

Article

Spatiotemporal Land Use and Land Cover (LULC) Dynamics and Its Drivers in the Melokoza District, South Ethiopia

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Abstract

Studies on land use and land cover changes are essential for predicting future trends and determining natural resource management decisions and the appropriate and precise detection of land use and land cover change is indispensable for obtaining detailed information. In this study, a purposive sampling technique was used for descriptive purposes. Geospatial approaches are powerful tools for analyzing these changes, offering precise, cost-effective, detailed, and advanced insights. This study focused on understanding the spatiotemporal dynamics of land use, land cover, and its drivers in Melokoza, utilizing Landsat images from 1993, 2013, and 2023, with a resolution of 30 m. Through supervised classification using the maximum likelihood method, this study identified six distinct land uses and land covers: forest, settlement, agriculture, shrubland, bare land, and water bodies. The findings revealed significant transformations, with a dramatic shift from natural forests to agriculture and settlements, which are driven by increasing human demands. Over the past three decades, forest and shrubland cover dropped to 29.89% and 12%, respectively, while settlement and agriculture increased by 154.6% and 231.9%. This transformation underscores the pressing need to address the conversion of formerly forested and shrub-covered areas into vibrant farming and settlement areas. To safeguard the stability and sustainability of our natural resources and ecosystems, stakeholders must focus on the pace of land use and land cover changes, mainly the deforestation linked to agricultural expansion and settlement growth.

Keywords: agriculture; forests; geospatial; GIS; Landsat images; remote sensing



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1. Introduction

Multifaceted and forceful land use and land cover (LULC) conversion at several scales has ecological and socio-economic consequences [1], impacting the performance of sustainable development goals. Moreover, researchers e.g., [2] have reported that land use and land cover change (LULCC) are among the most significant human-caused global variations affecting the natural environment and ecosystems. These changes are a dynamic and complex practice caused by many interacting processes, ranging from various natural factors to socio-economic conditions [3]. (Regarding the geographical patterns of changes over time, the functions and structures among the multiple alterations to the land covers are intricate [4,5]. Therefore, understanding the scope of LULC change, its driving forces, and their consequences is very crucial for the proper management of land resources [6] and

for creating effective strategies for sustainable land management [7,8]. According to [8], knowledge of LULCC also helps to monitor the impact on ecosystems and biodiversity, which is crucial for policymaking. Additionally, knowing the trajectories and extent of land use and land cover changes are essential to generate and provide helpful information to policymakers and development practitioners about the magnitude and trends of land use and land cover changes [9,10].

Environmental changes have a substantial influence on different land features across the landscape [11,12]. Among the most significant and readily apparent markers of changes in ecosystems and livelihood support systems are a change in land use and land cover [13,14]. Such changes are dynamic and non-linear, and they are caused by social, political, economic, and climatic forces operating at local, regional, and global levels [15–22]. Since the commencement of agricultural activities, each continent's land cover has considerably changed [23,24]. In most developing nations, including Ethiopia, these alterations to land use and land cover are influenced by various factors, such as population growth, increased agriculture, settlement, and demand for forest products [25,26]. Furthermore, government policies and markets are fundamental drivers that act at local, regional, and worldwide levels to reinforce or reduce trends in changes to land use and land cover [27,28].

Several studies have reported the impact of land use and land cover changes (LULCC) in various parts of Ethiopia [3,6,8,29–38]. These studies determined that rapid population growth is the leading source of agricultural expansion and settlement, which leads to deforestation and land degradation. Hence, the country has been experiencing significant LULC changes, mainly from the changes in natural resources to the farming system and from human settlement [39,40].

Food security, environmental preservation, and sustainable resource management depend on the comprehension of LULCC, along with their inspection and valuation [31,41–44]. According to [13,18,45,46], studies on LULCC are essential for forecasting anticipated future trends and making judgments about the planning of managing natural resources. Understanding how land use and land cover are frequently changing, as well as how anthropogenic and natural processes interact, is essential for producing knowledge, managing land resources effectively, and improving decision making [47–51]. Due to this, reliable land use and land cover information are required for better environmental analysis and sound decision making [50,52–55].

To generate reliable information, a great deal of research has been conducted around the world to monitor land use and land cover change (LULCC) [33,46,56,57]. During the nineteenth century, traditional methods were used to monitor these changes in land use and land cover. However, with technological innovations and user-generated content, researchers can extract meaningful information from satellite imagery more accurately and efficiently [58,59]. Similarly, with the advent of remote sensing and advances in geospatial technology, the monitoring of land use and land cover change has become more cost-effective, time-saving, dependable, and up-to-date [8,58–63].

After 1990, several methods and procedures have been used to map land use and land cover, in addition to detecting changes and monitoring [64,65]. Among the methods, remote sensing is a very sophisticated technique that is useful for obtaining timely and accurate information about the status of land use and land cover [66–77]. In addition, satellite images give excellent information regarding land use and land cover, and temporal geospatial data can be used to assess the changes [4,78,79]. The demand for more precise LULCC maps from satellite data is rising, especially when utilizing simple and more user-friendly platforms, like geographical information systems and Google Earth Engine (GIS & GEE) [63,80–82]. (Despite being medium-resolution data, many researchers have used Landsat images to track alterations to land use and land cover [43,83–85]. It is liked

because of its open accessibility and the fact that it has the longest history of worldwide data for earth observation [13]. Using Landsat data, [86] examined a large-scale monitoring program of alterations to the land covers.

To assess and ascertain the current status of resources and to make planning decisions for long-term resource management, LULC dynamics research is becoming an increasingly crucial topic in the investigation of environmental modification [51,65]. Hence, it is essential to define the main factors in the research region and monitor LULC's changing aspects quickly to develop and monitor future land management systems.

As mentioned earlier, in different parts of the country, a great deal of research has been conducted on land use and land cover changes and their related impacts. The Melokoza district was chosen as a potential research area due to its diverse land use and land cover, which reflect diverse ecological and economic activities. Additionally, the lack of prior studies in this region indicates a gap in knowledge and highlights the need for further exploration. Furthermore, the area is rich in natural resources, providing a unique opportunity to investigate the environmental and socio-economic dynamics that influence land use, land cover, and conservation efforts. Nevertheless, an integrated examination of these aspects concerning LULCC and its pattern of change is lacking in the research area. In light of this, the current study quantified spatiotemporal LULCC and its drivers in the Melokoza district between 1993 and 2023. To achieve this, this study utilized GIS and remote sensing techniques to examine the trends of LULCC in the past, along with the present, magnitude, and driving forces of LULCC in the Melokoza district during the last 30 years. This study examined the recurring satellite images linked to temporal and spatial characteristics of the Melokoza district. Findings from this investigation could contribute to information for decision makers, to land use and land cover planners and managers, and to others involved in sustainable development and natural resource management.

