# Heliyon 10 (2024) e28378

Contents lists available at ScienceDirect

# Heliyon



journal homepage: www.cell.com/heliyon

# Research article

5<sup>2</sup>CelPress

# Analysis of land use/ land cover changes and landscape fragmentation in the Baro-Akobo Basin, Southwestern Ethiopia

Kassahun Mulatu <sup>a, b, \*</sup>, Kitesa Hundera <sup>c</sup>, Feyera Senbeta <sup>d</sup>

<sup>a</sup> Department of Natural Resource Management, College Agriculture and Natural Resource, Mizan-Tepi University, Mizan Teferi, Ethiopia

<sup>b</sup> Department of Natural Resource Management, College Agriculture and Veterinary Medicine, Jimma University, Jimma, Ethiopia

<sup>c</sup> Department of Biology, College of Natural Science, Jimma University, Jimma, Ethiopia

<sup>d</sup> Center for Environment and Development, College of Development Studies, Addis Ababa University, Addis Ababa, Ethiopia

#### ARTICLE INFO

Keywords: Agroecological zones Fragmentation Land use/land cover Landscape metrics Satellite images

#### ABSTRACT

This study investigated the relationship between land use/land cover (LULC) changes and forested landscape fragmentation in the southwestern region of Ethiopia. Satellite images from 1986, 2002 and 2019 were collected and analyzed using standard procedures in ERDAS 2015 software. Fragstat 4.2.1 software was utilized to assess landscape fragmentation by examining a raster datasets derived from the classified LULC map over the research period. The study identified seven LULC classes in the study area. Findings revealed a substantial reduction in shrubland by 46.3%, dense forest by 23.75%, open forest by 17.3%, and wetland by 32.63%, while cropland increased by 38.06%, agroforestry by 20.29%, and settlements by 163.8% during the study period. These changes varied across different agroecological zones and slope gradients. Landscape metrics results indicated an increase in the number of patches and patch density for all LULC classes, demonstrating significant fragmentation of the landscape. The largest patch index, mean patch areas, and the percentage of landscape occupied by open forest, dense forest, shrubland, and wetland declined as a result of conversion to cropland, agroforestry, and settlement, Conversely, the largest patch index, the mean patch area and the percentage of the landscape occupied by agroforestry, cropland and settlement increased, indicating their increasing dominance in the landscape over the study periods. The findings highlighted the potential deleterious impacts of ongoing land use change and fragmentation on the environment, ecosystem function and local livelihoods. Therefore, it is crucial to implement appropriate conservation efforts and sustainable land management practices to mitigate the rapid change and fragmentation of land use and its negative impacts on sub-watershed ecosystems.

# 1. Introduction

Human activities have greatly influenced the way land has been used and covered over centuries, resulting in significant changes in land use/land cover (LULC) [1]. These human-caused impacts have affected critical ecological processes in the Earths system [2]. In the recent decades, there has been a sharp increase in LULC change in Africa, mainly due to rapid population growth and the associated overexploitation of natural resources [3].

https://doi.org/10.1016/j.heliyon.2024.e28378

Received 28 December 2023; Received in revised form 15 March 2024; Accepted 18 March 2024

Available online 20 March 2024

<sup>\*</sup> Corresponding author. Department of Natural Resource Management, College Agriculture and Natural Resource, Mizan-Tepi University, Mizan Teferi, Ethiopia.

E-mail address: kassahunmmulatu1972@gmail.com (K. Mulatu).

<sup>2405-8440/© 2024</sup> Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

A significant phase of LULC change has occurred in East African over the last 6000 years due to the emergence of new subsistence agriculture and technologies [4]. Like other parts of East African countries, Ethiopia experienced major LULC changes between 2000 and 3000 years ago, mainly related to the historical development of agriculture and human settlement [5]. Recent studies in the country have revealed that LULC change have increased and become more visible in recent decades [3,6–11]. Most of these studies have found that expansion of agriculture contributed significantly to the loss of natural habitats in many areas of the country [7, 12–14]. Thus, the conversion and loss of natural habitats have greatly influenced the spatial and temporal configuration of a landscape [6,15,16], the availability of ecosystem services, and the resilience of the regional ecosystem and livelihoods to climate change [17].

According to Refs. [17,18], studying LULC changes and associated landscape fragmentation is expected to improve our understanding of spatial and temporal dynamics, the magnitude and tendency of changes in a natural ecosystem and associated functions at different scales predicts and support science-information-based landscape management activities. Remote sensing data and geographic information systems have recently been widely used to analyze the evolution of LULC [10,17,19,20]. However, they are not sufficient to measure and describe changes in the composition and configuration of a landscape [20,21]. At the landscape level, landscape measurements combined with remote sensing data and geographic information systems are valuable for describing LULC variations and landscape patterns [6,16,17,22]. Although such results are crucial for planning long-term landscape management in Ethiopia, little attention has been paid to measuring and describing spatial and temporal pattern changes in the landscape [7,8], as well as changes in relation to topographic gradient [23–25].

The forest ecosystem in the southwestern part of Ethiopia is the center of origin of *Coffee arabica* L. and a source of diverse ecosystem goods and services [26,27]. The ecosystem also supports four of the seven major vegetation types in Ethiopia [28]. Due to anthropogenic factors, this region has recently experienced massive degradation, fragmentation and loss of forest [27,29–31]. The fragmented forest areas in the research areas are nevertheless an important ecosystem for watershed protection and biodiversity conservation in Baro-Akobo Basin. Nevertheless, little attention has been paid to the impacts of ongoing LULC change and its impacts on landscape dynamics, biodiversity and ecosystem services. Therefore, obtaining integrated data on LULC changes and landscape fragmentation in the research area is crucial for environmental protection and maintaining ecosystem service. Such studies are crucial in areas where biodiversity and ecological services are increasingly threatened [32]. This study examined LULC change in 1986, 2002 and 2019, examined its distribution and change along elevation and slope gradients, and quantified landscape metrics to track change in landscape pattern over time and space in the Bakro-Akobo sub-basin, in southwestern Ethiopia.



Fig. 1. Map of the study area.

### 2. Materials and method

#### 2.1. Description of the study area

This research was conducted in the Baro-Akobo Basin in the Bench-Sheko Zone in southwestern Ethiopia. The area is defined by latitudes from  $6^{\circ}44'24''$ N to  $7^{\circ}12'18''$ N and longitudes from  $35^{\circ}32'1''$ E to  $35^{\circ}53'2''$ E (Fig. 1). The study area is characterized by undulating landscape features containing the largest forest fragments in the country. The forest is part of the moist evergreen Afromontane forest [33]. The altitude varies between 1144 and 2696 m. a.s.l. The annual average precipitation and reference evapotranspiration are 1780 ( $\pm 270$ ) mm per and 1259 ( $\pm 12$ ) mm per year respectively [34]. The average air temperature varies between 13 and 27 °C [35]. The predominant soil type in the study is characterized by leptosols, nitisols, and fluvisols on ridges, hill slopes and flat valley floors [36]. The study area was predominantly inhabited by Bench peoples. The population of the study area was 276,732 (48.2% male and 51.8% female) in 2017, of which 92% were rural dwellers [37]. The community practices rain-fed farming and livestock farming as its main sources of their livelihoods. Coffee, korarima (Aframomum corrorima Braun), other cereal crops, and livestock sales are the main sources of income.

# 2.2. Sources of data

To examine how land use/land covers (LULC) dynamics of have changed over the past 33 years (1986–2019), a study employed a comprehensive approach. This approach involved combining remote sensing imagery, digital elevation model (DEM), topographic maps (at 1:50,000 scale) and additional datasets such as GPS records and Google Earth maps. Landsat TM (Thematic Mapper) images from 1986, Landsat ETM+ (Enhanced Thematic Mapper Plus) images from 2002 and Landsat OLI/TIRS (Operational Land Imager/ Thermal Infrared Sensor) images from 2019 were obtained free of charge from the United States Geological Survey (USGS) at http://glovis.usgs.gov (Table 1). All satellite images were taken in the same season (December and January) to avoid the effect of seasonal variations and were virtually cloud-free. The date of the images was selected based on important events such as the resettlement program in the region organized by the government of Ethiopian, changes in government policies and the availability of high quality images.

