Land use land cover change analysis and detection of its drivers using geospatial techniques: a case of south-central Ethiopia

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ABSTRACT

The rapid expansion of agriculture and human settlements has simplified natural ecosystems and harmed the earth’s biodiversity. The current study was conducted in south-central Ethiopia to identify LULC change dynamics, and analysis of their driving force using geospatial technology. A supervised maximum likelihood image classification method was employed in combination with the visual interpretation of satellite images to categorise and map LULC classes of the study landscape. Semi-structured interviews, field observations, key informants, and Focus Group Discussions (FGDs) were employed to identify major driving forces, periodic LULC changes and impacts. The classification result showed a considerable decline in forestland from (43.1%) in 1973 to (13.1%) in 2000. Similarly, grasslands declined from (45.5%) in 1973 to (6.3%) in 2018. On the other hand, cropland has increased from (9.24%) in 1973 to (32.04%) in 1986 likewise between 2000 and 2018 its coverage was augmented from 45.4% to 51.1%, respectively. Local communities perceived population growth, settlement, urbanisation, expansion of farmlands, and fuel wood collection as dominant drivers of LULC changes in the study area in the watershed. The respondents also observed that the decline in forest LULC triggered the loss of biodiversity, soil fertility, and water availability. Hence, local and national regimes must take adequate measures to minimise the rapid shift in land use and to balance the protection of the human livelihood with the environment.

1. Introduction

The rapid expansion of agriculture and human settlements has simplified natural ecosystems and harmed the earth’s biodiversity (Hailu et al., 2020). The integrity of ecosystem products and services would be jeopardised if land resources became more endangered and strained (Elias et al., 2019). Consequently, LULC changes have recently been a key concern topic of environmental agenda in the scientific research community because of its substantial impacts on global climate change (Elias et al., 2019), ecosystem services, and biodiversity (Phalan et al., 2011) biogeochemical processes (Houghton et al., 2012) socioeconomic and social well-being (Dwivedi et al., 2007; Mengistu et al., 2012), micro-climate conditions, groundwater recharge (Lambin & Geist, 2006), and environmental modification (Yohannes et al., 2020). LULC is the most significant risk to the depletion of natural resources, especially wetlands, forests, and diverse fauna throughout the world that in turn contributes to global environmental change (Belete et al., 2021). The conversion of forest cover to other land-use changes to meet human needs and wants is a major contributor to environmental degradation (Tesfaye et al., 2014), habitat destruction, and ecological imbalance on the surface of the earth (FAO, 2010). Forests are significant elements of biodiversity and vital means of income for thousands of people because they can provide food, medicine, precipitation, (FAO, 2016) freshwater, and storehouse for carbon sequestration that helps to mitigate the effects of global climate change (Belete et al., 2021). Despite the fact that forests serve vital environmental, cultural (Gurmessa, 2015) and socioeconomic roles in the survival of life on earth, the quality and quantity of forests in Ethiopia are diminishing on a regular basis due to LULC conversions (Keenan et al., 2015).

LULC changes are influenced by a wide range of drivers. The expansion of agricultural and settlement land, population growth, and charcoal production in South Central Ethiopia (Kindu et al., 2015), resident density in northern China (Peng et al., 2015), expansion of cultivated land in highlands of northern Ethiopia (Tsehay & Mohammed, 2015), and slope inclination in Southern Wollo (Belete et al., 2021). Furthermore, improper land management, resettlement plans, and rapid population expansion in northwestern lowlands (Binyam et al., 2015). Likewise, unfavourable administration strategies Daniel (2008), Illegal logging, fuel wood exploitation, and plantation (Yesuph & Dagnew, 2019) were cited as drivers of LULC in Ethiopia. Population increase, and poverty in Malawi (Asres et al., 2016). Land scarcity, population expansion, and urbanisation in Kenya (Mariye et al., 2021).
The conversion of the landscape can be realised by visiting locations on the ground (Mary et al., 2013). However, these traditional approaches are believed to be time-intensive, tedious, and costly that does not deliver a comprehensive outcome, whereas remotely sensed information can provide appropriate data swiftly, and examining time-based changes in the LULC dynamics rapidly and can identify environmental alterations precisely (Asmamaw et al., 2014; Asokan & Anitha, 2019; Degife et al., 2018; Schaefer & Thinh, 2019; Teklel. & Hedlund, 2000; Yuan et al., 2005; Zewdie & Csaplovies, 2017) and offer a better accuracy at low cost even over large geographical areas. Several scholars have attempted to use digital satellite image data (Abebe, 2018; Haque & Basak, 2017; Mengistu et al., 2012; Minale, 2013; Moges et al., 2015; Rahman, 2016; Rawat & Kumar, 2015; Shawul & Chakma, 2019; Singh, 1989) to address problems of LULC change detection in various parts around the world. Remote sensing (RS) and geographic information systems (GIS) became influential and significant methods for detecting LULC changes at multiple spatial scales (Dewan & Corner, 2014). GIS integrates the information obtained from RS to provide a comprehensive knowledge of LULC modelling (Twisa & Buchroithner, 2019). Accordingly, both RS and GIS have proven to be quite helpful for detecting LULC patterns (Attri et al., 2015; Lu et al., 2010). The remotely sensed data provide a substantial connection between the localised environmental study on conservation and monitoring of natural resources at several scales (Mariy et al., 2020). Kotoky et al. (2012) discussed that LULC studies are becoming increasingly important in various fields, including agricultural development, settlement surveys, effective land use plans, and ecological studies.

Employing Landsat images to evaluate LULC modification at the basin and sub-basin level, as well as identifying the pace and degree of land cover change is a significant approach to enhance proper management of natural resources (Meshesha et al., 2016). The assessment of LULC alterations and the factors that trigger these changes are the topic of ongoing scientific inquiry that has piqued the curiosity of a wide range of scientists (Angessa et al., 2019).

Tracking LULC change by using GIS and remote sensing technology provides quantitative analyses of the transformation. However, it fails to describe the relationship between the driving factors and the cause of their change (Daniel et al., 2018). The majority of previous research on LULC alterations was focused on particular areas, mainly in Northern Ethiopia and in the central Rift Valley Lake, and only evaluated the dynamics of LULC changes using remote sensing data (Belayneh et al., 2021); nevertheless, they did not offer explanations on local people’s views of the driving forces of LULC change (Burgi et al., 2017). In the Kembata Tembaro zone (KTz), studies on LULC change and analysing the driving factors are still limited or not yet conducted. Therefore, it is very essential to study how the community perceives the driving forces and realise the complex interdependence of LULC changes (Meyfroidt, 2013; Belayneh et al., 2021). The study site, Kembata Tembaro, is recognised for its cereal production, high population, and livestock but the area is prone to land degradation, deforestation, high soil erosion, and has experienced rapid and extensive LULC change which might lead to deterioration of the environment and the loss of ecosystem services that humans rely on for existence (Belayneh et al., 2021). Therefore, comprehensive information on the dynamics of LULC transition, driving factors, and causes of LULC change is necessary to build appropriate environmental regulations and suitable land management approaches for the entire study area and beyond. However, basic data on the trends, magnitude, and extent of the LULC modification in the study landscape have not been addressed so far, and consequently, the magnitude of the change, its driving factors, and consequences are poorly understood. In the study landscape, there is no practice of evaluating LULC dynamics using a combination of remote sensing and GIS approaches. The KTz in south-central Ethiopia is a significant example of a landscape in which it lacks attention to scientific information on LULC changes existed. Moreover, some decades ago, KTz district was known for its untouched forest LULC cover. However, it is currently facing great human influences that have placed the forest into a fragmented state. Dense forest areas were given to landless youth just disregarding the environmental importance of the forest ecosystem. Such activities are known to affect biodiversity (for instance, woody plant species, medicinal plants, and wild animals) more seriously. Furthermore, this study helps to fill scientific information shortages in the land management sector of Ethiopia in general and particularly in the southern central highlands of Ethiopia. Therefore, the main objective of the current study was designed to conduct LULC change detection using scientific tools such as GIS and remote sensing through spatial and temporal scales. However, the specific objectives were aimed to (1) determine dynamics and extent of LULC transition and (2) assess the driving factors and undertake remote sensing and GIS supported LULC change analysis over the last 45 years. This study is envisioned to be used by land use planners, environmentalists, decision-makers, and other stakeholders to formulate environmentally sound policies and planning strategies based on a robust understanding of the dynamics of LULC change. It is intended to provide guidelines for maintaining ecosystem services and preserving and utilising natural resources in KTz or alternative districts with similar settings.
2. Methods and materials

2.1. The study area

The study area is situated in Kembata Tembaro district (Figure 1) and is located about 350 km southwest of Addis Ababa (capital of Ethiopia). Geographically, the district positioned between 71°03′04″–75°00′94″ latitude and 37°34′1”–38°07′8″ longitude and covers about 44,883 ha (448.83 km2). The study landscape has a share of four woredas (The smallest administrative unit of the country), namely Doyogena, Angecha, Damiboya, and Kachabira. It is characterised by undulating mountainous topography, with an elevation stretching from 2300 to 3080 m.a.s. l. (KTDARDO, 2019).

In the study area, there are two rainy seasons with bimodal rainfall. ‘Maxxe Sana’ and ‘Gialichi Sana’ The average annual rainfall (Houghton et al.), in the area ranges from 1200 to 1800 mm. ‘Gialichi Sana’ locally denotes a shorter rainy season that extends from March to May and contributes 19.8% of the total rainfall (RF). In the study area, most farmers possess at least two land types: the main land and home gardens. The main land is allocated for home construction, cereal cultivation, grazing and tree plantations. Home gardens, on the contrary, are used for planting valuable crops such as Enset (Ensete ventricosum), vegetables, chat and fruit trees. Plots of land at distant locations from the homesteads are dedicated for the cultivation of annual crops such as barley, wheat, maize, teff, sorghum, beans and potatoes. ‘Maxxe Sana’ denotes the longer rainy seasons that account for 80% and occur between June, July, and August. During this period, the area receives a total annual average rainfall of about 1507 mm. The amount of rainfall is low during the dry season that falls between October and February. Crops are cultivated using the rainfall of the main ‘Maxxe Sana’ and ‘Gialichi Sana’ seasons but the majority of the crop husbandry takes place during the ‘Maxxe Sana’. Consequently, soil loss by water erosion occurs during this period. Winter frost and irregular rainfall patterns in the summer and spring are the two most significant factors affecting crop production in the study area. Because of rainfall-dependent farming, farmers are always concerned about rainfall intensity and duration. According to Ethiopian Agro-ecological zone classification, 22.25% of the district is classified as Dega (high land, 2400–3200 metres above sea level), 70.75% Woyina Dega (midland, 1800–2400 m. a. s l), and 7% Kolla (lowland, 500–1800) m. a. s l (Maryo, 2020). Based on meteorological data obtained from the nearby Angecha and Durame stations, the minimum monthly temperature ranges between 12.2°C in 1997 as depicted in (Figure 2), whereas mean annual maximum temperature reaches 25.4°C in 2009 (EMS, 2013).

Figure 1. Map of the study area. Lower Right: location of the study area in Ethiopia, Upper-right: location of the study area in Southern Region, Left side: study area with streams, contour, and Roads.
Total of (77.4%) 763, 245 people live in the rural area, while only (22.6%) 223,432 of the total population live in towns (CSA, 2013). The average population density was 728 people per km² (Maryo, 2020). The average land-holding size for each family is less than 1 ha per household. The agricultural system of the study area is mainly characterised by the mixed farming system where the rural people depend on both crop and livestock production for their livelihood. Cattle, sheep, goat, pack animals, and poultry are the most common domestic animals raised in the study landscape. Commonly known as ‘false babana’, Enset (Ensete verticosum) is the dominant land use, cultural heritage, and most important food security crop for the local community of the south-central region of Ethiopia. The overall land use of the study area is patterned in concentric circles around homesteads, and Ensete occupies the inner rings that surround the homestead. The fact that the south-central Ethiopia is known for its dense population concentration (due to historical and cultural reasons) and its suitable agro-ecological condition for human settlement, the natural vegetation cover of the study area has been depleted quite a long time ago. The only exception to this practice includes pockets of lands in holy sites, which preserved ancient trees, and farm boundary strips. In the study area, with steep sloppiness and extremely undulating geography, animals cannot access feeds near mountainous areas and are particularly kept close to the bottom and at marshy and swampy lands (Deribe et al., 2019).

