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ABSTRACT

Kafta Sheraro National Park (KSNP) has experienced rapid and consecutive destruction of dry woodland vegetation due to the influence of anthropogenic activities in the past three decades. However, to date, the change in woodland cover and its driving factors have not been addressed. This study aims to assess the spatial and temporal trends of land use/land cover change, seasonal vegetation cover change via the normalized difference vegetation index (NDVI), and human-induced drivers of change that occurred in the KSNP between 1988 and 2018 by using satellite imagery sensors (TM, ETM+ OLI), field observations, and local community interview data. The 2018 image results showed kappa coefficients of the dry season and wet season of 0.90 and 0.845, respectively. There was a continuous decline in woodland (29.38%) and riparian vegetation (47.11%) and an increasing trend in shrub bush land (35.28%), grassland (43.47%), bare land (27.52%), and cultivated land (118.36 km²) over the thirty-year period. Moreover, the results showed that bare land expanded from wet to drier months, while cultivated land and grazing land increased from dry to wet months. Based on the NDVI results, high to moderate vegetation was decreased by 21.47%, while sparse and non-vegetation expanded by 19.8% and 1.7%, respectively. Settlement and agricultural expansion, human-induced fire, firewood collection, gold mining, and charcoal production were the major proximate drivers that negatively affected park resources. Around KSNP, the local communities’ livelihood depends on farming (crop and livestock production). This expansion of farming is the main driver of woodland depletion, which leads to increased resource competition and a challenge for the survival of wildlife. Therefore, urgent sustainable conservation of park biodiversity by encouraging community participation in conservation practices and preparing awareness creation programs should be mandatory.

1. Introduction

Land use land cover (LULC) change is a human-dominated modification of the terrestrial surface of the Earth (Ellis, 2006) and a significant environmental issue that affects the ecological processes encountered on a global scale (Klimanova et al., 2018; Sleeter et al., 2012). The assessment of LULC change is a study of environmental change that is more closely associated with the expansion of settlement following agriculture (Wang et al., 2018) and rapid urbanization and deforestation (Hassan et al., 2016). The consequences of LULC change include forest fragmentation and cover reduction, land degradation, biodiversity loss (Cheruto et al., 2016; Haregeweyn et al., 2015; Maitima et al., 2009), climate change (Agidew and Singh, 2017), and degraded habitat quality (Hassan et al., 2016). The changes also have significant environmental consequences for the fluctuation of local climate conditions, lowering ground water tables, and alteration in surface runoff (Bewket and Abebe, 2013; Lambin et al., 2003; Lambin and Geist, 2006). The change in LULC was more associated with the rural people livelihood that depends on mixed farming of crop production and livestock (Asmame and Abegaz, 2017). LULC change was caused by the expansion of agriculture through unplanned and inappropriate land management practices to meet the food demand of the local communities (Agidew and Singh, 2017). In many areas of developing countries, LULC changes caused by deforestation have increased the agricultural production of rural communities (Maitima et al., 2009) because their livelihood depends on natural resources (Mwavu and Witkowski, 2008). It also has important impacts on the functioning of socioeconomic and environmental systems, with tradeoffs for...
sustainability, food security, and biodiversity (Lesschen et al., 2005). LULC change via deforestation, urbanization, and intensified or extensi-
ified agriculture also created negative influences on the water cycle (Hisdal and Tallaksen, 2000).

LULC change is the combined temporal interaction of social, eco-
nomic, institutional, and environmental factors (Hassan et al., 2016; Li
et al., 2009; Lambin et al., 2001). These change factors influence the
socioeconomic and living environments of the rural livelihood of many
regions of Sub-Saharan Africa (Maitima et al., 2010). In this region, high
poverty level, fuel production, expansion of settlement, and agriculture
were prioritized as drivers for LULC change (Mekuyie et al., 2018; Kamwi
et al., 2015; Kindu et al., 2015). Similarly, in semiarid areas of Ethiopia, the
expansion of croplands and overharvesting of woodlands were major
drivers of change (Zewdie and Caplovics, 2016). The government-led
resettlement program in Ethiopia was another core driver of LULC
change because the program was undertaken without due consideration
of natural resources and lacked a clear management plan for the sus-
tainable utilization of resources (Yadeta et al., 2022; Mamade et al.,
2021; Abera et al., 2020; Esa and Assen, 2017). Thus, the livelihood of
resettled communities depends on the production of agricultural crops at
the expense of woodland vegetation.

LULC change has increased the trend of biodiversity crises over the
last four decades globally (Sharma et al., 2018; Butchart et al., 2010;
Kraus et al., 2010). This global loss of biodiversity has great potential to
interrupt relevant ecological processes and hinder ecosystem services
that are essential for humans (Schmitz et al., 2014; Keesing et al., 2010).
LULC change directly affects global biodiversity, which contributes to
assessing recent regional and global climate change and future climate
scenarios (Dwivedi et al., 2005; Fan et al., 2007). Currently, biodiversity
is dominantly concentrated in protected areas (PAs) (Busis et al., 2015;
Coetsee et al., 2014; Geldmann et al., 2013). The resources in and around
PAs are more critical in developing nations of the communities living
adjacent to PAs because their livelihoods are often directly dependent on
the resources (Hartter and Southworth, 2009). In most parts of the world,
the activities of communities around PAs are expected to influence them
globally (Jones et al., 2018; Sala et al., 2000). LULC change around PAs
has direct impacts on PA biodiversity and its ecological processes (Jones
et al., 2009; Hansen and Defries, 2007). Over the last three decades,
LULC change has been occurring rapidly in PAs and is projected to
continue (DeFries et al., 2005; Beresford et al., 2018). Therefore, the
evaluation and monitoring of LULC changes in and around PAs have
become of paramount importance (Bailey et al., 2016).

The expansion of cultivated land has been largely at the expense of
forests; globally, during the 1990s, there was an average loss of 16
million hectares of forests per year (FAO, 2011). Agricultural expansion
has been reported to be the main driver of deforestation and lead to
biodiversity loss (Haines, 2009; Lepers et al., 2005). A conversion of
forest cover to other human-made land use, particularly to agriculture,
was reported from PAs of the conterminous United States (Lu et al.,
2018), Sagarmatha National Park, Nepal (Garrard et al., 2016), Semiariad,
India (Duraisamy et al., 2018), and PAs forest, Mexico (Sanchez Reyes
et al., 2017). The conversion of forests to agriculture has also become
a major problem in East (Lambin et al., 2003) and South Africa (Bailey
et al., 2016) due to rapid population growth and subsequent resource
competition. In Ethiopia, anthropogenic activities are the most signifi-
cant factors adversely altering natural resources (Marchani et al., 2018)
and contributing detrimental impacts on the environment and livelihood
of people (Momo and Kebreab, 2014). Most of the studies of LULC
change in Ethiopia have documented a considerable expansion of farm-
land at the expense of forest cover and other LULC (Lemonih, 2014).
A study in the Eastern Tigray region revealed a strong decrease in forest
and bushland in favor of arable and rangelands (Kassa et al., 2014).
Similarly, in the Kafa Humera district (around the study site), agricul-
tural land has largely expanded by shrinking the coverage of woodland
(Alemu et al., 2015; Zewdie and Caplovics, 2016). Extensive agricultural
expansion as a cost of woodland and dense forest decline was also
reported from Nechisar National Park (Fetene et al., 2015), Bale Moun-
tain National Park (Nune et al., 2016), and Bable Elephant Sanctuary
(Sintayehu and Kassaw, 2019).

Ethiopia is ecologically rich in biodiversity; however, the biological
resources of plants and wild animals are gradually shrinking (Tefera,
2011). Forest disturbance and the rapid rate of deforestation in the
country mainly occur due to poor resource management and government
land policy (i.e., the national government needs to ensure rapid economic
growth and poverty mitigation at the expense of natural resources
(Othow et al., 2017). To combat these problems, Ethiopia has established
21 national parks, 2 wildlife sanctuaries, 6 wildlife reserves, 20 control
hunting areas and priority forests, biosphere reserves, and community
conservation areas since 1966 (Vreugdenhil et al., 2012). However, most
of Ethiopia's PAs are increasingly degraded due to unsustainable natural
resource management, habitat degradation due to livestock encroach-
ment, illegal settlement, agricultural expansion, deforestation, border
conflicts of local communities, uncertain land tenure, and very low public
awareness of the importance of biodiversity and ecosystems (Young,
2012). Moreover, suitable wildlife habitats and their biological
diversity are decreasing due to the destruction and fragmentation of natural
habitats (Bekele and Yalden, 2013). However, the expansion of protected
areas in Ethiopia is increasingly occurring, and the suitable wildlife
habitats of almost all parks, including Kafa Sheraro National Park (KSNP),
are collapsing gradually from time to time.

