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Assessing of Forest Structure Using Earth Observation Data: A Case Study in Munessa Forest, Oromia Region, Ethiopia

Mulualem Kere*

Abstract

Understanding forest structure is crucial for estimating carbon emissions associated with forests, assessing forest degradation, and evaluating the success of forest restoration efforts. However, forest structure quantification is limited to the area of interest without considering the whole forest coverage. Forest structure may be easily assessed over a wide area using data from remote sensing. Thus, by combining ground observation with satellite-based light detection and ranging (LiDAR) and Sentinel-2 data, this study seeks to assess the forest structure of Munessa Natural Forest. The plantation tree species were categorized in this study using the object-based image analysis (OBIA) technique. Forest structures such forest height and aboveground biomass density with 7,810 and 2,426 footprint locations were assessed by Global Ecosystem Dynamics Investigation (GEDI) LiDAR data. The result shows that the Munessa Forest has five feature classes and is covered by 69% Natural forest, 4% Pinus patula, 9% Cupressus lusitanica, 10% eucalyptus, and 9% shrub. Across all study plots, the average tree height in the Munessa forest was 43.7 meters per hectare. The GEDI LiDAR-derived estimated forest structures (forest height) correlate (R=0.714) with the field measurement data from sample plots. A new age of large-area methodologies for predicting forest structure in various forest assessments is supported by the more substantial LiDAR data from the Global Ecosystem Dynamics Investigation (GEDI).

Keywords: Forest structure, earth observation data, remote sensing, Munessa, land cover analysis

INTRODUCTION

The word "forest" has diverse meanings in different parts of the world. The current Forest Resource Assessment defines a forest as land covering more than 0.5 hectares, with trees that are taller than 5 meters and have a canopy cover exceeding 10 percent, or trees that have the potential to reach these thresholds *in situ*. The young natural stands and all plantations established for forestry purposes that have yet to reach a crown density of 10 percent or tree height of 5 m are included under the forest, areas normally forming part of the forest area which are temporarily unstocked as a result of human intervention or natural causes but which are expected to revert to forest [1–3].

***Author for Correspondence**
Mulualem Kere
E-mail: mulualemkere100@gmail.com

Research Scholar, Department of Earth Sciences, Addis Ababa University, Ethiopia

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Forest structure refers to the circulation of individual plants and the connection of their attributes and values. Forest structure is influenced by natural forces, including wind, fire, and ecological succession. Forest structure is the driver for forest growth and ecological processes and is directly linked to forest ecosystem goods and services. A fully functioning forest ecosystem comprises primary producers, consumers, decomposers, and non-living environmental components.

The arrangement and composition of a forest significantly impact its productivity, species diversity, and the habitats it supports; ultimately shaping the ecosystem services it delivers. 'Forest structure' refers to a broad concept that can be understood and interpreted through different perspectives. Essential attributes of forest structure include structural type, size, shape, canopy cover, tree density, basal area (BA), stem volume (SV), biomass, tree species mixture, and spatial arrangement (vertical or horizontal) of components [4].

Forests provide vital livelihoods for millions of people and play a significant role in the economic development of many nations. However, despite their critical importance for supporting livelihoods and regulating the climate, forest resources worldwide face immense pressure. This pressure, driven by rising human and livestock populations and pervasive rural poverty, has led to widespread deforestation and degradation.

Globally, forests cover 4.03 billion hectares; which is approximately 30% of the earth's total land area. They account for 70% of terrestrial Gross Primary Productive (GPP) and 80% of earth's total plant biomass contains more carbon in biomass and soils than is stored in the atmosphere, 11.9% of Ethiopia's land area is covered with forests including closed forests plus woodlands were more than 90 million inhabitants, live in rural areas [5].

Munessa forest is one of the major timber product suppliers in the country and unfortunately puts the forest under severe pressure from illegal logging activities. Moreover, grazing and encroachment due to agricultural activities have become increasingly affected in the area in recent years (Abebe, 2008). To protect the ecological balance of the environment and to attain the forest resource necessities, assessment of scientific data on the species structure, composition, and distribution in the study areas become a major activity. One of the main objectives of the study is to estimate forests structure with different spatial characteristics more accurately, using various satellite data in affordable assessment techniques [6, 7].

Traditionally forest structures are gathered by field measurements using hand-held equipment, which is very expensive, time-consuming, and labor-intensive, as well as difficult to achieve and determine the forest structure of a large area of forests biomass. Remote sensing is an important technology in forest structure assessments and monitoring of different parameters. Remote sensing data has been proven effective in measuring forest structure parameters, including diameter at breast height (DBH), tree height, basal area, aboveground biomass density, and tree density. Recent studies suggest that divergent combinations of satellite data, i.e., multi-frequency SAR data, and optical and textural data improve forest parameters estimation [8].

