Automated Tree Counting Using Airborne LiDAR and Multispectral imagery: A Case of Entoto Forest Reserve, Ethiopia.

Getaw Meshesha Tessema

A Thesis Submitted to the Department of Architecture

College of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Degree of Master of Science in Geoinformatics Engineering

Office of Graduate Studies

Adama Science and Technology University

May, 2025

Adama, Ethiopia

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Approval

I/we, the advisors of the thesis entitled "**Automated Tree Counting Using Airborne LiDAR and Multispectral imagery: A Case of Entoto Forest Reserve, Ethiopia**" and developed by **Getaw Meshesha,** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Examiners of the thesis by Getaw Meshesha_have read and evaluated the thesis entitled "**Automated Tree Counting Using Airborne LiDAR and Multispectral imagery: A Case of Entoto Forest Reserve, Ethiopia**" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geoinformatics Engineering.

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Declaration

I hereby declare that this Master Thesis entitled "**Automated Tree Counting Using Airborne LiDAR and Multispectral imagery: A Case of Entoto Forest Reserve, Ethiopia**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation

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Recommendation

I/we, the advisor(s) of this thesis, hereby certify that I/we have read the revised version of the thesis entitled "**Automated Tree Counting Using Airborne LiDAR and Multispectral imagery: A Case of Entoto Forest Reserve, Ethiopia**" prepared under my/our guidance by **Getaw Meshesha** submitted in partial fulfillment of the requirements for the degree of Master of Science in Geoinformatics Engineering. Therefore, I/we recommend the submission of revised version of the thesis to the department following the applicable procedures.

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ACRONYMS

AGL	Above Ground Level
ASPRS	American Society for Photogrammetry and Remote Sensing
CHM	Canopy Height Model
3D	Three-Dimensional
GCP	Ground Control Point
GIS	Geographic Information System
GPS	Global Positioning System
GNSS	Global Navigation Satellite System
IMU	Inertial Measurement Unit
LiDAR	Light Detection and Ranging
NIR	Near Infrared
nDSM	Normalized Digital Surface Mode
NOAA	National Oceanic and Atmospheric Administration Coastal Services Center
OBIA	Object-Based Image Analysis
SSGI	Space Science and Geospatial Institute

ABSTRACT

Accurate and efficient tree counting is essential for forest inventory, biodiversity conservation, and sustainable forest management. This study presents an automated tree counting in the study area, by integrating airborne Light Detection and Ranging (LiDAR) and multispectral imagery. LiDAR provides high-resolution three-dimensional forest structure data, while multispectral imagery offers critical spectral information for vegetation classification and health assessment. Primary data, including LiDAR point clouds and aerial photographs, were obtained from the Space Science and Geospatial Institute (SSGI) during a flight on March 11, 2021, conducted at 4,556 meters above mean sea level, with a point density of 4 points/m² and an image resolution between 0.07 and 0.1 meters. Data were preprocessed using HxMap and Terasolid software, enabling geo-referencing, radiometric correction, and classification of ground and non-ground points. Advanced segmentation algorithms, machine learning models, and data fusion techniques were applied to delineate individual trees, resulting in the detection of 36,531 trees with heights ranging from 4 to 52 meters and trunk diameters (DBH) between 2 and 89 meters. Total estimated biomass in the study area reached 59,874,692 units. Validation against ground survey and high-resolution imagery collected in 2025 showed that 92 out of 100 randomly selected trees were correctly detected, with precision, recall, and F1-score values all exceeding 95%, demonstrating the reliability of the method. Variations in height and diameter were attributed to temporal differences between field and airborne data collection. The study concludes that integrating high-density LiDAR with multispectral imagery provides a scalable, accurate, and cost-effective solution for automated tree detection and forest assessment in complex environments. It is recommended that similar integrated methodologies be adopted in other forest regions of Ethiopia to support afforestation planning, carbon stock estimation, biodiversity management, and long-term forest monitoring, while also calling for expanded availability of high-resolution airborne data and improved field validation efforts.

Keywords: *Tree Counting, Segmentation, GIS, LiDAR, Multispectral Imagery*

1 INTRODUCTION

This chapter introduces the background and context of the study, outlines the key problems it addresses, defines the research objectives and questions, and discusses the significance, scope, and key terminology. The purpose is to provide a foundational understanding of why automated tree counting using airborne LiDAR and multispectral imagery is necessary and how it supports sustainable forest management.

1.1 Background of the study

Numerous global studies have validated the effectiveness of airborne LiDAR and multispectral imagery for tree counting and forest inventory. For instance, (Duncanson et al.,2014) and (Ayrey & Hayes, 2018) demonstrated the capability of LiDAR-derived canopy height models in temperate and coniferous forests. Regionally, studies in East Africa have begun to explore remote sensing applications for biomass estimation and forest mapping, though most rely on satellite imagery rather than airborne LiDAR. In Ethiopia, while biomass estimation has been explored using satellite data (e.g., Habitamu et al., 2020), there is a lack of empirical research specifically addressing automated tree counting using integrated airborne LiDAR and multispectral data. This empirical gap at the national level highlights the need for localized studies that adapt global methodologies to Ethiopian forest ecosystems.

Monitoring forest resources is essential for sustainable environmental management, biodiversity conservation, and climate change mitigation (FAO, 2020). Accurate information on tree count and distribution plays a crucial role in these efforts, informing policies and actions related to carbon stock estimation, habitat protection, and forest restoration initiatives (Asner et al., 2012). Traditionally, tree enumeration has relied on manual field-based surveys, which are not only labor-intensive and time-consuming but also prone to human error and limited in scope particularly in densely vegetated or inaccessible areas (Koch, 2010). Studying tree height and trunk diameter is essential for estimating aboveground biomass and understanding forest structure, which are key indicators of forest health and productivity (Asner et al., 2012; Dubayah & Drake, 2000). These metrics contribute to biodiversity conservation, carbon stock estimation, and forest growth modeling (Lefsky et al., 2002; Zolkos et al., 2013). Accurate tree count further supports effective planning in reforestation projects, forest degradation assessment, and climate change mitigation through initiatives like REDD+ (GOFC-GOLD, 2016; FAO, 2020). Understanding these characteristics at scale helps policymakers and environmental managers make data-driven decisions about land use, conservation priorities, and resource allocation (Wulder et al., 2012; Avitabile et al., 2016).

The need for more efficient, reliable, and scalable approaches has grown alongside global efforts such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation) and national forest monitoring programs (UN-REDD, 2015). In this context, automated tree counting using remote sensing technologies like airborne LiDAR and multispectral imagery has emerged as a promising solution. These tools offer high-resolution data that enable the precise detection and classification of individual trees over large areas, with minimal field intervention (Li et al., 2012). This study aligns with these broader goals by developing and evaluating a method suitable for the Ethiopian context, thereby contributing to improved forest management at both national and international levels.

A forest is a large area dominated by trees, shrubs and other plant species that form a dense canopy and provide habitats for a diverse range of animals, insects and organisms. Tree counting refers to the practice of quantifying the number and distribution of trees in a particular area. Forest inventory deals with the methods for obtaining detailed and accurate information about forest composition and structure (Spurr, 1951).

In order to address some of the most important worldwide issues pertaining to forest management and environmental sustainability, automated tree counting is essential. Because they store carbon, forests are essential for preserving ecological equilibrium, promoting biodiversity, and helping to reduce global warming. However, the effects of climate change, land-use change, and deforestation are posing a growing threat to their health and extent.

Stakeholders may obtain precise, fast, and scalable information about forest structures and tree densities by using automated tree counting, which is made possible by cutting-edge technologies including satellite photography, LiDAR, and machine learning (Wulder et al., 2016).

Through the use of automation, tree counting moves from time-consuming, regional procedures to effective, worldwide applications, enabling governments, non-governmental organizations, and researchers to make informed decisions on the planet's forests (Thompson, 2021).

Light detection and ranging (LiDAR) is an active remote sensing technology that uses laser beams to measure distances and create highly accurate 3D models of objects and surfaces (Wehr & Lohr, 1999).

LiDAR mapping is an accepted method of generating precise and directly georeferenced spatial information about the shape and surface characteristics of the Earth (NOAA, 2012). In recent years, it is emerged as a promising technology for remote sensing of forest structure and biomass. However, the challenge of accurately counting trees from airborne LiDAR data remains unresolved, thereby limiting the full potential of this technology in forest management. Therefore, there is a need for a robust and automated method for tree counting using Airborne LiDAR data that can accurately count and improve the efficiency and effectiveness of forest management practices. Several national reports issued over the recent years highlight the value and critical need of this data. The use of new remotely sensed data is causing a major change in how forest inventory is conducted (David et al., 2019). Among remote sensing techniques, LiDAR has rapidly gained popularity in forest inventory, due to its unique capability to measure the 3D structural information of trees directly (Anahita, 2017). Automated tree counting is a fundamental aspect of forest inventories and it plays a critical role in promoting sustainable forest management, preserving forest biodiversity, resource surveys, such as forest inventory, forest damage evaluation, vegetation mapping, ecological and recreational research, soil and geological surveys and ensuring the security of forest ecosystems (Dan et al., 2020). Having knowledge about individual trees can be highly advantageous in determining various values of forest resources, such as timber value, quality of habitat, or vulnerability to loss (Nicholas et al., 2012) . Traditionally, counting tree involved a time-consuming process of visual recognition by a specialist. However, when it comes to large areas such as a forest reserve, it is nearly impossible to obtain information about Number and tree distribution solely through fieldwork, especially beyond sample plots. Remote sensing techniques provide continuous, large-scale coverage, making them the most efficient method for assessing tree count and forest structure. In this perspective, more automated methods for forest mapping are needed to reduce costs and improve the accuracy. This study aims to accurately and efficiently determine tree counts and estimate biomass using integrated airborne LiDAR and multispectral imagery.

Counting trees serves as a foundational element in forest inventory, allowing for precise estimation of tree density, spatial distribution, biomass, and forest structure. This information is essential for sustainable forest management, carbon stock assessment, biodiversity conservation, and monitoring the impacts of deforestation and climate change. Automated tree counting further enhances this process by enabling scalable, cost-effective, and repeatable assessments across large forested landscapes.

1.2 Statement of the problem

Manual tree counting is labor-intensive, time-consuming, error-prone, and often impossible, especially in densely forested or inaccessible areas (Koch, 2010). While recent advancements in remote sensing technologies have led to the development of automated tree counting techniques, many rely solely on either LiDAR or multispectral imagery, each with inherent limitations. LiDAR excels in providing precise three-dimensional structural data but struggles with species differentiation (Popescu et al., 2003). In contrast, multispectral imagery supports species classification but lacks the detailed vertical structure necessary for accurate tree detection in complex canopies (Dalponte & Coomes, 2016; Fassnacht et al., 2016).

Previous studies, such as those by (Habitamu et al.,2020), focused on biomass estimation using satellite imagery without addressing individual tree counting; (Brodić et al., 2022) applied CHM and machine learning for individual tree detection but faced segmentation challenges in complex forests; (Rasmus et al., 2023) and (Linhai et al., 2024) employed deep learning for tree crown delineation using either imagery or low-density LiDAR, but did not fully explore the integration of multispectral and high-density LiDAR data. Furthermore, no studies to date have applied such integrated methods specifically within Ethiopian forest ecosystems, leaving a critical gap in automated tree inventory techniques adapted to local forest ecosystems.

To address these gaps, this study develops and validates an efficient methodology that integrates high-density airborne LiDAR with high-resolution multispectral imagery for automated tree counting in the Entoto Forest Reserve. By combining the structural precision of LiDAR with the spectral sensitivity of multispectral imagery and applying advanced segmentation and classification algorithms, this study provides a more accurate, scalable, and efficient approach to tree detection and biomass estimation. The aim of this study is to explore the use of LiDAR technology for tree counting and to develop efficient and accurate methods to assess and manage forested areas.

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of the study was to design, implement and validate an automated tree counting method using integrated airborne LiDAR and multispectral imagery data.

1.3.2 Specific Objectives

More specifically, the study aimed:

- To enable automated tree counting and classification using LIDAR and Multispectral data.
- To classify and separate individual trees from other vegetation and non-vegetation objects using height-based thresholds derived from LiDAR point cloud data and canopy height models.
- To analyze and characterize information on the diameter and vertical structure of the forest.

1.4 Research Questions

The major research questions, which were answered by this research include:

1. How can airborne LiDAR and Multispectral data be used to enable automated tree counting and classification?
2. How effectively can individual trees be distinguished from other vegetation and non-vegetation objects using height-based thresholds derived from LiDAR point cloud data?
3. What structural information about the forest canopy can be extracted and characterized using LiDAR-derived diameter and height metrics?

1.5 Significance of the study

The automated tree counting methodology will benefit stakeholders such as conservation agencies, forestry departments, and urban planners by improving decision-making regarding afforestation programs, timber production, carbon stock estimation, and biodiversity management. Furthermore, it sets a precedent for integrating advanced remote sensing techniques in Ethiopian natural resource assessments.

The study on automated tree counting using airborne LiDAR data and multispectral imagery could be significant for several reasons. Firstly, it provides a more efficient and cost-effective alternative to traditional field-based methods which can be time-consuming and labor-intensive as LiDAR technology enables rapid data acquisition over large areas with minimal manpower, ability to penetrate dense canopies and provide detailed 3D data, tree counting is more precise, data can be reused for periodic monitoring, making it a cost-effective tool for tracking changes in forest composition over time compared to repetitive field surveys. Secondly, LiDAR data can capture detailed information about the physical structure of forests including, the height and density of trees, which can be used to differentiate between individual trees. It enables forest managers to identify and address issues such as forest fragmentation, and damage from natural disasters. Accurate tree counting is also important for carbon accounting and estimating the amount of carbon stored in forests, which is critical for climate change mitigation efforts. LiDAR data can also provide valuable information on forest structure, which can help forest managers assess the quality of habitat for wildlife and identify areas that need restoration. Forest structure data can also be used to predict potential areas of forest fire risk and improve forest fire management. The study on automatic tree counting using airborne LiDAR technology holds substantial significance, especially for conservation efforts in Ethiopia, such as biodiversity monitoring, forest management, carbon stock assessment, restoration projects, and forest fire risk mapping.

On the other hand, the methodological significance of the study demonstrates how segmentation rules, height-based classification, and point cloud processing can be combined with object-based image analysis to enhance tree-level accuracy. This integrated approach addresses common limitations in previous methods, such as misclassification in dense canopies, limited species separation, and reliance on low-density LiDAR. By validating the model with field-collected data and high-resolution imagery, the study also offers a replicable framework for forest monitoring in similarly complex ecosystems.

Moreover, the use of airborne LiDAR data was significantly reducing the potential for errors in data processing and analysis. Overall, this study holds great promise for improving our understanding, researchers and forest managers to better monitor and protect these valuable natural resources.

1.6 Scope of the study

The scope of this study involves identifying, height measurement and counting trees using airborne LiDAR data. The study tries to develop a method to accurately detecting and counting trees from LiDAR data. Additionally, the study also examined forest cover biomass and classified trees based on height. The study also explores the capabilities of LiDAR data in its ability to penetrate through foliage, enabling the detection of trees and the ability to count individual trees. This study is geographically focused on the Entoto Forest Reserve, located in the northern highlands of Addis Ababa, Ethiopia, covering approximately 6.3 km^2 of planted and mixed forest types dominated by Eucalyptus species. Temporally, the study is constrained to LiDAR and multispectral datasets collected in 2021, with validation data from field surveys conducted in early 2025. Validation involved comparing automated tree counts with manually interpreted reference data, calculating overall accuracy, precision, and recall. The validation process involved comparing the automated tree counts against a manually interpreted reference dataset. Metrics such as overall accuracy, precision, recall, and F1-score were calculated to evaluate the performance.

Overall, the scope of the study trying to provide an assessment of the capabilities of LiDAR data in detecting and counting trees within a given area. The results of the study were demonstrated whether or not LiDAR data can be a reliable and efficient tool for forest management, particularly in monitoring and managing natural resources. The researcher focuses on Entoto as a case study area, because of Airborne LiDAR and multispectral imagery data is only available in this area.

1.7 Definitions of Key Terms

LiDAR (Light Detection and Ranging): A remote sensing technology that uses laser pulses to measure distances and generate precise three-dimensional (3D) models of surfaces (Lillesand et al., 2015).

Multispectral Imagery: Images captured across multiple wavelengths of light (e.g., visible and near-infrared) to analyze physical and chemical properties of surfaces, including vegetation (Jensen, 2015).

Canopy Height Model (CHM): A digital representation of the height of forest canopies derived from LiDAR data, typically showing tree height above the ground (White et al., 2013).

Normalized Digital Surface Model (nDSM): A model that shows height differences between the ground and objects (e.g., vegetation or buildings) obtained from LiDAR (Lillesand et al., 2015).

Point Cloud: A collection of data points in 3D space representing the surface of objects captured using LiDAR technology (White et al., 2013).

Biomass: The total mass of living vegetation, including trees, shrubs, and other plant species (FAO, 2010).

Tree Segmentation: The process of isolating individual trees from LiDAR data or imagery for analysis (White et al., 2013).

Ground Classification: A step in LiDAR data processing to distinguish ground points from non-ground features such as vegetation and buildings (Congalton & Green, 2019).

Random Forest Algorithm: A machine learning method used for classification and regression tasks, applied in this study for identifying and analyzing tree features (Breiman, 2001).

