Article

Spatio-temporal dynamics of land use- land cover and NDVI in Kersa District, South Western Ethiopia

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Abstract
The dynamics of land use-land cover changes is one of the phenomena which interweave the socio-economic, political, and environmental issues in Ethiopia. This project study investigated the land use-land cover (LULC) and NDVI changes in the Jimma zone, Kersa woreda, Ethiopia over a period of 30 years from 1990 to 2020. Four sets of Landsat imageries (i.e., 1990, 2000, 2010, and 2020) were the input The LULC change analysis revealed a continuous decline of forest lands throughout the first (1990-2000), second (2000-2010), and third (2010-2020) study periods by 24.5%, 23.6%, and 21.5%, respectively data from which LULC maps were produced and analyzed using remote sensing and GIS applications. On the contrary, settlement areas increased by 12.7% in the first, 13.9% in the second, and 13.9% in the third period. Agricultural lands also expanded over the study periods by 50.2%, 51.2%, and 52.1%, respectively. The NDVI change analysis revealed a continuous decline of forest lands that NDVI value of (1990-2020), decline from 0.789 high and -0.4 low to 0.559 high and -0.17 low respectively. The overall results of the analysis showed that between the years 1990 and 2020, forest lands, decreased while agricultural lands and settlement areas increased, respectively Therefore, it is important to prioritize and design strategies for better LULC systems and natural resource conservation for integrated and sustainable development.

Keywords land use-land cover; dynamics; NDVI; spatio-temporal dynamics.

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1. Introduction

A major environmental problem on the world is human-induced land use and cover changes (LULC) (Cheruto et al., 2016). Land cover refers to how the Earth's surface is covered by forests, wetlands, impervious surfaces, agricultural, and other types of land and water (Prakasam, 2010). Land use refers to how humans use the landscape, whether for development, conservation, or mixed uses. Land use includes recreation areas, wildlife habitats, agricultural land, and built-up land (Reis, 2008). Since the past 100 years, the human population and its influence have increased exponentially on land. Human alterations on the Earth's surface result in changes in the land cover. These changes significantly affect key aspects of Earth system functioning (including the balance of energy, water, and soil). Moreover, the pressure on limited natural resources, which is caused by an increase in population, contributes to changes in the land surface cover (Islam et al., 2018). In order to determine the rate and status of LULC change, understanding the past LULC pattern and current system to further estimate the future projection characteristics of human activities and the natural resources of local area. Due to rising of population number the pressure on particular land resources become higher from time to time the exposes natural resources to be vulnerable to degradation and lose (Mas et al., 2017) .

In Ethiopia, LULC changes are increasing every year, and it is causing significant environmental problems. It is mainly due to population growth, overgrazing, and other factors, such as local communities' insights towards land management, which leads to a massive amount of converting of environment and depletion of natural resource(Hurni et al., 2005).Research findings indicate that rapid population growth, increasing conversion of forest resources to cultivated land and settlement are key drivers of LULC change in Ethiopia (Negassa et al., 2020). High demand for forest products for energy production and house construction as well as free overgrazing by livestock are some of the causes of LULC change in the high land regions of Ethiopia (Assefa et al., 2021).

Over the last decade, the normalized difference vegetation index (NDVI) differencing method and classification method are widely used as a change detection method and provides detailed information for detecting and monitoring changes in land use-land cover (LULC).The normalized difference vegetation index (NDVI)(Liang et al., 2017) has been widely used for describing the spatiotemporal characteristics of LULC, with percent vegetation cover .The NDVI values range from - 1.0 to 1.0; low NDVI values are for common surface materials, and higher NDVI values are for green vegetation (Forkel et al., 2013) Negative NDVI values represent the water bodies. Closest to 0 NDVI values are represented by bare soil (Olmanson et al., 2016). The objective of this study was to detect and investigate changes in land use and land cover (LULC) and NDVI from 1990 to 2020 in the study area.

2. Materials and Method

2.1 Description of study area

The study is conducting in Kersa woreda, Oromia National Regional State, Jimma zone, Ethiopia. It is bordered on the south by Dedo district, on the southwest by Seka Chekorsa district, on the west by Mana district, on the north by Limmu Kosa district, on the northeast by Tiro Afeta district, and on the southeast by Omo Nada district. The area is located between 7.6739 latitude and between 36.8358 longitude. The altitude of this district ranges from 1740 to 2660 meters above sea level and covers slope range from § at 0º to very steep 71º. The district receives 2935 mm annual rainfall. Kersa district has a tropical rainforest climate under the Copen climate classification. Temperature at Kersa is in a comfortable range, with the daily mean staying between 20°C and 25°C year-round.

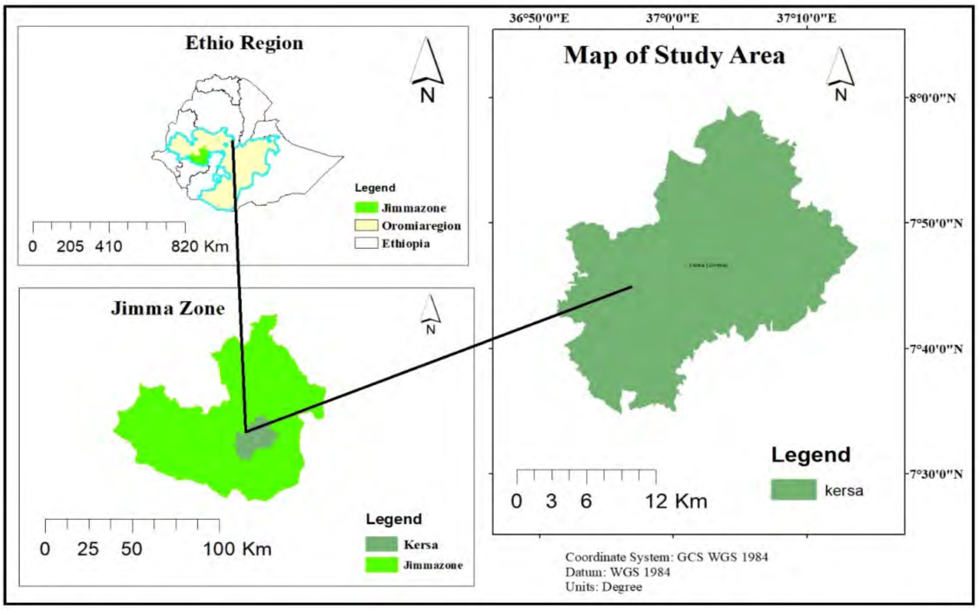

Fig. 1 Study area map.

