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Remote Sensing Based Assessment of Land Use and Tree Canopy Cover Dynamics in Selected Localities of Gamo Zone, South Ethiopia

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Abstract

Digital technologies are vital for mapping land uses/covers and enhancing forest monitoring practices. This study aimed to map land use/land cover changes, analyze tree canopy cover dynamics, and evaluate the role of improved cookstoves in forest conservation in selected localities of the Gamo Zone, Southern Ethiopia. Detailed spatiotemporal data were acquired using high-resolution satellite images, aerial photography, Global Forest Watch, Geographic Information System techniques, and ground truth (ground control points). The uses/covers classes were classified using a supervised classification technique. Magnitudes and rates of use/cover dynamics were computed using appropriate techniques. It was found that forest (79.1%) and agroforestry (13.76%) showed significant increases following the provision of improved cook stoves to households in the study localities. The findings confirm the effectiveness of implementing improved cook stoves in the conservation and sustainable management of forests. The study recommends scaling up the adoption of improved cook stoves through community engagement and targeted interventions, leveraging updated remote sensing technologies for continuous monitoring, and integrating findings into local forest management policies. These measures aim to support long-term biodiversity conservation, mitigate deforestation, and enhance ecosystem resilience in the Gamo Zone.

Keywords: Digital mapping, Forest monitoring, Global Forest Watch, Improved cookstoves

1. INTRODUCTION

Forests and tree-based ecosystems play a vital role in sustaining ecological integrity, biodiversity conservation, climate regulation, watershed protection, and rural livelihoods. Changes in forest cover and tree canopy distribution directly affect ecosystem services, including carbon sequestration, soil conservation, hydrological regulation, and habitat provision. Consequently, monitoring land-use and land-cover (LULC) dynamics and tree canopy cover changes has become increasingly important for understanding environmental transformations and designing effective conservation strategies (FAO, 2020).

Globally, forest ecosystems are experiencing unprecedented pressure from agricultural expansion, settlement growth, infrastructure development, fuelwood extraction, and other anthropogenic activities. These pressures have accelerated deforestation and forest degradation, resulting in significant reductions in tree canopy cover and associated ecosystem services. Assessing long-term LULC dynamics and tree cover changes is therefore essential for identifying the drivers of environmental change, evaluating conservation interventions, and supporting sustainable natural resource management (Wulder et al., 2017).

In Ethiopia, forest resources have undergone substantial decline over recent decades due to rapid population growth, agricultural encroachment, fuelwood extraction, and unsustainable land-use practices. Rural households remain heavily dependent on biomass energy, particularly fuelwood and charcoal, for cooking and heating purposes. This dependence contributes significantly to forest degradation, biodiversity loss, and declining tree cover in many parts of the country (FAO, 2020). Furthermore, the widespread use of traditional biomass-fueled cooking systems exacerbates environmental degradation while exposing households to harmful indoor air pollution, creating both ecological and public health challenges (WHO, 2016).

The Gamo Zone of southern Ethiopia represents one of the areas where these challenges are particularly evident. The zone contains diverse ecological landscapes and supports a large rural population whose livelihoods depend on agriculture and natural resources. Over time, increasing demand for agricultural land, fuelwood, and construction materials has exerted pressure on local forests and tree resources, contributing to changes in land-use patterns and tree canopy cover. Understanding the magnitude and spatial distribution of these changes is essential for developing sustainable land management and forest conservation strategies within the region.

To address environmental degradation associated with fuelwood consumption, several interventions have been introduced in the Gamo Zone. Among these, the Green Impact Fund Program implemented by VITA has promoted the adoption of Improved Cooking Stoves (ICS) through a Community-Led Total approach. The intervention aims to reduce household fuelwood consumption, decrease pressure on forest resources, and improve environmental sustainability. Improved cooking stoves have been widely recognized for their potential to reduce biomass consumption, lower greenhouse gas emissions, and minimize forest resource exploitation (Bailis et al., 2009). However, the extent to which such interventions contribute to measurable improvements in tree canopy cover and local forest conditions remains insufficiently understood.

Recent advances in Geographic Information Systems (GIS), remote sensing, and cloud-based geospatial platforms have created unprecedented opportunities for monitoring environmental change over time. Multi-temporal satellite imagery enables the assessment of LULC transitions, while global tree-cover datasets facilitate the detection of annual tree-cover loss and gain at multiple spatial scales. These technologies provide reliable and cost-effective approaches for evaluating the effectiveness of environmental conservation interventions and understanding landscape dynamics in data-scarce regions (Goodbody et al., 2019; Næsset et al., 2021).

Although numerous studies have documented forest cover change and deforestation trends in Ethiopia, most have focused on broader regional or national scales and have primarily examined general patterns of land-use change. Limited empirical evidence exists regarding the long-term dynamics of land use and tree canopy cover in the selected localities of the Gamo Zone, particularly in relation to community-based environmental interventions such as improved cooking stove programs. Furthermore, few studies have integrated historical LULC analysis with annual tree-cover gain and loss assessments to evaluate whether reductions in household fuelwood demand translate into observable improvements in local forest conditions.

This knowledge gap limits understanding of the environmental effectiveness of improved cooking stove interventions and constrains evidence-based decision-making for forest conservation initiatives. Therefore, this study seeks to contribute new empirical evidence by integrating remote sensing, GIS analysis, and Global Forest Watch data to examine both long-term land-use dynamics and recent tree canopy cover changes in selected localities of the Gamo Zone. Specifically, the study aims to: (i) analyze land-use and land-cover dynamics between 2002 and 2024; (ii) evaluate the effectiveness of VITA's improved cooking stove intervention implemented since 2020 in improving local tree canopy cover; and (iii) assess annual tree-cover loss and gain dynamics during the period 2001–2023 using Global Forest Watch datasets.

2. STUDY AREA AND METHODOLOGY

2.1 Study Area

Location: This study was conducted in three selected Kebeles: Yayke, Mele, and Dembele-Otora. Yayke Kebele is located in Mirab Abaya Woreda, Mele Kebele in Arba Minch Zuria Woreda, and Dembele-Otora Kebele in Geresse Woreda. All three Woredas are situated within the Gamo zone, south Ethiopia Regional State (Figure 1). In the Ethiopian administrative system, a Kebele is the smallest administrative unit, while a Woreda represents the next higher administrative level.

The topography of Yayke and Mele Kebeles is predominantly characterized by flat to gently undulating terrain, as both sites are located on the floor of the Ethiopian Rift Valley. The landscape is generally suitable for agricultural activities and exhibits limited topographic variation. The elevation of the two Kebeles ranges from approximately 1,170 to 1,300 m above sea level. But the Dembele-Otora *Kebele*, being part of the western Rift Valley escarpment and the elevated Gerresie district (*Woreda*), is characterized by rugged, steep, and dissected landscapes.

