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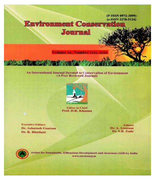

Spatiotemporal dynamics of land use/land cover changes and its drivers in *Bilate* watershed, central rift valley, Ethiopia

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ABSTRACT

Land use/land cover (LULC) changes influence the ecological function, consequence on ecosystem services, which are tightly linked to human wellbeing. However, quantification of the LULC changes and identifying the underlying factors remain patchy particularly in developing nations, despite this information is crucial to propose a feasible restoration action. Therefore, this study investigates the land use/land cover changes and its drivers in central Rift Valley, Ethiopia. GIS and Remote sensors i.e. Landsat 5 (TM), and Landsat 8 (OLI/TIRs) imagery sensors acquired from USGS, and field observation were used. Using the supervised classification method and the support of ArcGIS 10.5 and ERDAS IMAGINE 2014, all images were classified into various land cover types. Focus group discussions, key informant interviews, and structured questionnaire surveys were used to investigate the drivers of LULC change. NDVI was used to detect the vegetation cover change. Woodland, grassland, and barren lands were the major LULC types identified in this study. After 28 years, the woodland cover increased from 20.6% to 40.2% whereas the barren land decreased from 43.4% to 22.6%. Grassland showed very slight increment, i.e. from 35.9% to 36.9%. This implies that area enclosure plays a significant role in the restoration of degraded lands. The highest NDVI values (0.6) were determined in the year 2022 at the end of the classification. Focus group discussants and key informants confirmed that human-induced factors were the major drivers of LULC changes in the study area. Our findings indicated that human interventions are the key determinants of land use/land cover dynamics, and as a result, enforcement of the law and public education campaigns to change human behavior in support of the area enclosure approach are essential to restoring degraded land for the benefit and wellbeing of humans and nature while also advancing the achievement of the global goals.

Introduction

Changes in land use and land cover are very complicated processes that are greatly influenced by a variety of factors, including long-term natural climate changes, geomorphological and biological processes, and human-induced pressures on vegetation cover (Arsanjani, 2011; Gebrehiwot *et al.,* 2021). LULC changes have influenced the ecological conditions of the ecosystem (Yesuph & Dagnew, 2019). Consequently, it strongly affects ecosystem services and functioning (Wang *et al.,* 2015). In many semi-arid areas of sub-Saharan Africa, land degradation is a problem that needs to be addressed if it is to be restored (Emiru *et al.,* 2018; Yayneshet, 2011). Degradation of vegetation

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leading to eventually desertification is more pronounced in Africa than in any other continent (Mekuria *et al.,* 2019; Zeila & Jama, 2005). The same is true in Ethiopia (Gebreselassie *et al.,* 2016). Earlier studies (Gebrehiwot *et al.,* 2021; Kidane *et al.,* 2012) showed that population growth and settlement, agricultural expansion, deforestation, land clearing, and fire are the main causes of LULC change. Hence, (Feyisa *et al.,* 2017; Tesfaye *et al.,* 2016; Tsegay & Meng, 2021) argue that the use of area enclosure restoration practice is an effective strategy to reduce the degradation problem.The knowledge of temporal and spatial LULC change is crucial to understanding the current status of vegetation resources (Mohammed *et al.,* 2020) and predicting the consequences of vegetation degradation (Emiru *et al.,* 2018) which enables the development of other supportive applicable conservation strategies or enhances and improves conservation practice for further output. To plan locality-specific sustainable land use and resource management techniques in such area enclosures, precise and current spatiotemporal information on LULC dynamics, the underlying causes, and consequences of these changes are urgently required. The study area, *Bilate* watershed, is well experienced to be restored by area enclosure activities, but the area is still exposed to severe erosion and soil loss triggered by LULC changes. Therefore, it is essential to have a thorough understanding of the divers, consequences, and extent of LULC change to establish more appropriate environmental policies and land management strategies for the area and beyond. (Larjavaara & Muller-Landau, 2010). The degree of this change, its causes, and its effects are not fully understood because the LULC change in the Bilat watershed has not yet been fully examined. Therefore, the objective of this study was to detect, quantify, and map LULC dynamics and trends as well as to investigate the underlying causes of the LULC change.

Material and Methods

The study was carried out in the Central Ethiopian Rift Valley's Bilate Watershed. It covers 2032.11 ha. Three zones, i.e. Halaba, Kambata Temabaro, and Hadiya make up the Bilate watershed. One district was selected from each zone because of the presence of area enclosures and the adjacent open land. We selected *Weyera* district from Halaba zone. Six *Kebeles* (smallest administrative units: *Sheke Tena Woldia, Wanjana Woldia, Asore, Ashoka, Houlgeb kuke, Chambula*) were identified from this district, *Kedida Gamela* district was selected from *Kambata Tembaro* zone with *Hulegabezeto kebele. Misraq Badawacho* district was selected from *Hadyia* zone, and the kebele identified was 2nd *Keraniso*. The watershed is located between the latitudes of 7°12′33″ and 7°21′19″ and the longitudes of 38°06′00″ and 38°03′57″. The area features plain, sloppy, or undulating landscape types and an altitude range of 1654 to 1822 masl (Figure 1).