MATERIALS AND METHODS

Study Area

This study was carried out in Munessa forest which is one of the dense forests in the Arsi Zone forest enterprise owned by the state and controlled by Oromia forest and wildlife enterprise (OFWE), which is located 240 km south of Addis Ababa, Ethiopia (Figure 1) and bounded between a Latitude of 7°16´09´´N - 38°40´503´´E and a Longitude of 7°28´13´´N - 39°04´13´´E, it extends over an altitude range from 2100 m to 3100 m above meter sea level. This study covers the total area of about 285,821 ha (Figure 1).

Materials

Sampling Plot

Field data collection was carried out from February 18–25, 2022, and May 20–26, 2022. The fieldwork was undertaken across the Munessa forest and the surrounding study area. Ground truth points were established at field data collection using the Global position system (GPS) to validate satellite images obtained from remotely sensed data [8].

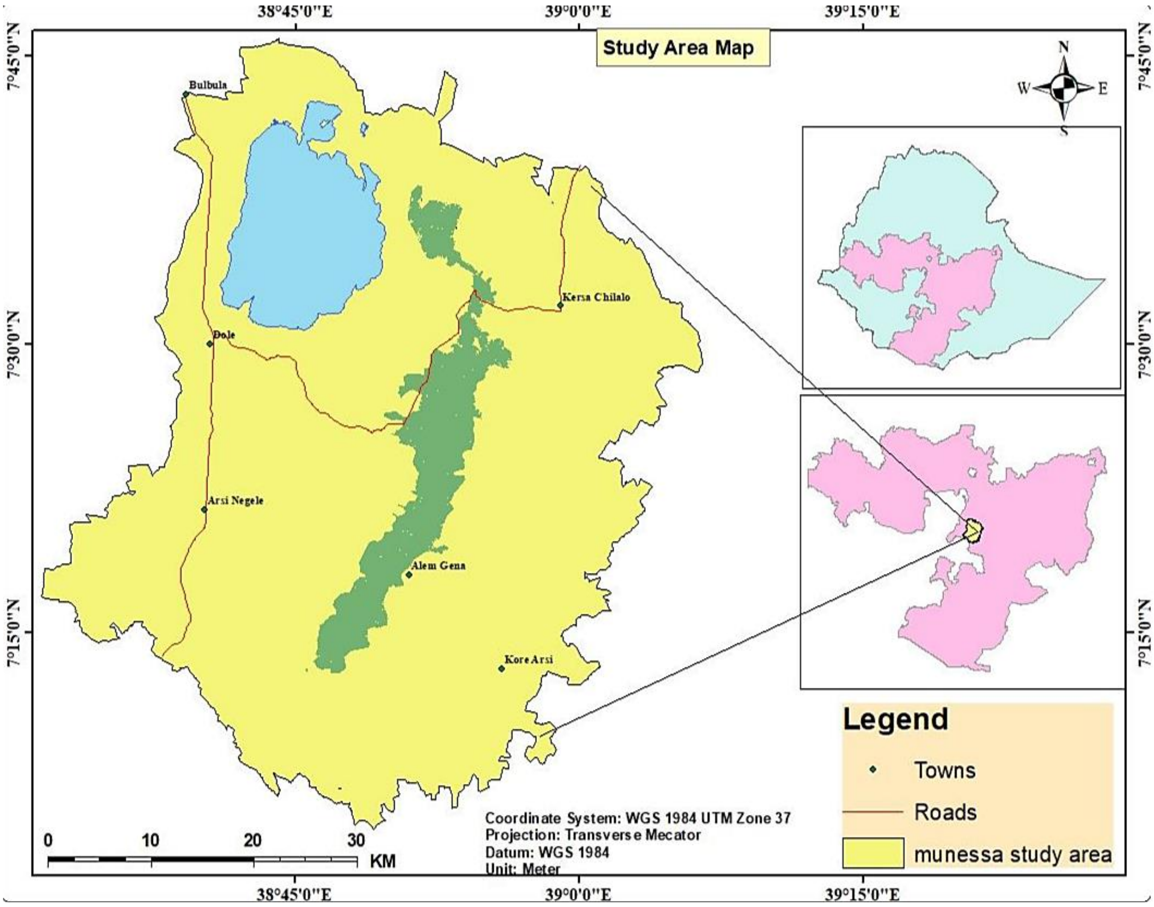

Figure 1. Location map of the study area.