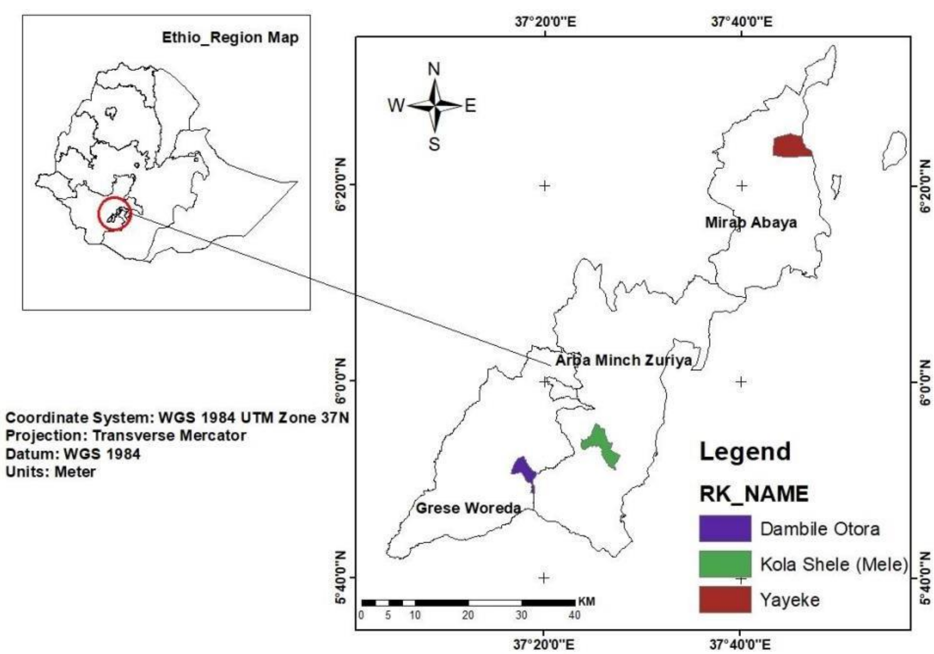

Figure 1. Location of sample study sites (Yayke, Mele, and Dembele-Otora *Kebeles)*

Climate: Yayke and Mele sites are characterized by a hot climate, and they experience a semi-arid climate, with a mean annual temperature of approximately 24°C and annual rainfall ranging from 581 to 1,153 mm. In contrast, Dembele-Otora Kebele is relatively cooler and wetter than Yayke and Mele due to its higher altitude. The area has a mean annual temperature of 16.7°C and receives between 800 and 1,406 mm of rainfall annually. The three study sites receive rainfall during two main rainy seasons. The first is the Belg season, which occurs from March to May (sometimes extending into June), while the second is the Meher season, which generally extends from August or September to November. These seasons constitute the principal crop-growing periods in the study area (National Meteorological Agency /NMA, 2019/).

2.2 Methods

This study employed an integrated geospatial approach combining remote sensing, GIS, field observations, and Global Forest Watch (GFW) datasets to assess land-use/land-cover (LULC) dynamics and tree canopy cover changes in selected Kebeles of the Gamo Zone. Multi-temporal satellite imagery was obtained from the United States Geological Survey (USGS) Earth Explorer and the Copernicus Open Access Hub. The datasets included Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery for 2002, Landsat 8 Operational Land Imager (OLI) imagery for 2013, and Sentinel-2 MultiSpectral Instrument (MSI) imagery for 2024. These satellite platforms provide reliable spatial and temporal data for land-cover mapping and vegetation analysis (Smith, 2019). Landsat imagery has a spatial resolution of 30 m, while Sentinel-2 imagery provides a spatial resolution of 10 m in the visible and near-infrared bands. To ensure seasonal consistency and minimize atmospheric effects, images acquired during the dry season (December–February) with cloud cover below 10% were selected.

In addition to satellite imagery, ancillary datasets including high-resolution Google Earth imagery, aerial photographs, and field observations were utilized to support image interpretation and validation. Ground surveys were conducted using GPS-enabled smartphones to collect reference points and verify land-cover classes. Ground-truth information is essential for improving the accuracy of remote sensing analyses and ensuring that classified land-cover categories correspond to actual field conditions (Wulder et al., 2017). The integration of remotely sensed data with field observations provides a robust basis for environmental monitoring and land-cover assessment (Jon, 2020).

Historical tree-cover loss and gain data for the period 2001–2023 were obtained from the Global Forest Watch platform. The datasets were downloaded in JSON and KML formats and incorporated into the GIS environment for analysis. The KML files were used to visualize and map the spatial distribution of annual tree-cover loss and gain, whereas the JSON files provided quantitative information for temporal trend analysis. These datasets complemented the satellite-based LULC analysis and facilitated the assessment of long-term forest-cover dynamics.

Image preprocessing was performed using ERDAS Imagine 2014, ArcGIS 10.8, and QGIS 3.x. The preprocessing workflow included layer stacking, radiometric calibration, geometric correction, orthorectification, image enhancement, and reprojection to the Universal Transverse Mercator (UTM) coordinate system based on the WGS 84 datum. Layer stacking enhanced spectral information by combining multiple image bands, thereby improving the discrimination of vegetation and land-cover classes (Lillesand & Kiefer, 2015). Radiometric and geometric corrections were applied to reduce atmospheric distortions and positional errors, ensuring consistency and accuracy across datasets (Cohen et al., 2017).

Land-use/land-cover classification was conducted using a supervised Maximum Likelihood Classification (MLC) algorithm. This statistical classifier assigns pixels to classes based on the probability of membership derived from spectral characteristics and has been widely recognized for its effectiveness in mapping complex land-cover categories (Anderson et al., 1976). Compared with simpler approaches such as minimum-distance and box classifiers, the MLC algorithm generally provides higher classification accuracy in heterogeneous landscapes. The classification process was supported by training samples derived from field observations, GPS reference points, high-resolution imagery, and local knowledge of land-use characteristics (Jensen, 2015).

Five major land-use/land-cover classes were identified and mapped: forest land, agricultural land, grassland, settlement/built-up areas, and water bodies. A stratified sampling approach was employed to ensure adequate representation of each land-cover category. Between 50 and 100 training polygons were collected for each class, resulting in more than 300 training samples distributed across the study area. These samples captured spectral variability within individual classes and improved classification performance.

Following classification, thematic land-cover maps were produced for each reference year. The accuracy of the classified maps was evaluated using independent validation points obtained from field surveys and high-resolution imagery. An error matrix (confusion matrix) was generated to calculate overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient. These metrics are widely used to assess the reliability and consistency of classification outputs and to determine the extent of agreement between classified and reference data (Congalton & Green, 2019). Field verification further enhanced the credibility of the results by comparing remotely sensed classifications with actual land-cover conditions on the ground (Anderson & Gaston, 2013).

