Land use and land cover change, and analysis of its drivers in Ojoje watershed, Southern Ethiopia

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ABSTRACT

There have been incredible changes that have taken place in the land use pattern globally over the last 50 years, which resulted from environmental degradation and climate change impacts. Quantitative analysis of the LULC dynamics helps in land-use management and ecosystem degradation at large. The study was conducted in the Doyogena district, southern Ethiopia to identify LULC change dynamics, and analyze the driving forces using combined approaches: remote sensing, field observations, in-depth household interviews, key informants, and Focus Group Discussions (FGDs). A supervised maximum likelihood image cataloging method was employed in conjunction with feature extraction of satellite images to categorize and map LULC classes of the study area. Satellite image handing out, classification technique, and remotely sensed data were processed using ArcGIS map 10.6, and ERDAS Imagine 2014. Common LULC categories were identified, and a change analysis was conducted. Accordingly, seven LULC categories were determined. The result showed a considerable decline in forestland from 1756.7 ha (38.8%) in 1973 to 71.6 ha (1.6%) in 2020. Similarly, wetlands have declined successively from 16.8 in 2000–2010 to 6.3 in 1986–2020 ha/year over the last three and half decades respectively. On the other hand, cropland has increased from 34.1% in 1986–2000 to 46.3% between 1986–2020, which is linked to population growth, settlement, and expansion of farmlands. The study watershed has experienced a considerable change in LULC change over the last >3 decades. Hence, local and national regimes should implement sustainable land planning, management strategies including integrated land-use planning, and policy reform into development projects and programs.

1. Introduction

Land is a vital natural resource with numerous economic, social, and ecological purposes. Thus, constant LULC dynamics occur due to societal growth and environmental influences [1]. Evaluating the LULC modifications and understanding tendencies of alteration are remarkable for strategic planning and executing the aspects of natural resource management [2]. The investigation of LULC modifications, demarcating and mapping of land covers, and documentation of the driving forces is significant for sustainable natural resource management [3]. LULC is frequently used term by many workers where land cover refers to the physical and biological cover of the surface of the land [4, 5, 6, 7, 8] whereas the land-use is the deployment of land for diverse purposes where humans manipulate the land [9] but the land conversion refers to the modification of land use owing to human interference [8, 10, 11, 12], which include settlement, industrial areas, infrastructure development and fishery [13].

Land resources provide diverse ecosystem services that are necessary for human survival on the earth and protecting the ecosystem integrity is under threat [9]. Consequently, LULC changes have recently been a key concern topic on the environmental agenda [2, 7, 14, 15, 16, 17, 18, 19] because of their substantial impacts on global climate change, biodiversity, and ecosystem services [20] biogeochemical processes [21] socio-economic and social well-being [14, 22], groundwater recharge [23], and environmental modification [24]. LULC is the most significant risk of the depletion of natural resources, especially wetlands, forests, and diverse fauna [25].

The conversion of forest cover to other land-use types to meet human needs is a major contributor to environmental degradation [26] habitat destruction, and ecological imbalance on earth [27]. Forests are a means of income for many people because they can provide food, medicine [28],
freshwater, air, and a storehouse for carbon [25]. Even though forests serve vital environmental, cultural [29], and socioeconomic roles in the survival of life on Earth, the quality and quantity of forests in Ethiopia are diminishing on a regular basis [30].

LULC changes are influenced by a wide range of drivers [12, 31, 32]. The expansion of agricultural and settlement land, population growth, and charcoal production have been identified as driving forces of LULC change [32], residents density in northern China [33], expansion of settlements in highlands [34], and the slope inclination [35]. Furthermore, institutional, technological, and cultural causes, improper land management, resettlement plans, agricultural investment, and rapid population expansion have been underlined as significant driving factors of LULC changes [35]. Likewise, unfavorable administration strategy by Daniel [36], Illegal logging, fuelwood exploitation and plantation [37], firewood collection, charcoal production, population increase, and poverty in Malawi [38], land scarcity, population expansion, and urbanization in Kenya [7] were mentioned as drivers of LULC change.

Remotely detected information can provide appropriate data swiftly. Thus, examining time-based alterations in the LULC dynamics rapidly offer a better accuracy at a low cost over large geographical areas [13, 39, 40, 41, 42, 43, 44]. Several scholars have attempted to use digital satellite image data to address problems of LULC change detection in various parts around the world [7, 19, 22, 39, 45, 46, 47, 48, 49, 50, 51]. Kotoky, et al. [51] discussed that LULC investigations are becoming increasingly important in various fields, including agricultural development, settlement surveys, effective land use plans, and ecological studies. Remote sensing (RS) and geographic information systems (GIS) methods have been used for detecting LULC changes at multiple spatial scales [52]. GIS integrates information obtained from RS to provide a comprehensive knowledge of LULC modeling [53].

Employing Landsat images to evaluate LULC modification at the watershed and sub-watershed level is a significant approach to enhancing natural resource management [6]. Tracking LULC change by using GIS and remote sensing technology provides quantitative analyses of the transformation. But, it fails to describe the relationship between the driving factors and the cause of their change [54]. The majority of previous research on LULC alterations was focused on particular areas of the country, mainly in Northern Ethiopia and the Central Rift Valley Lakes, and only evaluated the dynamics of LULC changes using remote sensing data [55]. Nevertheless, explanations of the local people's views on the driving forces of the LULC change were not delivered [56]. Similarly, in the Ojoje watershed, studies on LULC Change and the analysis of driving factors are still limited. Therefore, it is appropriate to study the perception of the community on the driving forces of LULC changes [55].