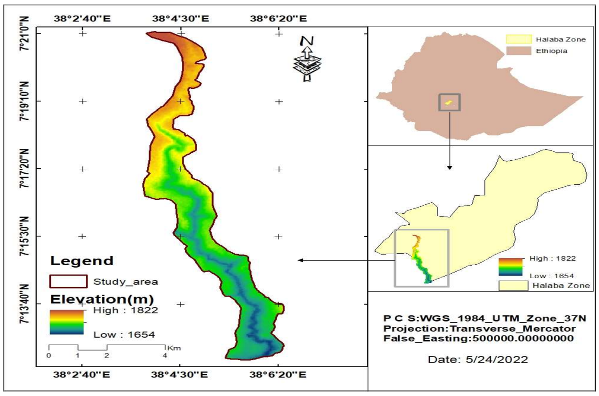

Figure 1: Map of the study area

The Ethiopian Rift, part of the Great Rift Valley's active rift system and characteristic of the area's warm climate with a width of roughly 1000 km, dominates the study area's geological formation (Wodaje, 2017). The soil types in the study area are *Chromic, orthic Luvsols,* and *Eutric Nitisols*, which have good potential for agricultural activities (Wodaje, 2017). The *Eutric Nitosols* is the most renounced for their fertility. *Ca.*, 80% of the soil is sandy loam, 15% is clay and 5% is sandy (Food *et al.,* 2003) in the study area. The long-term average rainfall in the watershed is approximately 1107 mm, and it has a bimodal pattern with *Belg* (a traditional division of the year with light rain) typically occurring from March to May and *Meher* (a traditional division of the year with heavy rain) typically occurring from June to September. In the research area, the annual average temperature is 26.2 °C.In general, there are two types of LULC in the study area right now: vegetation (trees, shrubs, grass, and herbs), and bare land. Natural and plantation forests are also present in the study area's vegetation cover, while areas of bare ground are covered by degraded grasslands and scattered rural settlements.

Data collection

To examine the LULC, path and raw satellite images of 1994, 2008, and 2022 years were used. Field observation and GPS point data (training sites and ground control points) were used within the study area. To understand the reality and the forces driving change and perceptions related to LULC changes, socioeconomic data were used to gather additional ancillary data from the elders, local community, and local administration through a set of questionnaires, interviews with key informants, and discussions in focus groups.

Sample size determination

The (Cochran, 1977) formula was used to determine the sample size for the household survey.

$$\boldsymbol{n} = \frac{\boldsymbol{Z^2 pq}}{\boldsymbol{e}} \qquad (1)$$

Where: n= sample size; Z2= confidence interval (1.96, constant); p = population percentage (0.5, constant); q = 1 - p; e=margin of error which is fixed at 0.05. An error margin of 5% and a confidence interval of 95% were used.

The calculated sample size was 384 and the sample size for each *kebele* was allocated proportionally (Table 1). The respondents were selected using a simple random sampling technique.

Table 1: Target population and sample size of each study kebele in the *Bilate* watershed

SN	Kebele Name	Household			
		Male	Female	Total	Sample Size
1	Sheke Tena Woldia	197	87	284	37
2	Wanjana Woldia	258	198	456	59
3	Ashoka	312	98	410	53
4	Asore	243	103	346	45
5	Houlgeb kuke	189	110	299	39
6	Chambula	186	79	265	34
7	Hulegabezeto kebele	396	172	568	73
8	2nd Keraniso kebele	257	91	348	45
	Total	2038	938	2976	384

We used three primary sources to collect information on the factors driving LULC change and the historical background of the watershed : semi-structured household questionnaire focus groups, and key informant interviews. Eight focus group discussions (one group for each *kebele*) were held using checklists to generate more evidence on the selected topics.Four to ten discussants were included in each group. Village administrators, development experts of natural resources, male households, and female households participated in the FGD. Twenty-four key informants (three in each *kebele*) were selected purposively with the help of the local administration and agricultural development experts to gain in-depth information about the study area. The key informants, who were people who had lived in the area for more than three decades and were assumed to have essential knowledge about their area, were given a list of open-ended questions.

Data acquisition

To assess the LULC variations of the research area, images from Landsat 5 TM and Landsat 8 OLI/TIRS of three carefully chosen years of the previous 28 years (1994, 2008, and 2022) were obtained from the USGS Earth Explorer website (http://earthexplorer.usgs.gov) (Table 2). Data acquisition from January to March as cloud effect/clear sky during data acquisition. The year 1994 was selected as the reference year of a baseline because it represents the pre-restoration period, and 2008 represents the period of the green legacy movement of the Ethiopian millennium. It was a year when enclosures activities were widely carried out in the study area. After the images were downloaded, projected, and stacked (pre-processed) to be displayed in the ERDAS IMAGINE software interface, the land cover map was generated within the framework of the Geographic Information System (GIS) and Remote Sensing (RS) Environment. The acquired multi-temporal satellite image covers a large area with a sensor spatial resolution of 30 meters for all spectral bands except band six (thermal band), which has a resolution of 60 meters, and band 8, which has a resolution of 15 meters and was left out of the scene. The remaining bands were stacked to get false-color composite (FCC) images in ERDAS IMAGINE 2014 software (Qiu & Jensen, 2004; Szuster *et al.,* 2011) The study was divided into three time periods: 1994, 2008, and 2022 (28-year spans). For better

Table 2: Satellite data and sources used in this study

Satellite images	Date of acquisition	Path	Row	Resolution	Sources	Application
Landsat 5	03/02/ 1994	169	055	30m	USGS Website	LULC Map
Landsat 5	25/02/ 2008	169	055	30m		
Landsat 8	2/02/ 2022	169	055	30m		

interpretation, the image was enhanced by displaying it in RGB true color composite (band 3, 2, 1) and included two infrared channels (4, 5, 3). For vegetated and non-vegetated land areas, green vegetation, and vegetation discrimination mapping, the former band combination bands 3, 2, and 1 were used. The latter band combination bands 4, 5, and 3 were employed for vegetation moisture differentiation and NDVI classification. The LULC map of the region was validated using high-resolution images (Google Earth Image).