Object-Based Image Analysis (OBIA): A technique that groups pixels into meaningful objects or segments for classification purposes (Jensen, 2015).

Validation: The process of assessing the accuracy of the results by comparing automated data with field measurements or high-resolution imagery (Congalton & Green, 2019).

Feature Extraction: The process of identifying and calculating relevant characteristics (e.g., tree height, crown width) from data for analysis (Jensen, 2015).

Geo-referencing: Aligning data to a coordinate system to ensure spatial accuracy and integration with other geographic data (Congalton & Green, 2019).

Vertical Forest Structure: The arrangement and layering of vegetation in a forest, including understory, mid-story, and canopy layers (FAO, 2010).

Near Infrared (NIR): A portion of the light spectrum (750–2500 nm) used in remote sensing to analyze vegetation properties and health (Jensen, 2015).

Field Verification: The process of collecting on-site data to validate remote LiDAR analyses (Congalton & Green, 2019).

Accuracy Assessment: Measuring the performance of automated methods by calculating metrics like precision, recall, and overall accuracy. (Congalton & Green, 2019)

Tree Crown: The part of a tree including its branches and leaves, used for measurements like diameter and density (Lillesand et al., 2015).

Forest Inventory: A systematic collection of data on forest resources, including tree counts, species composition, and biomass (FAO, 2010).

Sustainable Forest Management: Practices aimed at maintaining the biodiversity, productivity, and ecological health of forests over the long term (FAO, 2010).

Entoto Forest Reserve: The study area for this research, located in Ethiopia, known for its dense forest ecosystem.

2 Review of Related Literature

2.1 Introduction

This review examines the existing literature on using Airborne LiDAR and Multispectral imagery for tree counting in forests. LiDAR emits light pulses that measure distances to objects, creating high-resolution 3D maps. Its ability to penetrate tree canopies allows for accurate measurements of tree height, crown width, and foliage density, even in low light. Furthermore, the varying optical properties (reflectance and absorption) of different tree species enable species identification through spectral analysis of the LiDAR data. This technology offers a powerful tool for detailed forest inventory, including tree counts and volume estimations.

A cutting-edge technology with numerous forestry uses is LiDAR remote sensing, which evaluates vertical forest structure directly. Key forest structural features like canopy heights, stand volume, basal area, and above-ground biomass are precisely estimated by LiDAR sensors using the laser light substitute of radar. The findings can also be applied to land cover classification, habitat mapping, and forest wildlife management since sub canopy vegetation height depends on species composition, climate, and site quality (Dubayah et al., 2000).

2.2 Advancements in LiDAR Technology and its Application in Forestry

Recent advancements in Near-Infrared (NIR) LiDAR technology, particularly the development of high-density and multi-return LiDAR systems, have significantly improved the resolution and accuracy of forest data. These systems enable detailed recordings of ground and canopy surfaces, facilitating the creation of advanced algorithms for automatic tree counting. NIR LiDAR operates by emitting near-infrared light, which interacts with molecules in the target area to generate spectral signatures. This capability allows precise identification of materials and surfaces, making remote sensing indispensable for forest inventory and management (Laifi, 2012).

Recent studies have demonstrated the growing potential of integrating LiDAR and multispectral imagery for tree detection and forest structure analysis in complex landscapes. For example, (Duncanson et al.,2014) implemented a canopy height model (CHM) based segmentation method using airborne LiDAR to estimate tree counts and heights in mixed-species forests. Their results highlighted that LiDAR-derived CHMs are effective in delineating individual trees even in overlapping canopies.

LiDAR has demonstrated great potential in forestry applications, such as mapping and monitoring forest structures, estimating tree height and biomass, and providing detailed data for conservation and sustainable harvesting. Specific uses include creating accurate forest resource maps for inventory purposes, guiding timber harvesting to minimize environmental impact, and estimating carbon sequestration, which aids climate change mitigation efforts.

2.3 Forest Tree Counting

By providing high-resolution three-dimensional data for forest structures, Airborne Light Detection and Ranging (LiDAR) technology has completely transformed the inventory and management of forestry. Using aerial LiDAR data to count individual trees has various benefits, such as effective data collecting over broad regions, minimal disruption of the ground, and some capacity to penetrate canopy layers. (Unger et al., 2014)

The main difficulty in using LiDAR for tree counting is accurately identifying individual trees within the intricate and frequently overlapping structures of forest canopies. Initial approaches involved creating a Canopy Height Model (CHM) from LiDAR data, which depicts the height of the forest canopy relative to the ground. Peaks in the CHM were interpreted as the tops of individual trees, facilitating their detection and counting (Popescu et al., 2003).

Ayrey and Hayes investigated the integration of airborne LiDAR and WorldView-2 multispectral imagery for identifying individual trees and estimating forest metrics in coniferous forests in the United States. Their study demonstrated that combining LiDAR-derived structural features with spectral indices such as NDVI enhanced both species-level classification and crown delineation, showing that multispectral imagery complements the limitations of LiDAR-alone approaches (Ayrey & Hayes, 2018).

Theoretical discussions by (Wulder et al., 2012) explain how combining optical and structural data enables more detailed forest analysis than single-sensor use. The authors emphasize the complementarity of LiDAR (for structure) and multispectral imagery (for species or canopy health), supporting your method of integrated analysis.

2.4 Techniques and Algorithms for Forest Tree Counting using LiDAR Data

A variety of techniques have been proposed for autonomous tree counting using NIR LiDAR data, with machine learning, object-based image analysis, and voxel-based methodologies being the most commonly applied. Voxel-based techniques involve creating a three-dimensional grid of the forest and analyzing point density within each voxel. (Popescu et al., 2019)demonstrated that voxel-based approaches could effectively identify individual trees by studying the vertical distribution of LiDAR returns. Object-based image analysis, on the other hand, divides the LiDAR point cloud into discrete objects or clusters, which are then analyzed to identify trees.

This method has been effectively applied for tree top detection and density estimation, achieving successful tree counting and height predictions. Machine learning, particularly deep learning models like Convolutional Neural Networks (CNNs), has shown significant improvements in tree counting accuracy (Zhao et al., 2021).

CNNs have been employed for classifying and counting trees from LiDAR data, showing superior performance compared to traditional approaches. Notably, Near-Infrared (NIR) LiDAR data acquired by emitting laser pulses in the 750 nm to 2500 nm wavelength range can penetrate the vegetation canopy, producing high-resolution 3D point clouds that are particularly effective for tree detection and counting (Yang et al., 2022). Key techniques for tree detection using NIR LiDAR data include spectral analysis to identify unique tree signatures, classification based on height characteristics, feature extraction to capture physical tree properties, object-based analysis for canopy segmentation, and feature fusion, which combines spectral, spatial, and temporal data to enhance counting accuracy. These approaches collectively contribute to more precise and reliable tree detection and counting methods.

2.5 Importance of LiDAR Data in Tree Counting

LiDAR is a highly valuable tool for forest monitoring and management, offering a more efficient and cost-effective method for tree counting than traditional field-based approaches. Its ability to penetrate dense canopies and generate precise 3D point clouds of forest structure makes it superior to other remote sensing techniques, especially for large-scale inventories and long-term monitoring. The 3D data acquired by LiDAR enables accurate measurements of individual tree height, crown diameter, and biomass, which are essential for diverse applications such as species classification, carbon stock estimation, and biodiversity assessment. This technology is particularly relevant for addressing critical global issues like climate change mitigation and promoting sustainable forestry practices (Liu et al., 2020).

2.6 Previous Studies

Despite the advancements, there are still a number of difficulties in the area of automated tree counting with airborne LiDAR. The accuracy of tree detection in deep, multi-layered forests is one of the main problems.

The previous studies (Habitamu et al., 2020) evaluated how remote sensing (RS) data from Landsat-8, Sentinel-2, and Planet Scope can improve the estimation of aboveground biomass (AGB) over traditional field-based sample surveys (FBSS). It identified spectral variables and indices such as shortwave infrared reflectance and green leaf indices as valuable predictors for biomass modeling. While the study significantly improves AGB estimation, it does not address automated individual tree counting and relies exclusively on satellite imagery, ignoring the potential of airborne LiDAR, which excels in high-resolution canopy structure analysis and individual tree detection.

A refinement process for individual tree detection results obtained from airborne laser scanning data in a mixed natural forest was introduced, where local maxima filtering and canopy height models (CHM) were combined with machine learning techniques to reduce false-positive detections in treetop identification (Brodić et al., 2022). They Processed data using CHM-based ITD and refined it using various geometric and radiometric metrics and the result of Refinement methods effectively reduced false positives in complex deciduous and mixed forest environments. But they face for gaps High complexity in deciduous forests caused under- and over-segmentation errors and Limited focus on multispectral or NIR attributes, which could enhance discrimination between tree crowns and background vegetation.

Deep learning models have been employed to process large-scale datasets, enabling efficient tree-level counting, crown delineation, and height prediction in forest environments (Rasmus et al., 2023). By employing high-resolution image inputs, the study addresses the challenge of scaling up tree inventory methods from localized regions to national levels. The reliance on visible spectrum satellite imagery restricts the study's ability to differentiate tree species or detect trees in dense canopies. This gap could be addressed by integrating Near-Infrared (NIR) data to exploit its higher sensitivity to vegetation reflectance. The methodology shows limitations in accurately counting trees in heterogeneous terrains and densely forested regions due to overlapping crowns and variability in image quality. The absence of LiDAR-based height data integration restricts the model's capability to assess forest vertical structure comprehensively, which is crucial for biomass estimation and ecological studies.

The use of airborne LiDAR and aerial imagery has been explored for individual tree crown (ITC) delineation in the Taiga-Tundra Ecotone, demonstrating its effectiveness in complex forest transition zones (Linhai et al., 2024). The study employed Mask R-CNN, a deep learning model, alongside traditional methods such as the improved Multi-Scale Adaptive Segmentation (MSAS) and a local maximum clustering approach. The dataset incorporated low-density LiDAR data (0.8–1.1 pts/m^2) and high-resolution aerial images, demonstrating the feasibility of using sparse point clouds for large-scale tree extraction. But this study has gaps like, Low point density of LiDAR data, Manual sample labeling for deep learning consumes significant time and resources insufficient exploration of combining LiDAR with multispectral imagery for improved classification and biomass estimation. Previous studies in tree counting and forest structure analysis have demonstrated the value of using either LiDAR or multispectral imagery individually. For example, some researchers have effectively used LiDAR for estimating canopy height and detecting individual tree crowns, while others have employed multispectral data to distinguish between tree species based on spectral signatures. However, these single-sensor approaches often face limitations such as reduced accuracy in densely vegetated areas or difficulty in species classification under varying light conditions. Few studies have attempted to combine both data types, especially in the context of Ethiopian forests. This study seeks to bridge that gap by integrating LiDAR's structural insights with the spectral richness of multispectral imagery to enhance tree detection accuracy and applicability in complex forest environments like the Entoto Forest Reserve.

And I didn't got studies in Ethiopia that focuses on Automated Tree counting using Airborne LiDAR and Multispectral Imagery.

Therefore, the previous studies I reviewed above have their own limitations, such as Methodology they use, data and analysis mechanisms Software's the use, validation techniques, in my study I was addressed those gaps by using airborne LiDAR data with higher point density than the previous studies and high resolution aerial photograph collected simultaneously with the same sensor with the combination of sophisticated algorithms and machine learning approaches with airborne Point cloud data which is designed for feature extraction purpose.

2.7 Conceptual Framework

The conceptual framework for this study is structured around the integration of remote sensing data and analytical processes to support automated tree counting in complex forest environments. The independent variables are the remotely sensed datasets airborne LiDAR data, multispectral imagery, and trajectory data including GNSS/IMU measurements.

Airborne LiDAR provides detailed three-dimensional structural information about the forest canopy and terrain. Multispectral imagery contributes spectral properties that support vegetation classification and LiDAR matching. Trajectory data, derived from GNSS/IMU systems, ensures precise geolocation and spatial alignment of the LiDAR and imagery datasets by correcting for positional and orientation distortions during flight.

These inputs feed into a series of intervening variables, including data preprocessing techniques (e.g., noise filtering, geo-referencing, and ground classification), canopy height model (CHM) generation, segmentation methods (such as normal vector analysis and crown delineation), and classification algorithms (e.g., Random Forest or Object-Based Image Analysis). These operational stages transform raw data into interpretable units of analysis.

The dependent variables are the measurable forest attributes extracted from the automated analysis such as tree count, tree height, tree crown width, diameter at breast height (DBH), and biomass estimation. The framework shows a causal relationship where the type and quality of input data (independent variables), mediated through well-structured data processing techniques (intervening variables), directly influence the accuracy and reliability of the final forest metrics (dependent variables). This relationship emphasizes that the integration and alignment of LiDAR, multispectral, and trajectory data is fundamental for producing reliable and scalable results in automated forest inventory applications. Figure 2.1 bellow presents the conceptual framework of the study.

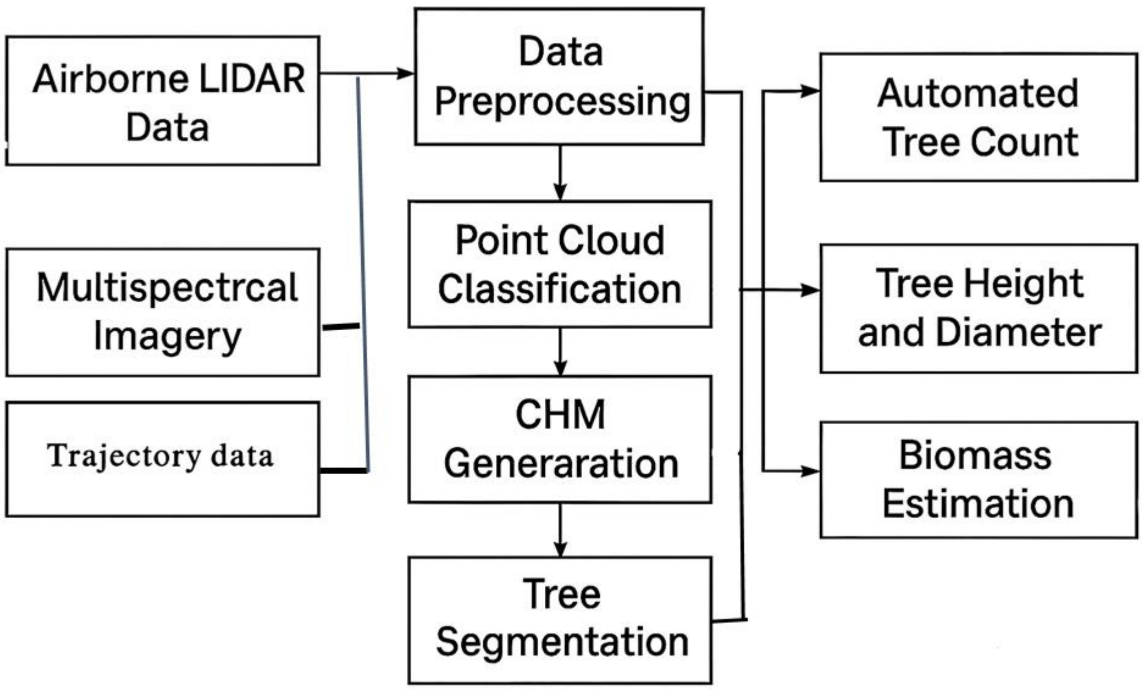

Figure 2. 1 conceptual framework

3 Methods and Materials

This chapter presents the methodology used to achieve the objectives of automated tree counting using LiDAR and multispectral imagery. It details the study area, data sources, collection techniques, processing tools, and analytical steps.

3.1 Description of the Study Area

3.1.1 Location

Entoto forest reserve is geographically located at 9˚5′0″-9˚5′30″ latitude and 38˚45′0″ - 38˚45′30″ longitude. The sample study area covers an area of 629.5 hectares. The study area is roughly bounded from the South by Gullele Sub city, from West and North West by Sululta Woreda of Oromia region, from East by Yeka sub city and North east by Yeka Terara.