The study area, the Ojoje watershed, is characterized by its high human and livestock population and cereal production, which is prone to land degradation, deforestation, and high erosion [57]. Therefore, knowledge of the dynamics of LULC conversion, driving factors, and causes of LULC change is necessary to build appropriate environmental protection and land management approaches for the entire watershed. The extent of the LULC change in the Ojoje watershed has not been addressed so far. Consequently, the magnitude of the change, its driving factors, and its causes are poorly understood. Therefore, the current study helps to fill the knowledge gap in the land management sector of Ethiopia in general and in particular, southern Ethiopia. Therefore, the main objective of the current study was 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 the dynamics and extent of LULC change and (2) assess the driving factors of LULC change over the last 34 years.

2. Methods and materials

2.1. The study area

Ojoje watershed is located in the northern part of the Doyogena District (Figure 1) and is located 258 km southwest of Addis Ababa (capital of Ethiopia). Geographically, the District is positioned between 7° 18’ 25”N–7° 21’ 49” N latitude and 37° 45’ 33” E–37° 48’ 51” E longitude and covers about 4525.1 ha/ha. The watershed has a share of five rural kebeles (peasant associations), namely Wagebeta, Gomera Gewada, Ancha Sedicho, Hawora Arara, and Doyogena. The watershed encompasses six rivers: three of which are permanent (Sana, Yabela, and Shanya), whereas the remaining three are intermittent (Shapa, Gondala, and Kasho). The intermittent rivers might not offer surface water flow throughout the dry season; they may only flow during certain seasons. Sana, Yabela, and Shanya rivers have a steady flow of water throughout the year and finally join into the Omo basin. Undulating mountainous topography with an elevation stretching from 2300–2800 m asl is the characteristic of the watershed. The slope of the farmland ranges from 2% to 65% where agricultural activities are practiced. The slope of the study landscape is categorized into 3 main types, namely level, moderate, and steep slopes that form 10.7 %, 63.9%, and 25.4%, respectively. Because of its topographical features, the study area experiences heavy soil erosion & gully formation [58].

There are two rainy seasons with bimodal rainfall in the study watershed: Maxxe Sana (long rainy season) and Glalichi Sana (short rainy season). Most of the crop husbandry takes place during the “Maxxe Sana” season. Accordingly, the majority of the soil loss by water erosion occurs this time. During the shorter rainy season crops like barley, wheat, maize, and potato are cultivated. The area receives a total annual average rainfall of about 1507 mm. The study district has varied agro-ecologies; 15% Dega (high land, 2400–3200 m a. s. l), 74% Woyna Dega (midland, 1800–2400 m a. s. l), and 11% Kolla (lowland, 500–1800 m a. s. l) [59]. The mean annual temperature is 19.4 °C [59].

Central Statistics Agency (CSA) report indicated that the total population of the study district is estimated to be 122,336 between 2007 and 2015 of which 62,363 males and 59,973 are females inhabitants respectively [60]. The average population density was 458 people per km². The average landholding size for each family is less than one hectare per household. The agricultural system of the study area is characterized by the mixed farming system where the rural people depend on crop and livestock production for their livelihood. The tree species grown in the district include Eucalyptus spp, Croton macrostachys, Juniperus procera, Erythrina spp, and Cordia africana [59].

2.2. Methods of data collection and analysis

The study area was not entirely contained within a single Landsat scene; 4 Landsat images were required to get complete coverage of the study landscape. Images used in this study were obtained from the data portal (https://earthexplorer.usgs.gov/) of the USGS [61], Earth Resources Observation and Science (EROS) Center. The path and row of these images were 169, and 55 for the dry seasons of (December to February) respectively, with 30 m spatial resolution for the spectral bands. We employed multispectral satellite data (Landsat 4, 5, 7, and 8 with sensors TM, TM, ETM+, and OLI) from 1986, 2000, 2010, and 2020, respectively, to identify and evaluate images. In addition, the LULC classifications were interpreted using socioeconomic and additional data sets following previous researchers [62, 63]. We obtained ASTER, DEM, and topographic map of the study area (1:50000) from the Geospatial Information Institute of Ethiopia, then the Images were orthorectified into Universal Transfer Mercator (UTM) Zone 37N, 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 digitized 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 2020 were interpreted via mirror stereocone for LULC type identification and classification, whereas post-classification change detection was used for the evaluation of LULC types on the aerial photographs [64]. For the creation of the
latest land cover map, Google Earth images, field inventories, and ground control points 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 use land cover analysis following Oettera et al. [65].

For the quantitative data analysis, data collected through focus groups, key informant interviews, and observations were used. We used SPSS Version 23 to analyze and summarize the quantitative data gained from general informants during a formal survey. To enhance the quality of the image, different mosaicking, sub-setting, and radiometric enhancement techniques (Haze reduction and Histogram equalization) were applied to the raw data following Belete, et al. [25].