Processing and analysis of data

Image pre-processing and classification

Image pre-processing is essential to avoid bias caused by noise and instrument artifacts (Chander et al., 2009; Giri, 2012). To acquire a more accurate representation of the images, geometric and radiometric corrections were applied during pre-processing. Moreover, in ERDAS IMAGINE 2014, contrast stretching techniques were utilized to enhance the visual interpretation of multi-temporal satellite images, and aerial photographs were used for ground truth verification. Using equalizing histograms and masking cloud coverage, the image's quality can be enhanced. Image classification is important to remote sensing, image analysis, and pattern recognition (Figure 2). The technique of categorizing pixels in an image is known as image classification (Anand, 2017; Urgesa *et al.,* 2016). Supervised classification was used to group pixels of similar spectral domains into classes. This classification approach necessitates the selection of training regions as the classification basis. For supervised classifications to be successful, the computer needs to be trained on the scene area beforehand. To reflect a certain land cover class, the user defines the original pixels' corresponding spectral classifications (Akubia *et al.,* 2020; Lillesand *et al.,* 2015). The Supervised Maximum Likelihood classifier algorithm classification system was employed to complete the classification process. Each land cover type is determined by a combination of fieldwork and personal experience (Asokan & Anitha, 2019; Qiu & Jensen, 2004). The clusters' shape, size, and direction are all factors that this classifier considers in addition to the cluster centers. To do this, the statistical distance was calculated using the covariance matrix and mean values of the groups.

To classify and assess accuracy, 150 GPS points (50 GPS points in each LULC) were collected from the field using GPS. The analysis began by using signature editor tools to define and collect training samples with the same reflectance value, then save the signature to begin the classification activity. The training sample was used to collect signatures from the image for categorization. Each sampled pixel was collected with the automated optical inspection (AOI) instruments, then classified using the signature editor. The satellite images were then divided into three categories (Woodland, Grassland, and Barren land) (Table 3).

Table 3: Description of LULC classes

LULC classes	Description
Woodland	Areas are dominantly covered with trees and shrubs.
Grassland	Permanently grassed regions, such as those found along ridges, steep slopes, and plain areas utilized for grazing, are typically both private and community.
Barren land	Places with deteriorated grasses, some bare ground (rocks), and sporadic rural small villages and farms.

Accuracy assessment

When assessing the value of field data (reference point) and classified images, accuracy assessment is useful (Congalton & Green, 2019; Elias et al., 2019). In the field, these references were generated using GPS and Google Earth data. It is very important to determine how accurate the referenced point is agreed with classified images of the remotely sensed data. LULC maps derived from remote sensing always contain some sort of errors due to several factors from classification technique to method of satellite data capture. The most common accuracy assessment elements include overall accuracy, producer's accuracy, user's accuracy, and kappa coefficient (Lu *et al.,* 2004).

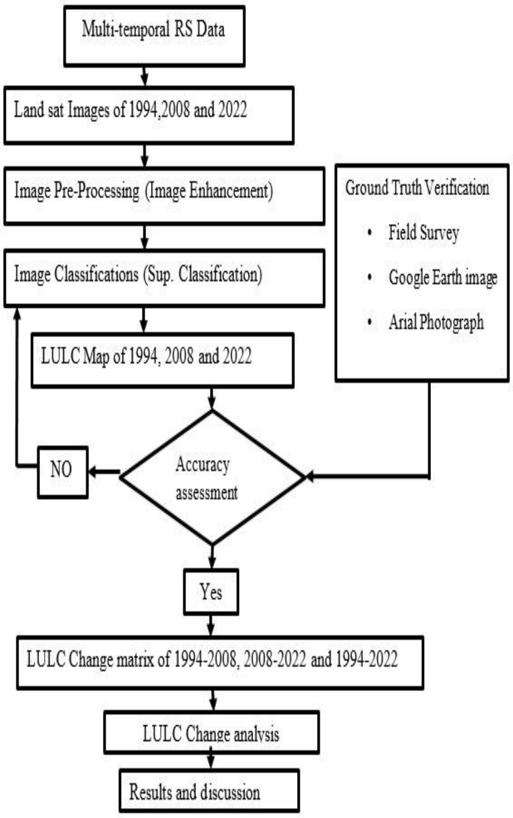

Figure 2: Flow chart of image classification

and the common tool to assess accuracy is the error matrix (Congalton & Green, 2019; Qiu & Jensen, 2004). These accuracy assessment elements were computed by using the following formula (Anand, 2017; Zewude *et al.,* 2022).

$$\textbf{Producer's Accuracy} = \frac{\textbf{total number of correct pixels in a category}}{\textbf{total number of pixels derived from reference data}}$$

$$\textbf{User's Accuracy} = \frac{\textbf{Total number of correct pixels in a category}}{\textbf{Total number of pixels derived from the reference data}}$$

$$\textbf{Overall accuracy} = \frac{\textbf{Sum of the diagonal elements}}{\textbf{Total number of accuracy sites (pixels)}}$$

Kappa coefficient (Khat) is a measure of the agreement between two maps taking into account all elements of the error matrix. It is defined in terms of an error matrix as given below:

$$(\textbf{Khat}) = \frac{(N\sum_{i=1}^{r} xii) - (\sum_{i=1}^{r} (x_{i+} * x_{+i}))}{N^2 - (\sum_{i=1}^{r} (x_{i+} * x_{+i}))} \quad (5)$$

Where;
r= number of rows in the error matrix
Xii = number of observations in row i and column i (on the major diagonal)
Xi+ = total observations in row (show as marginal total to right of the matrix)
X+I = total observations in column i (show as marginal total at bottom of the matrix)
N= total number of observations in included in the matrix

The kappa coefficient or statistics can be applied as a measure of how well the remotely sensed classification agrees with reference data. A value greater than 0.80 represents a strong or good classification; a value between 0.40 and 0.80 means moderate classification and a value less than 0.40 represents a poor classification or agreement (Anderson, 1976; Firdaus, 2014; Schowengerdt, 2012).