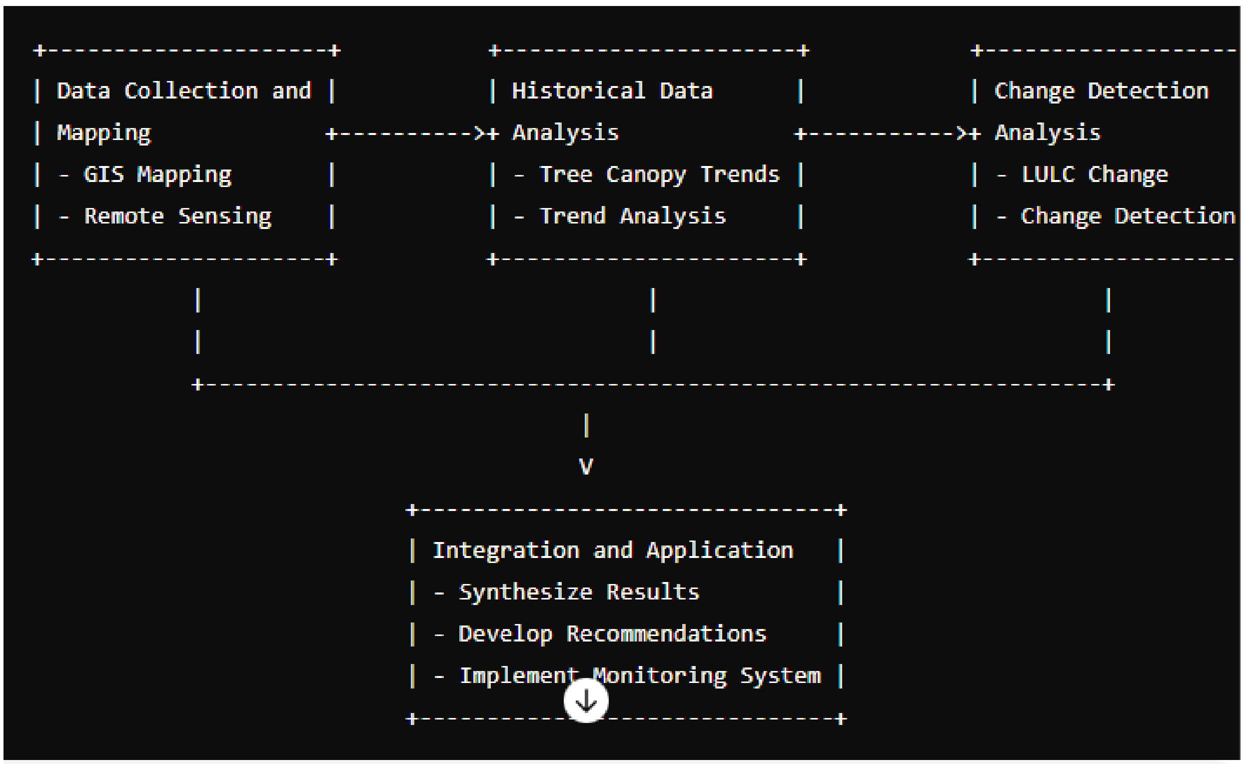

Figure 2. Conceptual framework

Land-use and land-cover dynamics were assessed using a post-classification comparison technique. This approach involves independently classifying images from different years and subsequently comparing the classified outputs to identify changes over time. Post-classification comparison was selected because it minimizes the influence of sensor and atmospheric differences while providing detailed information on the magnitude, direction, and nature of land-cover transitions (Jensen, 2015). Change detection analyses were conducted for the periods 2002–2013, 2013–2024, and 2002–2024. Area statistics, percentage changes, annual rates of change, and transition matrices were generated to quantify conversions among land-cover classes and characterize landscape transformation patterns.

Finally, annual tree-cover loss and gain statistics derived from Global Forest Watch were integrated with the LULC change analysis to evaluate long-term forest-cover dynamics. Time-series analysis was employed to identify trends and periods of significant forest change, thereby providing insights into the effectiveness of improved cooking stove interventions in reducing pressure on local forest resources and enhancing tree canopy cover within the study area.

3. RESULTS AND DISCUSSION

3.1 LULC Classes of the Study Area in 2002, 2020, and 2024

The LULC classes of the project sites (Yayke, Demele-Otora, and Mele *Kebeles*/localities), via the GIS tools-based interpretation of the areas' Landsat images of 2002, 2020, and 2024, were categorized into five classes: barren-land, forest, settlement, agriculture, and agroforestry.

Table 1. Area (in ha and %) of LULC classes of the study localities in 2002, 2020 and 2024

N0	LULC Classes	2002		2020		2024	
		Area (ha)	P (%)	Area (ha)	P (%)	Area (ha)	P (%)
1	Barren-land	1464	29.0	1081	18.3	105	1.8
2	Forest cover	950	15.0	1197	21.0	2144	36.4
3	Settlement	523	8.0	697	11.2	653	11.1
4	Agriculture	1599	26.1	1993	33.2	801	13.6
5	Agroforestry	1351	21.9	919	16.3	2184	37.1
	Total	5887	100.0	5887	100.0	5887	100.0

Source: own analysis, 2024

As it is illustrated in Table 1, barren land with 29% (1,464 ha) accounted for the largest area proportion of the project sites in 2002, when the proportion of settlement area (8% or 523 ha) was the smallest. During the first study year (2002), LULC classes such as agriculture, agroforestry, and forest cover constituted about 26.1% (1,599 ha), 21.9% (1,351 ha), and 15% (950 ha) of the total area of the study sites, respectively. The larger area share (29%) of the barren-land during the initial study period (2002) might indicate: (i) the dominance of semi-arid climate in Yayke and Mele areas due to the sites' location in the low-lying Rift-Valley region of Ethiopia; (ii) the absence of natural resources, including forest, conservation or rehabilitation measures 23 years ago or before; (iii) the relatively limited level of human intervention through agroforestry practice in 2002 in comparison to the high level of agroforestry activity in the latest study year, 2024.

An assessment was also made about the spatial extent of the five LULC classes of the study area in the year 2020. The findings reveal that the extent of agricultural land was almost one-third (33.2%) of the total area of the project sites, about 19 years later, in 2020. While the forest cover of the study area, with 21% (1,197 ha), experienced an increment in its spatial extent in 2020, the share of agroforestry, with 16.3% (919 ha), exhibited a decrease in the same year (2020) in comparison to its area extent about 19 years ago (2002). Similarly, the area coverage of barren land of the project sites had dropped to 18.3% (1,081 ha) in 2020.

In this study, what is amazing was the magnitude of dynamics in the area extent of the five LULC classes of the project sites in four (4) year intervals (2020 - 2024) as shown in Figure. 3, Figure. 4, and Figure. 5. Agroforestry and forest cover with the respective proportion of 37.1% (2,184 ha) and 36.4% (2,144 ha) accounted the first and second largest area coverage of the project sites in 2024. In other words, slightly less than three-fourths (73.5%) of the whole area coverage of the project sites was accounted for by the area of these LULC classes (agroforestry and forest) in the latest reference year (2024) of the study. However, barren land constituted an insignificant share (1.8%) of the study area in 2024.

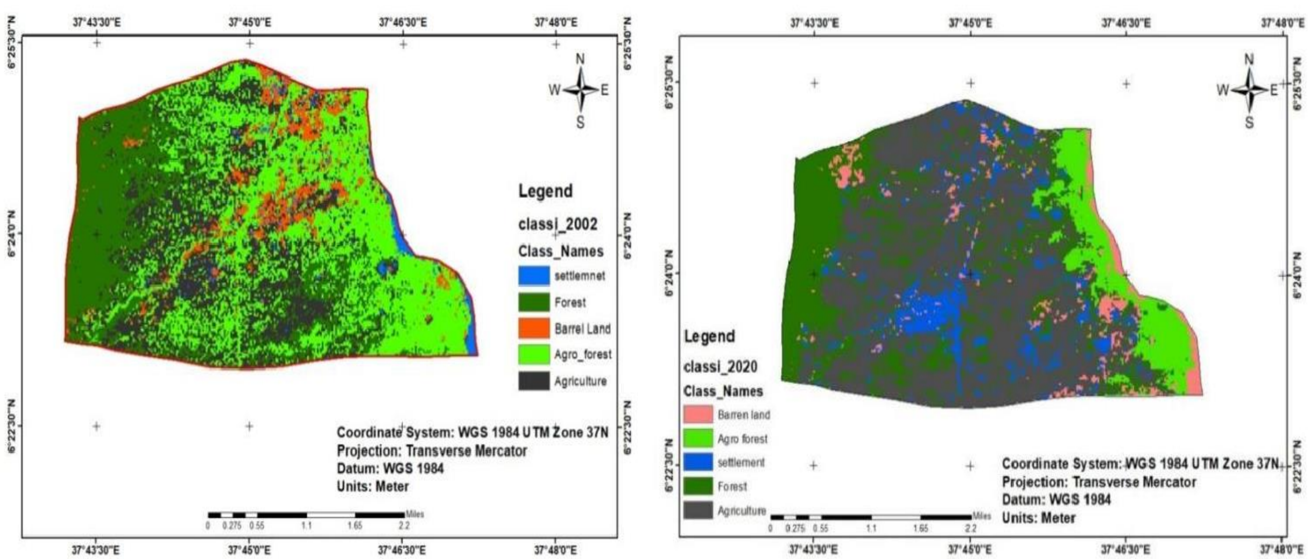

Figure 3. LULC of Yayke area: (i) in 2002 (left fig above) and (ii) in 2020 (right fig above)