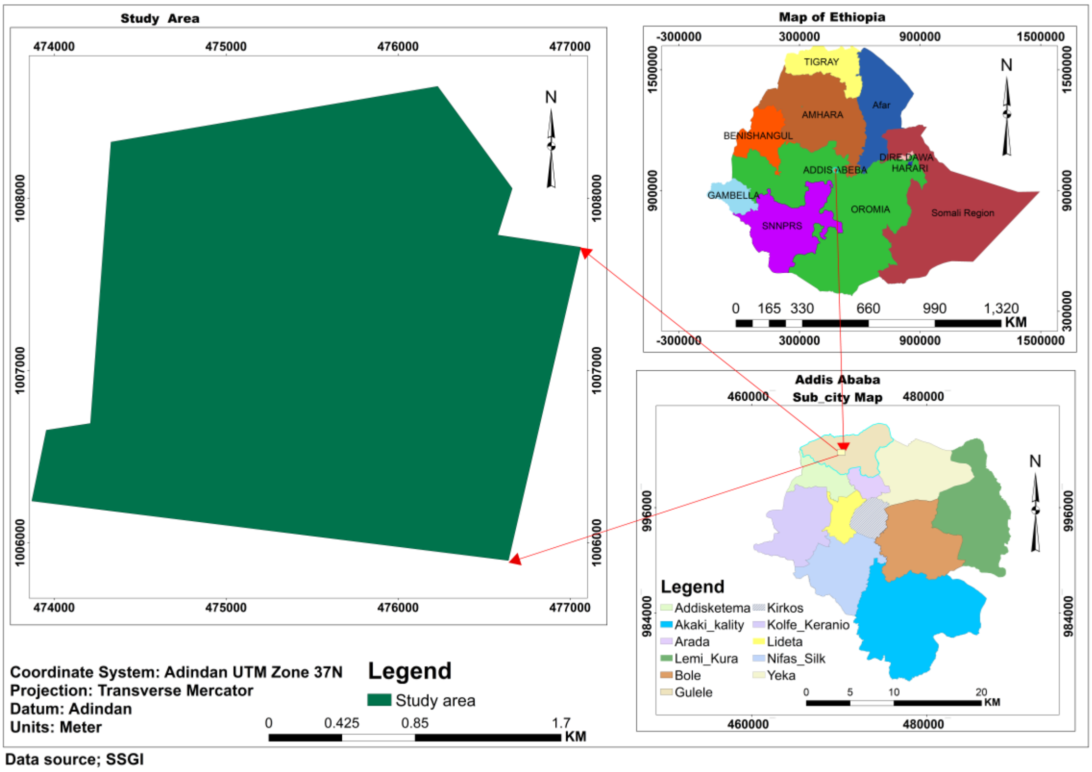

Figure 3. 1 Location map of the study area

Source: Computed using the city administration boundary shape file overlay with Ethio-GIS data

3.1.2 Topography

The topography of the Entoto Forest Reserve is characterized by varying elevations, offering a mixture of terrains average Elevation of 3200 m (Source: 5m DEM Generated from LiDAR data). The rugged and hilly landscape supports diverse vegetation types, with significant canopy coverage that creates a unique micro-environment. Elevations play a crucial role in defining the forest structure, contributing to diverse ecological niches.

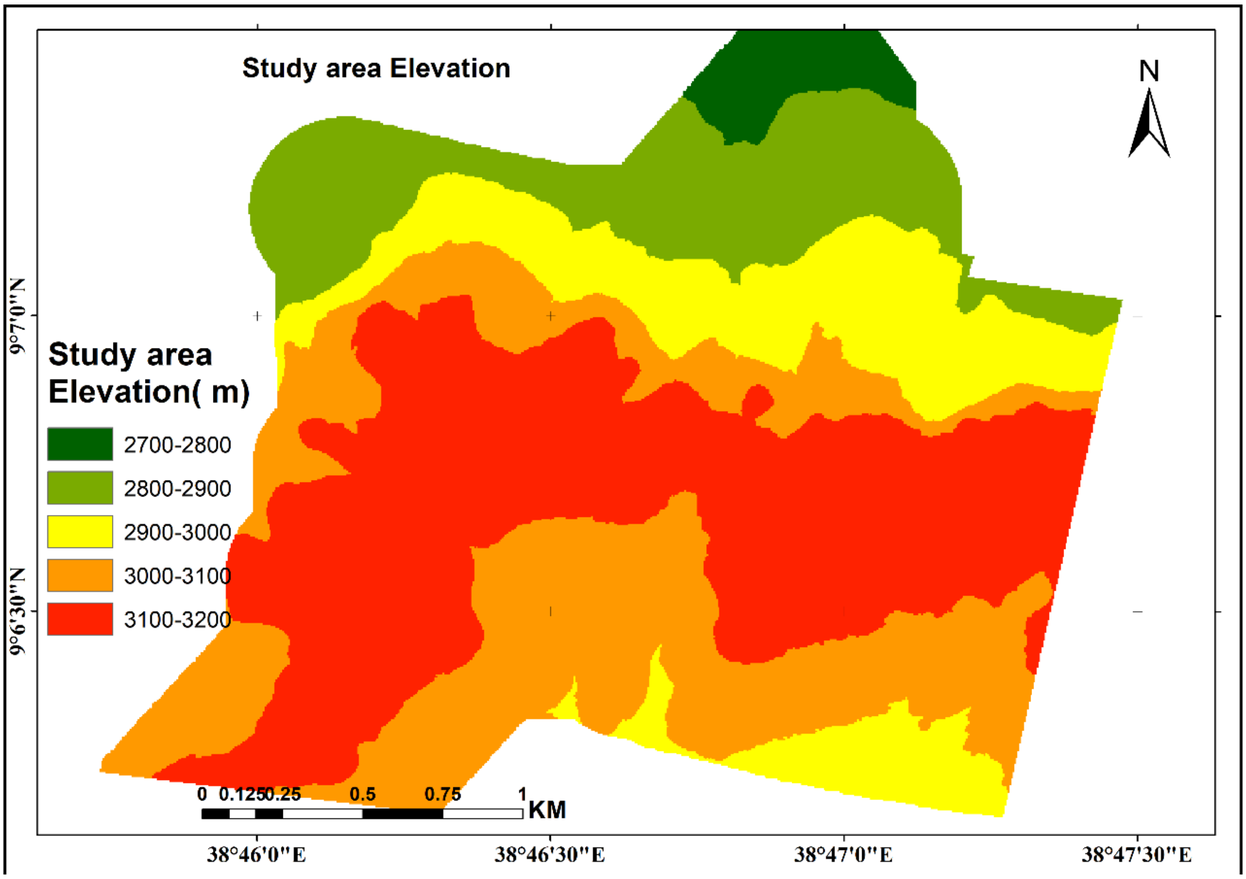

Figure 3. 2 Study area elevation(m)

3.1.3 Climate

The climate of the Entoto Forest Reserve is influenced by its location and elevation, likely characterized by:

Temperature: The temperature in the study area is considered moderate, primarily due to its high elevation, with an average annual temperature of approximately 14°C. This elevation-induced climate helps to mitigate the extreme heat commonly experienced in lower-altitude regions of Ethiopia (National Meteorological Agency, 2024).

Rainfall: The study area experiences a distinctly seasonal climate, marked by alternating wet and dry periods that shape the ecological dynamics of the area. The primary rainy season extends from June to September, during which time the forest receives the majority of its annual precipitation. This rainfall is critical for sustaining dense vegetation, maintaining soil moisture, and supporting overall ecological stability. According to data from the National Meteorological Agency of Ethiopia, the region records a mean annual maximum rainfall of approximately 280 mm during the peak rainy month typically July while the mean annual minimum drops to less than 10 mm during the dry season, often in December or January. The average total annual rainfall for the area is estimated to be around 1,200 mm. This reliable seasonal rainfall pattern plays a fundamental role in supporting the rich biodiversity and forest regeneration processes (National Meteorological Agency, 2024).

3.2 Methods

3.2.1 Research Approach and Design

This research work, conducted under the title "Automated Tree Counting Using Airborne LiDAR and Multispectral Imagery," primarily focuses on the application of airborne LiDAR data and multispectral imagery for the detection, measurement, and analysis of individual trees. The study addresses key aspects such as tree counting, height measurement, and canopy width calculation, all of which involve quantitative data obtained from high-resolution LiDAR point clouds and multispectral imagery. These data are analyzed using statistical methods to identify spatial patterns, compute tree metrics, and assess accuracy.

However, the study also incorporates supplementary qualitative data derived from expert opinions, field observations, and ground verification activities. These data sources provide contextual understanding and help validate the automated results, offering insights into local vegetation characteristics, species diversity, and environmental conditions that might affect detection performance.

Based on this combination of data types, the appropriate research design for this study is a mixed-methods research design. This design enables the integration of both quantitative and qualitative approaches, providing a comprehensive understanding of the research problem.

The quantitative approach in this study is used to achieve objectives related to numerical measurement and statistical analysis, such as estimating tree counts, computing canopy heights and widths, evaluating spatial distribution patterns, and calculating accuracy metrics (e.g., precision, recall, F1-score).

On the other hand, the qualitative approach focuses on interpretive and contextual aspects of the research. It emphasizes the collection and analysis of expert feedback, observational notes, and ground-truth validation data.

3.3 Source of Data

In this study, both primary and secondary data were used. The data from primary sources include information from local experts working in Space Science and Geospatial Institute (SSGI) or field observation or verification. The sample point cloud data from LiDAR acquisition were collected in order to obtain three-dimensional crown information about each tree crown by the near infrared (NIR) band and as the same time the height of the trees. This LiDAR point cloud data and aerial photo of the study area from Space Science and Geospatial Institute (SSGI) as Primary data. The other secondary data such as types of species from Ethiopian biodiversity institute, topographic map from SSGI, climate data from National Meteorological Agency, have been used to carry out this study.

3.4 Data Collection Techniques

The data collection technique was primarily collected point LiDAR data and aerial photo including GNSS acquisition with a sample flight acquired from the Ethiopian Space Science and Geospatial Institute (SSGI) using the LeicaTerrainMapper-2L Sensor with 150 MP RGB and NIR cameras from archival data collected during March11, 2021 with flight altitude of 4556m above mean Sea level and point density and image resolution obtained simultaneously 4 points per sqm. and 0.07 – 0.1 m respectively flown with fixed wing airplane in the East-West and north-east to south-west direction from Entoto Kotebe project by clipping of the sample study area. The necessary point cloud classification and image processing was conducted within the study area's selected boundary. The other data collection technique was field data verification as each tree matches its associated data segment from the point cloud extracted from NIR LiDAR data. Based on this, the validation was done with in 0.0093km^2 area coverage with in the study area purposively selecting with the assumption of this sample validation can represents the whole area under investigation.

3.5 Material and Software

In this study, for the purpose of achieving the stated objectives, the LiDAR sensors typically called TerrainMapper_2L with an integrated air born GPS and IMU that is laser-based remote sensing systems that emit light pulses with Laser wavelength 1,064 nm, Scan speed Programmable, 60-150 Hz (120-300 scans per second) and capture the reflected light from the surface to create high-resolution 3D models of the forest canopy was the primary material. The data produced from these sensors are saved as billions of 3D points, which will be analyzed using specialized software known as HxMap and its software package TerraSolid. The researcher used HxMap to Ingest raw LiDAR point clouds and multispectral imagery, Using GNSS/IMU data to accurately geo-reference both LiDAR and imagery data, ensuring spatial alignment, perform radiometric correction adjustments to ensure consistent reflectance values for multispectral images under varying conditions and LiDAR Matching. Terra Solid also used to Import, manage, and visualize LiDAR point clouds, to Perform noise filtering to remove erroneous points, classify ground and non-ground points (e.g., vegetation, buildings)

Additionally, spatial data analysis which required Geographic Information System (ArcGIS version 10.8, Global Mapper,) software's used. This software's used to create maps of the study area, overlay the LiDAR data with spatial data such as aerial photography of the study area and to visualize the results of the analysis. It also utilized in tree height categorization to easily visualize and categorize trees based upon different threshold with their own color.

The other was modified air craft to handle the project flight to capture at the same time point cloud data and aerial photography of the study area by using Leica Terrain Mapper_2L sensor and integrated GPS.

Way point inertial explorer is one of the main a software solution that was applied in this study for post-processing raw GPS and inertial measurement unit (IMU) data from airborne.

Leica Mission Pro software package for mission plan preparation of the study area is another important software that had already used before data collection.

3.6 Method of data analysis

LiDAR provides 3D point clouds, which can help in detecting tree heights and structures. Multispectral imagery offers spectral information across different wavelengths, useful for species identification and health assessment. Combining these might improve accuracy.

Integrating LiDAR with multispectral imagery creates a powerful approach for forest analysis. LiDAR provides highly accurate 3D structural information, such as tree height, canopy density, and individual tree segmentation. Meanwhile, multispectral imagery adds spectral details that help differentiate species, assess vegetation health, and even estimate biomass.

Tree counting using airborne LiDAR and Multispectral imagery data typically involves several steps, including data acquisition, data preparation, data analysis, result interpretation and validation to ensure accurate tree identification and counting. The following part provides a brief overview of the data analysis methodology that was implemented in such a study.

The first step in the data analysis process was pre-processing the acquired data. This part involves cleaning up the data to remove any noise or errors by applying Gaussian filtering or morphological operations to refine the CHM and remove small-scale variations, correcting for any instrument biases and geo-referencing the data to enable spatial analysis. In terms of corrections, both geometric and radiometric adjustments were applied to ensure the accuracy and consistency of the data used in the analysis. Geometric corrections involved aligning the LiDAR point cloud data with the ground coordinate system using trajectory data derived from GNSS (Global Navigation Satellite System) and IMU (Inertial Measurement Unit) measurements. This process corrected spatial distortions resulting from the movement of the airborne platform, variations in sensor orientation, and differences in terrain elevation, ensuring that the LiDAR and Multispectral data accurately represented the spatial structure of the forest. On the other hand, radiometric corrections were applied to the multispectral imagery to normalize the reflectance values across different image scenes and environmental conditions. This included atmospheric correction to remove distortions caused by particles and gases in the atmosphere, as well as reflectance calibration to standardize the spectral data so that it could be reliably used for vegetation classification and LiDAR matching. Together, these correction processes enhanced the quality and reliability of the remote sensing data, forming a robust foundation for accurate automated tree detection and forest analysis.

After this job has been done ground classification was accomplished in order to differentiate the ground and non-ground features by setting rules like starting from the ground surface found ≤ o.2m, low vegetation >0.2m-0.5m, medium vegetation >0.5m-2m, high vegetation above 2m height. Computation of height (nDSM= DSM – DTM). Terrasolid allows users to define specific rules and thresholds for filtering LiDAR data based on height differences, intensity, and return types. Multispectral or RGB imagery can refine the classification by identifying vegetation features.

Point cloud data segmentation into individual trees using Tarascan software was one of the main data analysis methods. Once individual trees have been identified, extraction of tree features of the segmented trees, including crown height, crown diameter and crown density was performed. These features can be calculated automatically from the point cloud data that helps us to know the number of tree. Random Forests or Object based image analysis (OBIA) algorithms was used to classify the trees based on their features.

Validation and refinement of results performed and that was achieved by comparing the classified results with ground-truth data collected manually and high resolution multispectral Images that can be collected with Leica terrain Mapper_2 Sensor the same time with point clouds by overlaying the result.

Finally, the results of the analysis were interpreted in the context of the study objectives.

3.7 Methodological framework

This study employs a mixed-methods approach combining LiDAR data processing, field verification, and statistical analysis to achieve its objectives. The overall workflow is visualized in Figure 3.9.

3.7.1 Data acquisition

This is the starting point, representing the raw data acquired for the study. LiDAR point cloud and Multispectral Imagery data was collected from Ethiopian Space Science and Geospatial Institute (SSGI) from archive data Entoto Kotebe project that was captured March11, 2021 by using the TerrainMapper-2 Sensor mounted on fixed wing aircraft capture 3D elevation data consists of point clouds with X, Y, and Z coordinates, along with intensity values with multiple return LiDAR allows differentiation between canopy layers (e.g., top canopy vs. understory vegetation).

Multispectral imagery contains multiple spectral bands (e.g., Red, Green, Blue, Near-Infrared (NIR), Shortwave Infrared (SWIR)). Helps in species classification, vegetation health analysis, and distinguishing between tree and non-tree objects and provides spectral information about the vegetation and other objects. 3D point cloud provides structural information about the terrain and vegetation. Trajectory data records the flight path of the airborne sensor, including GPS coordinates, altitude, speed, and orientation. This information is critical for georeferencing and aligning the LiDAR and multispectral datasets accurately.

3.7.2 Pre-processing of Trajectory, LiDAR, and Multispectral Imagery

The pre-processing of trajectory, LiDAR, and multispectral imagery is a crucial step in ensuring the accuracy and reliability of the data used for automated tree counting. This process involves multiple stages, including trajectory processing, LiDAR data pre-processing, and multispectral imagery correction, utilized by HxMap, Waypoint Inertial Explorer software’s.

3.7.2.1 Trajectory Processing

Trajectory processing is essential for aligning the airborne sensor data accurately in geographic space. This step involves the integration of GNSS and IMU data collected during the flight mission to refine the position and orientation of the sensor platform. Waypoint Inertial Explorer is used for this purpose, providing precise trajectory solutions by processing raw GNSS and IMU measurements. The software applies differential corrections using base station data or Precise Point Positioning (PPP) techniques to enhance the accuracy of the trajectory. The refined trajectory is then exported for further use in LiDAR point cloud georeferencing and image rectification.

3.7.2.2 LiDAR Data Pre-processing

The next step is the pre-processing of LiDAR data, which is crucial for generating an accurate representation of the forest structure. This was accomplished using HxMap software. HxMap, a high-performance processing suite, is used to manage and preprocess the raw LiDAR point cloud. It aligns the LiDAR data with the processed trajectory to generate a georeferenced point cloud. Additionally, noise filtering techniques are applied to remove outliers and low-quality returns caused by atmospheric interference or sensor errors.

Point clouds are typically collection of points in 3D space obtained from various sources such as laser scanners, LiDAR, or photogrammetry. On the other hand, Point cloud processing refers to the computational techniques used to analyze and manipulate three-dimensional point cloud data which includes data cleaning, point cloud registration or combining multiple point clouds into a single coordinate system, typically achieved by aligning the overlapping regions of the different point clouds.

The point cloud processing stage played a crucial role in the automated tree counting workflow, as it involved extracting meaningful tree-related information from the Airborne LiDAR data. Through careful processing, the raw point cloud data was refined, classified, and analyzed to accurately identify individual trees and estimate key parameters such as tree height, canopy dimensions, and spatial distribution. The integration of multispectral imagery further enhanced this process by improving tree segmentation and differentiation based on spectral characteristics.