Land use land cover (LULC) change is key information for scholars
who are working in land management studies (Kararakas et al., 2015).
Therefore, understanding the dynamics and driving forces of LULC
changes at the local and global levels is fundamental in developing
strategic planning and the analysis of land-related policies (Tekle and
Hedlund, 2000). To announce each LULC change, remotely sensed (RS)
and geographical information systems (GIS) are widely used data sources
(Karakas et al., 2015; Karakus et al., 2014). Comparatively, the combi-
nation of RS data and field observations can accomplish LULC change
detection more accurately than separately (Mucova et al., 2018) because
satellite data analysis alone might miss the drivers of LULC change
(Lambin and Meyfroidt, 2010). Human perception is significant for un-
derstanding LULC change patterns, driving forces, and consequences
(Burgi et al., 2017; Grinblat et al., 2015). Moreover, LULC change anal-
ysis acceptance and accuracy were maximized when satellite image
analysis was mixed with local residents’ participation (Garrard et al.,
2016; Nune et al., 2016; Kamwi et al., 2018). Therefore, the main
objective of this study was to assess the extent of LULC change and the
key drivers of change in Kafa Sheraro National Park (KSNP) between
1988 and 2018. The specific objectives were (1) to identify and delineate
different LULC categories and to show the spatial and temporal trends of the main LULC change; (2) to assess the wet and dry season
variations in NDVI and dry land forest vegetation cover change; and (3)
to explore the causes/driving factors of LULC change by the socioeconomic
conditions of the communities and their perceptions of LULC change and proximate drivers.

2. Materials and methods

2.1. Description of the study area

Kafa Sheraro National Park (KSNP) was designated a park in 2007
(Letter, Ng: 13/37/82/611) with an area of 2176.43 km². The park was
formerly named the “Shire Wildlife Reserve” and was established in 1973
with an estimated area of 750 km² governed by the Tigray national
region state. Kafa Sheraro National Park (KSNP) is located in Kafa
humera and Taitatay adiyabo weredas (districts) of the western and
northwestern zones of the Tigray region 1356 km from Addis Ababa
and 490 km from Mekelle city. The park is situated in northern Ethiopia
between latitude 14°05’–14°27’N and longitude 36°42’–37°39’E. The
park is bordered by Eritrea in the north and transverse by the Tekeze
River (Figure 1). The elevation of the park varies from 539 to 1130 m
above sea level (m.a.s.l.). The landforms of the areas are heterogeneous in nature and consist of a flat plain, undulating to rolling; some isolated hills and ridges, a chain of mountains, and valleys. The climate of the area is generally characterized by hot to warm semiarid and seasonal rainfall (Temesgen and Warkineh, 2020). The maximum monthly temperature is in April (43.7 °C), while the minimum monthly temperature is in December (19.2 °C) and January (19.1 °C). The mean monthly temperature ranges from 28.35 °C to 35.1 °C. The coolest temperature occurs in August, while the warmest temperature occurs from March to May. The rainfall pattern varies greatly with the months of the season. Short rains occur in June and September, and long rains occur during July (174 mm) and August (252 mm), whereas rare cases of rain in the remaining months appear (Figure 2).

The KSNP harbored more than 70 woody species, 46 trees, 18 shrubs, and 6 tree/shrubs. The most dominant and frequent tree species in the park are *Acacia mellifera*, *Combretum hartmannianum*, *Terminalia brownii*, *Balanites aegyptiaca*, *Dicrostachys cinerea*, *Acacia senegal*, *Acacia oryana*, *Boswellia papyrifera*, *Ziziphus spina-christi*, and *Anogeissus leiocarpus* (Temesgen and Warkineh, 2020). The park is also home to large mammals such as African elephant, Roan antelope, Oribi, Spotted hyena, Greater kudu, wart hog, Anubis baboon, Grivet monkey, crocodile, fish species and wintering migratory bird (Demoiselle crane) along the Tekeze River (Shoshani and Deemeke, 2008). Agriculture is the main source of livelihood and economic activities of the studied settlers. The livelihood of the local communities of the districts Kafta humera and Tahitay adiyabo weredas (surrounding the park) is dominated by mixed farming of crop livestock production (Dejene et al., 2013).

### 2.2. Data collection and sources

#### 2.2.1. Satellite image data

Landsat 5 thematic mapper (TM), Landsat 7 Enhanced thematic mapper plus (ETM+), and Landsat 8 Operational land imager/Thermal infrared sensor (OLI/TIRS) multispectral satellite sensor data were used to detect LULC changes from 1988 to 2018 (Figure 3). The images were downloaded from Earth Explorer (http://earthexplorer.usgs.gov) and covered by the path/row (170/50) of the Worldwide Reference System. The images with high resolution and minimum or no cloud cover were selected from a number of images for each period to minimize errors or confusion for classification. A total of 26 images for the dry and wet seasons, 5 for LULC change detection, and 21 for normalized difference vegetation index (NDVI) analysis were downloaded. The dry season period of the area was defined from November to May, and the wet season was defined from June to October. However, the images were taken for the wet season between September and October and for the dry season between March and April. These months were preferred for all
satellite image sensors because they were found to have no or minimum cloud cover and water vapor. A detailed explanation of each satellite sensor is described in Table 1 for LULC change classification and for NDVI analysis in Table 2.

2.2.2. Field observation data

Field visits were carried out from December 2018 to April 2018 for the dry season and from mid-June 2018 to the beginning of November 2018 for the wet season to identify major LULC types and to take field training points that are changed seasonally in the KSNP. Table 3 shows LULC change identified in the field in each season and cross-checked through interviews of local farmers’ focus group discussions (FGDs) with farmland inside and around the park. Accordingly, the local farmers interviewed that the plowing and sowing time of rain fed crops starts in June and that the crops are harvested from mid-November to December. After the rain fed crops are harvested, they could leave the land bare until the next sowing year (June) or be left totally free and shifted to a new area. Similarly, the grasses covered in the wet season appeared bare until the next rainy season (Table 3).

Fieldwork is mainly focused on observing and capturing the various LULC types using a digital camera, and each sampling location was recorded via the geographical positioning system (GPS) of handheld...
Garmin GPS-60. To emphasize, the classification was more accurate; more than 100 ground truths (latitude and longitude records) were collected from each LULC type of the 2018 image, and a total of 700 points were collected for seven classes. The accuracy assessment was basically good for the Landsat-8 (OLI) of the 2018 satellite image because the points directly show the recent feature of LULC categories. The ground control points were divided into two groups: one group for selecting training sites for classification and the second group for the accuracy assessment.

2.2.3. Socioeconomic survey

Sampling design: The drivers of LULC change in the study were collected from three basic sources: (1) household questionnaires, (2) focus group discussions, and (3) key informant interviews. As the park is located in two woredas (districts) of Kaffa humera and Tahitay adiyabo, seven Kebeles (the smallest governmental administrative units of Ethiopia) were purposively selected from the total, based on proximity to the park and their livelihood directly dependent on the resources of KSNP and its surrounding area. A systematic sampling method was used to select the representative sample respondents for the household interviews from individual kebeles, whereas the purposive sampling technique was used for focus group discussion and key informant interviews. The sample size of households was calculated using Eq. (1) sampling technique (Cochran, 1977).

\[
no = \frac{t^2pq}{e^2} \quad n = \frac{no}{1 + \frac{no}{N}}
\]

where, \(no\) = assumed simple random sample size of households (384); \(p = \frac{q}{q} = \frac{1}{1} + \frac{t^2}{1}\); \(e\) = estimated proportion of the population to be included in the sample (i.e., 50%); \(q = 1 - p\); \(t = \) uncertainty (number of standard errors) in the number of people depending on park resources of ±5% (at the 95% confidence interval level, \(Z = 1.96\)); \(e = \) the margin of error (0.05); \(n = \) sample size, and \(N = \) the total number of household heads (i.e., 5458). Using Eq. (1), the result of the sample size was 359; however, to compensate and cover the non-response of households, the sample size was increased by 10% (36). Therefore, the total sample size of the selected households in this study was 395 (Table 4).

For questionnaire distribution, households were systematically selected from each kebele. Thus, the first household selection started randomly from the settled households, and then the next households were selected systematically at every 9th interval in each kebele using the formula below until the given sample size was reached. Therefore, the size of the interval \(k\) for selection was calculated by \(k = \frac{N}{n}\), where \(k = \) the size of the interval for selection; \(N = \) total population (households); and \(n = \) the number of samples required for the study (Mota et al., 2019).

Household survey: The questionnaires had both open and closed-ended questions to gather information about the perceptions of the local communities on LULC changes and the drivers of change in KSNP from November 2018 to June 2019. The questionnaires covered 395 households from seven Kebeles (Table 4), and individual household responses took 50–70 min. The targeted populations for semi structured interviews were parks near communities (villagers) having direct interaction with KSNP, irrigation farm holders, and livestock owners. The questionnaires were designed to gather general household characteristics, forest coverage trends, perception of the local people on LULC change, and the drivers of change (Appendix-1).

Focus group discussions (FGDs): The investigator will collect data by gathering a group of participants together to discuss the relevant issue of the study. The FGDs were performed within seven Kebeles in the study area by involving elderly people who were older than 60 years and lived in the area for more than 28 years. The elders were consulted for the age and history of the land use type and the main drivers of LULC change of KSNP using open-ended questions. This has helped us to be aware of the ongoing LULC change (past and present drivers of LULC change) in the study area.