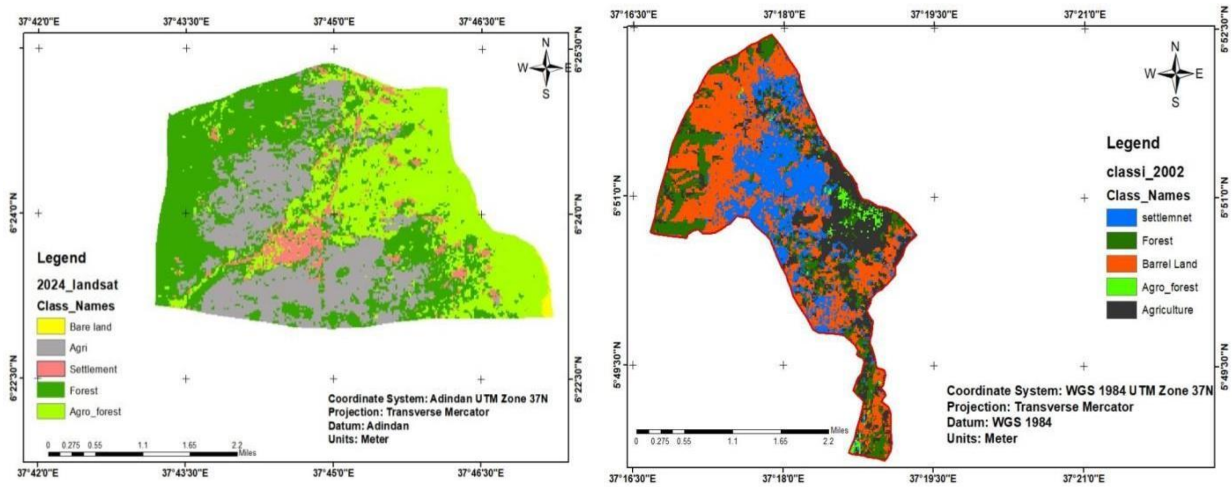

Figure 4. LULC of: (i) Yayke area in 2024 (left fig above) and (ii) Dembele-Otora area in 2002 (right fig)

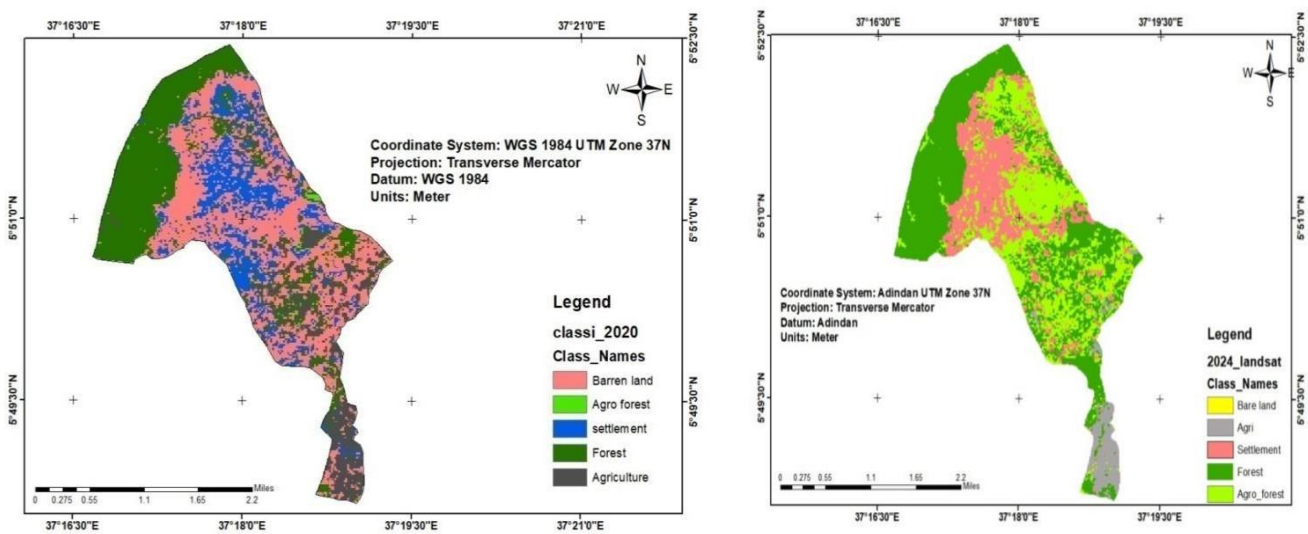

Figure 5. LULC of Dembele-Otora area: (i) in 2020 (left fig above) and (ii) in 2024 (right fig)

3.2 Magnitudes and Trends of LULC Changes in 2002 – 2024

This study has conducted change detection analyses among the LULC classes of the study sites over time (2002-2024). That is, the study has analyzed the magnitude and rate of LULC dynamics for 23 years from 2002-2024. Here, the 'magnitude' refers to the size of area gain or area loss (ha and %) due to the land conversion from one land use class to the other one in a given time interval, say, in 2002-

2020, 2020-204 and 2002-2024; and, the 'rate' refers to the average gain or loss (ha and %) in the area of each LULC class per year within a given time interval (period) described in Table 2.

Table 2. Magnitudes (M) and Rate (R) of changes of LULC classes of the study area in 2002-2024

LULC Class	2002	2020	2024	2002-2020		2020-2024		2002-2024			
	ha	ha	ha	M (ha)	%	M (ha)	%	M (ha)	%	R (ha)	%
Barren-land	1464	1081	105	-383	-26.2	-976	-90.3	-1359	-92.8	-61.8	-4.2
Forest cover	950	1197	2144	247	26.0	947	79.1	1194	125.7	54.3	5.7
Settlement	523	697	653	174	33.3	-44	-6.3	130	24.9	5.9	1.1
Agriculture	1599	1993	801	394	24.6	-1192	-59.8	-798	-49.9	-36.3	2.3
Agroforestry	1351	919	2184	-432	-32.0	1265	137.6	833	61.7	37.9	2.8
Total	5887	5887	5887	-	-	-	-	-	-		

Source: own analysis, 2024

As it is observed in Table 2, LULC classes such as forest, agriculture, and settlement of the study area with 26% (247 ha), 24.6% (394 ha), and 33.3% (174 ha), respectively, experienced increasing trends in 19 years from 2002 to 2020. Population growth and urbanization have contributed to the expansion of settlement. In contrast, the spatial extents of barren land and agroforestry of the project sites had declined by 26.2% (-383 ha) and 32% (-432 ha), respectively, in the same time interval or period. What is surprising about the study sites during the first period (2002-2020) was the decline in the area extent of agroforestry. The expansion of agriculture and settlement, and the conservation efforts-led improvement of the forest had contributed to the shrinkage in barren land, and agroforestry within 2002-2020 showed in Table 2.

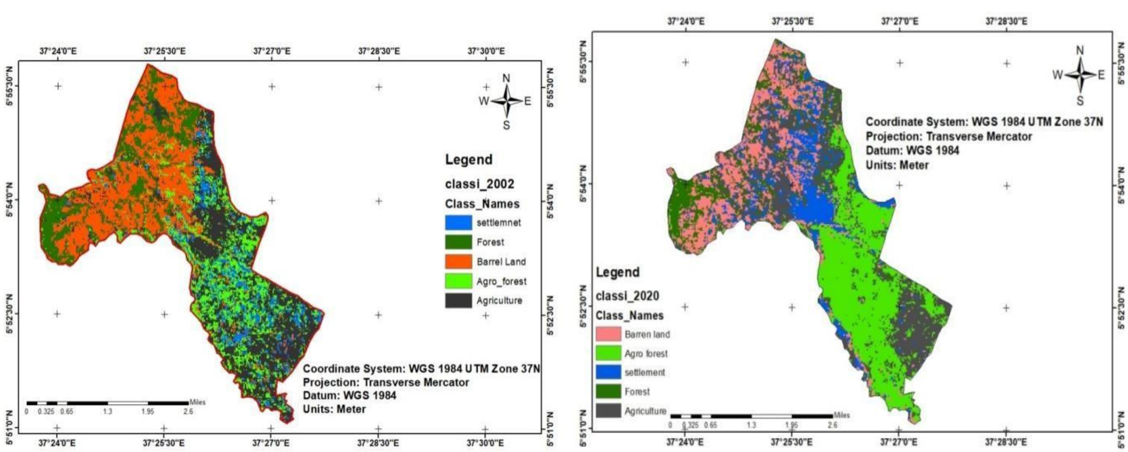

Figure 6. LULC of Mele *Kebele*/locality: (i) in 2002 (left fig above) and (ii) in 2020 (right fig)