# 2.3. Image preprocessing and classification approaches

In this study, ERDAS Imagine 2015 software packages were used to perform standard image processing techniques and image classification, while ArcGIS 10.4.1 was used to delineate the study area, collect raster datasets for fragmentation analysis, and map preparation. The satellite images underwent geometric correction to align with the Universal Transfer Mercator coordinate system and were georeferenced using the World Geodetic System (Zone 84), based on data specifically selected by Ethiopia. In addition, various image preprocessing techniques such as mosaicking, sub-setting based on area of interest (AOI), and radiometric enhancement (histogram equalization, haze reduction, and atmospheric correction) were applied to the raw data to improve the quality of the image before classification.

To categorize LULC types, the training site data was randomly distributed and used to identify training pixels for each LULC class. For current images, the training sites were determined using GPS readings, supported by high-resolution Google Earth images. For older historical images, training sites were determined through visual interpretation of raw images, information from local elders, and local knowledge from researchers, just like the techniques used by Refs. [38,39].

To support the LULC classification and identify the nature of change dynamics, focus group discussions, key informant interviews and field observations were conducted. A total of 20 key informants were recruited and interviewed based solely on their experience, expertise, and understanding of past and historical LULC changes. In addition, four intensive focused group discussions were held with 11–12 key informants (age >50 years) and a total of 47 elder farmers. They were selected for their proximity to a forest and had lived in a community for at least 35 years to ensure they had extensive knowledge of the area's natural environment during the study period. Field observations were conducted with key informants to gather data on the physical characteristics, uses, and conditions of the land under study, identify different land cover types and confirm the accuracy of the LULC classification.

Supervised classification was performed by applying Maximum Likelihood Classifier (MLC) for image classification. The maximum likelihood algorithm assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a given class, categorizing each pixel into the class with the highest probability (Arc GIS 10.4 Desktop Help). This technique assumes that the minority classes in the image have the opportunity to be included in their respective spectral classes, thereby minimizing the problem of unclassified pixels entering another class during classification [40]. The seven LULC categories that were discovered, ground truth validated and reported were (1) cropland, (2) agroforestry, (3) wetland, (4) settlement, (5) open forest,

Table 1		
Summary of Landsat images for land us	se/land cover	change study.

Year	Acquisition date	Sensor	Resolution	Number of bands	Path/Row
1986	1986/01/19	TM	$\begin{array}{c} 30 \times 30 \\ 30 \times 30 \\ 30 \times 30 \end{array}$	1,2,3,4&5	170/055
2002	2002/12/09	ETM+		1,2,3,4,5 &7	170/055
2019	2019/01/14	OLI/TIRS		1,2,3,4,5 &7	170/055

(6) dense forest, and (7) shrubland (Table 2).

# 2.4. LULC change detection

The changes in hectares for different LULC classes were calculated and analyzed for each specified period. The percentage of LULC change (trend) for individual LULC classes was calculated using the following formula [23].

Percentage of LULC change = 
$$\frac{(A_2 - A_1)}{A_1} \times 100$$

Where:  $A_1$  and  $A_2$  area of LULC type in the initial year and final year respectively.

The rate of individual LULC change per year was calculated by dividing the percentage of LULC change by the time interval, i.e., 2002–1986 (16 years), 2019–2002 (17 years), and 2019–1986 (33 years), as follows:

Annual rate of change(%) = 
$$\frac{(A_2 - A_1)}{A_1(t_2 - t_1)} \times 100$$

Where: time t<sub>1</sub> and t<sub>2</sub> are initial and final time.

A thematic change detection method was used to determine "from-to." information about which land use classes changed during the study period (1986–2019). A LULC transition matrix, constructed in the form of an area chart with columns for "initial state" classes and rows for "final state" classes, defined the type of LULC class transition (ha).

To evaluate prominent signals of landscape dynamics, change matrices were constructed for the transitions from 1986 to 2019. The areas of gain, loss, persistence, loss to persistence ratio (LP = loss/persistence), gain to persistence ratio (GP = gain/persistence), and net change (gain–loss) to persistence ratio (NP = net change/persistence) between LULC types was estimated using the methods described by Ref. [42]. Persistence is the LULC class that does not change between the start and end times of the change detection period.

A 30 m resolution digital elevation model (DEM) created from Aster an image was also used to examine LULC variation in response to topographic gradient (elevation and slope). This is because slope and elevation gradients are essential elements in defining resource gradients and climate complexity in relation to human contact [43] and thus influence the distribution and variation of LULC [44,45] and land management activities. Using ArcGIS 10.4.1, slope and elevation were calculated from a DEM and then reclassified into six and three classes, respectively. Slope was defined as  $0-5^{0}$ ,  $6-10^{0}$ ,  $11-20^{0}$ ,  $21-30^{0}$ ,  $31-40^{0}$ , and  $>41^{0}$ , while the elevation was classified as 500–1500 m (lowland), 1500–2300 m (midlands), and 2300–3200 m (highlands) according to agro-ecological categorization of the Ministry of Agriculture (MoA) [46]. Finally, thematic information illustrating the relationship between the LULC distribution and the changes in each elevation and slope class was collected using ArcGIS by overlaying the map of each LULC class in each study period (1986, 2002, and 2019) on a slope and elevation map.

#### 2.5. Accuracy assessment

The accuracy of the classified images was evaluated using random ground truth data from the field, original Landsat images, and a Google Earth map for each LULC class. Based on the specified minimum samples for categorizing images with LULC classes less than 12 [47,48], a total of 50–75 ground truth data were collected. During image classification accuracy, the training location data used for image classification was removed. An error matrix was used to assess the classification accuracy. The error matrix is a widely used approach to quantify classification accuracy and helps to calculate overall accuracy, kappa statistics, user accuracy and producer accuracy [47]. The overall accuracy, kappa coefficient, user's accuracy, and producer's accuracy were calculated using the approaches provided by Refs. [47,48].

# 2.6. Analysis of landscape fragmentation

Landscape fragmentation was examined using the spatial statistical tool FRAGSTATS (version 4.2.1), which calculated landscape metrics. FRAGSTATS provides landscape metrics with its diverse options [49,50]. Landscape measurements in FRAGSTATS are a good way to track changes in landscape patterns over time in relation to anthropogenic and natural variables [51,52]. The raster datasets

Table 2

Descriptions of identified land use/land cover classes.

Land use land class	Description
Agroforestry	Lands covered by plantation coffee and spices, woodlots and fruit trees grown within the homestead.
Crop land	Lands that are mainly designated for production of seasonal crops.
Dense forest	Land dominated by trees canopy density of greater than 40% [41].
Shrub land	Land cover dominated by bushes, shrubs and forest lands with canopy density less than 10% [41].
Settlement	An area where there are permanent inhabitants, man-made structures and activities, such as towns and roads.
Open forest	Land with tree cover of canopy density of 10% and more but less than 40% [41].
Wetlands	Includes areas that are waterlogged, marshy and swampy both in wet and dry seasons [40].

collected using ArcGIS 10.4.1 from LULC classes from three research periods (1986, 2002, and 2019) were used as input data sources for fragmentation analysis.

Among the various landscape metrics used to quantify different landscape aspects, those metrics that can capture the relevant characteristics of a landscape feature were selected to avoid duplication of information and increase the value of the landscape metrics for the aspect of the landscape being analyzed [53–55]. Class-level metrics were used in this study because they measure the abundance, spatial distribution, and pattern of a particular LULC class in the landscape [56–58]. Among them, largest patch index, number of patches, mean patch area, edge density, area-weighted mean shape index, mean Euclidean nearest neighbor distance, interspersion and juxtaposition, aggregation index and patch density were used from previous studies [57,58] (Table 3).