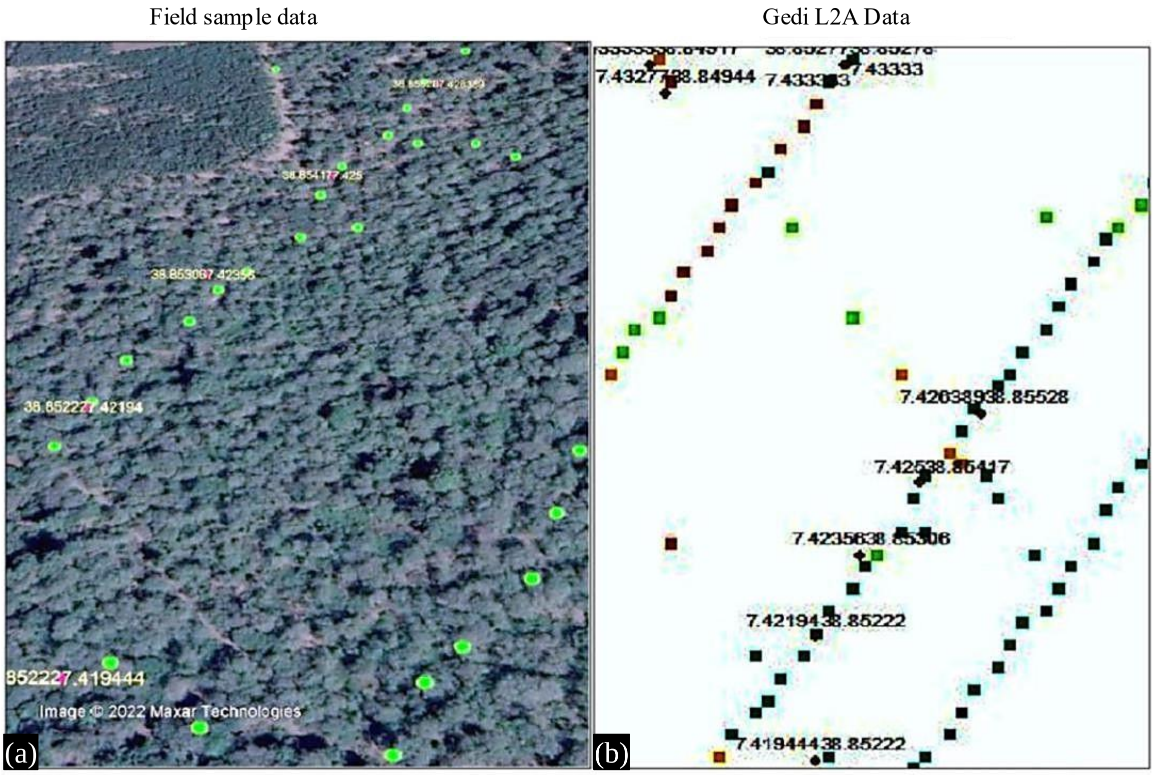

Figure 2. (a, b) GEDI L2A rh98 LiDAR data with field survey sample data in Munessa forest.

From the first field survey, and the second round of field surveys, 11 sample plots of different tree species of the forest in a square of 10 m × 10 m area were selected and measured. The height of individual trees was measured on the ground using a clinometer using cosine law.

Especially the second sample plot data, individual trees were measured on the ground using a standard instrument clinometer to verify GEDI LiDAR point data. The other data collection process was the same as the first, measuring height of the tree, DBH, GPS coordinate, and tree type identification as shown in Figure 2.

Remote Sensing Data

Sentinel-2A Image

The Sentinel data used for this study were captured from the United States Geological Survey (USGS). The sun-synchronous polar-orbiting Sentinel-2 satellites have a temporal resolution of 10 days with one satellite and 5 days with two satellites, between the latitudes of 84° North and 56° South. A nearly cloud-free Sentinel-2A image captured on 01 January 2021 was downloaded from the United States Geological Survey Hub in the form of two granules, 100 by 100 km.

GEDI LiDAR Data Acquisition and Processing

GEDI-derived Level 2A (L2A) and L4 data were used in the study (Figure 3). Above Ground Biomass Density (AGBD) existed before GEDI, footprint models were developed using simulated waveforms paired with ground-based field estimates of above-ground biomass density that are used to create the GEDI04 A product. For each GEDI shot, we filtered and selected the RH98 metric. RH98 is the relative height between the ninety-eighth percentile of the returned laser energy and the peak of the ground return. RH98 is selected because it is a robust metric used to estimate aboveground biomass by the GEDI science team.