2. Materials and Methods

2.1. Study Area Descriptions

This research was carried out in the Melokoza district, South Ethiopia, Gofa zone, which is situated at $6^{\circ}16'0''$ to $6^{\circ}38'0''$ north latitude and $36^{\circ}26'0''$ to $36^{\circ}50'0''$ east longitude (Figure 1). The elevation varies between 700 and 3200 m.a.s.l. The area experiences bimodal rainfall and receives rain for nine months, with an annual average of 1100–1300 mm. The minimum, maximum, and average recorded temperatures were 15.1°C , 27.5°C , and 22°C , respectively. As stated by the agriculture office of Melokoza, the district is home to 152,502 people, and it has extensive sesame and maize. The overall land coverage of the study area is 168,180.93 ha, of which 31,884.093 ha is covered by perennial crops, 6885 ha by annual crops, 33,687.15 ha by natural forest, and 48,620.78 ha by other land use. In Melokoza, 20.3% of farmers own more than two hectares of land, while 26.7% have a small land property of less than 0.5 hectares.

According to the Melokoza Department of Agriculture and Natural Resource Management, the study area's soil types were classified as clay (15%), loam (50%), and sandy loam (35%). In the higher altitudes, the vegetation consisted of woodland intermingled with highland bamboo and moist forest. The Sirso natural forest possesses the largest area coverage (3501.5 ha) in the study area.

2.2. Sampling Techniques

A purposive sampling technique was employed to carefully select districts, Kebeles, key informant interview (KII) participants, and focus group discussion (FGD) members. This thoughtful approach was guided by significant land use change and valuable land cover resources, like forest patches, as well as by the lack of empirical studies in the area,

leading us to the vibrant Melokoza district. To select key informants from the Kebeles Tata, Gaysa, Toba, and Tafa, individuals of >65 years of age with deep-rooted connections to the area were selected, allowing their rich experiences to illuminate the LULCC drivers.

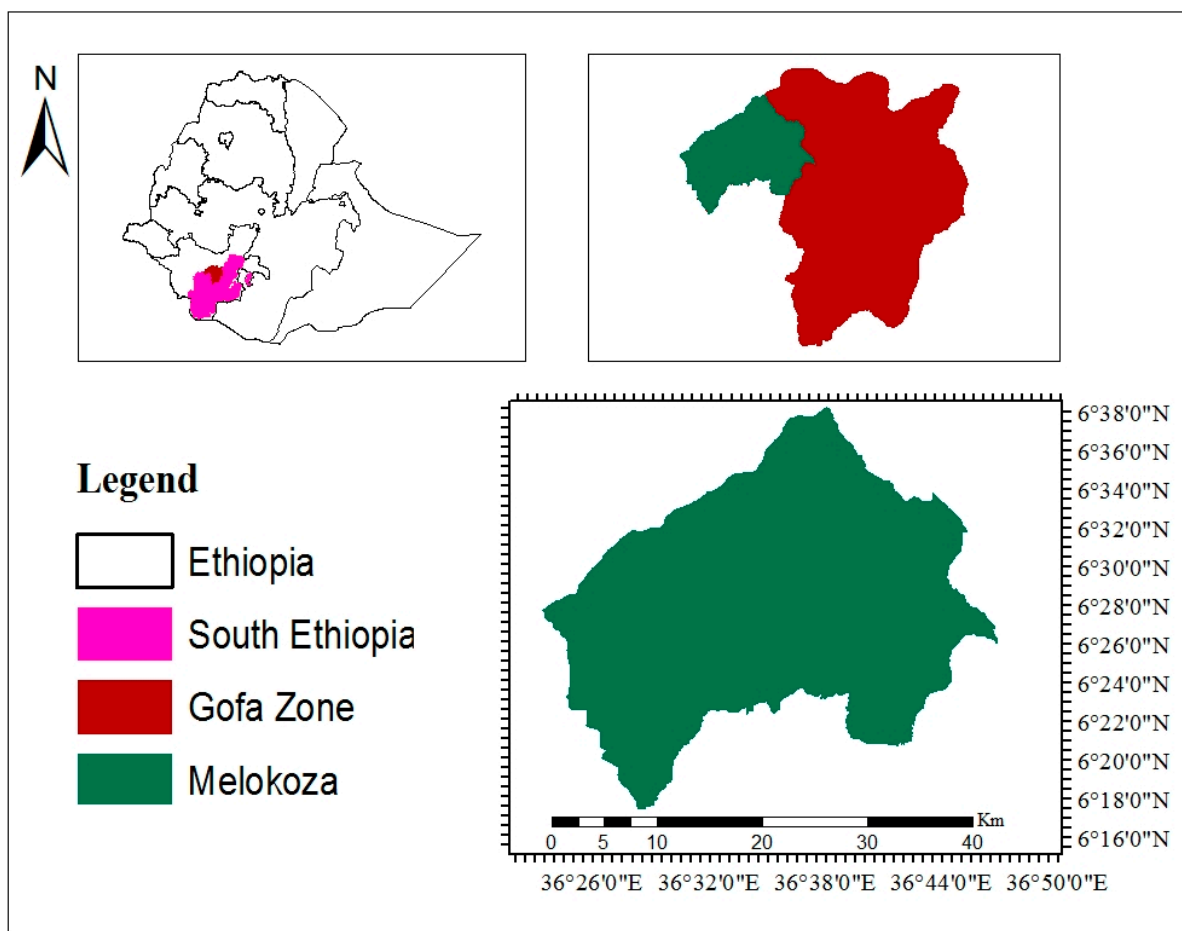


Figure 1. A map depicting the research area.

2.2.1. Sample Size Determination

To determine the sample size, Cochran's formula was used [87]:

$$n = \frac{N}{1 + N(e)^2},$$

where n = sample size for the research; N = total number of households in all Kebeles; e = maximum variability or margin of error 5% (0.05); and 1 = probability of the event occurring.

Therefore, sample size was determined based on the total number of households (i.e., 16,138) from the sampled Kebeles.

$$n = \frac{16138}{1 + 16138(0.05)^2} = 390$$

2.2.2. Data Sources and Collection

Both primary and secondary datasets were meticulously used to explore the dynamic transformation of land use and land cover (LULC). Primary data emerged through the thoughtful design of semi-structured questionnaires, insightful key informant interviews (KIIs), focus group discussions (FGDs), and field observations. In-depth interviews with

key informants, Kebele leaders, government officials, and experts were sought to unearth profound insights into the drivers of LULCC. Furthermore, FGDs served to validate and enrich the data, fostering meaningful dialogue within small, purposefully selected groups of participants. Field observations offered a vital lens into the reality of LULC practices. Simultaneously, a wealth of secondary data complemented the primary findings, with multi-temporal satellite images and ancillary data skillfully processed using ArcGIS10.3. Ground control points (GCPs), along with digitized and topographic maps, were instrumental in the precise geo-referencing of satellite images, weaving together a tapestry of knowledge and understanding.