The results of the point cloud processing demonstrated the effectiveness of LiDAR in capturing detailed three-dimensional structural information of trees. The classification of ground and non-ground points enabled the generation of a Digital Terrain Model (DTM) and a Canopy Height Model (CHM), which were essential for distinguishing individual tree crowns. The Figure 3.4 below shows processed Point clouds of the study area. By Computing the difference between the LiDAR elevation and the actual elevation from the GCP (Error = LiDAR Elevation - Checkpoint Elevation) the accuracy of this result was evaluated using RMSE.

$$\boldsymbol{RMSEz} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} (\boldsymbol{ZLiDAR,i} - \boldsymbol{ZGCP,i})^2} \quad \boldsymbol{\ldots\ldots\ldots}\text{(Eq- 1)}$$

Where:

- Z_{LiDAR},i is the elevation from the LiDAR at checkpoint i,
- Z_{GCP},i is the elevation of the checkpoint i,
- n is the number of checkpoints.

Using ASPRS standards, the researcher performed a thorough and standardized accuracy assessment of Point cloud using field-collected 10 GCPs the researcher found $RMSE_Z$ 13 cm see in Appendix ii. This process ensures that the data meets the required accuracy standards and is reliable for further analysis and applications.

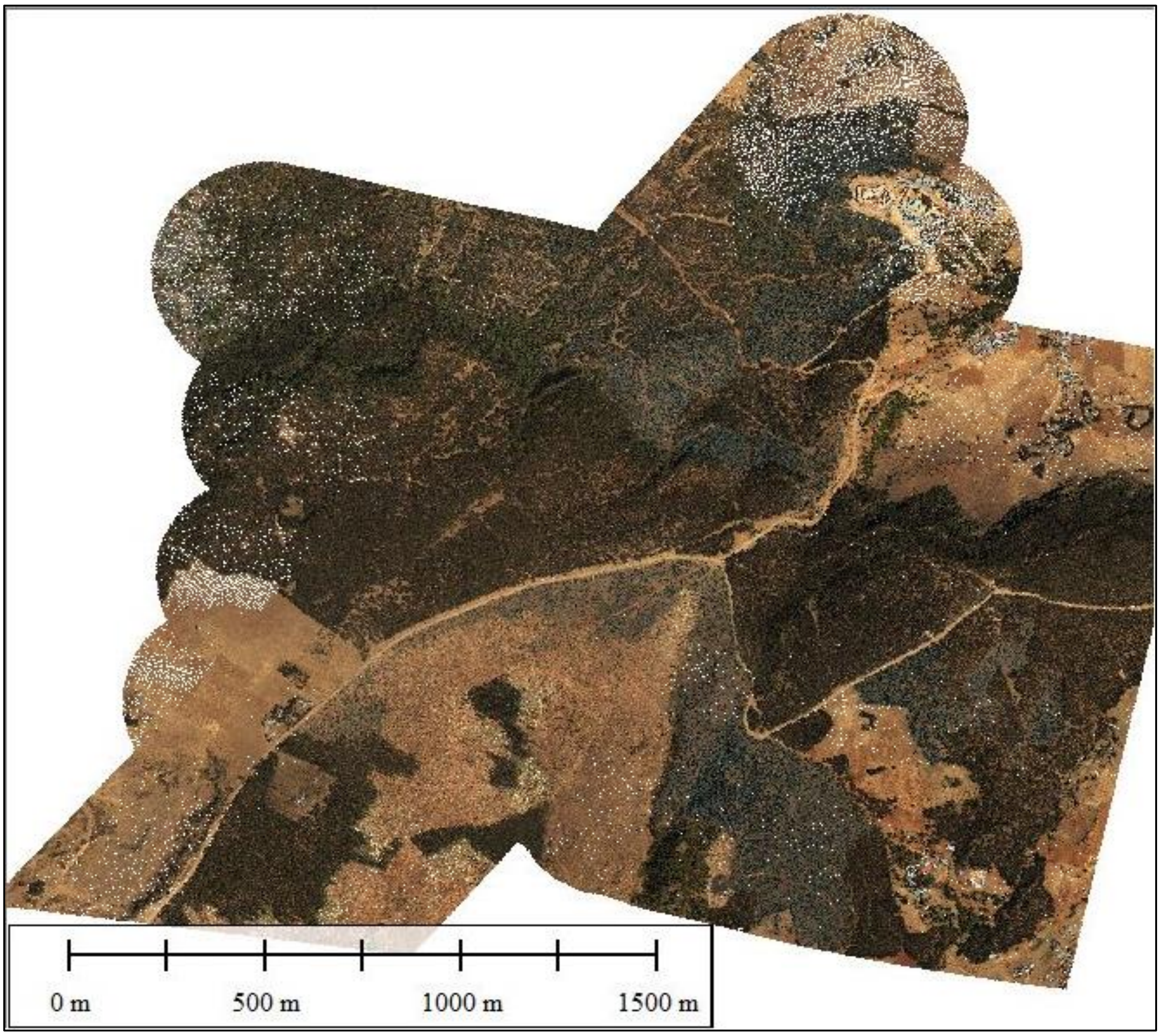

Figure 3. 3 Processed point cloud data

3.7.2.3 Multispectral Imagery Pre-processing

Multispectral imagery is an essential data source for enhancing tree classification and species differentiation. The pre-processing of multispectral imagery involves radiometric and geometric corrections to ensure that the data is spatially accurate and radiometrically consistent. HxMap was utilized for the initial processing, where the raw images are corrected for sensor distortions and aligned with the processed trajectory data. This step ensures that the imagery maintains accurate spatial alignment with the LiDAR dataset.

Further radiometric corrections, such as atmospheric correction and reflectance calibration, were performed to normalize the spectral values across different images.

These corrections help mitigate variations caused by changing illumination conditions, sensor artifacts, and atmospheric interference. Additionally, ortho-rectification was applied to remove geometric distortions and ensure accurate spatial alignment with other geospatial datasets. Once pre-processed, the multispectral imagery is ready for data fusion with the LiDAR point cloud to enhance the accuracy of automated tree counting.

By integrating these pre-processing steps, the study ensures that both LiDAR and multispectral imagery datasets are of high quality, geospatially accurate, and free of errors. This optimized dataset provides a strong foundation for subsequent tree counting algorithms, enabling precise detection, classification, and quantification of trees in the study area.

After Generating mosaic of those imagery the researcher Calculated the accuracy for 10 GCP (or checkpoint) by compare the measured position in the image with the known ground position based on ASPRS standards resulted 33 cm which is high accuracy.

$$\boldsymbol{RMSEX} = \sqrt{\frac{\boldsymbol{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} (\boldsymbol{X}i\ image - \boldsymbol{XGround}, \boldsymbol{i})^{\boldsymbol{2}}})$$

$$\boldsymbol{RMSEY} = \sqrt{\frac{\boldsymbol{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} (\boldsymbol{Y}\text{i image} - \boldsymbol{YGround}, \boldsymbol{i})^{\boldsymbol{2}}})$$

$$RMSE\ Horizontal = \sqrt{RMSEX2 + RMSEY^{\boldsymbol{2}}} \quad \textbf{\textit{.............(Eq- 2)}}$$

Where:

- Xiimage, Yiimage: Coordinates from the mosaic image
- Xiground, Yiground : True coordinates from Ground survey
- n: Number of control/validation points

3.7.3 Ground classification

The ground classification rule has been used in order to differentiate the ground and none ground objects. This is essential for creating a digital terrain model (DTM) and for calculating the height of objects above the ground. This has been done using various algorithms that analyze the spatial distribution and elevation of points. This process helps to easily identifying the vegetation class based on their height from the ground which is classified as low vegetation >0.2m-0.5m, medium vegetation >0.5m-2m, high vegetation above 2m. on the other hand, the ground surface is below o.2m.

The overall classification of this ground and none ground surface has done by using TerraSolid software (Macro Execution) to refine the LiDAR point cloud further. TerraScan, a module within TerraSolid, facilitates point classification by distinguishing ground, vegetation, and other object classes. The automatic classification routines help segment trees from non-tree objects, improving the efficiency of subsequent tree detection algorithms. Additionally, TerraMatch was used for strip adjustment, ensuring that overlapping flight lines are accurately aligned, reducing inconsistencies in the dataset. The final output was a well-structured and classified LiDAR point cloud that can be used for canopy height modeling and tree segmentation.

Figure 3.4 below show the ground classification rule in order to differentiate the ground and none ground objects. The overall classification of this ground and none ground surface were done by using TerraSolid software (Macro Execution).

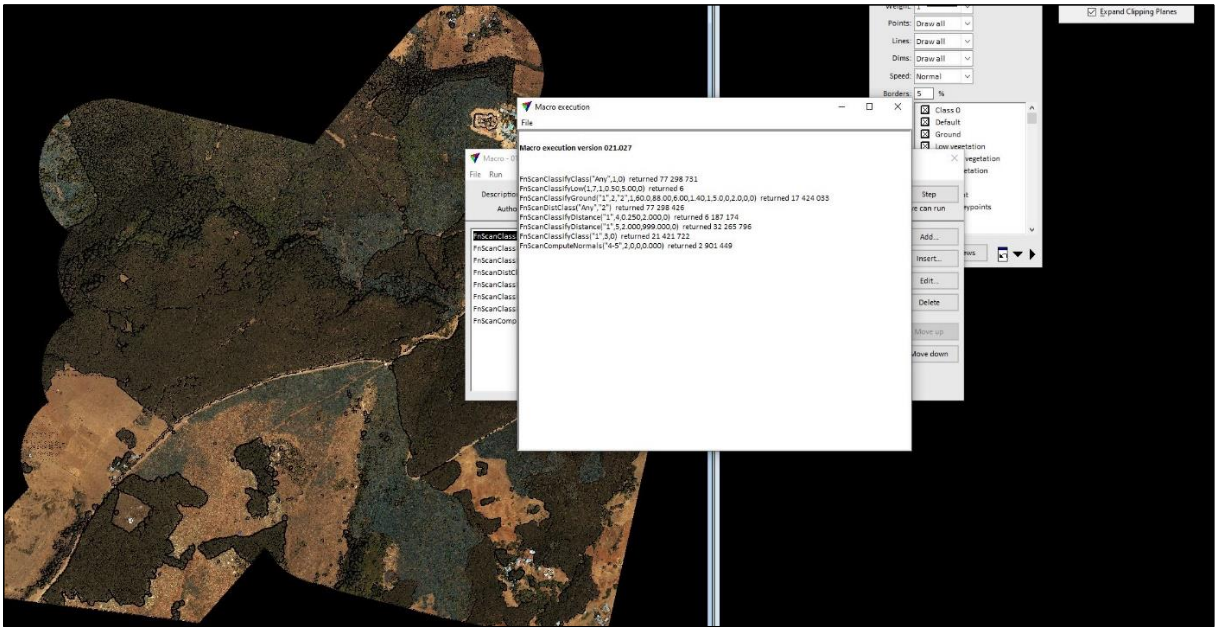

Figure 3. 4 Ground classification rules

I have generalized the classification shown on the Figure 3.5 bellow from 77,298,731 of points 17,424,033 points were classified as ground while, 21,421,722 points were classified as low vegetation. 6,187,174 points were also classified as medium vegetation, the high vegetation class account for 32,265,796, resulting in a total estimated biomass of 59,874,692 units in the study area.

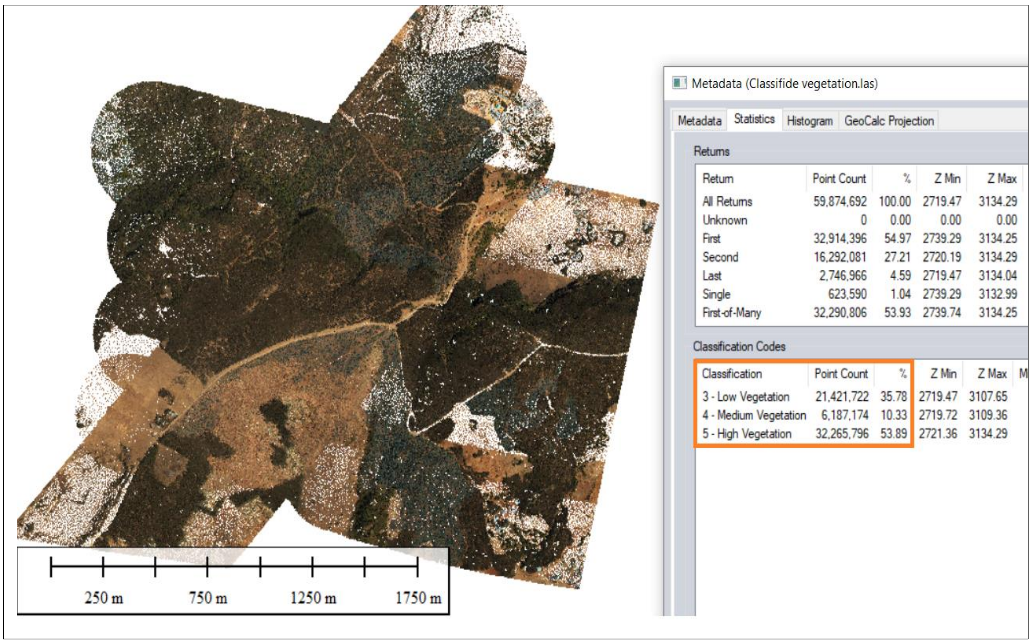

Figure 3. 5 Ground classification result

3.7.4 Computation of Distance from Ground

This step calculates the vertical distance of each point in the point cloud from the ground surface (DTM). This is crucial for determining the height of vegetation and other objects. This involves subtracting the elevation of the ground surface from the elevation of each point. The difference between the DSM and the DTM yields the Canopy Height Model (CHM), which represents tree heights. Mathematically, this can be expressed as:

CHM = DSM−DTM … (Eq- 3)

where:

- DSM is the Digital Surface Model representing the highest points (tree canopy or buildings),
- DTM is the Digital Terrain Model.

Through these computational steps, TerraSolid software facilitates the accurate derivation of tree heights, which is crucial for the automated tree counting process. The integration of LiDAR-derived CHM with multispectral analysis further improves the accuracy and reliability of the study's findings.

3.7.5 Normal Vector Computation

This step calculates the normal vector for each point in the point cloud to provide information about the local surface orientation, which is useful for identifying different objects and their boundaries. This involves analyzing the local neighborhood of each point to determine the direction perpendicular to the surface. To automatically count the trees, I have calculated these normal vectors for every point in the LiDAR data. By analyzing how these vectors change and cluster, I have figured out where individual trees are located and how they're shaped. This process helps us take vast amounts of data and turn it into meaningful information about the forest's structure.

3.7.6 Point grouping /segmentation

This step groups neighboring points in the point cloud that are likely to belong to the same object, helps to separate individual objects (e.g., trees) from each other, used to classify tree or estimate or enabling the tree counts. This has been done using various clustering or segmentation algorithms that analyze the spatial proximity and normal vectors of points. These features include measurements of canopy height, canopy density and other properties of the vegetation in the study area forest cover.

Tree segmentation has been used to dividing an image or point cloud containing trees in to distinct segments or regions corresponding to individual trees.

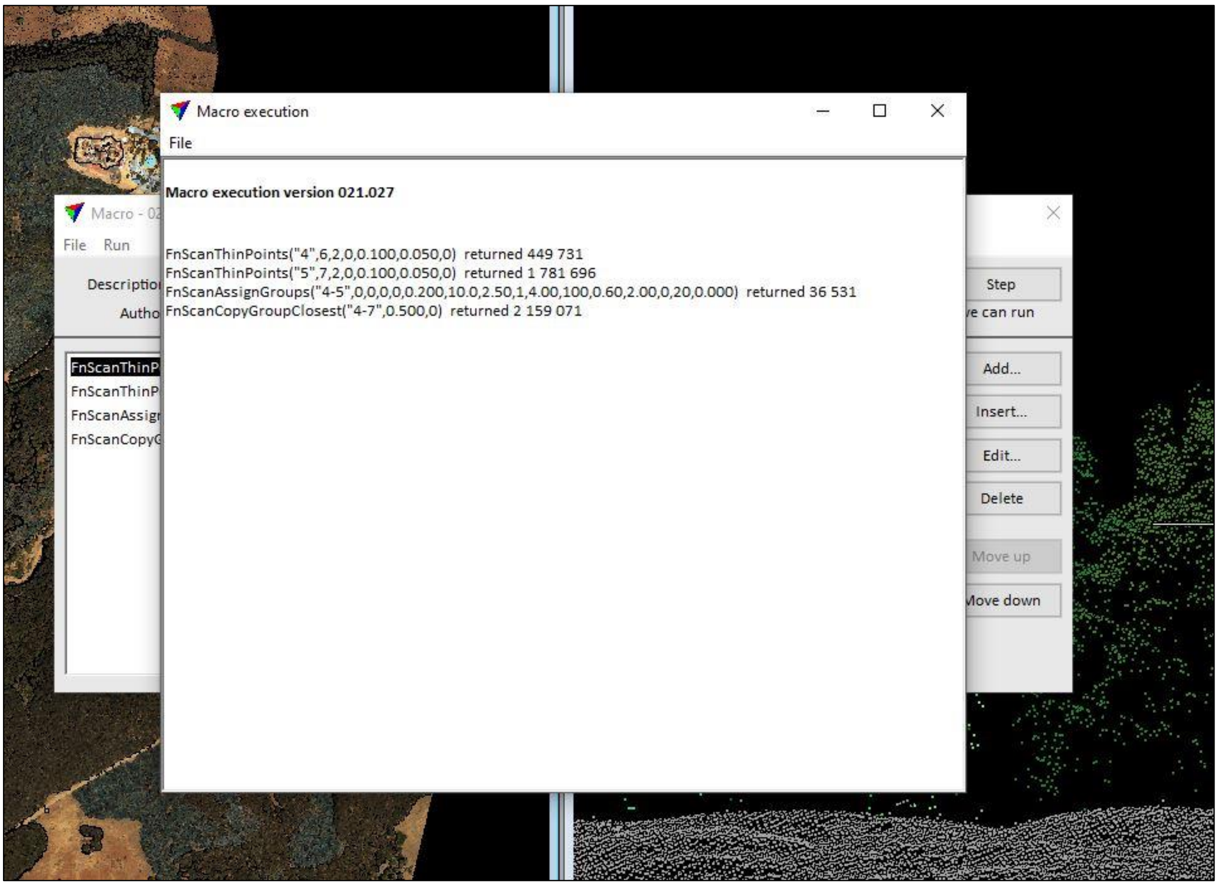

Figure 3. 6 Segmentation rule using macro execution

The above Figure 3.6 depicts, automatic grouping rules and results which needs refinement and prepared for tree segmentation.