2.2 Data source and type

In order to conduct this study, Landsat TM (1990, 2000, 2010), and Landsat OLI/TIRS (2020) were downloaded from the USGS between December and January along with cloud-reduced images The satellite images were selected at an interval of 10 years by taking into consideration the effect of the periodic variation in the analysis and the data sets were acquired in the same season to evade the impact of periodic alterations (Kindu et al., 2013) (Table 1) .

Table 1 Data source and type.

N°	Date type	Sensor	Acquisition date	Path and Row		Resolution	Sources
				Path	Row		
1	Landsat 4-5	TM	25/12/1990	169	059	30m	USGS
2	Landsat 4-5	TM	04/12/2000	169	059	30m	USGS
3	Landsat 4-5	TM	30/01/2010	169	059	30m	USGS
4	Landsat 8	OLI/TIRS	27/12/2020	169	059	30m	USGS

2.3 Satellite images processing and analysis

The process involved image pre-processing, image enhancement and image processing procedure flow.

♦ **Image Pre-processing:** Pre-processing involves those operations that are normally required prior to the main data analysis and extraction of information. Selecting appropriate satellite imagery is the first task in image data processing (Kiefer et al., 2015**)**

♦ **Image Enhancement:** The goal of image enhancement is to improve the visual interpretability of an image by increasing the apparent distinction between features in the scene(Gashaw et al., 2014). If the image is enhanced the distinct of features are clearer so that image analysis, classification, and interpretation are better. In addition, Image enhancement is used to increase the details of the image by assigning the image maximum and minimum brightness values to maximum and minimum display values, it is done on pixel values, and this makes visual interpretation easier and assists the human analyst. The original low dynamic range of the image is stretched to full dynamic range which is from 0 to 256 by using histogram equalization.

♦ **Image processing procedure flow:**

a) The first step in land use land cover change analysis was to collect satellite images using the path/row information from free satellite image provider websites.

b) The line stripe, haze, and noise error is removed from 2008 image which down loud from land sat 7 using erdas imager 15 software.

c) Layer Stacking: The layer stacking of bands was performed on the Erdas Imagine 15 software.

d) The layer stacked image tiles were clipped with study area shape file.

e) Image rectification was done to correct distortions resulting from the image acquisition process.

f) Projection: The image downloaded is in Universal Transverse Mercator projection and

g) It is projected to Geographic WGS 84.

2.4 Data analysis methods

Data analysis is the process of identifying and collecting data to be viewed and modeled, in the aim of discovering patterns or trends that can be used for conclusions and decision-making. In this study the changes in the LULC areas were detected using unsupervised ISO-Data algorithm for the four temporal dates. Image analysis involves processing an image into fundamental components to extract meaningful information. Image analysis can include tasks such as finding shapes, detecting edges, removing noise, counting objects, and calculating statistics for texture analysis or image quality. .ARCGIS 10.7, ERDAS imagine 15.1 and Microsoft excel were employed for satellite image processing and land use land cover change analysis. The rate of change was calculated for each land use/ land cover classes as rate of change (ha/year) (Abate, 2011).

$$\text{Rate of change (ha/year)} = (A - B)/C \quad (1)$$

where, A = Recent area of the land use and land cover in ha, B = Previous area of the land use and land cover in ha, and C = Time interval between A and B in years.

Overall change matrix was constructed to understand or observe the magnitude of change between different land use land cover.

2.4.1 Image classification techniques

For LULC classification, an iterative self-organizing (ISO) cluster, an unsupervised classification method, was chosen. ISO cluster method, known as ISO Data Analysis Techniques (ISODATA), is frequently used in remote sensing applications. It is based on object meta-clustering using the minimal distance center approach. Indeed, it was selected in this research because of its straightforward approach that requires minimal human intervention(Nuthammachot and Stratoulias, 2017) .Image classification is the process of dividing all channels within a multichannel digital remote sensing dataset into discrete surface cover categories or information themes (Akashkumar et al., 2022). For image data to be transformed into thematic data, image categorization is required. Multispectral classification is one of the most often used methods of information extraction (Unger Holtz, 2007). In this study classifying the images, unsupervised image classifications techniques were applied. Unsupervised classification technique is performed when there was little or no knowledge to the geography of the region where classification is undertaken.

Table 2 Description of LULC classes used to measure the changes in Kersa district (1990-2020).

	Description
Bare soil	Areas with no vegetation cover, stock quarry, stony areas, uncultivated agricultural lands
Settlement area	Residential, commercial, industrial, transportation and facilities
Agriculture	Almost all are coffee gardens, crop area and fruit tree.
Forest land	Area covered by dense tree natural or plant tree forming closed canopies and thick.