Key informant interviews (KII): The main objective of the key informant interviews was to collect detailed information from a wide range of people who selected specific groups who had first-hand information about the

Table 1. Data type and detailed description of satellite images used in LULC change analysis.

| Satellite | Sensor type | Path/Row | Acquisition date | Spatial Resolution(m) | Bands (B) used for spectral signature | Bands wave length (μm) |
|-----------|-------------|----------|------------------|-----------------------|--------------------------------------|-----------------------|
| Landsat5  | TM          | 170/50   | 23-10-1988       | 30                    | B1, B2, B3, B4, B5, B7             | 0.48–2.20             |
| Landsat5  | TM          | 170/50   | 19-10-1998       | 30                    | B1, B2, B3, B4, B5, B7             | 0.48–2.20             |
| Landsat7  | ETM+        | 170/50   | 06-10-2008       | 30                    | B1, B2, B3, B4, B5, B7             | 0.48–2.22             |
| Landsat8  | OLI/TIRS    | 170/50   | 10-10-2018       | 30                    | B2, B3, B4, B5, B6, B7             | 0.45–2.99             |

Note: TM = thematic mapper, ETM+ = enhanced thematic mapper plus, OLI = operational land imager, TIRS = thermal infrared sensor, USGS = United States Geological Survey, calendar order (day-month-year).

Table 2. Detailed description of satellite images used for normalized difference vegetation index (NDVI) analysis.

| Satellite ID | Sensor type | Path/Row | Acquisition date | Spatial Resolution(m) | Sources |
|--------------|-------------|----------|------------------|-----------------------|---------|
| Landsat5     | TM          | 170/50   | 13-03-1988       | 30                    | USGS    |
| Landsat7     | ETM+        | 170/50   | 20-10-2007       | 30                    | USGS    |
|              |             | 26-03-2007| 30                |                       |         |
|              |             | 06-10-2008| 30                |                       |         |
|              |             | 28-03-2008| 30                |                       |         |
|              |             | 09-10-2009| 30                |                       |         |
|              |             | 16-04-2009| 30                |                       |         |
|              |             | 12-04-2010| 30                |                       |         |
|              |             | 18-03-2010| 30                |                       |         |
|              |             | 15-01-2011| 30                |                       |         |
|              |             | 21-03-2011| 30                |                       |         |
|              |             | 01-10-2012| 30                |                       |         |
|              |             | 08-04-2012| 30                |                       |         |
| Landsat8     | OLI/TIRS    | 170/50   | 26-09-2013       | 30                    | USGS    |
|              |             | 20-03-2013| 30                |                       |         |
|              |             | 29-09-2014| 30                |                       |         |
|              |             | 21-03-2014| 30                |                       |         |
|              |             | 16-09-2015| 30                |                       |         |
|              |             | 08-03-2015| 30                |                       |         |
|              |             | 20-10-2016| 30                |                       |         |
|              |             | 26-03-2016| 30                |                       |         |

Note: TM = thematic mapper, ETM+ = enhanced thematic mapper plus, OLI = operational land imager, TIRS = thermal infrared sensor, USGS = United States Geological Survey, calendar order (day-month-year).
ongoing problems that happened in KSNP by the communities. The qualitative data collection from key informants was via direct individual interviews and focus group discussions. Thus, the researcher conducted three key informant interviews: (1) community administrators and professional experts (i.e., crop and livestock production, forest and wildlife conservation, soil and water conservation) of the study districts; (2) religious leaders in the districts; and (3) management, experts, and scouts of KSNP.

The questionnaire for focus groups (elderly people) and key informant interviews were arranged for qualitative data collection by preparing the outlined script and a list of open-ended questions from specific topics of the study objectives (i.e., forest cover trend, past and present LULC, causes of LULC change, and community attitude to LULC change). The questions prepared by the investigator for elderly people were short, clear, and phrased in their local language (i.e., Tigrigna), while for expert and professional informants; the questionnaires were broad and more formally phrased. Moreover, the selected groups engaged in detailed discussions, elaborations, and conversations on the issues raised (questionnaires). Finally, the investigator recorded the interview response both by note taking and audio recording.

2.3. Data analysis

2.3.1. Preprocessing of images

Before LULC classification and detection of changes, preprocessing of satellite images is an imperative process to develop an inline association between biophysical phenomena on the ground and acquired data (Coppin et al., 2004). Before any activities, Landsat images (TM 1998 and 1998, ETM + 2008 and OLI 2018) were geometrically rectified (geocoded) to the World Geodetic System 1984 (WGS 84) and set a projection to Universal Transverse Mercator (UTM) zone 37 N specific to Ethiopia. Geometric and radiometric (reflectance) calibration: During image acquisition, satellite images have different types of distortions/noise, which reduces the quality of the image. The calibration of Landsat imagery was performed based on the known solar geometry and on the gain and bias values provided by the Landsat metadata (Hilker et al., 2012). For better performance of the Landsat time series of LULC change analysis, consistent image sets of geometric and radiometric corrections are the two significant activities (Rani et al., 2017; Hansen and Loveland, 2012). For the present study, geometric and radiometric (reflectance) corrections were carried out to decrease negative atmospheric effects or correct for changes that occurred in scene illumination, atmospheric solar conditions, and viewing geometry, as applied by Chander et al. (2009). Likewise, images with clouds and cloud shadows were removed using a cloud mask (fmask function) with the ArcMap10.5 tool. Subsequent calibration activities, such as gap filling, layer stacking, and sub setting of bands, were undertaken.

2.3.1.1. Band color combination. This activity refines image interpretability by increasing differentiability among objects of the image for classification. According to Mohy et al. (2016), visual interpretation of images is an important step toward understanding the area of specific study and preparing for field surveys. Chavez et al. (1982) developed a quantitative statistical technique called the optimum index factor (OIF) that improves image visualization and selection of Landsat image band ratio color combination (Eq. (2)). The optimum index factor (OIF) was based on the variance (i.e., standard deviation) and the correlation among the different band ratios. The authors reported that the ratio combination with the largest OIF value that contained the most information content and the least amount of decomposition (lowest correlation coefficients) was selected for the optimum color composite.

$$\text{OIF} = \sum_{i=1}^{3} \text{SD}_i \sum_{j=1}^{3} |\text{CC}_j|$$

where, Sdi = standard deviation for ratio i; |CCj| = absolute value of the correlation coefficient between any of the three band color ratios.

In this study, for better visualization of different objects in the images, we created a color combination by taking band 7 for infrared (2.064–2.345 μm), 4 for near-infrared (1.547–1.749 μm), and 1 for blue (0.477–0.898 μm), which were chosen for TM 1998, 1998, and ETM + 2008. For OLI 2018, band 7 for infrared (2.107–2.294 μm), band 5 for near-infrared (0.851–0.879 μm), and band 4 for red (0.636–0.673 μm) were chosen. The preprocessing activities were performed using ENVI 5.3 software.

2.3.2. Land use/cover class classification

The images were classified using the supervised classification algorithms under ENVI 5.3 because we are familiar with the study landscape. This classification method may be preferable for LULC change detection if prior information about the landscape is gained through personal knowledge of the study area (Rogan and Chen, 2004). The individual LULC class signatures of polygons (training areas) were marked based on field observations, household knowledge, and color combinations of bands (image visual interpretation). Then, the image data set in the LULC class is placed via the maximum likelihood classifier (MLC). Even though there are different classifiers, the MLC algorithm was better performed using all the spectral bands fit to vegetation (Abyot et al., 2014; Rawat et al., 2013; Manandhar et al., 2009). This technique also has a greater probability of weighting minority classes that can be swamped by the large class during training samples taken from images. The minority classes in the image have the opportunity to be included in their respective spectral classes (reduce unclassified pixels) from entering into another class (Othow et al., 2017). Accordingly, seven major LULC classes were recognized in KSNP, and their description was based on the author’s prior knowledge of the study site and detailed field observations (Table 5).

2.3.3. Accuracy assessment

Accuracy assessment is useful to assess the quality of the data collected in the field and the classified images. This technique determines the sources of error encountered during the classification of satellite images (Congalton and Green, 2009). Accuracy assessment determines how accurate the ground truth data region of interest agreed with classified images of the remotely sensed data in which precision testing was conducted using the Kappa index (Keshikar et al., 2017; Smits et al., 1999). We compare the accuracy assessment of 1998, 1998, and 2008 using ground sample points taken from Google Earth maps, long-lived resident interviews, and previously published research reports. However, for the dry and wet seasons of the 2018 satellite image classification and accuracy assessment analysis, 100 points from each of the 7 classes (total of 700 points) of ground truth data in the form of reference points were collected using a geographic positioning system (GPS). Generally, the accuracy assessment was expressed using four parameters: user’s accuracy, producer’s accuracy, overall accuracy, and kappa coefficient, which were derived from the error (confusion) matrix following Eqs. (3), (4), (5), and (6) (Lillesand et al., 2008; Congalton and Green, 2009; Liu et al., 2007; Lung and Schaab, 2009).
The Kappa coefficient (\( K_c \)) is given by:

\[
K_c = \frac{N \sum D_{ij} / C_0 - \sum R_i C_j}{N^2 / C_0 - \sum R_i C_j}
\]

where, \( N \) = total number of pixels, \( m \) = number of classes, \( \sum D_{ij} \) = total diagonal elements of an error matrix (the sum of correctly classified pixels in all images), \( R_i \) = total number of pixels in row \( i \), and \( C_j \) = total number of pixels in column \( j \). The value of \( K_c \) ranges between +1 and −1.