# 3. Results and discussion

#### 3.1. LULC change analysis

#### 3.1.1. Image classification accuracy

The analysis of LULC showed that the overall accuracy of the classified map was 87.69% in 1986, 88.13% in 2002, and 92.14% in 2019, with corresponding Kappa statistics of 0.86, 0.86, and 0.91, respectively (Table 4). The producer's accuracy, which measures the accuracy of correctly identifying specific land cover classes, ranged from 77.94% to 94.92% across all study periods. The lowest producer's accuracy was observed in agroforestry in 1986, while the highest was observed in settlement and agroforestry in 2019. Similarly, the user's accuracy, which measures the accuracy of correctly identifying a particular land cover class from the classification map, ranged from 79.63% to 95%. The lowest and highest values were associated with open forest and shrubland, respectively. The producer's accuracy results showed that settlement, wetland and dense forest were correctly classified in 1986, while dense forest and cropland were correctly classified in 2002. In 2019, all LULC classes except cropland and open forest were correctly classified. In 1986, agroforestry had a producer's accuracy of 77.94%, while open forest had a producer's accuracy of 79.63% in 2002. This lower accuracy may be due to confusion in land cover classes during image processing as well as spatial and spectral resolution limitations [23,58,59]. However, the overall accuracy of the LULC maps exceeded the minimum threshold of 80% for reliable land cover classification [60–62]. The kappa statistics showed strong agreement between the classified map and the ground truth data, suggesting that the identified LULC classes accurately reflect the actual land cover on the ground [48]. Similar studies conducted in Ethiopia also reported high classification accuracies (>85%) [11,63].

#### 3.1.2. LULC change detection

The results from Table 5 and Fig. 2 indicate a significant change in the study landscape between 1986 and 2019. In 1986, agroforestry occupied the largest share of the area surveyed at 27.63%, while open forests, dense forests and cropland accounted for 21%, 20%, and 16.7%, respectively. Wetlands and settlements accounted for only 6.31% and 1.12%, respectively. In 2002, cropland was found to be the predominant land use type covering 34.04% of the surveyed landscape, followed by agroforestry with 21.05%, open forest with 18%, and dense forests with 15.84%. Wetlands, shrubland, and settlements had the lowest proportions in the study area. In 2019, agroforestry became the dominant land use at 33.24%, followed by cropland at 23.03%. Wetlands, shrublands, and settlements made up a relatively small proportion of the study area.

The results from Table 6 show that the analysis of LULC change between 1986 and 2002 showed notable declines in shrubland, agroforestry, wetland and dense forest. In return, there was a significant increase in cropland and settlement. Specifically, there was decline of 39.06% shrubland 23.82% agroforestry, 22.36% and 20.96% dense forest. Meanwhile, cropland recorded a growth of 104%, and settlement increased by 59.52% during the same period.

In the first study period there was a noticeable decrease in forest and wetland size, while the area used for agriculture increased. This was in contrast to the second study period. Information from reliable sources (key informants) reported that the Derg regime (1974–1991) initiated a large-scale settlement program between 1985 and 1988 in response to a drought in the northern region of Ethiopia. This program had a major impact on forest cover and various ecosystems as it involved converting dense natural forests into

# Table 3

Class level metrics used to measure fragmentation.

Landscape metric	Description
Percentage of landscape (%PLAND)	Proportion of the landscape occupied by certain land use/land cover class
Number of patches (NP)	Number of patches in the landscape of the same land use/land cover class
Largest patch index (LPI)	Percentage of the landscape comprised by the largest patch of the corresponding land use/land cover class
Edge density (ED)	Total length of edge of a certain land use/land cover class per unit area (m/ha).
Mean patch area (AREA_MN)	Mean area of patches of the same land use/land cover class $(m^2)$
Area-weighted mean shape index	It measures the complexity of patch shape of a particular land use/land cover class compared to a standard shape
(SHAPE_AM)	(square), by weighting patches according to their size.
Mean Euclidean nearest neighbor	Mean of minimum edge to edge distances to the nearest neighboring patch of the same type of a certain land use/
distance (ENN_MN)	land cover class (m)
Interspersion and juxtaposition index	Degree of interspersion of patches of this class, with all other classes
(IJI)	
Aggregation index (AI)	Percentage of neighboring pixel of the same land use/land cover class, based on single count method
Patch density (PD)	Number of patches per unit area (per 100 ha)

#### Table 4

Accuracy and kappa statistics for classified map of study area (1986-2019).

LULC class	1986	1986		2002		2019	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	
Shrub land	84.91	90.00	89.09	92.45	93.44	95.00	
Wetland	90.38	92.16	90.0	98.18	91.67	91.67	
Settlement	94.64	92.98	88.89	92.31	94.92	93.33	
Open forest	82.76	82.76	82.69	79.63	89.66	86.67	
Agroforestry	77.94	88.33	85.45	87.04	94.92	93.33	
Dense forest	98.08	85.0	91.84	86.54	93.33	93.33	
Crop land	88.14	83.87	92.31	81.36	87.30	91.67	
OA	87.69		88.13		92.14		
Kappa Statistics	0.86		0.86		0.91		

PA = producer's accuracy, UA = user's accuracy OA= Overall Accuracy.

Table	5
-------	---

Land use/land cover class and their respective area in during study periods (1986-2019).

	1986		2002		2019	
LULC class	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Settlement	1072.62	1.12	1711.07	1.79	2829.78	2.96
Wetland	6038.91	6.31	4688.55	4.9	4068.53	4.25
Shrub land	6920.37	7.24	4217.22	4.41	3718.60	3.89
Cropland	15,958.20	16.68	32,551.70	34.03	22,031.46	23.03
Dense forest	19,170.90	20.04	15,153.20	15.84	14,618.20	15.28
Open forest	20,058.20	20.97	17,192.90	17.98	16,590.90	17.35
Agroforestry	26,429.00	27.63	20,133.50	21.05	31,790.70	33.24
Total	95,648.20	100	95,648.2	100	95,648.2	100

agricultural and residential areas. A recent study by Ref. [64] found that these settlement programs had significant impacts on vegetation cover and conservation efforts. They found that several factors associated with these programs, such as population growth, expansion of farmland and settlements, deforestation, wildfires, unsustainable practices and poor management contributed to changes in vegetation cover [Fig. 2 near here.].

In the second period (2002–2019), all LULC declined except for settlements and agroforestry. Over the past three decades, LULC type of agroforestry has increased significantly, which can play a positive role in conserving biodiversity and mitigating climate change. According to key informants and the focus group, forest areas and croplands were converted into agroforestry land uses such as coffee (Coffee arabica L), korarima (Aframonum corrorima), khat (Catha edulis), bananas and eucalyptus trees. There has been a degradation of cropland, particularly due to increasing soil acidification and loss of soil fertility, as well as the increasing economic benefits of agroforestry-based agricultural products. Expanding agroforestry in such deforestation-prone areas yields brings numerous benefits such as curbing deforestation, protecting soil, protecting biodiversity and improving soil health. In addition, it provides economic benefits to local communities while promoting forest and species conservation. Studies supported this finding that agroforestry showed increasing trends in some parts of the central highlands and southern region of Ethiopia due to its high economic benefits and the drive to diversify and sustain production for better social, economic and environmental benefits [65,66].

This study showed that the natural environments of the study area, such as dense forests, open forests, shrublands and wetlands, continuously decreased during the study periods and lost their coverage by 23.75%, 17.29, 46.27%, and 32.63, respectively, during the study period. The natural forest cover decreased by 24.3%, which corresponds to deforestation 340 ha year. Recent studies [9,10,13, 40,44,67–70] supported this finding that significant forest areas were converted to other LULC classes. The current study found that settlement has increased by more than twofold in the last 33 years, indicating rapid population growth and infrastructural development in the study area. This finding was supported by the reported annual population growth rate in the SNNPR state, which increased by 2.9% with 90% of people living in rural areas [71]. This increase in population would increase the demand for agricultural land, biomass energy and wood for house construction, which directly impacts forests [20,72]. As reported by Refs. [73,74], the rural population in Ethiopia relies heavily on biomass energy from forests due to the lack of sustainable energy sources.

