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Forest cover change detection using Geographic Information Systems and remote sensing techniques: a spatio-temporal study on Komto Protected forest priority area, East Wollega Zone, Ethiopia

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Abstract

Background: Forest plays an important role in climate regulation and carbon sequestration. Komto Forest is one of the remnant natural forests found in Guto Gida district of East Wollega zone, Ethiopia, has been supporting the local community for construction, energy and household furniture. Currently, influenced by land use land cover change (LULCC), this forest has been declining at an alarming rate. Detecting LULCC and understanding the driving forces has important for supporting decision making processes. We examine variation in forest cover dynamics over the period 1991–2012 using Landsat TM image of 1991, ETM + of 2002 and OLI-TIRS of 2019.

Results: The LULCC detection results show that a dramatic increase of agricultural land from (24.78%) in 1991 to (33.5%) in 2019 with annual expansion rate (23.68%) per annum, where forest cover declined by 20.1% in 1991 and 37.38% in 2019 with annual decreasing rate of 4.18% per annum. Our finding indicates the increment of agricultural land, grassland, and settlement, while the dense and open forest cover shows a declining trend. The declining of forest coverage is likely to cause unpleasant environment and affects human wellbeing.

Conclusions: The massive declined in forest cover change are often associated with agricultural expansion in the periphery of the forest. Timber exploitation and charcoal production are other problems that contribute for the declining of forest coverage. Overall, our results suggest the need of participatory forest management and public awareness creation to sustain the Komto remnant forest.

Keywords: Change detection, Deforestation, Forest loss, Land cover change, Land use land cover

Background

Performing land use change detection is an important tool to understand the extent of land cover loss and gain over time. Understanding the characteristics, extent and pattern of land use land cover change (LULCC) is an important supporting tool for decision making processes (Armenteras et al. 2019; Abebe et al. 2019; Yan et al. 2018; Tolessa et al. 2017). Detecting land use change over time has become increasingly important consideration for environmental management (Kiswanto and Mardiany 2018; Mensah et al. 2019). Therefore, studying the rate of LULCC support a decision making processes. Due to world population boom and advancement in science and technology, the natural resources are overexploited for the sake of economic activities with high severity in developing countries. Agricultural expansion into the

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forest land, timber logging, charcoal production and firewood harvesting are the major drivers of deforestation in Africa (Declee et al. 2014; Muhati et al. 2018). Small holder farmers collect fuel wood, construction materials, wild foods, and other forest products for subsistence (Nerfa et al. 2020). The world's population is increasing from time to time. For instance, in 2015 the world population is about 7.3 billion, and expected to reach 9.7 billion in 2050, and 11.2 billion in 20100 (UN 2015). People are converting forest, and other land cover to agricultural lands to meet the demand of growing population. The conversion of forests to agricultural lands is expected to be continued in the future (Salghuna et al. 2018; Pellikkaa et al. 2018).

Changes in LULC can alter the supply of ecosystem services and affect the well-being of humanity (Rimal et al. 2019; Deng et al. 2013; Olson et al. 2008). The LULC has the potential to influence the biological processes, and alter the provision of ecosystem services (Gibson et al. 2018; Geng et al. 2015; Kishtawal et al. 2010). The change in LULC has an impacts on hydrological fluxes (Guzha et al. 2018), regional climate (Geng et al. 2015; Costa et al. 2003), agricultural production (Deng et al. 2013) and greenhouse gas emissions (Furukawa et al. 2015; Findell et al. 2007). Forest plays a vital role in regulating climate change through sequestering atmospheric carbon dioxide and mitigates global climate change.

Substantial research has been conducted to investigate the extent of land use land cover change (LULCC) in several countries at various times (Deng et al. 2013; Geng et al. 2015; Lark et al. 2017; Gibson et al. 2018; Ru-Mucova et al. 2018; Lei and Zhu, 2018). From the existing land use land cover class, forest is the most threatened by anthropogenic driven deforestation (Fokeng et al. 2019). At global level, forest area declined by 3%, from 4128 million hectare in 1990 to 3999 million hectare in 2015 (Keenan et al. 2015). It is predicted that forest area are projected to continue to decline at alarming rates in some regions (d'Annunzioin et al. 2015). In some places the forest coverage is slightly increased while in other places the forest coverage indicates a declining trend. For instance, tropical forest area declined at a rate of 5.5 million hectare per year while the temperate forest area expands at a rate of 2.2 million hectare per year (Keenan et al. 2015).

As reported by World Bank (2017), between 1990 and 2015, East Africa forest cover decreased annually by 1% while human population increased at an average annual rate of 2%. Thus, it is possible to correlate forest cover change with population growth. Africa is responsible for 27.4% of land degradation, and it is estimated that almost 500 million hectares are practically degraded (Ru-Mucova et al. 2018). Forest depletion and degradation affects the sustainability of agricultural production systems and endangers the economy of the country.

In Ethiopia three major factors affect LULCC: resettlement programmes, population growth and increasing agricultural investments (Degife et al. 2018). From 1995 to 2010, Ethiopia lost about 141,000 ha of forest (FAO 2011). Ethiopian forest loss and degradation has been studied by various researchers such as Geeraert et al. 2019; Belay and Mengistu, 2019; Minta et al. 2018; Feyissa and Gebremariam, 2018; Tolessa et al. 2017; Daye and Healey 2015; Tolera et al. 2008). Study conducted in the Gamo highlands of Ethiopia by Day and Healy (2015) indicates that the forest area decreased by 36.6%, with a decrease in number of forest patches by 16.1%. Ethiopian flora and fauna shows a declining trend due to extensive deforestation (Tolera et al. 2008). Forest depletion is a common problem in different parts of Ethiopia due to people dependence on forest for energy consumption as well as forest goods and services for survival. Erena et al. (2011) and Dinkayehu (2006) explained that Komto protected forest priority area is one of the remnant forest in Ethiopia threatened by forest over utilization in the form of charcoal extraction and timber production. The cause of Komto protected forest loss analyzed by (Erena et al. 2011; Dinkayehu, 2006), yet information on changes in spatio-temporal patterns is limited. This study therefore applied the combination of GIS and RS techniques and public opinion to estimate the spatio-temporal dynamics of Komto Protected Forest Priority Area.

Materials and methods

Description of the study area

The study was carried out in Komto Protected Forest priority area in Oromia National Regional State in Ethiopia, East Wollega Zone, Guto Gida district (Fig. 1).

Guto Gida district lies between 9° 4′30″ and 9° 06′ 30″ North Latitude, and 36° 36′ 30″, and 36° 38′ 30″ East Longitude. The study area lies between 2107 and 2493 m above sea level and receive 2067 mm annual rainfall. The study area is humid and moderately hot climate. The mean annual temperature is about 17.5 °C and the mean minimum and maximum temperature are 15 °C and 20 °C, respectively.