3.7.7 Group Classification

This step classifies the point groups into different categories (e.g., trees, buildings, other vegetation). This is crucial for isolating the point groups that represent trees. This has been done using machine learning algorithms that are trained on labeled data or using rule-based classification methods.

Proper classification ensures that only tree-related point groups are considered in the final tree counting analysis, reducing errors caused by non-tree objects.

3.7.8 Tree Extraction

In the context of LiDAR (Light Detection and Ranging) data analysis, a tree is typically defined as a tall, vertical vegetative structure that can be distinctly separated from other vegetation based on its height, canopy structure, and spatial characteristics. Trees are most commonly classified under the "high vegetation" category, which generally includes objects with heights greater than 2 meters above the ground surface. This threshold is widely accepted in remote sensing and forestry studies to distinguish trees from shrubs and other medium-height vegetation. LiDAR data allows for precise measurement of individual tree heights by calculating the vertical distance between the ground surface (Digital Terrain Model) and the highest point of the canopy (Digital Surface Model or Canopy Height Model). Depending on the study or application, trees may be further classified into height sub-classes, such as small trees (2–5 meters), medium trees (5–15 meters), and tall trees (above 15 meters). These classifications help in forest inventory, biomass estimation, and ecological assessments by enabling detailed analysis of forest structure and composition using high-resolution LiDAR datasets. In LiDAR-based vegetation analysis, trees are defined not only by their height but also by additional structural attributes such as point density, crown width, and canopy shape. To accurately detect and characterize individual trees, point density is a critical factor,it refers to the number of LiDAR returns per square meter (points/m²). For reliable individual tree detection, a minimum point density of 4–6 points/m² is often required, though higher densities (10–20 points/m² or more) significantly improve accuracy, especially in dense or complex forests.

Another important parameter is the crown width, which represents the horizontal spread of the tree canopy. LiDAR can estimate crown width by analyzing the spatial distribution of canopy points, often using algorithms such as local maxima filtering and watershed segmentation. Typical tree crown widths vary widely by species and tree age but often range from 2 to 10 meters in natural forests. LiDAR-derived crown shape and canopy volume metrics also aid in distinguishing individual trees, especially in multi-layered forests. These attributes height, point density, crown width, and shape collectively enable comprehensive forest structure modeling, facilitating applications such as species classification, biomass estimation, and ecological monitoring.

The Tarascan software has been used to extract individual trees from the nDSM. In this procedure, the point cloud is divided into segments according to its height and spatial properties. Software parameters has been adjusted to best suit the unique features of the Entoto forest. This step extracts the point groups that have been classified as trees, isolates the tree data for further analysis. Once the tree crowns extracted using tree segmentation, the count of individual trees has been determined by counting the number of tree crown objects. The tree detection algorithm successfully identified a significant portion of the trees present in the study area, with accuracy varying depending on forest density and species composition.

By leveraging both LiDAR structural data and multispectral imagery, the tree extraction process ensures accurate identification of individual trees. This extraction process allows us to count each tree accurately and measure its characteristics. I have been calculated crown diameter, tree height, and even estimate biomass. This meticulous extraction allows for a more precise understanding of forest structure and composition, which is vital for ecological research, forest management, and even carbon sequestration studies.

3.7.9 Validation and Manual Editing

The sample area has been purposively selected to represent typical forest conditions in Entoto Reserve.

Verification plot has been chosen from the study area using a stratified random sampling technique. The number of trees identified by the automated approach and the number of trees manually counted on the ground or on High Resolution Aerial Photograph that was captured at the same time during LiDAR mission compared within a plot. Any discrepancies have been looked into, and the automated procedure was adjusted as necessary. Until a satisfactory degree of accuracy is attained, this iterative process of verification and improvement has been continued.

3.7.10 Analysis

The final stage of the process focuses on analyzing the extracted tree data to generate meaningful insights and outputs. This stage plays a crucial role in ensuring that the processed data effectively represents forest characteristics, aiding in decision-making and further ecological studies.

One key aspect of this analysis is the generation of a Canopy Height Model (CHM). The CHM is a raster-based representation that captures the height variations of tree canopies across the study area. It is derived by subtracting the Digital Terrain Model (DTM) from the Digital Surface Model (DSM), effectively isolating the tree heights from the ground elevation. This model provides valuable information about forest structure, including tree height distribution, biomass estimation, and habitat assessment. It serves as a fundamental layer in ecological studies and forest management, helping researchers and decision-makers understand vegetation patterns and detect changes over time.

Another crucial component of the analysis is trunk measurement, which involves assessing various characteristics of tree trunks, such as their diameter at breast height (DBH), circumference, and even volume estimations. Accurate trunk measurements are essential for estimating tree biomass, carbon storage, and overall forest health. These measurements have been extracted using advanced LiDAR point cloud analysis, where it helps in identifying tree stems and determining their dimensions with high precision. Understanding trunk characteristics not only aids in forest inventory management but also supports conservation efforts by monitoring tree growth, detecting disease or damage, and evaluating sustainable logging practices. By integrating these analytical processes, researchers and forest managers can gain deeper insights into forest ecosystems, contributing to more informed environmental and conservation strategies.

After individual trunk cross-sections are detected, DBH may be approximated from point cloud circle fitting algorithms:

$DBH = (2 * \sqrt{\frac{A}{\pi}})\ldots\ldots$(Eq- 4)

Where:

- A is the cross-sectional area of the trunk estimated from LiDAR return points at ~1.3 meters above ground.

Alternatively, DBH can be measured directly from the spread of points in a horizontal slice of the point cloud at breast height.

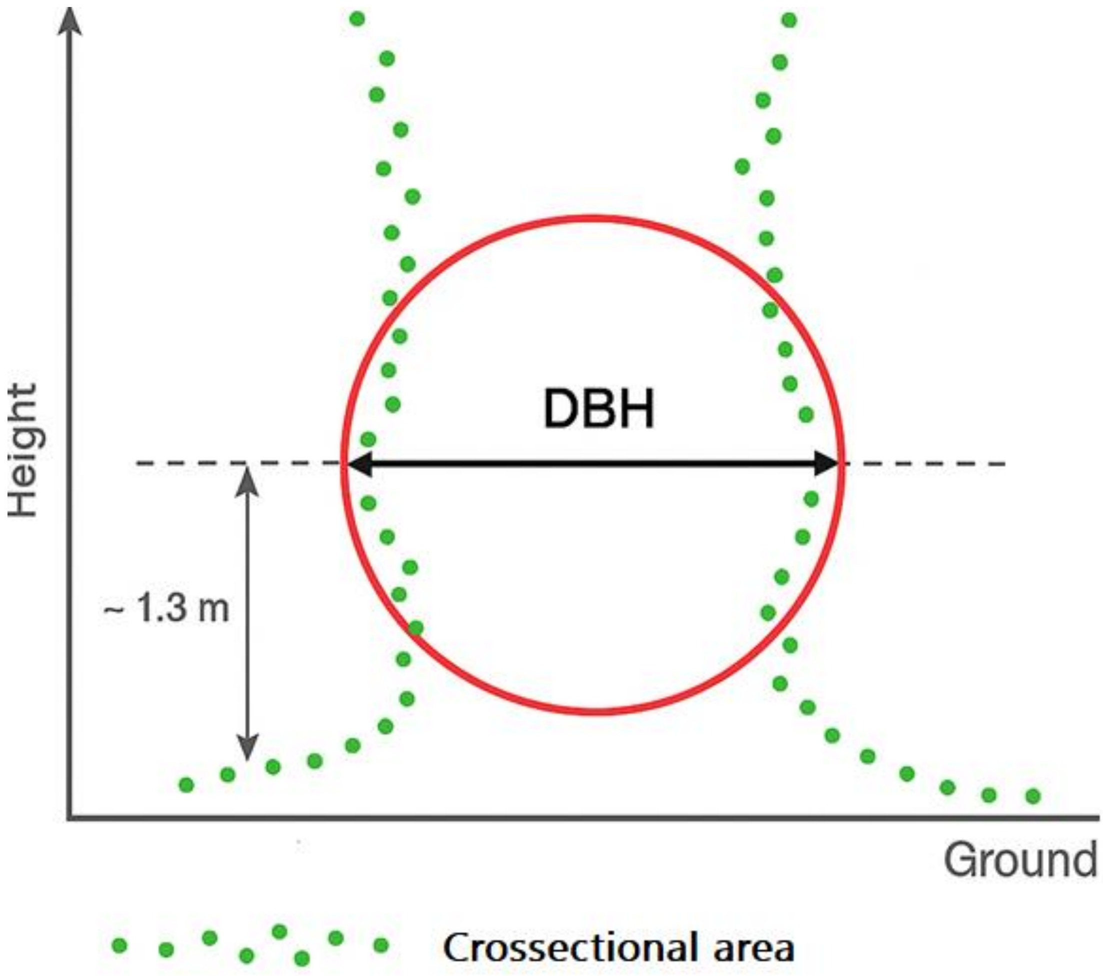

Figure 3. 7 DBH estimation from LiDAR Point cloud circle fitting Algorithm

3.7.11 Accuracy Assessment

After conducting research on automated tree counting using Airborne LiDAR and multispectral imagery, assessing the accuracy of the results is a crucial step in validating the effectiveness of the method. This process ensures that the automated approach reliably detects and counts individual trees by comparing its outputs with ground-truth data or manually derived reference datasets from High resolution aerial photograph. A thorough accuracy assessment helps identify potential errors, refine algorithms, and improve overall detection performance.

To evaluate accuracy, key performance metrics such as precision, recall, and F1-score are commonly used to measure how well the automated system identifies actual trees while minimizing misclassifications.

To calculate the accuracy, these standard formulas were used:

1. $Precision = \frac{True\ Positives}{True\ Positives+False\ Positives}$ (Eq- 5)

Where:

- True Positives: A tree that is present in the ground truth and automated system also detects it.
- False Positives: The automated system thinks it found a tree, but there's **no tree** at that location in the ground
- False negatives: A tree is present in the ground truth, but automated system **failed to detect it**.

This tells us the proportion of correctly identified trees among all trees detected by the algorithm or in simple term how many of the detected trees are actually trees?

2. $Recall = \frac{True\ Positives}{True\ Positives+False\ negstives}$ (Eq- 6)

This indicates how many actual trees were found by the system.

3. $F1\ score = 2x\frac{PrecisionxRecall}{Precision+Recall}$ (Eq- 7)

- Recall (R): How many of the actual trees were correctly detected?

This combines both precision and recall into a single number (0–1 scale).

Additionally, statistical measures like Change of height and Diameter help to measure differences between the tree heights from LiDAR vs. those from ground truth data.

4. $\boldsymbol{d(Height) = HLiDAR - HGround}$ **……** ***…(***Eq- 8)

Where:

- d(height) is the difference of height measured from LiDAR and ground truth data
- $H_{LiDAR,}$ is the height of the tree from LiDAR,
- H_{ground} is the corresponding height from ground truth,

$\boldsymbol{d(Diameter) = DLiDAR - DGround)}$**……** …(Eq- 9)

Where:

- d(Diameter) is the difference of Diameter measured from LiDAR and ground truth data
- D_{LiDAR}, is the diameter of the tree from LiDAR,
- D ground is the corresponding diameter from ground truth,

The integration of both LiDAR and multispectral data enhances this evaluation by leveraging their complementary strengths, LiDAR provides precise three-dimensional structural details, while multispectral imagery improves species differentiation and segmentation accuracy.

By analyzing the accuracy of the automated tree counting process, this research contributes to the refinement of remote sensing methodologies, ensuring their reliability in forest inventory and ecological studies. A well-executed accuracy assessment not only strengthens confidence in the results but also enhances the potential of these technologies for large-scale forest monitoring, conservation efforts, and sustainable resource management.

3.7.12 Methodological flow chart of the study area

Figure 3.8 presents the methodological flowchart illustrating the step-by-step process followed in this study for automated tree counting using integrated airborne LiDAR and multispectral imagery. The diagram outlines the sequential stages, beginning with data acquisition from the Ethiopian Space Science and Geospatial Institute. This includes LiDAR point cloud data, multispectral imagery, and associated GNSS/IMU trajectory information.

Following acquisition, the data undergoes extensive pre-processing, involving radiometric and geometric corrections, point cloud noise filtering, and accurate geo-referencing. The next phase entails ground classification using TerraSolid software to differentiate between terrain and vegetation points, which enables the creation of a Digital Terrain Model (DTM). This is essential for the derivation of the Canopy Height Model (CHM).

Subsequently, segmentation algorithms are applied to identify and extract individual tree crowns from the normalized point cloud data. Advanced classification methods such as random forest and object-based image analysis were then used to distinguish tree objects from other features like buildings, vehicles etc. Tree metrics like height, crown width, and diameter at breast height (DBH) are computed.

The final steps include validation and accuracy assessment, where the automatically detected trees are compared against ground-truth data and high-resolution imagery. The Figure effectively summarizes the entire analytical pipeline, from raw data to final output, ensuring a transparent and replicable methodological framework.

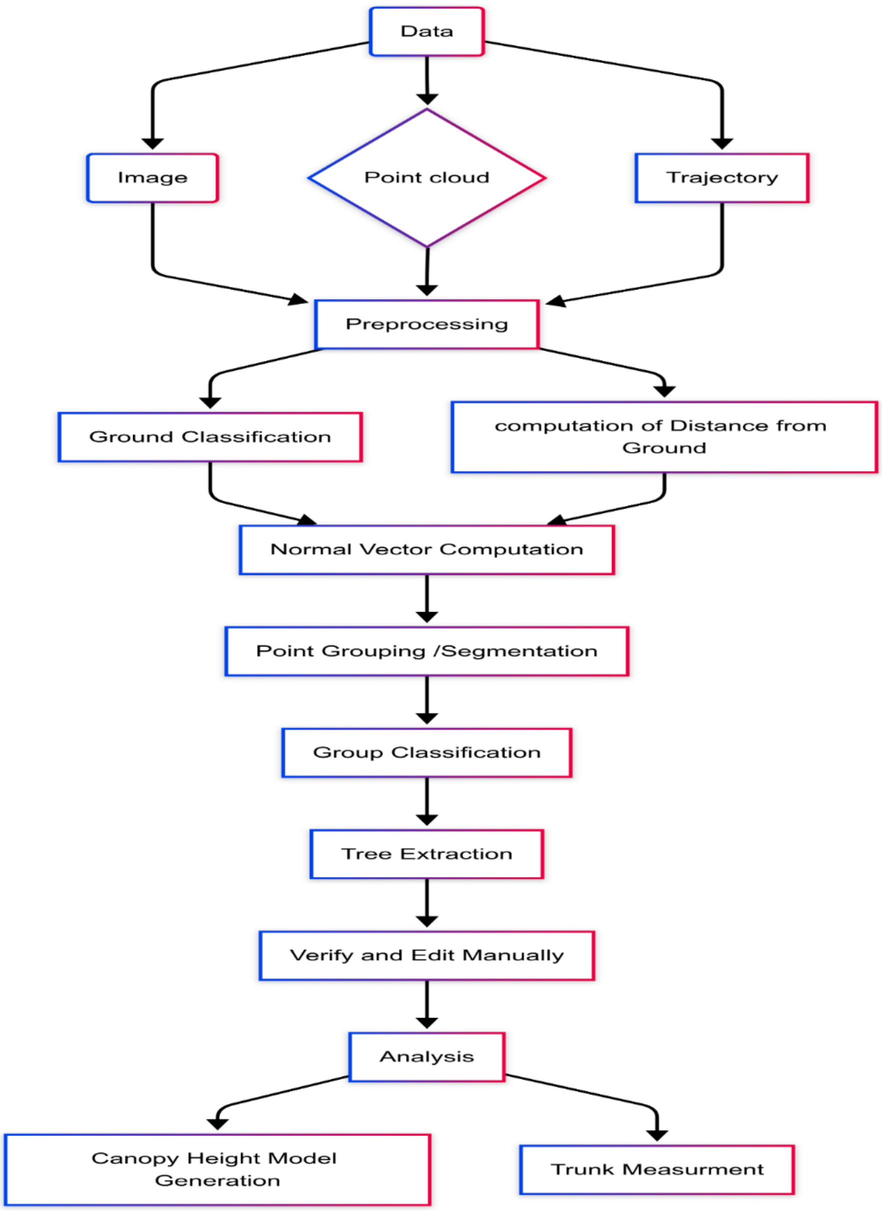

Figure 3. 8 Methodological flow chart of the study area

4 Results and Discussions

This chapter presents and interprets the findings of the automated tree counting process. It covers segmentation, counting, canopy height model generation, trunk measurement, and the validation of results. The results are analyzed in relation to the study objectives and compared with findings from previous studies.