In this study, LULC time series data were generated from multispectral Landsat satellite images, such as Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), and Operational Land Imagers (OLI), which were acquired and processed from the three separate years of 1993, 2013, and 2023 (Table 1). Landsat datasets were preprocessed with GIS software by applying basic image preprocessing techniques of editing, restoration, enhancement, image classifications, and image accuracy assessments. To facilitate the supervised classification, ground control points were collected for each land use as classification training locations and the ability to separate spatial signatures. The classification signature for each land use and land cover type was maintained within acceptable ranges and across land use cover types. A maximum likelihood classification algorithm was used to classify the images. Ground control points were also collected using GPS devices to assess classification accuracy for each land use type for the year 2023. In each type of imagery used, we only used a range of bands from red, green, blue, and near-infrared to determine the vegetation from other land uses.

Table 1. Explanation of data types and sources.

Year		Sensor		Date of Acquisitions	Path/Row	Band Resolution (m)	Cloud Cover	Source
1993	Landsat	4–5	TM	1993/03/04	169/056	30	1.00	USGS
2013	Landsat	8	OLI	2013/11/06	169/056	30	5.31	USGS
2023	Landsat	8	OLI	2023/01/18	169/056	30	0.62	USGS

2.2.3. Field Observation and Ground Control Point (GCP) Data Collection

Field observation captures real-time events and their contexts. This approach provides a profound understanding of the phenomena we studied [88]. In this spirit, field visits were conducted to immerse ourselves in the study area, enhancing our visual interpretation of the images and selecting reference points vital for training areas in supervised classification, alongside collecting ground control points (GCPs). During our fieldwork, 480 ground control points were collected across six distinct land use and land cover classes through random sampling techniques with a handheld GPS receiver. These invaluable reference data empower us to verify various land cover types and to assess accuracy, underscoring the significance of our journey in understanding the landscape.

2.2.4. Socio-Economic Data Collection

In this study, we harnessed the power of household questionnaire surveys, focus group discussions (FGD), and key informant interviews (KII) to unveil the driving forces behind land use and land cover (LULC) change in our vibrant study area. A thoughtful selection process led to the involvement of 390 households across four distinct Kebeles, with sample sizes determined by a careful calculation of household proportions. From the rich tapestry of our community, 73 respondents from Tata Kebele (70 male and 3 female), 129 from Toba Kebele (124 male and 5 female), 122 from Dhafa (120 male and 2 female), and

66 from Gaysa (62 male and 4 female) shared their invaluable insights. This method ensured that our sample truly reflected the diverse voices within the broader region. The survey questions were crafted in both close-ended and open-ended formats, which were designed to extract essential information about the dynamic LULC changes and their underlying drivers. Additionally, we engaged with 20 key informants (5 from each Kebele) and facilitated 8 enriching focus group discussions (2 individuals from each selected Kebele), all contributing to a deeper understanding of our shared environment.

2.3. Data Analysis

2.3.1. Land Cover Classification

Land capabilities, the susceptibility of current land use to specific management techniques, and the feasibility of various activities were thoroughly assessed to determine the appropriate types and quantities of land use and land cover classifications. A comprehensive preliminary field survey was conducted in the area, which was supplemented by Google Earth imagery to address inaccessible regions. During this survey, valuable insights were gathered from local elders regarding land use and land cover conditions and their driving factors. This study identified and analyzed six distinct LULC categories using satellite imagery: forest, settlement, agriculture, shrubland, bare land, and water body. The classification results for 2023 were meticulously analyzed and evaluated through an accuracy assessment technique to ensure they accurately reflected on-ground realities. This classification served as the foundation for the LULC class map. The approach included an unsupervised classification to gain insights into the overall classes and to identify suitable training sites. The outcomes from this unsupervised process were instrumental in selecting training locations for the subsequent supervised classification analysis. The image was then classified at the pixel level using the maximum likelihood classifier approach during the supervised classification phase.

2.3.2. Accuracy Assessment

At the end of land use and land cover classification, it is essential to document the categorical accuracy of the classification results. Classification is not finished until its correctness has been evaluated. One common technique for demonstrating classification accuracy has been achieved is by creating a classification error matrix. Error matrices compare the association among the related outcomes of automated classification and known reference data, or ground truth, category by category. Therefore, a confusion matrix was applied to determine whether the classification results were accurate by taking representative points from each kind of land use and land cover [89]. In this study, an accuracy assessment of the classification result was created based on the 2023 land use and land cover image classification using GIS software. The accuracy of the producer, user, overall, and kappa coefficient were calculated to determine how well the classified image resembled the actual characteristics on the ground. To effectively evaluate the results, the following accuracy assessment formula was applied:

$$\begin{aligned}
 \text{User Accuracy} &= \frac{\text{Numbrof correctly classified pixles in each category}}{\text{Total number of classified pixles in that category (the row total)}} \times 100, \\
 \text{Producer Accuracy} &= \frac{\text{Numbrof correctly classified pixles in each category}}{\text{Total number of reference pixles in that category (the column total)}} \times 100, \\
 \text{Overall Accuracy} &= \frac{\text{Numbrof correctly classified pixles in each category (diagonal)}}{\text{Total number of referenced pixles}} \times 100, \\
 \text{Kappa coefficient (Khat)} &= \frac{\text{Obs} - \text{Exp}}{1 - \text{Exp}},
 \end{aligned}$$

where Obs = observed correct, which represents the accuracy reported in the error matrix (overall accuracy); and Exp = expected correct, which represents correct classification.

2.3.3. Post Image Classification and Change Detection

Pixel-based statistical analysis was applied to make a post-classification comparison for the three separate images. In light of this, three comparisons were conducted using three classified maps from 1993, 2013, and 2023. These comparisons were between maps from 1993 and 2013, maps from 2013 and 2023, and maps from 1993 and 2023. The following formula was used to analyze the change rate for each type regarding land use and land cover:

$$\text{Rate of change} = \frac{(A - B)}{C}, \quad (1)$$

where A = recent areas of land use and land cover in ha, B = previous area of land use and land cover in ha, and C = time interval among A and B in years.