Software Used

This study used different data, instruments and Software to assess forest structure, land cover type processing and mapping, listed below in Table 1.

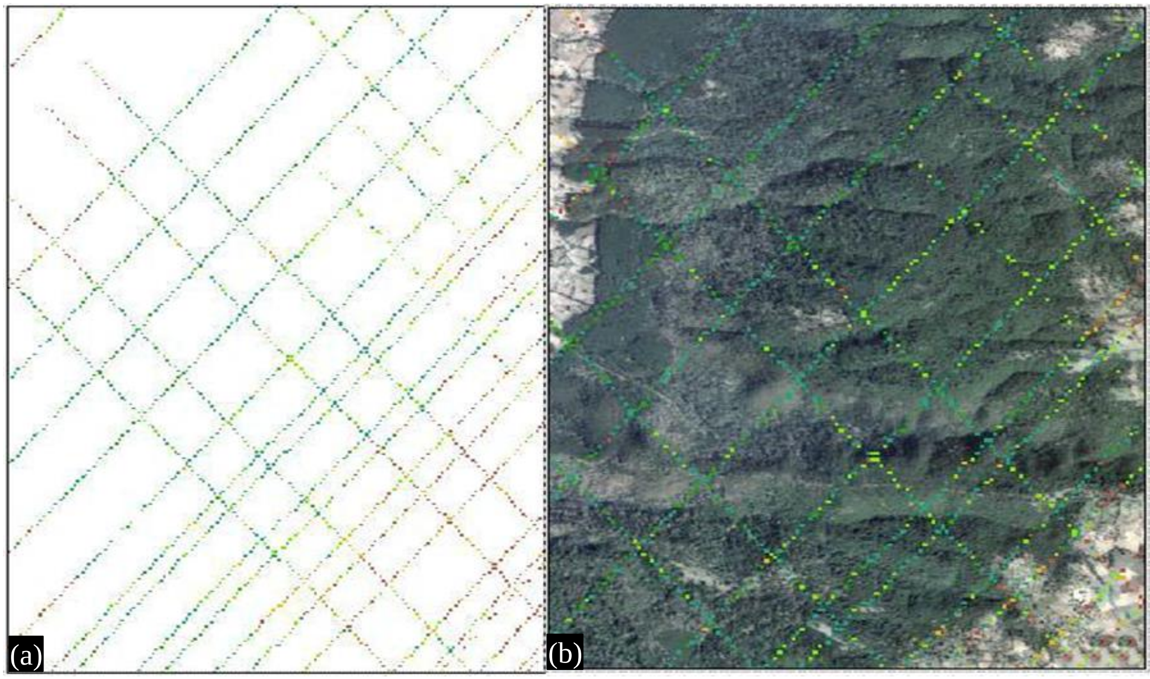

Figure 3. (a) Example of GEDI shot footprints the eight GEDI laser ground tracks and footprints are separated by 60 m along-track and 600 m across-track, (b) Sample data taken and overlay GEDI L2A RH8 data on aerial photograph.

Table 1. Summary of data source and material.

Data			
No.	***Type***	***Source***	
1	GEDI LiDAR Data	NASA	
2	Arial Photograph data	SSGI	
3	Sentinel-2A MSI	USGS or Copernicus	
4	GPS Point data	GPS Field survey	
6	Administrative data	SSGI	
7	Ancillary	Field Survey	
Software's			
No.	***Type***	***Source***	***Function***
1	ERDAS Imagine, 2015		For preprocessing Sentinel data
2	ArcGIS 10.8		LiDAR data interpolation and mapping
3	SAGA GIS 7.8.2	Open source	OBIA Classification
4	QGIS 3.18	Open source	Forest classification

Methods

The methodology used for the different processing steps necessary to implement approaches is outlined in objectives. In this study, the estimation methods of research were used for assessing forest structure analysis.

An overview of the workflow and the procedure implemented using the provided Sentinel and GEDI LiDAR data, with steps followed beginning from data acquisition, preprocessing, classification of a multi-temporal satellite image of the study area to extract the required information both secondary and primary data to answer the research questions.

DATA ANALYSIS

Image Preprocessing

Preprocessing is the first step in transforming raw data into a usable format by performing tasks such as cleaning, normalization, and correction of errors. The satellite data of sentinel collected from the USGS source was preprocessed using ERDAS imagine software.

Preprocessing includes importing, layer stacking, and sub-setting of the image based on the study area boundary of Munessa forest, geometric correction, radiometric correction, removal of stripes, and other image enhancement techniques.