2.2. Data sources and analysis

We accessed multi-sensor and multi-temporal Landsat images from the data portal (https://earthexplorer. usgs.gov) of the USGS and (EROS) centre to quantify the magnitude and direction of LULC change. The following factors were considered when selecting satellite images: (i) the principal events that occurred in the area and (Muriithi, 2016) image quality that reduces the impact of fire and clouds on land cover mapping. We accessed satellite images with a minimum cloud cover (<10%) between November and January, which is before the usual season of forest fires. Moreover, we employed multispectral satellite data (Landsat 4, 5, 7, and 8 with sensors MSS, TM, ETM+, and OLI) from 1973, 1986, 2000, and 2018, respectively, to identify and evaluate satellite images. The LULC classifications were interpreted using socio-economic and additional data sets following previous studies done by (Andualem et al., 2018; Dibaba et al., 2020; Mohajane et al., 2018).

We obtained ASTER, DEM, and topographic maps of the study area (1:50,000) from the Geospatial Information Institute of Ethiopia, then the images were orthorectified into Universal Transfer Mercator (UTM) Zone 37 N, World Geodetic System (WGS) 1984. Remote sensing and GIS tools, including ERDAS Imagine 2014 and ArcGIS 10.6, were used for image processing and data analysis, respectively. At first, images were converted to UTM and geo-referenced using a datum selected by WGS-84 for Ethiopia. We digitised the demarcated study area in Arc GIS 10.6 to overlay the view on the spatial databases generated by the photograph and the satellite image. Aerial photographs from 1986 to 2018 were interpreted via mirror stereoscope for LULC type identification and classification, whereas post-classification change detection was used for the evaluation of LULC types on the aerial photographs (Mariye et al., 2022). For the creation of

![Figure 2](https://example.com/figure2.png)  
*Figure 2.* A climate diagram showing temperatures from Angecha and Durame stations (1990–2015). Note: The red lines and vertical numbers on the left symbolise the area of cropland change in a hectare, while the blue lines and vertical numbers on the right indicate the population growth trend in the study landscape over the last four and half decades.
the latest land cover map, Google Earth image, field survey, and ground control points (GCPs) were used as major sources of data. LULC trends and dynamics were assessed using Landsat imagery, which provides a range of spatial, temporal, spectral, and multi-resolution capabilities for land cover analysis following Oettera et al. (2000). The assortment of the suitable image acquisition date is an essential for clear identification of the LULC types from satellite imagers (Berihun et al., 2019; WoldeYohannes et al., 2018). We coded and organised the household (HH) questionnaires before conducting analysis. Coding was established during the preparation of the questionnaires. For analysis, the collected data were input into an SPSS version 23 database following the coding system. HHs’ socioeconomic characteristics were analysed quantitatively using descriptive statistics. While the qualitative data of the FGDs, KIs, and observational notes were transcribed, arranged, and analysed. Then, we used SPSS Version 23 to analyse and summarise the quantitative data gained from general informants during a formal survey. In order to enhance the quality of the image, different mosaicking, sub-setting, and radiometric enhancement techniques (Haze reduction and Histogram equalisation) were applied to the raw data following Belete et al. (2021).

After the image was processed, signatures were distributed per pixel by identifying the land into seven classes of 1973 and 2000. Furthermore, seven LULC categories have been recognised for the years 2000 and 2018, respectively. Image cataloguing was based totally on the reflectance characteristics (false-colour composite) of the specific land cover classes and also supplemented with field observation (Belete et al., 2021), key informant interview, and FGDs. Each class was given a unique identification and assigned a selected colour to differentiate one from another. For each of the predetermined LULC categories, training samples had been selected via delimiting polygons around representative sites. During this time, Google Earth extension was employed to reduce confusion in interpreting the pixel. Furthermore, the results obtained from the supervised class with the help of ERDAS Imagine 2014 were imported to ArcGIS 10.6 for map layout preparation, reclassification, and pixel value estimation for all LULC classes (Belete et al., 2021; Othow et al., 2017). The conversion matrices were created using ERDAS Imagine 2014, and the source and destination of each land cover value were evaluated in an Excel spreadsheet (Kindu et al., 2013; Meshesha et al., 2016; Othow et al., 2017). In addition to calculating the area of LULC in hectares and percent, we also calculated the percentage change in LULC between the stated period following Braimoh (2006) and Pontius et al. (2004).

\[
\text{Area in hectare} = \frac{\text{Count} \times 900 \text{ or } 3600}{10,000} 
\]

(1)

\[
\text{Area in percent} = \frac{\text{Value of the identified pixel}}{\text{Number of pixels in total}} \times 100 
\]

(2)

\[
\text{Percentage of LULC change} = \left( \frac{P_{t_2} - P_{t_1}}{P_{t_1}} \right) \times 100 
\]

(3)

Where $P_{t_1}$ is the area of LULC at the initial period and $P_{t_2}$ is the area of LULC at the final period. A positive result indicates that the extent of LULC has increased, whereas a negative result indicates that the amount has decreased. We validated the classification results by constructing a confusion matrix as a basis for determining accuracy assessments (Belete et al., 2021; Miheretu & Yimer, 2017). To improve the image quality and to escalate the accuracy assessment, 300 GCPs from seven land cover classes (i.e. 35 grasslands, 38 bare lands, 35 settlements, 40 forestlands, 41 shrub lands, 41 wetlands, and 36 croplands) were used, respectively. Furthermore, we used topographic maps obtained from the Ethiopian Geospatial Information Institute to visualise the landscape of the whole study area (Anchan et al.). This study has applied both unsupervised and supervised cataloguing techniques following previous researchers (Belay & Mengistu, 2019; Congalton, 2001; Congalton & Green, 2009). We collected ground grothing points with the support of FGDs and KIs during the transect walk. In addition, Google Earth Engine images were used as a supplementary tool for GTPs. Moreover, GTPs for the 1973 and 1986 LULC maps were collected by using the false colour composite of 1973 and 1986 satellite images in conjunction with elder knowledge based on previous studies (Betru et al., 2019). In all scenarios, members of the KIs and FGDs were employed to collect GTPs by describing the dynamics of LULC occurring in and around their district. In supervised classification, specific land cover types are delineated using training sites, whereas in unsupervised classification, land cover classes are formed based on the number of classes requested. Moreover, we combined unsupervised classifications with visual signature editions based on the spectral values of recent images to determine the classification of older images 1973, MMS imagery (Andualem et al., 2018). A supervised signature extraction with the maximum likelihood algorithm was used to categorise the Landsat imagers (Amare, 2015; Congalton & Green, 2009).

In Table 1, a spatial resolution of $15\times15$ m is used for the panchromatic band 8. MMS: Multispectral Scanner; ETM+: Enhanced Thematic Mapper Plus; TM: Thematic Mapper; OLI-TIRS: Operational Land Imager and Thermal Infrared Sensor.

2.2.1. Socio-economic survey

To validate the data obtained from aerial photos and satellite imagery, a socioeconomic survey was...
undertaken with 121 randomly selected households. The district, administration, and household participants were chosen using a three-stage sampling technique that included purposive and random sampling, whilst the household respondents are being selected through systematic random sampling following Wubie et al. (2016). As a result, from the three elevation classes, namely Lower (500–1800 m above sea level), Middle (1801–2400 m. a. s. l.), and Upper (2401–3200 m. a. s. l.) using a household survey 40 households from the 2 sample areas and 41 households from one sample area were chosen, respectively. Sampling for the socio-economic survey was done in two phases. The first phase involved the assortment of the sampling sites, however, the second phase comprised selecting individual households from the chosen kebeles (the smallest government administrative structure in Ethiopia) using system sampling following previous approaches (Amare, 2015). Furthermore, FGDs were carried out with 30 participants (12 women and 18 men) to acquire additional information on the long-term LULC practices. In general, four FGDs were conducted whereby each group was composed of six participants i.e. development agents, farmers, Kebeles cabinet members, youth association, and community elders who had been selected through the kebeles administrative bodies and the knowledgeable community representatives. In order to engage in in-depth discussions, key informant interviews, and FGDs were conducted to acquire information regarding the past and present situations, including the drivers of LULC change within the study landscape (Mariye et al., 2022). For the in-depth discussion, 15 people (age >60 years) were purposefully chosen as key informants (Danano et al.) to gather data on the trends of LULC alteration over the past 4 and half decades. We calculated the study sample size following Kothari (2004)

$$n = \frac{Z^2.p.q.N}{e^2(N - 1) + Z^2.p.q}$$

(4)

Where \(n\) is the sample size and \(Z\) denotes the 95 confidence limit (interval) under the normal curve, which would be 1.96. \(P = 0.1\) (percentage of the population to be included in the sample that is 10 percent); \(q = \) none event occurrence = 1–0.1, which denotes (0.9). \(N = \) is the total number of households = 2100. \(e\) = allowable error term (margin of error or degree of accuracy) (0.05).

Thus

$$n = \frac{1.96^2 \cdot 0.1 \cdot 0.9 \cdot 2100}{0.05^2 \cdot (2100 - 1) + 1.96^2 \cdot 0.1} = 121$$

The overall procedure for the LULC change analysis was organised in the schematic diagram (Figure 3), and seven classes of LULC categories were identified (Table 2), and the description in Table 2 is provided from various supporting data (Kindu et al., 2013).

### 2.2.2. Satellite data pre-processing and classification

Due to systematic and random errors present in raw satellite images, these images cannot be directly utilised for any form of feature identification. Therefore, we applied the most common Landsat pre-processing operations such as image enhancement, conversion of radiance, solar correction, geometrical rectification, and normalisation were carried out to improve features and interpretability (Gebremicael et al., 2018; Lu & Weng, 2007) for LULC change following previous research study done by (Birhane et al., 2019; Tucker et al., 2004; USGS, 2019). The images produced by Landsat sensors are subject to distortion caused by sensor, solar, atmospheric, and topographic factors. Therefore, employing these methods would minimise effects to the extent that is desired for a given application. ERDAS imagine was used to implement topographic and atmospheric corrections for airborne imagery, which reduces errors and gets the actual reflectance values for each LULC classification (Lu & Weng, 2007). In this study, we consider the following gap-filling or destripping methods to remove Landsat image strips: Geostatistical Neighbourhood Similar Pixel Interpolator (GNSPI); the weighted linear regression (WLR) algorithm; and the direct sampling (Oestereicher et al., 2014) method. Furthermore, image difference was estimated as the difference in the total number of equivalently classified pixels between two images, which was computed by subtracting the initial state class totals from the final state class totals.

The basic sources of data to generate an up-to-date land cover map of the study area were Google Earth images and ground control point reading. The trends and dynamics of LULC changes were analysed using Landsat image that offers a multi-temporal, multi-spectral, and multi-resolution range of imagery for the land cover analysis of the current study following Oettera et al. (2000).

### 2.2.3. Change detection

Monitoring changes of the earth’s surface features enable us to realise the interactions between humans and their environment for health management and the use of natural resources as reported by Singh (1989). Numerous change detection techniques have been created and utilised for different applications. However, they can be broadly divided into post-classification and spectral change detection approaches (Singh, 1989). The post-classification approach evaluates the change in LULC based on a detail-categorised classification of land cover units (Ayele et al., 2018). Jianya et al. (2008) discussed that change detection approaches can be characterised in two groups: Bi-temporal altered detection is a direct comparison, post-analysis comparison, and uniform modelling that measures changes based on a simple...
Figure 3. Flowchart presenting techniques employed to attain the ultimate LULC change in the study area.

Table 1. Explanation of imagery statistics and sources used for LULC study in KTz.

| Satellite image | Imagery type | Imagery date   | Used bands | Source  | Spatial Resolution | Path/R | Bands/colour  |
|-----------------|--------------|----------------|------------|---------|--------------------|--------|---------------|
| Landsat_4       | MSS          | January–1973   | 4 bands    | USGS    | 57*57              | 169/55 | Multi-spectral |
| Landsat_5       | TM           | February–1986  | 5 bands    | USGS    | 28.5*28.5          | 169/55 | Multi-spectral |
| Landsat_7       | ETM+         | January–2000   | 8 bands    | USGS    | 15*15              | 169/55 | Multi-spectral |
| Landsat_8       | OLI-TIRS     | January–2018   | 8 bands    | USGS    | 30*30              | 169/55 | Multi-spectral |

Table 2. LULC categories and their description in the study landscape, Ethiopia.

| No  | Land cover type | Their explanations                                                                 |
|-----|-----------------|-----------------------------------------------------------------------------------|
| 1   | Settlement      | A land-use type that includes rural settlement area, educational, health, socio-economic facilities, residential houses, administrative buildings, small-scale industrial areas, etc. |
| 2   | Wetland         | Land use that is waterlogged and swampy during the wet season, which dries in the sunny season. |
| 3   | Cropland        | Smallholder farmers owned land that is used to grow cropland. It is characterised by tilled and planted, bare crop fields, and limited areas temporarily left as fallow. |
| 4   | Shrub land      | Areas covered by bushes, and shrubs > 20% cover, and mixed with grasses; less than 20% tree cover. |
| 5   | Forest land     | Land covered with dense trees > 80% canopy cover which includes evergreen forest land, mixed forest, and plantation forests |
| 6   | Grassland       | A land-use type where the land is dominated by grasses, forbs, and herbs with nil or little proportion of shrubs that are used for communal grazing. |
| 7   | Bare land       | Areas with little or no vegetation cover consist of exposed soil and/or rock outcrops, and quarries. |
two epochs timescale comparison whereas temporal trajectory analysis is a time series analysis and the changes are based on a ‘continuous’ time scale, focusing on both changes between dates and progress of the modification over the period. To obtain the information of LULC dynamics in terms of pattern and rate conversion, post-classification change detection analysis was carried out in ERDAS Imagine 14 using classification images of 1973, 1986, 2000, and 2018. According to Lu et al. (2004), accuracies of change discovery results depend on the performance of the image processing and categorisation approach.

