Vol. 15(3), pp. 38-50, July-September 2023
DOI: 10.5897/JHF2019.0578
Article Number: E7CD2FE70951
ISSN: 2006-9782

http://www.academicjournals.org/JHF

Journal of Horticulture and Forestry

Review

Assessment of forest cover changes in and around Jorgo Wato Forest, West Wollega, Oromia, Western Ethiopia

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Received 18 February 2019; Accepted 21 November 2019

Detecting and identifying the changes in land cover provides the updated information about forest cover changes. Identifying forest cover change is also necessary information for planning and management of sustainable use of natural resources. This study was conducted to detect the dynamics of forest cover change in and around Jorgo Wato forest, West Wollega zone of Oromia National Regional State. In order to assess forest cover changes, the whole study period was categorized into three periods; 1986-1995, 1995-2006 and 2006-2016.Satellite images of Landsat TM, ETM+and OLI/TIRS were used in this study. Support Vector Machine of supervised classification and post classification was used for image classification, and results the overall accuracy of up to 99.65%, and both Maximum Producer's and User's accuracies were 100% while Kappa statistic ranged between 98.59 and 99.18%. The result of change analysis revealed that, dense forests class experienced positive change from 20.3% in 1986 to 44.33% in 2016 whereas sparse forests and shrubs declined from 37.02% in 1986 to 24.27% in 2016, and farmlands and others from 42.59% in 1986 to 31.26% in 2016 variation through 30 years. An important implication of the observed changes is due to expansion of coffee plantations and plantations of different tree species by the community during Dergue regime (1974-1991) and by Oromia Forest and Wildlife Enterprise till now. Not only focusing on plantation forests rather focusing on more diverse species is better than focusing too few/single species is the main motivation for protection and sustainable forest management.

Key words: Accuracy, assessment, change detection, satellite image.

INTRODUCTION

Forest is a land spanning more than 0.5 ha with trees higher than 5 m and a canopy. Cover of more than 10%, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or

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urban land use (FRA, 2015). Forests are valuable resources and dominated by various tree species. They have enormous ecological and economic significance in terms of safeguarding the fragile ecosystem, contributing to the national economy and are of great importance to rural and urban people as a source of fuel wood and charcoal (Teketay, 2001). It also provides ecological, economic, social, and aesthetic services to natural systems and humankind, influence climate through exchanges of energy, water and carbon dioxide in the atmosphere (Bonan, 2008). In 2015, forest covers 3999Mha globally. This is equivalent to 31% of global land area or 0.6ha for every person on the planet (FAO, 2015). A further 1204 Mha are covered by other wooded land.

Conversion of forest cover in general has severe long term environmental and socioeconomic consequences globally as well as locally, such as global climate change, habitat fragmentation and degradation, species extinction etc. As population expands, demands for resources such as food, water, timber, fuel etc. increases posing high pressure on the landscape (Phong, 2004). The application of Remote Sensing is a potent technique for surveying, mapping and monitoring earth resources. This technology combined with GIS which outperform in storage, handling and analysis of geographic data and socioeconomic data to provide a broader application.

In Ethiopia, there are about 80 National Priority Forest Areas (Young, 2012). Among these, Jorgo Wato forest is one which is located in Oromia Regional National State, West Wollega zone, Nole Kaba district and covers an area of about 8503.78 ha (OFWE, 2017). However, protection of these areas from deforestation has not been effective due to encroachment to search for new land especially for agriculture, coffee plantation mainly due to absence of good forest policy and lack of legal status of these priority areas.

Jorgo Wato forest, despite its economical, hydrological and biological importance both regionally and nationally, the area is under serious threat due to unsustainable use of the natural resources (Tadesse et al., 2011; ZARD, 2013). The forest cover of the study area has been deteriorating and endemic tree species are under threats. This position puts a great challenge on the existence of an ecosystem functioning and made the forested areas to be changed to other land use purposes like agricultural land especially coffee plantations etc. specifically around Jorgo Wato forest (Tadesse et al., 2011). Therefore, the objective of the study was to assess the dynamics of forest cover change in and around Jorgo Wato forest over the last three decades (1986 to 2016).

LITERATURE REVIEW

Application of remote sensing and GIS to monitor forest cover change

Remote sensing is an attractive source of thematic maps such as those depicting land cover as it provides a map like representation of the Earth‟s surface that is spatially continuous and highly consistent, as well as available at a range of spatial and temporal scales. Thematic mapping from remotely sensed data is typically based on an image classification (Foody, 2002). Remote sensing has a wide range of applications in the fields of agriculture, forestry, and land cover land use. Remote Sensing and GIS technologies are really useful and important for monitoring forest cover changes. The application of Remote Sensing is a potent technique for surveying, mapping and monitoring earth resources.

The potential of remote sensing and GIS in the field of forestry becomes established over many years through the use of aerial photos and satellite imagery interpretations in forest cover change detection analysis, for the production of cover map and inventory analysis (Lillesand et al., 2008). Multi temporal data gives for change detection analysis. The icons of earlier years can compared with the recent scenes, to physically measure of the differences in the sizes and extents of forest cover changes. Satellite data have become a major application in forest cover change detection because of the repetitive coverage of the satellites at short intervals (Whittle et al., 2012). Change detection as defined by Vreugdenhil et al. (2012) is a process of identifying changes in the state of an object or phenomenon by observing images at different times.

Global forest cover

About 44% of global forest area is found in countries classified as tropical and another 8% is in sub-tropical countries, 26% in temperate and 22% in boreal countries (FAO, 2015). Over the past 25 years the rate of net global deforestation has slowed by more than 50% (FAO, 2015) (Table 1).