This research has also examined the magnitudes of changes in the LULC classes of the study area in 2020-2024, as shown in Figure.6 in order to ensure inclusiveness of the latest years in the study in Table 2. The spatial extent of agroforestry has increased by 137.6% (1,265 ha) within a very short time interval (2020-2024). Similarly, forest cover of the study area has also increased by 79.1% (947 ha) in the five-year duration. However, the agricultural area and barren land of the study area have decreased by 59.8% (-1,192 ha) and 90.3% (-976 ha), respectively, in the same period (2020-2024). The decline of agricultural land could be attributed to several factors, including the adoption of agroforestry practices that combine agriculture with forestry, reducing the need for large tracts of agricultural land. Besides, urban expansion and changes in economic priorities might have influenced this decline. However, the integration of trees within agricultural systems has enhanced land productivity and sustainability, reducing the pressure on large-scale monoculture agriculture (Vita, 2024).

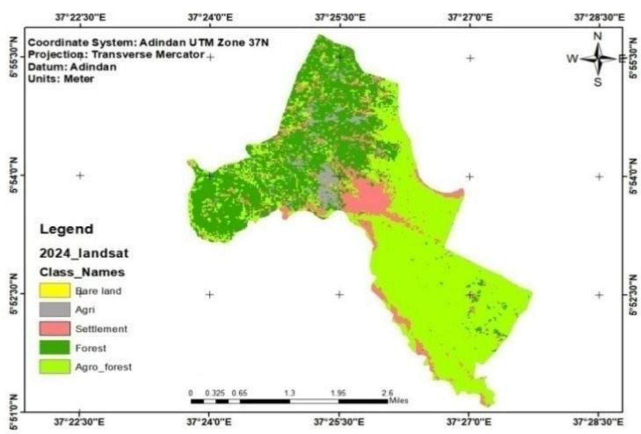

Figure 7. LULC of Mele *Kebele*/locality in 2024

Again, an assessment was made on the magnitudes and annual rates of changes in the LULC classes of the study area for the whole study period, 2002-2024 as showed in Figure.7. Forest, agroforestry and settlement of the study area have increased by 125.7% (1,194 ha), 61.7% (833 ha) and 24.9% (130 ha), respectively, in 2002-2024. In other words, the three LULC classes of the area have been increasing by the respective rates of 5.7% (54.3 ha), 2.8% (37.9 ha), and 1.1% (5.9 ha) per/year (on average) in the last 22 years (see the last two 'Columns' of Table 2). On the contrary, the barren land of the study area has shrunk by 92.8% (-1,359 ha) in 2002-2024, while cropland (agriculture) has decreased by 49.9% (-798 ha) in the same period. While the decreasing rate of barren land was 4.2% (-61.8 ha) per/year, the declining rate of agricultural land was 2.3% (-36.3 ha) per annum in each of the last 22 years (2002-2024) accounted in the study described in Table 2.

The reduction of barren land reflects a positive transformation in the landscape due to land rehabilitation initiatives, particularly agroforestry practices (Vita, 2024). The introduction of agroforestry practice (by Vita) has played a pivotal role in converting barren land into other productive ecosystems. Agroforestry enables rehabilitation of degraded lands and promotes biodiversity conservation and climate resilience (Green et al., 2021). The reduction of barren land is a clear indicator of these changes, which are essential for mitigating environmental degradation.

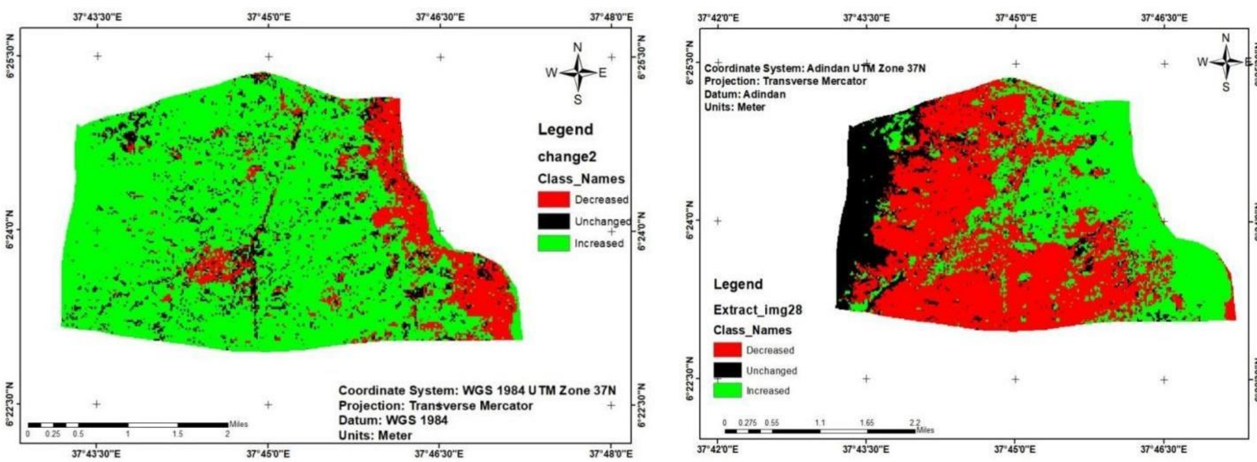

Figure 8. LULC Change of Yayke Area in: (i) 2002-2020 (left fig) and (ii) 2020-2024 (right fig)

In Figure. 8 (i) and (ii), the dark-shaded region illustrates the portion of Yayke *Kebele* that had revealed ‘no change’ in LULC in both 2002-2020 and 2020-2024. The red-shaded part of Figure. 8 (i) represents the decrease in barren land and agroforestry area in 2002-2020, and the same color of Fig. 8 (ii) also represents the shrinkage of agriculture, settlement, and barren land of Yayke *Kebele* in 2020-2024. But, the green-shaded part of Fig. 8 (i) shows the increase in forest, agriculture, and settlement in 2002-2020, and the area of Fig. 8 (ii) that is shaded with the same color represents the increment in forest cover and agroforestry area of the *Kebele*/locality in 2020-2024.