Research methods and design

This study used the combination of GIS and RS technologies to detect a spatio-temporal dynamics of Komto Protected Forest Priority Area, Guto Gida district, East Wollega Zone, Oromia National Regional State, Ethiopia. Likewise, focused group discussions (FGD), key informant interviews (KII), and household questionnaire survey were

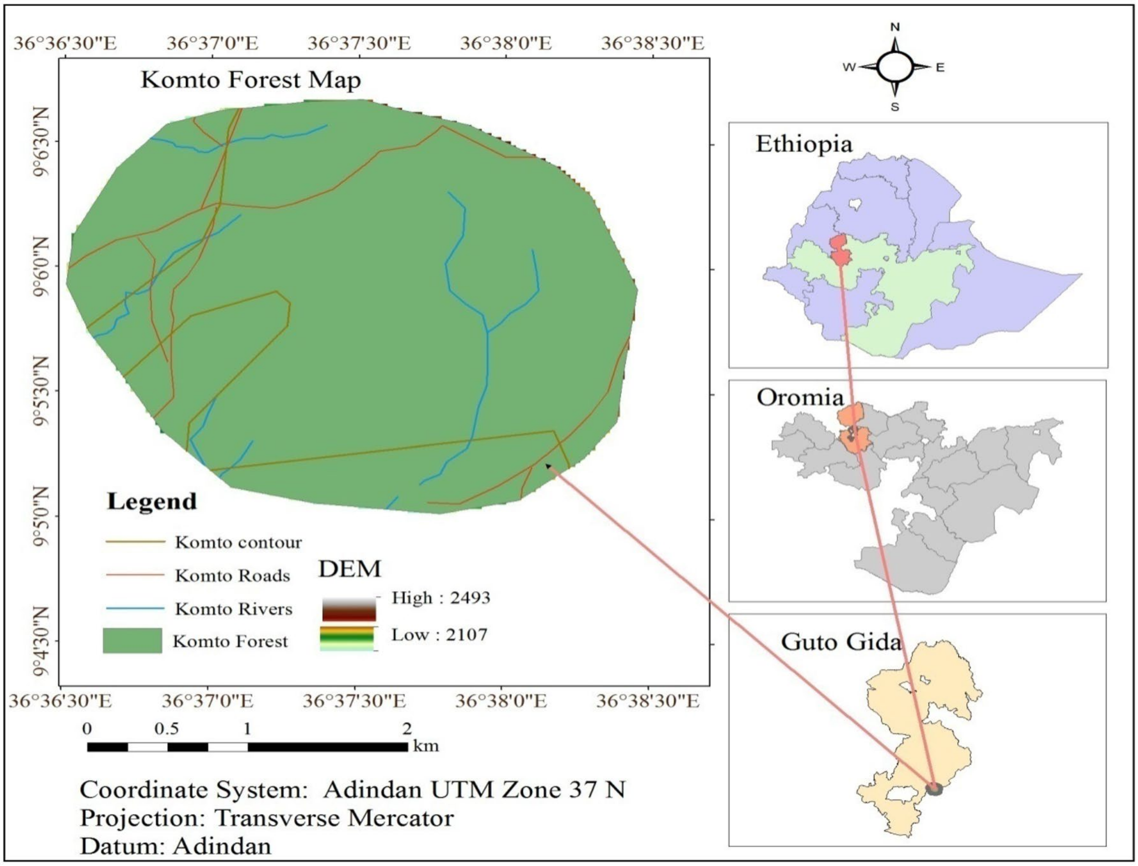

Fig. 1 Location and topography of the study area

used for qualitative information about the land use change of the study area (Fig. 2). The qualitative information collected through FGD, KII, and household survey was integrated with GIS and RS results for spatio-temporal forest cover change analysis.

Household's questionnaire surveys were carried out in the two villages namely Dalo Komto and Gari, based on proximity to forest area (Geographical location). Both open and closed ended questionnaire was primarily designed in English language and later translated into Afaan Oromoo (dominant language in western parts of Ethiopia) to get the required information on socio-economic characteristics of the households, cause of deforestation or forest cover change and consequences of deforestation in the study area. Due to homogeneity of the study area population, we used simple random sampling method techniques. The total numbers of households' size in the study villages (797) were taken from village registry. The sample size was determined by using Kothari (2004) sample size determination formula and decided proportional to the total population size (Eq. 1).

$$\mathrm{no} = \frac{\mathrm{Z}^2(\mathrm{p})(\mathrm{q})}{\mathrm{d}^2}\mathrm{n1} = \frac{\mathrm{no}}{1+\frac{(\mathrm{no})}{\mathrm{N}}}. \tag{1}$$

where: no = desired sample size when population greater than 10,000; n1 = finite population correction factors when population less than 10,000; Z = standard normal deviation (1.96 for 95% confidence level); P = 0.1 (proportion of population to be included in sample i.e. 10%); q = is 1−P i.e. (0.9); N = is total number of population; d = is degree of accuracy desired (0.05).

Following Kothari (2004) sample size determination formula, a total of 118 housing hold units were randomly selected from two villages; 61 from Dalo Komto and 57 from Gari (Table 1).

A key informant interview (KII) is another technique used to explore what is happened and happening on forest cover change in the study area. Key informant interview is a depth interviews with people who know about particularly situation in the community (USAID 1996).

A focused group discussion (FGD) was conducted to collect qualitative information about forest cover change

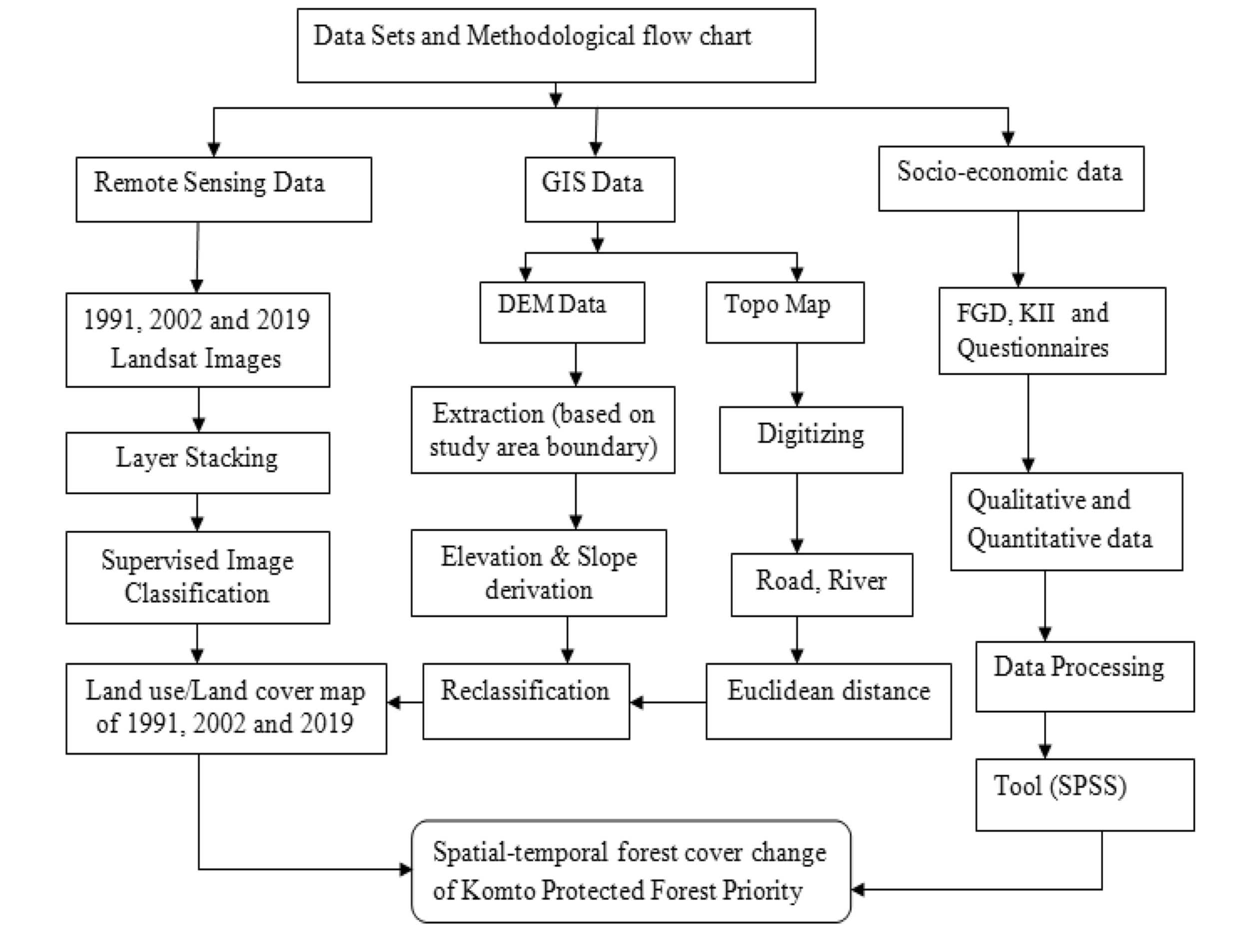

Fig. 2 Methodological flow chart

Table 1 Selected household unity of the study area

Name of villages	Total member of HHs	Sample size
Dalo Komto	410	61
Gari	387	57
Total	797	118

along some tangible evidence. The FGD was performed following Denscombe (2007) by a researcher to explore their attitude and perceptions, feelings and ideas about the spatio-temporal forest cover change of Komto forest.