2.4.2 NDVI

Several vegetation indices have been developed of which, NDVI is the most commonly used one despite the development of many new indices that take into account soil behavior (Lambin et al., 2003). It is used to distinguish healthy vegetation from others or from non-vegetated areas (Tuxen et al., 2008) using red and near-infrared reflectance values and this was integrated in the post-classification analysis to discriminate between the green cover and barren land. This research used NDVI based on the red band and near infrared band of Landsat and this was derived using expression given in Equations2. Normalized Difference Vegetation Index (NDVI**)**

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (2)$$

where NIR is the spectral reflectance measurements acquired in the near-infrared region (band), and R is red band. The spectral reflectance measurements acquired in the red region (Band).

2.4.3 Accuracy assessment

This study used ArcGIS 10.8 and Google Earth Pro tools to analyze and classify satellite images from 1990 to 2020 based on satellite and actual geographical land utilization to detect LULC changes. For this purpose, we conducted accuracy assessments to evaluate the classified images and LULC changes. To do accuracy assessment for the classified images, 100 random sample points were created. Reference points were collected for the 1990, 2000, 2010 and 2020 classified images from the corresponding Google Earth images. Then, the classified images were compared with the reference images by means of error matrix. Various measures of accuracy assessment such as producer accuracy, user accuracy, over all accuracy and Kappa coefficient were done.

$$\text{overall Accuracy(OA)} = \frac{\text{sum of diagona altallied(correctly indentified}}{\text{total number of samples}} \text{X100} \qquad (3)$$

$$\text{User Accuracy (UA)} = \frac{\text{Samples correctly identified in the row}}{\text{Row total}} \text{x100} \qquad (4)$$

$$\text{Produser Accuracy (PA)} = \frac{\text{Samples correctly identified in the colluman}}{\text{Colluman total}} \text{x100} \qquad (5)$$

$$\text{Kappa coiffent(KC)} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} x_{i+} x_{+i}}{N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{+i})} \qquad (6)$$

where r is the rows number in the matrix, xii is the number of observations in row i and column i (the diagonal elements), $x+i$ and $xi+$ are the marginal total of row i respectively, and N is the observations' number.

2.5 Work flow chart

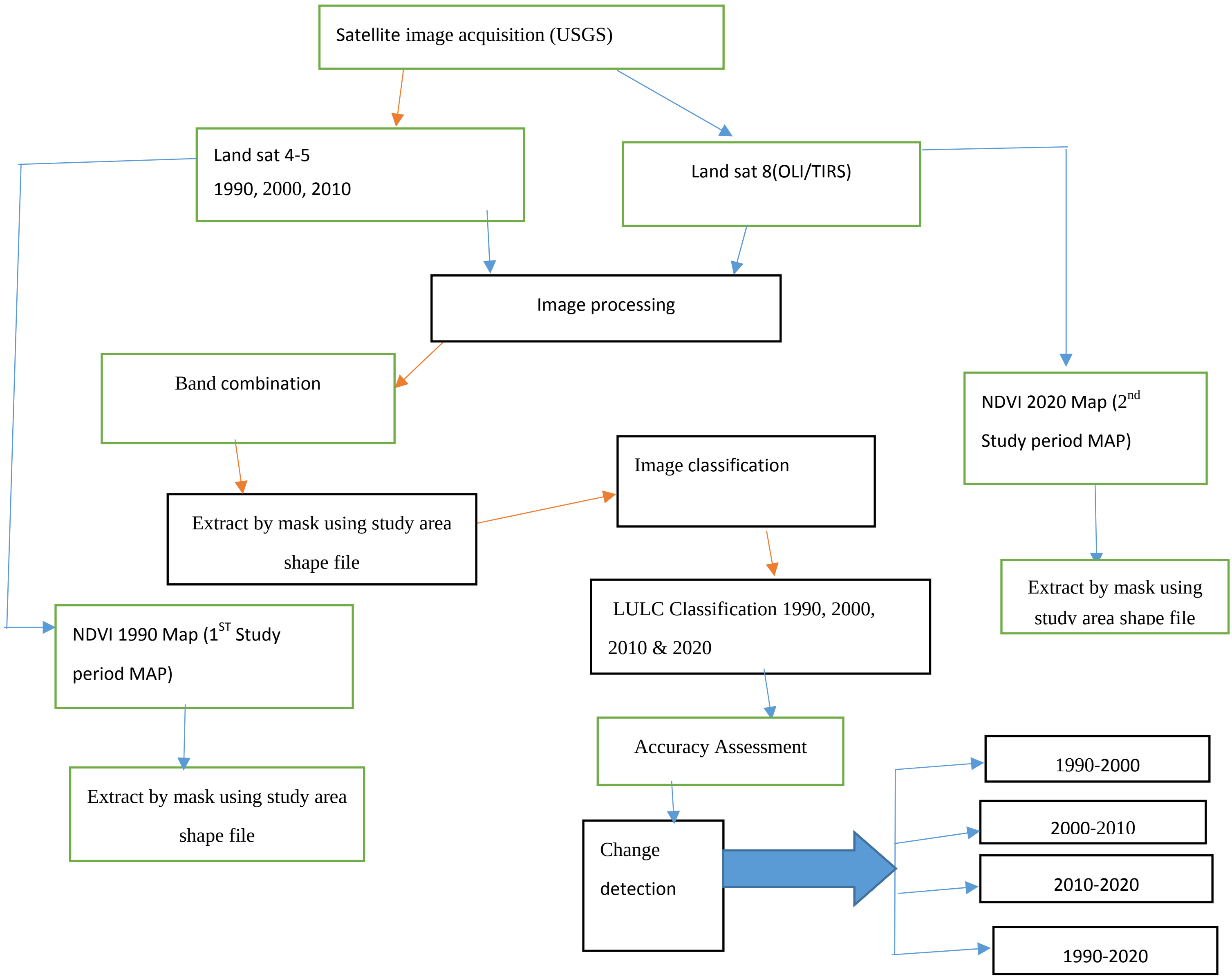

Fig. 2 Flow chart of the study.