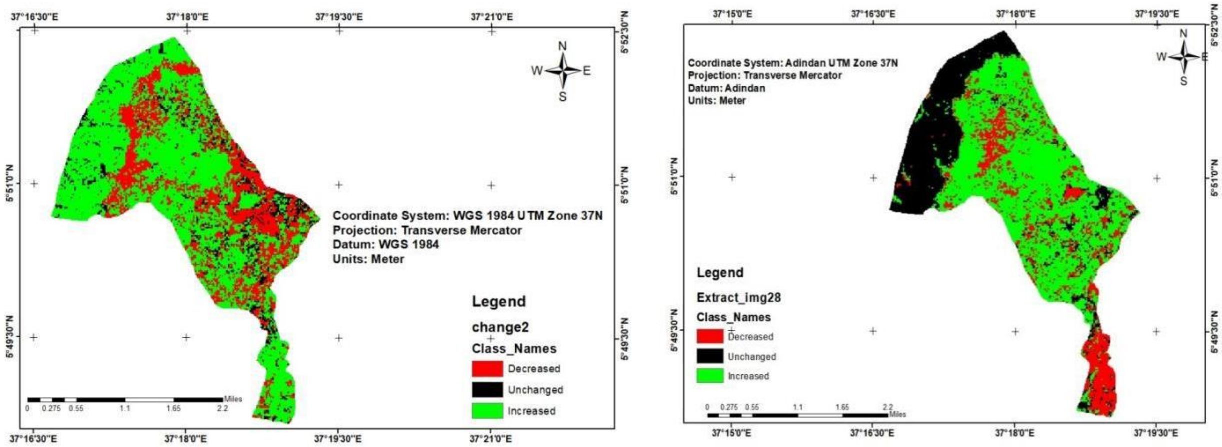

Figure 9. LULC Change of Dambele-Otora in: (i) 2002-2020, left fig and (ii) 2020-2024, the right fig

The increment of forest cover in the project sites showed in Figure.9 (Yayke, Dembele-Otora and Mele *Kebeles*) reflects the success of afforestation efforts, including the tree planting program supported by Vita. The project has not only contributed to the expansion of forest but it also played a significant role in carbon sequestration, which enables to mitigate climate variability and change. The forest restoration efforts, through agroforestry and reforestation, also aims to improve soil health, prevent erosion, enhance water retention capacity of the soil, and foster forest regeneration and ecosystem health (Turner et al., 2024). The introduction of improved cooking stove at household level has enabled conserved use of biofuels, which (in turn) suppresses the firewood and charcoal extraction-induced human pressure on the local forest resource – a further contribution of the project to forest conservation.

The red-shaded part of Figure 9 and Figure.10 represents the decrease in barren-land and agroforestry of Dambele-Otora *Kebele* [Figure 9 (i)] and Mele *Kebele* [Figure 10 (i)] in 2002-2020 while the green-shaded part portrays an increase in forest, agriculture and settlement in 19 years. Again, the green-shaded part of Figure 9 and Figure10 illustrates the increment in forest and agroforestry area of Dambele-Otora *Kebele* described in Figure 9 (ii) and Mele *Kebele* Figure10 (ii) in 2020-2024 but the red-shaded portion demonstrates the decline in barren-land, agriculture and settlement areas of both sites in the same period (2020-2024).

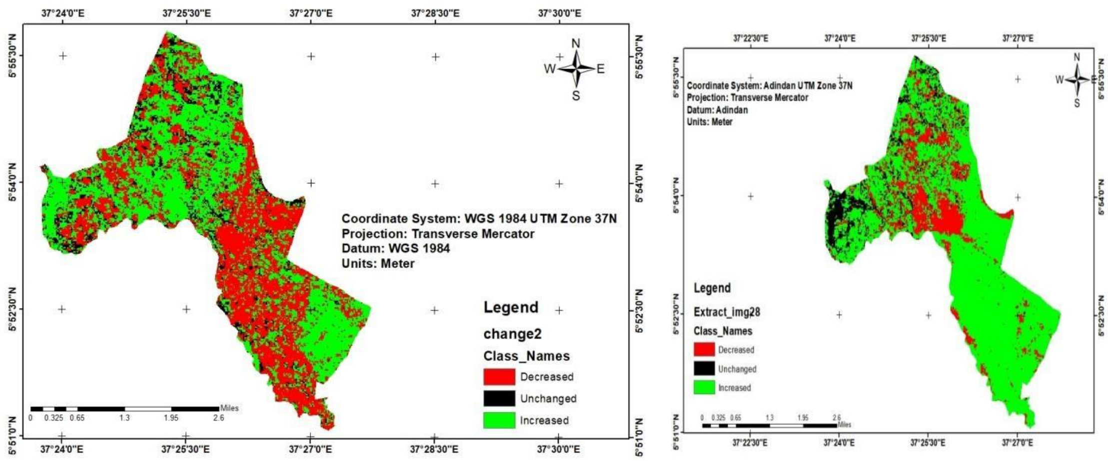

Figure 10. LULC Change of Mele *Kebele* in: (i) 2002-2020, left fig and (ii) 2020-2024, the right fig

The significant increase in agroforestry area is closely linked to Vita's efforts to promote sustainable land management practices that integrate trees into agricultural systems. These practices not only boost agricultural productivity but also contribute to food security and environmental sustainability.

Vita’s capacity-building initiatives have been instrumental in educating farmers on the benefits and techniques of agroforestry. Through training programs, farmers learn how to select appropriate tree species, manage tree-crop interactions, and implement sustainable practices that optimize yields while preserving the environment. The integration of cassava cultivation in agroforestry systems, particularly in areas like Dembele Otora, provides additional income sources for farmers, enhancing their economic resilience (Vita, 2024).

The environmental benefits of agroforestry are particularly evident in lowland regions like Dembele, where the practice helps sequester carbon dioxide, improve soil structure, and reduce greenhouse gas emissions. These benefits are crucial in the context of climate resilience, supporting the sustainability of agricultural landscapes and fostering long-term food security (WRI, 2020).

3.3 Tree (Forest) Cover Dynamics of the Study Area Using Data from the Global Forest Watch

Global Forest Watch (GFW) is an innovative online platform that provides real-time data and tools for monitoring forests worldwide. Launched by the World Resources Institute (WRI), GFW leverages satellite imagery, cloud computing, and crowdsourcing to offer comprehensive and accessible information on forest cover changes, deforestation, and land use dynamics (Hansen et al., 2013). It enables governments, businesses, researchers, and the public to make informed decisions regarding forest conservation and management by providing timely and transparent data (Weisse & Goldman, 2019). GFW's capabilities facilitate the detection of illegal logging activities, support sustainable land-use planning, and enhance the accountability of forest governance (Hansen et al., 2013; WRI, 2020).

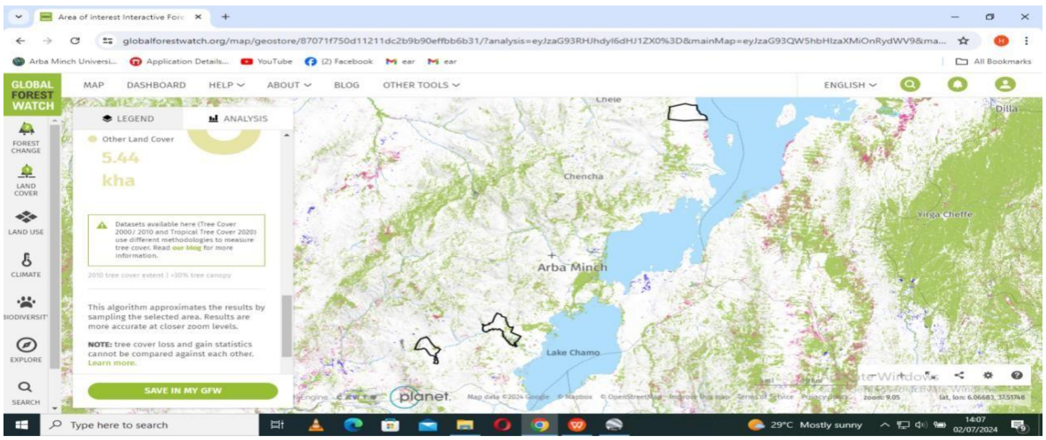

Figure 11: Global Forest Watch Dashboard

As it is seen in Figure 11, the region is made up of different habitats, including East Sudanese Savannah and Somali Acacia-Commiphora bushlands and thickets. This region has no Intact Forest. The majority of the region has a warm and temperate climate with high humidity and warm summers. It also has areas of equatorial climate with dry winters. It is part of the Tropical and Subtropical Grasslands, Savannahs, and Shrublands biome. The location is predominantly land. The area of 5.89 ha, located in a mountainous area, is the same as the vector boundary used for the study area, which is 5887 ha.