According to Singh (1989), change detection is used when someone is interested to know changes that have taken place in a particular region provided that satellite data over that area can be easily attained. The key objective of the change detection technique is to obtain alterations in two or more images of the identical sites captured at, unlike periods. Different approaches have been adopted for change detection depending on its application such as algebra-based, transform-based, classification-based, neural network and fuzzy-based, and other change detection approaches (Asokan & Anitha, 2019).

3. Result and discussion

3.1. Accuracy assessment for LULC maps from (1973–2018)

Based on the results of the post-classification accuracy assessment, the overall user accuracy evaluation was found to be highest for wetland (100%) and lowest for cropland (70.6%) in 2018, respectively, as depicted in (Table 3). During the final study periods, the producer accuracy, which is the proportion of properly classified data from total classified data was (92.7%) for bare land, (90.9%) forest, (81.4%) settlement, (100%) cropland, (91.1%) shrub land, (81%) grassland, and (85.4%) wetland, respectively, as shown in (Table 3). The overall user accuracy for the classified maps of grassland and shrub land was (79.1%) to (97.8%) for the second study period. Producer accuracy for individual LULC classes was highest for grassland (100%) and lowest for wetland (81%) in 2000. We collected a total of 785 Ground Control Points (GCPs) from a Global Positioning System (GPS) during our field visit and translate the walk with the help of Google Earth engine. Out of which, 485 points were used for supervised classification, while the remaining 300 points were used for assessing the accuracy of satellite images. We retrieved the 1973 and 1986 reference points using Google Earth, Landsat images, historical reports and maps, and field observations in 2018. A high resolution of Google Earth was used to better identify the land-use classes on the historical maps of 1973 obtained from the Ethiopian mapping agency since the resolution of the maps was poor. Many other studies have used the same approach in cases where the historical maps were poor (Fasika et al., 2019; Gashaw et al., 2017; Tilahun, 2015). This study used a random sampling technique to select points. As a result, enough spatial distribution of sampling points was attained for each LULC class. The accuracy measure was worked out based on the confusion matrix that comprises the Producer’s and User’s accuracy (Asokan & Anitha, 2019; Thakkar et al., 2017). In order to compute the user accuracy, we divided the number of correctly classified pixels in each class by the number of training set pixels per classified class, which indicates the percentage of correctly classified pixels per LULC class (Othow et al., 2017). Producer accuracy is computed by dividing the number of correctly classified pixels by the total number of pixels (reference totals), showing the percentage of correctly classified pixels using the reference data following Belete et al. (2021). The low accuracy record of producers and users may have been related to the similarity of land cover classes at a spectral level. Belete et al. (2021) explain that low producer’s accuracy indicates that the ground reference points for a category are classified incorrectly, while low user accuracy suggests that pixels could be classified that do not exist on the ground. The overall classification accuracy was weighted by the number of samples in each class, i.e. the sum of all samples on the diagonal divided by the total number of cells (36 + 35 + 40 + 41 + 38 + 41 + 35)/300, which equals 88.7%. This result indicates that 88.7% of LULC classes have been properly classified. Overall, kappa statistics of 0.87 was achieved for the classification period of 2018 images, which means that there is 87% in better agreement than would be expected by chance alone (Table 3).

The kappa coefficient ranges from +1 to −1 indicates the level of accuracy between the reference data (true data) and the analysed images. In a study by Hassan et al. (2016), the kappa coefficient is associated with three possible groups of the covenant: the value over 0.80 shows strong agreement, the value between 0.40 and 0.80 denotes moderate covenant, and the value below 0.40 indicates poor covenant (Belete et al., 2021). We also computed a Kappa statistic for each classified map to measure the accuracy of the classification results. According to the maps from 1986, 2000, and 2018, the overall accuracy found to be was 88.3%, 87.6%, and 88.7%, whereas kappa values were 0.84, 0.84, and 0.87 for each classified map from 1986, 2000, and 2018, respectively. Accordingly, for the subsequent analysis and change detection, this kappa accuracy was generally considered reasonable. Kappa statistics for 2018 demonstrated a strong covenant, while for 1986 and 2000 good agreement was obtained as shown in (Table 3). Finally, it was calculated following the previous study approach proposed by Tilahun (2015).
Table 3. Accuracy of LULC change maps for 1986, 2000, and 2018.

| LULC | CL | GL | FL | SHL | BL | WL | SL | UA% | K |
|------|----|----|----|-----|----|----|----|-----|----|
| 2018 | CL | 36 | 2  | 2  | 2  | 2  | 2  | 4   | 70.6| 0.87|
|      | GL | 0  | 35 | 0  | 0  | 2  | 3  | 4   | 85.4|    |
|      | FL | 0  | 2  | 40 | 0  | 0  | 0  | 95.2|    |
|      | SHL| 0  | 2  | 2  | 41 | 0  | 0  | 91.1|    |
|      | BL | 0  | 0  | 0  | 2  | 38 | 0  | 95  |    |
|      | WL | 0  | 0  | 0  | 0  | 41 | 0  | 100 |    |
|      | SL | 0  | 2  | 0  | 0  | 1  | 2  | 35  | 87.5|    |
|      | PA%| 100| 81 | 90.9| 91.1| 92.7| 85.4| 81.4|    |
|      | OAA%| 88.7|    |    |    |    |    |    |    |
| 2000 | CL | 49 | 0  | 2  | 5  | 0  | 0  | 87.5| 0.84|
|      | GL | 4  | 34 | 3  | 2  | 0  | 0  | 79.1|    |
|      | FL | 3  | 0  | 33 | 2  | 0  | 1  | 84.6|    |
|      | SHL| 0  | 0  | 0  | 45 | 0  | 0  | 97.8|    |
|      | BL | 0  | 0  | 0  | 0  | 0  | 0  | 90  |    |
|      | WL | 1  | 0  | 0  | 0  | 0  | 0  | 0   |    |
|      | SL | 0  | 0  | 0  | 0  | 0  | 0  | 0   |    |
|      | PA%| 86 | 100| 87 | 83.3| 0  | 81 |    |
|      | OAA%| 87.6|    |    |    |    |    |    |
| 1986 | CL | 43 | 0  | 4  | 2  | 0  | 0  | 87.8| 0.84|
|      | GL | 2  | 39 | 6  | 3  | 0  | 0  | 78  |    |
|      | FL | 0  | 2  | 40 | 0  | 0  | 0  | 95.2|    |
|      | SHL| 2  | 1  | 0  | 44 | 0  | 0  | 93.6|    |
|      | BL | 0  | 0  | 0  | 0  | 0  | 0  | 0   |    |
|      | WL | 0  | 0  | 0  | 0  | 0  | 0  | 0   |    |
|      | SL | 0  | 0  | 0  | 0  | 0  | 0  | 0   |    |
|      | PA%| 91.5| 92.9| 80 | 89.8| 0  | 0  |    |
|      | OAA%| 88.3|    |    |    |    |    |    |

Note: CL: Crop land; GL = Grass land; FL = Forest land; SHL = Shrub land; BL = Bare land; WL = Wetland; SL = Settlement land; UA = User accuracy; PA = Producer accuracy; OAA = Overall accuracy; K = Kappa statistics.

\[
K = \frac{N \sum_{i=1}^{n} m_{ii} - \sum_{i=1}^{n} (G_iC_i)}{N^2 - \sum_{i=1}^{n} (G_iC_i)}
\]

Where: \(i\) denotes the class number, \(N\) represents the total number of classified values in comparison to truth values, \(m_{ii}\) is the number of values that fall into the truth class \(i\) and are also classified as values found along the diagonal of the confusion matrix, \((G_i)\) indicates the sum of all predicted values belonging to class \(i\), and \((C_i)\) are the total number of truth values in class \(i\). Where \(\sum_{i=1}^{n} m_{ii}\) and \(\sum_{i=1}^{n} (G_iC_i)\) are calculated using the equations given below.

\[
N = 36 + 43 + 44 + 45 + 41 + 48 + 43 = 300
\]

\[
\sum_{i=1}^{n} m_{ii} = 36 + 35 + 40 + 41 + 38 + 41 + 35 = 266
\]

\[
\sum_{i=1}^{n} (G_iC_i) = (36 + 51) + (43 + 41) + (44 + 42) + (45 + 45) + (41 + 40) + (48 + 41) + (43 + 40) = 12,800
\]

\[
K = \frac{300(36 + 35 + 40 + 41 + 38 + 41 + 35) - (36 + 51) + (43 + 41) + (44 + 42) + (45 + 45) + (41 + 40) + (48 + 41) + (43 + 40)}{300^2 - (36 + 51) + (43 + 41) + (44 + 42) + (45 + 45) + (41 + 40) + (48 + 41) + (43 + 40)}
\]

\[
K = \frac{90000 - (1836 + (1763 + (1848 + (1825 + (1640 + (1968 + (1720))))))}{90000 - (1836 + (1763 + (1848 + (1825 + (1640 + (1968 + (1720)))))}
\]

\[
K = \frac{97800 - 12,800}{90000 - 12,800} = \frac{67000}{77200} = 0.867 - 0.87 \text{ (value of kappa coefficient for 2018)}
\]

The greater the kappa coefficient the better is the segmentation accuracy (Asokan & Anitha, 2019). The rate of LULC conversion for the four periods from 1973–1986, 1986–2000, and 2000–2018, and 1973–2018 was computed using the previous research approach conducted by Amanuel and Mulugeta (2014).

\[
R = \frac{Y_2 - Y_1}{t}
\]

Where \(R\) = rate of change; \(Y_2\) = recent year land-use/cover in ha; \(Y_1\) = initial year LULC in ha, and \(t\) = interval year between initial and recent year.

### 3.2. Status of LULC classification in the study landscape

In the initial study period (1973), grasslands covered 45.5% (20,401.1 ha) followed by forestland 43.1% (19,318.6 ha), croplands 9.24% (4141.2 ha), shrub land 2.01% (901.1 ha), and bare lands (0.1%) wet lands accounted the lowest percentage of the study landscape, whereas the settlement lands were totally lost (Table 4). However, in the second study period (1986), croplands were dominant LULC classes, which accounted for 32.04% (14,360.03 ha), followed by grasslands 27.67% (12,401.1 ha), shrub lands 23.9% (10,705.8 ha), forestlands 16.29% (7302.03 ha), wetland 0.1% (32.1 ha), but bare land occupied the minimum share of the study area. In the third period (2000),
about (45.4%) of the study area was occupied by croplands, followed by shrub land 23.9% (10, 745.2 ha), grassland 14.2% (6345.8 ha), forestland 13.1% (5882.3 ha), wetlands 3.2% (1431.6 ha), whereas bare land and settlements share the lowest percentage. In the final study period (2018), approximately 51.1% (22, 913.8 ha) of the study area was covered by croplands followed by Shrub land 23.5% (10, 545.5 ha), forestland 10.8% (4850.9), grassland 6.3% (2816.9), wetland 3.9% (1733.6 ha) even though bare lands and settlement accounted the lowest proportion of the study area (Table 4). The areal extent of LULC changes and their distribution, for each time phase, are illustrated (Table 4 and Figure 4). The LULC changes were classified into 4-time series (1973–1986), (1986–2000), (2000–2018), (1973–2018), and LULC maps of the study landscape and the subsequent statistical precision are shown in (Figure 5, and Table 5), respectively.