2.3.4. The NDVI or Normalized Difference Vegetation Index

A normalized difference vegetation index (NDVI) was analyzed to determine the health coverage of the vegetation in the study area. According to the NDVI principle, values must always fall between -1 and $+1$. For example, if you have a negative value, it is almost certainly water. However, if your NDVI rating is close to $+1$, you likely have dense green leaves. However, when NDVI readings are near zero, there are no green leaves, and the area may be urbanized. Values near zero (-0.1 to 0.1) are typically associated with barren landscapes of rock, sand, or snow. Shrub and grassland are represented by low positive values (about 0.2 to 0.4), whereas temperate and tropical rain forests are indicated by high values (values approaching 1) [90]. The slope of the line was used to deduce the direction of the vegetation variation (either decreasing or increasing) and the strength of the variation from the trend line's steepness (such as, for example, no change, minimal change, moderate change, or severe change). To calculate the NDVI, band 3 (Red) and band 4 (Near Infrared) signified Landsat 7, whereas band 4 (Red) and band 5 (Near Infrared) signified Landsat 8. The NDVI was calculated using the following formula:

$$\text{NDVI} = \frac{\text{IR} - \text{R}}{\text{IR} + \text{R}}, \quad (2)$$

where IR is the reflectance value of the infra-red band (Band 4 and 5), and R is the reflectance value of the red band (3, 4):

$$\text{Landsat 4–5 TM} = (\text{B04} - \text{B03}) / (\text{B04} + \text{B03})$$

$$\text{Landsat 7 ETM+ NDVI} = (\text{B04} - \text{B03}) / (\text{B04} + \text{B03})$$

$$\text{Landsat 8 NDVI} = (\text{B05} - \text{B04}) / (\text{B05} + \text{B04}) \quad [91].$$

In this research, the NDVI values were used to determine the vegetation health or coverage (Table 2).

Table 2. The reference NDVI values for the different land uses.

Different Class	NDVI Value Ranges
Water	-0.28 – 0.015
Built up	0.015 – 0.14
Barren land	0.14 – 0.18
Shrub and grass land	0.18 – 0.27
Sparse vegetation	0.27 – 0.36
Dense vegetation	0.36 – 0.74

Source: [92].

2.3.5. Socio-Economic Data Analysis

In this study, our primary focus in integrating socio-economic data with quantitative remote sensing data was to draw invaluable insights from the local community, enriching our understanding of the study's results. We meticulously analyzed the collected data using both quantitative and qualitative techniques. The qualitative data analysis involved a thorough identification, examination, and interpretation of the patterns and themes within the textual data, revealing how these elements addressed our research questions [93]. Descriptive statistics were used to explore the qualitative data from FGDs and key informant interviews, frequencies, and percentages. Simultaneously, the quantitative data from the household survey were analyzed using Microsoft Excel, and these were then presented through frequencies, percentages, and tables, illuminating the findings in an impactful manner.

3. Results

3.1. Land Use and Land Cover

The findings of the LULCC from 1993 to 2023 are summarized in Figure 2. Overall, the six land use and land cover classes were distinguished in the study area and assigned a proportionate coverage area.

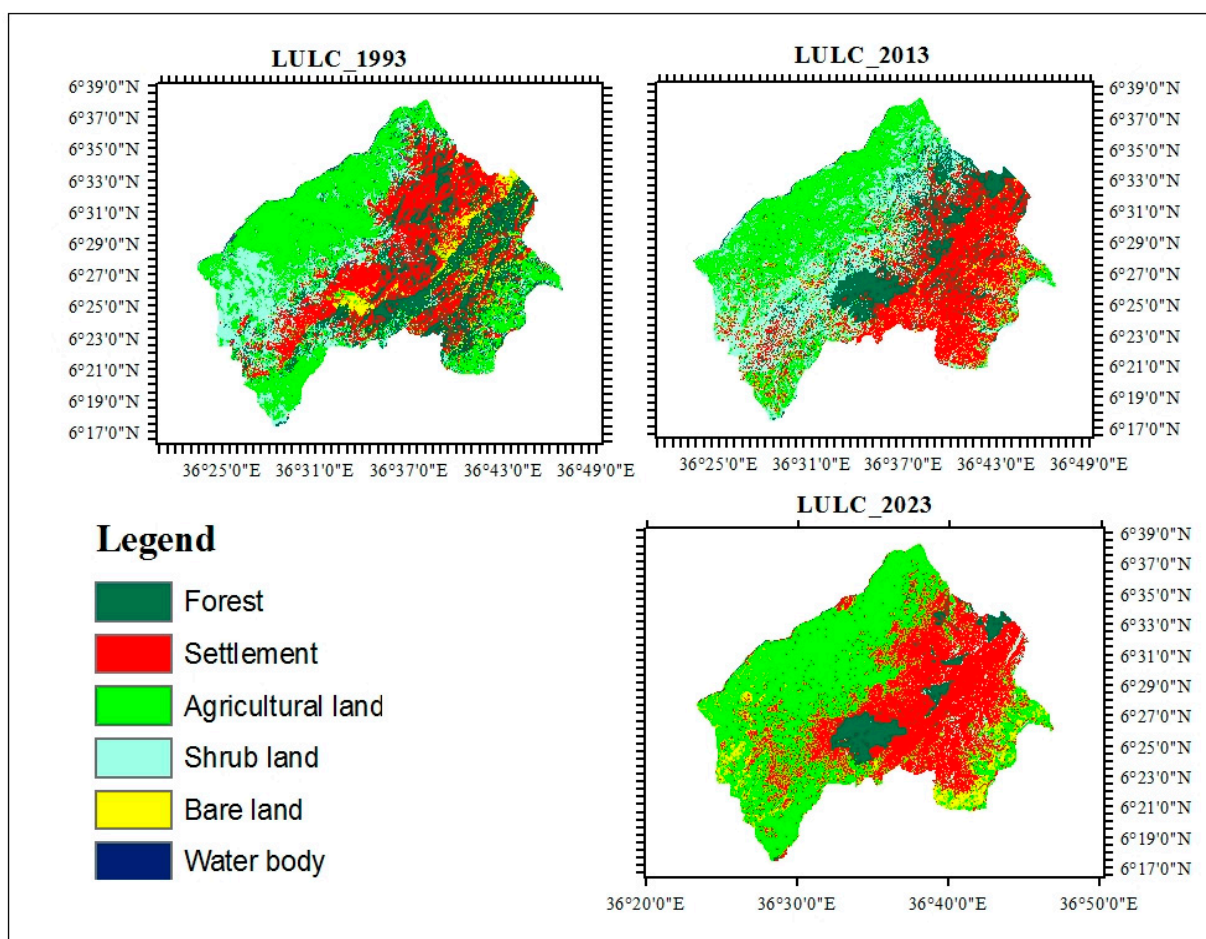


Figure 2. LULCC for the three time periods (1993–2023) of the Melokoza district.

Tables 3–5 provide a summary of the LULCC trend from 1993 to 2023 based on six classes and given a comparable amount of covered area.

Table 3. The land use and land cover change (km²) between the years 1993 and 2013. The reference year was 1993 and the change recorded was for 2013.

1993	2013					
	Forest	Settlement	Agricultural Land	Shrubland	Bare Land	Water Body
Forest	34.357	112.615	14.412	16.073	6.486	0.0019
Settlement	67.752	45.095	8.1996	72.858	1.547	0.0234
Agricultural land	9.3481	37.982	179.502	54.075	5.604	0.2035
Shrub land	5.3964	19.915	48.1830	66.435	0.821	0.0255
Bare land	18.035	10.276	0.7370	1.1141	2.257	0.0105
Water body	1.9499	0.4666	2.8143	13.356	0.173	1.9969

Table 4. The land use and land cover change (km²) between the years of 2013 and 2023. The reference year was 2013 and the change recorded was for 2023.