### 2.3.4. Land use land cover (LULC) change

The magnitude of change is a degree of expansion (+) or reduction (−) in the LULC size of the classes. The percent rate of LULC change was computed by Eq. (7) (Duraisamy et al., 2018; Bekele et al., 2019; Asmame and Abegaz, 2017; Esa and Assen, 2017).

\[
\text{Change rate} \left( \% \right) = \frac{\text{Area of final year} - \text{area of initial year}}{\text{Area of initial year}} \times 100
\]

The annual rate of change per year was calculated using Eqs. (8) and (9) (Alawamy et al., 2020).

\[
\text{Annual rate of change} \left( \text{km}^2 / \text{year} \right) = \frac{\text{Area of final year} - \text{area of initial year}}{\text{Time interval b/n initial & final years}}
\]

\[
\text{Annual rate of change} \left( \% \right) = \frac{\text{Area of final year} - \text{area of initial year}}{(\text{Time interval b/n initial & final years}) \times (\text{Area of initial year})} \times 100
\]
Note: In this analysis, the index was computed based on the difference in red band 4 (0.64–0.67 μm) reflectance and NIR band 5 (0.85–0.88 μm) reflectance of Landsat-8 OLI of both dry (March 2018) and wet season (October 2018) satellite images. In addition, for the TM and ETM+ sensors, the red band was 3 (0.63–0.69 μm), and the NIR band was 4 (0.77–0.89 μm).

The study site is located in a semiarid region, where climate variables are limiting factors for vegetation cover determination. From the climate variables, precipitation has a direct relation with the spatial and temporal changes in the NDVI. Due to the absence (discontinuous) of remotely sensed satellite images between 1996 and 2006, the NDVI mean with climate variable analysis was conducted between 2007 and 2016. In these periods, continuous satellite image data were directly matched with the recorded precipitation and temperature of the same years and seasons. Thus, the statistical relationship between the NDVI response and precipitation and/or temperature separately was examined through a simple linear regression model for one decade of data as applied with Eq (12).

\[
\text{NDVI} = a \pm b \times \text{rainfall or temperature} + \varepsilon
\]  

\[
\text{LANDSAT} - 5.7 \text{NDVI} = \frac{\text{Near-infrared (band 4) - Red (band 3)}}{\text{Near-infrared (band 4) + Red (band 3)}}
\]

\[
\text{LANDSAT} - 8. \text{NDVI} = \frac{\text{Near-infrared (band 5) - Red (band 4)}}{\text{Near-infrared (band 5) + Red (band 4)}}
\]

Independent variables consisted of the descriptive information of the sampled households. Hence, there were seven determinant socioeconomic variables used in the analysis: age categories, gender, household size, education level, settlement duration, agricultural land size, and distance from settlement to the KSNP border. Thus, this analysis evaluated the impact probability of the independent variables on the dependent variables. Additionally, the correlations between the trends of different LULC change types were computed, and a statistically significant association was identified at p < 0.05. All the above-listed statistical tests (i.e., Pearson's chi-square ($X^2$), regression and correlation) were performed.

Figure 4. Wet season land use/land cover change class map derived from October 23, 1988, October 19, 1998, October 06, 2008, and October 16, 2018, Landsat images.
using R-statistical Package (R-Core Team, 2019) and IBM SPSS statistics (IBM Corp, 2019).

2.3.7. Ethics approval and research site permission

The study ethics were reviewed and approved by the College of Natural & Computational Science, Research Department Graduate Committee (DGC, 2018) and Ethiopian Wildlife Conservation Authority Research Ethics Review Committee. Prior to the field visit and data collection, a permission letter was obtained from the Ethiopian wildlife conservation authority for the selected study site of Kafta Sheraro National Park (KSNP). Before distributing the questionnaire, the objective of the study was briefly explained to participants, and verbal consent was collected. The questionnaire excluded personal identifiers (privacy) such as the names of interviewees.

3. Results and discussion

3.1. Land cover classification map and seasonal variation of accuracy assessment

The LULC spatial distributions of Kafta Sheraro National Park (KSNP) were classified well in both the wet season from 1988 to 2018 (Figure 4) and the dry season in 2018 (Figure 5). The overall accuracies (OA) during 1988, 1998, and 2008 were 88.6%, 88%, and 82.26%, respectively, while the Kappa coefficients (Kc) were 0.85, 0.84, and 0.79, respectively (Table 6). The wet and dry season classification accuracy assessment of KSNP is considered reliable and acceptable agreement for the classified image of 2018. Based on the ground truth recorded data of 2018, the overall accuracies (OA) for images of wet and dry seasons were 86.9% and 91.96% with Kappa coefficients (Kc) of 0.845 and 0.90, respectively (Tables 7 and 8). The wet season OA and Kc of the study were higher than those of the Central Rift Valley of Ethiopia (Mesfin et al., 2020), protected and communal areas of Namibia (Kamwi et al., 2018), and Quirimbas National Park, Mozambique (Mucova et al., 2018). Similarly, the dry seasons of OA and Kc are also higher than the Bale Mountain National Park, Ethiopia (Nune et al., 2016), Maputaland-Pondoland-Albany Biodiversity hotspot (Bailey et al., 2016), and Tarangire and Katavi National Parks (Mtui et al., 2017).

Figure 5. Dry season land use/land cover class map derived from March 16, 2018, Landsat image.

| Land use land cover classes | 1988 | 1998 | 2008 |
|-----------------------------|------|------|------|
|                             | UA (%) | PA (%) | UA (%) | PA (%) | UA (%) | PA (%) |
| Woodland                    | 90.46 | 87.15 | 93.79 | 94.15 | 88.69 | 66.54 |
| Shrub-bushland              | 77.65 | 82.20 | 84.20 | 92.39 | 75.54 | 86.64 |
| Riparian forest             | 93.73 | 85.40 | 64.06 | 86.77 | 76.81 | 91.33 |
| Grassland                   | 77.57 | 96.35 | 96.92 | 88.59 | 75.47 | 94.65 |
| Agricultural land           | --   | --   | 64.78 | 73.03 | 68.03 | 60.58 |
| Water body                  | 100.00 | 97.84 | 97.06 | 88.55 | 99.30 | 85.94 |
| Bareland                    | 97.71 | 95.09 | 87.09 | 95.87 | 95.31 | 96.64 |
| Overall accuracy (OA)       | 88.6% | 88%   | 82.26% |
| Kappa coefficient (Kc)      | 0.85  | 0.84  | 0.79  |

Table 6. Accuracy assessment (error matrix) for 1988, 1998, and 2008 Landsat images.

| Classified data | Ground truth data |
|-----------------|-------------------|
|                 | Wood land | Shrub bushland | Riparian forest | Grass land | Agricultural land | Water body | Bareland | Total | UA (%) |
| Woodland        | 129       | 0             | 7               | 0           | 1                 | 0          | 137       | -     | 88.97  |
| Shrub-bushland  | 6         | 92            | 0               | 6           | 0                 | 0          | 104       | -     | 88.46  |
| Riparian forest | 0         | 0             | 128             | 0           | 0                 | 0          | 128       | -     | 96.80  |
| Grassland       | 0         | 22            | 0               | 146         | 1                 | 0          | 14        | 183   | 73.00  |
| Agricultural land| 0       | 0             | 0               | 1           | 88                | 0          | 0         | 89    | 98.88  |
| Water body      | 1         | 0             | 0               | 0           | 74                | 0          | 75        | 98.67 | -      |
| Bareland        | 0         | 5             | 0               | 18          | 0                 | 0          | 88        | 111   | 79.28  |
| Total           | 136       | 119           | 135             | 171         | 90                | 74         | 102       | 827   | -      |
| PA (%)          | 88.36     | 77.31         | 89.63           | 82.49       | 93.62             | 98.67      | 85.44     | -     | -      |

Table 7. Wet season confusion matrix for the 2018 OLI classified image.

Note: classes are shown by the number of classified pixels, UA = user accuracy, PA = producer accuracy.
The user's accuracies (UA) and producer's accuracies (PA) of the wet season woodland, riparian forest, agriculture, and water body were greater than 88% reasonably classified for the tested year (Table 7). Dry season riparian forest, irrigated land, river water, and bare land were relatively well classified, above 91% for all tested maps (Table 8).

Comparatively, the dry season accuracy in 2018 was quantified to be higher than that in the wet season, and these results are in agreement with a study in tropical semiarid areas (Msigwa et al., 2019). These authors tested and approved that wet and dry seasonal accuracy exhibited an increasing trend from wet to drier seasons. In our study, the low classification accuracy or higher confusion error of the wet season grassland and woodland cover in 2018 was mostly caused by confusion with other related land cover classes. For example, in the wet season, grass is often confused with cultivation, and woodland is confused with shrub-bush land due to the limited spatial resolution and image quality (Msigwa et al., 2019) also observed that wet season grassland had low classification accuracy. As reported by Duraisamy et al. (2018), during the wet season, there was a high vegetative cover of crops and natural vegetation, which creates confusion or makes it difficult to differentiate among them. Furthermore, a study in Burkina Faso also revealed the highest classification accuracy in the dry season and the lowest classification accuracy in the wet season (Liu et al., 2007).

