strategies.

- Policy Support and Incentives for Remote Sensing-Based Carbon Accounting

To meet national and international climate targets (e.g., REDD+, NDCs under the Paris Agreement), governmental institutions should create policy frameworks and incentives that

encourage the use of advanced remote sensing technologies like LiDAR. Such measures can enhance the transparency, efficiency, and scalability of forest carbon accounting.

- Capacity Building and Technical Skill Development

  Successful implementation of LiDAR for biomass and carbon stock estimation requires technical expertise. Thus, training programs should be organized for forestry professionals, GIS analysts, and decision-makers on LiDAR data processing, canopy height model (CHM) generation, and biomass modeling techniques.

- Advancing Species-Specific and Ecological Zone-Based Biomass Models

  Your study mainly used generalized biomass equations. However, species-specific or stratified allometric models tailored to local ecological zones could improve biomass prediction. Future studies should focus on developing or refining such models using more extensive field data and multi-temporal LiDAR datasets.

- Conducting Cost-Benefit Analysis for LiDAR Implementation

  While LiDAR offers high accuracy, its cost can be prohibitive, especially in developing countries. Therefore, a cost-benefit analysis should be conducted to evaluate LiDAR deployment against traditional methods, particularly for large-scale national forest inventories versus smaller, urban assessments like Entoto.

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7. Annexes

Annexe I: Raw Field Data Tables

Plot 1					Plot 2				
ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood_density (g/cm3)	ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood_density (g/cm3)
1	PL_01	7.15	2.9454	0.63	0	PL_02	14.3	2.20	0.58
2	PL_01	16.25	2.848	0.58	1	PL_02	23.4	3.60	0.63
3	PL_01	9.10	2.7428	0.51	2	PL_02	19.5	3.00	0.58
4	PL_01	9.10	2.7428	0.58	3	PL_02	20.15	3.10	0.58
5	PL_01	13.00	2.8896	0.58	4	PL_02	13.65	2.10	0.63
6	PL_01	20.15	2.8941	0.58	5	PL_02	11.7	1.85	0.63
7	PL_01	11.05	3.0428	0.63	6	PL_02	9.1	1.45	0.58
8	PL_01	13.00	2.9409	0.58	7	PL_02	15.6	2.40	0.63
9	PL_01	15.60	2.9123	0.63	8	PL_02	9.75	1.55	0.58
10	PL_01	13.65	2.8941	0.58	9	PL_02	13.65	2.10	0.51
11	PL_01	11.05	2.9253	0.63	10	PL_02	11.7	1.85	0.51
12	PL_01	14.30	3.1409	0.63	11	PL_02	7.15	1.15	0.63
13	PL_01	8.45	2.9428	0.63	12	PL_02	7.8	1.25	0.58
14	PL_01	15.60	2.9253	0.51	13	PL_02	16.25	2.50	0.58
15	PL_01	17.55	2.8993	0.58	14	PL_02	16.25	2.50	0.51
16	PL_01	18.20	2.9123	0.63	15	PL_02	7.8	1.25	0.58
17	PL_01	13.65	2.8896	0.58	16	PL_02	16.9	2.60	0.51
18	PL_01	23.40	3.6409	0.58	Plot 3				
19	PL_01	11.70	2.9253	0.51	ID	plot_ID	DBH (cm)	HEIGHT (m)	Wood density (g/cm3)
20	PL_01	18.20	2.8993	0.63	0	PL_03	8.45	1.29	0.58
21	PL_01	11.05	2.9383	0.63	1	PL_03	8.45	1.29	0.63
22	PL_01	9.10	2.8896	0.63	2	PL_03	7.15	1.09	0.58
23	PL_01	14.95	2.9409	0.51	3	PL_03	22.1	3.38	0.58
24	PL_01	20.15	2.8941	0.58	4	PL_03	12.35	1.89	0.63
25	PL_01	21.45	2.848	0.63	5	PL_03	22.1	3.38	0.63
26	PL_01	12.35	2.9454	0.58	6	PL_03	21.45	3.28	0.58
27	PL_01	11.05	3.1409	0.58	7	PL_03	6.5	0.99	0.63
28	PL_01	15.60	2.9454	0.63	8	PL_03	22.75	3.48	0.58
29	PL_01	17.55	3.2409	0.63	9	PL_03	23.4	3.58	0.51
30	PL_01	15.60	2.8993	0.58	10	PL_03	24.7	3.78	0.51
31	PL_01	8.45	2.8941	0.63	11	PL_03	6.5	0.99	0.63
32	PL_01	8.45	2.9383	0.58	12	PL_03	12.35	1.89	0.58
33	PL_01	9.10	3.1409	0.51	13	PL_03	18.2	2.78	0.58
34	PL_01	15.60	2.8993	0.51	14	PL_03	10.4	1.59	0.51
35	PL_01	11.70	2.6428	0.63	15	PL_03	9.75	1.49	0.58