After the image was processed, signatures were distributed per pixel by identifying the land into seven classes between 1986 and 2000. Furthermore, seven LULC categories have been recognized for the years 2010 and 2020, respectively. Image cataloging was based totally on the reflectance characteristics (false-color composite) of the specific land cover classes and also supplemented by employing field observation [25], key informant interviews, and FGD. Each class was given a unique identification and assigned a selected color to differentiate one from another. For each of the predetermined LULC categories, training samples had been selected via delimiting polygon around representative sites. During this time, the 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, reclassified, and computed pixel values for all LULC classes [25, 66]. The conversion matrices were created using ERDAS Imagine 2014, and each land cover value was analyzed in an Excel sheet to indicate the source, and destination of different land cover categories [6, 66, 67], we calculated the LULC area cover in hectares and percentage, as well as the percentage of changes between the stated period.

Area in hectar = \[ \frac{\text{Count} \times 900 \text{ or } 3600}{10,000} \]  
(1)

Area in percent = \[ \frac{\text{Value of the identified pixel}}{\text{Number of pixels in total}} \times 100 \]  
(2)

Percentage of LULC change = \[ \left( \frac{P_{t2} - P_{t1}}{P_{t1}} \right) \times 100 \]  
(3)

where \( P_{t1} \) is the area of LULC at the initial period and \( P_{t2} \) is the area of LULC at the final time. A positive result indicates that the extent of an issue has increased, whereas a negative result indicates the amount has decreased. We validated the classification results by constructing a confusion matrix as a basis for determining the accuracy of assessments [25, 68]. The selection of the suitable image acquisition date is imperative to a clear identification of LULC types from satellite imagery. During the study, image-gaining dates were designated based on the availability of cloud-free imageries to evade classification mistakes [69, 70]. Ground truths were not available for the aerial photographs taken 47 years ago. Therefore, the interpretation and classification were not supported by ground truths. However, historical data were used to confirm the

Figure 1. Location map of Ojoje watershed with its elevation model.
interpretation. In contrast, the 2020 satellite image allowed for ground truth to be established. To establish the classification in the latter case, seven homogenous areas were selected for each LULC unit as a training site. For the final period (2020), 235 ground truth points from seven land cover classes (i.e. 37 grasslands, 21 bare lands, 24 built-up areas, 44 forests, 40 shrublands, 0 wetlands, and 40 cropland) were used to assess image quality and accuracy. Furthermore, the topographic maps obtained from the Ethiopian Geospatial Information Institute were used to visualize the landscape of the whole watershed [71]. The detailed properties of Landsat data used in this study are illustrated (Table 1).

This study has applied both unsupervised and supervised cataloging techniques following previous researchers [72, 73, 74]. Unsupervised cataloging was practiced to detect key land cover of the watershed. This result and data from GPS collected points; supervised image classification approaches were employed. Supervised cataloging was carried out by sample polygons (ground truth points). In supervised classification, specific land cover types were delineated using training sites, whereas, in unsupervised classification, land cover classes were 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 (1975, MMS imagery). A supervised signature extraction with the maximum likelihood algorithm was used to categorize the Landsat imagery [15, 72].

2.2.1. Socio-economic data/household survey

To validate the data obtained from aerial photos and satellite imagery, a socioeconomic survey was undertaken with 120 randomly selected households. The district, administration, and household participants were chosen using a three-stage sample technique that included purposive and random sampling, whilst the household respondents are being selected through systematic random sampling following Wubie, et al. [75]. As a result, from the three elevation classes, namely Lower (500–1800 m a. s. l.), Middle (1801–2400 m a. s. l.), and Upper (2401–3200 m a. s. l) using a household survey 40 households from each of the 3 sample areas were selected. 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 of selecting individual households from the chosen kebeles (the smallest government administrative structure in Ethiopia) by using system sampling following previous approaches [15]. Furthermore, focus group discussion (FGDs) was carried out with 20 participants (8 women and 12 men) to acquire additional information on the long-term LULC practices. In general, four FGDs were conducted where each group was composed of five participants (i.e. five development agents, five farmers, five Kebele cabinet members, and five community elders who had been selected through the kebele administrative bodies, and the knowledgeable community representatives. In order to have engaged in in-depth discussions, key informant interviews, and focus group discussions (FGD) were conducted to acquire information regarding the past and present situations, including the drivers of LULC change within the study landscape [64]. For the in-depth discussion, 10 people (>65 years) were purposefully chosen as key informants (KI) to gather data on the trends of LULC alteration over the past 3 and half decades. We calculated the study sample size following Kothari [76].

\[ n = \frac{z^2 \cdot p \cdot q \cdot N}{e^2(N - 1) + z^2 \cdot p} \]  

where \( n \) is the sample size and \( Z \) denotes the 95 confidence limit (interval) under the normal curve, which would be 1.96. \( P = 0.1 \) (per centage 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 \( n = \frac{1.96^2 \cdot 0.1 \cdot 0.9 \cdot 2100}{0.05^2(2100 - 1) + 1.96^2 \cdot 0.1 \cdot 0.9} = 120 \)

The overall procedure for the LULC change analysis was organized in the schematic diagram (Figure 2), and seven classes of LULC categories were identified (Table 2), and the description in Table 2 is provided from various supporting data [67, 77].

2.2.2. Ethical clearance

Ethical clearance and approval letter to conduct the current study were obtained from Tongji University, China Research Ethics Committee. Then, the support letter was written by Doyogena District Agriculture and Rural Development Office, and given to the respective Kebele administration to communicate to households at the village level. Then, verbal consent was obtained from farm household interviewees under study, and the confidentiality of the information given by the respondent was maintained.