2013	2023					
	Forest	Settlement	Agricultural Land	Shrubland	Bare Land	Water Body
Forest	49.815	62.119	17.026	7.373	0.493	0.009
Settlement	2.831	155.856	45.346	6.41090	15.900	0.007
Agricultural land	0.174	17.547	221.419	0.334	14.361	0.004
Shrub land	2.033	56.220	155.928	2.253	7.474	0.004
Bare land	2.033	56.220	155.927	2.253	7.474	0.004
Water body	0.007	0.506	0.0299	0.005	0.003	1.712

Table 5. The land use and land cover change (km²) between the years of 1993 and 2023. The reference year was 1993 and the change recorded was for 2023.

1993	2023					
	Forest	Settlement	Agricultural Land	Shrubland	Bare Land	Water Body
Forest	11.316	130.622	32.750	2.506	6.747	0.0002
Settlement	25.326	106.334	56.191	6.915	0.705	0.000
Agricultural land	3.486	25.871	231.943	3.749	21.585	0.076
Shrub land	0.255	24.922	104.239	0.409	10.940	0.008
Bar land	14.477	12.555	2.119	2.374	0.899	0.007
Water body	0.149	2.168	15.889	0.787	0.084	1.675

The main types of land use and land cover during the research period from 1993, 2013, and 2023 are summarized in Figure 3.

The changes in the rate of the LULC classes are clearly illustrated in Figure 4.

3.2. Detecting NDVI Changes and Forest Health

Figure 5 shows the NDVI values of 1993, 2013, and 2023 within the study area.

3.3. The Results of Accuracy Assessment

The findings from the accuracy assessment are concisely outlined in Table 6, which summarizes the results in detail.

3.4. Drivers of LULC Changes

The results of the household questionnaire survey determined seven major driving forces of LULCC were summarized in Table 7. Among these drivers, agricultural expansion and settlement expansion represent the most significant percentages, showcasing the dynamic evolution of the study area.

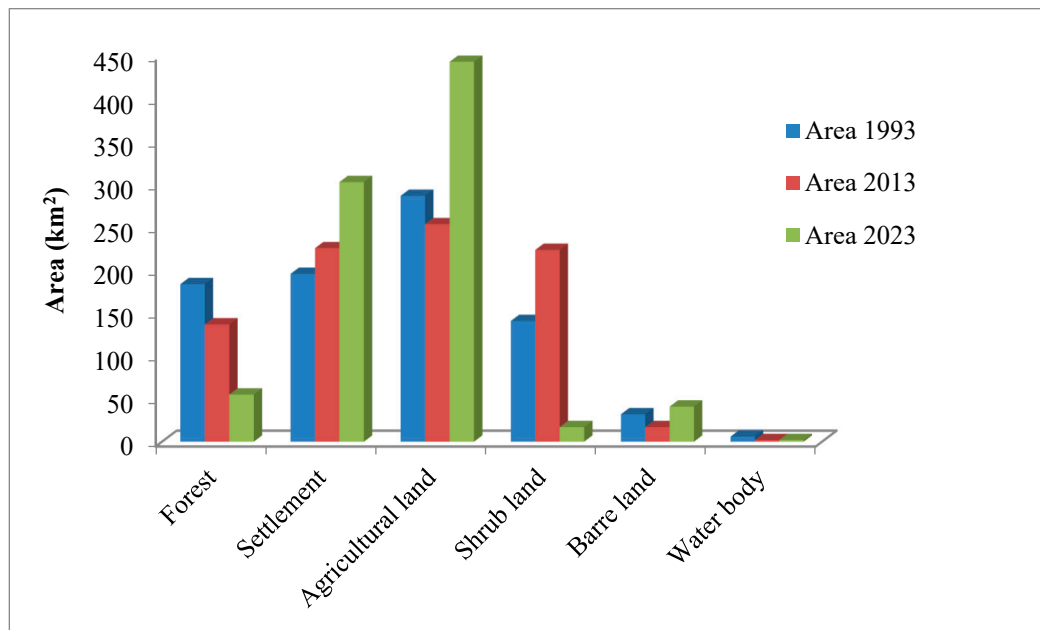


Figure 3. The LULCC areas between the three time periods.

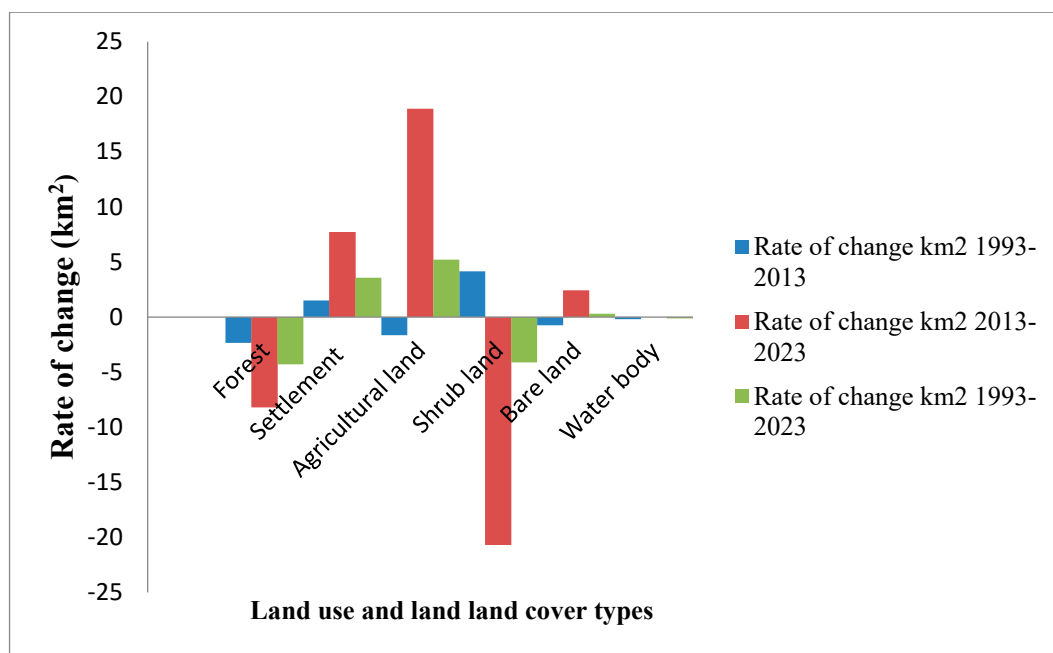


Figure 4. The rate of change in land use and land cover throughout the span of the study period.

Table 6. The overall accuracy, producer accuracy, user accuracy, and kappa (Khat) coefficient values.