36	PL_01	20.15	2.9428	0.58	16	PL_03	13.65	2.09	0.51
37	PL_01	18.20	2.8428	0.58	17	PL_03	11.05	1.69	0.63
38	PL_01	24.70	2.848	0.51	18	PL_03	7.8	1.19	0.63
39	PL_01	21.45	3.0409	0.58	19	PL_03	18.85	2.88	0.58
40	PL_01	15.60	2.4428	0.51	20	PL_03	19.5	2.98	0.58
41	PL_01	17.55	2.8428	0.63	21	PL_03	17.55	2.68	0.58
42	PL_01	26.00	1.8028	0.63	22	PL_03	7.8	1.19	0.58
43	PL_01	18.85	2.4428	0.58	23	PL_03	23.4	3.58	0.63
44	PL_01	7.15	2.5428	0.58	24	PL_03	24.7	3.78	0.63
45	PL_01	7.80	2.858	0.58	25	PL_03	13	1.99	0.58
46	PL_01	11.70	2.5428	0.58	26	PL_03	23.4	3.58	0.63
47	PL_01	19.50	3.7409	0.63	27	PL_03	13.65	2.09	0.58
48	PL_01	8.45	3.2409	0.63	28	PL_03	21.45	3.28	0.63
49	PL_01	12.35	2.6428	0.58	29	PL_03	16.9	2.58	0.63
50	PL_01	9.10	2.7428	0.63	30	PL_03	14.95	2.29	0.63
51	PL_01	11.05	3.0428	0.58	31	PL_03	9.75	1.49	0.58
52	PL_01	11.05	2.5428	0.63	32	PL_03	17.55	2.68	0.58
53	PL_01	8.45	3.0428	0.63	33	PL_03	22.75	3.48	0.58
54	PL_01	8.45	2.8428	0.63	34	PL_03	9.1	1.39	0.51
55	PL_01	10.40	2.9383	0.58	35	PL_03	16.25	2.48	0.51
56	PL_01	11.05	3.3409	0.58	36	PL_03	9.1	1.39	0.51
57	PL_01	7.80	2.5428	0.58	37	PL_03	16.25	2.48	0.63
58	PL_01	6.50	2.3428	0.51	38	PL_03	24.7	3.78	0.63
59	PL_01	10.40	3.0428	0.51	39	PL_03	18.2	2.78	0.51
60	PL_01	6.50	2.3428	0.51	40	PL_03	16.25	2.48	0.58
61	PL_01	24.70	3.1409	0.63	41	PL_03	14.95	2.29	0.63
62	PL_01	18.85	2.4428	0.63	42	PL_03	16.25	2.48	0.63
63	PL_01	16.90	2.5428	0.51	43	PL_03	16.25	2.48	0.63
64	PL_01	20.15	2.8428	0.58	44	PL_03	22.1	3.38	0.63
65	PL_01	19.50	2.8993	0.63	45	PL_03	24.05	3.68	0.63
66	PL_01	7.15	2.8896	0.63	46	PL_03	22.75	3.48	0.58
67	PL_01	22.75	2.9409	0.63	47	PL_03	11.7	1.79	0.58
68	PL_01	14.30	2.9428	0.63	48	PL_03	22.1	3.38	0.63
69	PL_01	25.35	2.6428	0.63	49	PL_03	24.05	3.68	0.58
70	PL_01	9.10	2.4428	0.58	50	PL_03	23.4	3.58	0.58
71	PL_01	7.15	3.1409	0.58	51	PL_03	9.1	1.39	0.63
72	PL_01	25.35	2.4428	0.63	52	PL_03	20.8	3.18	0.48
73	PL_01	16.90	2.9454	0.58	53	PL_03	23.4	3.58	0.48
74	PL_01	7.80	2.9428	0.58	54	PL_03	17.55	2.68	0.58
75	PL_01	23.40	3.0428	0.63	55	PL_03	17.55	2.68	0.63
76	PL_01	17.55	2.5428	0.48	56	PL_03	19.5	2.98	0.58