Remote sensing data processing

This study used remote sensing data for forest cover change detection in Guto Gida district of East Wollega zone, Ethiopia from 1991 to 2019. The image processing task was carried out using (Earth Resource Data Analysis System) ERDAS Imagine 2015 software. Radiometric correction and cloud detection methods were performed for noise removal following (Lin et al. 2015; Wang 2016). For land use land cover classification, Landsat MSS Image of 1991, Landsat ETM + Image of 2002 and Landsat 8 OLI image of 2019 were used (Table 2).

Landsat imagery preprocessing and supervised classification methods were performed for forest cover change detection techniques following (Churches et al. 2014; Wu et al. 2017; Lu and Weng 2005; Lillesand et al. 2004), which involves the use of multi-temporal datasets to discriminate areas of land cover change between dates of imaging (Garai and Narayana 2018).

Images were classified into five LULC classes; dense forest, open forest, agricultural land, grassland, and settlement (Table 3). The forest in the study area has been further classified as dense forest (found in the core and greener pixels) and open forest (less dense found in the periphery of the forest) based on variation in tone and Normalized Difference Vegetation Index (NDVI) values. During supervised classification and ground verification, areas found in center of dense forest and having similar pixel values was

Table 2 Data types and sources

No	Data type	Source	Spatial resolution (m)
1	Landsat images (Landsat 5 TM (1991), Landsat 7 ETM + (2002) & Landsat 8 OLI/TIRS (2019)	United States Geological Survey (USGS)	30
2	Digital Elevation Model	ASTER	30
3	Topographic Map	Ethiopian Geospatial Information Institute (EGII)	
4	GPS data	Field survey	
5	Socio-economic data	Questionnaire survey and expert interview	

Table 3 Land use and land cover classes

No	Land use/land cover type	Description
1	Dense forest	Area covered by dense forest
2	Agricultural land	Areas covered with perennial and annual crops
3	Grass land	Area covered by sparse trees with dense grasses
4	Settlement	Dispersed rural settlements and homesteads
5	Open forest	Composed predominantly of regeneration forest from the past disturbance

Source: Classified images of the years (1991, 2002 and 2019)

categorized as dense forest and the one that were less dense were categorized as open forest. During supervised image classification, a total of 81 ground control points were taken from different LULC classes.

Forest cover change detection technique

Change detection involves the use of multi-temporal datasets to discriminate areas of land cover change between dates of imaging. It is widely used in the application of remote sensing that examines multi-temporal datasets (Dalmiya et al. 2019; Stehman and Foody 2019). Othow et al. (2017) used remote sensing change detection techniques to analyze the rate of LULCC with special emphasis on forest cover change in Gog district of Gambella Regional State in Ethiopia. It has the capacity to detect many kinds of land cover change for any given time (Zhu et al. 2014). In order to detect the changes of forest ecosystem over the years 1991, 2002 and 2019 multi-temporal Landsat data were acquired. To perform forest change analysis, post-classification change detection comparison methods was employed. Then the raster data was converted into vector layer by using Arc GIS 10.5 software and LULC classes was classified. After classification of LULC their maps was prepared, and forest cover changes of the study area were analyzed.

Accuracy assessment

The accuracy assessment reflects the real difference between our classification and the reference map or data (Lillesand et al. 2004; Pouliot et al. 2014; Tsutsumida and Comber 2015; Disperati and Virdis 2015). If the reference data is highly inaccurate, assessment might indicate that classification results are poor.

Producer's accuracy is the map of accuracy from the point of view of the map maker (the producer). This is how often are real features on the ground correctly shown on the classified map or the probability that a certain land cover of an area on the ground is classified as such. It is also the number of reference sites classified accurately divided by the total number of reference sites for that class (Eq. 2).

$$\text{Producer Accuracy} = \frac{\text{Total number of pixels in a category}}{\text{Total number of pixels of that category derived from the reference data (i.e., row total)}}. \quad (2)$$

User's accuracy is the accuracy from the point of view of a map user. The User's accuracy essentially tells us how often the class on the map will actually be present on the ground. The User's accuracy is complement of the commission error, User's accuracy = 100%-commission error. The User's accuracy is calculating by taking the total number of correct classifications for a particular class and dividing it by the row total (Eq. 3).

$$\text{User's Accuracy} = \frac{\text{Total number of pixels in a category}}{\text{Total number of pixels of that category derived from the reference data (i.e., column total)}}. \quad (3)$$

Overall accuracy was used to calculate a measure of accuracy for the entire image across all classes present in the classified image (Eq. 4). The collective accuracy of map for all the classes can be described using overall accuracy, which calculates the proportion of pixels correctly classified.

$$\text{Overall Accuracy} = \frac{\text{Sum of the diagonal elements}}{\text{Total number of accuracy sites pixels (column total)}}. \quad (4)$$

To calculate the percentage of LULUC (%), the initial and final LULC area coverage was compared following Garai and Narayana (2018) as indicated in Eq. 5.

$$\text{Change percentage} = \frac{(\text{Present LULC area} - \text{Previous LULC area})}{\text{Previous LULC area}} \times 100 \quad (5)$$

The kappa statistics value is a measure of the agreement between classification and reference data (Wang et al. 2012; Mishra et al. 2019). Landis and Koch (1977) ranked the kappa values, ranging from −1 to 1, into three groups: (1) greater than 0.80 represented strong agreement (2) between 0.40 and 0.80 represented moderate agreement, and (3) less than 0.40 represented poor agreement between the classification and reference data. According to Wongapakaran et al. (2013), the Kappa coefficient lies typically ranged from 0 to 1.00 (Wongpakaran et al. 2013), where the latter indicates substantial agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy.

Results and discussions

Forest cover changes (1991–2019)

Multi spectral images from Landsat TM, ETM+ and OLI images of 1991, 2002 and 2019 were used to evaluate forest cover changes in the study area. Images were classified into five LULCC. These included; dense forest, open forest, grassland, agricultural land, and settlements. Land cover/use over the study period within Komto forest was dynamic by land cover conversion sequences like conversion to agricultural land, and settlements. Because of rapid population growth and increasing demand of open land for agricultural lands, the forest coverage is declining in several places in Ethiopia. The declining trends of forest coverage in Ethiopia is confirmed by several studies (Minta et al. 2018; Geeraert et al. 2019; Feyissa and Gebremariam 2018; Belay and Mengistu, 2019; Tolessa et al. 2017; Daye and Healey, 2015; Tolera et al. 2008). Similar to other African countries, Ethiopia is experiencing forest depletion because of agricultural expansion, timber logging, charcoal production and firewood harvesting (Declee et al. 2014; Erena et al. 2011; Dinkayehu 2006). The classification of the multidate Landsat images for the years 1991, 2002 and 2019 revealed that Komto protected forest priority area has been experiencing declining trends over time.