3 Results and Discussion

3.1 Land use and land cover classes

The study found that the Kersa woreda has experienced noticeable changes in LULC at a different rate over the period of 30 years. Thus, agricultural lands, forest lands, settlement areas, bare land were identified as major LULC classes in the study area (Figs 3 & 4, Table 3) The ISO cluster unsupervised classification technique was used to generate the LULC map presented in Figure 3.

For the study area four land use land cover classes were identified. These were settlement, Agricultural land, forest and bare land. The land use land cover classification result for the study year 1990, 2000, 2010 and

2020 indicated in (Table 3). In 1990, the largest area was covered by Agricultural land 50.27% (48784.191 ha). The settlement, forest and bare land were covered 12.73% (13533.32 ha), 24.5% (22911.48 ha) and 12.5% (10831.83 ha) respectively. The land use land cover classification for the year 2000, as a year of 1990, the largest area was covered by Agricultural land 51.28%. The land use land cover classification for the year 2010, the largest area was covered as a year 2000 by Agricultural it was increased to 52.14.In final year (2020) land use land cover classification analysis shows that the same classes of change as fourth observation year, but covering different quantity agricultural land increase to 52.25%, Settlement area 14.888%, while forest land and bare land decrease to 20.94% and 11.91% respectively.

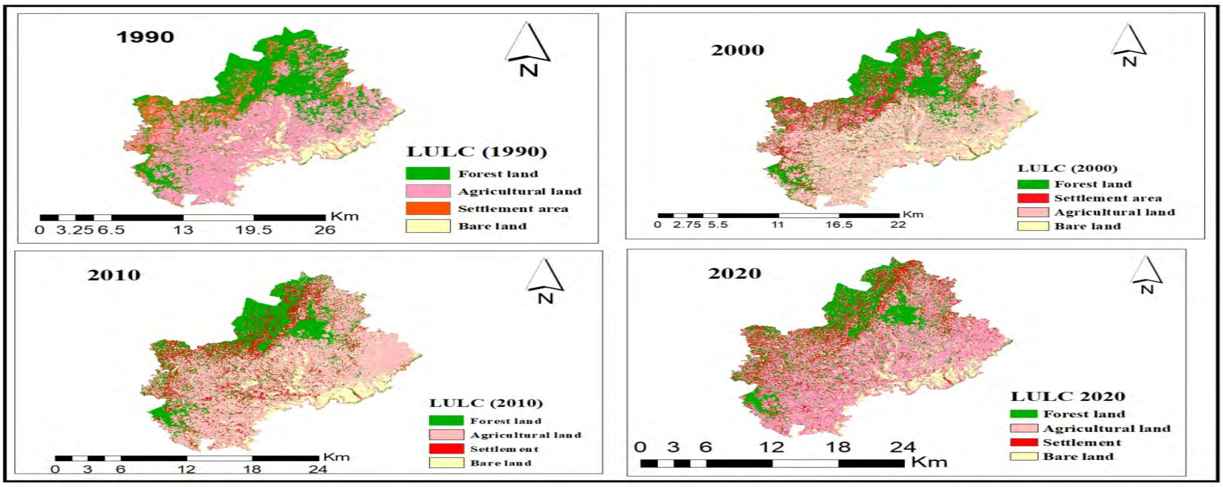

Fig. 3 LULC map of Kersa district of the study periods (1990 - 2020).

Table 3 LULC classification with the area in hectare (ha) and percentage (%) share (1990-2020).

Land Use -Land Cover (1990 -2020)								
LULC Class	1990		2000		2010		2020	
	ha	%	ha	%	ha	%	ha	%
Forest land	23775.8639	24.5	22911.48	23.60921897	20893.42489	21.5296	20321.87	20.9
Agricultural land	48784.191	50.27	49768.01	51.28362719	50605.48952	52.14635	50708.34	52.3
Settlement area	12353.7448	12.73	13533.32	13.94545502	13483.54988	13.8941	14447.87	14.9
Bare land	12130.5428	12.5	10831.83	11.16169883	12062.6521	12.42994	11566.26	11.9
Total	**97044.3426**	**100**	**97044.63**	**100**	**97045.11638**	**100**	**97044.34**	**100**