	Forest	Settlement	Agriculture	Shrub Land	Bare Land	Water Body	Totals	User's Accuracy
Forest	32	2	0	0	0	0	34	94%
Settlement	0	37	0	0	0	0	37	100%
Agriculture	0	0	36	1	0	0	37	97%
Shrub land	0	0	0	34	0	0	34	100%
Bare land	0	0	0	2	35	0	37	95%
Water body	0	0	0	0	5	20	25	80%
Totals	32	39	36	37	40	20	204	
Producer's Accuracy	100%	94.87%	100%	92%	87.5%	100%		
Khat							89%	

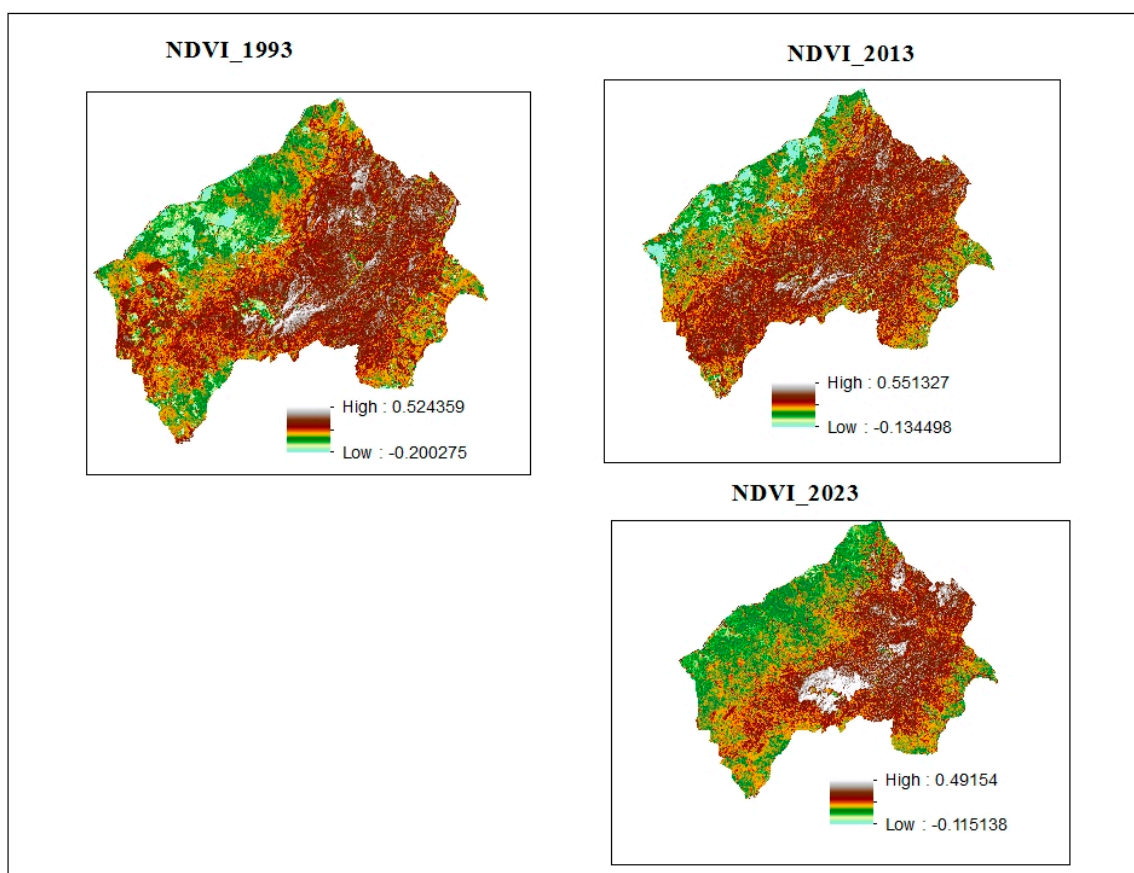


Figure 5. NDVI changes for the years 1993–2023.

Table 7. The major drivers of LULC changes in the study area.

Drivers	Frequency	%	Rank
Tree cutting and charcoal production	40	10	4th
Agricultural expansion	120	30	1st
Settlement expansion	100	25	2nd
Infrastructure expansion, such as roads, etc.	10	2.5	7th
Growing population and urbanization	80	20	3rd
Hydroelectric dam construction	20	5	6th
Lack of designed policy interventions of LULCC	30	7.5	5th
Total	400	100	

4. Discussion

In this study, the LULCC time series data were generated from multispectral Landsat satellite images, revealing the dynamic changes in our landscape. Utilizing GIS software, we meticulously processed Landsat datasets through essential techniques, such as editing, reinstatement, enhancement, image classification, and accuracy assessment. These methods enabled us to categorize and identify the diverse land use and land cover types throughout the study. Ultimately, this study discovered six distinct land use and land cover classes. These classified land use and land cover classes confirmed that there were conversions of land use and land cover from one type of land classes to another. Remarkably, agricultural land and settlement emerged as the predominant classifications, highlighting the evolving relationship between humanity and the earth. The largest land cover type in 1993 was agricultural land. Moreover, trends of decreasing and increasing were noted for all LULCs in 1993, 2013, and 2023.

In 2023, the study area's central region was covered by forest patches, with a few patches on the northern side. Mainly, agriculture was clustered in the west, and settlements were widely dispersed throughout the study area from the east to the middle, with a smaller number throughout the southern and other parts (Figure 2). Farmers have noted that soil fertility, good weather patterns, and the accessibility of the Omo River for irrigation are the fundamental causes of agriculture's dominance in the western part. The greater portion of the water body was found in the Omo River basin, where the Koysha hydroelectric project was located.

Similarly, as shown in Figure 2, the elderly people living in the study area confirmed that settlement was mainly noticed in the middle of the year of 1993. This was likely due to the area's appropriate topography in addition to an unlawful land capture technique that involved clearing the forest for settlement. The vast amounts of settlement and agricultural lands were later shifted to shrub after the local authorities forced the illegal settlers to leave the forest region and its vicinity later in 2013. Since urbanization is increasing, according to the elders, many rural dwellers prefer to reside in the eastern part. Also, there was an overall shift in settlement from the center to the east between 1993 and 2013 (Figure 2). Additionally, between 2013 and 2023, settlements in the south and southeast shifted to bare land. These were related to the construction of highways and dams, such as, for instance, the Great Koysha hydroelectric dam that is being built in the south and the Sawula to Melokoza highway in the southeast. The removal of certain materials from the ground and natural landslides were the reason why the south and southeast shifted to bare land (Figure 2).

Tables 3–5 provide a summary of the LULCC trend from 1993 to 2023 based on six classes and given a comparable amount of covered area. The classification of land cover according to the six land use and land cover types identified throughout the three occasions shows the conversion of the different land use classes. The main land uses that gradually increased throughout the study session were agriculture and settlements. For example, agricultural land increased by 88.50% from 1993 to 2013, 174.41% from 2013 to 2023, and 154.36% from 1993 to 2023. Bare land increased at a significant rate due to the Koysha hydroelectric power dam and highway constructions that might fragment the forest and thus make bare land. Forest-covered lands were mainly converted into agriculture and settlement. The largest change in forest cover to other land use types recorded between 1993 and 2013 was forest to agriculture, followed by forest to settlement. Similarly, between 2013 and 2023, more forest-covered lands were converted to agriculture, followed by settlements. In the area, conversions of shrubland, forest, bare land, water bodies, and agricultural land to settlement were mainly related to the increment of urbanization and human population growth.