The change detection analysis result shows the dynamics of land-use/cover types such as dense and open forest, agricultural land, grassland, and settlement were found in the study area. Agricultural land, grassland, and settlement were increased while there was a reduction in dense and open forest cover. Similar to agricultural expansion, forest logging, firewood harvesting, and increase built up area (settlement) are depleting the forest resources within the Komto forest priority area. It was asserted that through time series analysis there has been a significant LULCC especially the conversion of agricultural land and settlement at the expense of other LULC classes in the Komto protected forest priority area.

Figure 3 shows a great variation of LULC over the study period. Both dense and open forest indicates a declining trend while the remaining land use such as grass land, agricultural land and settlement show increased in area coverage (Fig. 3). The grassland land cover class shows a slight increase over the study period.

In 1991, the highest extent of the study area was covered with dense forest 312.94 ha (32.73%), while open forest, grassland, agricultural land and settlement represented 173.86 ha (18.19%), 84.87 ha (8.88%), 236.92 ha (24.78%) and 147.33 ha (15.41%), respectively. By the year 2002, the areal coverage of agricultural land, grassland and settlement increased by 279.07 ha (29.21%), 92.65 ha (9.71%) and 167.31 ha (17.50%), respectively. Statistical data shows that the coverage of dense forest and open forest area decreased by 250.06 ha (26.16%) and

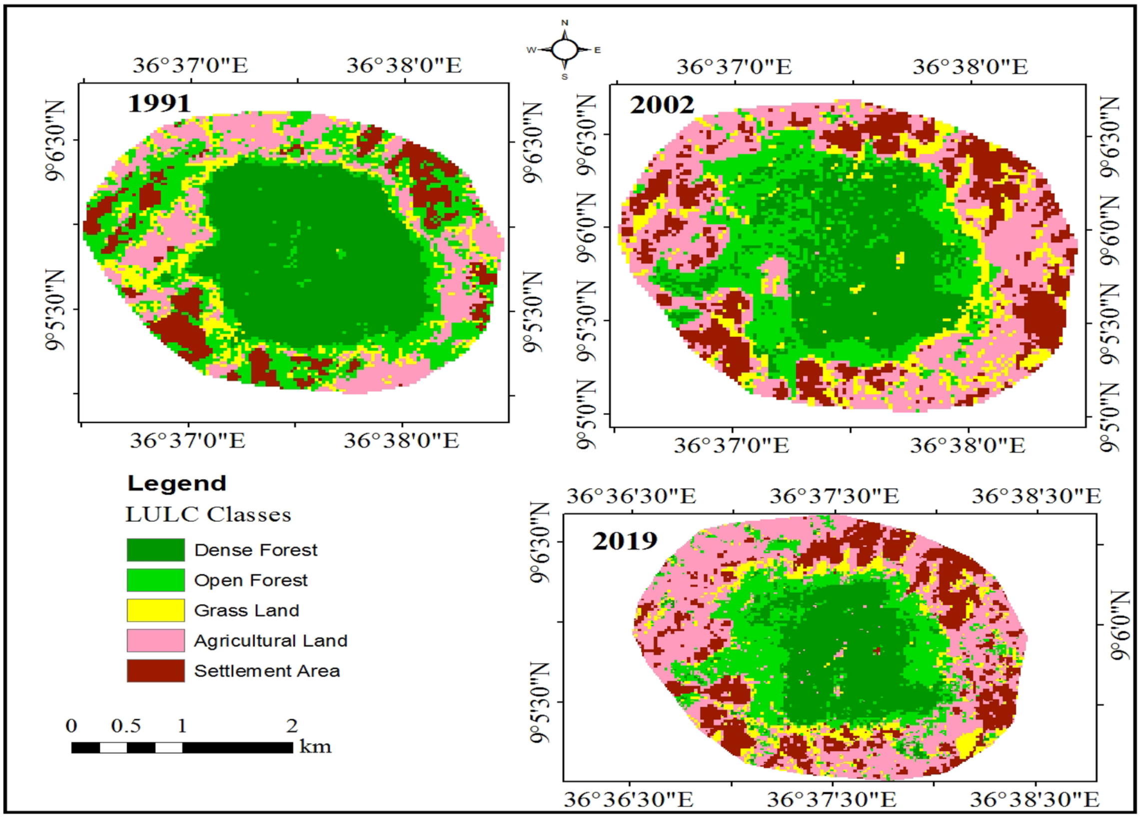

Fig. 3 Land use land cover map of 1991, 2002 and 2019

Table 4 Land use land cover areas in 1991, 2002 and 2019

Land cover	1991		2002		2019	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Dense forest	312.94	32.73	250.06	26.16	195.95	20.50
Open forest	173.86	18.19	166.7	17.44	154.30	16.14
Grass land	84.87	8.88	92.65	9.71	97.14	10.16
Agricultural land	236.92	24.78	279.07	29.21	320.23	33.50
Settlement	147.33	15.41	167.31	17.50	188.32	19.70
Total	956	100	956	100	956	100

166.7 ha (17.44%), respectively by the year 2002. In 2019, the coverage of dense forest and open forest decreased by 195.95 ha (20.50%) and 154.30 ha (16.14%) while the coverage of grassland, agricultural land and settlement increased to, 97.14 ha (10.16%), 320.23 ha (33.50%) and 188.32 ha (19.70%), respectively. The analysis of LULCC, we found that the agricultural land expanded rapidly at the expense of forest land and other land use over the last 28 years in the study area (Table 4). Results from FGDs and interview revealed that Komto forest cover change was declined due to settlements, agricultural activities, cutting of tree for wood, charcoal, furniture, and construction purpose (Degife et al. 2018).

The overall accuracies for the three reference years: 1991, 2002 and 2019 are 81.6%, 80% and 85% with the Kappa statistics of 0.81, 0.83 and 0.86 respectively (Table 5). The Kappa statistics value greater than 0.80 (80%) represents a strong agreement and a value between 0.60 and 0.80 represents a substantial agreement (Landis and Koch 1977). A result of user's accuracy shows that in 1991 the maximum class accuracy was for settlement (94%) and the minimum was for grass land (72%).

Table 5 Accuracy assessments for 1991, 2002 and 2019

Land cover class	1991		2002		2019	
	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)
Dense forest	77	91	91	83	79	93
Open forest	67	76	83	61	68	76
Agricultural land	90	81	77	85	92	73
Grass land	90	72	62	79	93	83
Settlement	96	94	84	87	98	96
Overall accuracy	81.6		80		85	
Overall kappa statistics	0.81		0.84		0.86	