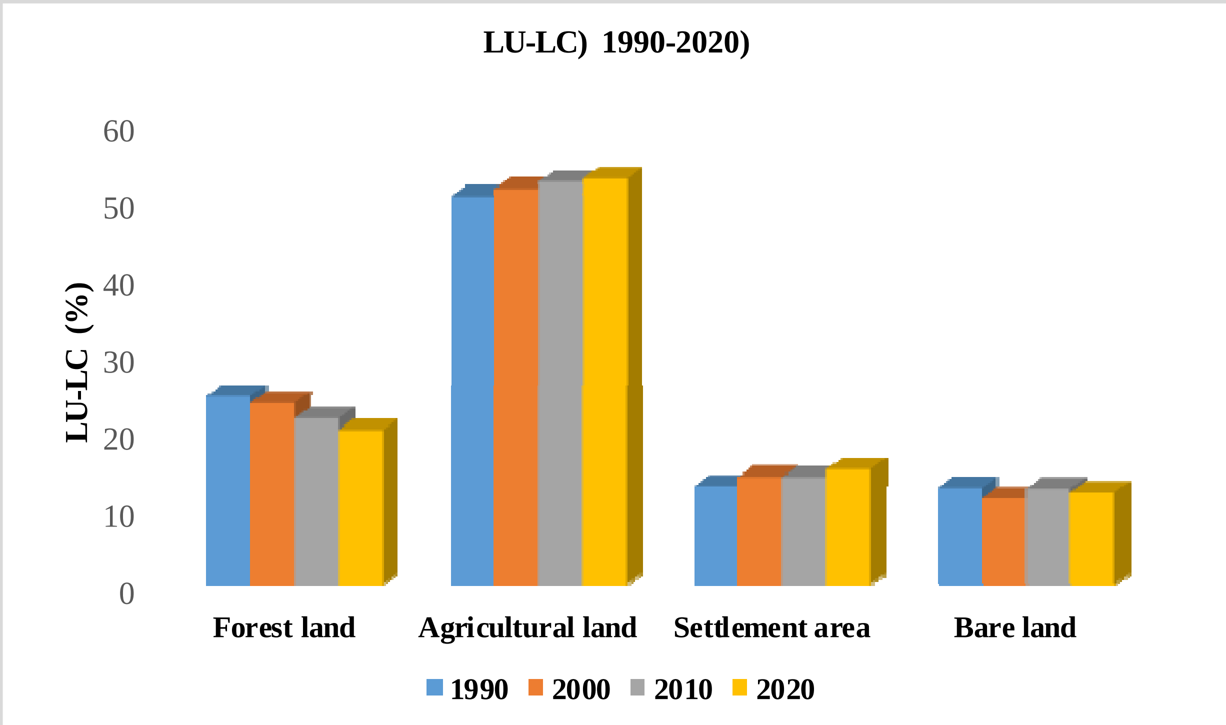

Fig. 4 Percentage share of LULC classes of the Kersa district (1990-2020).

3.2 Land use and land cover dynamics detections

Evidence from this study showed that over the entire study periods (1990-2020), the landscape of the targeted study area experienced some change in LULC in different rates of transformation (Figs 5, 6, 7 and 8). Table 4 shows that between the years 1990 and 2020, forest lands, and bare land declined by 3.559% and 0.58%, while agricultural lands and settlement areas increased by 1.98%, and 2.15%, respectively.

The change analysis showed that the rate and the trend of conversion varied distinctly among the different classes and intervals of the study periods. LULC classification result shows that in the first study period (1990), the landscape was dominated mainly by agricultural lands covered almost 50.27% followed forest lands by (24.5%), settlement areas (12.73%), and bare land (12.5%). Table 4 reveals that in 2000, agricultural lands and settlement areas increases to 51.28% and 13.95% respectively. When forest land and bare land was decreases to 23.6% and 11.16% respectively. Likewise, in 2010, the percentage share of the classes showed that 52.15% of the study area covered by agricultural lands, settlement areas (13.89%), forest lands (21.53%), and bare land (12.43%). In the last study period (2020), 52.25% and 14.89% of the study area were under agricultural lands and settlement areas, while the share of forest lands, and bare land detracted to20.94%, and 11.92% respectively. As the analysis of satellite imageries revealed agricultural lands and settlement areas progressively expanded.

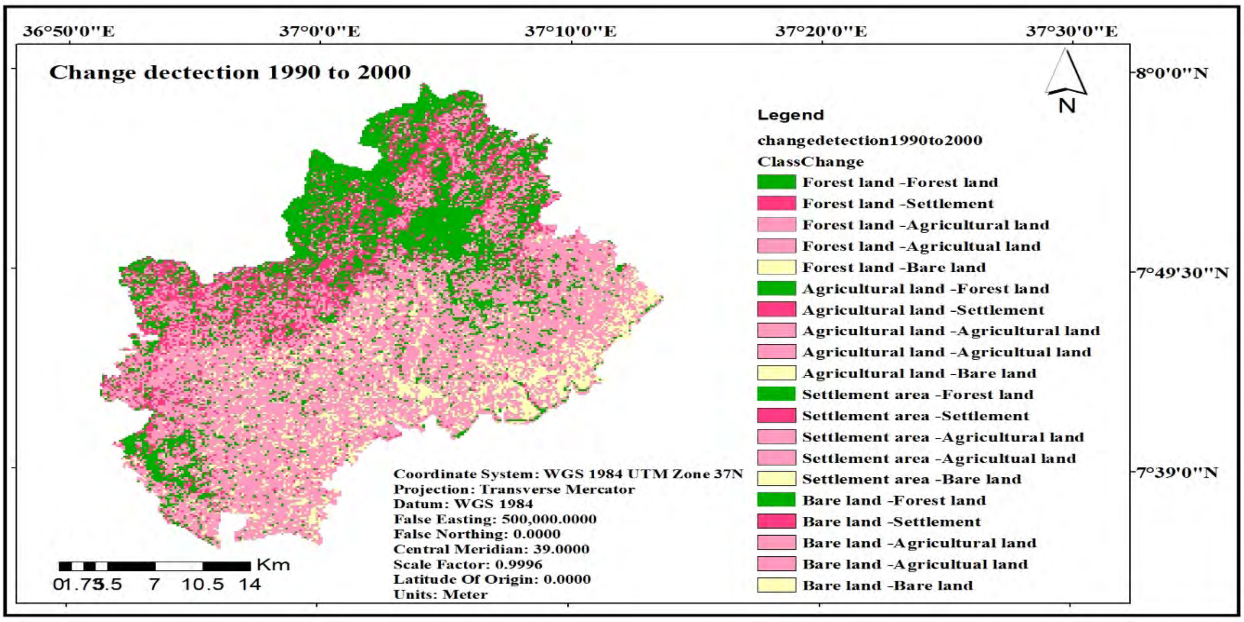

Fig. 5 LULC Change detection map of Kersa district from1990 to 2000.