As depicted in Tables 3–5 and Figures 2–4, agricultural land and settlement increased throughout the study sessions at the expense of other land use and land cover classes. Across the country and worldwide, similar findings have been reported. The present research results are in line with the studies conducted in Brazil, Africa, Central Asia, Eastern China, and Southeast Asia. For example, the increasing desire for food goods and households has led to an expansion of agriculture and settlement [94]. The greatest net agricultural expansion, according to [95], was observed in Africa, with South America and Asia following. As a rising need for food is driving agricultural development in historically less developed savannas and woodlands, this expansion is representative of Sub-Saharan Africa in general and East Africa in particular [96].

Furthermore, LULCC research conducted in Ethiopia has shown that agriculture and settlement have grown at the expense of forests and shrublands [26,97–104]. For example, the research by [97] in the Andassa watershed revealed that, between 1985 and 2015, the

percentage of farmland increased from 62.7 to 76.8%, which destroyed forests and biological resources related to the increased population growth.

A comparable effect of the agricultural development on LULCCs in the Gambella region has also been documented [105]. Similarly, ref. [106] reported that agricultural growth accounts for 73% of all deforestation in emerging nations. According to [107–109], the development of agricultural land to meet the communities' food needs has had a notable effect on other land uses.

Conferring to the past studies done in Ethiopia, the increase in population number is the primary driver for LULC modification [88,110–112]. These results holds true for the present conditions of population increase in the study area; for example, according to the 1994 national census, the Melokoza district had a total population of 74,992, with 37,349 males and 37,573 females. By contrast, the 2007 Census conducted by the Central Statistical Agency (CSA) showed significant growth in the district's population, reaching 120,398. This increase included 59,877 men and 60,521 women, highlighting the demographic changes within a relatively short period. Population growth is one of the primary driving forces behind land use and land cover change (LULCC) in the study area. The result in (Table 7) indicates that 30% and 25% of respondents identified high expansion of agriculture and settlement as the main underlying drivers of LULC change. This study showed that forests gave way to agricultural land and subsequently to settlement, as verified by the rapid annual increment rate in agriculture and settlement, as well as by the small reduction rate in an area covered with shrubs and forests. This trend indicates that land previously covered by forest, shrubland, and grassland is increasingly being converted into farmland and settlement. As the population continues to rise, so too does the demand for land for crop production and wood products necessary for energy and construction. This study aligns with previous research in Ethiopia, which has consistently identified agriculture, settlement, and population growth as the key factor driving LULC change [44,88,110,113–115]. (Likewise, according to [115,116], there is a growing demand for agriculture because of the swift increase in population.

Like the findings of the current study, a notable decrease in forest cover has been reported across different regions of Ethiopia, such as, for example, by [117] on the Senbat watershed between 1957 and 1980. This deforestation or decrease in forest and shrubland covers was mainly caused by an increase in agriculture, settlement, and animal production. Similarly, a study conducted along the Lake Basaka basin by [118] showed that the amount of forest cover decreased from 42.2% in the early 1960s to scarcely 6% in 2008. Results from this investigation and others serve as markers or evidence for Ethiopia's widespread deforestation. Also, [119] claimed that, during the Derge era, a sizable percentage of the forest resources were transformed into different land uses, such as agriculture and settlement. Similarly, it has been explained by other authors e.g., [99,107,113] that these alterations of land use and land cover may be permitted by institutional enforcement and a lack of clearly defined policies.

Policy and institutional factors play a pivotal role in shaping our environment. The household survey results (Table 7) reveal that 7.5% of respondents believe the absence of strong policies and effective institutional frameworks is a significant underlying cause of the LULC changes in the Melokoza district. Focus group discussions and key informant interviews underscore this notion, highlighting the challenges posed by weak law enforcement and poorly defined policies. These issues lead to mismanagement, illegal settlements, and misuse of precious natural resources. The presence of illegal settlers, tree-cutting, and charcoal producers underscores the urgent need for better management of LULCC. Historical perspectives, such as the findings by [120], emphasize that extensive forest resources have drastically transformed during the Derge regime. Similarly, studies by [99,107,113] re-

inforce the idea that well-defined policies and robust institutional enforcement are essential to preserve our land and ensure a sustainable future. The household survey results (Table 7) reveal that fuelwood collection and charcoal production are pivotal factors in the landscape change within the study area. Remarkably, 10% of respondents identified these activities as key drivers of land use and land cover change (LULCC) in the study area. It is inspiring to note that approximately 99.5% of respondents rely on fuelwood as their primary energy source for cooking. In Ethiopia, wood serves not only as the main energy source, but also as a vital construction material for both rural and urban communities. This study aligns with the findings of [121,122], highlighting that tree cutting for domestic and commercial purposes remains a significant force behind the forest degradation that leads to LULCC. The abovementioned factors are also an observable fact confirmed by the present study.

Various researchers e.g., [31,117,118,123–125] have reported that growing population and urbanization are causing a swift conversion of forested areas into agricultural land and settlements in Ethiopia. The findings of the current study imply declining rates of forest and shrub lands and increasing rates of agricultural land and settlement. The abovementioned studies broadly demonstrated to what extent agriculture and settlement expanded into forest cover throughout the study periods. Thus, the depletion of natural resources has led to a degradation of the ecosystem of the entire landscape. Population growth is among the major reasons contributing to LULCC in Ethiopia [120].). Based on the findings of the present study, the same holds true in the study area. The idea proposed by [4] also confirms the outcomes of this investigation.

This scenario has caused a swift deterioration of natural resources, with the most affected being forest resources, soil layers that have already experienced erosion, ongoing loss of nutrients, and landslides. A study by [126] indicate that, in Ethiopia, urgent action is required to address the issue of land use and land cover and land degradation by applying appropriate technology to enhance forest resources management and sustainable agricultural production. This recommendation also applies to the Melokoza districts.

Throughout the investigation, variations were found in the yearly percentage of alterations to the land use and land cover. Likewise, from various areas in the country, similar findings have been reported [102,127] that LULC change is intricate and interconnected since it involves the growth of a single type of land use at the overhead of another. According to the household survey in (Table 7), 5% of the respondents believed that, in the study area, the great Koysha hydroelectric dam construction caused a decrease in the shrubland and forest cover and an increase in bare land. The construction of an artificial dam has an influence on the cover of other land use and land cover classes, such as forestlands, shrublands, and grasslands [128,129]. According to the local elders, in 2013, the government evicted the illegal settlers from in and around the forests. Due to this, shrublands were changed to forest and agricultural lands were converted to shrublands. The same result was also reported from different areas [117,121].