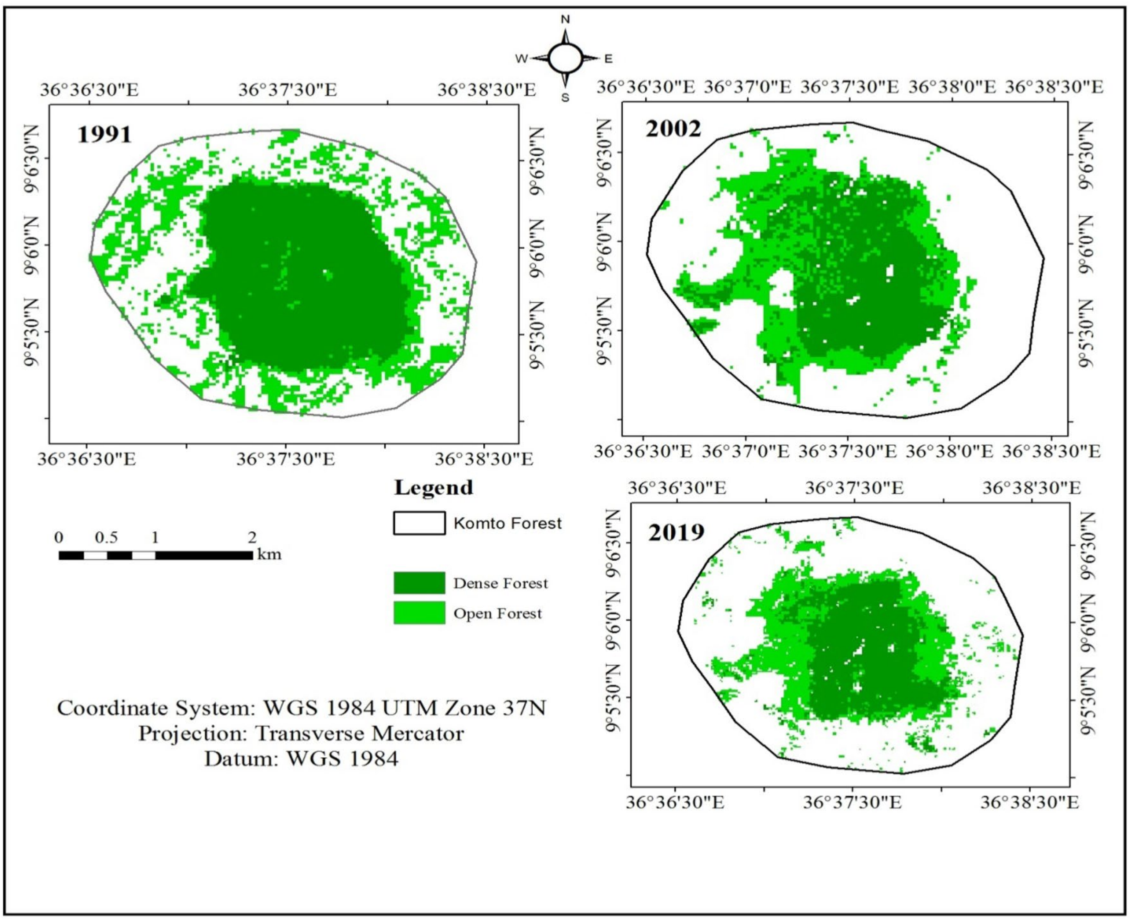

Fig. 4 Forest covers Map during 1991, 2002 and 2019

In 2002, user's accuracy ranges from lowest accuracy (62%, grassland) to relatively correctly classified (91%, dense forest) whereas in the period 2019, it was ranges from 72% grassland, 94% settlement. Results of producer's accuracy showed that settlement, dense forest and settlement were relatively correctly classified: 96%, 91% and 96% in 1991, 2002 and 2019 respectively. The lowest accuracy was open forest (67%), grass land (62%) and open forest (67%) in 1991, 2002 and 2019, respectively.

Rate of forest cover change

Analysis of forest cover change was done using geospatial technologies. Figure 4, indicates the rapid declining of dense and open forest because of high demand from the community for logging for charcoal and timber production (Dinkayehu 2006), agricultural purpose (Pellikkaa et al. 2018; Geeraert et al. 2019) and income generation from forest resources. The dense forest cover, which was 312.94 ha in 1991, declined to 250 in 2002 and about 196 ha in 2019 with the overall declining rate of 37.38% over the last 28 years (Table 6). Whereas, the rates of open forest cover change from year 1991 to 2002 were −4.12%, from year 2002 to 2019 it was −7.44% and from the year 1991 to 2019 it was decline by −11.25%. Our study report that forest coverage decreased rapidly in the study area, which is consistent with previous studies (Geeraert et al.2019; Belay and Mengistu 2019; Minta et al. 2018; Feyissa and Gebremariam 2018; Tolessa et al. 2017; Daye and Healey 2015; Tolera et al. 2008).

Detected changes by post classification

Land cover change analysis by post classification method revealed that twenty-one types of land conversion happened over the study period (1991–2019). Change detection shown in Table 7 indicates that dense forest decreased by 193 ha over the last 28 years for the sake of agricultural land expansions. The high conversion of forest to agricultural land is an indication of community dependent on agriculture as the main livelihood in the region. This finding is consistent with the study conducted by (Declee et al. 2014) in Congo forest.

Table 8, shows dense forest has decreased by 5.72 ha/year between 1991 and 2002, and continued to decline in coverage by 3.18 ha/year from 2002 to 2019 and from the

Table 6 Forest cover area of Komto forest and rate of change (1991, 2002, 2019)

Year	Dense forest cover	Open forest cover	Rate of change		
	Area (ha)	Area (ha)	1991–2002 %	2002–2019 %	1991–2019 %
1991	312.94	173.86	−20.1	−21.64	−37.38
2002	250.06	166.7	−4.12	−7.44	−11.25
2019	195.95	154.30			

Table 7 Land cover changes detected by post classification methods

	LULCC (1991–2002)	Hectare	LULCC (2002–2019)	Hectare	LULCC (1991–2019)	Hectare
1	AL to DF	6	DF to OF	4	AL to DF	3
2	AL to OF	10.8	DF to G	31	AL to OF	4
3	AL to G	32	DF to AL	170	AL to G	15
4	AL to S	33	DF to S	73	AL to S	13
5	OF to DF	38	OF to DF	25	OF to DF	18
6	OF to AL	88	OF to G	47	OF to G	52
7	OF to G	40	OF to AL	98	OF to AL	104
8	OF to S	85	OF to S	90	OF to S	101
9	S to OF	8	AL to DF	32	S to DF	14
10	S to AL	26	AL to OF	6	S to OF	6
11	S to G	24	AL to G	23	S to G	32
12	DF to OF	19	AL to S	19	S to AL	25
13	DF to AL	150	G to DF	7	DF to OF	5
14	DF to G	10	G to OF	12	DF to G	61
15	DF to S	60	G to AL	24	DF to AL	193
16	G to DF	11	G to S	16	DF to S	81
17	G to OF	10			G to DF	2
18	G to AL	12			G to OF	18
19	G to S	12			G to AL	29
20					G to S	22

DF Dense forest, *OF* open forest, *S* settlement, *AL* agricultural land, *GL* grass land

Table 8 Annual rate of forest cover change

Land cover	Area (ha)			Area lost in ha		
	1991	2002	2019	1991–2002	2002–2019	1991–2019
Dense forest cover (ha)	312.94	250.06	195.95	− 5.72	− 3.18	− 4.18
Open forest cover (ha)	173.86	166.7	154.30	− 0.65	− 0.73	− 0.7

year 1991 to 2019 it was declined by 4.18 ha/year. There was also a reduction in open forest coverage in the study area. From 1991 to 2002 and from 2002 to 2019 there was forest loss because of agricultural land expansion in the periphery of the forest area. The total loss of open forest between 1991 to 2002 was about 0.65 ha/year. The open forest declining trends was continued between the years 2002 to 2019 by 0.73 ha/year. Generally, over the last 28 years the open forest in the study area showed a declining trends of open forest by 0.7 ha/year. The declining trends of open forest in the study area are associated with agricultural expansions, illegal timber exploitation, and charcoal production.

LULC conversions of Komto forest priority

Major LULC conversion within Komto forest priority area was presented in Fig. 5. The LULC conversion map showed that dense forest converted to agricultural land, grassland, open forest and settlement. Similarly, the open forest also converted into agricultural land, grassland, settlement and dense forest.