2.2.3. Image pre-processing and cataloging

Due to systematic and random errors present in raw satellite images, those images cannot be directly utilized for any form of feature identification. We applied the most common Landsat pre-processing steps, including geo-referencing, co-registration [78, 79], and conversion of radiance, solar correction, atmospheric, topographic, and relative correction to be utilized for LULC change following [61, 80, 81]. In this study, we considered the following gap-filling or destriping methods to remove Landsat image strips: Kriging and co-Kriging, Geostatistical Neighborhood Similar Pixel Interpolator (GNSPI), the weighted linear regression (WLR) algorithm; and the direct sampling [82] method. The images produced by Landsat sensors are subject to distortion caused by sensor, solar, atmospheric, and topographic factors. Therefore, employing these methods would minimize effects to the extent that is desired for a given application [83]. This process is mainly determined by the type of image, the orientation of the sensors, and the amount of noise interfering with the image [44]. Furthermore, these techniques were applied to multi-date satellite images to facilitate visual comparison between topographies and to enhance interpretability. For this reason, Earth Resource Data Analysis System (ERDAS) was used to implement topographic and atmospheric correction for airborne imagery, which reduces errors and gets the actual reflectance0 values for LULC classification [79]. The image difference was estimated as the difference in the total number of equivalently classed pixels between 2 images, which was computed by subtracting the initial state class totals from the final state class totals.

Finally, the identification and classification of LULC types on aerial photographs were assumed by visual interpretation with a mirror

| No | Period | Imagery type | Path | Row | Imagery date | Resolution (m) | Source | Bands/color |
|----|--------|--------------|------|-----|--------------|----------------|--------|-------------|
| 1  | 1986   | Landsat TM   | 169  | 55  | 19/01/1986   | 30°30          | USGS   | Multi-spectral |
| 2  | 2000   | Landsat TM   | 169  | 55  | 12/02/2000   | 30°30          | USGS   | Multi-spectral |
| 3  | 2010   | Landsat ETM+ | 169  | 55  | 21/01/2010   | 30°30          | USGS   | Multi-spectral |
| 4  | 2020   | Landsat OLI  | 169  | 55  | 14/02/2020   | 30°30          | USGS   | Multi-spectral |
| 5  | Topographic maps | - | - | - | 1:50,000 | EGIA | - |

Table 1. Explanation of imagery statistics, and sources used for LULC study Oojole watershed.
stereoscope. The trends and dynamics of LULC change were analyzed by 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. [65].

2.2.4. Change detection
Monitoring changes in the earth’s surface features enable us to realize the interactions between humans and their environment to health management and the use of natural resources as reported by Singh [19]. Jianya, et al. [84] discussed that change detection approaches can be characterized in two groups: Bi-temporal altered detection is a direct comparison, post-analysis comparison, and uniform modeling which measures changes based on a simple ‘two epochs timescale comparison, whereas temporal trajectory analysis is a time series analysis and the changes are based on a ‘continuous’ timescale, focusing on both changes between dates and progress of the modification over the period. The

Figure 2. Flowchart presenting techniques employed to attain the ultimate LULC change in the Ojoje watershed.
post-classification approach evaluates the change in LULC based on a
detail-categorized classification of land cover units [85]. To obtain the
information of LULC dynamics in terms of pattern and rate conversion, a
post-classification change detection analysis was carried out in ERDAS
Imagine 2014 using classification images from 1986, 2000, 2010, and
2020. According to Lu, et al. [86], accuracies of the change discovery
results depend on the performance of the image processing and cate-
gorization approach.

The key objective of the change detection technique is to obtain the
change in two or extra images of the identical sites captured at different
periods. Different approaches have been adopted for change detection
depending on their applications such as algebra-based classification-
based, and other change detection approaches [44].

2.2.5. Accuracy assessment for the LULC maps

For grassland, bare land, built-up area, forestland, shrubland, and
cropland the overall user accuracy evaluation was found to be 82.2, 91.3,
77.4, 86.3, 93, and 95.2% respectively as depicted in Table 3. During the
last study periods, the producer accuracy, which is the proportion of
properly classified data from total classified data, was 80.8 % for bare
land, 88% forest, 82.8% built-up area, 93% for cropland, 86.9% for
shrubland, and 90.2% for grassland, respectively (Table 3). We collected
a total of 585 Ground Control Points (GCPs) from a Global Positioning
System (GPS) during our field visit and with Google Earth image. Out of
which, 350 points were used for supervised classification, while the
remaining 235 points were used for assessing the accuracy of satellite
images. Accuracy assessment was conducted using topographic maps for
the classified images of 1986, 2000, and 2010. A total of forty-two, forty-
three and one hundred eighty-two points were randomly distributed
across the classified image and topographic map, respectively, over three
periods. The land cover class that had been assigned on images and
manually on maps and resulted in 40 points from the total of 42 points
(95.2%) in 1986, 42 points from the total 43 points (97.9%) in 2000 and
181 points from the total of 182 (99.5%) images were well matched
between both on images and topo-graphic maps. GCPs were chosen for
each LULC class in proportion to their areal extent on the image,
employing Congalton’s thumb rule for better accuracy assessment. 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 [44,
87]. To compute the user accuracy, we divided the number of correctly
classified pixels in each class by the number of training set pixels per

Table 2. LULC categories and their description in Ojoje watershed, Ethiopia.