Forest cover of Ethiopia

The estimated forest cover of Ethiopia is 12,499 ha in 2015 (FRA, 2015). Forest area and annual change rate of Ethiopian forest coverage beginning from 1990 to 2010 was summarized (Table 2).

Global and Ethiopian planted forest area

Global planted forest area increased from 167.5 Mha in 1990 to 277.9 Mha in 2015 with the increase varying by region and climate domain. From the 277.9 Mha of planted forests in 2015, 56% are in the temperate zone, 15% boreal, 20% tropical and 9% subtropical (Payn et al., 2015). The reasons for contributing net increases in forest area includes reduced pressure on forests as a result of economic growth, declining rural populations or

Table 1. Global forest area change

Year	Forest (000ha)	Annual change (000ha)	Annualized change
1990	4 128 269		
2000	4 055 602	-7267	-0.18
2005	4 032 743	-4572	-0.11
2010	4 015 673	3414	-0.08
2015	3 999 134	-3308	-0.08

Source: (FAO 2015).

Table 2. Planted forest area of Ethiopia in between 1990-2015

Planted forest (1000 ha)					Annual change rate							
					1990-2000		2000-2010		2010-2015		1990-2015	
1990	2000	2005	2010	2015	1000 ha/yr.	%	1000 ha/yr.	%	1000 ha/yr.	%	1000 ha/yr.	%
491	491	491	511	972	0.0	0.0	2	0.4	92.2	13.7	19.2	2.8

Source: (FAO 2015).

Table 3. Trends in extent of forests from 1990–2010

Forest Area (1000 ha)				Annual change rate					
				1990-2000		2000-2005		2005-2010	
1990	2000	2005	2010	1000 ha/yr.	%	1000 ha/yr.	%	1000 ha/yr.	%
15,114	13,705	13,000	12,296	-141	-0.97	-141	-1.05	-141	-1.11

Source: (FRA 2015).

improved agricultural productivity and effective policies aimed at expanding forest area (FAO, 2016a).

A total of other naturally regenerated forest for 2015 in Ethiopia is 11,527,000 ha and planted forest area of 972,000 ha (FAO, 2015). The planted forest and annual change rate of planted forest coverage of Ethiopia from 1990 to 2015 (Table 3) (FAO, 2015). Forest gains occur through natural expansion or planting or deliberate seeding on non-forested land that is, afforestation, reforestation or agricultural land abandoned or forest policies might be put in place to encourage tree planting with the aim of meeting anticipated future needs for forest goods and environmental (FAO, 2016a).

MATERIALS AND METHODS

Description of the study sites

The study was conducted in/around Jorgo Wato Forest of Nole Kaba District, West Wollega, Oromia National Regional State. Three kebeles surrounding the forests (Harbu Abbaa Gadaa, Siba Sillase and Siba Dalo) were selected based on their forest coverage and community interaction towards forest and forest to community. Nole Kaba is one of the 21 administrative districts of West Wollega Zone and the district has 27 Kebeles, of which 25 Kebeles are rural Kebeles and 2 Kebeles are urban/town administrations. Nole Kaba (Bube town is the capital town of the district), which is situated at a distance of 491 km from Finfinnee and 50 km from the zone capital city Gimbi (441 km from Finfinnee called regional capital city) (NKDAO, 2017). Jorgo Wato forest is situated at a distance of about 10 km from Bube town to the direction of southeast along gravel road. Jorgo Wato forest is absolutely located between 08° 43′ 00″N to 08° 50′ 00″N and 35° 47′ 30″E to 35° 55′00″E (Figure 1). The district have three climatic conditions of high altitude (21%), mid altitude (65%) and low altitude (14%) and ranges from 1525 m.a.s.l to the maximum 2576 at peak of mountain Jorgo Wato. The mean annual temperature varies from 13.5-27.5°C and annual rainfall pattern ranges between 1600-2000 mm (NKDAO, 2017; OFWE, 2017).

According to the data obtained in March, 2017 from Nole Kaba District Administration office, the populations of the district are 85,706 (41,485 males and 44,221 females). Out of this, 77,262 (37,142 males and 40,120 females) are lives in rural administrative kebeles, while 8,444 (4,343 and 4,101 females) are lives in the urban administrative kebeles. The total area coverage of the district is about 65,557 ha of land. Among this coverage, agricultural land, coffee plantation, forest area, grazing land and lands used for the community services occupy area coverage of 11,834, 16,476, 19,476, 3,837 and 13,091 ha, respectively. This indicates that, more than half which means 54.8% of the area is covered by coffee plantation and forest area.