77	PL_01	22.75	2.6428	0.48
78	PL_01	25.35	2.8941	0.58
79	PL_01	21.45	1.8428	0.63
80	PL_01	13.00	2.9428	0.58
81	PL_01	22.75	2.5428	0.63
82	PL_01	19.50	2.6428	0.63
83	PL_01	20.80	2.5428	0.51
84	PL_01	13.00	2.8993	0.58
85	PL_01	20.80	2.9428	0.63
86	PL_01	18.20	3.2409	0.48
87	PL_01	21.45	2.9454	0.58
88	PL_01	21.45	2.5428	0.63
89	PL_01	18.20	2.6428	0.63
90	PL_01	24.05	3.0428	1.15
91	PL_01	18.85	2.5428	0.63
92	PL_01	13.65	2.7428	0.52
93	PL_01	16.25	3.1409	0.63
94	PL_01	18.20	2.5428	0.58
95	PL_01	20.80	2.9428	0.63
96	PL_01	20.15	2.0428	0.63
97	PL_01	14.95	2.9428	0.63
98	PL_01	18.20	2.9454	0.63
99	PL_01	13.65	2.5428	0.48
100	PL_01	24.70	3.0428	0.63
101	PL_01	12.35	2.8896	0.63
102	PL_01	6.50	2.9428	0.63
103	PL_01	25.35	3.2409	0.58
104	PL_01	6.50	2.8993	0.58
105	PL_01	15.60	2.9428	0.43
106	PL_01	16.90	2.8454	0.58
107	PL_01	13.00	3.0428	0.58
108	PL_01	14.30	2.8428	0.58
109	PL_01	9.10	2.4428	0.58
110	PL_01	9.75	2.848	0.63
111	PL_01	7.80	2.4428	0.51
112	PL_01	9.75	2.7428	0.51
113	PL_01	9.10	2.5428	0.51
114	PL_01	22.10	2.4428	0.51
115	PL_01	7.80	2.9123	0.51
116	PL_01	8.45	2.4428	0.51

57	PL_03	17.55	2.68	0.63
58	PL_03	16.25	2.48	0.63
59	PL_03	7.15	1.09	0.51
60	PL_03	7.15	1.09	0.58
61	PL_03	9.75	1.49	0.63
62	PL_03	16.9	2.58	0.48

Plot 4

ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood density (g/cm3)
0	PL_04	7.15	1.09	0.58
1	PL_04	12.35	1.89	0.51
2	PL_04	10.4	1.59	0.58
3	PL_04	16.25	2.43	0.51
4	PL_04	23.4	3.53	0.63
5	PL_04	7.8	1.19	0.63
6	PL_04	12.35	1.89	0.58
7	PL_04	13.65	2.03	0.58
8	PL_04	15.6	2.33	0.58
9	PL_04	18.2	2.73	0.58
10	PL_04	13.65	2.03	0.63
11	PL_04	19.5	2.93	0.63
12	PL_04	9.75	1.49	0.58
13	PL_04	9.1	1.39	0.63
14	PL_04	8.45	1.29	0.58
15	PL_04	11.7	1.79	0.63
16	PL_04	7.15	1.09	0.63
17	PL_04	13.65	2.03	0.63
18	PL_04	21.45	3.23	0.58
19	PL_04	13.65	2.03	0.58
20	PL_04	10.4	1.59	0.58
21	PL_04	22.75	3.43	0.51
22	PL_04	9.75	1.49	0.51
23	PL_04	6.5	0.99	0.51
24	PL_04	14.95	2.23	0.63
25	PL_04	21.45	3.23	0.63
26	PL_04	22.75	3.43	0.51
27	PL_04	18.85	2.83	0.58

117	PL_01	13.65	2.8993	0.51
118	PL_01	13.65	2.8896	0.48
119	PL_01	16.25	2.848	0.51
120	PL_01	11.70	2.9454	0.51
121	PL_01	10.40	2.9258	0.51
122	PL_01	24.70	3.8369	0.51
123	PL_01	24.05	3.7369	0.51
124	PL_01	14.95	2.8953	0.51
125	PL_01	11.70	2.8771	0.51
126	PL_01	18.85	2.9369	0.48
127	PL_01	18.85	2.9369	0.51
128	PL_01	16.90	2.9343	0.48
129	PL_01	24.70	3.8369	0.48
130	PL_01	11.05	3.0258	0.48