Figure 12: Tree cover loss of the study area in 2001 - 2023 (source: own design using data of the GFW, 2024)

Figure 12, which was designed based on data from the GFW, illustrates the dynamics (rise and fall) in the magnitude of tree cover loss of the study area in the period 2001-2023. The detailed interpretations and year-by-year analyses are presented under this section.

During 2001-2003, the three *Kebeles* (localities) of the Gamo zone experienced a smaller level of tree cover loss in 2001 but no significant loss in 2002 and 2003. The area showed a slight increase in tree cover loss in 2004, and the loss further increased in 2005. In 2006-2008, the study area exhibited a consistent, low, or insignificant level of tree cover loss in 2006, although the magnitude of loss was significantly high (peak) in 2007; however, the magnitude of the loss was relatively smaller in the next year, i.e., 2008. In 2009-2010, the study area was marked with little or no notable tree cover loss (Figure 12). In the area, the period 2011-2012 was marked with a significantly higher level of tree cover loss in 2011, although the level of loss revealed a pronounced decline in 2012, as described in Figure 12.

As displayed in Figure 12, the target sites of the Gamo zone experienced significantly different realities in tree cover changes in the next five years (2003-2017) in comparison to the observed facts in the preceding and succeeding periods. Compared to 2012, the target sites experienced an increase in the magnitude of tree cover loss in the year 2013. The level of tree cover loss had further increased to the extent that the loss reached its peak in 2014. The year 2014 was the period when the study area exhibited the highest level or magnitude of tree cover loss of the entire years (2001-2023) accounted for in the GFW data-based assessment of tree cover dynamics. The target sites also exhibited a high (third) level of tree cover loss in 2015, even if the magnitude of loss in 2015 was significantly smaller than that of 2014. Again, the area experienced an increasing level of tree cover loss in 2016 when the magnitude of loss was larger than that of 2015 but slightly smaller than that of 2014 (Figure. 12). In the study area, the year 2017 was marked with (by) the smallest (and declining) magnitude of tree cover loss in comparison to the facts of the other four years in 2013-2017 showed in Figure.12.

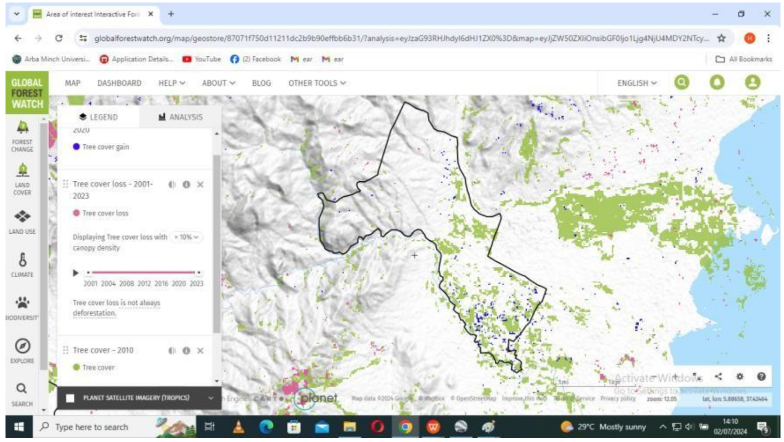

Figure 13. Area of Mele *Kebele* where tree cover exceeds 25% in the GFW dash board

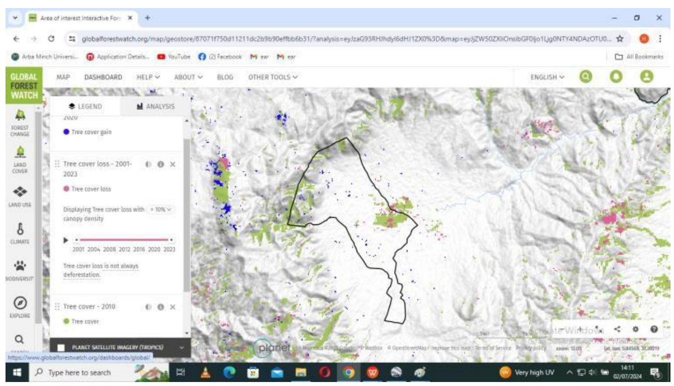

Figure 14. Area of Dembele Otora *Kebele* where tree cover exceeds 25% in the GFW dashboard

The target *Kebeles* (localities) of Gamo zone revealed significantly different facts about tree cover dynamics in the last six years (2018-2023) considered in the study; this is true because, the magnitude of tree cover loss of the study area was insignificant in all the six years (2018-2023) except in the year 2020. For the sake of clarity (for instance), the area exhibited a further noticeable decline in the magnitude of tree cover loss in 2018 in comparison to the previous year (2017). The magnitude of tree cover loss in the area had also further dropped to the extent that it became insignificant in 2019. However, the study area experienced a slight increment in the magnitude of loss of tree cover in 2020. In contrast, the magnitudes of tree cover loss of the target sites were negligible (or insignificant) in the latest three years (2021, 2022, and 2023) accounted in the study Figure.12.

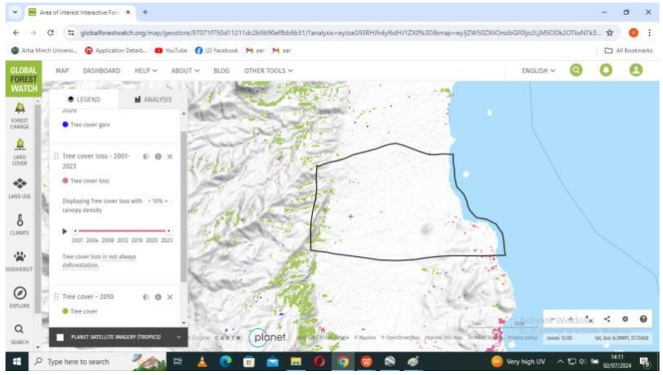

Figure 15. Area of Yayeke *Kebele* where tree cover exceeds 25% in the GFW dashboard

Figure. 13, Figure. 14, and Figure. 15 display Mele, Dembele-Otora, and Yayeke *Kebeles* (localities), respectively, where the share of tree cover of each site (*Kebele) exceeded* 25% during the last reference (study) year (i.e., 2024). Generally, the GFW data-based assessment results revealed that the target sites of the Gamo zone had experienced no clear patterns in the trend of tree cover dynamics in more than two decades (2001-2023). That is, the study area experienced significant magnitude of tree cover loss in 2007, 2011, 2013-2017 and to a lesser extent in 2005; however, the level of loss was low/small (in 2001, 2004, 2008 and 2020) and it was negligible in 2002-2003, 2006, 2009-2010, 2012, 2018-2019 and 2021-2023. The study area showed an insignificant level of tree cover loss in the period 2018-2023, except in 2020 (Fig. 12); this (conversely) confirms or mirrors the improvement in the forest cover of the localities about which this study is made. The change detection result of the study also revealed that the forest cover of the study area has increased by 79.1% between 2020-2024, as shown in Table 2. Fig. 16, Fig. 17, and Fig. 18 also display the Mele, Dembele-Otora, and Yayeke *Kebeles* (localities), respectively, where the share of tree cover of each site (*Kebele) exceeded* 15% during 2024.