Change detection matrix

Pixel-based classified images were used to produce change information on the land classes and observed changes taking place. Thus, a change matrix was produced with the help of ERDAS IMAGINE 2014. The land cover map for the three-period series of images was analyzed based on LULC types of the study area using tables and graphs. To determine the magnitude, trend, and rate of LULC changes in the watershed, the area comparison analysis was made by subtracting the total area of each class of 1994 from 2008, 2008 from 2022, and 1994 from 2022 which the result could be positive (increasing) or negative (decreasing). The percent and rate of LULC change were computed by the following formula (Demissie *et al.,* 2017; Hegazy & Kaloop, 2015; Yesuph & Dagnew, 2019).

$$\textbf{Percent of change} = \frac{\mathbf{X - Y}}{\mathbf{Y}} \times \mathbf{100} \quad (6)$$

$$\textbf{Rate of change} \left(\frac{\textbf{ha}}{\textbf{year}}\right) = \frac{\mathbf{X - Y}}{\mathbf{Z}} \quad (7)$$

Where:
X = Recent area of the land use/land cover in ha,
Y = Previous area of the land use/land cover in ha and
Z = Time interval between X and Y in years.

Cross-tabulation matrix was used to differentiate the changes of each category at the expense of others

and its general structure follows the format displayed in Table 4. The rows display the categories of initial time, and the columns display the categories of subsequent or recent time. Entries on the diagonal (that is, P_{jj}) indicate the amount of LULC category which remained persistent in class j between the period and are used to calculate the gains and the losses of LULC classes while the diagonal entries show the size of the area that transitioned from category "i" to a different category "j" during the time interval (Aldwaik & Pontius Jr, 2012; Yesuph & Dagnew, 2019). For ease of reference, the equations and notation used to compute various components are presented as follows:
The proportion of the watershed Pi + that is occupied by class i, initial time is given by (Eq. 8):

$$\mathbf{Pi+}=\sum_{i=1}^{n}\mathbf{Pij} \qquad (8)$$

Where n is the total number of LULC classes. Similarly, the proportion of the watershed P+j that is occupied by class j in recent times is given by (Eq. 9)

$$\mathbf{P+j}=\sum_{i=1}^{n}\mathbf{Pij} \qquad (9)$$

Similarly, the following equations were used to determine the gain, loss, persistence, swap, and total change for all four-classified imagery (Braimoh, 2006; Kindu *et al.,* 2013).
The Gain (G_{ij}) was calculated through the difference between the total value for recent time (P_{+j}) and the persistence (P_{ij}), using Eq. 10:

$$\mathbf{G_{ij}=G_{+j}-G_{jj}} \qquad (10)$$

On the other hand, the Loss (L_{ij}) was the difference between the total values for the initial time file (P_{j+}) and the persistence, using Eq. 11:

$$\mathbf{G_{ij}=G_{+j}-G_{jj}} \qquad (11)$$

The swapping (S_j) is the exchange between the categories i.e. the proportion of a given class that changes location, while the total surface area remains the same. It denotes concurrent gain (i.e., the difference between class i and persistence) and loss (i.e., the difference between class j and persistence) of a given LULC class. Swap shows the fact that a lack of net change does not necessarily imply a lack of change in LULC in the watershed. Through the use of Eq. 11, it was determined to be two times the minimum value of the gains and losses.

$$\mathbf{S_j=2\times MIN(P_{j+}-P_{jj},P_{+j}-P_{jj}} \qquad (11)$$

The net change shows the definite change between the two time periods. The total was determined by subtracting the Total row from the Total column. The total change for each category (Cj) was the sum of net change (Dj) and the swapping (Sj), or the sum of gain and loss (Eq. 12).

$$\mathbf{C_j=(D_j+S_j)} \qquad (12)$$

If the net change is zero (implying gain is equal to loss), then the swap is twice the loss or gain.

Table 4: A 3 × 3 LULC Conversion matrix for comparing two maps from different points in time

	Recent time					
Initial time	**LULC1**	**LULC2**	**LULC3**	**Total initial**	**Loss**	**LULC1**
LULC1	P11	P12	P13	P1+	P1+-P11	P11
LULC2	P21	P22	P23	P2+	P2+-P22	P21
LULC3	P31	P32	P33	P3+	P3+-P33	P31
Total Recent	P+1	P+2	P+3	1		P+1
Gain	P+1-P11	P+2-P22	P+3-P33			P+1-P11

Note: "P" refers to any conversion from one LULC to another and the number refers to columns and rows of LULC categories Source: Modified from (Adugna et al., 2017; Yesuph & Dagnew, 2019).

The exposure of each LULC class for a change was evaluated using the loss to persistence ratio (Lp = loss/persistence); gain to persistence ratio (Gp = gain/persistence) and net change to persistence ratio (Np = net change/persistence) (Randolph, 2004; Yesuph & Dagnew, 2019). A given land use or cover class has a higher probability of changing to another LULC than persisting in its current condition when G_P and L_P values are greater than one (Dibaba et al., 2020; Talukdar *et al.*, 2020). The land use/cover class is more likely to lose area to other LULC classes than to gain from them if Np had a negative value.Finally, two types of data were produced;

namely, three LULC maps, which illustrate the changes in a spatial context and various tables which exhibit the amount of areas for each LULC category, and a cross-tabulation matrix which demonstrates the LULC transition from category to a category at different study periods. ArcGIS 10.5 was used for data analysis, management, spatial referencing, geo-referencing, and layout for final mapping, and ERDAS IMAGINE 2014 for image processing, classification, and change detection of the final LULC maps as well as the socioeconomic data, also analyzed by SPSS v 21.