Socio economic characteristics households

During household questionnaire survey, a total of 118 were interviewed, out of which 95 (80.5%) males and 23 (19.5%) were females. Concerning the demographic data, the majority of the sample households were 36–46 age groups in the study area which constitutes 37% while

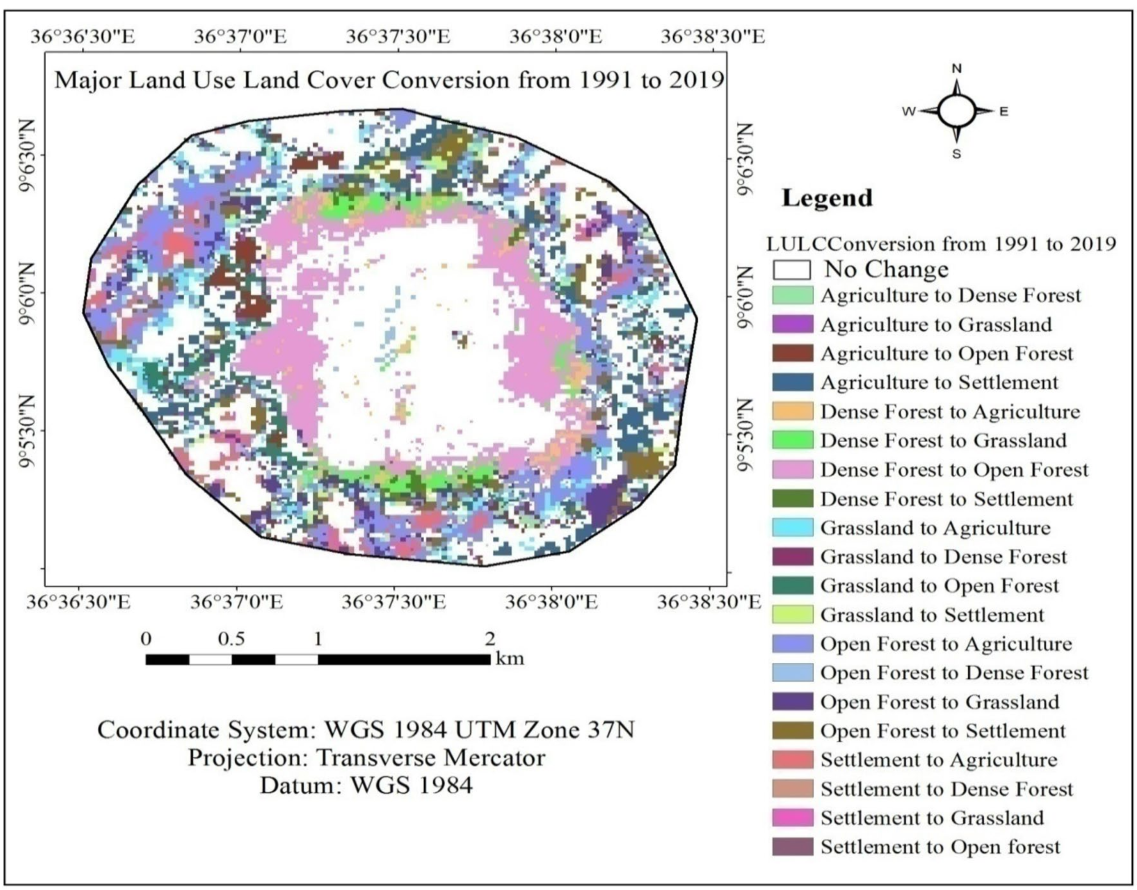

Fig. 5 Major LULC conversion from 1991 to 2019

Table 9 Age distribution of household heads

Age	Frequency	Percent (%)
25–35	14	11
36–46	45	37
47–57	43	35
58–67	19	15
> 68	3	2
Total	118	100.0

25–35, 47–57 and > 68 of the respondents were 11%, 35%, 15% and 2%, respectively (Table 9).

Similar to other parts of the country, agriculture is the main economic activities that directly affecting forest resources. As indicated in Fig. 6, the majority (78%) of income source for households was farming, while 20.3% depend on selling of wood and charcoal and the remaining 1.7% depending on selling of cash crops. The collection of fuel wood, construction materials, and other forest products for subsistence contributes for forest loss (Nerfa et al. 2020). The dependence of small holder farmers on forest products accelerates the rate of forest loss.

Majority of the community (96%) used forest products for house construction (Fig. 7). The remaining 4% of the local community use glass and concrete for construction purpose. Loss in the amount of forest because of timber exploitation is a long term issue for both the government and the local community which requires policy intervention. This implies the majority of the local community use timber for construction material which accelerates deforestation.

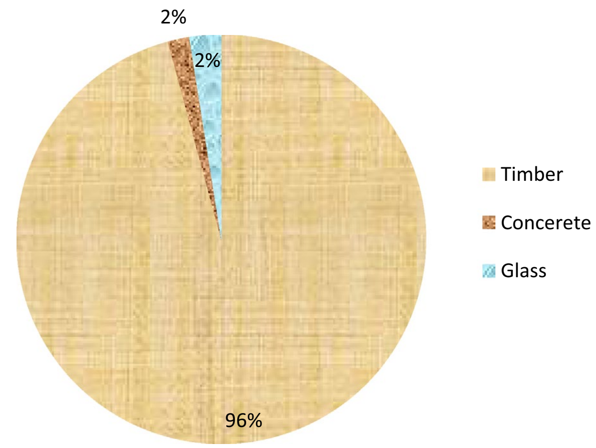

Fig. 7 Source of construction materials

The increased demand for forest resources, in the form of fire wood and charcoal within and outside of the study area has been the causes of forest degradation for Komto protected forest priority area. Demand of forest resources for construction, energy, grazing, and household furniture contributes for the declining of forest coverage. Therefore, combinations of driving forces contributed for

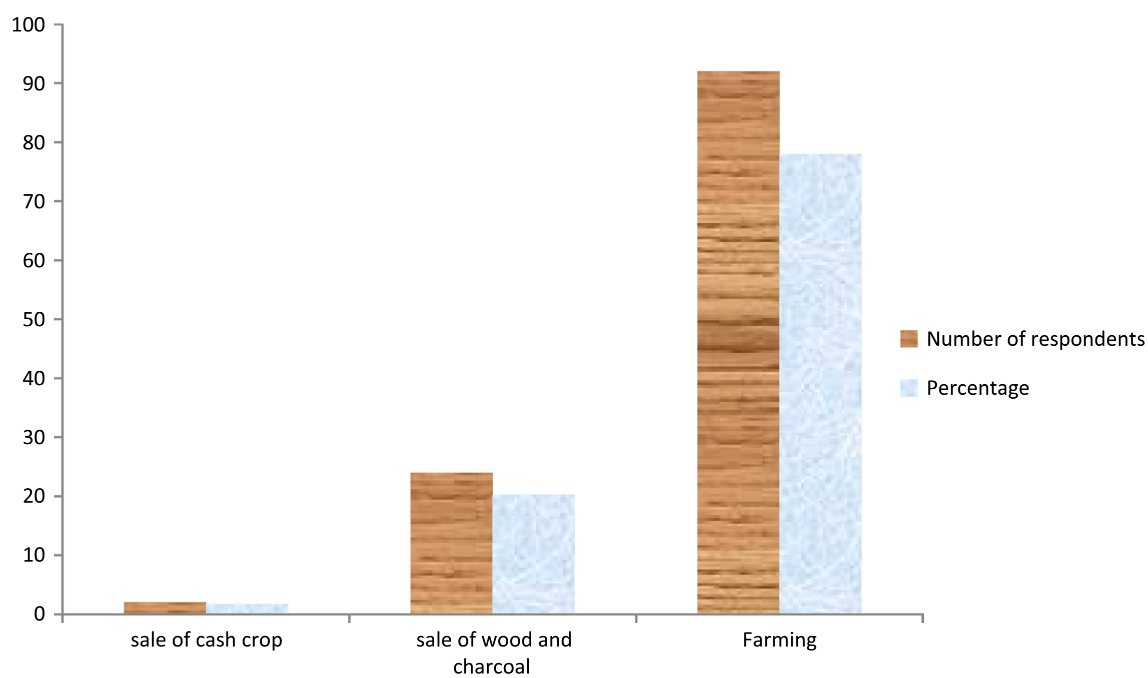

Fig. 6 Households major source of income

Table 10 Major cause of deforestation

Major cause of deforestation	Total	Percent
Cultivated land expansion	60	50.8
Cutting trees for fire wood	35	29.7
For charcoal production	18	15.3
Grazing lands	5	4.2
Total	118	100.0

the observed LULCC in Komto forest priority area. The main drivers of forest depletion as reveled by Muhati et al. (2018) were timber extraction, cutting trees for construction, illegal charcoal production and firewood collection. The rapid population growth in the study area and its surrounding has accelerated the declining land coverage of Komto forest priority area.