Image Segmentation

Image segmentation is employed to divide remote sensing images into geographic objects with uniform properties.

During the segmentation process, the region-growing technique was utilized, which is available in the segmentation tool of SAGA-GIS.

Object-based Image Classification

Object-based image classification relies on fuzzy logic to integrate a diverse array of object features effectively. In this approach, a two-step process is involved, segmentation of the imagery into discrete objects, and classification of those. Figure 4 after segmentation with SAGA in QGIS, the analyst selects training areas for each class and classifies the pixels based on their similarity to these training areas and the predefined statistics (Figure 4).

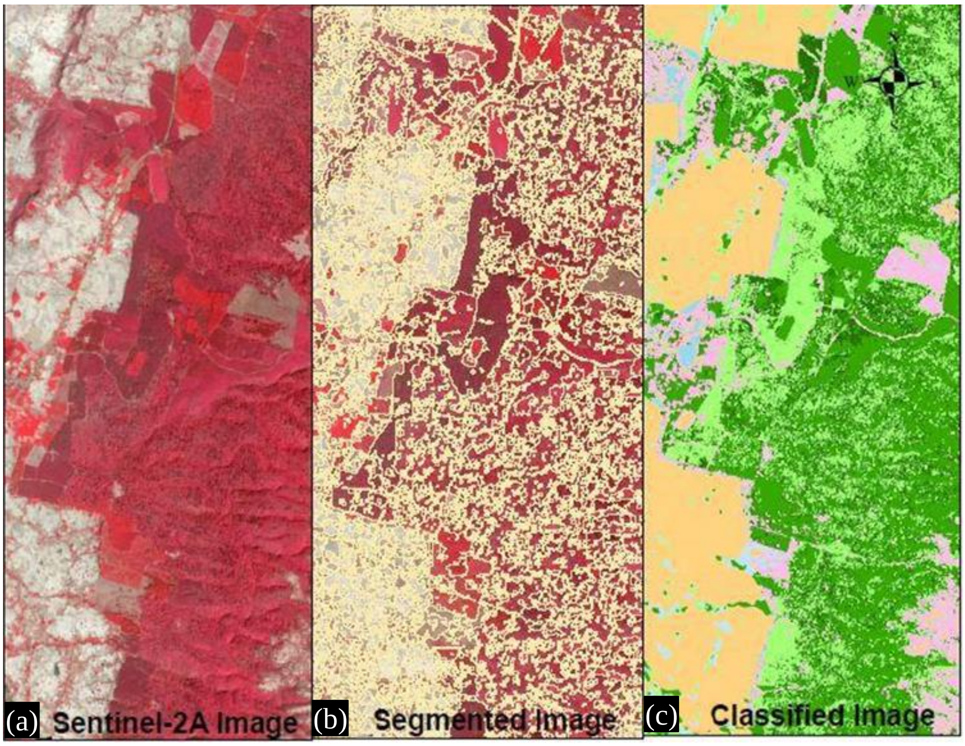

Figure 4. (a) Sentinel-2A image, (b) Segmented image and (c) OBIA Classified image of Munessa forest.

Accuracy Assessment

An accuracy assessment evaluates classifications by comparing them to ground truth or reference data. This method was computed by evaluating how well the classifications represent the real world. The most widely used measures (overall, producer's, user's accuracies, and kappa coefficient) for accuracy assessment could be derived from confusion matrices.

The accuracy assessment was evaluated by different ground truth data such as field survey data, high-resolution satellite data, Google Earth, and aerial photographs. The overall accuracy reflects the average of the user's accuracy and the producer's accuracy. For this, the purpose of validating the assessment, 64 field sample points and 100 points from aerial photographs were captured.

Forest Structure Analysis

The structure of forests was described based on five structural features: diameter at breast height (DBH), height, basal area, tree density, and above-ground biomass density. These features help in understanding the size, volume, and density of trees in a forest.

Tree Height

Height exposes something about the age of plants and also tells something about a disturbance. Tree height was classified into ten classes and the class was compared to other tree structures.

Above Ground Biomass Density (AGBD)

To estimate above-ground biomass density, all tree species in the sample plots with DBH $\geq$ 10 cm were identified and recorded.