# 3.1.3. LULC transition

The LULC transition matrix shows significant transitions between the seven LULC classes (Table 7) during the study periods. During the study period, approximately 50.43% of the entire landscape experienced varying degrees of transition between LULC classes. There was a significant decline in shrubland, open forest and cropland cover during this period, largely due to conversion to other land uses. Specifically, 88.06%, 62.5%, and 44.2% of the shrubland, open forest, and dense forests were converted into different LULC types (Table 8). Agricultural land, including agroforestry and cropland, acquired 70%, 48%, and 31% of its area, respectively, from the area originally covered by open forest, shrub land and dense forest in 1986. In 2019, shrubland gained the most (77.51%), followed by cropland (67.95%), settlements (66.52%) and open forest (54.67%). Dense forests and wetlands, on the other hand, recorded the smallest gains at 24.52% and 3.12% respectively. Compared to other LULC classes, areas dominated by human activities such as



Fig. 2. Land use/land cover map of the study area in 1986, 2002 and 2019.

Table 6	
Land use/land cover changes result depicting percentage change and annual rate of change for the stud	ly periods (1986–2019)

	Cover change (%	b)		Rate of change gain(+)/loss(-)/year			
LULC	2002–1986	2019-2002	2019–1986	2002–1986	2019–2002	2019–1986	
Settlement	+59.52	+65.38	+163.82	+3.72	+3.85	+4.96	
Wetland	-22.36	-13.22	-32.63	-1.4	-0.78	-0.99	
Shrub land	-39.06	-11.82	-46.27	-2.44	-0.7	-1.4	
Cropland	+103.98	-32.32	+38.06	+6.5	-1.9	+1.15	
Dense forest	-20.96	-3.53	-23.75	-1.31	-0.21	-0.72	
Open forest	-14.28	-3.5	-17.29	-0.89	-0.21	-0.52	
Agroforestry	-23.82	+57.9	+20.29	-1.49	+3.41	+0.61	

agroforestry, cropland, and settlement experienced the greatest growth. Approximately 45.4% of settlement, 53.6% of cropland and 53.7% of agroforestry area in 2019 came from natural systems such as dense forest, open forest, shrubland and wetlands.

The study found that croplands, open forests and shrublands had a loss-to-persistence ratio (LP) greater than one, indicating a higher probability of transition to other LULC classes rather than remaining stable [44,45]. The gain-to-persistence ratio (GP) for cropland, open forest, settlement and shrubland was also greater than one, showing a stronger tendency for these LULC types to increase rather than persist in their current state. Shrubland, settlement and cropland had high NP values, suggesting that they are less persistent LULC classes throughout the LULC matrix. Shrubland, dense forest and open forest had negative NP values, indicating higher loss compared to their persistence. The negative NP values for these LULC types further suggest that their coverage decreased over time, with the loss greater than the gain [75,76].

#### Table 7

Tomal	waa /lamd	00	tuomoitiom	ma a turine	of otraday	londoom	a batawa am	1006	1 2010
Lano	use/iand	cover	transmon	mairix	OF STUDY	Tanuscabe	- perween	1980 at	ICI 2019.

	LULC (ha) in 1986							2019 Total
LULC (ha) in 2019	Agroforestry	Cropland	Dense forest	Open forest	Settlement	Shrub land	Wetland	
Agroforestry	16,081.31	7174.53	1033.89	4968.88	105.02	1610.11	816.96	31,790.70
Cropland	6930.88	7060.43	1505.06	3779.82	20.05	1704.59	1030.63	22,031.46
Dense forest	577.19	110.75	11,034.50	2777.75	0	118.01	0	14,618.20
Open forest	1150.85	847.74	4805.59	7521.32	0	2264.70	0.7	16,590.90
Settlement	702.61	325.94	78.42	207.55	947.55	349.58	218.13	2829.78
Shrub land	961.14	402.49	702.7	795.38	0	826.19	30.7	3718.60
Wetland	25.02	36.32	10.74	7.5	0	47.16	3941.79	4068.53
1985 Total	26,429.00	5958.20	19,170.90	20,058.20	1072.62	6920.34	6038.91	95,648.17

Bolded number along diagonal shows LULC class remains unaltered (persistence) between 1986 and 2019.

# Table 8

Persistence characteristics of d	different land use/land	cover between 1986 and	2019
----------------------------------	-------------------------	------------------------	------

Land cover	1986 Total	2019 Total	Persistence (%)	Gain %	Loss %	Absolute value of net change (%)	Total change (ha)	GP	LP	NP
AF	26,429.00	31,790.70	60.85	49.42	39.15	10.27	26,057.08	0.98	0.64	0.34
CL	15,958.20	22,031.46	44.24	67.95	55.76	12.19	23,868.80	2.12	1.26	0.86
DF	19,170.90	14,618.20	57.56	24.52	42.44	17.92	11,720.10	0.32	0.74	-0.42
OP	20,058.20	16,590.90	37.5	54.67	62.5	7.83	21,606.46	1.21	1.67	-0.46
Stl	1072.62	2829.78	88.34	66.52	11.66	54.86	2007.30	1.99	0.13	1.86
SL	6920.37	3718.60	11.94	77.51	88.06	10.55	8976.38	3.5	7.38	-3.88
WL	6038.91	4068.53	65.27	3.12	34.56	31.44	2213.86	0.03	0.53	-0.5

AF = agroforestry, DF = Dense forest, SL = shrub land, CL = crop land, OF = open forest, Stl = settlement, WL = wetland, GP = Gain-to-persistence ratio, LP = loss-to-persistence ratio, NP = Net persistence ratio.

#### 3.2. Distribution and change in LULC across agro-ecology

The distribution of LULC in the agro-ecological zones (AEZ) shown in Fig. 3 was highly variable. Agroforestry, open forest and cropland mainly populated the lowlands (500–1500 m) and the midlands (1500–2300 m). However, dense forest dominated in the highlands (2300–3200 m) in all study periods (1986, 2002 and 2019). This suggests that the conversion of forest areas to agricultural land, particularly agroforestry and cropland, was more widespread in the lowlands and midlands. This observation suggests that these areas were well suited for agricultural activities and human settlements. In 1986, agroforestry covered most of the lowlands (51%), followed by open forests (30%) and croplands (12.7%). Likewise, in 2002, the predominant LULC types were open forest (32.8%), agroforestry (29.2%) and cropland (28.52%). Notably, cropland more than doubled during this period, suggesting the conversion of other LULC types into agricultural land. As of 2019, agroforestry, open forest and cropland remained the predominant LULC types.

In 1986, highland areas contained most of the dense forest, occupying 95.5% of the land. However, there was a gradual decline in the subsequent years as the distribution decreased to 93.43% in 2002 and further decreased to 89.31% in 2019. The trends in LULC show a significant change in the agro-ecological zones over the years. In the lowlands and midlands there was a significant conversion of forest areas into agricultural land, with an increasing emphasis on cropland. In contrast, there has been a decline in dense forest cover in the highlands. The growth of agroforestry underlines the recognition of its environmental and sustainability benefits. This finding is consistent with the study of [24], which showed that there tends to be more cropland and less forest at lower elevation. The



Fig. 3. Proportion of study area occupied by each LULC class along altitude during the study periods (1986-2019).

study conducted by Ref. [23] also found that the agricultural area increased in the midlands of the Ethiopian highlands due to its favorable conditions for crop cultivation [Fig. 3].

The changes in LULC varied significantly in the different AEZs during the study periods, as shown in Table 9. The proportion of shrubland and wetlands decreased while settlement areas increased in all AEZs. These changes were driven primarily by agricultural expansion and population growth in the study area. Between the reference periods and 2019, cropland cover increased by 81.5% in lowland and by 22.4% in midlands, but decreased in highland areas. On the other hand, agroforestry decreased in lowlands but increased in midland and highlands during the study period. The proportion of open forest decreased in the lowlands and midlands but increased in the highlands, while dense forest decreased in the midlands and highlands. This suggests that agriculture and settlement expanded into previously dense, forested highlands areas due to increased demand for forest products and deterioration of soil fertility in lowland areas, leading to further deforestation and forest degradation in the highlands.