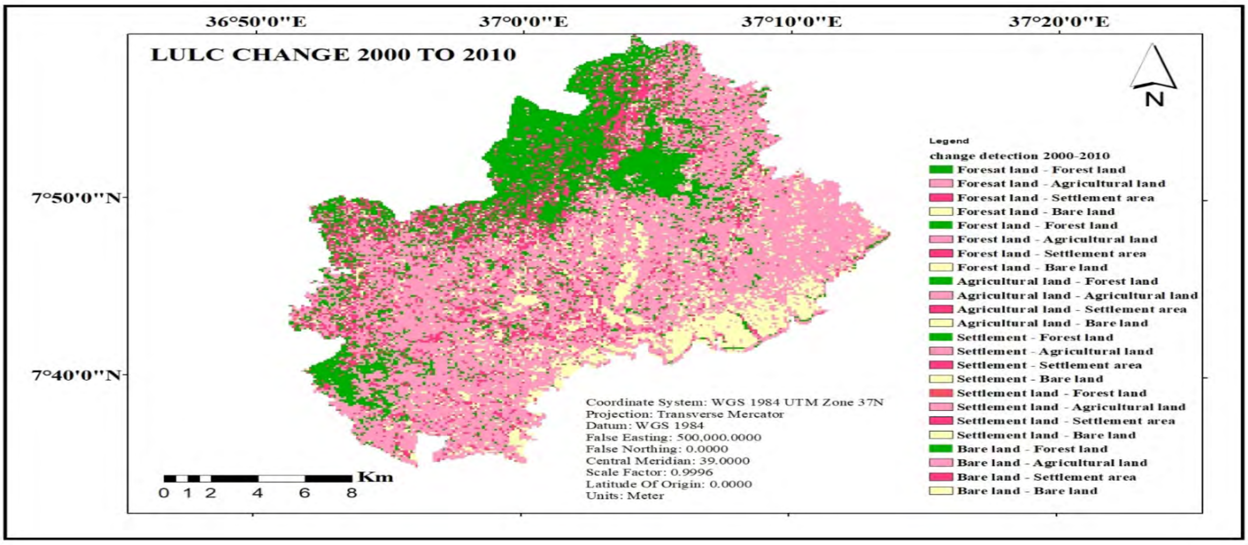

Fig. 6 LULC Change detection map of Kersa district from 2000 to 2010.

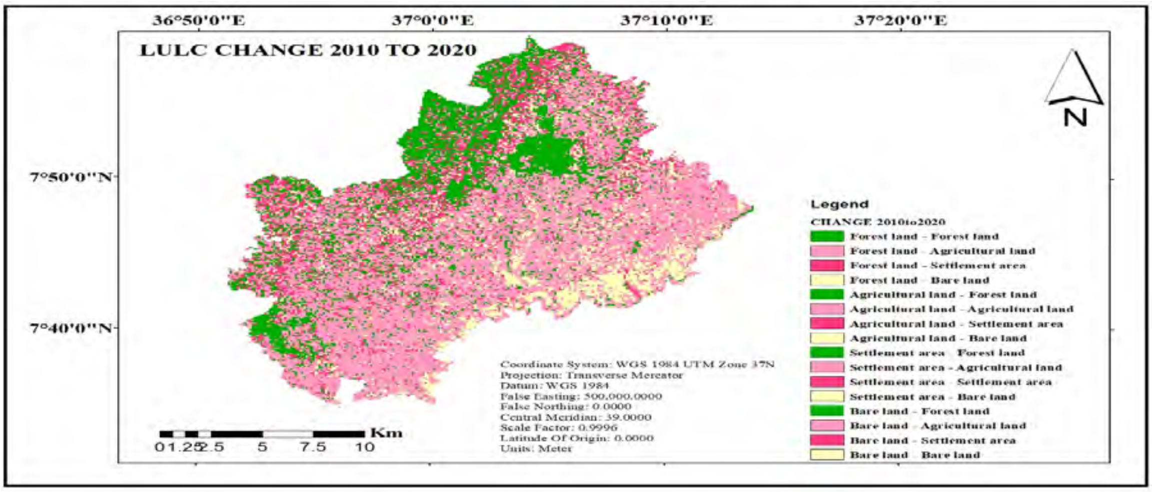

Fig. 7 LULC Change detection map of Kersa woreda district from 2010 to 2020.

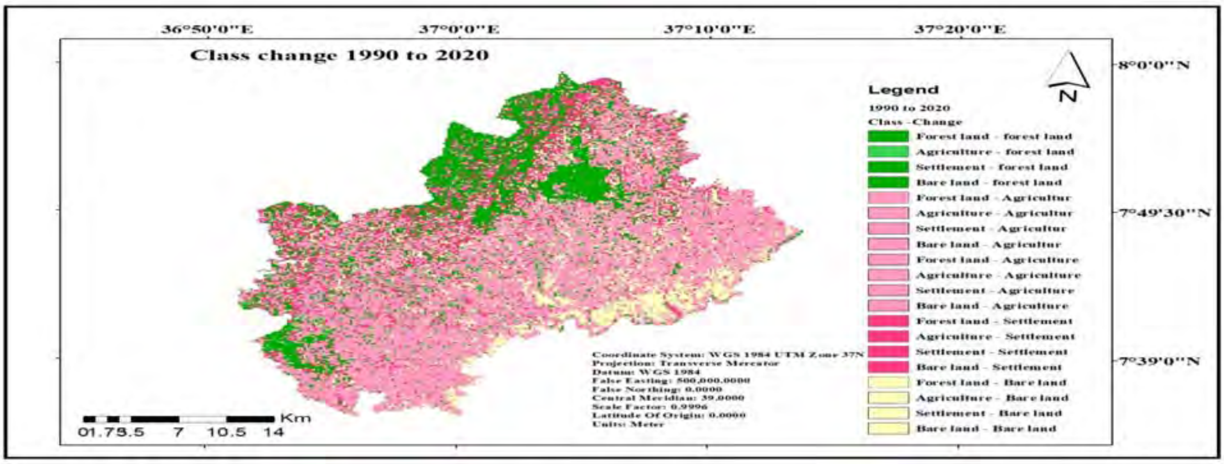

Fig. 8 LULC Change detection map of Kersa district from1990 to 2020.

Table 4 LULC change of Kersa district during the study periods (1990-2020).