3.3. Dynamics of LULC change between 1973 and 2018

3.3.1. State of cropland LULC

The majority of the rural inhabitants in Kembata Tembaro district, as elsewhere in Ethiopia, rely mainly on agriculture, especially crop cultivation. The LULC trend analysis conducted over the past four consecutive study periods 1973–1986, 1986–2000, 2000–2018, and 1973–2018 shows that the study area experienced substantial LULC changes (Table 5). Between 2000 and 2018, the amount of cropland augmented with an annual increasing rate of 142.3 ha/year. The study landscape recorded an expansion in cropland between 1973 and 1986 of 4141.2 ha (9.2%) which then increased to 14, 360 ha (32%), whereas in the final period (2018) the overall situation was changed and it occupied the largest portion 22, 913.8 ha (51.1%) followed by shrub land (23.5%), forest (10.8%), and grassland (6.3%). The remaining shares were covered by grassland, bare land, and wetland. Between 1973 and 1986 cropland gained 246.8% area from other land cover classes and experienced a positive rate of change (Table 7). This type of transition is typically caused by rapid population expansion happened at the expense of grasslands, and forestland. According to evidence collected through key informant interviews and discussions with FGDs, the expansion of croplands, as well as the reduction of grassland and forestland cover was happened as a result of population pressure. Moreover, as discussed by participants of the FGDs, during this period, crop lands were abundant and the population pressure was low in most places of the study area. Between 1973 and 1986, the highest annual increase rate of cropland (and hereafter the loss of grassland, forestland, and bare land) has been noted, which may be related to a rise in small-scale farming. These findings are consistent with previous research by Shiferaw and Singh (2011), Siraj et al. (2018), and Hailu et al. (2020) who have found 65% augmentation in cropland respectively. Obviously, in subsistence farming, when modern technology is not used, agricultural input is insufficient or non-existent, boosting yields is achieved by bringing additional parcels of land under farming, and this is specifically what has been seen in the current study area. The current research results are consistent with those of many previous Ethiopian studies. For instance, Amanuel and Mulugeta (2014) indicated agricultural land increased by 19.16%, 52.11%, and 65.6% in 1973, 1986, and 2004, respectively. Similarly, Alemu et al. (2015) point out that the percentage of cropland has increased from 23.5% in 1985 to 39.11% in 2010, respectively. Alike, findings were reported by Andualem et al. (2018), who have found that cropland increased by 13.78% between 2007 and 2018. Agidew and Singh (2017) also come up with similar outcomes observing that cropland cover increased by 55.23% between 2000 and 2010. Moreover, the current results are in opposition to that of a study by Deribew and Dalacho (2019) that outlines the decline of cropland due to prolonged drought, outbreaks of disease, and the displacement of people, between 1973 and 1986, leading to a conversion of cropland to grassland and shrub land. However, in the current study area informants have reported that the drought happened for just a short time and was not severe. Furthermore, Martinez et al. (2009) documented a significant reduction of farmland in Mexico, with an annual decreasing rate of − 7% and − 20% between 1973–1990 and 1990–2003, respectively.

3.3.2. State of Wetland LULC

Land covered by wetlands in the study landscape was 15.6 ha accounting for (0.04%) of the total area in 1973. The wetland cover extent and its proportional share in the years 1986, 2000, and 2018 were (0.07%), (3.2%), and (3.9%), respectively. The land cover of wetland had shown a continuous increase in the study area (Table 4). In summary, the trend analysis revealed that wetlands increased by (1718 ha) between 1973 and 2018, with a percentage change of (112.8%) and an annual increasing rate of (38.2%). These study findings contradict the outcomes of (Y. Belayneh et al., 2018), who found a significant decrease and full drying up of wetlands in Ethiopia. Similarly, Hailu et al. (2020) found out that from 1973 to 2019, there was a steady reduction in the entire area of wetland, with an average lessening rate of 172.6 ha/year.

3.3.3. State of Bare LULC

At the beginning of the current study, bare land covered only a few areas 35.41 ha in (1973), 20.3 ha in the second period, and 1.21 ha in the third period.
However, this had expanded to 1399.55 ha (3.2%) in the final study period (2018). Between 1973 and 1986 the bare land LULC showed increasing and decreasing trends. However, in general, the LULC trend analysis showed that bare land augmented by (1364.1 ha) in the final study period (1973–2018), with a percentage change of (3852.4%) and an annual increasing rate of 30.31 ha/year has been recorded over the last 45 years. This could be attributed to the sloppy area cultivation practices and incompatible farming methods. Informants confirmed that several people confessed to engaging in deforestation to increase their productivity and expand agricultural land. Moreover, growth in the human population in the study area in conjunction with migration and formal settlement programmes led to an increase in the bare land cover. In the current study area, climate change and soil erosion (e.g. water and wind erosion) linked to inadequate land management resulted in infertile and bare land. This finding is in contrast with research done by Hailu et al. (2020) who reported a decline in bare land from 2872.1 ha (7%) in 1973 to 551.34 ha (1.3%) in 2019. Despite this, the current study finding is in covenant with those from a wide range of previous studies in Ethiopia and beyond. For example, (Tolesa et al., 2017) in the central highlands of Ethiopia, from 0 in 1973 to (739.08%) in 2015, and Siraj et al. (2018) noticed an increase in bare land with an annual rate of 5.23 ha per year between 1973 and 2015, and Bekele et al. (2018) observed an increased rate of 91 ha per year from 1998 to 2011, Olorunfemi et al. (2018) reported similar findings in southern Nigeria. Additionally, Abate (2011) reported that bare land expanded at an annual increasing rate of 256 ha per year between 1972 and 1985.

3.3.4. State of Forestland LULC

The study results showed there was a continuous percentage loss of forestland in all study periods. Its share was 19, 318.62 ha (43.1%), 7302.03 ha (16.29%), 5882.33 ha (13.13%), and 4850.91 (10.82%), in 1973, 1986, 2000, and 2018, respectively (Table 4). The reason for this may have been the rapid annual population growth in the area by 2.8% (CSA, 2007) which likely required more agricultural land. Moreover, the result revealed that the forest cover of the study area has been gradually declining at an annual rate of – 321.5 ha/year between 1973 and 2018 (Table 5). This finding is in agreement with the study by Assen and Nigussie (2009) and Siraj et al. (2018), both of which recognised that Ethiopia’s forest cover had been converted into other land uses. The findings of this study are similar to those of several previous Ethiopian studies. For example, Degife et al. (2018) have described forestland decline from 16.41% in 1987 to 15.50% in 2017, and Daye and Healey (2015) indicated analogous outcomes in south-west Ethiopian, and Degifea et al. (2019) reported a similar trend in the Lake Hawassa watershed, and Dibaba et al. (2020) noticed that lessening of forest coverage from (21.55%) in 1987, (17.61%) in 2020, and (9.18%) in 2017. Likewise, WoldeYohannes et al. (2018) also stated forestland has declined at an annual rate of 1.71 ha/year during 1985–2010. Similarly (Hassen & Assen, 2017) conveyed the shrinking of forest coverage by 23.1% between 2004 and 2014. Agidew and Singh (2017) stated that there was a decline in forestland in Northeastern Ethiopia. Tewabe et al. (2020) also indicated analogous outcomes. Amanuel and Mulugeta (2014) reported that forestland declined at an average rate of 22.64 ha/year from 1973 to 2004. It also reported the decline of forestland in the lake Wanchi watershed. In contrast to the current study, Andualem et al. (2018) found that between 2007 and 2018, the forest LULC increased by 1.46%. Similarly, Gebrelibanos and Assen (2013) confirmed that there was a consistent increase in forest cover between 1964 and 2006. Informants of the current study mentioned the following reasons for the loss of the forest. Fundamental reasons include the outbreak of the 1985/86 famine, which forced families to extract locally available forest resource. Similarly, raise in population caused division of forestland and other shrub lands aimed to maximum production. Furthermore, in 1991/92 there was a downfall of the military government and replacement of non-military government caused weak and low enforcement where forestlands were illegally converted into other land use types (Demissie et al., 2017). Youths with no farms and farmers with very small farm land contribute negatively to the LULC changes by cutting trees for firewood and charcoal, which poses a burden upon the existing forest.

Table 4. Area covered their status and percentage change of the classified LULC categories between 1973, 1986, 2000, and 2018 in the study landscape.

| LULC Classes     | 1973    |   | 1986    |   | 2000    |   | 2018    |   |
|------------------|---------|---------|---------|---------|---------|---------|---------|---------|
|                  | area (ha) | %   | area (ha) | %   | area (ha) | %   | area (ha) | %   |
| Crop land        | 4141.2  | 9.24 | 14,360.03 | 32.04 | 20,351.64 | 45.41 | 22,913.82 | 51.13 |
| Grass land       | 20,401.072 | 45.5 | 12,401.1 | 27.67 | 6345.77 | 14.16 | 2816.98 | 6.29 |
| Forest land      | 19,318.62 | 43.1 | 7302.03 | 16.29 | 5882.33 | 13.13 | 4850.91 | 10.82 |
| Shrub land       | 901.11 | 2.01 | 10,705.8 | 23.9 | 10,745.21 | 23.98 | 10,545.5 | 23.53 |
| Bare land        | 35.41 | 0.1 | 2.03 | 0.01 | 1.21 | 0.03 | 1399.6 | 3.12 |
| Wet land         | 15.60 | 0.04 | 32.09 | 0.072 | 3.19 | 0.03 | 1733.6 | 3.87 |
| Settlements land | 0 | 0 | 10.03 | 0.02 | 55.26 | 1.23 | 552.69 | 1.23 |
| Total            | 44,813.03 | 100 | 44,813.03 | 100 | 44,813.03 | 100 | 44,813.03 | 100 |
lands. There are many resource poor individuals who practice this form of economic activity in the area, especially jobless and landless youths. This situation needs immediate attention; otherwise, it will result in severe socioeconomic and environmental disruptions.

3.3.5. State of Grassland LULC

In the mid–1970s, grasslands were the dominant type of LULC within the area. Within the mid-20th, grassland was rapidly substituted by cropland because of high rates of population raise and also the need for a various range of products, pushing farmers to alter some of their lands to other land-use categories. Grassland covered a total area of (45.5%) in 1973, (27.7%) in 1986, (14.2%) in 2000, and (6.3%) in the study area in 2018. Based on the current LULC change analysis, grasslands exhibited a considerable decline by (~7999.97 ha) with a percentage change of (~39.2%) and an annual decreasing rate of ~615.4 ha/year changes in the initial study period (1973–1986) and by (~3528.8 ha) an annual lessening rate of change ~196 ha/year in the third period, respectively (Table 5). In summary, the LULC trend analysis revealed that grassland lessened by (~17,584.1 ha) between 1973 and 2018, with a percentage change of (~86.2%) and an annual declining rate of (~390.8%). FGDs and key informant interviews corroborate with satellite data, which reveals a continual decrease during the study period, which is connected to periodic fires that occur during the dry period and the expansion of farming activities. Moreover, based on responses from local residents obtained through interviews and group discussions, an increase in the desire for agricultural production on existing land and the establishment of new households in the study landscape may have contributed to the reduction of grass land. Thus, the present study found that conversion of grass land into cropland and settlement is a common practice in the study landscape. This finding is consistent with the result of Asmamaw (2011) who have found that grasslands in northeastern Ethiopia declined from 5.8% in 1980 to 4.1% in 2006 with an annual decreasing rate of 1.17%. Abate (2011) reported that grasslands declined by 73 ha/year between 1972 and 1985 in the south Wello highlands. Agidew and Singh (2017) described a decline in grassland between 1973 and 2015 in Northeastern Ethiopia. Bekele et al. (2018) reported that grassland progressively declined during the study period from (1985–2011) in the Awash river basin. A study conducted by WoldeYohannes et al. (2018) also conveyed similar results in southern Ethiopia during 1985–2010. Mikias (2015) also arrived at similar outcomes indicated that grazing land was reduced by an annual rate of 13.58 ha/year. Similarly, Tewabe et al. (2020) reported that there was a lessening of grassland at an annual rate of 10 ha/year in 1986–2018. Andualem et al. (2018) had stated grassland cover decreased by 15.97% between 2007 and 2018 in the Ribb watershed.

3.3.6. State of shrub LULC

Shrub land was the second largest in percentage cover between the third and fourth periods when compared to the other LULC categories that accounted for 10, 745.21 ha (23.9%) and 23.53% (Figure 4). The amount of shrub lands, on the other hand, decreased steadily in the third period while declining with a percentage change of (~1.86%) and an annual shrinking rate of (~11.1) ha/year (Tables 5 and 7). Shrub land experienced the biggest conversion with nearly 667 ha (73.65%) of its entire area transformed to cropland 499 ha (49.6%), wetland 115 ha (12.7%), and the rest to other LULC categories as depicted in (Table 6). According to key informants and FGDs, this year also experienced a time when Ethiopia was severely impacted by famine and drought. Shrub land significantly diminished in the third period, when this land cover was officially disseminated for youth’s for cultivation activities. This might be attributable to the expansion of cropland and settlement area at the expense of shrub land. In general, the LULC trend analysis showed that shrub land augmented by (9644.37 ha) in the final
Figure 5. Classified LULC map of the study area in 1973, 1986, 2000, and 2018.