# 3.3. Distribution and LULC change along slopes

The distribution of LULC classes on different slope gradients showed that all LULC classes were present in different proportions (Fig. 4). Agroforestry and cropland were the predominant classes on lower slopes, suggesting a preference for agricultural activities in less steep terrain. Steeper slopes were less preferred for agriculture due to difficult intensive cultivation, inaccessibility, high susceptibility to soil erosion and landslides, shallow soil depth and low productivity. However, dense forests and shrubland were dominated on steeper slopes. These results are consistent with previous studies suggesting that forests increasingly dominate steeper areas [2,23,77] [Fig. 4].

There were notable differences in LULC changes along slopes during the study period (Table 9). In contrast to dense forests and open forests, agroforestry, cropland and settlements showed an increasing trend across all slope gradients. The dense forest, on the other hand, recorded a significant decline of 34.45%, on a slope with of 0 to  $5^0$ , 25.5% on slopes with a slope of  $11-20^0$  and 21.73% on slopes above  $41^0$ . In contrast, agroforestry increased by 57.26% on slopes of 0 to  $5^0$ , 36.4% on  $21-30^0$  and 65.2% on  $30-40^0$  and 79% on slope greater than  $41^0$ .

The analysis shows that there were notable changes in LULC along slopes during the study periods. The study also showed that dense forest has declined significantly, while agroforestry, cropland and settlements have increased significantly across all slope gradients. The expansion of agriculture and settlements on steeper slopes can have harmful effects on the environment, such as increased soil erosion and landslides, which can lead to the loss of fertile topsoil, clogged waterways and increased sedimentation in downstream areas, negatively impacting aquatic ecosystems. Furthermore, the shifting of the LULC along the slopes was highlighted by the key informants and the FGD. They discovered that the forested mountain slopes were gradually transforming into human-dominated landscapes. They further explained that soil erosion, acidification, a loss of soil fertility and the associated decline in agricultural productivity, as well as rising costs of agricultural inputs (such as chemical fertilizers and selected seeds) forced farmers to move to steep slopes and vulnerable areas for search productive land. A study conducted by Ref. [78] found that deforestation of steep slope areas increased the sediment yield of the studied area and also led to the closure of a hydroelectric power plant due to increased sediment loads [79]. These pointed out that the impacts of the LULC change, particularly deforestation and forest degradation along the slope areas associated with the expansion of agriculture expansion and settlement, caused serious socioe-conomic and environmental damage in the region.

#### 3.4. Landscape pattern analysis

The analysis result based on class metrics showed the changes in landscape patterns from 1986 to 2019 (Table 10). Over the last 33 years, landscape measurements have shown increasing fragmentation of landscape features. The proportion of dense forest, open forest and shrubland (PLAND) decreased continuously throughout the study period. The overall decline in PLAND of forest area, including shrubland, can be attributed to the reduction in the proportion of forest in the landscape. This decline is mainly due to the conversion of



Fig. 4. Proportion of study area occupied by each LULC class along the slope during the study periods (1986–2019).

#### Table 9

Percentage change	ge in LULC t	types along	altitudinal rang	ge and slope grad	dient between s	tudv pe	eriods (19	86 and 2019).
	,	, p						

LULC class	Altitudinal range (m)			Slope gradient							
	500-500	1500-2300	>2300	0-50	6-10 <sup>0</sup>	$11 - 20^{0}$	$21 - 30^{0}$	$31 - 40^{0}$	>400		
AF	-22.1	+28.85	+288.61	+58.26	+8.11	+5.56	+36.4	+65.21	+179.05		
DF	+30.73	-25.97	-6.48	-34.45	-14	-25.5	-0.57	-5.47	-21.73		
SL	-44.64	-46.55	-30.21	-52.82	-44.82	-48.02	-40.68	-45.56	+56.92		
CL	+81.41	+22.39	-30.72	+43.91	+19.27	+27.27	+35.36	+140.27	+48.89		
OF	-10.46	-22.32	585.43	-46.31	-24.96	1.61	-28.09	-15.15	-34.38		
Stl	+230.25	+143.43	+160.2	+384.67	+155.2	+111.84	+103.24	+309.67	+23.0		
WL	-72.2	-5.15	-83.33	-23.24	+31.06	+0.87	-35.88	-56.71	-3.55		

Note: AF = agroforestry, DF = Dense forest, SL = shrub land, CL = crop land, OF = open forest, Stl = settlement, WL = wetland.

Table	10
-------	----

Class level metrics for seven land use/land cover	r type investigated in	three periods (1986, 2	2002, and 2019) of the stu-	dy landscape.
				· · · · · · · · · · · · · · · · · · ·

Year	LULC class	Landscape metric									
		PLAND	NP	PD	LPI	ED	AREA _MN	SHAPE _AM	ENN _MN	IJI	AI
1986	Agroforestry	13.18	11,129	5.55	2.57	61.42	2.37	28.66	72.1	66.95	65.16
	Crop land	7.96	9160	4.57	0.35	29.93	1.74	4.28	86.95	45.04	71.96
	Dense forest	9.56	4373	2.18	7.06	12.13	4.38	9.55	125.17	58.93	90.68
	Wetland	3.01	7539	3.76	0.82	14.54	0.8	5.16	98.29	71.85	64.03
	Open forest	10.0	16,460	8.21	1.31	51.9	1.22	14.4	77.93	71.52	61.2
	Shrub land	3.45	8496	4.24	0.73	18.01	0.81	6.02	97.43	76.81	61.08
	Settlement	0.53	4797	2.39	0.05	4.89	0.22	2.53	152.05	61.69	31.72
2002	Agroforestry	10.04	17,576	8.76	1.33	56.77	1.15	16.78	74.33	68.41	57.71
	Crop land	16.23	6723	3.35	4.44	41.96	4.84	23.18	82.6	60.44	80.74
	Dense forest	7.55	3422	1.71	5.55	10.28	4.43	8.48	133.54	39.62	90.01
	Wetland	2.34	8595	4.29	0.31	12.53	0.55	4.73	114.2	75.36	60.05
	Open forest	8.57	12,706	6.33	1.7	39.32	1.35	13.24	88.93	73.62	65.75
	Shrub land	2.1	7855	3.92	0.11	13.28	0.54	3.43	117.5	86.79	52.86
	Settlement	0.85	7077	3.53	0.01	7.79	0.24	1.74	123.83	58.78	31.73
2019	Agroforestry	15.34	23,932	11.93	7.0	84.58	1.29	53.46	43.77	76.58	79.39
	Crop land	10.16	13,898	6.93	0.51	43.41	1.47	6.78	58.79	57.78	84.07
	Dense forest	4.79	7130	3.56	5.26	15.99	2.19	12.68	89.84	41.05	92.41
	Wetland	2.82	27,274	13.6	0.31	25.17	0.21	4.5	54.08	68.05	66.62
	Open forest	8.27	31,826	15.87	0.86	63.48	0.52	9.69	50.42	72.31	71.31
	Shrub land	1.85	15,037	7.5	0.05	16.36	0.25	2.4	64.91	79.86	67.09
	Settlement	1.38	22,344	11.14	0.04	15.82	0.12	2.38	67.41	56.26	57.01

forests to other land use classes and division into smaller patches. A significant increase in the number of patches (NP) for dense forests, open forests, and shrublands indicate that there has been a higher degree of fragmentation in the last 33 years [57,80]. The decrease in the largest patch index (LPI) and average patch size (AREA\_MN), coupled with the increase in the number of patches and patch density, confirms the rapid fragmentation and degradation of these land use classes. The decline in LPI also indicates that the largest patches of dense forest, open forest and shrubland in the study area are shrinking over time [58].