LULC	change_1990-2000		change 2000-2010		change 2010-2020		change b/n 1990-2020	
	ha	%	ha	%	ha	%	Ha	%
Forest land	864.38	0.89	2018.06	2.08	571.55	0.59	3453.99	3.56
Agricultural land	-983.82	-1.014	-837.48	-0.86	-102.84	-0.11	-1924.14	-1.98
Settlement area	-1179.571073	-1.22	49.77	0.05	-964.32	-0.99	-2094.12	-2.16

Bare land	1298.712967	1.34	-1230.82	-1.26824	496.39	0.51	564.29	0.58

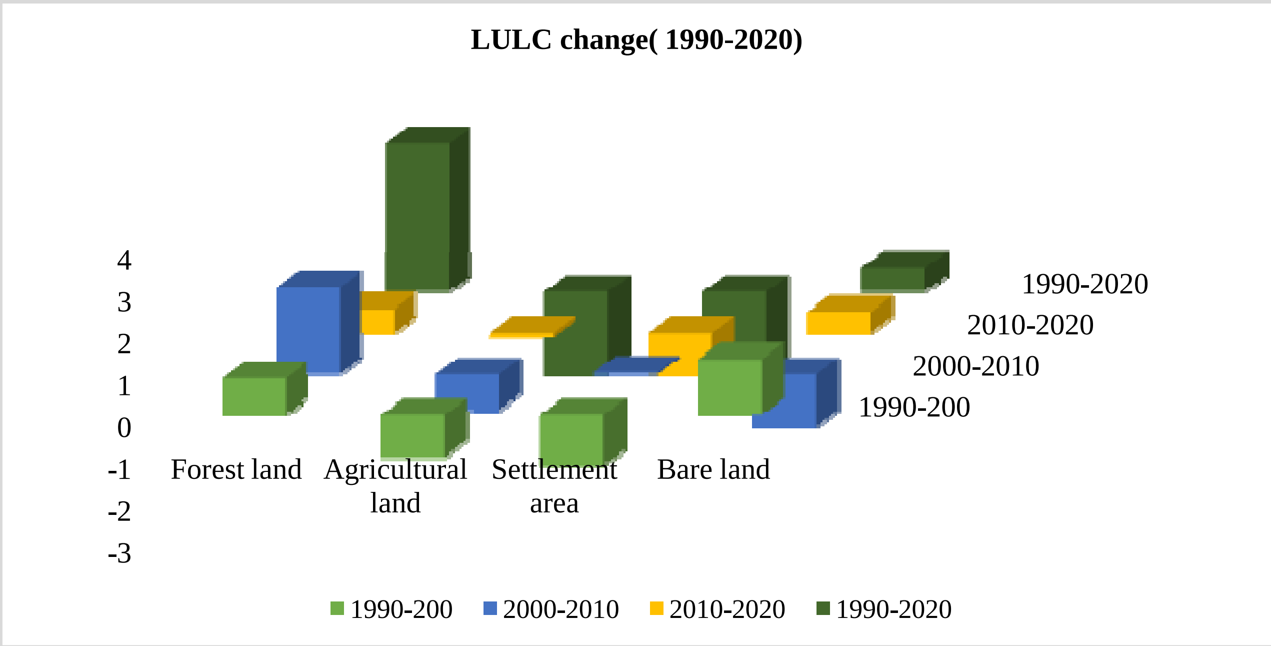

Fig. 9 LULC change of Kersa district during the study periods (1990-2020).

3.3 NDVI Analysis and Dynamics Detection

3.3.1 NDVI Analysis

A Higher value of NDVI infers the presence of healthy vegetation in the area while its lower value is the indicator of sparse vegetation. The NDVI value calculated from Landsat satellite image of the year 1990 ranges from 0.785 to -0.4. The NDVI value calculated from Landsat satellite image of the year 2000 ranges from 0.788 to -0.23. The NDVI value calculated from Landsat satellite image of the year 2010 ranges from 0.703 to -0.3. While the NDVI value calculated from Landsat satellite image of the year 2020 ranges from 0.559 to -0.171(Fig. 12).

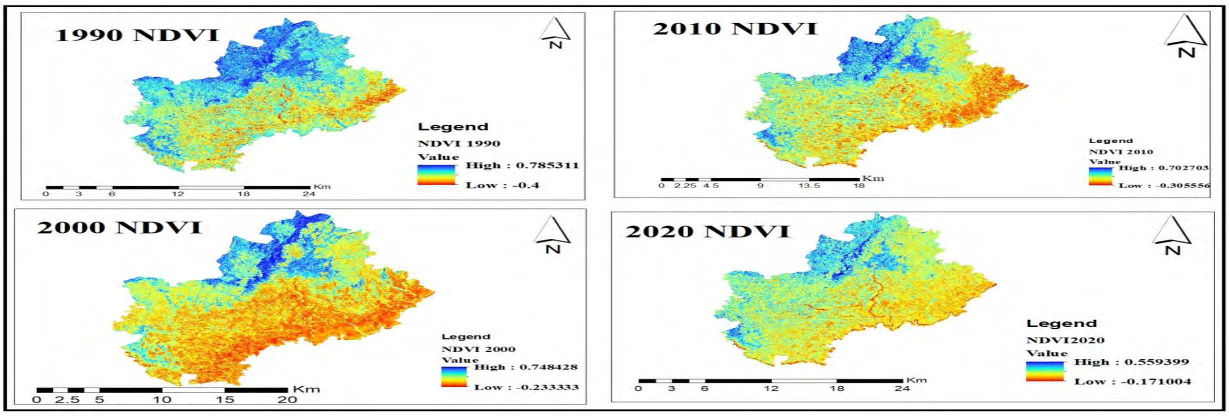

Fig. 10 NDVI value during the study period (1990 - 2020).