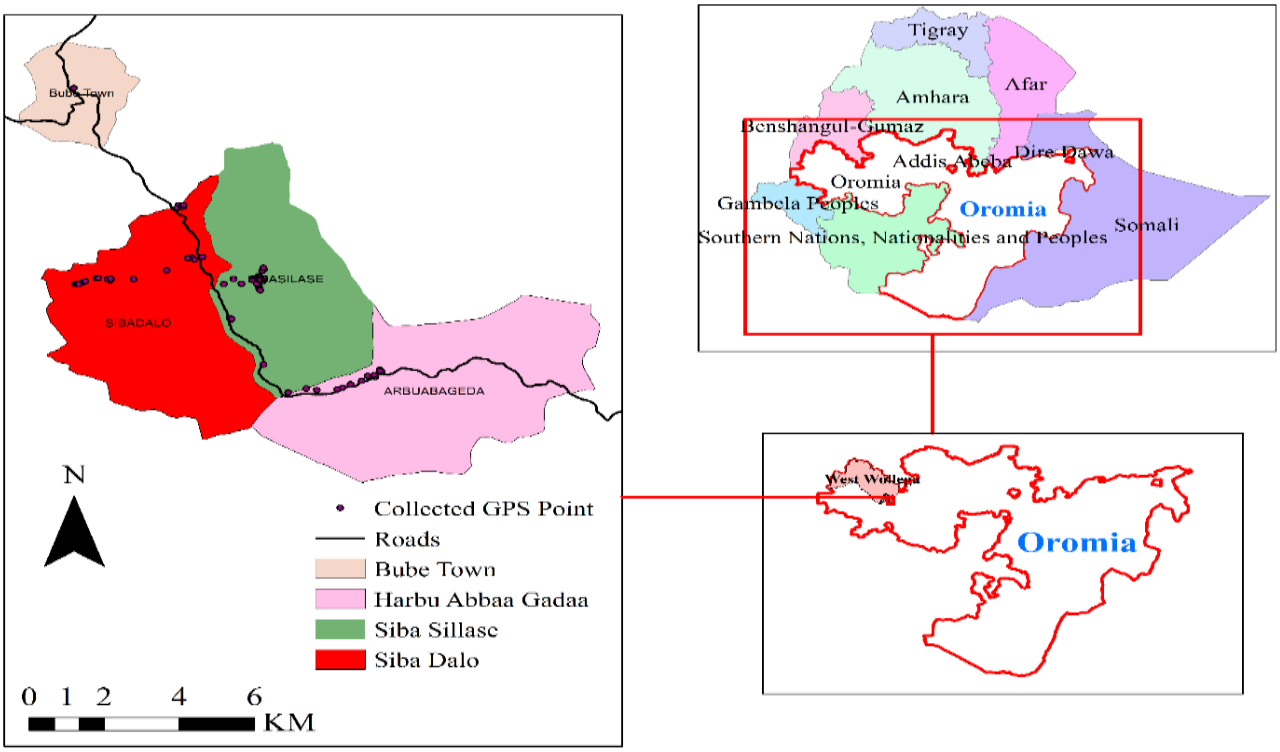

Figure 1. Location of Study Area Map.
Source: Author.

Remote sensing data sources, data collection and pre-processing methods

Imagery acquired by sensors of Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) satellites between path 170 and row 54 were used. The imageries were downloaded freely from USGS (United States Geological Survey) data portal (https://earthexplorer.usgs.gov/and https://landsatlook.usgs.gov/viewer.html/assessed from 15-22 May, 2017). All the imagery used was of low or no cloud cover and acquired during dry seasons of the years between 1986 and 2016 at approximately 10 years intervals. The selected months of the year were suitable for obtaining cloud free images and minimizing confusion in spectral signatures of forest and non-forest green vegetation such as agricultural crops and grasslands and maximizing the contrast between forest and non-forest land uses during dry seasons. The area is dominated by rain fed agriculture, spectral contrast between forest and agricultural land is expected to be higher during dry seasons. The path 170 and row 54 covers the total forest area of Jorgo Wato. The major characteristics of Landsat images used in this study were summarized (Table 4).

Before using the available satellite images obtained freely from USGS portal, image pre-processing like registration/geometric correction, atmospheric correction and layer stacking were applied to all images using ENVI version 5.1 software (ENVI Manual, 2012). The aim of preprocessing techniques is to improve the image data to suppress the unwanted distortions and to enhance some features of the input image. When processing high resolution images, the image size is needed to be reduced because of the reason that processing on high resolution images takes a longer time.

Registration/Geometric correction: is registration to reference images to geographic coordinates and/or correct them to match base image geometry. Ground control points (GCPs) can be selected interactively from display windows and/or vector windows. Warping is performed using polynomial functions, Delaunay triangulation, or rotation, scaling, and translation (RST). Resampling methods include nearest neighbor, bilinear, and cubic convolution. Comparison of base and warped images using ENVI"s multiple Dynamic Overlay capabilities allows quick assessment of registration accuracy. All images were corrected to Universal Transverse Mercator (UTM) zone 37N, datum WGS-84 and co-registered with less than 0.5 pixel mean square error for all images.

Radiometric/Atmospheric correction: Atmospheric correction was applied to all images using Quick Atmospheric Correction (QUAC) module in ENVI version 5.1. QUAC is an atmospheric correction method for multispectral and hyper spectral imagery that works with the visible and near infrared through shortwave infrared (VNIR-SWIR) wavelength range. QUAC performs best when the imagery is uniformly illuminated, such as clear sky conditions or when airborne sensors fly under complete cloud cover. If the imagery contains clouds and cloud shadows, mask out of the clouds and shadows must be needed. QUAC works directly with the observed pixel spectra in a scene, without ancillary information. If a sensor does not have proper radiometric or wavelength calibration, or if the solar illumination intensity is unknown, QUAC can still retrieve reasonably accurate reflectance spectra as long as the scene is diverse and there are enough dark pixels to allow for a good estimation of the baseline spectrum.

Layer stacking: is a technique to build a new multiband file from georeferenced images of various pixel sizes, extents, and

Table 4. Characteristics of Landsat images used in the study

No	Sensor type	Acquisition date	Source	Cloud cover	Spatial resolution	Path	Row
1	Landsat TM	1986/02/20	USGS	0	30*30	170	054
2	Landsat TM	1995/03/17	USGS	6	30*30	170	054
3	Landsat ETM+	2006/01/18	USGS	0	30*30	170	054
4	OLI/TIRS	2016/02/23	USGS	0	30*30	170	054

*Landsat TM, Landsat 7 ETM+ and OLI/TIRS are Thematic Mapper, Enhanced Thematic Mapper Plus and Operational Land Imager and Thermal Infrared Sensor, respectively.
Source: Author.

projections. The input bands will be resampled and re-projected to a common user selected output projection and pixel size. The output file will have a geographic extent that either encompasses all of the input file extents or encompasses only the data extent where all of the files overlap.