3.2. Trends of land use/land cover change during the period 1988–2018

Kafta Sheraro National Park (KSNP) experienced extensive LULC change due to increased settlement coupled with the expansion of farming activities from 1988 to 2018. However, woodland area coverage during 1988 was the largest; a continuous decline was observed in the three consecutive decades of the study period. The highest decline was

| Classified data | Ground truth data |
|-----------------|-------------------|
| Woodland        | 117               |
| Shrub-bushland  | 79                |
| Riparian forest | 2                 |
| Grassland       | 0                 |
| Irrigated land  | 0                 |
| River water     | 0                 |
| Bare land       | 2                 |
| Total           | 120               |
| UA (%)          | 76.47             |
| PA (%)          | 97.50             |
| Overall accuracy| 91.96%            |

Table 9. Area extent of land use/land cover types in 1988, 1998, 2008, and 2018.

| Land use land cover classes | 1988 km² | 1988 % | 1998 km² | 1998 % | 2008 km² | 2008 % | 2018 km² | 2018 % |
|-----------------------------|----------|--------|----------|--------|----------|--------|----------|--------|
| Woodland                    | 1,251.88 | 57.98  | 1,132.08 | 52.44  | 1,007.32 | 46.66  | 884.03   | 40.95  |
| Shrub-bushland              | 374.91   | 17.36  | 402.36   | 18.64  | 436.82   | 20.23  | 507.18   | 23.49  |
| Riparian forest             | 83.77    | 3.88   | 60.92    | 2.82   | 52.48    | 2.41   | 44.31    | 2.05   |
| Grassland                   | 371.03   | 17.18  | 417.52   | 19.34  | 496.35   | 22.99  | 532.34   | 24.66  |
| Agricultural landa          | 0.00     | 0.00   | 64.79    | 3.00   | 95.57    | 4.45   | 118.35   | 5.48   |
| Water body                  | 48.30    | 2.24   | 49.22    | 2.28   | 34.59    | 1.60   | 35.02    | 1.62   |
| Bareland                    | 29.13    | 1.35   | 32.09    | 1.48   | 35.85    | 1.66   | 37.75    | 1.75   |
| Total                       | 2,159    |        | 2,159    |        | 2,159    |        | 2,159    |        |

*a Cultivation area was absent in 1988, but crop cultivation clearly started in 1993.

Table 10. Magnitude and annual rate of change in different LULC categories of KSNP from 1988-2018*

| Land use land cover classes | 1988–1998 km² | 1988–1998 % | 1998–2008 km² | 1998–2008 % | 2008–2018 km² | 2008–2018 % | Change between 1988-2018 km² | Change between 1988-2018 % | Annual rate of change/year 1988-2018 km²/year |
|-----------------------------|---------------|-------------|---------------|-------------|---------------|-------------|-------------------------------|-------------------------------|---------------------------------|
| Woodland                    | –119.81       | –9.57       | –124.8        | –11.0       | –123.3        | –12.2       | –367.85                       | –29.38                       | –12.3                           | –0.98                          |
| Shrub-bushland              | 27.45         | 7.32        | 34.46         | 8.56        | 70.36         | 16.1        | 132.27                        | 35.28                        | 4.41                            | 1.17                           |
| Riparian forest             | –22.85        | –2.73       | –8.78         | –14.4       | –7.83         | –15.0       | –39.46                        | –47.11                       | –1.32                           | –1.57                          |
| Grassland                   | 46.49         | 12.53       | 78.82         | 18.88       | 35.99         | 7.25        | 161.31                        | 43.47                        | 5.38                            | 1.45                           |
| Agricultural landa          | 64.80         |             | 30.78         | 47.5        | 22.78         | 33.8        | 118.36                        | 33.8                         | 3.94                            |                                 |
| Water body                  | 0.92          | 1.89        | –14.63        | 29.7        | 0.42          | 1.23        | –13.29                        | –27.51                       | –0.44                           | –0.92                          |
| Bareland                    | 2.94          | 10.08       | 3.78          | 11.8        | 1.30          | 3.61        | 8.02                          | 27.52                        | 0.27                            | 0.92                           |

*Negative sign (–) indicates that the land use/land cover class was decreasing in the entire time span.
observed from 1998 to 2008 by 11.0% (124.8 km²), while the lowest decline was 9.57% (119.81 km²) between 1988 and 1998. In thirty years (1988–2018), woodland decreased by 29.38% (367.85 km²) at an average rate of 12.3 km² (0.98%) per year (Tables 9 and 10). The riparian forest declined consecutively from 1988 to 1998 and 1998 to 2008 by 27.3 km² (22.85%) and 14.4 km² (8.78%), respectively. However, in the 3rd period (2008–2018), the forest slightly declined by 7.85 km² (15%). In the three decade study, this class decreased by 39.46 km² (47.11%) at an annual rate of 1.32 km² (1.57%) per year (Tables 9 and 10). Because these periods took place, widespread expansion of dry season irrigated land and wet season rain fed crops occurred. The increase in settlement around the park, agricultural expansion, and firewood collection had a great impact on the destruction of woodland cover. The depletion of the Tekeze riverside riparian forest was due to extensive irrigated crop cultivation undertaken since 1993. In contrast, the dry season of bare land, agricultural land, grassland, and shrub bush land was highly expanded throughout the study period (1988–2018). Similar findings were reported from the Babile elephant sanctuary (1977–2017) study, in which woodland and riparian forests decreased, whereas agricultural land and bare land continuously increased (Sontayehu and Kasum, 2019). In contrast to the present finding, the authors found a reduction in shrub bush land, as this class of land cover was the second next to woodland in their study periods. Birhan et al. (2018) also supported that shrub land was the dominant land cover from 1985 to 2015 in Hugum-burda National forest priority areas that declined. Farmland expansion at the expense of woodland decline was also stated in Bale Mountain National Park (Muhammed and Elias, 2021; Solomon et al., 2014). Shrub land, grass (grazing land), settlement, cultivation, and bare land increased as extensive woodland was destroyed between 1986 and 2009 (Mesfin et al., 2020; Bekele et al., 2019; Garedew et al., 2009). Moreover, in advance of cultivated land, a remarkable increasing trend was shown at the expense of forest cover (Berihun et al., 2019; Bewket and Abebe, 2013). Abera et al. (2020) reported that woodland and dense forest decreased by 34.6% and 59.9%, respectively, while cultivation expanded by 15.16 km²/year. Therefore, including the current study in KSNP, all the listed case studies in Ethiopia showed that agricultural land has expanded intensively at the expense of dense forest and woodland cover decline.

The increase in shrub bush land was maximum, 16.1% (70.36 km²), from 2008 to 2018. From 1988 to 2018, the shrub bush land cover increased by 132.27 km² (35.28%) at a rate of 4.41 km² (1.17%) per year. The highest expansion of grassland in the study area was 18.88% (79.82 km²) between 1988 and 2016 and 83.8% (0.87 km² year⁻¹), while shrub, farmland and bare land expanded by 18.6% (0.23 km² year⁻¹), 57.7% (0.92 km² year⁻¹), and 0.114 km² year⁻¹, respectively (Esa and Assen, 2021). Between 1986 and 2009, shrub land increased by 23.5% and agricultural land by 0.16 km² year⁻¹ (24.1%), while forestland decreased by 33.5% (Dinka and Chaka, 2019). In contrast to the present study, grassland and bare land declined while agricultural land increased (Andarge et al., 2020).

From 1988 to 2018, major LULC class transformation from and to highlighted grassland gained a large area from woodland (353.7 km²) and subsequent shrub bush land (71.2 km²). However, grassland gained negligible area from the rest of the land use/land cover classes. Similarly, agricultural land gained significant area from woodland (71.8 km²), grassland (12.6 km²), riparian vegetation (11.9 km²), and shrub bush land (20.8 km²). The highest loss was computed from woodland and shrub bush land class types during the studied period (Table 11).

| Conversion (transition) class types | Area coverage km² | % |
|-------------------------------------|-------------------|---|
| Change from class 1988               | Change to class 2018 |    |
| Woodland                            | Shrub-bushland     | 174.3 | 15.0 |
| Woodland                            | Grass land         | 353.7 | 30.5 |
| Woodland                            | Agricultural land  | 71.8  | 6.2  |
| Shrub-bushland                      | Grass land         | 71.2  | 18.0 |
| Shrub-bushland                      | Woodland           | 134.8 | 30.3 |
| Shrub-bushland                      | Agricultural land  | 20.5  | 9.7  |
| Riparian forest                     | Shrub-bushland     | 11.5  | 12.9 |
| Riparian forest                     | Woodland           | 40.1  | 45.0 |
| Riparian forest                     | Agricultural land  | 11.9  | 6.9  |
| Grass land                          | Agricultural land  | 12.6  | 2.8  |

Figure 6. Seasonal land use/land cover class (bare land, cultivation, grassland, and water) cover change in Kafa Sheraro National Park (KSNP) in March and October 2018.
3.2.1. Seasonal LULC change

In addition to temporal variation in LULC change, some classes varied their proportion and rate of change seasonally (i.e., dry and wet seasons). Thus, the comparison between the wet season (October 2018) and dry season (March 2018) satellite images of LULC change classification of KSNP was computed (Figures 4 and 5). The results indicated that the land cover class of bare land increased by 26.3% (568.46 km²) from the wet season toward the drier season because the total rain fed crop field and grazing areas were changed into bare ground during long dry months. In contrast, cultivation (rain-fed crops), grazing land, and water decreased by 5.15% (111.26 km²), 24.06% (519.5 km²), and 0.97% (21 km²), respectively, from wet months to drier months. Bareland was very small in the wet season but increased toward drier months, whereas grassland and agriculture were relatively small in the dry season but increased in the wet season (Figure 6). The pronounced change in bare land occurred due to the harvesting of rainfed crops and dried and removed pasture during the prolonged dry months. According to (Msigwa et al., 2019), LULC change variation occurred between dry season irrigated crops and wet season rain fed crops. They suggested that during the dry season, bare land is increasing, while in the wet season, bare land is very small.