Significant fragmentation and isolation occurred in both forest land and wetland area during the study periods, as indicated by decrease in PLAND and LPI and increase in NP. The increase in edge density (ED) for forest and wetland land use types suggest that these were fragmented, resulting in smaller and more heterogeneous areas. Studies have shown that fragmented habitats suffer from limited resources and increased vulnerability to edge effects, which can lead to local extinctions of specialized species [81–83]. This fragmentation has widespread negative impacts, reducing biodiversity, altering trophic interactions, and reducing resilience to environmental disturbances [83–85]. Research suggest that habitat fragmentation can lead to a decline in biodiversity of between from 13% to 75% [83], with up to 90% of wildlife species lost in highly fragmented [86]. This highlights the importance of implementing effective conservation strategies that prioritize the protection and restoration of extensive forest and wetland landscapes to conserve biodiversity and protect vital ecosystem services essential to both human society and the overall health of the landscape are of crucial importance.

The analysis carried out on various patches of agroforestry, croplands, and settlements revealed certain trends and changes over time. The study found that indicators such as PLAND, LPI, NP, PD and SHAPE\_AM showed an increasing trend, suggesting that these patches are more fragmented. The increase in PLAND and LPI indicates that the proportion of the study area covered by large patches of agroforestry and croplands has increased. Likewise, the settlement areas have diverse landscape features, with a significant increase in NP. Together with the increase in PLAND and ED, this suggests that the settlement area have also become more complex and fragmented. The increase in NP, PD and PLAND also means the expansion of settlement areas, which is due to population growth and increasing housing construction. The analysis also highlights the accumulation of settlement area due to accelerated urbanization, which is reflected in the overall decline in IJI.

#### 4. Conclusion

The research combined analysis of LULC changes with landscape metrics to assess the changes in land use and the degree of fragmentation within the Baro-Akobo Basin sub watershed. The study helps determine the extent and location of the change and provides the opportunity to compare the change in matrix boundaries over the specified study period. The research has shed light on the significant changes in LULC over the study period (1986-2019). These changes have led to increasing fragmentation, particularly in forested areas that have experienced significant decimation. Agriculture and settlements dominate the lowlands and midlands, while there is still significant amount of forest in the highlands. However, agricultural and settlement activities have increased in the highland regions, resulting in deforestation and degradation of forest resources. The analysis also revealed that slope steepness played an important role in determining the distribution and changes of LULC. The lower slopes were predominantly agricultural land and settlements, while the steeper slopes continued to be covered by forests and shrubs. However, expansion of agriculture and settlements occurred on all slopes contributing to the fragmentation and degradation of forest resources. The fragmentation analysis also highlights that this LULC change has resulted in significant change in landscape patterns and increased fragmentation. Forests and wetlands are highly fragmented and isolation, resulting in smaller and more heterogeneous patches. The decline in the proportion of land (PLAND) and the increase in the number of forest and wetlands patch (NP) indicate the degradation and fragmentation of these vital ecosystems. Furthermore, the landscape metrics showed increasing fragmentation in agroforestry, croplands and settlements, with the proportion of these land use types in the landscape increasing at the expense of the natural ecosystem. This indicates their growing dominance in the landscape during the study period. Overall, these results provide important insights into the patterns of landscape change, the degree of fragmentation and the potential impacts of human activities in the Baro-Akobo Basin sub-watershed on environmental and ecosystem services. Therefore, the finding highlights the urgent need for conservation efforts and sustainable land management practices to mitigate the negative impacts of land use change and fragmentation on the sub-watershed's ecosystems and livelihoods. Further research may be required to examine the key drivers and impacts of these changes, as well as possible sustainable land resource management strategies to mitigate the rapid LULC changes in the region.

# Statement of ethics

All respondents gave permission for the interviews to be conducted for this study, and they were fully informed about the goals of the study and how the information they provided would be used and kept safe.

# Data availability statement

Data will be made available on request.

#### CRediT authorship contribution statement

Mulatu Kassahun: Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. Kitesa Hundera: Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. Feyera Senbeta: Writing – review & editing, Validation, Supervision, Methodology.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

# References

- K.K. Goldewijk, N. Ramankutty, Land use changes during the past 300 years, in: W.H. Verheye (Ed.), Land-Use, Land Cover and Soil Sciences: Land Cover Land Use and Global Change, Eolss publishers Co. Ltd, Oxford, UK, 2009, pp. 147–168.
- [2] W. Steffen, J. Grinevald, P. Crutzen, J. Mcneill, The Anthropocene: conceptual and historical perspectives, Phil Trans R Soc A 369 (2011) 842-867.
- [3] T. Belay, D.M. Ayalew, Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia, Remote Sens Appl Soc Environ. 15 (2019) 100249.
- [4] R. Marchant, S. Richer, O. Boles, C. Capitani, C.J. Courtney-Mustaphi, P. Lane, et al., Drivers and trajectories of land cover change in East Africa: human and environmental interactions from 6000 years ago to present, Earth Sci. Rev. 178 (2018) 322–378.
- [5] J. Nyssen, G. Simegn, N. Taha, An upland farming system under transformation: Proximate causes of land use change in Bela-Welleh catchment (Wag, Northern Ethiopian Highlands), Soil Res. 103 (2009) 231–238.
- [6] T. Tolessa, F. Senbeta, M. Kidane, Landscape composition and configuration in the central highlands of Ethiopia, Ecol. Evol. 6 (2016) 7409–7421.
- [7] M.A. Wubie, M. Assen, M.D. Nicolau, Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia, Environ Sys Res 5 (8) (2016).
- [8] E.H. Esa, M. Assen, Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia, Environ Sys Res. 6 (4) (2017).
- [9] W.D. Takala, T. D Adugna, K. Miegel, Drivers and implications of land use/land cover dynamics in Finchaa catchment, Northwestern Ethiopia, Land 9 (2020) 113.
- [10] M.N. Dangia, D.M. Tsega, D.G. Obsi, Forest cover change detection using Geographic Information Systems and remote sensing techniques: a spatio-temporal study on Komto Protected forest priority area, East Wollega Zone, Ethiopia, Environ Sys Res 9 (1) (2020).