4.1 Results

4.1.1 Tree Segmentation Based on individual tree Groups

Tree segmentation refers to the process of dividing an image or point cloud into distinct segments or regions that correspond to individual trees. This process is essential in forest inventory and management, as it allows for the extraction of tree-specific attributes such as height, crown diameter, and location. Segmentation is typically performed on high-resolution data obtained from airborne LiDAR, multispectral imagery, or a combination of both. LiDAR point clouds, in particular, are widely used due to their ability to capture detailed three-dimensional structural information of the forest canopy. Techniques such as watershed segmentation, region growing, and point clustering are commonly applied to these datasets to accurately delineate individual tree crowns (Li et al., 2012).

Figure 4.1 illustrates the distribution of tree groups identified through the automated tree detection and classification process. In the figure, each tree group is visually distinguished by a unique color, allowing for clear differentiation and spatial understanding of the grouping results. These tree groups were generated automatically based on segmentation algorithms applied to the remote sensing datasets. The analysis resulted in the identification of a total of 36,531 distinct tree groups, demonstrating the effectiveness of the automated system in accurately recognizing and organizing individual trees or clusters within the study area.

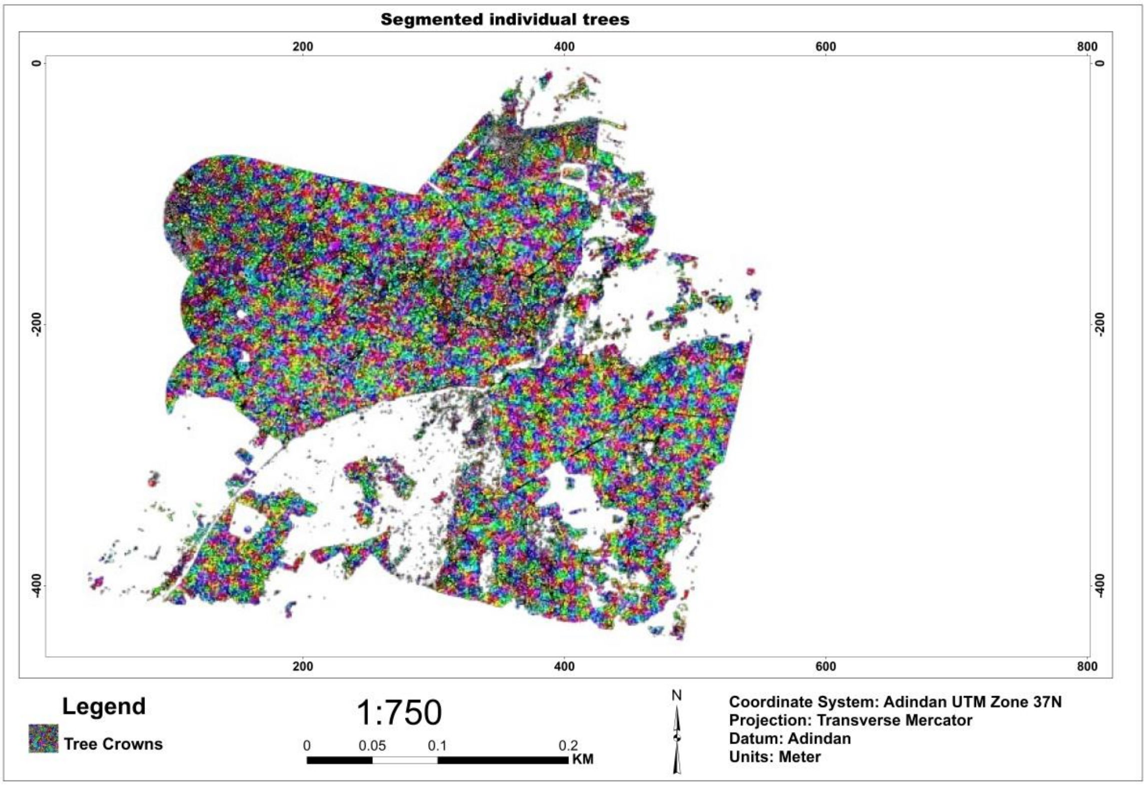

Figure 4. 1 segmented Trees

4.1.2 Tree Counting

Once the tree crowns have been extracted as explained above in tree segmentation, the count of individual trees was determined by counting the number of tree crown objects. This count then provides 36531 of the total number of trees in the surveyed area as shown in the Figure 4.2 bellow with point cloud.

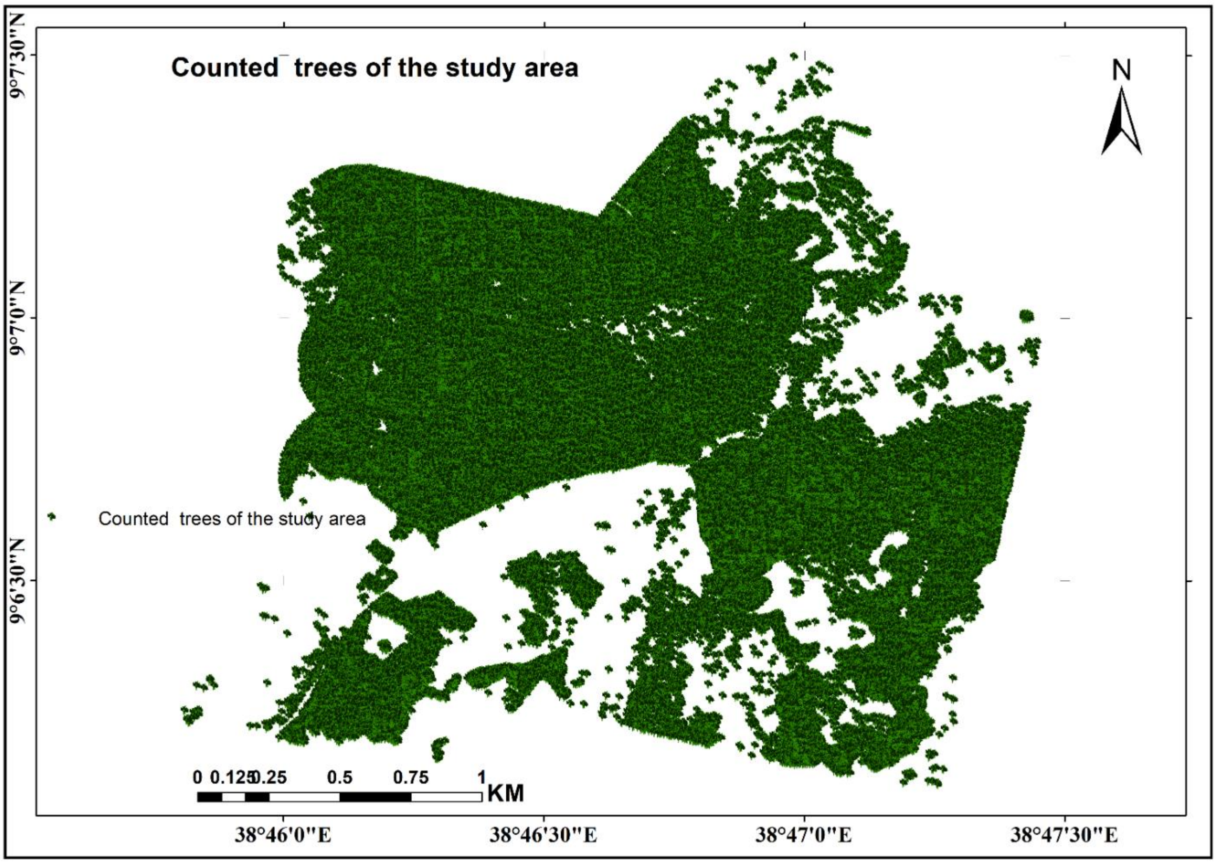

Figure 4. 2 Counted trees of the study area

Figure 4.3 illustrates a sample individual tree profile derived from airborne LiDAR point cloud data, highlighting the vertical structural characteristics of a tree. The main purpose of this Figure is to demonstrate how LiDAR technology captures detailed three-dimensional information, enabling accurate measurement of key forest attributes such as tree height and diameter at breast height (DBH). By displaying the vertical profile, the Figure visually supports the methodology used for tree segmentation and measurement, showing how individual trees are identified and analyzed within the dataset. This representation underscores the effectiveness of the automated approach in extracting reliable tree metrics essential for forest inventory and management.

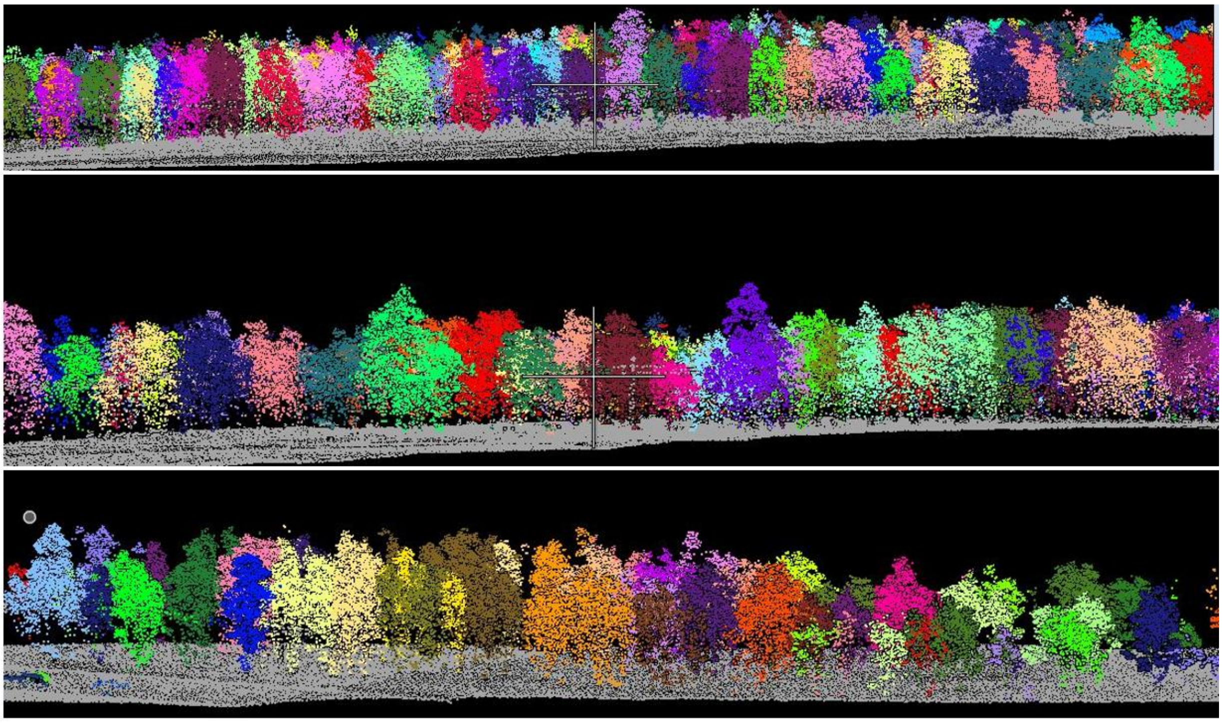

Figure 4. 3 Sample individual tree profile

4.1.3 Canopy Height Model Generation

The canopy height is calculated by subtracting the terrain elevation from the highest point within the vegetation layer of the study area. This is done by considering all the non-ground points within the LiDAR point cloud. This provides a representation of the height of objects in the landscape, including trees. The goal is to create a smooth surface that represents the vegetation height across the study area. The performance of CHM generation depends on the quality and density of the input data. Higher point density helps in capturing detailed information about the vegetation structure, resulting in more accurate CHM.

As it is depicted in appendix iii, each individual trees have been presented with its own xyz coordinate value corresponding to height (H) and diameter(D).

4.1.4 Tree Categorization based on height

Tree categorization is the way by which grouping into different height classes, such as short/lowest, medium and tall/high trees based on defined thresholds that provides valuable information about the vertical structure of a forested area.

After identifying individual tree in the area under investigation I have categorized those trees based upon their height by fixed interval of 5 classes by the help of ArcMap v.10.8.2

the result as indicated below in Figure 4.4 out of 36531 total number of trees covering 6295000m^2 of the surveyed area the height of the tree is within 4m to maximum of 52m. the first interval is from 4m to 11 m and the total number of tree within this category accounts for12510, the second interval was from 12m to 16m which holds 13089.number of trees, while the third class ranges from 17m to 23m and the total number of threes is 6346 on the other hand, the fourth class includes from 24m to 30.m containing 3372 number of trees and the last category falls under the height of 31m to 52m with 1214number of trees.

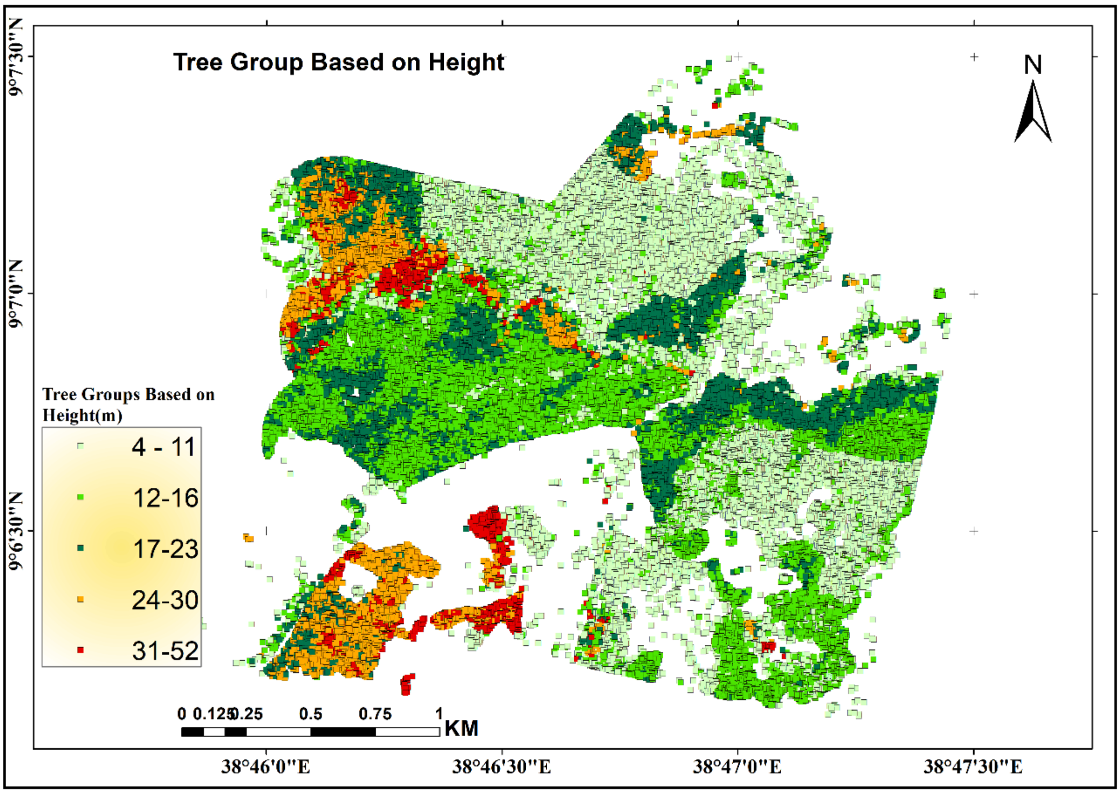

Figure 4. 4 Tree groups based on Height

4.1.5 Trunk Measurement

Trunk measurement is a vital step in the automated tree counting process, especially when leveraging advanced remote sensing technologies like airborne LiDAR and multispectral imagery. This process involves detecting and analyzing the structural attributes of tree trunks, primarily focusing on parameters such as diameter at breast height (DBH), circumference, and trunk height. Airborne LiDAR provides highly detailed three-dimensional point cloud data, which makes it possible to identify individual tree stems and extract their geometric features with remarkable precision.

Incorporating trunk measurements into the analysis allows for more accurate tree counts, particularly in dense forest areas where canopy overlap might lead to underestimation or overestimation. This data is not only essential for counting trees but also for assessing forest biomass, estimating carbon stock, and monitoring forest growth dynamics.

As shown in the Figure 4.5 bellow out of 36531 total number of trees covering of the surveyed area the diameter(D) of the tree is within 2 m to maximum of 89m, the first interval is from 2m to 11 m and the total number of tree within this category accounts for15181, the second interval was from 12m to 15m which holds 11109.number of trees, while the third class ranges from 16m to 24m and the total number of threes is 8753 on the other hand, the fourth class includes from 25m to 38 m containing 1332 number of trees and the last category falls under the height of 39m to 89m with 156 number of trees.