Figure 7. Seasonal variability in NDVI (greenness status) in Kafta-Sheraro National Park (KSNP) for the wet season (a and c) and dry season (b and d) during the 1988 and 2018 satellite images.

Figure 8. Vegetation cover change distribution of Kafta-Sheraro National Park in 1988 (a) and 2018 (b).
3.3 Temporal and seasonal changes in NDVI

The seasonal variation in the average NDVI between wet and dry seasons was observed and reported in several semiarid areas (Amri et al., 2011; Ferreira et al., 2003). Illegal fire, extensive agriculture, charcoal production, and other related human-induced drivers of LULC change negatively affected the vegetation resources of the park. To detect vegetation cover changes over a thirty-year period, normalized difference vegetation index (NDVI) analyses of the 1988 and 2018 wet and dry season satellite sensors were utilized. Figure 7 indicates the NDVI threshold-based difference between the dry (mid-March) and wet (mid-October) months of 1988 and 2018. The pixel count of the wet season showed a higher NDVI value of 0.85 in 1988 and 0.84 in 2018 from June to mid-October; the park areas are dominated by vegetated woodland, shrubland, and riparian (Riversides) vegetation. During the dry season, from the end of December to the end of March, the maximum NDVI value was 0.64 in 1988 and 0.49 in 2018. During the dry season, dominant vegetated areas were concentrated on the sides of water points (hereafter Tekeze River sides and its tributary rivers) and the eastern riversides irrigated fruit plantations of the park. Our result concurred with a study in semiarid areas of Uganda, which indicated that the mean NDVI of the wet season was higher than that of the dry season (Egeru et al., 2014).

The present reclassification analysis of NDVI also showed a significant change in areas of vegetation cover (Figure 8 and Table 12). The high- to moderate-density vegetation cover in 1988 was approximately 66.67%. However, the magnitude of its cover in 2018 declined to 45.2%. In the entire period of 1988–2018, high- to moderate-density vegetation was reduced by 464.6 km². The sparse vegetation covered 29.8% of the total area of the park in 1988 but expanded to 49.6% in 2018. Sparse vegetation coverage increased by 428.1 km² from the total area of the park between 1988 and 2018. Moreover, the coverage of nonvegetation increased from 3.5% in 1988 to 5.2% in 2018. Nonvegetation showed an expansion of 36.5 km² from 1988 to 2018 (Table 12). The NDVI results also indicated a significant change in vegetation cover; the amount of high- to moderate-density vegetation cover declined by 21.47%, while sparse vegetation cover increased by 19.8% from the total area of KSNP. On the other hand, nonvegetation cover increased by 36.5 km² between 1988 and 2018. In agreement with the present study, the dense vegetation cover declined by 26.1%, whereas nonvegetation increased by 14.3 km² between 2000 and 2018 (Abera et al., 2020). In the Kafta humera district (surrounding the park), woodland vegetation converted by cropland leads to expanding bare ground during the dry season (Zewdie and Csaplovics, 2016).

3.4 Seasonal NDVI-precipitation/temperature relationship

According to the wet and dry season Landsat data, the interannual variation in NDVI during the 10-year period (2007–2016) was computed. The dry season mean NDVI indicated a significant decreasing trend (p < 0.05), while the wet season variation was nonsignificant over time. The dry season maximum mean NDVI value occurred in 2007 and 2008, while the minimum value occurred in 2016. In the wet season, the minimum and maximum mean NDVI values were 0.21 in 2012 and 0.33 in 2007, respectively (Figure 9a and b). In contrast, the rainfall did not show significant (p > 0.05) variation in the specified period (Figure 9c and d). The relationship between NDVI and climate variables (rainfall and temperature) was also explored. The results showed a significant positive correlation between NDVI and temperature (R² = 0.5, p = 0.01) and a negative correlation with rainfall (R² = 0.14, p = 0.1). The total annual rainfall (R² = 0.02, p = 0.8) and average annual rainfall (R² = 0.04, p = 0.7) were not significantly correlated with NDVI. The results indicate that the seasonal variation in NDVI is influenced by both temperature and rainfall, with temperature having a stronger effect.

**Table 12. Normalized difference vegetation index (NDVI) of land cover change (area in km² and %) in Kafta Sheraro National Park between 1988 and 2018.**

| Land cover class | 1988 | 2018 | Change (km²) |
|------------------|------|------|---------------|
|                  | km²  | %    | km²          | %    |          |
| High-moderate density vegetation | 1439.4 | 66.67 | 974.8 | 45.2 | -464.6 |
| Sparse vegetation    | 643.5 | 29.8 | 112.6 | 5.2 | +428.1 |
| Nonvegetation (water & riverside sand) | 76.115 | 3.5 | 112.6 | 5.2 | +36.5 |
| Total              | 2,159 | 100 | 2,159 | 100 |         |

Figure 9. The interannual variation in the seasonal mean NDVI between 2007 and 2016 showed significant variation in the dry and wet seasons (a and b) (Source: Present study). However, the pattern of total annual rainfall (c) and average annual rainfall (d) between 1996 and 2016 did not significantly change over time for Kafta Sheraro National Park (ENMA, 2018).
and temperature) was analyzed for a ten-year period (2007–2016) because satellite image data were absent before 2007 and some values of daily rainfall and temperature were missing. Figure 10a-d summarizes the statistical analysis between the seasonal mean NDVI, mean annual rainfall (value scale in log10 to fit NDVI values), and mean temperature between 2007 and 2016. Even if there was a change in seasonal rainfall and temperature, the correlation relationship of wet and dry season NDVI with these two climate variables was not statistically significant (p > 0.05). The variation and slight decreasing trends in NDVI might occur due to the dominant nature of the scattered woodland vegetation composition of the park and several activities of the local communities, such as extensive woodland conversion to cultivation and extinguishing of illegal fire and fuel wood collection. In line with our findings, vegetation cover change in Nechsar National Park was due to human-driven deforestation (Fetene et al., 2015). Similarly, temporal reduction of NDVI in dry land Ethiopia changed the woodland cover due to the expansion of cropland, settlements, and fuel wood harvesting (Zewdie and Csaplovics, 2016).

The variation in seasonal rainfall and temperature trends in the study period was not consistent with the mean NDVI trends in the wet and dry seasons. This directly reflects the influence of rainfall and temperature, which were not considered the main drivers of vegetation cover change in the KSNP. Due to limited local meteorological stations, a lack of advanced recording instruments and skilled manpower leads to low accuracy of climate variable data. Therefore, the statistical analysis revealed that precipitation and temperature were not considered the main drivers of vegetation dynamics; rather, human-induced factors were the major actors in the vegetation cover decline of the park. Moreover, dry season vegetation areas along the Tekeze Riversides are independent of annual rainfall, as they directly access water from the bank of the river. However, the seasonal decreasing trends of NDVI are more interlinked with increasing human driving activities, such as the conversion of woody vegetation to seasonal cultivation and bare land, loss of vegetation by fire, firewood collection, and charcoal production. Consistent with our study results in Africa, the Sahel also showed that human-induced activities increase vegetation degradation (Evans and Geerken, 2004). Moreover, however, Ethiopian dry land vegetation productivity is dominantly controlled by the availability of moisture (Hailu et al., 2015); the low correlation between precipitation and NDVI is due to the decline in vegetation cover (Li et al., 2004). This is an indication of a slight response of degraded woodland area to precipitation (Zewdie and Csaplovics, 2016).