A revised and 265 improved allometric equation was adapted from Chave for aboveground biomass density estimation and divided by the plot area:

$$AGB = 0.0673(\rho \times D2 \times H) \wedge 0.976 \quad (1)$$

Diameter at Breast Height (DBH)

Diameter at Breast Height (DBH) is carried out at about 1.3 m height from the ground using a measuring tape.

$$DBH) = C/\pi\ldots \qquad (2)$$

Where, C is circumference of the tree at breast height, π (pi) = 3.14

Basal Area

Basal area calculations were made on the diameter measurements of the stem with DBH of >10 cm and above. It is expressed in square centimeter/ hectare (cm^2/ha) (Hutchings, 1986; Mueller-Dombois and Ellenberg, 1974). There is a direct relationship between DBH and basal area.

$$\text{Basal area} = \Sigma\pi\ (DBH/2)2\ldots \qquad (3)$$

Where, d is diameter at breast-height and π = 3.14

RESULTS

Forest Type Classification and Mapping

The result of this study identified the most dominant forest type class applied in five type's classes using object-based image classification techniques: natural forest, *Pinus patula*, *Cupressus lusitanica*, *Eucalyptus globulus*, and *E. saligna* and others. The classification identified in forest cover area of Munessa forest covers 21,836 hectares, and (69%) of the area (Table 2).

Tree Density

Stem density of the trees were computed by number of individual trees in the total sample plots counted and converted hectare. The sum of individuals per species is calculated in terms of species density per convenient area unit such as a hectare (Mueller - Dombois and Ellenberg 1974).

$$\text{Tree}\ \frac{\text{Density}}{\text{ha}} = \frac{\text{individuals of a tree}}{\text{Total area covered}} * 10{,}000 \qquad (4)$$

Covered by natural forest, while *Cupressus lusitanica*, *Eucalyptus globulus* and *E. saligna*, *Pinus* classes in the study area. According to the classification of forest type, the total *patula* and other covers the remaining 31% of the study area. Finally, validated the classified forest class by using field GPS points taken from Munessa forest and prepared forest type classification maps, area extent, and its percentage in a respectively.

Munessa Forest Classification and Area in Percent

Accuracy Assessment of Object-based Image Analysis (OBIA) Classification

The study was resolved. The overall accuracy and Kappa statistic of classification produced by the object-based method were 84.5% and 0.8055, respectively, while the computed user's and producer's accuracies of object-based classification were shown in Figure (2).

Some of the class seems to be underestimated while the other classes are overestimated in the object-based classification approach (Figures 5 to 7).

Table 2. Forest type and corresponding area coverage.

Forest Type Class	Area (ha)	Percentage (%)
Natural Forest	15042	69
Cupressus lusitanica	1673	8
Pinus Patula	988	4
Eucalyptus globulus and E. saligna	2135	10
Others	1998	9
Total	**21,836**	**100%**

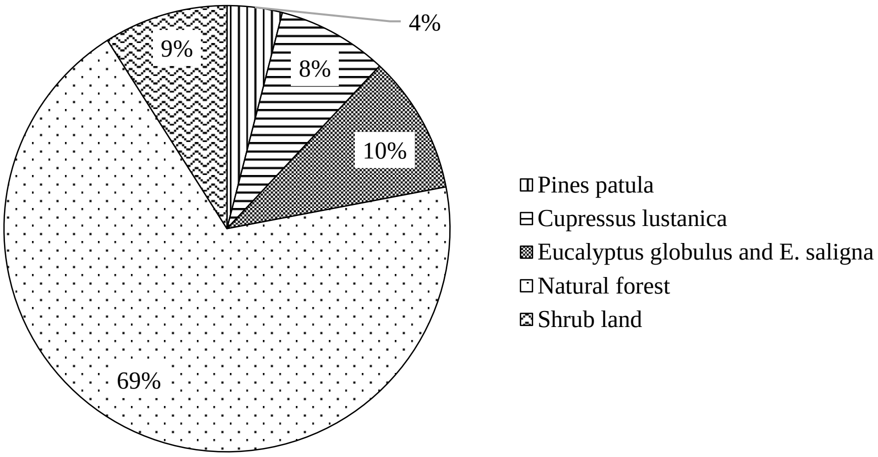

Figure 5. Area coverage of Munessa forest type classification in Sentinel-2A satellite image.