In general, the current investigation clearly shows that, overall, rising agricultural and settlement expansion has resulted in a decline of forest and shrubland expanses, which has caused the landscape to become more fragmented. Numerous prior studies conducted in various regions of Ethiopia by different authors e.g., [15,20,121,130,131], as well as studies from numerous tropical countries [132,133], have provided evidence of this. Therefore, nations and nationalities at local, regional, and large global scales should pay attention to the land use and land cover change leading to natural resource degradation and global climate change.

Figure 5 depicts the large dark and light brown colors of the forest region, indicating the drop in forest covers. Hence, the highest and lowest NDVI values of the study periods from 1993–2023 were 0.52 and −0.20, 0.55 and −0.13, and 0.49 and −0.12, respectively.

Meanwhile, the NDVI values of 1993, 2013, and 2023 were 0.52, 0.55, and 0.49, respectively, which are acceptable ranges for sparse and dense vegetation. These imply that greenness or vegetation cover was elevated in the research period between 1993 and 2013 and decreased between 2013 and 2023. The increase in the NDVI for the urban area, settlement, and water bodies in green can be disregarded because the NDVI is only useful for monitoring vegetation. It is evident that, throughout the thirty years, nearly the whole forest had an NDVI decline.

Figure 6 displays the comparison between the NDVI statistics for the years 1993–2023. The NDVI values for 1993, 2013, and 2023 were -0.20 , 0.52 , 0.27 , and 0.08 ; -0.13 , 0.55 , 0.31 , and 0.08 ; and -0.12 , 0.49 , 0.17 , and 0.08 , respectively, for the min, max, mean, and standard deviation. The year 2013 showed an escalation in the max and mean values (0.55 and 0.31), whereas the year 2023 showed a decrease in the max and mean values (0.49 and 0.17). The statistical data differences between study sessions revealed an increase from 1993 to 2013 and a decline in 2023 of the max and mean values, respectively. Also, this implies the decline of vegetation healthy coverage.

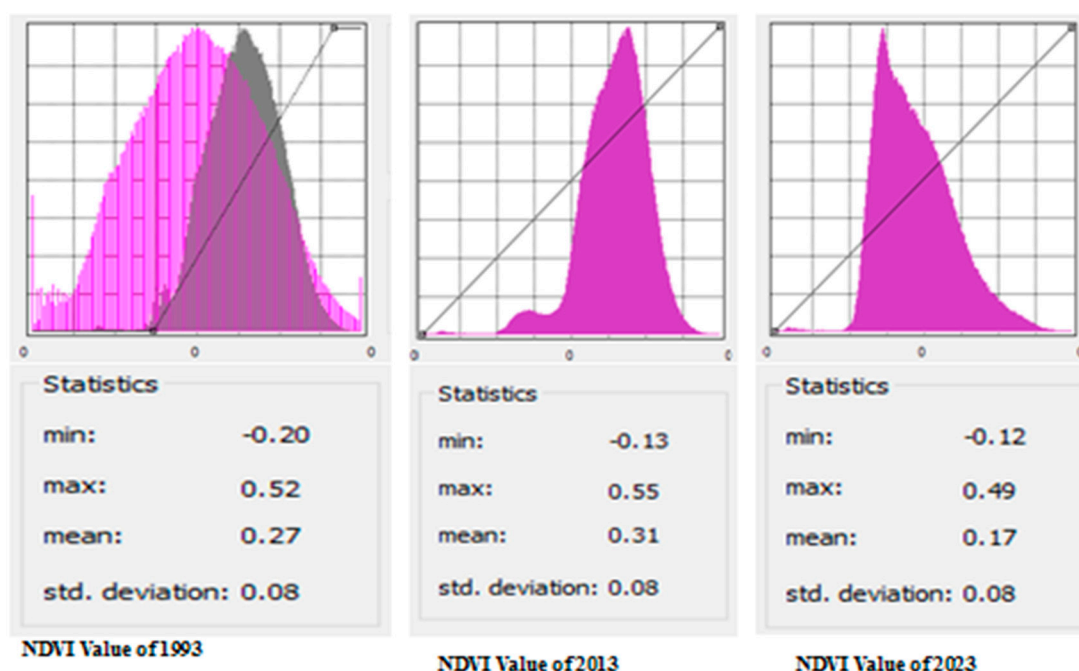


Figure 6. Histogram of the maximum and minimum NDVI values.

Between 1993 and 2013, the mean NDVI score showed that the healthiness of the forests was enhanced, but this then decreased in 2023. An increase in NDVI values determines the increase in the health of vegetation covers, whereas a decrease in NDVI values determines the decline in the vegetation health cover of an area. NDVI values imply the decline scenario of the vegetation cover in the study area. Similar findings have been reported by studies conducted elsewhere [90,133].

The classification was carried out with overall accuracies, showcasing the potential of our approach (Table 6). The results revealed that the user accuracy for individual classes ranged from an impressive 80% to a perfect 100%, while the producer accuracy varied between 87.5% and 100%. Although lower producer accuracy was observed for bare land at 87.5%, this highlights the challenges faced in identifying the grassland and bare land during the drought season and its low ground cover condition [118]. The resulting LULC map achieved an admirable Kappa (k) of 0.89, reflecting a strong alignment between the reference data and the remotely sensed classification [134]. With a Kappa statistic exceeding

80%, a remarkable agreement was witnessed [135]. Thus, the present study's Kappa statistic of 89% stands as a testament to the strength of our findings.

5. Conclusions

To better understand the past and contemporary land use and land cover, this study examined the periodic satellite images associated with the geographical and temporal elements of the Melokoza district. In light of this, this study's core purpose was to analyze the spatiotemporal LULCC progress in the study area from the years of 1993 to 2023. This study used Landsat images (4–5 and 8) and GIS and remote sensing tools to investigate the past and present trends of LULCC. Six land use and land cover classes were identified using supervised classification approaches. The research area has exhibited dynamic alterations in land use and land cover over spatiotemporal and geographical scales from 1993 to 2023. This change has ensured that forestland classes are at the forefront of the conversion to two main land uses, such as agriculture and settlement, due to economic and demographic changes. Also, the normalized difference vegetation index (NDVI) values showed declined trends throughout the study years. The factors mentioned above imply the decline in vegetation health in the study area. The lack of strong institutional and technological support is the primary influence of LULCC changes in the Melokoza district. The viability of agriculture, settlement, and the related obtainability of natural resources in the study area may be seriously jeopardized if this state is permitted to proceed with this trend. Thus, natural resource managers, environmental specialists, and other stakeholders should play a key role in raising public awareness regarding LULCCs and promoting the long-term conservation of natural resources, particularly forestland, through the implementation of a green legacy program in the research area to mitigate local, regional, and global climate changes.

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