NDVI (Normalized difference vegetation index) data

One of the most widely used indices for computing green vegetation is the Normalized Difference Vegetation Index (NDVI) (Gandhi *et al.,* 2015; Warkineh & Hailemicael, 2021). It is useful for identifying vegetation from non-vegetation land cover. Areas of barren rock, sand, or snow usually show very low NDVI values (for example, 0.1 or less). Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate NDVI values (approximately 0.2 to 0.5). High NDVI values (approximately 0.6 to 0.9) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage (Ghorbani *et al.,* 2012; Helbich, 2019). NDVI values were calculated on composite image and used band 3 (Red) and 4 (Near Infrared) for Landsat 5, and band 4 (Red) comes with band 5 (Near Infrared) for Landsat 8. NDVI approaching calculation of greenness degree of image correlates with vegetation crown density. NDVI correlates with chlorophyll content and its value is between -1 to 1. NDVI is calculated as follows (Costa *et al.,* 2020; Eastman *et al.,* 2013; Gandhi *et al.,* 2015; Zaitunah *et al.,* 2018).

$$\mathbf{NDVI} = \frac{\mathbf{near\ infrared} - \mathbf{red}}{\mathbf{near\ infrared} + \mathbf{red}} \qquad (12)$$

Where
NIR is the near-infrared reflectance and RED is the red reflectance.

In this NDVI analysis, the higher positive values are classified as vegetation and values close to zero are classified as mixed vegetation. While the negative value including zero is classified as barren land (Gandhi *et al.,* 2015).

Results and Discussion

Land use/land cover distribution (1994 to 2022)

The distribution of land use/land cover categories in the study area was examined from January to March using satellite images. These LULC categories were divided into three land classes (i.e. Woodland, Grassland, and Barren land). The final LULC categories (1994 to 2022) showed that woodland was the most predominant LULC category in the study area followed by grassland and barren land. Focus group discussion and key informants' interviews showed that the increment of woodland cover could be linked with the practice of area enclosure restoration activities in the *Bilate* watershed. Earlier studies (e. g. Emiru *et al.,* 2018; Feyisa *et al.,* 2017; Warkineh & Hailemicael, 2021) showed that the use of area enclosure for vegetation restoration was the key contributor to the increase in vegetation coverage along the time gradient.The temporal trend of LULC change in the last three decades showed a magnificent change (Figure 3). In addition to that, the rate of woodland change was fast compared to the other LULC categories (i.e. Grassland and Barren land in the last three decades due to area enclosure restoration practiced). In 1994, barren land accounted for the largest area coverage (883 ha = 43.4% of the total area) in the study area. Conversely, the woodland cover was the least (419 ha = 20.6%) (Figure 3 and Table 5). Our findings may imply that the study area was severely degraded prior to the application of the area enclosure. Grassland counted for 730 ha or 35.9% in 1994. Moreover, in 2008, the woodland and grassland attained the highest coverage, being 770.1 ha (37.9%) and 747 ha (36.8%) of the total area, respectively. In the same year, barren land covered the smallest share (515 ha = 25.3%) of the total area. Our findings indicated that after 28 years, the LULC dynamics of the study area were significantly changed. In 2022, Woodland (816.03 ha = 40.2%) nearly covered twice the area of barren land (466.38 ha = 22.9%). Grassland (749.7 ha, or 36.9%) occupied the remaining space in the research area. Previous studies (e.g. Abera *et al.,* 2016; Araya, 2014; Feyisa *et al.,* 2017; Solomon *et al.,* 2022; Yayneshet, 2011) reported the increment of woodland and grassland due to the area enclosure confirming that it is a promising approach to the reverse lost vegetation in a specific area.

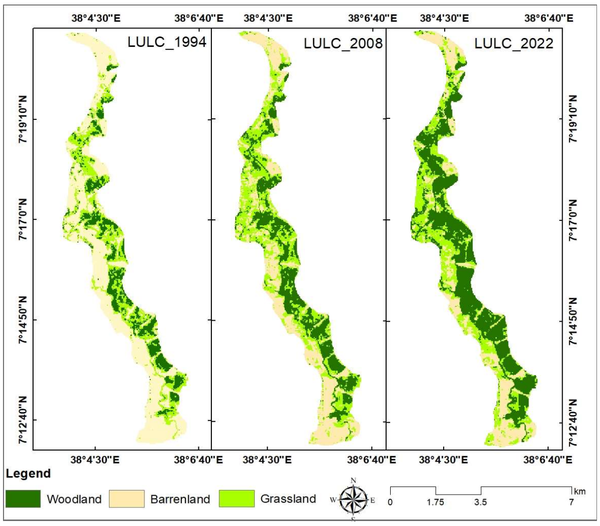

Figure 3: Land use/land cover map of *Bilate* watershed under different periods

Table 5: Area coverage by LULC classes in the *Bilate* watershed during various periods

LULC Class	1994		2008		2022	
	Area (ha)	% of total	Area (ha)	% of total	Area (ha)	% of total
Woodland	419	20.6	770	37.9	816	40.2
Grassland	730	35.9	747	36.8	750	36.9
Barren Land	883	43.4	515	25.3	466	23.0
Total	2032	100	2032	100	2032	100

Table 6: Error matrix classification accuracy assessments of images from 1994, 2008, and 2022

LULC Types	1994		2008		2022	
	P (%)	U (%)	P (%)	U (%)	P (%)	U (%)
Woodland	92.2	94	95.9	94	96.1	98
Grassland	90.6	96	93.9	92	91.8	90
Barren land	97.8	90	92.3	96	94	94
Overall accuracy (%)	93		94		94	
Kappa coefficients	0.90		0.91		0.91	

U=user's accuracies, P=producer's accuracies

Furthermore, as stated by the elders and confirmed in the ground, continuous community based integrated watershed management interventions and restoration programs appear to make significant contributions to the enhancements of the watershed's vegetation cover. A restoration trend was also visible in the watershed's enclosed areas, which was caused by livestock and human interference is avoided. However, studies (e.g. Bufebo & Elias, 2021; Dingamo *et al.,* 2021; Tewabe & Fentahun, 2020; Warkineh & Hailemicael, 2021) showed that the major depletion trend was observed degradation of woodland and expansion of farmland/agriculture.