In contrast to the present study, reports have shown that NDVI change (either increasing or decreasing) is driven by precipitation/temperature in arid and semiarid areas of Africa (Ghebrezgabber et al., 2020; Martiny et al., 2006) and in other countries, such as Spain, Iraq, and China (Naif et al., 2020; Chu et al., 2007; Fensholt et al., 2012; Pei et al., 2019; Sanz

| Household characteristics | Categories | Calculated values |
|---------------------------|------------|------------------|
| Gender                    | Male       | 74.0%            |
| Age                       | -          | Min: 22; mean: 44.7; max: 75 years |
| Ethnic category           | Tigraway   | 86.0%            |
|                           | Kunama     | 14.0%            |
| Family size               | 2–5; 6–8   | Min: 2; mean: 5; max: 8 |
| Education status          | Formal (1–12th grade) | 74.2% |
| Resettlement status       | Formal (1–12th grade) | 71.7% |
| Distance from settlement to park | 5–10 km; 11–15 km; >15 km | Min: 6.5; mean: 12.6; max: 21 km |
| Respondents alternative income | 12.9% |
| Energy for cooking         | Fuelwood   | 94.7%            |
| Farmland holding size     | 1–3 ha; 4–7 ha; >7 ha | Min: 1; mean: 4.2; max: 10 ha |
| Crop use (home consumption and sale) | 72.4% |
| Source of livelihood & income | Crop production | 1 (rank) |
| Land tenure (land use permits) | Legal | 86.0% |

N = total number of the sampled households interviewed for this study; min = minimum; max = maximum.
Table 14. The main livelihood and economic activities ranked by respondents (N = 395).

| Activities                                | Number of respondents (n) | %    |
|-------------------------------------------|---------------------------|------|
| Crop production (rainfed and irrigated)   | 197                       | 50.0 |
| Livestock rearing                         | 25                        | 6.3  |
| Mixed crop and livestock                  | 173                       | 43.7 |
| Private and government employee           | 22                        | 5.5  |
| Self business                             | 17                        | 4.3  |
| Fuelwood (charcoal and firewood collection)| 5                         | 1.3  |
| Gold mining and aromatic resin collection | 7                         | 1.8  |

The total number of respondents was 395; however, overcounts are predictable due to multiple responses of households to questions.

et al., 2021). NDVI controls the growth of vegetation conditions, temporal biomass accumulation, and changes (Zhao et al., 2014). The spatiotemporal variation in NDVI was determined by the variation in the temporal distribution of precipitation (Xia et al., 2014). On the other hand, the huge differences in the vegetation cover between the dry and wet seasons were due to climatological and anthropogenic effects (Al-Saady et al., 2015). Similarly, in the Gojeb district, Ethiopia, and the Three-North Shelter Forest of China, vegetation degradation is mainly influenced by both human-induced factors and rainfall variability (Huang and Kong, 2016; Dagnachew et al., 2020).

3.5. Local community perception of the drivers of LULC change

3.5.1. Demographic and socioeconomic information of the sampled households

The age of the sampled household heads (N = 395) ranged from 22 to 75 years old, with an average of $44.7 \pm 13.7$ (SD) years, and more than fifty percent of respondents’ age category (22-41 years) was in the productive region. Approximately 74% of the sampled households were male. The household size ranged from two persons to 8 persons, with an average of 5 persons. The farm size of the respondents varied from 1 to 10 hectares, with an average of 3.9 hectares. With respect to their education status, 74.2% of the respondents attended formal education, and 25.8% attended informal education (Table 13). Approximately three-fourths of the sampled households were engaged in crop production and mixed crops and livestock. However, a small portion of the respondents were involved only in livestock rearing and other additional activities coupled with farming. Crop production was ranked as the topmost important source of livelihood/income, followed by mixed crop and livestock farming in the districts (Table 14). The most important types of crops produced in the study area were rainfed: Sesamum indicum, Sorghum bicolor, Eleusine coracana, Eragrostis tef, and Zea mays L., whereas irrigated crops included Muza species, Mangifera indica, Carica papaya, Allium cepa, Allium sativum, Solanum tuberosum, and Capsicum annuum.

3.5.2. Local community response to trends of LULC variables

Local community perception of major LULC change types and other associated variables of change showed statistical significance (p < 0.001). The participants were well aware that woodland and riparian forest (Tekeze River side vegetation of the park) significantly declined in the whole study period (p < 0.001). The local communities provided confidential evidence for the decline of approximately 90.3% woodland and 88.7% riparian vegetation of KSNP and its surroundings. In contrast, approximately 57.3% of the respondents recognized that the distance from the water source to the settlement showed constant trends. However, agricultural land, grazing area (grassland), bare land, resettlement, and road access to the park significantly increased throughout the studied periods (p < 0.001) (Figure 11).

3.5.3. Main (immediate) drivers of LULC changes in KSNP

The drivers of LULC change were both proximate and underlying (Munthali et al., 2019; Bewket and Abebe, 2013). For this discussion, more emphasis is given to the proximate drivers of LULC change. During the surveyed period, the participants identified 13 pronounced factors as key drivers of the observed LULC change in KSNP. The expansion of legal and illegal settlements, cultivated land, illegal fire following encroachment by cultivation, seasonal grazing, firewood collection, and traditional gold mining were prioritized as the top significantly (p < 0.001) ranked drivers (Table 15). Likewise, from key informant interviews and focus group discussions (FGDs), similar feedbacks were also recorded, and they were strengthened; expansion of settlements and agriculture, firewood collection, charcoal production, and land tenure (administration) problems were identified as the main causes of LULC change in the study area.

These main drivers were generated by a scarcity of resources in the moderate- and high-altitude areas of the region following resettlement from dense to less populated areas, low awareness regarding the

![Figure 11. Respondents' awareness of the trend of LULC and related variables (N = 395).](image)
environmental benefits of natural resources, lack of access to renewable energy sources (i.e., solar energy and electric cities) and high poverty. According to the household survey, focus group discussion and key informant interviewers’ resettlement schemes by the government and a few illegally were highly expanded in the study area between 1991 and 2003. From the household response, approximately 71.7% were resettlers (Table 13). Due to the program, new settlement communities, namely, Tekeze, Maytemen, Maykeyh, Fre-Selam, Wuhedet, and Mayweyni, were established near KSNP. Similar studies in Ethiopia showed that resettlement programs have brought significant LULC and massive clearance of forests and depletion of much natural vegetation cover in Hawa Galan and Chewaka districts, Oromia (Yadeta et al., 2022; Abera et al., 2020), Gelda district, Amhara (Esa and Assen, 2017), and Esira district of the South region (Mamude et al., 2021).

The majority of the sampled households (~94.7%) utilized wood and wood products for cooking (Table 13). These activities led to the destruction of dominant woodland outside and inside the KSNP. As stated by the focus group discussion and key informant interviews, the woodland of the park is not only used as source energy but also used as a source of alternative income by the local communities. This result is in line with Central Rift Valley, Ethiopia (Bekele et al., 2019), Gelana, Ethiopia (Asmame and Abegaz, 2017), Dedza, Malawi (Munthali et al., 2019), and Quirimbas National Park, Mozambique (Mucova et al., 2018), which revealed that firewood collection and charcoal making were the main drivers of LULC change.

The area has great potential for nonrenewable natural resources, and traditional gold mining is a common activity that negatively changes the land cover of the study site (Figure 12a). The activity of gold mining also leads to a drift population from other areas toward the mine sites and increased settlements in the whole surrounding area of KSNP, and they even constructed temporary structures as a place of residence inside the park. According to vegetation surveyed by KSNP, the above listed activities destroy the natural vegetation by uprooting the plants’ root profile and are an approximate cause for extinguishing illegal fire

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**Table 15. Main drivers of LULC change recognized by local communities’ perceptions in Kafta Sheraro National Park (N = 395<sup>1, 2, 3, 4, 5</sup>).**

| Recognized land use land cover change drivers | Number of households choosing the drivers<sup>6</sup> | Total<sup>7</sup> score | Ranking<sup>8</sup> |
|-----------------------------------------------|-----------------|---------------------|---------------------|
| Legal and illegal resettlement                | 156             | 1011                | 0.18                |
| Expansion of cultivated land                  | 104             | 806                 | 0.14                |
| Illegal fire                                  | 83              | 673                 | 0.12                |
| Expansion of grazing land                     | 74              | 652                 | 0.11                |
| Firewood collection                           | 59              | 546                 | 0.09                |
| Traditional gold mining                       | 37              | 444                 | 0.08                |
| Charcoal production                           | 35              | 435                 | 0.07                |
| Land administration problem                   | 29              | 368                 | 0.06                |
| Natural resin collection                      | 20              | 268                 | 0.047               |
| Ethio-Eritrean war (civil war)                | 14              | 165                 | 0.030               |
| Drought                                       | 11              | 145                 | 0.025               |
| Eritrean community intervention               | 7               | 125                 | 0.022               |
| Permanent and seasonal road                   | 0               | 53                  | 0.009               |
| Σ weight total                                | 5691            |                     |                     |

<sup>1</sup> Weight = R1C1 + R2C2 + R3C3 + R4C4.

<sup>2</sup> Index = R1C1 + R2C2 + R3C3 + R4C4/Σ R1C1 + R2C2 + R3C3 + R4C4 (5691).

<sup>3</sup> The negative importance of drivers decreases from Rank (1) to Rank (4).

<sup>4</sup> The total number of respondents was 395; however, overcounts are predictable due to multiple responses of households to questions.

<sup>5</sup> The total number of respondents was 395; however, overcounts are predictable due to multiple responses of households to questions.