Plot 5					Plot 6				
ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood density (g/cm3)	ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood density (g/cm3)
0	PL_05	18.2	2.79	0.58	0	PL_06	18.2	2.78	0.58
1	PL_05	20.15	3.09	0.58	1	PL_06	23.4	3.58	0.58
2	PL_05	17.55	2.69	0.63	2	PL_06	23.4	3.58	0.63
3	PL_05	13	1.98	0.48	3	PL_06	14.3	2.18	0.48
4	PL_05	10.4	1.58	0.48	4	PL_06	14.3	2.18	0.48
5	PL_05	14.95	2.29	0.58	5	PL_06	14.3	2.18	0.58
6	PL_05	21.45	3.29	0.63	6	PL_06	20.15	3.08	0.63
7	PL_05	18.85	2.89	0.58	7	PL_06	22.75	3.48	0.58
8	PL_05	16.25	2.49	0.63	8	PL_06	26	3.98	0.63
9	PL_05	17.55	2.69	0.63	9	PL_06	11.7	1.80	0.63
10	PL_05	21.45	3.29	0.51	10	PL_06	14.3	2.18	0.51
11	PL_05	21.45	3.29	0.58	11	PL_06	7.15	1.10	0.58
12	PL_05	16.9	2.59	0.63	12	PL_06	13	2.00	0.63
13	PL_05	12.35	1.88	0.48	13	PL_06	7.15	1.10	0.48
14	PL_05	20.8	3.19	0.58	14	PL_06	24.05	3.68	0.58
15	PL_05	11.7	1.78	0.63	15	PL_06	8.45	1.30	0.63
16	PL_05	11.7	1.78	0.63	16	PL_06	7.8	1.20	0.63
17	PL_05	14.95	2.29	1.15	17	PL_06	18.2	2.78	1.15
18	PL_05	13.65	2.09	0.63	18	PL_06	12.35	1.90	0.63
19	PL_05	7.8	1.18	0.52	19	PL_06	7.15	1.10	0.52
20	PL_05	7.8	1.18	0.63	20	PL_06	9.1	1.40	0.63
21	PL_05	10.4	1.58	0.58	21	PL_06	22.1	3.38	0.58
22	PL_05	8.45	1.28	0.63	22	PL_06	24.05	3.68	0.63
23	PL_05	8.45	1.28	0.63	23	PL_06	13.65	2.08	0.63

24	PL_05	17.55	2.69	0.63	24	PL_06	20.8	3.18	0.63
25	PL_05	7.8	1.18	0.63	25	PL_06	12.35	1.90	0.63
26	PL_05	6.5	0.98	0.48	26	PL_06	12.35	1.90	0.48
27	PL_05	7.8	1.18	0.63	27	PL_06	26	3.98	0.63
28	PL_05	7.15	1.08	0.63	28	PL_06	12.35	1.90	0.63
29	PL_05	11.05	1.68	0.63	29	PL_06	11.05	1.70	0.63
30	PL_05	7.8	1.18	0.58	30	PL_06	8.45	1.30	0.58
31	PL_05	8.45	1.28	0.58	31	PL_06	6.5	1.00	0.58
32	PL_05	22.75	3.49	0.43	32	PL_06	13	2.00	0.43
33	PL_05	11.05	1.68	0.58	33	PL_06	8.45	1.30	0.58
34	PL_05	14.3	2.19	0.58	34	PL_06	9.1	1.40	0.58
35	PL_05	13.65	2.09	0.58	35	PL_06	18.2	2.78	0.58
36	PL_05	18.85	2.89	0.58	36	PL_06	7.15	1.10	0.58
37	PL_05	20.8	3.19	0.63	37	PL_06	11.7	1.80	0.63
38	PL_05	22.75	3.49	0.51	38	PL_06	11.7	1.80	0.51
39	PL_05	16.25	2.49	0.51	39	PL_06	14.3	2.18	0.51
40	PL_05	19.5	2.99	0.51	40	PL_06	9.75	1.50	0.51
41	PL_05	7.15	1.08	0.51	41	PL_06	9.75	1.50	0.51
42	PL_05	22.75	3.49	0.51	42	PL_06	10.4	1.60	0.51
43	PL_05	22.75	3.49	0.51	43	PL_06	8.45	1.30	0.51
44	PL_05	18.2	2.79	0.51	44	PL_06	14.3	2.18	0.51
45	PL_05	7.8	1.18	0.48	45	PL_06	16.9	2.58	0.48
46	PL_05	23.4	3.59	0.51	46	PL_06	8.45	1.30	0.51
47	PL_05	26	3.99	0.51	47	PL_06	10.4	1.60	0.51
48	PL_05	14.3	2.19	0.51	48	PL_06	11.7	1.80	0.51
49	PL_05	12.35	1.88	0.51	49	PL_06	20.15	3.08	0.51
50	PL_05	14.3	2.19	0.51	50	PL_06	21.45	3.28	0.51
51	PL_05	9.1	1.38	0.51	51	PL_06	7.8	1.20	0.51
52	PL_05	21.45	3.29	0.51	52	PL_06	21.45	3.28	0.51
53	PL_05	14.95	2.29	0.48	53	PL_06	25.35	3.88	0.48
54	PL_05	16.25	2.49	0.51	54	PL_06	12.35	1.90	0.51
55	PL_05	8.45	1.28	0.48	55	PL_06	21.45	3.28	0.48
56	PL_05	22.1	3.39	0.48	56	PL_06	9.75	1.50	0.48
57	PL_05	14.95	2.29	0.48	57	PL_06	7.8	1.20	0.48
58	PL_05	24.05	3.69	0.50					
59	PL_05	8.45	1.28	0.50					
60	PL_05	22.75	3.49	0.49					
61	PL_05	6.5	0.98	0.49					
62	PL_05	16.9	2.59	0.49					
63	PL_05	24.7	3.79	0.49					
64	PL_05	22.1	3.39	0.49					