Reference data were collected through ground truth based characterization of the existing land cover types in March, 2017 by using GPS Garmin 72H. Smaller areas were sampled as points by assuming a center of 30 m by 30 m square grid to match the pixel size of the Landsat reflective bands, while large homogenous areas were marked as polygons. Major land cover types of the areas were characterized through discussion with local people, experts, Kebele managers, community leaders and visual interpretations. Time difference between image acquisition and ground surveying was about one month and no major land cover change was assumed to have occurred within this time difference. No ground data or other sources of reference data were available for classification and accuracy assessment of historical images of 2006 and earlier. Therefore, reference data were obtained from true color composites of images of all the years. All satellite images were clipped (sub-set) via regions of interests for covering only the study area. In order to interpret and discriminate the surface features clearly, all satellite images were composed using Red, Green and Blue (RGB) color composition.

Classification, accuracy assessment and change analyses

The classification workflow uses either unsupervised or supervised or decision tree methods to categorize pixels in an image into many classes. Unsupervised classification without providing training data, or perform a supervised classification, where you provide training data and specify a classification method while decision tree classifier uses a series of binary decisions to place pixels into classes. In this study, supervised image classification methods were employed to categorize the images using ground truths (training areas) with the help of Google Earth. A total sample size of 655, 485, 576 and 753 pixels were collected for Landsat images of 1986, 1995, 2006 and 2016 through proportionate stratified random sampling. From the total collected sample size, 70% of the collected pixels were used for classification while 30% used for an accuracy assessment.

Support Vector Machine (SVM) is one of the tools among supervised classification and used to identify the class associated with each pixel. ENVI‟s SVM provides a hierarchical, reduced resolution classification process that improves performance without significantly degrading results. It is most effective when operating in areas that contain homogenous features. The SVM classifier trains and runs on the reduced resolution image and ROIs. Support Vector Machine often yields good classification results from complex and noisy data. It separates the classes with a decision surface that maximizes the margin between the classes. ENVI‟s implementation of SVM uses the pairwise classification strategy for multiclass classification.

Accuracy assessment: Post classification is used to classify rule images, to calculate class statistics and confusion matrices. Calculating confusion matrix shows the accuracy of a classification result by comparing a classification result with ground truth information. In this study, ENVI Classic can calculate a confusion matrix using ground truth ROIs. The final output of confusion matrix were reported in the form of an overall accuracy, kappa coefficient, producer‟s and user‟s accuracies for each of the classified images.

Change analysis: Change analysis was obtained by applying of Land Change Modeler (LCM) of the IDRISI Selva version 17 software. Analyzing the change at different times, helps in determining the level of the change. For this purpose, the whole time range has been grouped into four periods (1986-1995, 1995-2006, 2006-2016 and 1986-2016). Change analyses and change detection of each land cover classes were undertaken by using ENVI version 5.1 and IDRISI Selva version 17, respectively and encompasses a broad range of methods used to identify, describe, and quantify differences between images of the same scene at different times or under different conditions (ENVI Manual, 2012) (Table 4).

Description of the standards applied to classify land cover types were made by stakeholders, key informants, forestry experts and experts of natural resources (Table 5). Key informants and farmers focus groups discussions were also under taken to gather enough information about the study area regards to forest coverage. Jorgo Wato forest is one of the national forest priority areas surrounded by the community and selected for this study based on the interaction of the local community towards the forest, severity of forest decline, conversion of forest coverage to other land uses or other land uses to forests including plantation. FGDs interview with the concerned bodies (such as elders, kebele leaders, kebele managers, natural resource experts, forestry experts etc.). A total of 12 FGDs, 3 FGDs per each kebeles having a group member of 5 to 9 participants and 3 FGDs of experts having a group member of 4 to 6 were undertaken.

Land cover changes were analyzed by applying various change detection techniques (supervised classification, visual comparison of features and confusion matrix analysis) following recommendations by Lu et al. (2004). The authors suggest that good change detection research should provide information on: 1) area change and change rate 2) spatial distribution of changed types 3) change trajectories of land cover types and 4) accuracy assessment of change detection results as cited by Feyisa et al. (2016). Major contributors of changes especially emphasis to forest cover, were identified. Change analyses were undertaken in the ranges of 1986-1996, 1996-2006 and 2006-2016 years.

Regions of Interests area was identified and indicated (Figure 2) in order to undertaken image classification, confusion matrix and change detection of the classified land cover class categories of the study area.

Table 5. Descriptions of Land cover classes

No.	Land cover type	Description
1	Dense forests	Dense natural forests/dense trees of *Aningeria adolffii fredricci*, *Ficus sur, Syzegium guineense, Albizia species, Croton macrostachyus, Euclea schimperi*, *Spathoda species, Prunus africana, Maesa lanceoleta, Juniperus procera, Acacia abyssinica, Myrica salicifolia*/Reejjii, *Hagenia abyssinica, Milletia ferrugenia, Cordia africana, Dracaena steudner,* Coffee based forests, Plantation forests of *Cupressus lusitanica, Eucalyptus species, Pinus patula, Gravillea robusta.*
2	Sparse forests and shrubs	Sparse and short tree species and other green vegetation (both natural and plantation tree species) grow near and around homesteads, along the roads, along the streams, live fences, scattered trees on farmlands, scattered on grazing areas, scattered on farmland boundaries, patches of coffee and coffee shade trees.
3	Farmland and others	Lands for agricultural purposes for cultivation of maize, teff, sorghum, fallow lands for one or more years, built up, settlements, roads, grazing lands, bare lands.