| No. | Land cover type | explanation |
|-----|-----------------|-------------|
| 1   | Cropland        | Land owned by smallholder farmers to grow cropland. It is characterized by tilled and planted, bare crop fields, and limited areas temporarily left as fallow. It is used for the cultivation of annual and perennial crops as well as for cattle raising. |
| 2   | Wetland         | Land use that is waterlogged and swampy during the wet season, which dries in the sunny season. |
| 3   | Shrub land      | Areas covered by small trees, bushes, and shrubs mixed with grasses; less than forests. |
| 4   | Forest land     | Land covered with dense trees, mixed forest, and plantation forests. |
| 5   | Grassland       | The land is dominated by grasses, forbs, and herbs with nil or little proportion of shrubs. |
| 6   | urban built-up area | It includes rural settlement areas, educational, health, socio-economic facilities, residential houses, administrative buildings, small-scale industrial areas, transportation infrastructures, and playgrounds. |
| 7   | Bare land       | Areas with little or no vegetation cover consist of exposed soil and/or rock outcrops and quarries. |

Table 3. An error assessment table of the Ojoje watershed (2020).

| Classified Data | Reference Data | Users accuracy % |
|-----------------|----------------|------------------|
| Grass land      | 37 2 3 3 0 0 45 | 82.2            |
| Bare land       | 2 21 0 0 0 0 23 | 91.3            |
| Built-up area   | 0 3 24 2 2 0 31 | 77.4            |
| Forest land     | 0 0 2 44 2 3 51 | 86.3            |
| Shrub land      | 2 0 0 1 40 0 43 | 93              |
| Crop land       | 0 0 0 2 40 0 42 | 95.2            |
| Wet land        | 0 0 0 0 0 0 0   | 0               |
| Column tot      | 41 26 29 50 46 43 235 |               |
| Producer accuracy % | 90.2 80.8 82.8 88 86.9 93 0 |               |

Note: The overall classification accuracy is 87.7% whereas the overall Kappa Statistics is 0.85%.

Table 4. The area coverage of different LULC in 1986, 2000, 2010, and 2020.

| Land cover class | 1986     | 2000     | 2010     | 2020     |
|------------------|----------|----------|----------|----------|
|                  | Area (ha) | %        | Area (ha) | %        | Area (ha) | %        | Area (ha) | %        |
| Cropland         | 1078.9   | 23.8     | 1583.1   | 34.9     | 2246.4   | 49.6     | 3333.03   | 73.7     |
| Wetland          | 304.1    | 6.72     | 286.5    | 6.3      | 0        | 0        | 0         | 0        |
| Shrub land       | 694.2    | 15.3     | 913.9    | 20.3     | 790.5    | 17.5     | 3142.0    | 6.9      |
| Forestland       | 1756.7   | 38.8     | 1178.7   | 26.1     | 734.4    | 16.2     | 716.6     | 1.6      |
| Grassland        | 679.6    | 15.1     | 534.7    | 11.8     | 673.2    | 14.9     | 615.4     | 13.6     |
| Built-up area    | 11.6     | 0.26     | 28.2     | 0.6      | 7.9      | 0.17     | 28.7      | 0.7      |
| Bare land        | 0        | 0        | 0        | 0        | 7.9      | 0.17     | 28.7      | 0.7      |
| Total            | 4525.1   | 100      | 4525.1   | 100      | 4525.1   | 100      | 4525.1    | 100      |
classified class, which indicates the percentage of correctly classified pixels per land cover class [66]. Producer accuracy was 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. [25]. 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 \( (37 + 21 + 24 + 44 + 40 + 40 + 0)/235 \), which equals 87.7%, and overall kappa statistics of 0.85 was achieved for the classification periods of images, which means that there is 85% in better agreement than by chance alone (Table 3).

The Kappa coefficient ranges from +1 to -1 indicating the level of accuracy between the reference data (true data) and the analyzed images. In a study by Hassan, et al. [88], the kappa coefficient is associated with three possible groups of the covenant: the value over 0.80 shows a strong covenant, the value between 0.40 and 0.80 denotes a moderate covenant, and the value below 0.40 indicates poor covenant [25]. These ranges indicate strong conformity between the 2020 LULC classification and the reference data. We also computed a Kappa statistic for each classified map in order to measure the accuracy of the classification results. Accordingly, the resulting classification of land use/cover maps had a Kappa statistic of 0.85 for each period. For the subsequent analysis and
Table 5. Rate of LULC alteration from the time when (1986–2020) in Ojoje watershed.

| Land cover classes | 1986–2000       | 2000–2010       | 2010–2020       | 1986–2020       |
|--------------------|-----------------|-----------------|-----------------|-----------------|
|                    | Area change (ha) | Rate of change ha/year | Area change (ha) | Rate of change ha/year | Area change (ha) | Rate of change ha/year | Area change (ha) | Rate of change ha/year |
| Crop land          | 504.3           | 34.1            | 663.17          | 38.8            | 1086.7          | 45.4            | 2254.1          | 46.3            |
| Wetland            | –17.6           | –1.2            | –286.5          | –16.8           | 0               | 0              | –304.1          | –6.3            |
| Shrub land         | 219.7           | 14.8            | –123.5          | –7.2            | –476.3          | –19.9           | –380.05         | –7.8            |
| Forest land        | –578.04         | –39             | –444.3          | –26             | –662.9          | –27.7           | –1685.2         | –34.6           |
| Grassland          | –144.9          | –9.8            | 138.5           | 8.1             | –57.8           | –2.4            | –64.2           | –1.3            |
| Built-up area      | 16.5            | 1.12            | 44.71           | 2.6             | 88.4            | 3.7             | 149.6           | 3.1             |
| Bare land          | 0               | 0               | 7.9             | 0.5             | 21.83           | 0.91            | 29.7            | 0.61            |
| Total              | 1481.1          | 100             | 1708.45         | 100             | 2393.76         | 100             | 4866.83         | 100             |

Note: The area of each LULC class that stayed unaltered is shown by the bold diagonal values, while the off-diagonal numbers reflect the modified area.