Accuracy assessment

To assess the classification's accuracy, the LULC map was put up against the reference data. As a result, overall classification accuracies scored were 93%, 94%, and 94%, for the classified Landsat imageries of 1994, 2008, and 2022, respectively (Table 6). The overall accuracy standard of 85% was first proposed by (Anderson, 1976), and it is currently acknowledged and used as a benchmark in map accuracy assessment. Our analysis's total accuracy rating is higher than the accepted threshold. The outcome indicated that there is a reasonable correspondence between the classified image and the reality it represents. For the years 1994, 2008, and 2022, respectively, a kappa coefficient result was found to be 0.90, 0.91, and 0.91. The Kappa coefficients revealed that the three classified images each indicated higher or good classification performance or strong agreement, with a Kappa value ranging from 0.40 to 0.85 (Anderson, 1976; Congalton, 1991; Congalton & Green, 2019; Elias *et al.,* 2019; Tewabe & Fentahun, 2020).

Rate of land use/land cover change

Our findings show that throughout the entire study period (1994–2022), the area of grassland and woodland rose while the area of barren land significantly decreased (Figure 4 and Table 7). In the initial period (1994–2008), the amount of woodland vegetation increased by 351.3 ha, or approximately 25.1 ha/year, whilst the amount of barren land decreased by -369.8 ha (-26.3 ha/year). The rate of growth of woodland was 45.9 ha (3.3 ha/year) between 2008 and 2022. In contrast, both the first and second periods saw a significant decrease in the barren land. Under this year (2008), area enclosures activities were widely practiced in the study area, (i.e. there is no degradation, woodland increment also not too much visible). Given that the area has been protected from human and animal interference, woodland was found to show the highest rate of change, increasing by 28.4 ha/year, followed by grassland at 1.4 ha/year.

Table 7: Rate of changes in land use/land cover classes (1994 to 2022)

LULC class	1994		2008		2022	
	Area (ha)	Change rate (ha year^{-1})	Area (ha)	Change rate (ha year^{-1})	Area (ha)	Change rate (ha year^{-1})
Woodland	351	+25.1	45.9	+3.3	397.2	+28.4
Grassland	16.6	+1.2	2.8	+0.2	19.4	+1.4
Barren Land	-369.8	-26.3	-48.5	-3.5	-416.5	-29.8

Note. "+" = increased, "-" = decreased the magnitude of particular land use/land cover type

During the entire period (1994-2022), the barren land class had the highest negative value (-416.5 ha/year). In general, the results verified a series of LULC rate changes in the study area over the past 28 years (1994-2022). The study indicates that woodland has grown significantly over the past 28 years as a result of the area enclosure restoration practices used. Consequently, areas that had before been barren had transformed to a larger extent into woodland and grassland. These findings are in agreement with the studies (e.g. Araya, 2014; Mekuria *et al.,* 2020; Tsegay & Meng, 2021) that depicted the area enclosure reverses land degradation into a productive landscape and increases vegetation cover.

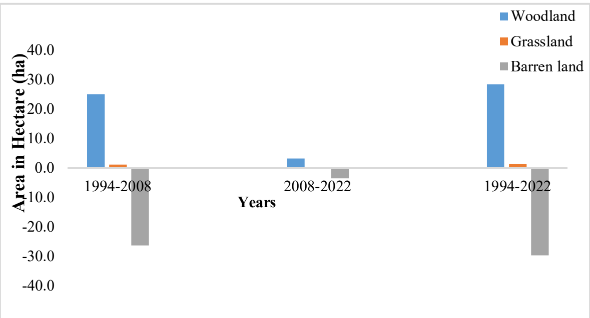

Figure 4: The extent and rate of change in the study area land use/land cover

From the result, grassland had been relatively high persistence value (426.9 ha) in the *Bilate* watershed from 1994 to 2022time period. Similar to how barren land displayed the highest values for losses of LULC classes and woods the highest values for gains, In addition, from 1994 to 2022, most of the additional woodland came from grassland and barren land (Table 8 and 5). This implies that the area within the watershed had the highest overall change. Besides, the barren land class was mainly replaced by grassland and woodland. Studies (e.g. Dessie & Christiansson, 2008; Shiferaw & Singh, 2011; Zewude *et al.,* 2022) said that many studies have been carried out in the highlands of the country's central and northern regions, where land degradation and deforestation were already a big concern many years ago.In contrast, these studies noted a rise in vegetation cover over the preceding three decades as a result of area enclosure restoration initiatives taking place in the studied area. Similarly, studies (e.g. Kasim *et al.,* 2015; Mohammed *et al.,* 2020; Tsegay & Meng, 2021) show that the vegetation cover was increased due to area enclosure restoration activities and community-managed forests. Therefore, based on this finding, it can be noted that human interventions are what ultimately decide how the LULC changes. Studies (e. g, Abera *et al.,* 2016; Urgesa *et al.,* 2016) stated that the conservation of biological diversity in protected areas was successful through the intervention of local communities through management activities. Our findings are in support of these studies.

Table 8: LULC gain, loss, and absolute net changes in ha for *Bilate* watershed (1994–2022)

LULC Class	Total		Persistence	Gain	Loss	Total change	Absolute net change
	1994	2022					
Woodland	419	816	377.3	438.8	41.6	480.4	397.2
Grassland	730	750	426.9	322.8	303.5	626.3	19.3
Barren land	883	466	406.4	59.9	476.5	536.4	416
Total	4026	4054	1210.6	821.5	821.6	1643.1	832.5

Persistence and vulnerability of land use/land cover dynamics

The ratio's magnitude always displays the gains to persistence ratio, loss to persistence ratio, and net change to persistence ratio (which tells how many times the LULC types gain/loss than its persistence) (Kasim *et al.,* 2015; Zewdie & Csaplovies, 2015). In this study, woodland classes have gain to persistence ratios (G/P) that are greater than one