Table 5. Rate of LULC dynamics from the time when (1973–2018) in the study landscape.

| LULC Classes  | AC (ha)  | RC (ha/year) | AC (ha)  | RC (ha/year) | AC (ha)  | RC (ha/year) | AC (ha)  | RC (ha/year) |
|---------------|----------|--------------|----------|--------------|----------|--------------|----------|--------------|
| Crop land     | 10,218.8 | 786.1        | 5991.6   | 428          | 2562.2   | 142.3        | 18,772.6 | 417.2        |
| Grass land    | –7999.97 | –615.4       | –6055.3  | –432.5       | –328.8   | –196         | –17,584.1 | –390.8       |
| Forest land   | –12,016.6| –924.4       | –1419.7  | –101.4       | –1031.4  | –57.3        | –14,467.7 | –321.5       |
| Shrub land    | 9804.7   | 754.2        | 39.4     | 2.82         | –199.7   | –11.1        | 9644.37  | 214.3        |
| Bare land     | –33.4    | –2.6         | –0.82    | –0.06        | 1398.3   | 77.7         | 1364.1   | 30.31        |
| Wet land      | 16.5     | 1.3          | 1399.5   | 99.9         | 301.99   | 16.8         | 1718     | 38.2         |
| Settlement    | 10.03    | 0.77         | 45.2     | 3.2          | 497.4    | 27.6         | 552.7    | 12.3         |

Note: AC = Area of change; RC = Rate of change
study period (1973–2018), with a percentage change of (1070.3%) and an annual increasing rate of (214.3 ha/ year). This finding is in contrast with those of several earlier Ethiopian studies. For example, (Angessa et al., 2019) stated that shrub land declined annually at a rate of 1.3% in the lake Wanchi watershed. Agidew and Singh (2017) identified that shrub lands decreased from 28.4% to 24.6% between 1973 and 2015. Amare (2015) came up with comparable outcomes that identified a decline in bushland cover in the Infraz watershed. In covenant with the current study, Mikias (2015) reported that shrub land increased by an annual rate of 22.8 ha/year between 1973 and 2010.

3.3.7. State of settlement LULC

In the image of 1986, the settlement LULC is identified as a separate class. Within this period, it covered 10.03 ha (0.02%) and quickly expanded to 552.7 (1.23%) of the total study area in 2018. The size of the settlement increased from 0% in 1973 to 0.12% in 2000 and further augmented to 1.23% in 2018 (Table 4). The trend showed a consistent expansion of the settlement LULC over the last four and a half decades being analysed from (1973–2018). There has been a significant expansion of rural settlement at the expense of forestland, indicating widespread deforestation in the study area. These findings are consistent with Miheretu and Yimer (2017) they reported that settlement areas had expanded between 1964 and 2014 in the Gelana sub-watershed. Initially, when the study started in the year 1973, the pattern of settlement land was covering 0% of the total studied area. However, in 2018 the observed LULC pattern was augmented with coverage of 552.69 ha (Table 4). This could be associated with the growth of residential and other infrastructures, as well as settlers’ occupancy of public lands. During the specified years, this land cover has changed at an increasing rate. In the final study period (1973–2018), the overall percentage expansion of settlement was 55,269%, with an annual increasing rate of 12.3 ha/year. In terms of the settlement, a higher percentage increase does not mean the land was covered with housing in the study period; rather, it refers to the proportion of land covered by housing during that period.

3.3.8. LULC change matrix

The LULC conversion matrices were analysed to determine where the major LULC changes originated and went. A summary of the results of the analysis from 1973 to 2018 is presented in Table 6. However, the extent of the changes in each LULC class has all been different,
even though all the classes have been undergoing changes in the study area. The outcome revealed that between 1973 and 2018 there was a significant LULC dynamics in which (30 ha) of bare land, (19,207) of forestland, (4197) cropland, (894) shrub lands, (20,347) grasslands, and (11 ha) of wetlands were changed one to another, respectively (Table 6). The forestland, which covered 15,411 ha in the initial year (1973), was changed into 4828 ha in the final study period (2018). It was gained from other land use categories and was lost to other land-use types. Therefore, unchanged coverage was 3796 ha. It gained 82, 900, and 49 ha from cropland; grassland, and shrub land, respectively. Similarly, its original coverage was changed to the cropland, shrub land, grassland, and settlement with the extent of 7002, 6468, 1266, and 249 ha, respectively (Table 6). Cropland was a major portion of the study area that gained additional area from other LULC categories, which comprise forestland (7002), shrub land (449), grassland (12,649), wetland (6), and bare land (15), respectively, over the last four and half decades. From this example, the unchanged coverage was 2733 ha. Conversely, cropland had been changed to another form of LULC category, which comprises settlement, grassland, shrub land, forestland, bare land, and wetland with the extent of 51, 280, 597, 82, 170, and 284 ha, respectively (Table 6).

\[
\text{Loss} = \text{Row total} - \text{diagonals of each class (unchanged)} \quad (7)
\]

\[
\text{Net change} = \text{gain} - \text{loss} \quad (8)
\]

\[
\text{Gain} = \text{Column total} - \text{diagonals of each class (unchanged)} \quad (9)
\]

\[
\text{Net persistence} = \text{Net change/diagonals of each class (unchanged)} \quad (10)
\]

The amount of land area for each LULC type in the initial study year (1973) is summed in the row, and the amount of land area converted to each LULC type in the year 2018 is summed in the column. The area of each LULC class that stayed unaltered is shown by the bold diagonal values, while the off-diagonal numbers reflect the changed area. The amount of land that was changed from one land-cover type to another is represented by the values in each cell as depicted in (Table 6). On the other hand, grassland, which covered 20,347 ha in the initial study period (1973), was changed into 2799 ha in 2018. Moreover, it acquired additional land from other LULC categories, mainly forestland (1266), cropland (280), and shrub land (7) ha, respectively (Table 6). Likewise, its original coverage was changed to (12,649), cropland (3238), bare land (1002), wetland (1061), forest (900), settlement (251) ha, respectively, during the last four and half decades. Shrubland has obtained additional areas from other LULC categories that encompass mainly the forestland (4668), grassland (3238), cropland (597) ha over the last four and a half decades. Correspondingly, its original coverage was largely changed to the cropland (449 ha), wetland (115), forestland (49), bare land (41) ha, respectively. From this example, unchanged coverage was 227 ha. The bare land, which covered 30 ha in the first year (1973), was changed into 1383 ha in the final study period (2018). It gained from other land use types and lost to other land-use types. Therefore, the unchanged coverage was 2 ha. It gained 170, 1002, 41,168 ha from cropland; grassland, shrub land, and forestland, respectively. Likewise, its original coverage was changed to the cropland, shrub land, wetland, and forestland with the extent of 15, 8, 4, and 1 ha, respectively, as illustrated in (Table 6). In general, cropland, bare land, wetlands, and shrub lands experienced the least persistent cover types, while grassland was the most persistent (Table 6). The net change-to-persistence ratio was large for forestland (positive), cropland (negative), grass land (positive) and bare land (negative), wetland (negative), and shrub land (negative), respectively, as shown in (Table 6). Throughout the total landscape, 8006 ha (i.e. the sum of diagonal elements) remain unchanged (Table 6). Contrary to other land uses, cropland to shrub land experienced the largest change matrix.

3.3.9. Rate of LULC dynamics

Table 7 already illustrates the rate of change in cropland, grassland, forestland, wetland, barren land, bush land, and settlement area cover for the study landscape. This result indicates that although resources are fixed, land cover types are subject to varying rates of change. However, the rate of change varies considerably among the various land cover types. The LULC analysis disclosed that cropland and settlement area expanded at rates of 417.2 ha/year and 12.3 ha/year, respectively, between 1973 and 2018, resulting in the loss of grassland, and forestland. In the same period, grassland and forestland decreased by –390.8 ha/year and –321.5 ha/year, respectively. In contrast to the first and second study periods, between 2000 and 2018 bare land increased by 77.7 ha/year. However, in the same study period grass, forest, and shrub land rapidly decreased with the annual rate of –196 and 57.3 and –11.1 ha/year (Table 5). In the last 45 years, wetland, settlement areas, shrub, and bare land have grown at a rate of 38.2, 12.3, 214.3, and 30.31 ha/year, respectively. In contrast, forestland and grass land have declined at an average rate of –321.5 and –390.8 ha/year, respectively.

3.4. The major drivers of LULC change in the study landscape

We collected data from KIs and FGDs on factors that drive LULC changes as well as the perceptions of local people about the alterations. These interviews and
discussions were guided by a checklist of questions during the KIs and FGDs aimed at understanding the trends, patterns, and driving forces of LULC modifications. A key outcome of the KIs and FGDs was to identify the major proximate drivers and underlying causes of LU/LCC. An overall of more than 12 elements were mentioned by the informants as the major drivers of LULC changes in the study landscape (Figure 6). Conversely, there were differences in each of the factors to which the local community viewed as drivers of LULC changes. The majority of the respondents (>96.5%, N = 180) have identified population growth, agricultural expansion, settlement, and charcoal production, respectively, as the major important drivers for the observed LULC change in the study landscape. The LULC change analysis indicates that the cropland in the study area has increased significantly over the last 45 years (1973–2018). Likewise, a significant number of respondents (96.5%) believed that LULC changes were caused by human interference, mainly agricultural expansion. In response to the significant increase in food demand, crop lands have been expanding by encroaching uncultivated areas upon forest lands.

Additionally, 82% and 79.6% of the respondents perceived the lack of alternative income sources or financial resources and poverty as among the major drivers of LULC changes in the study landscape. Lack of law enforcement (70%), construction (78.8%), bush fires (56%), and firewood by (25%) were revealed as important dynamics accountable for LULC modifications in the study landscape for over the last four and a half decades. The informants reported that livestock was permitted to graze on the residual crop stalks on the croplands after harvest and on the shared grazing lands, which diminished grasslands over the study periods (Figure 7).

On the contrary, respondents had a low perception of land-related policy (11%) and demand for timber (14%) as significant drivers of LULC changes. The informants reported soil erosion as an important cause for the decline of agricultural production, and soil fertility, particularly in the upper stream part of the study landscape. Key informants and FGD discussants revealed the disappearance of versatile indigenous tree types such as Cordia Africana shrinking of communal grazing lands, and the deterioration of highly valuable medicinal plant species are other influences of the LULC change in the study watershed. During the field study, we observed that the pasture lands were insufficient for supporting the livestock population in the area, which could have impacted household income leading to an overreliance on the available natural resources, which inevitably would have damaged the ecosystem.

From a range of different divers, respondents perceived 12 human-related activities as major drivers of LULC change in the study landscape as depicted in (Table 8). The ranks are derived based on how the variables were selected frequently by the respondents during the period under review (Munthali et al., 2019). Population growth, settlement, agricultural expansion, charcoal production, and lack of financial resources were the top five ranked underlying drivers of LULC changes in the study area, with population growth, settlement, and agricultural expansion ranked first, second, and third, respectively (Table 8). Similar results were also revealed during key informant interview and FGDs in which population growth, settlement, and agricultural expansion were identified as the main causes of LULC change in the study landscape.

In this study, about (78.6%) of the sampled households were male-headed and (21.4%) females, respectively (Table 9). The average ages of the respondent were found to be 43.5 years. The average number of active labour force and land holding of the respondents were also identified 4.3 persons and 1.8 hectare, respectively (Munthali et al., 2019). Among the entire respondents, 60% of them owned less than 2 hectare of land, whereas 14% owned greater than 2 hectares. With respect to their education level, 60% of the sampled respondents were illiterates, 37.1% can read and write and 2.9% have attended primary education and above, respectively. The socioeconomic and demographic attributes of the sampled households are presented in Table 9. The majority of the sampled respondents were married, about 81%, whereas 19% of them are unmarried. The farm size of the respondents varied from <1.25 to >2 ha, with an average of 1.8 ha (Munthali et al., 2019). Approximately, 85% of the sampled household respondents were involved in agricultural occupations, and a small portion of the defendants (25%) were involved in off-farm activities, such as government employee and business.