The survey results revealed that agricultural land expansion (50.8%) in the periphery of the forest is the most contributing factors for forest loss which were followed by fire wood collection (29.7%) and charcoal production (15.3%). Grazing lands contributes for about 4.2% of deforestation (Table 10).

Conclusions

In the present study, geospatial techniques has been used in analyzing spatio-temporal forest cover change at Komto forest priority area using three sets of landsat image. The results of this study revealed that significant amounts of forest cover area occurred over the past 28 years. In 1991, dense forest covers 32.73%, which was declined to 26.16% in 2002 and declined to 20.5% in 2019. Open forest also shows a remarkable decreasing trend, i.e., 18.19% in 1991 and 16.14% by the year 2019. In contrast, agricultural land use rapidly increased in area coverage from 24.78% in 1991 to 29.21% and 33.50% in the year 2002 and 2019, respectively. Our results revealed that agriculture expansion, timber, charcoal and fuel wood production is the main driving forces for Komto forest cover change. Information about changing patterns of forest coverage and its key drivers is a critical tool for forest conservation strategic planning. The results of this study give a good explanation for addressing the drivers dense and open forest loss in the study area as well as other regions in developing countries. Finally, the study recommends policy intervention to protect Komto forest priority area from loss and degradation.

Abbreviations

ERDAS: Earth Resource Data Analysis System; FAO: Food and Agriculture Organization of the United Nations; FGD: Focus Group Discussion; FPA: forest priority area; GIS: Geographic Information System; KII: key informant interview; LULC: land use land cover; LULCC: land use land cover change; MSS: multi spectral scanner; OLI/TIRS: operational land imager/thermal infrared sensor; RS: remote sensing; UN: United Nation; USAID: United States of America International Development; USGS: United State Geological Survey.

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Authors' contributions

MDN has conceived of the study, participated in data acquisition, data analysis and interpretation. DTM has participated in research design, supervision of data collection, entry and analysis and manuscript editorial works and DOG made participated in research design, manuscript draft writing and revision. All authors agreed to publish on Journal of Environmental Systems Research. All authors read and approved the final manuscript.

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Availability of the data and materials

The data is included in the manuscript.

Ethics approval and consent to participate

Not applicable since this research did not involved human subject.

Consent for publication

We have agreed to submit for Environmental Systems Research and approved the manuscript for submission.

Competing interests

The authors declare that they have no competing interests.

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References

Abebe MS, Derebew KT, Gemeda DO (2019) Exploiting temporal-spatial patterns of informal settlements using GIS and remote sensing technique: a case study of Jimma City, Southwestern Ethiopia. Environ Syst Res. https://doi.org/10.1186/s40068-019-0133-5

Armenteras D, Murcia U, Gonzalez TM, Baron OJ, Arias JE (2019) Scenarios of land use and land cover change for NW Amazonia: impact of forest intactness. Glob Ecol Conserv 17:e00567

Belay T, Mengistu DA (2019) Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. RSASE 15:100249

Churches SE, Wampler PJ, Sun W, Smith AJ (2014) Evaluation of forest cover estimates for Haiti using supervised classification of landsat data. Int J Appl Earth Obs 30:203–216

Costa MA, Botta A, Cardille JA (2003) Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia. J Hydrol 283:206–217

d'Annunzioin R, Sandker M, Finegold Y, Min Z (2015) Projecting global forest area towards 2030. Forest Ecol Manage 352(7):124–133

Dalmiya CP, Santhi N, Sathyabama B (2019) A novel feature descriptions for automatic change detection in remote sensing images. Egypt J Remote Sens Space Sci 22(2):183–192

Daye DD, Healey JR (2015) Impacts of land use change on sacred forests at the landscape scale. Glob Ecol Conserv 3:349–358

Declee B, Mayaux PH, Hansen M, Amani PL, Sannier C, Mertens B, Hausler T, Siwe RN, Poilive H, Gond V, Rahm M, Haarpaintner J, Lubamba JPK (2014) Evolution of forest cover at a national and regional scale and drivers of change. In: De Wasseige C, Flynn J, Louppe D, Hoil F, Mayaux PH (eds) Forest of Congo Basin-State of the forest 2013. Weyrich, Belgium, pp 21–46

Degife AW, Zabel F, Mauser W (2018) Assessing land use and land cover changes and agricultural farmland expansions in Gambella Region, Ethiopia, using Landsat 5 and Sentinel2a multispectral data. Helyiyon 4:e00919. https://doi.org/10.1016/j.heliyon.2018

Deng X, Li Z, Huang J, Shi Q, Li Y (2013) A revisit to the impacts of land use changes on the human wellbeing via altering the ecosystem provisioning services. Adv Meteorol. https://doi.org/10.1155/2013/907367

Denscombe M (2007) The good research guide for small-scale social research projects, 3rd edn. McGraw-Hill, New York

Dinkayehu Y (2006) The role of Oromia credit and saving share company micro finance program in improving the living standards of poor people: a case study in Guto Wayu District. A Thesis submitted to the School of Graduate Studies of Addis Ababa University. Addis Ababa, Ethiopia

Disperati L, Virdis SGP (2015) Assessment of land-use and land-cover changes from 1965 to 2014 in Tam Giang-Cau Hai Lagoon, central Vietnam. Appl Geogr 58:48–64

Erena MG, Yosef M, Bekele A (2011) Species richness, abundance and habitat preference of rodents in Komto protected forest, Western Ethiopia. J Agric Biol Sci 2(6):166–175

Feyissa G, Gebremariam E (2018) Mapping of landscape structure and forest cover change detection in the mountain chains around Addis Ababa: the case of Wechecha Mountain, Ethiopia. RSASE 11:254–264

Findell KL, Shevliakova E, Milly PCD, Stouffer RJ (2007) Modeled impacts of anthropogenic land cover change on climate. J Clim 20:3621–3634

Fokeng RM, Forje WG, Meli VM, Bodezemo BN (2019) Multi-temporal forest cover change detection in the Metchie-Ngoum Protection Forest Reserve. EJRS, West Region of Cameroon **(in press)**

Food and Agriculture Organization (2011) The state of the world's land and water resources for food and agriculture (SOLAW) Managing systems at risk. Food and Agriculture Organization of the United Nations, Rome and Earthscan, London

Furukawa T, Kayo C, Kadoya T, Kastner T, Hondo H, Matsuda H, Kaneko N (2015) Forest harvest index: accounting for global gross forest cover loss of wood production and an application of trade analysis. Glob Ecol Conserv 4:150–159

Garai D, Narayana AC (2018) Land use/land cover changes in the mining area of Godavari coal fields of southern India. EJRS 21:375–381