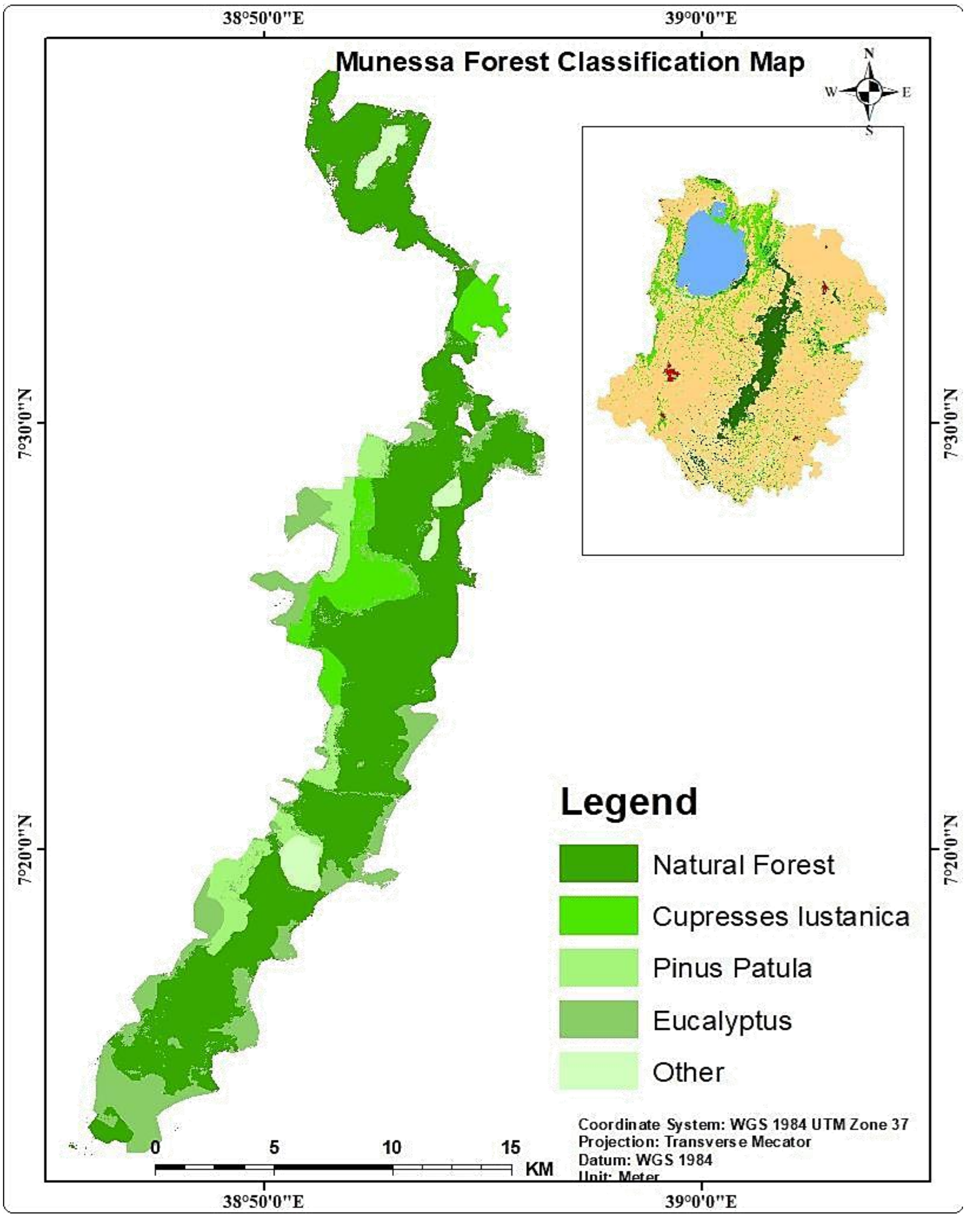

Figure 6. Munessa forest type classification map using object-based approaches.