- [11] A.T. Angessa, B. Lemma, K. Yeshitela, Land-use and land-cover dynamics and their drivers in the central highlands of Ethiopia with special reference to the Lake Wanchi watershed, Geol. J. 86 (2021) 1225–1243.
- [12] B. Alemu, E. Garedew, Z. Eshetu, H. Kassa, Land Use and land cover changes and associated driving forces in north western lowlands of Ethiopia, Int Res J AgricSci Soil Sci 5 (1) (2015) 28-44.
- [13] S.H. Nune, T. Soromessa, D. Teketay, Land Use and land cover change in the Bale mountain Eco-region of Ethiopia during 1985 to 2015, Land 5 (4) (2016) 41.
- [14] B.G. Haile, Drivers of land use/land cover change in the Guraferda district of Bench-Maji zone, southwestern Ethiopia, Res Rev J Ecol Environ Sci. 6 (1) (2018).
- [15] V.T.S. Kabba, J. Li, Analysis of land use and land cover changes, and their ecological implications in Wuhan, China, J. Geogr. Geol. 3 (2011) 104–118.
  [16] S. Wang, S. Wang, Land use/land cover change and their effects on landscape patterns in the Yanqi Basin, Xinjiang (China), Environ. Monit. Assess. 185 (12)
- [10] S. wang, S. wang, Land use/rand cover change and their effects on randscape patterns in the randi basin, Ainjiang (China), Environ. Mont. Assess. 165 (12) (2013) 9729–9742.
- [17] A. WoldeYohannes, M. Cotter, G. Kelboro, W. Dessalegn, Land Use and land cover changes and their effects on the landscape of Abaya-Chamo basin, southern Ethiopia, Land 7 (1) (2018) 2.
- [18] M. Cotter, K. Berkhoff, T. Gibreel, A. Ghorbani, R. Golbon, E.A. Nuppenau, J. Sauerborn, Designing a sustainable land use scenario based on a combination of ecological assessments and economic optimization, Ecol. 36 (2014) 779–787.
- [19] M. Bürgi, C. Bieling, K. Von Hackwitz, T. Kizos, J. Lieskovský, M.G. Martín, et al., Processes and driving forces in changing cultural landscapes across Europe, Landsc. Ecol. 32 (11) (2017) 2097–2112.
- [20] Y. Belayneh, G. Ru, A. Guadie, Z.T. Lakew, M. Tsega, Forest covers change and its driving forces in Fagita Lekoma district, Ethiopia, J. Res. 31 (2020) 1567–1582.
- [21] J. Southworth, D. Munroe, H. Nagendra, Land cover change and landscape fragmentation Comparing the utility of continuous and discrete analyses for a western Honduras region, Agric. Ecosyst. Environ. 101 (2004) 185–205.
- [22] Y. Zhao, K. Zhang, Y. Fu, H. Zhang, Examining land-use/land-cover change in the lake Dianchi Watershed of the Yunnan-Guizhou plateau of Southwest China with remote sensing and GIS techniques: 1974–2008, Int. J. Environ. Res. Publ. Health 9 (11) (2012) 3843–3865.
- [23] M. Kindu, T. Schneider, D. Teketay, T. Knoke, Land use/land cover change analysis using Object-based classification approach in Munessa-Shashemene landscape of the Ethiopian highlands, Rem. Sens. 5 (2013) 2411–2435.
- [24] E. Birhane, H. Ashfare, A.A. Fenta, H. Hishe, M.A. Gebremedhin, H.G. Wahed, N. Solomon, Land use land cover changes along topographic gradients in Hugumburda national forest priority area, Northern Ethiopia, Remote Sen Appl Soc Environ 13 (2019) 61–68.
- [25] L. Birhanu, B.T. Hailu, T. Bekele, S. Demissew, Land use/land cover change along elevation and slope gradient in highlands of Ethiopia, Remote SenApplSoc Environ 16 (2019) 100260.
- [26] F. Senbeta, M. Denich, Effects of wild coffee management on species diversity in the Afromontane rainforests of Ethiopia, Ecol. Manag. 232 (2006) 68-74.
- [27] G. Tadesse, E. Zavaleta, C. Shennan, M. FitzSimmons, Policy and demographic factors shape deforestation patterns and socio-ecological processes in southwest Ethiopian coffee agroecosystems, Appl. Geogr. 54 (2014) 149–159.
- [28] I. Friis, Forests and Forest Trees of Northeast Tropical Africa: Their Natural Habitats and Distribution Patterns in Ethiopia, Djibouti and Somalia, Royal Botanical Gardens, London, 1992.
- [29] K. Getahun, J. Poesen, A. VanRompaey, Impacts of resettlement programs on deforestation of moist evergreen Afromontane forests in southwest Ethiopia, mount, Res. Dev. 37 (4) (2017) 474–486.
- [30] H. Kassa, S. Dondeyne, J. Poesen, A. Frankl, J. Nyssen, Transition from forest-based to cereal-based agricultural systems: a review of the drivers of land use change and degradation in Southwest Ethiopia, Land Degrad. Dev. 28 (2) (2017) 431–449.
- [31] A.O. Manlosa, P. Rodrigues, G. Shumi, K. Hylander, J. Schultner, I. Dorresteijn, et al., Harmonising Biodiversity Conservation and Food Security in Southwestern Ethiopia, Pensoft publisher, Sofia Bulgaria, 2020.
- [32] H.T. Kassa, Impact of Deforestation on Biodiversity, Soil Carbon Stocks, Soil Quality, Runoff and Sediment Yield at Southwest Ethiopia's Forest Frontier, Ghent University, Belgium, 2017. Doctoral Thesis.
- [33] I. Friis, W. Demisse, L. Breuge, Atlas of the Potential Vegetation of Ethiopia, The Royal Danish Academy of Sciences and Letters, Copenhagen, 2010.
- [34] J. Grieser, R. Gommes, M. Bernardi, New LocClim-the local climate estimator of FAO, Geophys. Res. Abstr. 8 (2006) 08305.
- [35] M. Tadesse, B. Alemu, G. Bekele, T. Tebikew, J. Chamberlin, T. Benson, Atlas of the Ethiopian Rural Economy, CSA and IFPRI, Addis Ababa, Ethiopia, 2006.
- [36] O. Dewitte, A. Jones, O. Spaargaren, H. Breuning-Madsen, M. Brossard, A. Dampha, R. Zougmore, Harmonization of the soil map of Africa at the continental scale, Geoderma 211 (2013) 138–153.
- [37] Federal Demographic Republic of Ethiopia Central Statistical Agency (CSA), Population Projection of Ethiopia for All Regions at Wereda Level from 2014 2017, CSA, Addis Ababa, 2013.
- [38] H. Kuma, F. Feyessa A. Demissie, Land-use/land-cover changes and implications in Southern Ethiopia: evidence from remote sensing and informants, Heliyon 8 (3) (2022) e09071.
- [39] A.E. Abdurahman, Y.N. Wondifraw, K. Hundera, Past and future land-use/land-cover change trends and its potential drivers in Koore's agricultural landscape, Southern Ethiopia, Geocarto Int. 38 (1) (2023) 2229952.
- [40] O.O. Othow, S.L. Gebre, D. O Gemeda, Analyzing the rate of land Use and land cover change and determining the causes of forest cover change in Gog district, Gambella regional state, Ethiopia, J. Remote Sens. GIS 6 (4) (2022).
- [41] A.K. Batar, T. Watanabe, A. Kumar, Assessment of land-use/land-cover change and forest fragmentation in the Garhwal Himalayan region of India, Environ. Times 4 (2017) 34.
- [42] A.K. Braimoh, Random and systematic land-cover transitions in northern Ghana, AgriEcosys Environ 113 (2006) 254–263.
- [43] X. Wang, D. Zheng, Y. Shen, Land use change and its driving forces on the Tibetan Plateau during 1990-2000, Catena 72 (2008) 56-66.
- [44] E. Hietel, R. Waldhardt, A. Otte, Analysing land-cover changes in relation to environmental variables in Hesse, Germany, Landsc. Ecol. 19 (2004) 473-489.
- [45] H. Qasim, H. Klaus, M. Termansen, L. Fleskens, Modeling land use change across elevation gradients in district swat, Pakistan, Reg. Environ. Change 13 (2013) 567-581.
- [46] Ministry of Agriculture (MoA), Agro-Ecological Zones of Ethiopia, MoA, Addis Ababa, 2000.
- [47] R.G. Congalton, K. Green, Assessing the Accuracy of Remotely Sensed Data: Principles and Practices, second ed., CRC Press, Taylor & Francis Group, 2009.
- [48] T.M. Lillesand, R.W. Kiefer, J.W. Chipman, Remote Sensing and Image Interpretation, seventh ed., Wiley, USA, 2015.
- [49] N.H.K. Linh, S. Erasmi, M. Kappas, Quantifying land use/cover change and landscape fragmentation in Danang City, Vietnam: 1979-2009, Int. Arch. Photogram. Rem. Sens. Spatial Inf. Sci. 39 (2012) B8;
  - [a] S.S. Kumar, A.P. Chandra, D. Singh, Land Use fragmentation analysis using remote sensing and Fragstats, in: P.K. Srivastava, S. Mukherjee, M. Gupta, T. Islam (Eds.), Remote Sensing Applications in Environmental Research, Springer International Publishing, Switzerland, 2014, pp. 155–176.
- [50] J.T. Zhang, B. Xu, M. Li, Vegetation patterns and species diversity along elevational and disturbance gradients in the Baihua mountain Reserve, Beijing, China, Mt. Res. Dev. 33 (2) (2013) 170–178.
- [51] M. Maimaitiyiming, A. Ghulam, T. Tiyip, F. Pla, P. Latorre-Carmona, Ü. Halik, M. Caetano, Effects of green space spatial pattern on land surface temperature: implications for sustainable urban planning and climate change adaptation, ISPRS J. Photogrammetry Remote Sens. 89 (2014) 59–66.
- [52] K. McGarigal, E. Ene, FRAGSTATS v4.2.1: Spatial Pattern Analysis Program for Categorical Maps, Computer software program produced by the authors at the University of Massachusetts, Amherst, 2012. Available online: http://www.umass.edu/landeco/research/fragstats/fragstats.html.
- [53] X. Yang, Z. Liu, Quantifying landscape pattern and its change in an estuarine watershed using satellite imagery and landscape metrics, Int. J. Rem. Sens. 26 (23) (2005) 5297–5323.
- [54] K. McGarigal, FRAGSTATS Help. Documentation for FRAGSTATS, 4, 2015, https://www.umass.edu/landeco/research/fragstats/documents/fragstats.help.4.2. pdf.
- [55] K. Mcgarigal, S.A. Cushman, M.C. Neel, E. Ene, FRAGSTATS: Spatial Pattern Analysis Programme for Categorical Maps, Computer software programme produced by the authors at the University of Massachusetts, Amherst, 2002. www.umass.edu/landeco/research/fragstats.html.