![Figure 6. Rate of LULC change from the time when (1973–2018) in the study area. Note: Ptn; Production; Plcy; Policy; FRe; Financial resources; LENt; Law enforcement; Exp; Expansion](image-url)
Table 8. Drivers of LULC change ranking.

| Drivers                        | Percent (%) | Rank |
|--------------------------------|-------------|------|
| Population growth              | 12.2        | 1    |
| Settlement                     | 12.09       | 2    |
| Agriculture Expansion          | 12.02       | 3    |
| Charcoal Production            | 11.77       | 4    |
| Lack of Financial resources    | 10.2        | 5    |
| Poverty                        | 9.91        | 6    |
| Construction                   | 9.8         | 7    |
| Lack of Law enforcement        | 8.72        | 8    |
| Bush fires                     | 6.97        | 9    |
| Firewood                       | 3.11        | 10   |
| Demand for timber production   | 1.74        | 11   |
| Land related Policy            | 1.37        | 12   |

3.5. Analysis of LULC changes from 1973–2018 in the study landscape

Demissie, al., 2017; Eshetu, 2014; Kindu et al., 2015), and the weak institution in the study landscape (Temesgen et al., 2013). As per pieces of evidence from field observation and FGDs, it was also a period when a military government (Dirge) has proclaimed a ‘National production and cultural development campaign’ that was aimed at maximising agricultural produce after a great famine and drought period that took place in 1985. The KIs and FGDs outcomes with local communities confirmed that it was a time for the application of agricultural fertilisers; massive settlements in the forested area and reallocation of vegetated land to farm less peasants. The collection of local building material and fuel wood, and civil war in the middle of 1990 and 1991 were additional causes for the forestland declines. In contrast to the current study carried out by Gebrelibanos and Assen (2013) in the highlands of Northern Ethiopia confirmed that there was a consistent increase in forest cover between (1964–2006), whereas in line with the present study declining in forest coverage by (23.1%) was observed between 2004 and 2014 in Lake Tana watershed of Ethiopia (Hassen & Assen, 2017). Wetlands were also diminished throughout the whole study period. This is also associated with the reallocation of wetland areas for newly married youth as a result of the ever-increasing human population in the area, establishment of some infrastructures like community health centres, schools, farmer training centres, etc. as it was confirmed by FGDs. Moreover, overgrazing of wetlands assisted in the conversion of wetlands to settlements and croplands as described during the FGDs. Conversely, croplands, urban built-up areas, and bare lands showed an increasing trend throughout the entire study period. Zeleke and Hurni (2001) described similar trends owing to the expansion of cropland causing the shortage of appropriate land for agriculture for the ever-growing population in the area. Furthermore, high human population growth in the area (Figure 8) and the aforementioned national campaign also assisted for such escalation to croplands that corroborates the result of FGDs. Likewise, degraded land was augmented by over 44% throughout the whole study period. Conversely, grasslands and shrub lands indicated both dwindling and growing trends all over the study periods (Table 4), showing the temporal variations of land cover classes and the columns of spatial variation of land cover classes.

3.6. Implications for policy formulation

Agricultural policy in Ethiopia prohibits the cultivation of steep slopes (more than 30% gradient)

Table 9. Household characteristics sampled in the study area.

| Household Characteristic | Value by Percent (%) |
|--------------------------|----------------------|
| Gender                   |                      |
| Male                     | 78.6                 |
| Female                   | 21.4                 |
| Age (Year)               |                      |
| < 45                     | 64.3                 |
| > 45                     | 35.7                 |
| Education                |                      |
| Illiterate               | 60                   |
| read and write           | 37.1                 |
| Primary and above        | 2.9                  |
| Income obtained from 1 ha of land (ETB) |      |
| < 140,000                | 1.4                  |
| 140,000–200,000          | 8.6                  |
| >200,000                 | 90                   |
| Active labour force in the household (person) |     |
| < 3                      | 24.3                 |
| 3–5                      | 60.0                 |
| >5                       | 15.7                 |
| Total area of land owned (Ha) |          |
| < 1.25                   | 24.3                 |
| 1.25–2                   | 60                   |
| >2                       | 14.3                 |
| Marital status           |                      |
| Married                  | 81                   |
| Unmarried                | 19                   |
| Occupation               |                      |
| Farmer                   | 85                   |
| Off-farm activities      | 25                   |
| Ethnic composition       |                      |
| Kembata                  | 78                   |
except for protective forestry (MoA, 1995). Several factors have contributed to the degradation of the watershed, including steep slope cultivation, disturbance of spare mountain plant covers by animals and humans, poverty, and food insecurity. In order to reward farmers who practice effective land management, the agricultural policy of the region or district should provide financial incentives. A reduction in land tax should be offered to farmers who accept courses of training and prove that they have learned from them when extension agents insist to monitor their progress. The conservation of the land use should be in the form of positive practices, rather than simply prohibiting certain bad ones (FAO, 1986). The government needs to coordinate various departments in order to manage resources sustainably. Moreover, Ethiopia needs to adopt an effective population policy to reduce the high fertility rate through family planning. Agricultural lands become scarce and fragmented due to overpopulation, which further contributes to resource pressures and environmental degradation. The policy conserving high slopes for forests should be intensified by re-afforestation, promoting more suitable soil and water conservation practices. Land degradation must avoided just as women’s health must be protected from degradation.

3.7. Perceptions on LULC Change from the local community

All the respondents (N = 180) witnessed population growth and the expansion of cultivated land as the foremost drivers of LULC alterations. According to the 2007 Residents and Housing Information of Ethiopia, the total number of inhabitants of the study district was 78, 565 (CSA, 2007). However, inhabitants were projected to be 93, 170 in 2014 and 182, 338 in 2017 (CSA, 2013). They also pointed out that human arrivals from the adjacent regions, predominantly at the beginning of the Socialist Administration (Dirge regime) in Ethiopia, have amplified the stress to the forest resources and increased the area of the cropland cover leading to the LULC modification. According to key informants, the major causes of increase in population pressure in the study area are the natural reproduction of indigenous populations, in-migration, urbanisation and resettlement. Data synthesised from key informant interviews and FGDs alluded to population growth as the most important driver of the demographic element that is triggering LULC change. As noted in the Ethiopian Central Statistics report, the area under study has seen a rapid increase in population in the past four and a half decades, which leads to an increase in food consumption from agricultural expansion (Figure 8). Rapid population growth resulted in growing farmland and the destruction of forests. An increase in population will negatively affect the natural environment due to the high demand for resources.

LULC changes are dynamic and nonlinear, which means that conversion from one land use to another does not follow the same pattern owing to natural or manmade reasons such as policy changes, population expansion, and a loss in land productivity. The military administration announced the nationalisation of all rural land by removing private and common property rights, giving all land use rights (Meshesha et al., 2014). This policy made the state the only owner of the property and land-related resources, rendering the state incapable
of monitoring and enforcing regulations. As a result of poor land management techniques, forest area has been converted to settlements and cropland and has been severely degraded (Mekasha et al., 2014; Tolessa et al., 2017). The current government of Ethiopia likewise continues the same situation, where land is owned by Ethiopia’s nations, nationalities, and people, in terms of Article 40 (3) of the constitution was ratified in (FDRE, 1994). As a result, many land-use categories may be simply converted to cultivated land. In Ethiopia, for example, peasants possess more legal rights over forests if they convert them to cropland, as the law declares forests as state property. Farmers are compelled to legally or illegally change forests into cultivation land in order to secure the usage of the land for an undetermined period of time. According to LULC trend analysis, forest cover declined over the study period (1973–2018). This is consistent with the findings of other LULC studies done in Ethiopia (Meshesha et al., 2014; Minale and Rao, 2012; Tsegaye et al., 2010) and other tropical areas (Lira et al., 2012; Oestreicher et al., 2014).

Because of government and policy changes, forests were converted into cropland, and settlement resulted in the reduction of ecosystem services. The extensive use of forestland in tropical countries has led to an adverse impact on forest ecosystems as evident by several studies in relation to agricultural policy (Lira et al., 2012; Oestreicher et al., 2014). According to the current study area, forestland has been lost and cropland and settlements have expanded. The current demographic changes and the continued variation in LULC coupled with uncertain climate conditions, significantly affect livelihoods and put the farmer’s production system under pressure. The discussions also revealed that some native trees, which were used for house construction, are in danger, like Prunus Africana, Podocarpus falcatus, and Cordia Africana. Furthermore, the area also experienced a shift in household energy use from fuelwood to crop residue, cow dung, and eucalyptus plantations due to deforestation. Historically, 95% of the households utilised the natural forest and shrubland for energy sources before 20 years ago, but today a few of them have access to natural forest and shrubland to collect wood for cooking and heating. In the focus group discussion, female respondents explained that previously, when the women collected fuelwood from the natural forest, they took chances for socialisation and informal communication with their friends and discussed social issues. Currently, they consider deforestation as a disadvantage since they have lost such communication. In the interview sessions, women are faced with long distances to travel to fetch water for household consumption since the nearby water sources have dried up, and climate change is cited as a cause for the drying of small brooks and springs. The male farmers in the present-day move their livestock long distances to reach water sources for drinking.

4. Conclusion and recommendation

Remote sensing data analysis indicated a notable decline in forest cover and a considerable increase in cropland in the study landscape during the last four and a half decades. The trend of LULC alterations viewed by respondents was congruent with the findings reported from remote sensing image analysis. Seven LULC categories were identified in the current study where significant land-use changes occurred in the area throughout the reference years of 1973, 1986, 2000, and 2018. Forestland declined from 19, 318.62 ha (43.1%) in 1973 to 4850.91 ha (10.8%) in 2018. The study further revealed that the total amount of forestland cleared between 1973 and 2018 was estimated to be 14,467.7 ha (74.9%); similarly, grasslands declined from (39.2%) in 1973–1986 to (86.2%) in 1973–2018 ha/
year over the last four and a half decades, respectively. Conversely, the settlement land has risen from 1003% to 55,269% during a similar study period. The findings revealed that forest and grasslands were the most predominant LULC type in the earlier decade, but it is now preceded by croplands. There has been an increasing trend towards croplands, settlements, and bare lands throughout the entire study period at the expense of other LULC classes. This implies that the natural resource conservation measures that have been practiced by the governmental and non-governmental organisations in the study area did not bring the desired conservation effects.

The majority of the respondents perceived population growth, settlement, agricultural expansion, and charcoal productions were recognised as dominant drivers of LULC change in the study area. If the LULC trend continues, it will have major environmental and economic ramifications, as well as a negative influence on local people’s livelihoods. In order to maintain sustainable rural livelihoods, appropriate land resource management policies, and designing appropriate population strategies that are based on community level should be considered.

To reduce and mitigate the rapid rates of LULC conversions at local, distant downstream systems and elsewhere with similar social-ecological settings, the application of integrated LULC management strategies is critically important. In this regard, it is suggested that (1) Promote the rehabilitation and conservation of the natural vegetation covers and environmentally sensitive areas, so as to benefit both the upstream and downstream landscape dwellers. (2) Control the expansion of crop cultivation into marginal lands including steep slopes through the application of smart agricultural practices that increase the efficiency of using limited space with increased crop production. (3) Integrate multipurpose perennial highland fruit tree plantation with Enset dominant agroforestry system. Further more, we recommend that policy instruments such as tax incentives for those who take care of their lands, support for off-farm economic activities in rural areas, increase agricultural production through provision of affordable inputs, and implement the land registration and certification process as quickly as possible.

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Author’s contribution

Conceptualisation: Melesse Maryo, Data curation: Mehari Mariye, Formal analysis: Mehari Mariye, Investigation: Mehari Mariye, Methodology: Mehari Mariye, Software: Mehari Mariye, Supervision: Melesse Maryo and Li Jianhua, Validation: Melesse Maryo and Li Jianhua, Writing – original draft: Mehari Mariye, Writing – review and editing: Mehari Mariye, Melesse Maryo and Li Jianhua. All authors reviewed the results and approved the final version of the manuscript. The author declares responsibility for conceiving and designing the study, collecting data, analysing and interpreting the results, and drafting the manuscript.

References

Abate, S. (2011). Evaluating the land use and land cover dynamics in boorea woreda of south wollo highlands, Ethiopia. Journal of Sustainable Development in Africa, 13 (1), 87–107.

Abebe, S. K. (2018). Assessment of land use/land cover change using GIS and remote sensing techniques: A case study of dendi district Oromiya Regional State, Ethiopia. Journal of Environment and Earth Science, 8, 123–128.

Agidew, A. A., & Singh, K., N. (2017). The implications of land use and land cover changes for rural household food insecurity in the Northeastern highlands of Ethiopia: The case of the Teleyyen sub-watershed. Agriculture & Food Security, 6(56). https://doi.org/10.1186/s40066-017-0134-4

Alemu, B., Garedew, E., Esthetu, Z., & Kassa, H. (2015). International Research Journal of Agriculture and Soil Science. International Research Journal of Agriculture and Soil Science, 5, 1, 28–44. https://doi.org/10.14303/irjas.

Amanuel, A., & Mulugeta, L. (2014). Detecting and quantifying land use/land cover dynamics in Nadda Asendabo Watershed, South Western Ethiopia. International Journal of Environmental Sciences, 3(1), 45–50.

Amare, S. (2015). Land use/cover change at infras watershed, northwestern Ethiopia. Journal of Landscape Ecology, 8(1), 78–83. https://doi.org/10.1515/jlec-2015-0005

Andualem, T. G., Belay, G., & Guadie, A. (2018). Land use change detection using remote sensing technology. Journal of Earth Science & Climatic Change, 9(10), 1–6. https://doi.org/10.4172/2157-7617.1000496

Angessa, A. T., Lemma, B., & Yeshietela, K. (2019). Land-use and land-cover dynamics and their drivers in the central highlands of Ethiopia with special reference to the Lake Wanchi watershed. GeoJournal, 86(3), 1225–1243. https://doi.org/10.1007/s10708-019-10130-1

Asmamaw, B. L., Mohammed, A. A., & Lulseged, D. T. (2014). Land use/cover dynamics and their effects in the Gerado catchment, northeastern Ethiopia. International Journal of Environmental Studies, 68(6), 883–900. https://doi.org/10.1080/00207233.2011.637701

Asokan, A., & Anitha, J. (2019). Change detection techniques for remote sensing applications: A survey. Earth Science Informatics, 12(2), 143–160. https://doi.org/10.1007/s12145-019-00380-5

Asres, R. S., Tilahun, S. A., Ayele, G. T., & Melesse, A. M. (2016). Analyses of land use/land cover change dynamics in the upland watersheds of upper blue Nile Basin. Springer
Braimoh, A.K. (2006). Random and systematic land-cover transitions in northern Ghana. *Agriculture, Ecosystems & Environment*, 113, 254–263.