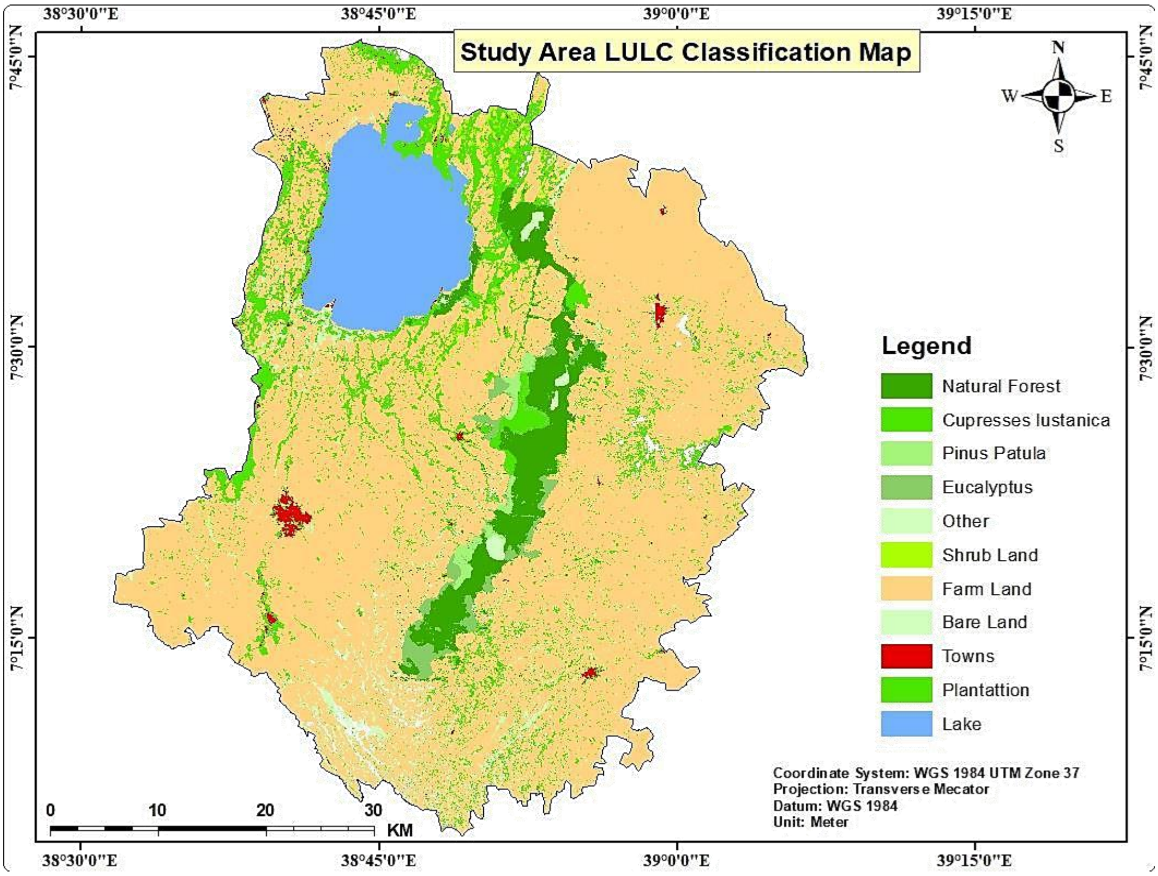

Figure 7. Land use land cover classification map with forest class of the study area.

Table 3. Classification accuracy assessment of object-based approach.

Class	Reference	Classified	Number	Producers	Users
	Totals	*Totals*	*Corrects*	*Accuracy (%)*	*Accuracy (%)*
Natural Forest	9	8	5	77.7	87.5
Cupressus lusitanica	8	7	6	75	85.7
Pinus patula	7	9	6	85.7	66.6
Eucalyptus globulus	5	6	5	100	83.3
and *E. saligna*					
Others	6	5	5	83.3	100
Overall accuracy					84.5
Kappa coefficients					0.80

Forest Structure

Field Estimation of Forest Structure

Some important parameters for describing vegetation structure such as DBH, height, density, basal area, and AGBD were described below in precise quantitative terms. The forest structure can be described in terms of tree density (stems/ha), basal area (m^2/ha), and size class distributions (SCDs). The total number of stems, total basal area, average tree height, and diameter at breast height of the study were presented in field sample techniques. Results measured from the field sampled plots attributes were summarized in different parameters as indicated below in Table 3.

Diameter at Breast Height (DBH)

The DBH was classified into six classes. Those showed that the density decreases with the increase in DBH values. The average value of DBH in different species for this study area is 48.2 cm discussed in Figure 5. According to the sample, the individual of Natural forest shows the highest a DBH of Pinus patula is the lowest, measuring 12.7 cm, while the species with the highest DBH has 18.8 cm [9, 10].

CONCLUSION

This study demonstrates the importance of integrating advanced remote sensing technologies, such as GEDI LiDAR and Sentinel-2 data, with ground-based observations to assess forest structure comprehensively. The findings highlight that Munessa Natural Forest is predominantly covered by natural forest, with varying contributions from plantation species and shrubs. The correlation between GEDI LiDAR data and field measurements underscores the reliability of remote sensing techniques for estimating key forest attributes, including tree height and biomass density. By offering accurate and cost-effective methods for large-scale forest assessments, this study paves the way for better forest management practices, aiding efforts to monitor carbon storage, evaluating degradation, and implementing restoration strategies. Advanced methodologies like these are vital for ensuring the sustainable utilization of forest resources and preserving ecological balance in the face of growing environmental challenges.

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