3.3.2 Dynamics detection

The NDVI values extremely decreased from 1990 to 2020 due to expansion of agricultural land, settlement, and bare land with aggravates, the decline of forest cover in the study area (Table 5 and Fig. 13).

Table 5 NDVI change of Kersa district during the study periods (1990-2020).

	NDVI values		**Year**	**Change of NDVI b/n 1990-2020**	
	High	Low		High	Low
1990	0.7853	-0.4	1990-2000	0.0369	-0.1667
2000	0.7484	-0.2333	2000-2010	0.0457	0.0722
2010	0.7027	-0.3055	2010-2020	0.1428	-0.1355
2020	0.5599	0.17	1990-2020	0.2254	-0.23

3.4 Accuracy assessment

3.4.1 Producer and user accuracy

Data obtained from Land sat images, user's accuracy and producers' accuracy also explained for all the four classified images. Users' accuracy measure the percentage of pixels or points mapped as a given class is included belongs to that class on the ground and producers' accuracy measure the percentage to which the ground reference data itself was correctly classified. Results of user's accuracy in this study showed that in 1990 the maximum class accuracy was 92.8%, which was bare land where correctly classified and the minimum was agricultural land with an accuracy of 85.7% as presented in table 6 below. In 2000, the class accuracies range from85.7% to 100% where as in the period 2010, it ranges from 81.61% to 100% and final the user accuracy 2020, range from 87.5% to 100% as indicated in tables 6 respectively. Producer accuracy was ranges from 57.1% to 93.3%, for all study period (Table 6).

Table 6 Error matrix of classified satellite imagery of the Kersa district.

Classification accuracy Landsat 5 (TM) 1990							
LULC class	Forest land	Agriculture land	Settlement area	Bare land	Total	User Accuracy	Kappa
Forest land	8	1	0	0	9	0.89	0
agricultural land	1	6	0	0	7	0.86	0
Settlement area	1	1	16	2	20	0.8	0
Bare land	0	1	0	13	14	0.93	0
Total	10	9	16	15	50	0	0
P-_Accuracy	0.80	0.66	1	0.866	0	0.86	0
Kappa	0.00	0.00	0	0.000	0	0	0.807
over all accuracy					45		0.9
Classification accuracy Landsat 5 (TM) 2000							
LULC Class 2000	Forest land	Settlement	Agricultural	Bare land	Total	U-Accuracy	Kappa
Forest land	8	0	0	0	8	1	0
Settlement	1	7	0	0	8	0.87	0
Agricultural	1	0	19	0	20	0.95	0

Bare land	1	1	0	12	14	0.86	0
Total	11	8	19	12	50	0	0
P-Accuracy	0.727	0.875	1	1	0	0.92	0
Kappa	0	0	00	0	0	0	0.888
over accuracy					46		0.92
Classification accuracy Landsat 5 (TM) 2010							
LULC 2010Class	Forest land	Agricultural land	Settleme nt	Bare land	Total	U-Accuracy	Kap pa
Forest land	4	0	0	0	4	1	0
Agricultural land	0	19	1	1	21	0.90	0
Settlement	1	1	12	0	14	0.86	0
Bare land	2	0	0	9	11	0.82	0
Total	7	20	13	10	50	0	0
P-Accuracy	0.57	0.95	0.92	0.90	0	0.88	0
Kappa	0	0	0	0	0	0	0.82 9
Over all accuracy					44		0.88
Classification accuracy Landsat 8 (OLI) 2020							
LULC 2020 Class	Forest land	Agricultural land	Settlement area	Bare land	Total	U-Accuracy	Kappa
Forest land	5	0	0	0	5	1	0
Agricultural land	0	13	0	0	13	1	0
Settlement area	0	1	14	1	16	0.875	0
Bare land	1	0	1	14	16	0.875	0
Total	6	14	15	15	50	0	0
P-_Accuracy	0.833	0.928	0.933	0.933	0	0.92	0
Kappa	0	0	0	0	0	0	0.889
over all accuracy					46		0.92

3.4.2 Over all accuracy and Kappa Coefficient

Over all accuracy is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows an overall result of the tabular error matrix. In this study, accuracy assessment was carried out to ensure the classification of the LULC maps would be reliable. The reference data were compared to the classified LULC map. Overall, classification accuracy for the LULC accuracy assessments for the study periods 1990, 2000, 2010 and 2020 was 90%, 92%, 88 %, and 92%, respectively. In addition, in the year of 1990, 2000, 2010 and 2020, the kappa coefficients were 0.807, 0.888, 0.829, and 0.889.

4 Conclusion

This study aimed to determine LULC change and estimate the vegetative index (NDVI) from 1990 to 2020 in Southwestern Ethiopia. Landsat-based images of 30 m × 30 m spatial resolution covering the studied region were used to determine LULC and change for the years 1990, 2000, and 2010 of Landsat 5 (TM), 2020 of Landsat 8 (OLI-TIRS).

In the study area, the forest cover was reduced from 23775.8639ha (24.5%) to20321.87 ha (20.94%) in 2020. In 1990, 12.73% of the area was occupied by settlers, but in 2020, that number had changed to14.88791 %. The NDVI change analysis revealed a continuous decline of forest lands that NDVI value of (1990-2020), decline from 0.789highy & -0.4 low to 0.559highy& -0.17 low respectively and the NDVI dynamics from 1990 to 2020 in Kersa district varied significantly and land was converted into non-vegetative areas. It was determined that the population increased due to settlement growth.

The agricultural sector is primarily focused on obtaining food for the increasing population, which means that governmental capacity is lacking to support mitigation. The government should employ the abilities of Remote Sensing and GIS technology for mapping to provide adequate and reliable spatial information and data that are useful to develop the effective management and monitoring of LULC changes in Ethiopia.

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