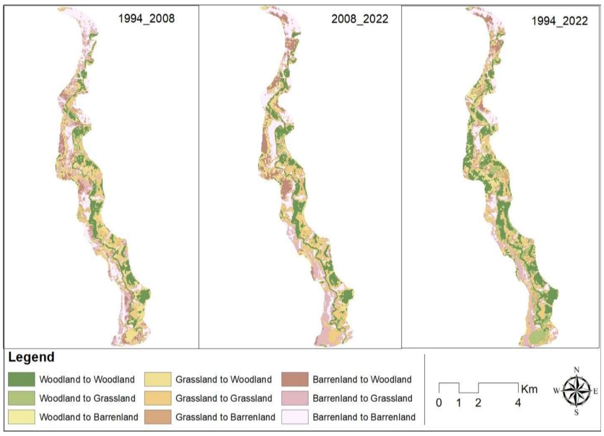

Figure 5: Map of changes in land use/land cover between 1994 and 2022

showing a tendency toward gain rather than loss. The loss to persistence (L/P) ratio of barren lands, on the other hand, is more than 1, showing that the LULC is vulnerable to changes in other land cover groups. This implies a higher restoration tendency of the watershed and increment of vegetation cover rather than degradation. Gain to persistence ratio and loss to the persistence of barren land is closer to zero value, indicating that the barren land class is insignificant compared to its persistence (Table 9).

Table 9: Gain to persistent (G/P), loss to persistent (L/P), and net change to persistent (N/P) ratio of land use/land cover classes in *Bilate* watershed (1994–2022)

LULC Class	Persistence (P)	Gain (G)	Loss (L)	G/P	L/P	N/P
Woodland	377.3 ha	438.8 ha	41.6 ha	1.2	0.1	1.05
Grassland	426.9 ha	322.8 ha	303.5 ha	0.8	0.7	0.05
Barren land	406.4 ha	59.9 ha	476.5 ha	0.1	1.2	-1.03
Total	1210.6 ha	821.5 ha	821.6 ha	2.1	2.0	0.07

When the gain to persistence ratio (G/P) is larger than one, the LULC has a higher chance of gaining than of persisting. Moreover, the LULC is vulnerable to changes in other land cover classes since the loss to persistence ratio (L/P) value is higher than one (Akubia *et al.,* 2020; Viana & Rocha, 2020). Also, grassland LULC classes have gain to persistence and loss to persistence values that are both lower than one, indicating that they are less vulnerable to both of these outcomes. The net change to persistence (N/P) is negative barren land, showing net loss compared to persistence. The loss of barren land may be related to restoration activities due to the increase of woodland and grassland in the study area. The net change to persistence (N/P) woodland area is significantly increased. Grassland also experienced a net increase in size, but it also showed a comparable loss in the same period. Similarly, studies (e.g. Birhane *et al.,* 2017; Mengistu *et al.,* 2005; Tesfay, 2018) stated that the area of the enclosure is currently a meaningful solution for the restoration of degraded lands.

Normalized difference vegetation index (NDVI)

In this study, it has been observed that the vegetation cover was more in 2008 and 2022 with maximum NDVI values of 0.42 and 0.63, respectively. This indicated that during the period of the study restoration activities were increased. The highest value shows high vegetation cover. Studies (e.g. Abebe *et al.,* 2014; Asmare & Gure, 2019; Yimer *et al.,* 2015) reported that area enclosure restoration activities promoted vegetation coverage and enhanced restoration processes and degraded lands were replaced by vegetation. However, the result of the NDVI value had 0.11 in 1994 which indicates that the area had lower vegetation covers during the first decade (Figure 6).

The area, which is placed in the northern, northwest, and northeast parts of the study area resulted in a higher NDVI value and the area is woodland area enclosure and grassland. This report is also in line with (Araya, 2014; Fikadu & Argaw, 2021) who reported that area enclosure was one of the reason factors for the increase of vegetation coverage and the NDVI value increment. However, barren land was placed in the southern part of the study area indicating relatively low NDVI values. (Eastman *et al.,* 2013; Ya'acob *et al.,* 2014) stated that the value of NDVI closed to zero indicates that the area is devoid of vegetation or barren land. According to the NDVI results from our study, there was a significant change in the amount of vegetation cover; the amount of high-moderate density vegetation cover increased by 40.2 %, while the amount of barren land decreased by 22.9 % from the entire area of the *Bilate* watershed.

Land use/land cover change drivers profile of the respondent

In the *Bilate* watershed, families ranged in size from 2 to 14 persons per household, or 5 people on average.

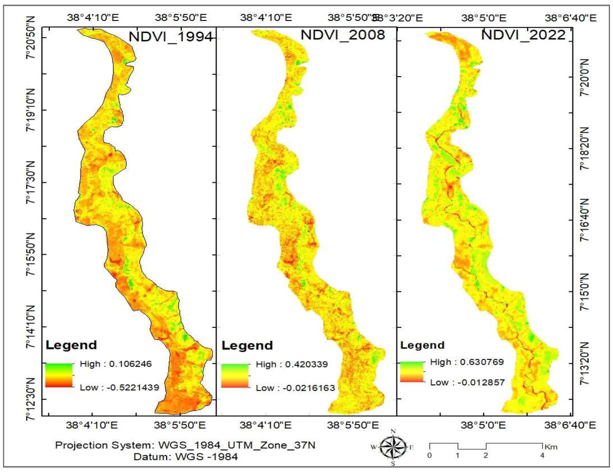

Figure 6: Normalized difference vegetation index maps of the study area (1994-2022)

The age range of the respondents was 18 to 69, with the majority falling between the ages of 41 and 69 (70%). Almost participants were married. According to their gender distribution, 69% of respondents were men and 31% were women. The respondents represent 14 % of the sampled households who were formally educated and 76% of the sampled households' non-educated members. This represented a serious limitation to the transfer of technology and emphasized the value of perhaps inadequate education. The majority of the studied household members, three fourth were involved in livestock and mixed crop production. Only a small percentage of the respondents, however, said they were only engaged in farming and related occupations besides raising their income. This confirmed earlier findings from various regions of Ethiopia and showed that crop and livestock output accounted for more than half of total household income(Asresie *et al.,* 2015; Taffesse *et al.,* 2012).