- [56] D. Smiraglia, T. Ceccarelli, S. Bajocco, L. Perini, L. Salvati, Unraveling landscape complexity: land use/land cover changes and landscape pattern dynamics (1954–2008) in contrasting Peri-urban and agro-forest regions of Northern Italy, Environ. Man 56 (4) (2015) 916–932.
- [57] M. Kumar, D.M. Denis, S.K. Singh, S. Szabó, S. Suryavanshi, Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed, RemoteSens App Soc Environ. 10 (2018) 224–233.
- [58] G. Dessie, J. Kleman, Pattern and Management of deforestation of in the south-central rift valley region of Ethiopia, Mt. Res. Dev. 27 (2007) 162-168.
- [59] J.R. Anderson, E. Hardy, J. Roach, R. Witmer, A Land Use and Land Cover Classification System for Use with Remote Sensing Sensor Data, vol. 964, Geological Survey Profession Paper, Washington, UAS, 1976, pp. 1–28.
- [60] J.R. Thomlinson, P.V. Bolstad, W.B. Cohen, Coordinating methodologies for scaling land cover classifications from site-specific to global, Remote Sens. Environ. 70 (1) (1999) 16–28.
- [61] S.Ö. Turan, A. Günlü, Spatial and temporal dynamics of land use pattern response to urbanization in Kastamonu, Afr. J. Biotechnol. 9 (2010) 640-647.
- [62] K.T. Deribew, D.W. Dalacho, Land use and forest cover dynamics in the North-eastern Addis Ababa, central highlands of Ethiopia, Environ Sys Res 8 (1) (2019) 1–18.
- [63] A. Abera, T. Yirgu, A. Uncha, Impact of resettlement scheme on vegetation cover and its implications on conservation in Chewaka district of Ethiopia, Environ Syst Res 9 (2) (2020).
- [64] T. Meragiaw, V.P. Singh, R. Verma, P.K. Srivastava, Assessing agroforestry cover and its economic benefits in the central highlands and southern region of Ethiopia, J.of Agrof. 76 (2) (2022) 145–162.
- [65] H. Temesgen, W. Wu, A. Legesse, E. Yirsaw, B. Bekele, Landscape-based upstream-downstream prevalence of land-use/cover change drivers in southeastern rift escarpment of Ethiopia, Environ. Monit. Assess. 190 (2018) 166.
- [66] M.G. Ghebrezgabher, T. Yang, X. Yang, X. Wang, M. Khan, Extracting and analyzing forest and woodland cover change in Eritrea based on Landsat data using supervised classification, Egyptian J Remote Sen Space Sci 19 (2016) 37–47.
- [67] A.Y. Yimam, A.D. Bantider, Land use/cover patio-temporal dynamics, driving forces and implications at the Beshillo catchment of the Blue Nile Basin, North Eastern Highlands of Ethiopia, Environ Sys Res 8 (2019) 21.
- [68] M. Obeidat, M. Awawdeh, A. Lababneh, Assessment of land use/land cover change and its environmental impacts using remote sensing and GIS techniques, Yarmouk River Basin, north Jordan, Arabian J. Geosci. 12 (2019) 685.
- [69] S. Twisa, M.F. Buchroithner, Land-use and land-cover (LULC) change detection in Wami river basin, Tanzania, Land 8 (2019) 136.
- [70] Federal Demographic Republic of Ethiopia Central Statistical Agency (CSA), Summary and Statistical Report of the 2007 Population and Housing Census, CSA, Addis Ababa, 2008.
- [71] F. Senbeta, Community Perception of land use/land cover change and its impacts on biodiversity and ecosystem services in Northwestern Ethiopia, J Sustain Develop Afri 20 (1) (2018).
- [72] E.G. Mandefro, Poverty of energy and its impact on living standards in Ethiopia, J Electr Comp Eng (2020) 1-6.
- [73] Z. Yurnaidi, S. Kim, Reducing biomass Utilization in the Ethiopia energy system: a national modeling analysis, Energies 11 (2018) 1745.
- [74] A.Y. Yesuph, A.B. Dagnew, Land use/cover spatiotemporal dynamics, driving forces and implications at the Beshillo catchment of the Blue Nile Basin, North Eastern Highlands of Ethiopia, Environ Syst Res 8 (2019) 21.
- [75] D.S. Teshome, H. Taddese, T. Tolessa, M. Kidane, S. You, Drivers and implications of land cover dynamics in Muger sub-basin, Abay basin, Ethiopia, Sustainability 14 (2022) 11241, https://doi.org/10.3390/su141811241.
- [76] X. Wu, Z. Tang, H. Cui, J. Fang, Land cover dynamics of different topographic conditions in Beijing, Front. Biol. China 2 (2007) 463-473.
- [77] H. Kassa, A. Frankl, S. Dondeyne, J. Poesen, J. Nyssen, Sediment yield at southwest Ethiopia's forest frontier, Land Degrad. Dev. 30 (6) (2019) 695-705.
- [78] Ethiopian Electric Power Corporation (EEPCO), Decommission of Dembi Hydro Electric Power Plants. Dembi Power Plant Environmental Impact and Feasibility Study Report. Final Report, Ethiopian Electric Power Corporation, Addis Ababa, 2000.
- [79] C. Kamusoko, M. Aniya, Land use/cover change and landscape fragmentation analysis in TheBindura district, Zimbabwe, Land Degrad. Dev. 18 (2007) 221–233.
  [80] L. Fahrig, Effects of habitat fragmentation on biodiversity, Annu. Rev. Ecol. Evol. Syst. 34 (2003) 487–515.
- [81] M.C. Fitzpatrick, S.R. Keller, K.E. Lotterhos, Does niche breadth or niche position predict abundance and population dynamics in a fragmented landscape? Ecography 38 (7) (2015) 305-313.
- [82] N.M. Haddad, L.A. Brudvig, J. Clobert, K.F. Davies, A. Gonzalez, R.D. Holt, et al., Habitat fragmentation and its lasting impact on Earth's ecosystems, Sci. Adv. 1 (2) (2015) e1500052.
- [83] J. Fischer, D. B. LindenmayerLandscape modification and habitat fragmentation: a synthesis, Global Ecol. Biogeogr. 16 (3) (2007) 265-280.
- [84] W.F. Laurance, Theory meets reality: how habitat fragmentation research has transcended island biogeographic theory, Biol. Conserv. 141 (7) (2008) 1731–1744.
- [85] K.J. Kuipers, J.P. Hilbers, J. Garcia-Ulloa, B.J. Graae, R. May, F. Verones, M.A. Huijbregts, A.M. Schipper, Habitat fragmentation amplifies threats from habitat loss to mammal diversity across the world's terrestrial ecoregions, One Earth 4 (10) (2021) 1505–1513.