Regions of Interests area was identified and indicated (Figure 2) in order to undertaken image classification, confusion matrix and change detection of the classified land cover class categories of the study area.
Source: Author.

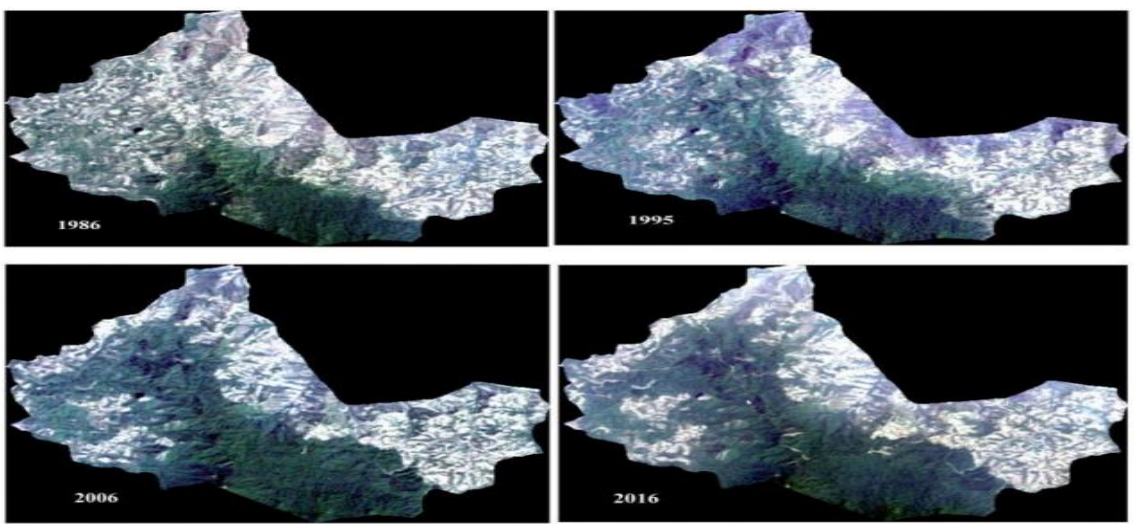

Figure 2. Identified Regions of Interests of 1986, 1995, 2006 and 2016 Satellite images.
Source: Author.

RESULTS AND DISCUSSION

Classification and accuracies

Produce‟s and user‟s accuracy as well as overall accuracy and Kappa coefficient for each land cover types category and each of the classified images were assessed (Table 7 and Figure 3). The overall classification accuracy for over the period of 1986, 1995, 2006 and 2016 was 99.22, 99.27, 99.65 and 99.32% with kappa coefficient of 98.59, 98.67, 99.18 and 98.61%, respectively (Table 6). This result is in agreement with Fitzgerald and Lees (1994) argued that, the values of kappa coefficient (K) ranges between 0 (no agreement) and 1 (complete agreement). These values are poor agreement when K < 0.4 (40%), good agreement when K values ranges between (0.4 or 40% ≤ K ≤ 0.75 or 75%) and excellent agreement when K > 0.75 (75%).

Land cover classes of 1986, 1995, 2006 and 2016

The Largest proportion of an area was covered by farmlands and others (42.63%) and sparse forests and shrubs (37.05%) while dense forests class categories accounts about 20.32% in 1986. In 1995, sparse forests

Table 6. Producer's and User's accuracies classification by year (in percent)

Land cover classes	1986		1995		2006		2016	
	Prod.	User's	Prod.	User's	Prod.	User's	Prod.	User's
Dense forests	99.57	99.48	99.88	99.70	99.93	99.83	99.79	99.77
Sparse forests and shrubs	93.22	94.50	91.58	95.85	90.38	95.92	94.41	93.43
Farmlands and others	99.70	99.59	99.60	99.21	99.81	99.52	99.17	99.43
Overall accuracy (%)	**99.22**		**99.27**		**99.65**		**99.32**	
Kappa coefficient (%)	**98.59**		**98.67**		**99.18**		**98.61**	

Land Cover Classes of 1986, 1995, 2006 and 2016
Source: Author.