Perception of local community towards land use/land cover change drivers

The majority of respondents (n=354: 92.19%) indicated that the study area's current vegetation cover is denser than it was at the start of the previous three decades. This implies that respondents generally had a positive perception of the study area's historical land cover pattern. The community is resistant to adapting technologies since 76% of the respondents did not have a formal education, as a result, the local community's influence on the vegetation cover finally leads to a change in LULC. This result is also in line with the LULC change observed in the remote sensing data interpretation. Similarly, studies (e.g. (Asmare & Gure, 2019; Gebregziabher & Soltani, 2019; Kassaye Mekonen *et al.,* 2022) indicated that people's perceptions about area enclosure play an important role in landscape features and land use/land cover dynamics.Our findings also revealed that the insight of respondents on drivers of land use/land cover change showed a significant association with sources of income (x^2=19.21, df = 2, P < 0.001), educational level (x^2= 12.01, df = 2, P < 0.01), and gender (x^2=15.11, df = 1, P < 0.001). While the distance from the area enclosure or watershed and family sizes were independent or there is not associated with the existing drivers of land use/land cover change in the community. Studies (e.g. Ali, 2009; Gebrehiwot *et al.,* 2021; Warkineh & Hailemicael, 2021) also revealed a relationship between the number of families, distance from the protected area, and the land holding size of respondents was not significantly influenced by the perception of respondents on the drivers of LULC change.

Drivers of LULC change in *Bilate* watershed

The FGD participants and key informants in the study area engaged in a series of discussions and interviews, and the results showed that the management system of the area enclosures in the watershed is the primary cause of LULCC. The management strategy and system worked well; they conserved or protected the increase of agricultural investment, illegal fuel wood cutting and extraction, illegal stone extraction, overgrazing, and expansion of illegal and unplanned settlements. Hence the LULC change is driven by the expansion of agriculture investment, illegal logging and fuel wood extraction, illegal stone extraction, overgrazing, and expansion of illegal and unplanned settlements (Figures 7) (i.e. However, these driving forces are not significantly processed in Remote sensing imagery, but from local community perspective these factors were affected the area enclosure, and on the future, it will be expanded, e.g. recently some part of area enclosure was transferred to the local agricultural investor yet, theses induce factor are not processed by remote sensing but the problem exists now a day). Studies (e.g. Kindu *et al.,* 2015; Sewnet, 2015; Zewude *et al.,* 2022) show that the management approach and strategy were significantly important for the improved and sustained protected areas. Moreover, (Melese, 2016; Minale, 2013) stated that the discussion and interviews with focus groups discussion and key informants indicated that the expansion of illegal firewood extraction and the expansion of illegal and unplanned settlements were the major drivers of LULC change in natural vegetation. On the other hand, other studies (e.g. Elias *et al.,* 2019; Gebreselassie *et al.,* 2016) reported that population increase, poverty, and food insecurity were the main forces for LULC change throughout time. Such illegal cuttings have also happened as a result of t rapid human population demand for large amounts of wood for construction. Anthropogenic pressure is cited as the primary source of vegetation changes (Alemu *et al.,* 2015; Elias *et al.,* 2019; Tesfaye *et al.,* 2014). (e. g. illegal cutting and fuelwood extraction). Overgrazing by cattle inside the enclosure may result in the trampling and browsing of seedlings and saplings of some plant species, as well as damaging the vegetation cover. Similarly, studies (e.g. Feyisa *et al.,* 2017; Melese, 2016) stated that the main reason for the vegetation change in this central Ethiopian Rift valley is due to agricultural activities. According to the field observation, most of the farmlands were located near *Bilate* watershed

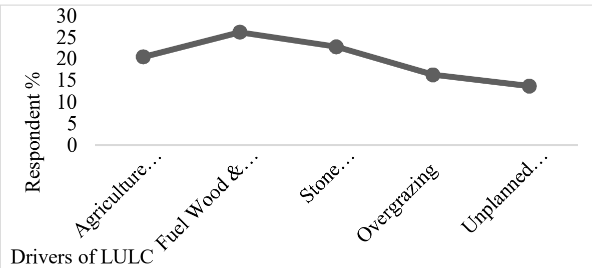

Figure 7: Drivers of LULC changed from 1994 to 2010 in *Bilate* watersheds

which allowed the owner of the farm to gain access to the nearby area enclosure. Previous studies (e.g. Othow *et al.,* 2017; Rahmato, 2011; Zewude *et al.,* 2022) also indicated that the investors are leasing is situated close to national parks, woods, and other protected areas. According to the findings of survey interviews and focus groups, the fragmentation of forests and the establishment of unauthorized settlements inside of area enclosures by the local population are the other two primary proximal causes of vegetation degradation in the Bilate watershed.

Conclusion

LULC affiliated with human demand increases land degradation thereby affecting the ecological functions of the ecosystems. The ecological and socioeconomic conditions were impacted by the LULC changes that were seen in the research area. Here, the LULC analysis showed that before the area enclosure was put into place, there had been significant land degradation. However, the final LULC change maps showed a progressive change in vegetation cover between the study periods. As Enclosures in the study area were not fully protected, some factors were still driving LULC change. The results of FGDs, KIIs, and field observations showed that LULC changes and socioeconomic dynamics have a strong relationship; as the population increases, there is an increased need for agricultural land, grazing land, fuel wood, and settlement areas to meet the growing demand for food and energy, as well as an increased population of livestock. Based on our findings the following recommendations are forwarded:

- Establishing and implementing Community-based area enclosure restoration activities in the watershed.
- Supporting local initiatives, such as alternative income and off-farm economic activity that aim to boost household income in the local community.
- Encourage the adoption of modern stoves for effective energy utilization.
- Implementing effective enforcement of forest laws, policies, and awareness raising campaigns.

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Conflict of interest

The authors declare that they have no conflict of interest.

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