Burgi, M., Bieling, C. K., Hackwitz, V., Kizos, T., Lieskovsky, J., Marti’ n, M. G., McCarthy, S., Mu Ller, M., Palang, H., Pleninger, T., & Printzmann, A. (2017). Processes and driving forces in changing cultural landscapes across Europe. *Landscape Ecol*, 32(11), 2097–2112. https://doi.org/10.1007/s10107-017-0513-z

Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International Journal of Wildland Fire*, 10(4), 321–328. https://doi.org/10.1071/wf01031

Congalton, R. G., & Green, K. (2009). Assessing the accuracy of remotely sensed data: Principles and practices (2nd ed.). *Boca Raton: Taylor & Francis*, 11(6), 448–449. https://doi.org/10.1016/j.jag.2009.07.002

CSA, (2007). Summary and statistical report of the 2007 population and housing census results. CSA. (2013). Population projection of Ethiopia for all regions at woreda level from 2014-17. Central Statistical Agency.

Daniel, A. M. (2008). Remote sensing and GIS-based Land use and land cover change detection in the upper Dijo river catchment, Silte zone, southern Ethiopia. 1–34.

Daniel, B., Tena, A., Asfaw, K., Geta, Z., & Asfse, M. M. 2018. Land use and land cover dynamics in the Kelda watershed, Awash River basin, Ethiopia. *Environment Hazards*, 18(3), 246–265. https://doi.org/10.1080/17477891.2018.1561407

Teshome, T., & Mengistu, D. A. (2019). Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, 15. https://doi.org/10.1016/j.rsase.2019.100249

Belay, T., & Mengistu, D. A. (2019). Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, 15. https://doi.org/10.1016/j.rsase.2019.100249

Bekele, D., Alamirew, T., Bekele, A., Zeleke, G., & Melesse, A. M. (2018). Land use and land cover dynamics in the Keleta watershed, Awash River basin, Ethiopia. *Environmental Hazards*, 18(3), 246–265. https://doi.org/10.1080/17477891.2018.1561407

Belayneh, B., Eyasu, E., & Medina-Solis, C. E. (2021). Land use/land cover change and its driving forces in Shenkolla Watershed, South Central Ethiopia. *The Scientific World Journal*, 2021, 1–13. https://doi.org/10.1155/2021/9470918

Belayneh, Y., Ru, G., Guadie, A., Teffera, Z. L., & Tsega, M. (2018). Forest cover change and its driving forces in FagitaLekoma District, Ethiopia. *Journal Forest Resources*, 117(5), 1567–1582. https://doi.org/10.1007/s11676-018-0383-8

Belete, F., Maryo, M., & Teka, A. (2021). Land use/land cover dynamics and perception of the local communities in Bita district, south western Ethiopia. *International Journal of River Basin Management*, 1–12. https://doi.org/10.1080/15715124.2021.1938092

Beriahun, M. L., Tsunekawa, A., Haregeweyn, N., Meshesha, D. T., Adgo, E., Tsubo, M., Masunagaf, T., Fenta, A. A., Sultan, D., & Yibelalt, M. (2019). Exploring land use/land cover changes, drivers and their implications in contrasting agro-ecological environments of Ethiopia. *Land Use Policy*, 87, 1–15. https://doi.org/10.1016/j.landusepol.2019.104052

Betru, T., et al, Tolera, M., & Sahle, K., et al (2019). Trends and drivers of land use/land cover change in Western Ethiopia. *Applied Geography*, 104, 83–93.

Binyam, A., Efrem, G., Zewdu, E., & Kassa, M. (2015). Land use and land cover changes and associated driving forces in North Western Lowlands of Ethiopia. *International Research Journal of Agriculture and Soil Science*, 5(1), 28–44. https://doi.org/10.14303/irjas.2014.063

Birhane, E., Ashfare, H., Fenta, A. A., Hishe, H., Gebremedhin, M. A., Wahed, H. G., & Solomon, N. (2019). Land use land cover changes along topographic gradients in Hugumburda national forest priority area, Northern Ethiopia. *Remote Sensing Applications: Society and Environment*, 13, 61–68. https://doi.org/10.1016/j.rsase.2018.10.017

Braimoh, A.K. (2006). Random and systematic land-cover transitions in northern Ghana. *Agriculture, Ecosystems & Environment*, 113, 254–263. https://doi.org/10.1007/978-3-319-18787-5_5

Assen, M., & Nigussie, T. (2009). Land use/cover changes between 1966 and 1996 in Chirokella micro-watershed, Southeastern Ethiopia. *East African Journal of Sciences*, 3 (1), 1–8. https://doi.org/10.4314/eajsc.v3i1.42778

Attri, P., Chaudhtry, S., & Sharma, S. (2015). Remote Sensing & GIS based Approaches for LULC Change Detection. *International Journal of Current Engineering and Technology*, 5, 2347–5161.

Ayele, G. T., Tebeje, A. K., Demissie, S. S., Belete, M. A., Jemberrie, M. A., Teshome, W. A., Mengistu, D. T., & Teshale, E. Z. (2018). Time series land cover mapping and change detection analysis using geographic information system and remote sensing, Northern Ethiopia. *Air, Soil and Water Research*, 11, 1–18. https://doi.org/10.1177/1178622117751603

Bekele, D., Alamirew, T., Bekebed, A., Zeleke, G., & Melesse, A. M. (2018). Land use and land cover dynamics in the Keleta watershed, Awash River basin, Ethiopia. *Environmental Hazards*, 18(3), 246–265. https://doi.org/10.1080/17477891.2018.1561407

Belay, T., & Mengistu, D. A. (2019). Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, 15. https://doi.org/10.1016/j.rsase.2019.100249
EMS, (2013). . Ethiopian Meteorological Service Database. Addis Ababa. Eshetu, A. A. (2014). Forest resource management systems in Ethiopia: Historical perspective. International Journal of Biodiversity and Conservation, 6(2), 121–131. https://doi.org/10.5897/IJBC2013.0645 FAO, (1986). The highlands reclamation study – Ethiopia final report. Food and Agriculture Organization of the United Nations, Rome. Volumes 1 and 2. FAO, (2010). Global forest resources assessment country report. Ethiopia PP43. FAO. (2016). State of the world’s forests 2016. Forests and agriculture: Land-use challenges and opportunities. Rome, 107. Fasika, A., Motuma, T., & Gizaw, T. (2019). Land Use Land Cover Change Trend and Its Drivers in Somodo Watershed South Western, Ethiopia. African Journal of Agricultural Research, 14, 102–117. F.D.R.E. (1994). Federal Democratic Republic of Ethiopia (FDRE), 1994, Constitution of the Federal Democratic Republic of Ethiopia (p. 50). Addis Ababa. Gasaw, T., Tulu, T., & Argaw, M. (2017). Erosion risk assessment for prioritization of conservation measures in Geleda watershed, Blue Nile basin, Ethiopia. Environmental Systems Research, 6(1), 1–14. https://doi.org/10.1186/s40068-016-0078-x Gebreliabanos, T., & Assen, M. (2013). Land use/land cover dynamics and their driving forces in the Hirmi watershed and its adjacent agro-ecosystem, highlands of Northern Ethiopia. Journal of Land Use Science, 10(1), 81–94. https://doi.org/10.1080/1747423X.2013.845614 Gebremicael, T. G., Mohamed, Y. A., van der Zaag, P., & Hagos, E. Y. (2018). Quantifying longitudinal land use change from land degradation to rehabilitation in the headwaters of Tekeze-Atbara Basin, Ethiopia. Science of the Total Environment, 622–623, 1581–1589. https://doi.org/10.1016/j.scitotenv.2017.10.034 Gurmesa, F. (2015). Forest loss and climate change in Ethiopia. Research Journal of Agriculture and Environmental Management, 4(5), 216–224. Hailu, A., Mammo, S., & Kidane, M. (2020). Dynamics of land use, land cover change trend and its drivers in Jimma Geneti District, Western Ethiopia. Land Use Policy, 99, 1–11. https://doi.org/10.1016/j.landusepol.2020.105011 Haque, I. M., & Basak, R. (2017). Land cover change detection using GIS and remote sensing techniques: A spatio-temporal study on Tanguar Haor, Sunamganj, Bangladesh. The Egyptian Journal of Remote Sensing and Space Sciences, 20(2), 251–263. x. https://doi.org/10.1016/j.ejrs.2016.12.003 Hassan, Z., Shabbir, R., Ahmad, S. S., Malik, A. H., Aziz, N., Butt, A., & Erum, S. (2016). Dynamics of land use and land cover change (LULC) using geospatial techniques: A case study of Islamabad Pakistan. SpringerPlus, 5(1), 1–12. https://doi.org/10.1186/s40064-016-2414-z Hassen, E. E., & Assen, M. (2017). Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia. Environmental Systems Research, 6(4), 1–13. https://doi.org/10.1186/s40068-017-0081-x Houghton, R. A., House, J. I., Pongratz, J., van DerWerf, G. R., DeFries, R. S., Hansen, M. C., Le Quere, C., & Ramankutty, N. (2012). Carbon emissions from land use and land-cover change. Biogeosciences, 9(12), 5125–5142. https://doi.org/10.5194/bg-9-5125-2012 Jianyia, G., Haigang, S., Guorui, M., & Qiming, Z. (2008). A review of multi-temporal remote sensing data change detection algorithms. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences Beijing, China, XXXVII Part B7. Keenan, R. J., Reams, G. A., Achard, F., de Freitas, J. V., Grainger, A., & Lindquist, E. (2015). Dynamics of global forest area: Results from the FAO global forest resources assessment 2015, Forest Ecology and Management, 352, 9–20. https://doi.org/10.1016/j.foreco.2015.06.014 Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2013). Land use/land cover change analysis using object-based classification approach in munessa-shashemene landscape of the Ethiopian highlands. Remote Sensing, 5(5), 2411–2435. https://doi.org/10.3390/rs5052411 Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2015). Drivers of land use/land cover changes in Munessa-Shashemene landscape of the south-central highlands of Ethiopia. Environmental Monitoring and Assessment, 187(7), 1 17. https://doi.org/10.1007/s10661-015-4671-7 Kothari, C. R. (2004). Research methodology methods & techniques (2nd ed.). New Age International (P) Limited. Kotoky, P., Dutta, M. K., & Borah, G. C. (2012). Changes in Landuse and Landcover along the Dhansiri river channel assam – A remote sensing and GIS approach. Journal Geological Society of India, 79(1), 61–68. https://doi.org/10.1007/s12594-012-0002-6 K.T.D.A.R.D.O. (2019). Kembata Tembaro District Agriculture and Rural Development Office. Information on Socio-Economic and Geo-Spatial Annual Statistical Abstract. southern central Ethiopia. Lambin, E. F., & Geist, H. J. (2006). Land-use and landcover change: Local processes and global impacts. Springer Science & Business Media. Lira, et al (2012). Land-use and land-cover change in Atlantic Forest landscapes. Forest Ecology and Management, 278, 80–89. Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. International Journal of Remote Sensing, 25(12), 2365–2407. https://doi.org/10.1080/014311603100013986 Lu, D., et al, Mausel, P., & Brondizio, E., et al (2010). Change detection techniques. International Journal of Remote Sensing, 25, 2365–2401. https://doi.org/10.1080/014311603100013986 Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, 28(5), 823–870. https://doi.org/10.1080/01431160700746456 Mariye, M., Maryo, M., Changming, Y., Lakew Teffera, Z., Weldegebrail, B. (2020). Effects of land use and land cover change on soil erosion potential in Berhe district: a case study of Legedadi watershed, Ethiopia. International Journal of River Basin Management, 20(1). https://doi.org/10.1080/17515124.2020.1767636. Mariye, M., Maryo, M., & Jianhua, L. (2021). The study of land use and land cover (LULC) dynamics and the perception of local people in Aykoleba, Northern Ethiopia. African Journal of Environmental Science and Technology, 15(7), 282–297. https://doi.org/10.5897/AJEST2021.3022 Mariye, M., Maryo, M., & Li, J. (2022). The Study of Land Use and Land Cover (LULC) dynamics and the perception of local people in Aykoleba, Northern Ethiopia. Journal of the Indian Society of Remote Sensing, 50(5), 775–789. https://doi.org/10.1007/s12524-021-01462-y Martinez, M.L., et al, Pérez-Marqueo, O., & Vázquez, G., et al (2009). Effects of land use change on biodiversity and ecosystem services in tropical montane cloud forests of Mexico. Forest Ecology and Management, 258, 1856–1863. Mary, T., Ekwai, P., & Tahir, H. (2013). Evaluation of land use/land cover changes in Mekelle City, Ethiopia using Remote Sensing and GIS. Computational Ecological and Software, 3(1), 9–16.
Maryo, M. (2020). Agrobiodiversity in Enset-based agricultural landscapes of Kambatta Tembaro. International Book Market Service Ltd, Omniscriptum Publishing Group.