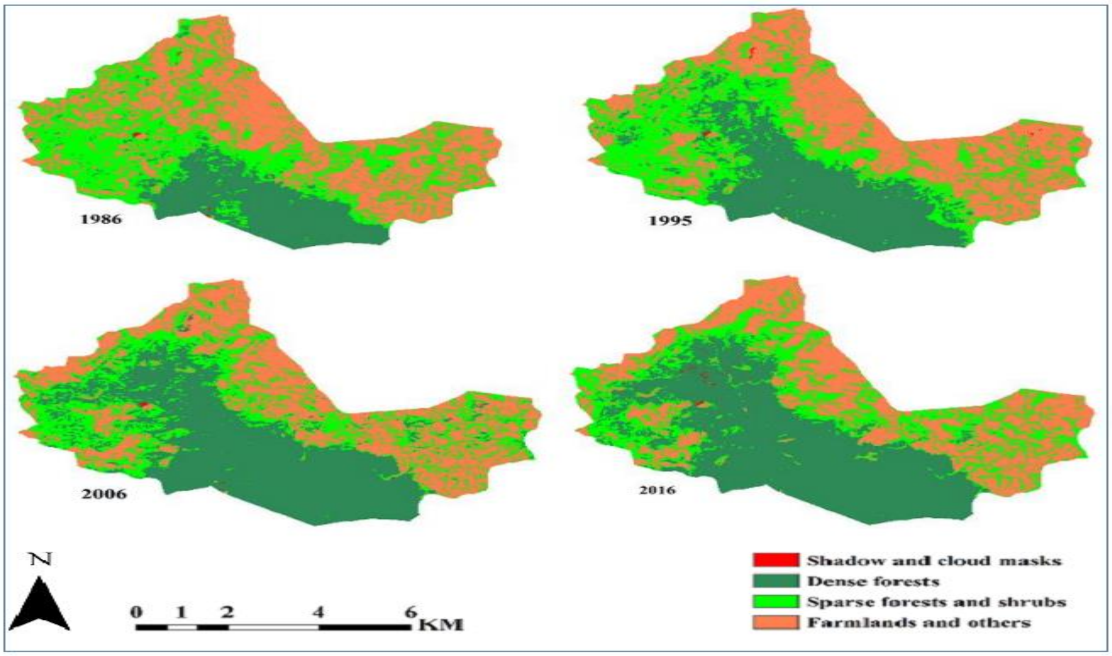

Figure 3. Classified satellite images of 1986, 1995, 2006 and 2016.
Source: Author.

Table 7. Area coverage and percentage statics of land cover class from 1986-2016

Land cover classes	**1986**		**1995**		**2006**		**2016**	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Dense forests	1732.05	20.32	2487.78	29.19	3472.02	40.72	3782.70	44.4
Sparse forests and shrubs	3158.64	37.05	2752.83	32.29	2234.16	26.20	2070.45	24.3
Farmlands and others	3633.75	42.63	3283.56	38.52	2820.87	33.08	2667.06	31.3
Total	**8524.44**	**100.00**	**8524.17**	**100.00**	**8527.05**	**100.00**	**8520.21**	**100.00**

Source: computed from the classified Landsat 1986, 1995, 2006 and 2016 images.
N.B: Percentage of area coverage = (Area of the year/total area)*100
Source: Author.

and shrubs, and farmlands and others showed a consistent decrease while dense forests class categories increased. Dense forests class category accounts 40.72% in 2006 and 44.4% in 2016 (Table 7).

Table 8. Extent of land cover classes change in 1986-1995, 1995-2006, 2006-2016 and 1986-2016 years

Land cover classes	1995		1986		Change (ha)	Average rate of change (ha)
	Area (ha)	%	Area (ha)	%		
Dense forests	2487.78	29.19	1732.05	20.32	755.73	83.97
Sparse forests and shrubs	2752.83	32.29	3158.64	37.05	-405.81	-45.09
Farmlands and others	3283.56	38.52	3633.75	42.63	-350.19	-38.91
Total	**8524.17**	**100.00**	**8524.44**	**100.00**		
Land cover classes	2006		1995		Change (ha)	Average rate of change (ha)
	Area (ha)	%	Area (ha)	%		
Dense forests	3472.02	40.72	2487.78	29.19	984.24	89.48
Sparse forests and shrubs	2234.16	26.20	2752.83	32.29	-518.67	-47.15
Farmlands and others	2820.87	33.08	3283.56	38.52	-462.69	-42.06
Total	**8527.05**	**100.00**	**8524.17**	**100.00**		
Land cover classes	2016		2006		Change (ha)	Average rate of change (ha)
	Area (ha)	%	Area (ha)	%		
Dense forests	3782.70	44.4	3472.02	40.72	310.68	31.07
Sparse forests and shrubs	2070.45	24.3	2234.16	26.20	-163.71	-16.37
Farmlands and others	2667.06	31.3	2820.87	33.08	-153.81	-15.38
Total	**8520.21**	**100.00**	**8527.05**	**100.00**		
Land cover classes	2016		1986		Change (ha)	Average rate of change (ha)
	Area (ha)	%	Area (ha)	%		
Dense forests	3782.70	44.4	1732.05	20.32	2050.65	68.36
Sparse forests and shrubs	2070.45	24.3	3158.64	37.05	-1088.19	-36.27
Farmlands and others	2667.06	31.3	3633.75	42.63	-966.69	-32.22
Total	**8520.21**	**100.00**	**8524.44**	**100.00**		

N.B: Change = (Area of the final year- Area of initial year), Average rate of change = change/number of year interval
Source: Author.

Forest cover change analysis

The land cover change of 1986-1995, 1995-2006, 2006-2016 and 1986-2016 was quantified by using differences from the earlier periods to later periods. The result of change analysis using LCM tools of two decades of land cover maps of the study area showed significant changes in all land cover class categories over the study periods. Empirical evidence from (Table 8) indicates that, sparse forests and shrubs, and farmlands and others class showed a declining net change through the study periods of 1986-1995. Whereas dense forests class showed an increasing net change during 1986-1995. This indicates that, high conversion of sparse forests and shrubs, and farmlands and others class to dense forests has been seen in the study area during the study period. Between the periods of 1986 and 1995 (Table 8), dense forests and, sparse forests and shrubs showed maximum changes. The former increased to 755.73 ha (mean rate of 83.97 ha/yr) while the later decreased with -405.81 ha (mean rate of -45.09 ha/yr). Farmlands and others have also reduced with -350.19 ha and the rate of reduction over the period has been estimated as -38.91 ha/yr.