65	PL_05	15.6	2.39	0.48
66	PL_05	14.95	2.29	0.48
67	PL_05	22.1	3.39	0.48
68	PL_05	16.25	2.49	0.48
69	PL_05	10.4	1.58	0.47
70	PL_05	8.45	1.28	0.47
71	PL_05	9.1	1.38	0.47

Plot 7					Plot 8				
ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood density (g/cm3)	ID	Plot_ID	DBH (cm)	HEIGHT (m)	Wood density (g/cm3)
0	PL_07	9.75	1.52	0.58	0	PL_08	11.7	1.87	0.52
1	PL_07	15.6	2.41	0.63	1	PL_08	21.45	3.26	0.63
2	PL_07	22.1	3.41	0.58	2	PL_08	24.7	3.76	0.58
3	PL_07	20.8	3.21	0.58	3	PL_08	20.8	3.16	0.63
4	PL_07	22.1	3.41	0.63	4	PL_08	22.1	3.36	0.63
5	PL_07	10.4	1.62	0.63	5	PL_08	14.95	2.26	0.63
6	PL_07	7.8	1.22	0.58	6	PL_08	18.85	2.86	0.63
7	PL_07	13	2.01	0.63	7	PL_08	17.55	2.66	0.48
8	PL_07	9.75	1.52	0.58	8	PL_08	22.75	3.46	0.63
9	PL_07	10.4	1.62	0.51	9	PL_08	24.05	3.66	0.63
10	PL_07	14.95	2.31	0.51	10	PL_08	11.05	1.77	0.63
11	PL_07	7.15	1.12	0.63	11	PL_08	11.05	1.77	0.58
12	PL_07	11.7	1.82	0.58	12	PL_08	20.8	3.16	0.58
13	PL_07	20.8	3.21	0.58	13	PL_08	24.7	3.76	0.43
14	PL_07	6.5	1.02	0.51	14	PL_08	18.2	2.76	0.58
15	PL_07	25.35	3.91	0.58	15	PL_08	17.55	2.66	0.58
16	PL_07	7.15	1.12	0.51	16	PL_08	18.2	2.76	0.58
17	PL_07	13.65	2.11	0.63	17	PL_08	11.05	1.77	0.58
18	PL_07	25.35	3.91	0.63	18	PL_08	21.45	3.26	0.63
19	PL_07	16.25	2.51	0.58	19	PL_08	12.35	1.97	0.51
20	PL_07	6.5	1.02	0.58	20	PL_08	13.65	2.06	0.51
21	PL_07	15.6	2.41	0.58	21	PL_08	6.5	1.07	0.51
22	PL_07	18.85	2.91	0.58	22	PL_08	11.05	1.77	0.51
23	PL_07	7.8	1.22	0.63	23	PL_08	9.75	1.57	0.51
24	PL_07	17.55	2.71	0.63	24	PL_08	6.5	1.07	0.51
25	PL_07	14.3	2.21	0.58	25	PL_08	6.5	1.07	0.51
26	PL_07	7.8	1.22	0.63	26	PL_08	9.75	1.57	0.48
27	PL_07	24.05	3.71	0.58	27	PL_08	15.6	2.36	0.50
28	PL_07	6.5	1.02	0.63	28	PL_08	10.4	1.67	0.50
29	PL_07	7.8	1.22	0.63	29	PL_08	11.7	1.87	0.50
30	PL_07	7.8	1.22	0.63	30	PL_08	14.95	2.26	0.49