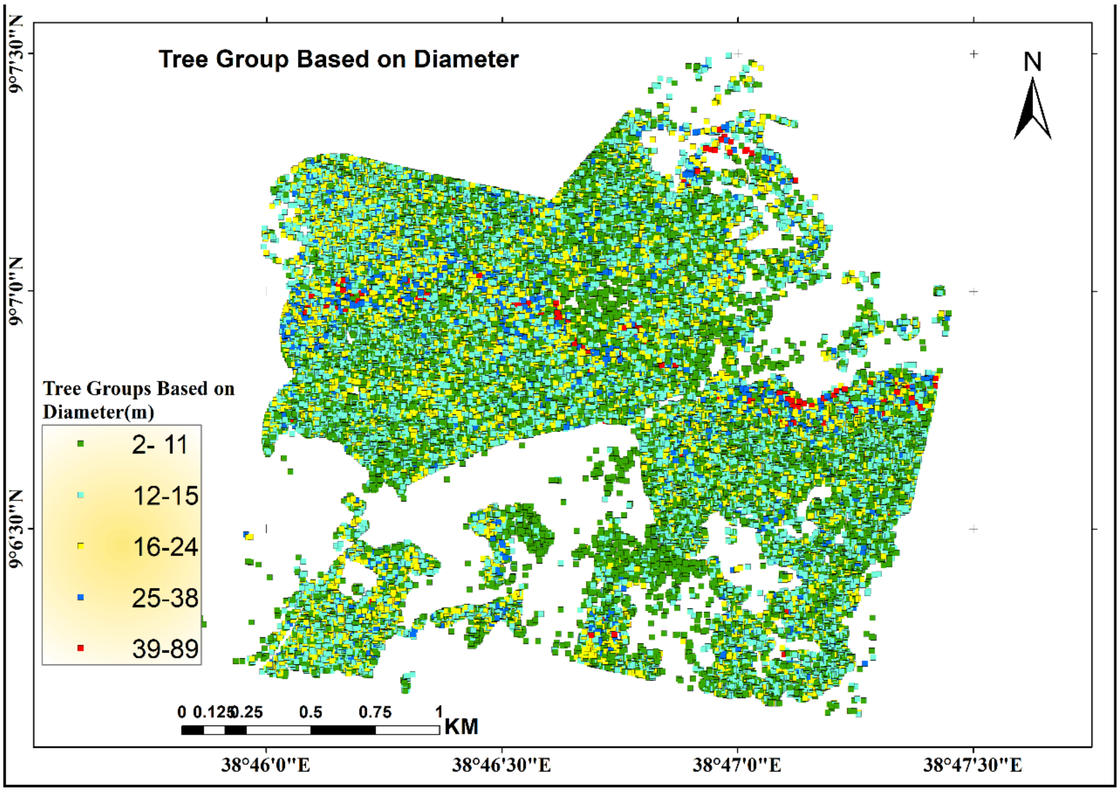

Figure 4. 5 Tree groups based on Diameter

4.2 Discussion

4.2.1 Tree Segmentation and Counting

The use of airborne LiDAR integrated with multispectral imagery has proven highly effective for segmenting and counting trees in the Entoto Forest Reserve. A total of 36,531 individual trees were identified using segmentation algorithms tailored to high-resolution point cloud data. This process, which involved distinguishing tree crowns from other forest elements, was enhanced by the superior spatial accuracy and penetration capabilities of LiDAR. These findings align with those of (Popescu et al., 2003), who demonstrated that tree tops could be effectively detected using peaks in Canopy Height Models (CHM) derived from LiDAR data.

In similar work, (Brodić et al., 2022) showed the value of refining initial tree detections using machine learning to reduce false positives, especially in mixed forest environments. However, unlike their study, which suffered from segmentation challenges in deciduous forests, my approach yielded highly distinct crown separations due to the application of high-density LiDAR data and field calibration.

The segmentation process involved separating tree crowns from other objects in the point cloud using clustering and classification algorithms. As visualized in the color-coded segmentation (Figure 4.1), each unique color represents an individual tree group.

4.2.2 Canopy Height Model (CHM) Generation

The Canopy Height Model was constructed by subtracting the DTM from the DSM. The result was a detailed map of vertical vegetation structure across the study area. This methodology, which effectively highlights height differences between the canopy and ground level, is consistent with best practices in LiDAR-based forest monitoring as discussed by (Liu et al., 2020) and (NOAA, 2012). The high point density (4 points/m^2) in this study allowed for capturing subtle variations in canopy structure, improving the reliability of the height estimates.

The CHM served not only as a key layer for tree segmentation but also as a baseline for estimating biomass and evaluating forest age structures, as supported by (Anahita, 2017), who emphasized CHM's role in deriving inventory parameters.

4.2.3 Tree Categorization by Height

Tree height categorization revealed a diverse vertical profile in the study area forest, with trees ranging from 4 to 52 meters. The majority (around 70%) were classified within the lower and middle height classes (4–23 m), indicating either a young forest or a secondary regrowth phase. This stratification is essential for understanding forest dynamics, biodiversity, and management priorities, similar to the work of (Latifi, 2012), who noted that vertical forest structure influences habitat quality and ecosystem functions.

Compared to global studies such as (Rasmus et al., 2023), which also categorized tree heights using satellite data, my study provided finer spatial resolution and better vertical accuracy thanks to LiDAR's ability to directly capture three-dimensional canopy attributes. Having established tree heights, the next step involved categorizing the trees based on predefined height intervals

4.2.4 Trunk Measurement and Diameter Classification

By using the LiDAR point cloud and applying circle-fitting algorithms, the study derived accurate measurements of trunk diameters. The researcher classified trees into five diameter classes, ranging from 2 m to 89 m, out of a total of 36,531 trees identified, the largest proportion 15,181 trees or approximately 41.5% fell within the 2 to 11meter diameter range. This was followed by 11,109 trees (30.4%) in the 12 to 15meter range, and 8,753 trees (24%) in the 16 to 24meter category. A smaller proportion of trees 1,332 trees or 3.6% were classified within the 25 to 38meter range, while only 156 trees (0.4%) had diameters between 39 and 89 meters.

This distribution suggests that the forest is primarily composed of younger or medium-aged trees, with fewer large-diameter, mature specimens, indicating a forest in a phase of regrowth or moderate development. These insights are essential for biomass estimation and forest resource planning, as trunk diameter strongly correlates with wood volume and carbon storage potential. (Nicholas, 2012) emphasized that knowing individual tree attributes, such as trunk diameter, is key for assessing forest productivity, carbon stock, and ecological value.

Unlike studies limited by sparse point clouds or satellite imagery (e.g., Jing et al., 2024), this study benefitted from high-resolution airborne LiDAR, which facilitated reliable trunk characterization even under dense canopy cover.

4.3 Validation and Accuracy Assessment

4.3.1 Validation of Tree Counting Using Ground truth data

A random sample of 100 trees was selected within approximately 0.0093 km² validation area out of this the first 30 trees was used to validate Height and Diameter in the study area. The results showed that 92 trees were correctly identified by the LiDAR-based system (True Positives), 5 were incorrectly classified as trees (False Positives), and 3 actual trees were missed (False Negatives). Based on these data in Appendix iv, using mathematical formulas (Eq-4-9) the validation was conducted.

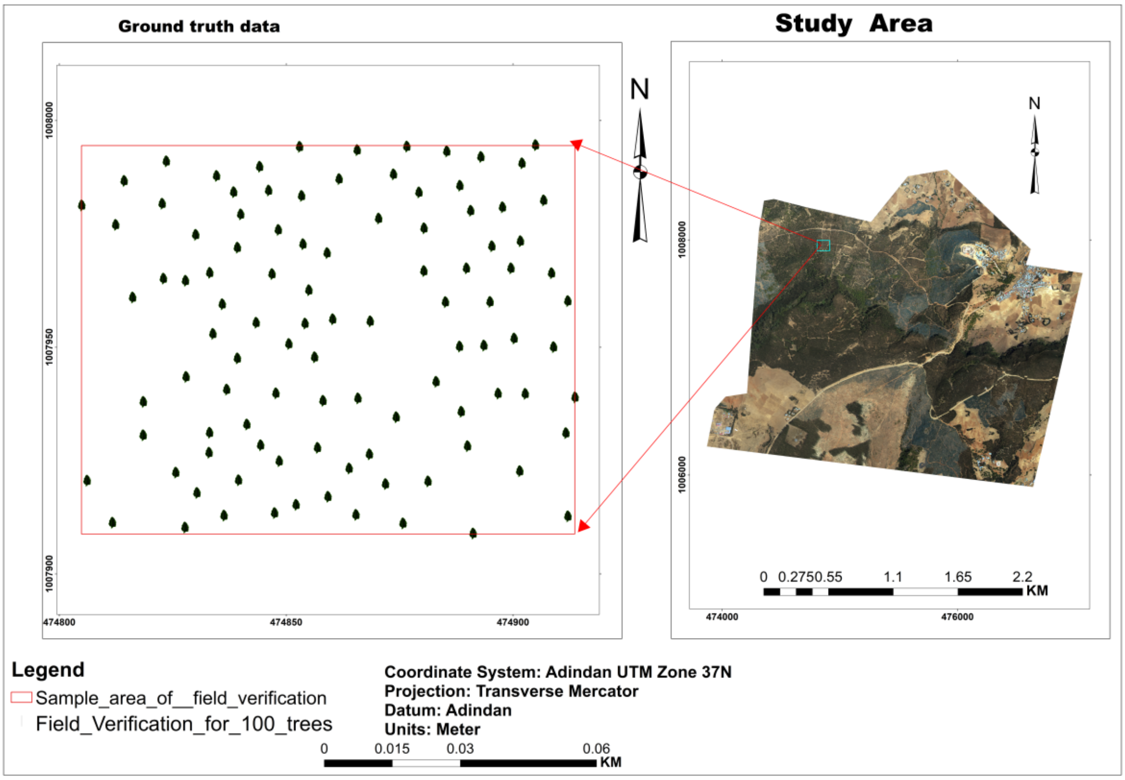

Figure 4. 6 Validation of Tree Counting Using Ground truth data

The validation process, which included comparing LiDAR-derived results with field-measured data, confirmed the reliability of the automated methods. With a precision of 94.85%, recall of 96.8%, and F1 score of 95.8%, the algorithm exhibited a strong balance between sensitivity and specificity. The increase in tree height and diameter between the LiDAR and field data for the first 30 trees indicates growth, as the data were collected at different times. These results indicate that the automated method is more precise and consistent than manual fieldwork, especially in dense forest regions like Entoto.

Table 4. 1 Accuracy Assessment for 100 Sampled Trees using Ground truth data

Metric	Description	Value
Sample Size	Total number of trees sampled from the study area	100
True Positives (TP)	Trees correctly identified by the LiDAR-based method	92
False Positives (FP)	Non-tree objects misclassified as trees by the system	5
False Negatives (FN)	Actual trees missed by the automated detection	3
Precision (%)	TP / (TP + FP) = 92 / (92 + 5)	94.85
Recall (%)	TP / (TP + FN) = 92 / (92 + 3)	96.84
F1 Score (%)	2 * (Precision * Recall) / (Precision + Recall)	95.83
Overall Accuracy (%)	(TP / Sample Size) * 100	92.00

These results are consistent with those found by (Yang et al., 2022), who applied convolutional neural networks to tree detection from LiDAR data and reported high precision in tree classification. Moreover, the incorporation of multispectral data into the classification process improved crown differentiation, consistent with the findings of (Zhao et al., 2021).

Overall, this study addressed the gaps noted in previous works such as limited point density, poor canopy segmentation, and inadequate validation by integrating high-resolution LiDAR and multispectral data with robust processing algorithms. The Entoto Forest Reserve, being a densely vegetated and topographically complex area, served as a rigorous testing ground, proving the scalability and applicability of this approach for similar forest ecosystems in Ethiopia and beyond.

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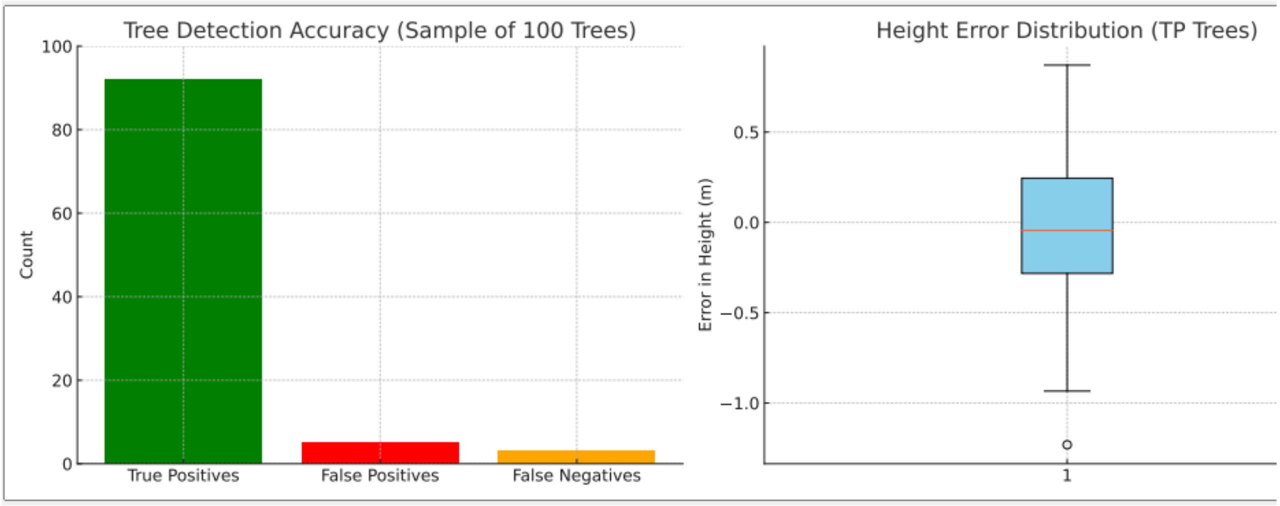

Figure 4. 7 Accuracy Assessment Results

Left Chart: Shows the confusion matrix, most trees were correctly detected, while right Chart A box plot showing the distribution of height estimation errors.

4.3.2 Validation of Tree Counting Using High-Resolution Multispectral Imagery

To ensure the reliability of the tree counting results generated from high-resolution multispectral imagery, a rigorous validation process was carried out using manually interpreted reference data. This reference dataset was developed by visually identifying and digitizing individual tree crowns from an orthorectified aerial photograph from the study area. This manual interpretation, often referred to as ground-truthing is a common and effective practice in remote sensing validation, as it provides a high-confidence baseline for comparison (Ke & Quackenbush, 2011).

Table 4. 2 Accuracy Assessment of Automated Tree Detection using imagery.

Metric	**Value (%)**
Precision	98.00
Recall	98.00
F1-Score	98.00
Overall Accuracy	98.00

The automated tree counting method demonstrated a high level of agreement with the reference dataset derived from manually digitized aerial photographs. Out of the 100 randomly selected tree samples used for validation, 98 were correctly identified by the automated detection algorithm, yielding a precision of 98%, which indicates that nearly all detected trees were indeed true trees. Similarly, the recall which measures how many of the actual trees in the reference set were detected also stood at 98%, confirming that the algorithm successfully captured the majority of trees present in the area. The F1-score, a harmonic mean of precision and recall, was calculated to be 98%, reinforcing the balanced and consistent performance of the method in both identifying and correctly classifying tree objects.

These results reflect a strong correlation between the automated analysis and ground-truth data, signifying the reliability of the methodology applied. The consistency across all three metrics highlights that the approach is not only accurate but also robust and generalizable for similar forest environments. Such high validation scores are in line with findings from other recent studies utilizing object-based classification and LiDAR-derived canopy height models for individual tree detection (e.g., Popescu et al., 2019; Coomes et al., 2017).

This validation process fills a common methodological gap observed in earlier studies that often focused heavily on algorithmic performance but lacked rigorous and transparent accuracy assessment. By incorporating a well-defined sampling method, spatial validation techniques, and robust statistical evaluation, this research provides a more comprehensive framework for validating tree detection results derived from high-resolution multispectral data (see in appendix i the distribution and datasets from high resolution aerial photograph).

The main findings of the study, including the number of trees detected, their spatial distribution, height classification, and validation results. The high level of accuracy achieved demonstrates the effectiveness of integrating LiDAR and multispectral data for automated tree detection. The findings are discussed in the context of forest monitoring and environmental management.

5 Conclusion and Recommendations

5.1 Conclusion

In conclusion, the study demonstrates that automated tree counting using integrated airborne LiDAR and multispectral imagery is a viable, accurate, and scalable approach to forest inventory in Ethiopia. It effectively overcomes traditional challenges of manual tree enumeration and offers valuable insights into forest structure, biomass, and carbon stock estimation. This work contributes to the broader goals of sustainable forest management and climate resilience. Through a carefully designed and executed methodology spanning from data acquisition and pre-processing to segmentation, classification, and validation, a total of 36,531 individual trees were automatically identified with a high degree of spatial precision.

By fusing 3D structural data from LiDAR with spectral information from multispectral images, the research enabled precise segmentation of tree crowns, generation of a reliable Canopy Height Model (CHM), and accurate classification of trees based on both height and trunk diameter. The analysis revealed a forest dominated by younger to mid-aged trees, with the majority ranging from 4 to 23 meters in height and 2 to 11 meters in diameter. These insights are critical for understanding forest composition, estimating biomass, and supporting sustainable forest management and conservation planning.

A key achievement of this work lies in its rigorous validation. Comparison with high-resolution aerial imagery and field-verified data revealed precision, recall, and F1-scores all above 95%, and overall accuracy of above 92% confirming that the automated approach is not only efficient but also reliable. These results demonstrate significant improvement over traditional manual methods, especially in complex, densely vegetated landscapes like Entoto.