An area previously covered by a given land cover type may not be completely covered with the same land cover class after a gap of years. Hence, some portion of the area will be covered by other types of land cover types. During 1995-2006 study periods, dense forests classes were increased by 984.24 ha (with average change rate of 89.48 ha/year) while sparse forests and shrubs and, farmlands and others were reduced to -518.67 ha (-47.15 ha/year) and -462.69 ha (-42.06 ha/year), respectively (Table 8).

During 2006-2016, dense forests were still expanding (increased by a change of 310.68 ha), sparse forests and shrubs, and farmlands and others were declined with a change of -163.71 ha and -153.81 ha, respectively (Table 8). Considering the overall study periods, a significant increase in the areal extent of dense forests has been observed; from 1732.05 ha (20.32%) in 1986 to 3782.70 ha (44.4%) in 2016 with 2050.65 ha (68.36 ha/year) variation across 30 years. Although sparse forests and shrubs, and farmlands and others reduced; sparse forests and shrubs from 3158.64 ha (37.05%) in 1986 to 2070.45 ha (24.3%) in 2016 with a variation of -1088.19 ha (-36.27 ha/year), farmlands and others from 3633.75 ha (42.63%) in 1986 to 2667.06 ha (31.3%) in 2016 with -966.69 ha (-32.22 ha/year) variation through 30 years (Table 8).

Sparse forests and shrubs, in addition to its conversion

Table 9. Detection change of 1986-1995, 1995-2006, 2006-2016 and 1986-2016 years

Land cover classes	Converted to	1986-1995		1995-2006		2006-2016		1986-2016	
		Areas in (ha)	Areas in %	Areas in (ha)	Areas in %	Areas in (ha)	Areas in %	Areas in (ha)	Areas in %
Dense forests	Sparse forests and shrubs	61.38	2.32	83.61	3.46	165.15	9.72	11.97	0.34
	Farmlands and others	9.54	0.36	7.2	0.3	23.85	1.40	10.44	0.3
Sparse forests and shrubs	Dense forests	652.95	24.69	967.59	40.07	480.15	28.27	1383.93	39.20
	Farmlands and others	780.21	29.5	442.44	18.32	425.97	25.1	575.28	16.3
Farmlands and others	Dense forests	171.63	6.49	105.66	4.38	26.73	1.57	684.9	19.4
	Sparse forests and shrubs	969.12	36.64	808.02	33.47	576.63	33.95	863.73	24.47
Total		**2644.83**	**100.00**	**2414.52**	**100.00**	**1698.48**	**100.01**	**3530.25**	**100.01**

Source: Author.

to dense forests, have been changed into farmlands and others. About 29.5 and 24.69% of sparse forests and shrubs were converted to farmlands and others, and dense forests class category, respectively. Although, 36.64 and 6.49% of farmlands and others category over the period were transformed to sparse forests and shrubs, and to dense forests, respectively (Table 9; Figure 4A). Forest cover change detection from 1995- 2006 indicates that, 967.59 ha (40.07%) and 442.44 ha (18.32%) of sparse forests and shrubs were converted to dense forests and, farmlands and others, respectively (Table 9; Figure 4B).

Large amount of land cover conversions from farmlands and others to sparse forests and shrubs, and sparse forests and shrubs to dense forests were recorded between the periods of 2006-2016. About 33.95% of farmlands and others were converted to sparse forests and shrubs class while 28.27% of sparse forests and shrubs were converted to dense forests (Table 9; Figure 4C). Large amount of sparse forests and shrubs were converted to dense forests class accounts 1383.93 ha (39.20%) while 863.73 ha (24.47%) of farmlands and others were converted to sparse forests and shrubs during 1986-2016 periods (Table 9; Figure 4D).

The maximum gains were recorded by dense forests class, whereas maximum losses were registered by sparse forests and shrubs during the periods of 1986 to 2016 intervals (Table 10; Figure 5C). The largest contributors for dense forest increment were derived from sparse forests and shrubs (1372 ha) followed by farmlands and others (674 ha) during the assessment periods of 1986-2016 (Figure 4D). This indicates that, dense forests class has been dramatically increased; whereas sparse forests and shrubs, and farmlands and others were declined over the study durations.

Different authors put the reasons of forest cover increment from time to time in different parts of the world in general and Ethiopia in specific. Forest gains occur through natural expansion or through planting or deliberate seeding of non-forested land that is, afforestation, reforestation (FAO, 2016a), vegetation rehabilitation mechanisms of an area enclosure (Kiros, 2014), conversion of agricultural land to forest may be the result of natural forest expansion or tree planting, forest policies (FAO, 2016a). In the study area this is true, every person must have the right to participated in plantation activities in a cluster of young group, women‟s group and elder group since its demarcation (Key informants). Land cover class patterns showed an expansion of dense forests class and shrinkage of sparse forests and shrubs, and farmlands and others. This is caused due to expansions of coffee plantations, protection of the existed indigenous tree species and plantations of other exotic tree species expansions (Tables 8 and 9; Figure 5A).The study area forest is currently managed by Oromia Forest and Wildlife Enterprise, annually about 100,000 numbers of seedlings/yr has been planted (OFWE, 2017) and an individual person must have done plantation on 2% of their own individual lands (responses from FGDs).