Figure 4. Drivers of land-use/cover change in Ojoje watershed between 1986 and 2020. Note: - CL; Communal land FL; Forest land RF; Rainfall and AI; Alternative income.

change detection, this kappa accuracy was generally considered reasonable. Finally, it was evaluated following Butt, et al. [89], and Asokan and Anitha [44].

Kappa = P(A) = P(E)/1 – P(E)  \hspace{1cm} (5)
P (E) is the number of times the K raters are expected to agree only by chance and P (A) is the number of times the K raters agree. Where P (A) and P (E) are calculated using the equations; (6) and (7) as follows

P(A) = \( \frac{(CP + UP)}{(TP)} \) \hspace{1cm} (6)
P(E) = \( \frac{(CP + MA)(CP + FA) + (FA + UP)(MP + UP)}{TP^2} \) \hspace{1cm} (7)

where CP refers to changed pixels, UP-unchanged Pixels; TP denotes the total number of pixels, MA-missed alarms rate, and FA -false alarms rate, respectively. TP is the Output of FA, MA, UP, and CP. The greater the kappa coefficient the better is the segmentation accuracy [44]. The rate of LULC conversion for the four periods from 1986–2000, 2000–2010, 2010–2020, and 1986–2020 was computed using the previous research approach [90].

R = \( \frac{Y_2 - Y_1}{T} \) \hspace{1cm} (8)

where \( Y_1 \) = initial year LULC in ha, and \( T = \) time interval between initial and recent year. Where \( R = \) rate of change; \( Y_2 = \) recent year LULC in ha.

3. Result

3.1. LULC classification

In 1986, forestlands covered 38.8% (1756.7 ha) of the study watershed, followed by croplands 23.8% (1078.9 ha), and shrubland 15.3% (694.2 ha) (Table 4).
However, in the second study period (2000), croplands were the dominant LULC classes which accounted for 34.9% (1583.1 ha), followed by forestlands 26.1 (1178.7 ha), and shrublands 20.3% (913.9 ha). In the third study retro (2010) about 50% of the study watershed area was occupied by croplands, followed by shrubland 17.5% (790.5 ha), and forestland 16.2% but wetlands were lost. During the study period (2020) about 74% (3333 ha) of the study area was covered by croplands, followed by grasslands 13.6% (615.4 ha), whereas bare lands and wetlands accounted for the lowest proportion (Table 4). The areal extent of LULC changes and their distribution, for each time phase, are illustrated in Table 4 and Figures 3 and 4.

The study period of LULC changes into four-time series, which include (1986–2000) the first, (2000–2010) the second, (2010–2020) the third, and (1986–2020) the fourth time series, respectively. The classified LULC maps of the study watershed and the subsequent statistical precision are presented in Table 5 and Figures 3 and 4.

### 3.2. LULC changes between 1986 and 2020 in the Ojoje watersheds

The majority of the rural inhabitants rely on agriculture, especially crop growing. The percentage of land that has been progressively raised from 1986 to 2020, and used for crop production was quite high (Table 4). On the other hand, the entire area of wetland decreased at an average rate of 6.3 ha/year (Table 5). The agricultural lands have grown from 0.17% in 2000 to 3.6% in 2020, whereas the remaining four land units, namely forest, shrubland, grassland, and wetland have depicted a declining trend, but contributed to an increase in urban built-up areas and croplands, respectively (Table 6). The present study confirmed the highest percentage change in the wetland (Table 7), and the extent of these changes was 99.77%, followed by forestland, shrubland, and an urban built-up area, which encompass 97.8%, 92.1%, and 73.4%, respectively over the whole study periods. The LULC transformation matrix analysis of 34 years from 1986 to 2020 of the study landscape is shown in Table 6.

### 3.3. The major drivers of LULC change in the Ojoje watershed

Informants identified thirteen elements as drivers of LULC change in the study area (Figure 4). Informants differed in their views on the impact of each LULC driver. The majority of the respondents (>94%, n = 180) have identified population growth, expansion of farmlands, and fuel-wood collection, respectively as key drivers (Figure 4) for the observed LULC change in the study watershed.

Additionally, 82% and 78.8% of the respondents perceived the lack of alternative income sources and distribution of communal lands to landless youths to be among the major drivers of LULC changes in the study landscape. According to FGDS discussants, the livestock were permitted to graze on the residual crop stalks in the crop field after harvest and on the communal grazing lands, which diminished grasslands over the study periods.

### 4. Discussion

#### 4.1. Changes to LULC in the Ojoje watershed

The amount of cropland increased at the rate of 46.3 ha/year between 1986 and 2020. This change is typically caused by rapid population expansion, which happened at the expense of grasslands, shrublands, and forestlands as confirmed by the key informants. Between 1986 and 2020, the highest increase in the percentage of cropland (74%) has been noted, which is related to a rise in small-scale farming (Table 5). Previous researches reported a 44%, 36.4%, and 65% rise in cultivated land by [91, 92] respectively. When subsistence farming is not supported by modern technology, agricultural yield boosting can be attained by the addition of parcels of land under farming, and this is exactly seen in the current study area [90, 93, 94, 95]. Similarly reported progressive agricultural land increase at different periods from different localities.