Moreover, this research addresses existing gaps in the literature, particularly in the Ethiopian context, where few studies have applied such low -resolution remote sensing images for forest inventory purposes. The findings contribute valuable knowledge that can inform policy, enhance monitoring programs, and support climate-related initiatives such as carbon stock assessments.

In summary, this study validates the potential of combining airborne LiDAR with multispectral imagery for accurate, large-scale, and repeatable forest assessments. It offers a scalable solution for forest managers, researchers, and policymakers seeking cost-effective methods to monitor, manage, and protect forest ecosystems. The approach developed here lays a solid foundation for future innovations in ecological modeling, forest restoration projects, and biodiversity monitoring across similar forested environments.

5.2 Recommendations

Based on the key findings of this study particularly the successful identification of 36,531 trees using integrated airborne LiDAR and multispectral imagery with over 95% accuracy several specific, actionable recommendations are proposed for relevant stakeholders:

- **Adoption of Integrated Remote Sensing in Forest Inventory**

Ethiopian Forestry Development (EFD), Ministry of Agriculture, Regional Forestry Offices use integrated airborne LiDAR and multispectral imagery for national forest inventory to enhance accuracy in tree counting, biomass estimation, and to assess vertical structure of canopies.

- **Capacity Building in Advanced Geospatial Technologies**

Ethiopian Space Science and Geospatial Institute (SSGI), universities, and technical training institutions develop and offer training programs on LiDAR processing, multispectral image analysis, and automated tree segmentation to build skilled professionals in forestry and geospatial fields.

- **Integration of Automated Tree Counting into Forest Management Plans**

Forestry planners, regional environmental bureaus, and conservation agencies incorporate outputs of automated tree counting into forest regeneration monitoring, reforestation planning, timber resource assessment, and climate-related forest policy formulation.

- **Extension of the Method to Other Ecological Zones**

Research institutions, environmental NGOs, universities replicate and adapt this methodology in different ecological regions such as lowland forests, commercial plantations, and dry Afromontane woodlands to test its accuracy and scalability.

5.2.1 Future Research Directions

While this study successfully demonstrated the potential of integrating airborne LiDAR and multispectral imagery for automated tree counting, it also opened up avenues for further research and methodological refinement. To build upon this work and address the limitations encountered, the following directions are recommended for future studies:

- **Enhancing Tree Species Classification with Hyperspectral Data**
  Future studies could incorporate hyperspectral imagery in addition to multispectral data to improve tree species identification and classification. Hyperspectral sensors capture a much broader range of wavelengths, allowing researchers to distinguish between species more precisely, assess tree health, and detect subtle vegetation changes.

- **Longitudinal Monitoring for Forest Change Detection**
  Conducting repeated LiDAR and multispectral data acquisitions over time would allow for monitoring forest dynamics, including tree growth, mortality, and regeneration patterns. This time-series analysis could be vital for detecting long-term ecological trends and assessing the effectiveness of conservation programs.

- **Integrating UAV (Drone) Platforms for Small-Scale Studies**
  While airborne LiDAR systems are highly effective, they can be expensive and logistically complex. Future research could explore the use of UAV-mounted LiDAR and multispectral sensors for localized studies, providing a cost-effective solution for frequent monitoring in smaller or inaccessible areas.

- **Validation with Diverse Ground-Truth Techniques**
  Expanding the ground validation process using advanced tools such as terrestrial LiDAR scanners or mobile laser scanning systems can improve the accuracy of automated methods and help calibrate models for broader application across varying forest types.

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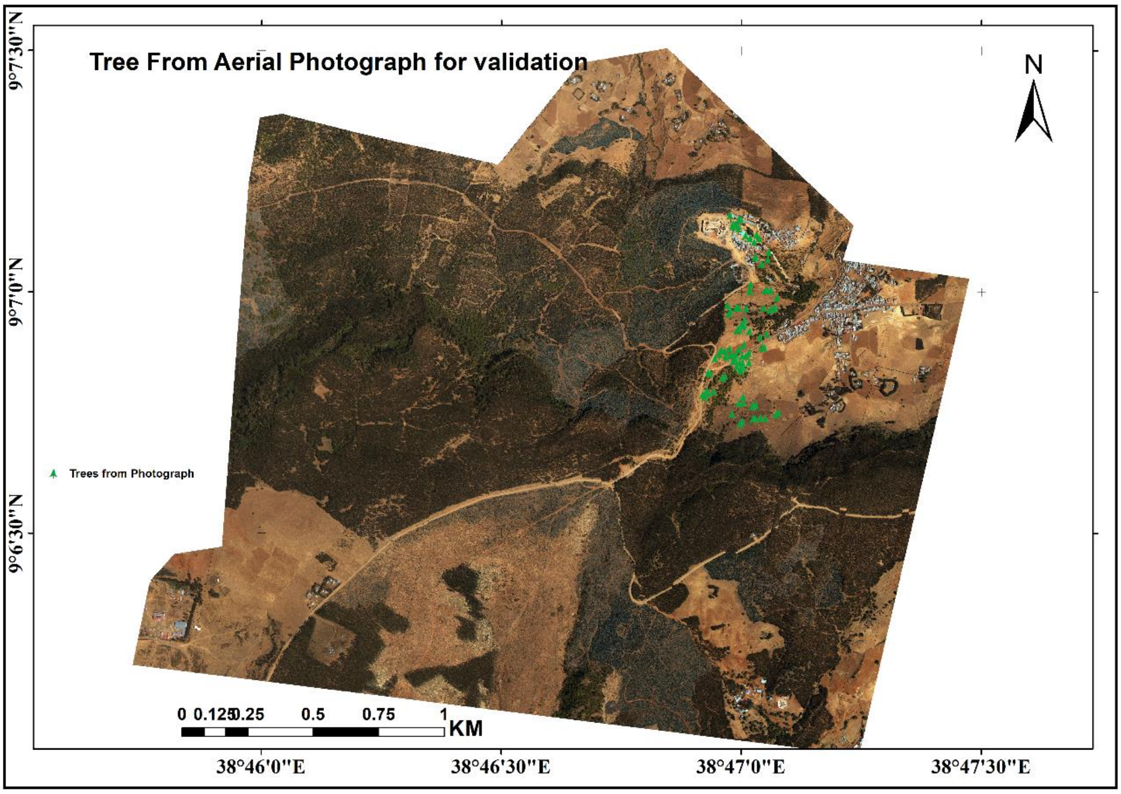
APPENDIX

Appendix i: Tree data sets for Validation of Tree Counting Using High-Resolution Multispectral Imagery



Appendix ii: Vertical Accuracy of LiDAR Point Cloud

Entoto_Kotebe LiDAR ground classified vertical accuracy report using GCP (Premark)

ID	X	Y	Z	ELEVATION	DZ	DZSQ
EK01	473251.93	1005022.65	2955.53	2955.58	0.05	0
EK02	473612.06	1005706.56	2984.58	2984.83	0.25	0.06
EK03	474561.42	1005740.02	2991.93	2991.96	0.02	0
EK05	476181.8	1006321.93	3009.29	3009.4	0.11	0.01
EK06	476903.38	1006556.55	3070.75	3070.95	0.2	0.04
EK07	477863.84	1005809.16	3037.15	3037.26	0.11	0.01
EK08	478617.44	1006419.54	3125.46	3125.54	0.08	0.01
EK09	479236.55	1005473.37	3077.3	3077.43	0.12	0.01
EK10	480202.24	1006064.31	3153.77	3153.88	0.11	0.01
EK12	474429.88	1006600.93	3054.14	3054.22	0.08	0.01
					RMSE	0.13

Appendix iii: Sample Attribute of individual trees out of 36531 trees

No	X	Y	Z	H	D		No	X	Y	Z	H	D
1	474441.4	1008199	2840.91	10.14	12.1		21	476249.2	1008242	2901.41	5.56	12.9
2	474389.1	1008153	2837.27	7.31	10.9		22	476249.6	1008294	2878.49	7.79	40.2
3	474393.1	1008139	2841.42	9.74	11.7		23	476195.8	1008262	2899.81	5.51	6.5
4	474394.1	1008143	2840.05	9.98	10.8		24	476162.9	1008296	2881.56	6	43.3
5	474400.8	1008149	2838.75	9.52	10.1		25	476276.5	1008304	2866.11	17.87	13.6
6	474426.4	1008140	2846.44	8.66	13.3		26	476298.2	1008297	2864.36	8.97	28.1
7	474413.3	1008131	2843.03	12.55	12.4		27	476287	1008299	2867.6	8.13	15.8
8	474409	1008111	2846	12.29	11.8		28	476272.7	1008291	2875.68	10.03	12.4
9	474427.2	1008118	2846.83	9.47	15.2		29	476268.3	1008300	2869.14	6.59	14.6
10	474440.6	1008127	2848.34	10.81	16.5		30	476273.9	1008286	2881.45	7.98	10.6
11	474439.9	1008110	2850.04	12.14	15.5		31	476303.8	1008275	2879.25	7.48	32.7
12	474438.2	1008132	2847.46	9.11	11.2		32	476329.7	1008281	2869.3	8.12	32.7
13	474463.1	1008153	2844.25	11.64	19.6		33	476312.3	1008298	2861.4	11.13	14
14	474450.8	1008169	2840.75	8.81	11.2		34	476321.4	1008295	2861.22	8.11	11.7
15	474434.2	1008176	2840.68	8.39	15.7		35	476367.7	1008226	2888.42	6.21	16.2
16	474432.7	1008169	2842.27	7.41	9.6		36	476359.7	1008207	2891.03	9.27	16.5
17	474443.5	1008160	2843.16	11.45	13.6		37	476370.4	1008210	2889.15	8.37	19.3

18	474436.9	1008160	2842.66	8.68	12.8		**38**	476387.5	1008215	2885.63	8.41	18
19	474423.3	1008161	2842	10.1	13.3		**39**	476395.4	1008205	2883.72	21.55	9.9
20	474412.3	1008170	2839.75	8.4	10.4		**40**	476383.3	1008226	2885.38	6.87	16

Appendix iv: Sample data collected from the field for Validation of result

Tree_ID	X	Y	Z	Height_LiDAR (m)	Height_Manual (m)	dH (m)	Diameter_LiDAR (m)	Diameter_Manual (m)	dD (m)	Automated_Detected	Manual_Detec
1	474815	1008078	2899.4	4.41	5.79	1.38	2.79	3.9	1.11	Yes	Yes
2	474824	1008083	2899.32	8.25	10.21	1.96	1.73	2.69	0.96	Yes	No
3	474823	1008073	2899.91	8.33	11.32	2.99	2.83	3.78	0.95	Yes	No
4	474813	1008069	2899.81	9.1	10.33	1.23	2.72	4.94	2.22	Yes	Yes
5	474805	1008073	2899.88	9.81	10.53	0.72	1.37	3.24	1.87	Yes	Yes
6	474828	1008056	2903.99	11.81	12.69	0.88	1.13	3.25	2.12	Yes	Yes
7	474817	1008053	2900.77	8.13	9.16	1.03	1.19	2.35	1.16	Yes	Yes
8	474823	1008057	2901.27	6.58	7.28	0.7	1.03	1.89	0.86	Yes	Yes
9	474828	1008035	2906.61	10.36	11.29	0.93	1.18	2.45	1.27	Yes	Yes
10	474819	1008029	2903.4	6.17	8.34	2.17	2.3	3.24	0.94	Yes	Yes
11	474819	1008022	2903.83	7.51	10.34	2.83	1.14	3.11	1.97	Yes	Yes
12	474826	1008014	2908.02	4.63	6.2	1.57	1.61	2.21	0.6	No	Yes
13	474828	1008002	2911.35	4.2	5.07	0.87	2.61	2.69	0.08	Yes	Yes
14	474812	1008003	2906.28	11.7	12.74	1.04	1.04	1.85	0.81	Yes	Yes
15	474807	1008012	2904.55	10.69	11.12	0.43	2.55	2.38	-0.17	Yes	Yes
16	474860	1008009	2922.36	9.57	10.32	0.75	1.54	1.99	0.45	Yes	Yes
17	474848	1008005	2915.98	7.27	8.62	1.35	1.22	1.62	0.4	Yes	Yes
18	474831	1008009	2910.78	5.39	6.39	1	2.32	2.66	0.34	Yes	Yes
19	474837	1008004	2913.52	5.25	8.96	3.71	2.19	3.43	1.24	Yes	Yes
20	474840	1008012	2911.81	6	7.14	1.14	2.67	2.98	0.31	Yes	Yes
21	474833	1008018	2909.83	8.39	9.45	1.06	2.4	2.85	0.45	Yes	Yes
22	474845	1008020	2912.17	9.72	11.54	1.82	2.53	3.65	1.12	Yes	Yes
23	474849	1008016	2913.66	9.28	10.3	1.02	1.54	2.53	0.99	Yes	Yes
24	474853	1008007	2917.34	6.24	7.12	0.88	1.34	2.16	0.82	Yes	Yes
25	474857	1008019	2917.12	11.64	13.67	2.03	2.43	2.98	0.55	Yes	Yes
26	474864	1008015	2921.98	9.9	11.1	1.2	2.53	2.88	0.35	Yes	Yes
27	474869	1008018	2923.28	8.43	10.91	2.48	2.88	3.08	0.2	Yes	Yes
28	474866	1008005	2925.32	8.89	9.52	0.63	1.78	2.75	0.97	Yes	Yes
29	474872	1008011	2926.86	7.36	8.32	0.96	1.71	2.54	0.83	Yes	Yes
30	474882	1008012	2930.45	5.98	7.4	1.42	2.48	2.98	0.5	Yes	Yes
31	474876	1008003	2930.95							Yes	Yes
32	474890	1008020	2931.97							Yes	Yes
33	474902	1008014	2936.34							Yes	Yes
34	474912	1008023	2935.48							Yes	Yes
35	474913	1008004	2940.11							Yes	Yes
36	474892	1008000	2936.52							Yes	Yes
37	474909	1008058	2925.65							Yes	Yes
38	474912	1008052	2927.96							Yes	Yes
39	474900	1008059	2923.37							Yes	Yes
40	474902	1008065	2921.95							Yes	Yes
41	474896	1008064	2921.09							Yes	Yes
42	474895	1008052	2924.61							Yes	Yes
43	474894	1008042	2926.82							Yes	Yes
44	474903	1008031	2931.22							Yes	Yes
45	474901	1008043	2927.77							Yes	Yes
46	474909	1008042	2930.1							Yes	Yes
47	474914	1008030	2933.93							Yes	Yes
48	474897	1008031	2930.48							Yes	Yes
49	474889	1008027	2929.17							No	Yes
50	474883	1008034	2926.51							Yes	Yes
51	474889	1008042	2925.53							Yes	Yes
52	474866	1008030	2919.28							Yes	No
53	474875	1008026	2923.83							Yes	Yes
54	474859	1008030	2915.58							Yes	Yes
55	474848	1008031	2911.7							Yes	Yes
56	474842	1008024	2910.75							Yes	Yes
57	474834	1008023	2909.31							Yes	Yes
58	474837	1008032	2908.95							Yes	Yes
59	474840	1008039	2908.93							Yes	Yes
60	474857	1008039	2914.38							Yes	Yes
61	474851	1008042	2911.76							Yes	Yes
62	474855	1008054	2911.76							Yes	Yes
63	474855	1008047	2912.44							Yes	Yes
64	474834	1008045	2907.17							Yes	Yes
65	474836	1008051	2907.42							Yes	Yes
66	474844	1008047	2909.4							Yes	Yes
67	474834	1008058	2905.88							Yes	Yes
68	474840	1008064	2906.99							Yes	Yes
69	474847	1008058	2909.83							Yes	Yes
70	474854	1008064	2910.91							No	Yes
71	474859	1008062	2912.68							Yes	Yes
72	474861	1008048	2914.37							Yes	Yes
73	474869	1008047	2918.47							Yes	Yes
74	474886	1008052	2922.77							Yes	Yes
75	474881	1008058	2919.95							Yes	Yes

76	474890	1008059	2921.86							Yes	Yes
77	474881	1008068	2917.78							Yes	Yes
78	474880	1008076	2916.31							Yes	Yes
79	474889	1008077	2917.49							Yes	Yes
80	474886	1008085	2915.9							Yes	Yes
81	474877	1008086	2915.12							Yes	Yes
82	474874	1008080	2915.02							Yes	No
83	474866	1008085	2911.67							Yes	Yes
84	474862	1008079	2911.77							Yes	Yes
85	474871	1008070	2915							Yes	Yes
86	474854	1008075	2908.86							Yes	Yes
87	474849	1008067	2908.64							Yes	Yes
88	474840	1008071	2905.72							Yes	Yes
89	474830	1008066	2902.86							Yes	Yes
90	474839	1008076	2903.36							Yes	Yes
91	474845	1008081	2903.29							Yes	Yes
92	474835	1008079	2901.92							Yes	Yes
93	474847	1008076	2905.66							Yes	Yes
94	474853	1008086	2905.26							Yes	Yes
95	474893	1008084	2917.13							Yes	Yes
96	474902	1008082	2918.46							Yes	Yes
97	474891	1008072	2919.11							Yes	Yes
98	474898	1008072	2919.81							Yes	Yes
99	474907	1008074	2920.47							Yes	Yes
100	474905	1008086	2918.27							Yes	No