Geeraert L, Hulsmans E, Helsen K, Barecha G, Aerts R, Honnay O (2019) Rapid diversity and structure degradation over time through continued coffee cultivation in remnant Ethiopian Afromontane forests. Biol Conserv 236:8–16

Geng X, Wang X, Yan H, Zhang Q, Jin G (2015) Land use/land cover change induced impacts on water supply service in the upper reach of Heihe River Basin. Sustainability 7:366–383

Gibson L, Munch Z, Palmer A, Mantel S (2018) Future land cover change scenarios in South African grassland-implications of altered biophysical drivers on land management. Helyiyon 4:e00693

Guzha AC, Rufino MC, Okoth S, Jacobs S, Nobrega RLB (2018) Impacts of land use and land cover change on the surface runoff, discharge and low flows: evidence from East Africa. EJRH 15:49–67

Keenan RJ, Reams GA, Achard F, de Freitas JV, Grainger A, Lindquist E (2015) Dynamics of global forest area: results from the FAO Global Forest Resources Assessment 2015. Forest Ecol Manag 352:9–20

Kishtawal CM, Niyogi D, Tewari M, Pielke RA, Shepherd JM (2010) Urbanization signature in the observed heavy rainfall climatology over India. Int J Climatol 30:1908–1916

Kiswanto TS, Mardiany Sumaryono (2018) Completing yearly land cover maps for accurately describing annual changes of tropical landscapes. Glob Ecol Conserv 13:e00384

Kothari CR (2004) Research methodology methods & techniques, 2nd edn. New Age International (P) Limited, New Delhi

Landis JR, Koch GG (1977) The measurement of observer agreement for categorical data. Biometrics 33:159–174

Lark TJ, Mueller RM, Johnson DM, Gibbs HK (2017) Measuring land-use and land-cover change using the U.S. department of agriculture's cropland data layer: cautions and recommendations. Int J Appl Earth Obs Geoinf 62:224–235

Lei C, Zhu L (2018) Spatio-temporal variability of land use/land cover change (LULCC) within the Huron River: effects on stream flows. CRM 19:35–47

Lillesand T, Ralph M, Kiefer W (2004) Remote sensing and image interpretation, 4th edn. Wiley, New York

Lin CH, Lin BY, Lee KY, Chen YC (2015) Radiometric normalization and cloud detection of optical satellite images using invariant pixels. ISPRS J Photogramm 106:107–117

Lu D, Weng Q (2005) Urban classification using full spectral information of Landsat ETM+ imagery in Marion Country, Indiana. Photogramm Eng 71:1275–1284

Mensah AA, Sarfo DA, Partey ST (2019) Assessment of vegetation dynamics using remote sensing and GIS: a case of Bosomtwe Range Forest Reserve, Ghana. Egypt J Remote Sens Space Sci (TSI) 22(2):145–154

Minta M, Kibret K, Thorne P, Nigussie T, Nigatu L (2018) Land use and land cover dynamics in Dendi-Jeldu hilly-mountainous areas in the central Ethiopian highlands. Geoderma 314:27–36

Mishra PK, Rai A, Rai SC (2019) Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. EJRS. https://doi.org/10.1016/j.ejrs.2019.02.001

Muhati GL, Olago D, Olaka L (2018) Land use and land cover changes in a sub-humid Montane forest in an arid setting: a case study of the Marsabit forest reserve in northern Kenya. Glob Ecol Conserv 16:e00512

Nerfa L, Rhemtulla JM, Zerriffi H (2020) Forest dependence is more than forest income: development of a new index of forest product collection and livelihood resources. World Dev 125:104689

Olson JM, Alagarswamy G, Andresen JA, Campbell DJ, Davis AY, Ge J, Huebner M, Lofgren BM, Lusch DP, Moore NJ, Pijanowski BC, Qi J, Thornton PK, Torbick NM, Wang J (2008) Integrating diverse methods to understand climate and interactions in East Africa. Geoforum 39:898–911

Othow OO, Gebre SL, Gemeda DO (2017) Analyzing the rate of land use land cover change and determining the causes of forest cover change in Gog District, Gambella Regional State, Ethiopia. J Remote Sens GIS. https://doi.org/10.4172/2469-4134.1000219

Pellikkaa PKE, Heikineimo V, Hieanen J, Schafer E, Siljander M, Heiskanern J (2018) Impact of land cover change on aboveground carbon stocks in Afromontane landscape in Kenya. Appl Geogr 94:178–189

Pouliot D, Latifovic R, Zabcic N, Guindon L, Olthof I (2014) Development and assessment of a 250 m spatial resolution MODIS annual land cover time series (2000–2011) for the forest region of Canada derived from change-based updating. Remote Sens Environ 140:731–743

Rimal B, Sharma R, Kunwar R, Keshtkar H, Stork NE, Rijal S, Rahman SA, Baral H (2019) Effects of land use and land cover change on ecosystem services in the Koshi River Basin, Eastern Nepal. Ecosyst Serv 38:100963

Ru-Mucova SA, Filho WL, Azeiteiro UM, Pereira MJ (2018) Assessment of land use and land cover changes from 1979 to 2017 and biodiversity and land management approach in Quirimbas National Park, Northern Mozambique, Africa. Glob Ecol Conserv 16:e00447

Salghuna NN, Prasad PRC, Kumari JA (2018) Assessing the impact of land use and land cover changes on the remnant patches of Kondapalli reserve forest of the Eastern Ghats, Andhra Pradesh, India. EJRS. https://doi.org/10.1016/j.ejrs.2018.01.005

Stehman SV, Foody GM (2019) Key issues in rigorous accuracy assessment of land cover products. Remote Sens Environ 231:111199

Tolera M, Asfaw Z, Lemenih M, Karltun E (2008) Wood species diversity in a changing landscape in the south-central highlands of Ethiopia. Agric Ecosyst Environ 128(1–2):52–58

Tolessa T, Senbeta F, Kidane M (2017) The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. Ecosyst Serv 23(C):47–54

Tsutsumida N, Comber AJ (2015) Measures of spatio-temporal accuracy for time series land cover data. Int J Appl Earth Obs 41:46–55

United Nations Department of Economic and Social Affairs. 2015. The World Population Prospects: 2015 Revision. https://www.un.org/en/development/desa/publications/world-population-prospects-2015-revision.html. Accessed 7 Aug 2019

USAID (1996) Conducting key informant interviews. Center for development information and evaluation. USAID, Washington, DC, pp 1–4

Wang SP (2016) Stripe noise removal for infrared image by minimizing difference between columns. Infrared Phys Technol 77:58–64
Wang SQ, Zheng XQ, Zang XB (2012) Accuracy assessments of land use change simulation based on Markov-cellular automata model. The 18th biennial conference of international society for ecological modeling. Procedia Environ Sci 13:1238–1245
Wongpakaran N, Wongpakaran T, Wedding D, Gwet KL (2013) A comparison of Cohen's Kappa and Gwet's AC1when calculating inter-rater reliability coefficients: a study conducted with personality disorder samples. BMC Med Res Methodol 13:61
Wu C, Du B, Cui X, Zhang L (2017) A post—classification change detection method based on iterative slow feature analysis and Bayesian soft fusion. Remote Sens Environ 1999:241–255
Yan F, Zhang S, Kuang W, Du G, Chen J, Liu X, Yu L, Yang C (2018) Comparison of cultivated landscape changes under different management modes: a case study in Sanjiang plain. Sustainability 8:1071. https://doi.org/10.3390/su8101071
Zhu Z, Curtis C, Woodcock E (2014) Continuous change detection and classification of land cover using all available landsat data. Remote Sens Environ 144:152–171

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