### Table 7. Land use transformation in Ojoje watershed from 1986–2020.

| Land cover category | 1986 LULC (area %) initial year | 2020 LULC (area %) final year | Image Difference |
|---------------------|---------------------------------|--------------------------------|-----------------|
|                     | Built up area                   | Forest land                    | Grass land      | Bare land | Wet land | Row Total | Class Total |
|                     | 26.62                           | 0.141                          | 58.169          | 4.366     | 0.423    | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
|                     | 3.779                           | 2.336                          | 72.137          | 1.935     | 0.43     | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 4.465                           | 4.123                          | 80.773          | 7.929     | 1.705    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0.601                           | 0.048                          | 34.467          | 0.324     | 0.183    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 67.836          | 61.159    | 0.234    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 99.776          | 99.491    | 0.727    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 97.766          | 0         | 1.972    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 99.491          | 0         | 97.852   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 97.792          | 0         | 64.703   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 98.88           | 0         | 76.836   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 98.75           | 0         | 98.708   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 98.708          | 0         | 91.862   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 97.38           | 0         | 67.224   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 99.325          | 0         | 93.766   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|                     | 0                               | 0                              | 92.107          | 0         | 66.803   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |

**Note:** Bold numbers on the diagonal indicate unchanged LULC percentage from 1986 to 2020 and their corresponding proportions, whereas others are the areas changed from one class to another.
According to data obtained from Landsat image analysis, the wetlands have changed because of agricultural runoff from farmlands, which resulted in a reduction of wetland coverage of the Ojoje watershed. The finding is consistent with the reports of [96], whose findings showed the drying up of wetlands due to the high topographical condition of the Ojoje watershed. There are small and scattered wetlands that were difficult to spot using Landsat images, and the majority of them were considered grassland in this cataloging. Hailu, et al. [1] found a steady reduction in the entire area of the wetland, with an average rate of 172.6 ha/year.

The increase in bare lands is linked with anthropogenic activities like habitat change through deforestation, overgrazing, and the impact of climate change. This finding contradicts the study done by Hailu, et al. [1] who has reported a decline of bare land from 7% in 1973 to 1.3% in 2019 in Western Ethiopia. However, the study is consistent with earlier findings, including [97] in the central highlands and Olorunfemi, et al. [98] from southern Nigeria. Abate [99] also reported a bare land continual expansion at a pace of 256 ha/year.

The decrease in the trend of the forest cover is associated with the cropland expansion. Informants of the current study area mentioned the outbreak of the 1985/86 famine that forced families to extract locally available resources (forest resources). Similarly, the rise in population growth caused the division of forestland and other shrublands’ maximum production, which is consistent with the study by Mariye et al. [47]. Furthermore, during 1991/92 a downfall of the military government caused weak law enforcement where forestlands were illegally converted into other land-use types [100]. The study by [101] depicted the conversion of the majority of Ethiopia’s existing forest cover to other land use categories. Similar other findings were reported by [42, 102]. WoldeYohannes, et al. [69] indicated forestland declined at a rate of 1.71 ha/year in the Abaya-Chamo basin from 1985to 2010 and 23.1% between 2004 and 2014 in the Lake Tana watershed [103].

Informants have confirmed the conversion of grassland into other land-use types such as cropland. Many scholars, including Abate [99], WoldeYohannes, et al. [69], and Bekele, et al. [97] have reported similar findings. Mikias [104] indicated that grazing land was reduced by an annual rate of 13.58 ha/year in Ethiopia. Tewabe, et al. [105] reported the shrinking of grassland at the rate of 10 ha/year during the 1986–2018 periods.

The decline in Shrubland might be attributable to the expansion of cropland and built-up areas. The current finding is consistent with Angessa, et al. [106], who have discussed shrubland decline at a rate of 1.3% per year. Agiewd and Singh [107] showed a decrease in shrublands from 28.4% to 24.6% from 1973to 2015. Nonetheless, Mikias [104] has reported an increase in shrubland by an annual rate of 22.8 ha from 1973to 2010.

The increase in the built-up area could be associated with the growth of residential and other infrastructures and the occupation of public lands by settlers. The finding is consistent with Mihiretou and Yimer [88] who have discussed urban built-up areas increment over 50 years (1964–2014) in the Gelana sub-watershed.

The findings demonstrated that there were considerable LULC dynamics between 1986 and 2020 that involved a change from one land-use type to another, including 42 ha of urban built-up land, 1631 ha forestland, 218 ha cropland, 582 ha shrublands, 243 ha grasslands, and 301 ha wetlands all changing hands. In the final year of the study, the forestland that occupied, 1669 ha in the first year (1986) was reduced to 769 ha (2020). It benefited from other land use categories while losing to others. As a result, the coverage remained constant at 38 ha, gained 27 ha from agriculture, and its initial coverage was altered to cropland and shrubland, with 1254 and 320 ha, respectively (Table 6). Cropland was a major portion of the study area which gained additional area from other LULC categories, which comprise forestland (1254 ha), shrubland (538 ha), grassland (233 ha), and wetland (202 ha), respectively over the study period. Thus, unchanged coverage was 859 ha. On the other hand, cropland has been changed to another form of LULC category, which comprises urban built-up area and grassland with an extent of 41 and 85 ha, respectively.