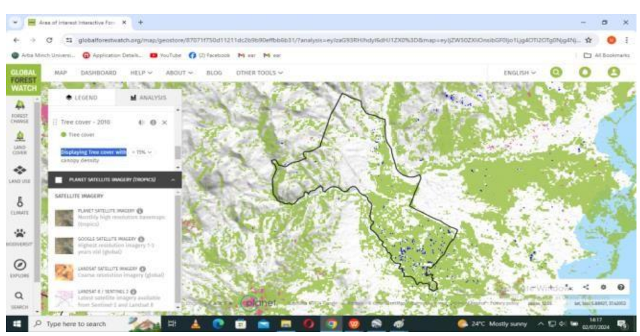

Figure 16. Area of Mele *Kebele* where tree cover exceeds 15% in the GFW dash board

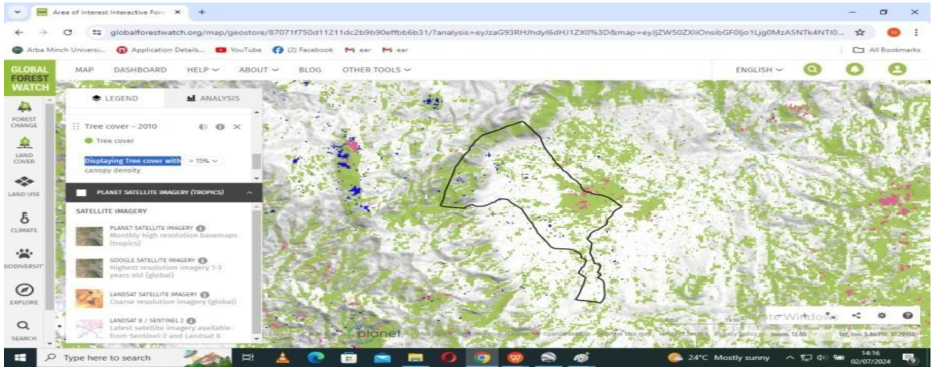

Figure 17. Area of Dembele-Otora *Kebele* where tree cover exceeds 15% in the GFW dashboard

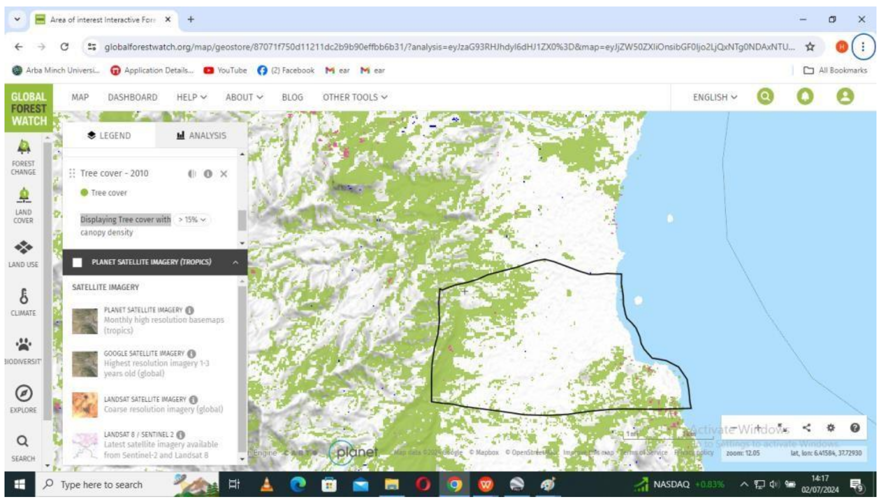

Figure 18. Area of Yayeke *Kebele* where tree cover exceeds 15% in the GFW dashboard

4. CONCLUSION

This study examined land-use/land-cover (LULC) dynamics and tree-cover changes in selected Kebeles of the Gamo Zone between 2002 and 2024 using remote sensing, GIS, and Global Forest Watch (GFW) datasets. The results revealed substantial changes in the composition and spatial distribution of major land-cover classes during the study period. Forest cover exhibited a consistent increase during both the 2002–2020 and 2020–2024 periods, while barren land continuously declined. Agricultural land and settlement areas expanded between 2002 and 2020 but showed a reduction during the subsequent period. In contrast, agroforestry land decreased during 2002-2020 and increased considerably between 2020 and 2024.

The notable increase in forest cover observed during the post-2020 period suggests a possible positive contribution of the improved cooking stove (ICS) intervention implemented by VITA. Reduced dependence on fuelwood may have lowered pressure on local forest resources, thereby supporting forest regeneration and conservation efforts. These findings highlight the potential role of sustainable household energy technologies in promoting environmental sustainability and enhancing community-based natural resource management.

The Global Forest Watch analysis of tree-cover dynamics for the period 2001–2023 did not reveal a consistent long-term trend in annual tree-cover change. Instead, the data indicated periods of substantial tree-cover loss, particularly between 2013 and 2017, followed by relatively lower levels of loss after 2018. Although this finding appears different from the increasing forest cover observed in the LULC analysis, the two results are not necessarily contradictory. The LULC assessment measured changes in broader land-cover categories and captured transitions among forest, agroforestry, agricultural, and other land uses across multi-year intervals.

In contrast, the GFW dataset specifically records annual tree-cover loss and gain events based on canopy-cover thresholds and satellite-detected disturbances. Differences in spatial resolution, classification methods, forest definitions, and temporal scales may therefore produce varying estimates of forest dynamics. Furthermore, increases in forest area identified through LULC classification may occur simultaneously with localized tree-cover losses detected by GFW, particularly in landscapes characterized by small-scale clearing, regeneration, and agroforestry expansion.

These complementary findings underscore the importance of integrating multiple geospatial datasets when evaluating forest dynamics. While the LULC analysis provides information on long-term landscape transformation, GFW data offer detailed insights into annual tree-cover disturbances and recovery processes. Together, they present a more comprehensive understanding of environmental change in the study area.

Despite its contributions, the study has several limitations. The analysis relied primarily on remotely sensed imagery and secondary datasets, both of which are subject to classification uncertainties, differences in spatial resolution, and potential interpretation errors. In addition, the relatively short period following the implementation of the ICS intervention limits the ability to establish a direct causal relationship between stove adoption and observed improvements in forest cover. Future studies should incorporate household-level fuelwood consumption data, longer monitoring periods, and field-based forest inventories to strengthen the evaluation of intervention impacts. Inclusive, the study demonstrates that integrating sustainable energy interventions with community-based conservation initiatives can contribute to reducing pressure on forest resources and supporting landscape restoration. Such approaches have significant implications for climate change mitigation, biodiversity conservation, and sustainable rural livelihoods in Ethiopia and other regions facing similar environmental challenges.

5. RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed:

- ✓ Government agencies and non-governmental organizations (NGOs) should expand the dissemination and adoption of improved cooking stoves within and beyond the study areas to reduce dependence on fuelwood and support forest conservation.
- ✓ Continuous awareness and training programs should be provided to rural households to enhance understanding of the environmental, economic, and health benefits associated with improved cooking stove adoption.
- ✓ Government institutions, NGOs, and stove manufacturers should collaborate to improve the affordability, accessibility, and distribution of improved cooking stoves, particularly for low-income households.
- ✓ Local communities should be encouraged to strengthen agroforestry practices, which provide multiple benefits, including fuelwood production, income diversification, soil conservation, and enhanced ecosystem services.
- ✓ Policymakers should develop or strengthen policies and incentive mechanisms that promote the adoption of clean and energy-efficient cooking technologies in rural areas.
- ✓ Future research should examine the long-term impacts of improved cooking stove interventions using household-level energy consumption data, socioeconomic indicators, and longer-term forest monitoring datasets to better quantify their contribution to forest conservation and climate change mitigation.

Authorship contribution: Hailemariam Atnafu was responsible for the conceptualization, methodology, formal analysis, visualization, and writing of the original draft. Lemma Tadesse contributed through validation, supervision, and editing of the manuscript.

Data availability and materials: The data supporting the findings of this study are available from the corresponding author. The data can be made available from the author upon reasonable request from the editors.

Declaration of the use of AI in this document: AI tools, including editmyenglish.com, were utilized to aid in editing and refining the final text version, ensuring clarity, accuracy, and adherence to ethical guidelines. The authors have reviewed the final content and are responsible for it.

Ethics and Consent to Participate declarations: not applicable

Conflict of Interest

The authors declare that they have no known financial or non-financial conflicts of interest that could have influenced this work.

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