Mengistu, D. A., Waktola, D. K., & Woldetsadik, M. (2012). Detection and analysis of land-use and land-cover changes in the Midwest escarpment of the Ethiopian Rift Valley. Journal of Land Use Science, 7(3), 239–260. https://doi.org/10.1080/1747423X.2011.562556

Meshesha, T. W., Tripathi, S. K., & Khare, D. (2016). Analyses of land use and land cover change dynamics using GIS and remote sensing during 1984 and 2015 in the Beressa Watershed Northern central highland of Ethiopia. Modelling Earth Systems and Environment, 2(168), 1–12. https://doi.org/10.1007/s40808-016-0233-4

Meshesha, D.T., et al, Tsuenkawa, A., & Tsubo, M., et al (2014). Land-use change and its socio-environmental impact in Eastern Ethiopia’s highland. Regional Environmental Change, 14, 757–768.

Meyfroidt, P. (2013). Environmental cognitions, land change, and social–ecological feedbacks: An overview. Journal of Land Use Science, 8, 341–367. https://doi.org/10.1080/1747423X.2012.667452

Miheretu, B. A., & Yimer, A. A. (2017). Land use land cover changes and their environmental implications in the Gelana sub-watershed of Northern highlands of Ethiopia. Environmental Systems Research, 6(7). https://doi.org/10.1186/s40068-017-0084-7

Mikias, B. M. (2015). Land Use/Land Cover dynamics in the central rift valley region of Ethiopia: case of arsi Negele District. African Journal of Agricultural Research, 10(5), 434–449. https://doi.org/10.5897/AJAR2014.8728

Minale, A. S. (2013). Retrospective analysis of land cover and use dynamics in gilgel abbay watershed by using GIS and remote sensing techniques, Northwestern Ethiopia. International Journal of Geosciences, 4(7), 1003–1008. https://doi.org/10.4236/ijg.2013.47093

Minale, A.S., & Rao, K.K. (2012). Impacts of land cover/use changes of Gilgel Abbay catchment of Lake Tana on climate variability, Northwestern Ethiopia. Applied Geomatics, 4, 155–162.

MoA. (1995). Land use systems and soil conditions of Ethiopia.

Moges, K. B., Amare, S. M., & Alemu, B. D. (2015). Multitemporal Land use land cover change and dynamics of blue nile basin by using GIS and remote sensing techniques, North-Western Ethiopia. International Journal ofEnvironmental Sciences, 4(2), 81–88.

Mohajane, M., Essahalou, A., Oudija, F., El Hafyani, M., El Hmaid, A., El Ouali, A., Randazzio, G., & Teodor, A. A. (2018). Land use/land cover (LULC) using Landsat data series (MSS, TM, ETM+ and OLI) in azrou forest, in the central middle atlas of Morocco. Environments, 5(131), 1–16. https://doi.org/10.3390/environments5120131

Munthali, M. G., Davis, N., Adeola, A. M., Botai, J. O., Kamwi, J. M., Chisale, H. L. W., & Oromoogunje, O. O. I. (2019). Local perception of drivers of land-use and land-cover change dynamics across Dedza District, Central Malawi region. Sustainability, 11(3), 832. https://doi.org/10.1007/s12493-010-1083-2

Muriithi, F. K. (2016). Land use and land cover (LULC) changes in semi-arid sub-watersheds of Laikipia and Athi River basins, Kenya, as influenced by expanding intensive commercial horticulture. Remote Sensing Applications: Society and Environment, 3, 73–88. https://doi.org/10.1016/j.rsease.2016.01.002

Oestreicher, J. S., Farella, N., Paquet, S., Davidson, R., Lucotte, M., Mertens, F., & Saint-Charles, J. (2014). Livelihood activities and land-use at a riparian frontier of the Brazilian Amazon: Quantitative characterization and qualitative insights into the influence of knowledge, values, and beliefs. Human Ecology, 42(2), 521–540. https://doi.org/10.1007/s10745-014-9667-3

Oettera, D. R., Cohenb, W. B., Berterretchea, M., Maiersperger, T. K., & Kennedy, R. E. (2000). Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. Remote Sensing of Environment, 76(2), 139–155. https://doi.org/10.1016/S0034-4257(00)00202-9

Oluronfemi, E. I., Fasinmirin, J. T., Olufayo, A. A., & Komolafe, A. A. (2018). GIS and remote sensing-based analysis of the impacts of land use/land cover change (LULCC) on the environmental sustainability of Ekiti State, southwestern Nigeria. Environment, Development and Sustainability, 22(2), 661–692. https://doi.org/10.1007/s10668-018-0214-z

Othow, O. O., Legesse, G. S., & Obsi, G. D. (2017). Analysing the Rate of land use and land cover change and determining the causes of forest cover change in Gog District, gambella regional state, Ethiopia. Journal of Remote Sensing & GIS, 6(4). https://doi.org/10.4172/2469-4134.1000219

Peng, G., Xiang, N., Bing, W., & Zheng, Y. (2015). Land use changes and its driving forces in hilly ecological restoration area based on gis and rs of northern China. Scientific Reports, 5, 1–11. https://doi.org/10.1038/srep11038

Phalan, B., Onial, M., Balmford, A., & Green, R. E. (2011). Reconciling food production and biodiversity conservation: Land Sharing and Land sparing compared. Science, 333(6047), 1289–1291. https://doi.org/10.1126/science.1208742

Pontius, R.G., Shusas, E., & McEachern, M. (2004). Detecting important categorical land changes while accounting for persistence. Agriculture, Ecosystems & Environment, 101, 251–268.

Rahman, M. T. (2016). Detection of Land Use/Land cover changes and Urban Sprawl in Al-Khobar, Saudi Arabia: An analysis of multi-temporal remote sensing data. ISPRS International Journal of Geo-Information, 5(15), 2–17. https://doi.org/10.3390/ijgi51020015

Rawat, J. S., & Kumar, M. (2015). Monitoring land use/cov/er change using remote sensing and GIS techniques: A case study of Hawalbhag block, district Almora, Uttarakhand, India. The Egyptian Journal of Remote Sensing and Space Sciences, 18(1), 77–84. https://doi.org/10.1016/j.ejrs.2015.02.002

Schaefer, M., & Thinh, N. X. (2019). Evaluation of land cover change and agricultural protection sites: A GIS and remote sensing approach for Ho Chi Minh City, Vietnam. Heliyon, 5 (5), e01773. https://doi.org/10.1016/j.heliyon.2019.e01773

Shawul, A. A., & Chakma, S. (2019). Spatiotemporal detection of land use/land cover change in the large basin using integrated approaches of remote sensing and GIS in the Upper Awash basin, Ethiopia. Environmental Earth Sciences, 78(141), 1–13. https://doi.org/10.1007/s12665-019-8154-y

Shiferaw, A., & Singh, K. L. (2011). Evaluating the land use and land cover dynamics in Borena Woreda South Wollo Highlands, Ethiopia. J. Bus. Econ, 2(1), 69–104. 2. EBE

Singh, A. (1989). Review Article Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10(6), 989–1003. https://doi.org/10.1080/01431161890803939

Siraj, M., Zhang, K., & Moges, K. (2018). Retrospective analysis of land use land cover dynamics using GIS and remote sensing in central highlands of Ethiopia. Journal of Landscape Ecology, 11(2), 31–52. https://doi.org/10.2478/jjelc-2018-0005

TekleL., K. & Hedlund, L. (2000). Land cover changes between 1958 and 1986 in Kulu District, Southern Wello, Ethiopia. Mountain Research and Development, 20(1), 42–51.
Temesgen, H., Nyssen, J., Zenebe, A., Haregeweyn, N., Kindu, M., Lemenih, M., & Halle, M. (2013). Ecological succession and land use changes in a lake retreat area (Main Ethiopian Rift Valley). *Journal of Arid Environments*, 91, 53–60. https://doi.org/10.1016/j.jaridenv.2012.12.001

Tesfaye, S., Guyassa, E., Raj, J. A., Birhane, E., & Wondim, G. T. (2014). Land Use and Land Cover Change, and woody vegetation diversity in human driven landscape of Gilgel Tekeze Catchment, Northern Ethiopia. *International Journal of Forestry Research*, 1, 1–10. dx. https://doi.org/10.1155/2014/614249

Tewabe, D., Fentahun, T., Li, F., & Li, F. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *Cogent Environmental Science*, 6(1), 1778998. https://doi.org/10.1080/23311843.2020.1778998

Thakkar, A. K., Desai, V. R., Patel, A., & Potdar, M. B. (2017). Post-classification corrections in improving the classification of Land Use/Land Cover of arid region using RS and GIS: The case of Arjuni watershed, Gujarat. *India the Egyptian Journal of Remote Sensing and Space Sciences*, 21(1), 79–89. https://doi.org/10.1016/j.ejrs.2016.11.006

Tilahun, A. (2015). Accuracy Assessment of Land Use Land Cover Classification using Google Earth. *American Journal of Environmental Protection*, 4, 193.

Tolessa, T., Senbeta, F., & Kidan, M. (2017). The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. *Ecosystem Services*, 23, 47–54. https://doi.org/10.1016/j.ecoser.2016.11.010

Tsegaye, et al (2010). Land-use/cover dynamics in Northern Afar rangelands, Ethiopia. *Agriculture, Ecosystems & Environment*, 139, 174–180.

Tsehaye, G., & Mohammed, A. (2015). Land use land cover dynamics and their driving forces in the Hirmi watershed and its adjacent agro ecosystem highlands of Northern Ethiopia. *Journal of Land Use Science*, 10(1), 81–94. https://doi.org/10.1080/1747423X.2013.845614

Tucker, C. J., Grant, D. M., & Dykstra, J. D. (2004). NASA’s Global Orthorectified Landsat data set. *Photogrammetric Engineering and Remote Sensing*, 70(3), 313–322. https://doi.org/10.14358/PERS.70.3.313

Twisa, S., & Buchroithner, M. F. (2019). Land-use and land-cover (LULC) change detection in Wami River Basin, Tanzania. *Land*, 8(136), 1–15. https://doi.org/10.3390/land8090136

USGS. (2019). Landsat Collection 1 Level 1 product definition. *Survey, D.o.t.I.U.S.G Ed.

WoldeYohannes, A., Cotter, M., Kelboro, G., & Dessalegn, W. (2018). Land use and land cover changes and their effects on the landscape of Abaya-Chamo Basin, Southern Ethiopia. *Land*, 7(2). https://doi.org/10.3390/land7010002

Wubie, M. A., Assen, M., & Nicolau, M. (2016). Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia. *Environmental Systems Research*, 5(8), 1–12. https://doi.org/10.1186/s40068-016-0058-1

Yesuph, A. Y., & Dagnew, A. B. (2019). Land use/cover spatiotemporal dynamics, driving forces and implications at the Beshillo catchment of the Blue Nile Basin, North Eastern Highlands of Ethiopia. *Environmental Systems Research*, 8(21), 1–30. https://doi.org/10.1186/s40068-019-0148-y

Yohannes, H., Soromessa, T., Argaw, M., & Dewan, A. (2020). Changes in landscape composition and configuration in the Beressa watershed, Blue Nile basin of Ethiopian Highlands: Historical and future exploration. *Helijyon*, 6(9), 1–17. https://doi.org/10.1016/j.helijyon.2020.e04859

Yuan, F., Bauer, M. E., Heinert, N. J., & Holden, G. R. (2005). Multi-level land cover mapping of the Twin Cities (Minnesota) metropolitan area with multi-seasonal Landsat TM/ETM+ Data. *Geo-Carto International*, 20(2), 5–14. https://doi.org/10.1080/10106040508542340

Zeleke, G., & Hurni, H. (2001). Implications of land use and land cover dynamics for mountain resource degradation in the Northwestern Ethiopian Highlands. *Mountain Research and Development*, 21(2), 184–191.

Zewdie, W., & Casplovics, E. (2017). Remote Sensing based multi-temporal land cover classification and change detection in northwestern Ethiopia. *European Journal of Remote Sensing*, 48(1), 121–139. https://doi.org/10.5721/EuJRS20154808