On the other hand, grassland acquired additional land from other LULC categories, mainly forest land (43), cropland (85), and wetland (84) ha, respectively (Table 6). Likewise, shrubland has obtained additional area from another LULC category that encompasses mainly the forestland (320) ha over the last three and half decades. Correspondingly, its original coverage was largely changed to the cropland (538 ha). The percentage change of urban built-up area, forest land, shrubland, cropland, wetland, and grassland was 73.3%, 97.8%, 92.11%, 20.19%, 99.77%, and 38.84%, respectively over the last three and half decades (Table 7). This shows that the cropland is the least changed category (about 80%). Similar results have been reported from Central Malawi where 96% of agricultural land remained unchanged [38].

4.2. Perception of the local community on the LULC change

During the field study, it was observed that the communal grazing land was inadequate to support the livestock population in the area, which in turn may lead to ecosystem degradation. The informants reported soil erosion and the resulting soil fertility problems as an important cause for the decline of agricultural production, particularly in the upper part of the Ojoje watershed. Key informants and FGDs discussed the disappearance of versatile indigenous tree types such as Cordia africana of communal grazing lands, and the deterioration of highly valuable medicinal plant species are other influences of the LULC change in the study watershed. Similarly, the loss of plant biodiversity, including valuable woody species and medicinal plant species were reported [25].

Pieces of evidence from field observation and FGDs there was also a period when a military government (Dirge) proclaimed a “National production and cultural development campaign” that aimed at maximizing agricultural produce after a great famine and drought of 1985. The FGD outcomes showed that it was a time for the application of agricultural fertilizers, massive settlements in the forested area, and reallocation of vegetated land to newly engaged peasants. The uppermost negative (~39%) rate of decline of forest lands in the first study period could be linked with the government change, as was explained in the former studies [32, 100, 108], and the weak institution [109].

The collection of local building material and fuelwood for various purposes and the civil war in the middle of 1990 and 1991 were additional causes of the forestland decline. Nevertheless, Gebrelibanos and Assen [110] reported a consistent increase in forest cover between (1964and 2006), whereas in line with the present study a decline in forest coverage by (23.1%) was observed between 2004 and 2014 in the Lake Tana watershed [103]. Focus group discussants confirmed that the reallocation of wetlands for newly married youth and for the establishment of some infrastructures like community health centers, schools, farmer training centers, etc led to a decline in wetlands. Moreover, overgrazing of wetlands assisted in the conversion of wetlands to settlements and croplands as described during the FGDs. Wetlands were diminished throughout the whole study period. High human population growth in the area (Figure 5) and the aforementioned national campaign also assisted in escalation to croplands that corroborates the result of FGDs. Likewise, degraded lands augmented by over 44% throughout the whole study period. Conversely, grasslands and shrublands 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. Conversely, croplands, urban built-up areas, and bare lands showed an increasing trend throughout the entire study period. Zeleke and Hurmi [111] 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.

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 Doyogena district was 78,565 [112], and 122,338 in 2017 [60]. 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. The data synthesized from key informant interviews and FGDs alluded to population growth as the most important driver of the demographic element [59] that is triggering LULC change. But the local people’s perception of the LULC drivers study in central Malawi reported firewood collection, charcoal production, and timber to be the first top-ranked drivers of the LULC changes [38]. Thus, the long experience of the local community regarding the local conditions can be corroborated by science and can be used by decision-makers, environmentalists, and other stakeholders in establishing the management and environmental planning strategies, and the conservation of natural resources. During FGDs elder people depicted that charcoal production has been increasing over time in the study watershed.

5. Conclusion

Remote sensing data analysis indicated a notable decline in forest cover and a considerable increase of cropland in the Ojoje watershed during the last three and 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 by the current study where significant land-use changes occurred in the area throughout the reference years of 1986, 2000, 2010, and 2020. Forestland declined from 1756.7 ha (38.8%) in 1986 to 71.6 ha (1.6%) in 2020. The study further revealed that the total forestland cleared between 1973 and 2020 was estimated to be 185.2 ha (34.6%). Similarly, wetlands declined from 16.8 in 2000–2010 to 6.3 in 1986–2020 ha/year during the last study period respectively. Conversely, the built-up area has risen from 1.2% to 3.1% during the study period. The finding revealed that forest and shrublands were the most predominant LULC types, which are preceded by croplands. There has been an increasing trend toward croplands, built-up, and bare lands throughout the entire study period at the expense of other LULC classes. The study watershed revealed that croplands experienced the greatest expansion, while wetlands and shrubland experienced the highest decline.

The majority of the respondents perceived population growth, urbanization, fuelwood collection, and expansion of farmlands as dominant drivers of LULC change in the study watershed. If the current LULC change trend continues, there will be biodiversity and ecosystem degradation, which will harm the livelihood of the local people. Therefore, adequate measures to ensure judicious use of natural resources, appropriate land management, and designing appropriate population strategies and policies are recommendable to the study area. It seems mandatory to implement a sustainable land management approach by mobilizing the local communities through a participatory approach. Moreover, implementing integrated watershed management approaches is advised to reduce and mitigate LULC conversion at the local and distant downstream systems of the Ojoje watershed.

Declarations

Author contribution statement

Mehari Mariye, Li Jianhua & Melesse Maryo: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

No data was used for the research described in the article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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