31	PL_07	13.65	2.11	0.58	31	PL_08	9.75	1.57	0.49
32	PL_07	15.6	2.41	0.58	32	PL_08	11.05	1.77	0.48
33	PL_07	10.4	1.62	0.58	33	PL_08	8.45	1.37	0.48
34	PL_07	18.2	2.81	0.51					
35	PL_07	9.75	1.52	0.51					
36	PL_07	18.85	2.91	0.51					
37	PL_07	11.05	1.72	0.63					
38	PL_07	24.05	3.71	0.63					
39	PL_07	21.45	3.31	0.51					
40	PL_07	22.1	3.41	0.58					
41	PL_07	11.7	1.82	0.63					
42	PL_07	23.4	3.61	0.63					
43	PL_07	22.75	3.51	0.63					
44	PL_07	24.05	3.71	0.63					
45	PL_07	23.4	3.61	0.63					
46	PL_07	25.35	3.91	0.58					
47	PL_07	10.4	1.62	0.58					
48	PL_07	24.7	3.81	0.63					
49	PL_07	22.1	3.41	0.58					
50	PL_07	11.05	1.72	0.58					
51	PL_07	11.05	1.72	0.63					
52	PL_07	11.05	1.72	0.48					
53	PL_07	26	4.01	0.48					
54	PL_07	22.75	3.51	0.58					
55	PL_07	16.25	2.51	0.63					
56	PL_07	9.75	1.52	0.58					
57	PL_07	7.8	1.22	0.63					
58	PL_07	16.25	2.51	0.63					
59	PL_07	19.5	3.01	0.51					
60	PL_07	6.5	1.02	0.58					
61	PL_07	11.05	1.72	0.63					
62	PL_07	10.4	1.62	0.48					
63	PL_07	21.45	3.31	0.58					
64	PL_07	7.15	1.12	0.58					
65	PL_07	9.75	1.52	0.58					
66	PL_07	7.15	1.12	0.58					
67	PL_07	13	2.01	0.58					
68	PL_07	7.8	1.22	0.58					
69	PL_07	21.45	3.31	0.58					
70	PL_07	17.55	2.71	0.58					
71	PL_07	17.55	2.71	0.58					

72	PL_07	24.7	3.81	0.58
73	PL_07	26	4.01	0.58
74	PL_07	22.75	3.51	0.58
75	PL_07	16.9	2.61	0.58

Annex II: Formulas and Calculations

Allometric equations used for AGB estimation

AGB= 0.0673× (ρ×D2×H) 0.976

Carbon stock conversion formulas

$$C = AGB * CF$$

Annex III: Estimated Monthly Height Growth Rates of Major Tree Species in the Study Area (2021–2025 Adjustment Basis)

Species	Common Name	Monthly Height Growth (cm)	Growth Notes
Eucalyptus globulus	ባህር ዛፍ	~2.5–3.0 (first 2 years)	Fastest growth in 3rd–4th year; up to 3 cm/month in establishment phase under good conditions (FAO, n.d.).
Juniperus procera	ጥድ	~0.25	Slow growth: 5.7 cm in 225 days ≈ 0.76 cm/month (Eyob Tenkir, 2024).
Olea europaea subsp. cuspidata	ጠያራ	~0.13	Very slow: 1 cm in 225 days ≈ 0.13 cm/month (Eyob Tenkir, 2024).
Hagenia abyssinica	ኮሶ	~0.32	Moderate: 7.1 cm in 225 days ≈ 0.32 cm/month (Eyob Tenkir, 2024).
Podocarpus falcatus	ዝግባ	~0.41	Moderate: 5.9 cm in 225 days ≈ 0.26 cm/month (Eyob Tenkir, 2024).
Acacia spp.	ግራር	Variable (often 2–5)	Growth rates depend on species; many *Acacia* can grow 2–5 cm/month in favorable conditions.

Summary of estimated growth

Species	Height at 0 days (cm)	Height at 225 days (cm)	Total Growth (cm)	Average Monthly Growth (cm)
Juniperus procera	13.2	18.9	5.7	0.76
Olea europaea cuspidata	30.9	31.9	1	0.13
Hagenia abyssinica	21.4	28.5	7.1	0.95
Podocarpus falcatus	15.4	18.6	3.2	0.43