**Figure 12.** Traditional gold mining activities (a) preparing land for irrigated planting (b) and cultivations of banana (c) and cereal crops (d) along the Tekeze riversides of Kafta-Sheraro National Park (Photo by Fitsum Temesgen, 2018–2019): Remark: The photo (Figure 12c) refers to the corresponding author while conducting field work (identifying land/use cover classes of rainfed crops & ground truth recording).
dominant woodland and riparian forest transformed into cultivation, grazing land, and bare land. As a consequence, the land surface was left with scattered vegetation and bare ground, which immediately showed how the natural vegetation (plant biodiversity) was lost over time and limited the habitat range of the wildlife. Moreover, the change in woodland was expanding into farmland, leading to encroachment of the African elephant habitat and creating a major challenge for their free movement.

Similarly, our questionnaire assessment also confirmed that the range of wildlife before 30 years was anywhere in the park area. Recently, the suitable habitats for wildlife have shrunk and collapsed in specific areas in the park because agricultural expansion coupled with the extinguishing of illegal fire has progressively increased. Second, the encroachment of livestock, firewood and charcoal collectors and traditional gold miners

Table 16. The impacts of household demographic and socioeconomic status on attitudes toward the top four recognized drivers of LULC change in Kafa Sheraro National Park.

| Independent variables | B   | S.E  | Wald | p value |
|-----------------------|-----|------|------|---------|
| 1. Expansion of cultivated land (driver-dependent variable) |
| Age                   | 0.42| 1.87 | 0.17 |
| Gender (1 – male)     | 0.20| 0.42 | 0.52 |
| Education level (0 – Informal) | – | – | – |
| Education level (1 – 8 grade)* | –4.78| 1.08| 19.43 | 0.00|
| Education level (2 – 9-12 grade) | 0.05| 0.41| 0.02 | 0.89|
| Household size        | 0.73| 0.41| 3.08 | 0.08|
| Settlement duration*  | –0.79| 0.31| 6.60 | 0.01|
| Agricultural land size| 0.41| 0.27| 1.41 | 0.14|
| Distance from settlement to park | 0.22| 0.29| 0.08 | 0.44|
| 2. Resettlement (driver-dependent variable) |
| Age                   | 0.44| 1.10 | 0.29 |
| Gender (1 – male)     | 0.47| 2.70 | 0.10 |
| Education level (0 – Informal) | – | – | – |
| Education level (1 – 8 grade)* | –2.10| 0.54| 15.21 | 0.00|
| Education level (2 – 9-12 grade) | 0.09| 0.41| 0.05 | 0.82|
| House hold size       | 0.55| 0.38| 2.12 | 0.14|
| Settlement duration   | 0.22| 0.29| 0.60 | 0.44|
| Agricultural land size* | –1.23| 0.66| 3.46 | 0.045|
| Distance from settlement to park | 0.18| 0.27| 0.43 | 0.51|
| 3. Human induced fire (driver-dependent variable) |
| Age                   | 0.44| 0.29 | 0.64 | 0.42 |
| Gender (1 – male)     | 0.24| 0.39 | 2.70 | 0.10 |
| Education level (0 – Informal) | – | – | – |
| Education level (1 – 8 grade)* | –3.31| 0.64| 26.74 | 0.00|
| Education level (2 – 9-12 grade) | 0.16| 0.41| 0.15 | 0.70|
| House hold size       | –0.05| 0.02| 0.00 | 0.89|
| Settlement duration   | 0.17| 0.30| 0.33 | 0.56|
| Agricultural land size| 0.09| 0.28| 0.59 | 0.59|
| Distance from settlement to park | 0.22| 0.25| 0.61 | 0.43|
| 4. Expansion of grazing (driver-dependent variable) |
| Age                   | 0.57| 0.45 | 1.61 | 0.20 |
| Gender (1 – male)     | 0.03| 0.30 | 0.01 | 0.93 |
| Education level (0 – Informal) | – | – | – |
| Education level (1 – 8 grade)* | –3.83| 0.82| 21.97 | 0.00|
| Education level (2 – 9-12 grade) | 0.31| 0.41| 0.59 | 0.44|
| House hold size*      | –0.31| 0.42| 0.34 | 0.045|
| Settlement duration*  | –0.41| 0.27| 1.41 | 0.14|
| Agricultural land size| 0.23| 0.29| 3.78 | 0.04|

* = significant at 5% (0.05), S. E = standard error; B = coefficient of explanatory variable.

Female and informal education set as zero (i.e., References variables).
led to disturbance and displaced wildlife from the long existing habitat and shifted to new habitat patches. The increasing demand of the local communities for irrigated crop cultivation, livestock grazing, water for home and livestock consumption, and other resource utilization were obstacles to wildlife movement and access to water, especially during the dry season. Such activities increased the conflict between elephants and humans. Moreover, the shift of the riparian forest LULC class into farmland (irrigated area) around water points is the immediate cause for wildlife free movement and blocks water access. Most likely, wildlife is forced to migrate outside the park boundary even far from neighboring countries. This report concurs with Ellis (2006) study that LULC change dramatically reduced biodiversity. Similarly, in the northern highlands of Ethiopia, LULC change was reported as an indication of plant and wildlife species loss (Asmame and Abezag, 2017). A study in PAs of Mexico also indicated a reduction in temperate and vegetation cover threatened to the whole biodiversity of the site (Sancheza Reyes et al., 2017). A recent study in Bale Mountain National Park revealed that the decreasing trends of grassland and forestland while increasing farmland LULC led to increased habitat fragmentation and reduced the size and loss of available core area for the existing core-dependent endemic wildlife species (Muhammed and Elias, 2021). Furthermore, the expansion of agriculture threatens elephant habitats and increases competition for resources between humans and elephants (Sintayehu and Kassaw, 2019). The decline in woody savanna in Tarangire National Park was also an indication of a threat to wildlife conservation (Mtui et al., 2017).

4. Conclusion and recommendation

The results of a three-decade (1988–2018) study indicated that intensive and extensive LULC changes were observed in Kaffa Sherraro National Park (KSNP). The proportional change in the park was used to determine the total LULC types in three different periods. Thus, recognizing and mapping LULC is important in planning continuous studies on natural resource management. The most important change was observed in the decline of woodland and riparian forest from 1,251.9 km² and 83.77 km² in 1988 to 884 km² and 44.31 in 2018, respectively. In contrast, agricultural land expanded from 64.79 km² in 1998 to 118.35 km² in 2018 from the total park area. LULC classes of shrub bush land, grassland, water bodies, and bare land have shown relatively moderate changes. The serious degradation of woodland and riparian vegetation of the park resulted in the encroachment of shrub bush land and an increase in sparse vegetation cover ground (bare land), cultivated land, and grazing land. The major depletion trend was observed from woodland to rainfed crop cultivation and from riparian vegetation to irrigated land. In general, the period between 1998 and 2008 showed the highest change compared with the other two periods (i.e., 1988 to 1998 and 2008 to 2018). This large change was possible due to the high resettlement program around the PA in that period relative to the other periods. The seasonal change in grassland and cultivation enormously expanded from the drier season to the wet season, whereas bare land showed pronounced expansion from wet months to drier months (Figure 6). The results of the NDVI analysis indicated that the dense woodland and riverside vegetation decreased from 66.67% in 1988 to 45.2% in 2018, while nonvegetation increased from 3.5% in 1988 to 5.2% in 2018. Based on field observations and interviews with local people, the gradual change in the vegetation cover of the park was mainly driven by increasing human-induced pressure on the natural resources. However, our results indicated that rainfall and temperature were not considered the main drivers of the extensive change in vegetation cover in the KSNP. The major habitat change factors are expansion of settlement and riverside/rainfed cultivation, human-induced fire, grazing, firewood collection, traditional gold mining, charcoal production, land administration problems, and natural resin collection, which degrade the wildlife habitat and limit their movement routes. The increasing trend of LULC change directly and negatively influences wildlife habitats, as the area is known home to African elephants and other wild animals.

Therefore, it is paramount to detect LULC changes and current environmental features and consider these features for each land use class in terms of revealing the feasibility of the land use potential in the study districts. Understanding the past and present LULC change drivers that are interlinked with the livelihood of local communities is essential. Manage and exclude newly opened settlements in natural forest areas and consider water resources, agricultural areas, and settlement areas when planning sustainable natural resource management in the area. Attention should be given to the sustainable conservation of park biodiversity by encouraging community participation in conservation practices, preparing awareness creation programs, and controlling all illegal activities practiced in and around KSNP. Furthermore, this study provides baseline information for setting effective land use planning and advanced management options for park sustainability. Natural structural features of the district area map for each land use should be located by local administrators for future forest and wild animal management. Fourteen percent (Table 13) of the local residents had unclear land rights (i.e., no legal land permit) and misbalanced access to land, which causes uncontrolled expansion of agriculture unless uniformly secured land rights are recommended to all households to minimize illegal expansion of farming and related issues.

Declarations

Author contribution statement

Fitsum Temesgen Hailemariam, Msc; Bikila Warkineh Dullo, Assistance Prof; Alemaeye Hailicemail, Mesgeo, Assistance Prof.; 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 included in article/supp. material/referenced in article.

Declaration of interest’s statement

The authors declare no competing interests.

Additional information

No additional information is available for this paper.

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