The majority of planted tree species served the community as coffee shades (responses from elders/key informants and FGDs). As a visual

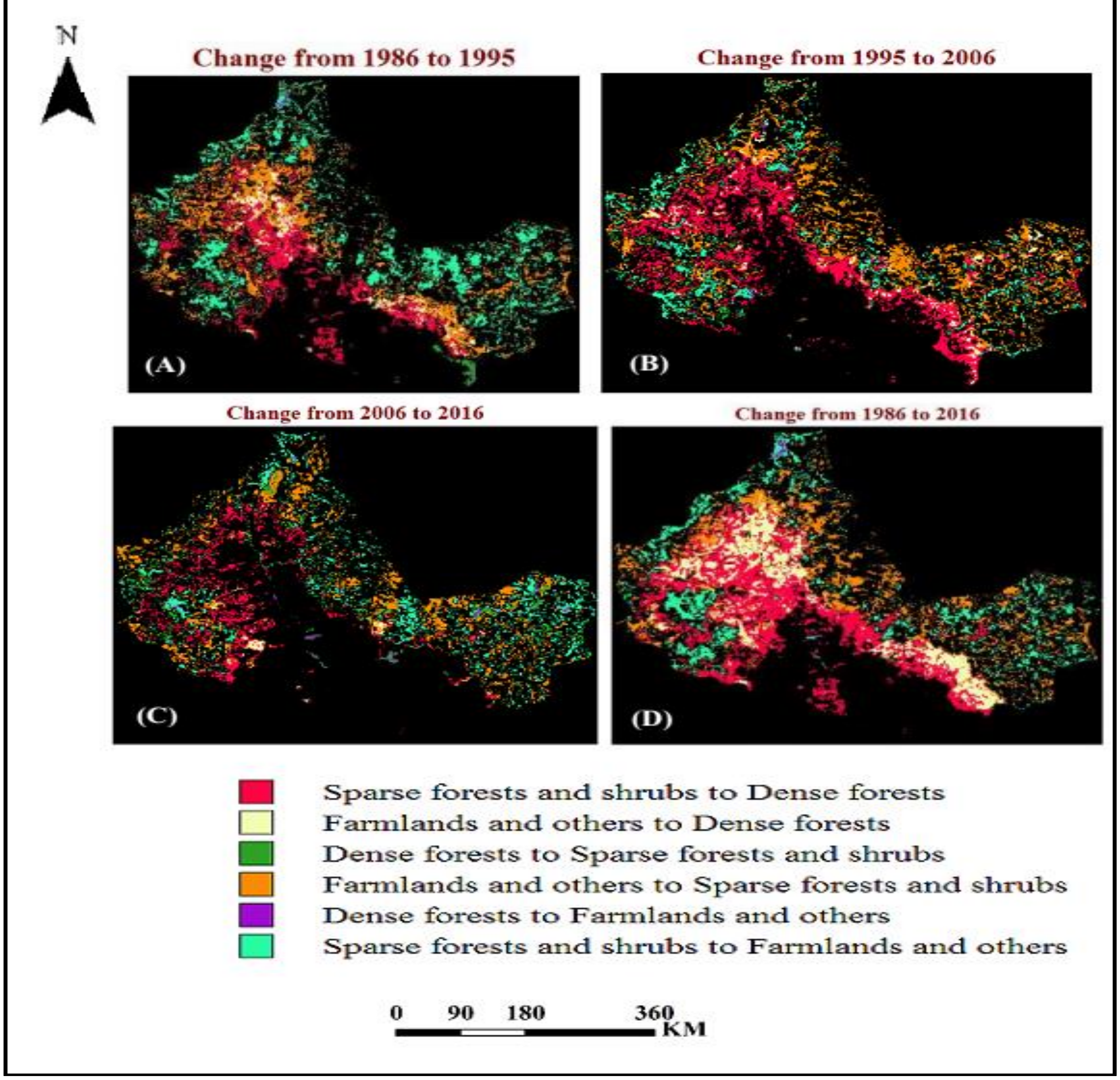

Figure 4. Map showing land cover class change detection from A) 1986-1995, B) 1995-2006 C) 2006-2016 and D) 1986-2016.
Source: Author.

observation during the study periods, most lands of the area were covered by coffee plantations under the upper layer of tree coverage. This results in areal increment of forest coverage of the area due to the importance of trees for coffee shades. Some of the last remaining forest fragments in Ethiopia have experienced rapid recent conversion to coffee farms, plantations and agricultural fields (Tadesse et al., 2014).

Forest cover increments of the study area were observed after campaign plantation activities have been done by the communities since the Dergue regime period (1974-1991). However, the present study indicates that, dense forests land cover class was the leading among the other land cover classes (Table 8). This increment might have been the result of mass plantations of exotic tree species, protection of the existed indigenous tree species, expansion of coffee plantation activities, emigration/destruction of the community living near/close to the forested areas, expanding land for plantation (collecting from the communities), restriction of livestock and human entrance (collection of forest and forest product) starting from the periods of delineation time. A study done by Warra et al. (2013) indicates that, regeneration of vegetation is affected by strong restriction on livestock encroachment, firewood collection, and fire control.

According to data collected from Oromia Forest and Wildlife Enterprise of West Wollega District, Harbu Abbaa Gadaa, Siba Dalo and Siba Sillase kebeles covered by a total area of 3611.24 ha of forests (OFWE,

Table 10. Gains and losses by categories in hectares during 1986-1995, 1995-2006, 2006-2016 and 1986-2016

Land cover classes	1986-1995		1995-2006		2006-2016		1986-2016	
	Gains (ha)	Losses(ha)	Gains (ha)	Losses(ha)	Gains (ha)	Losses(ha)	Gains (ha)	Losses(ha)
Dense forests	+827	-72	+1077	-92	+510	-199	+2073	-23
Sparse forests and shrubs	+1031	- 1437	+892	-1411	+743	-906	+877	-1965
Farmlands and others	+791	-1141	+452	-914	+450	-604	+586	-1553

NB: The right side (-) show that decreasing while the left side (+) increasing.
Source: Author.

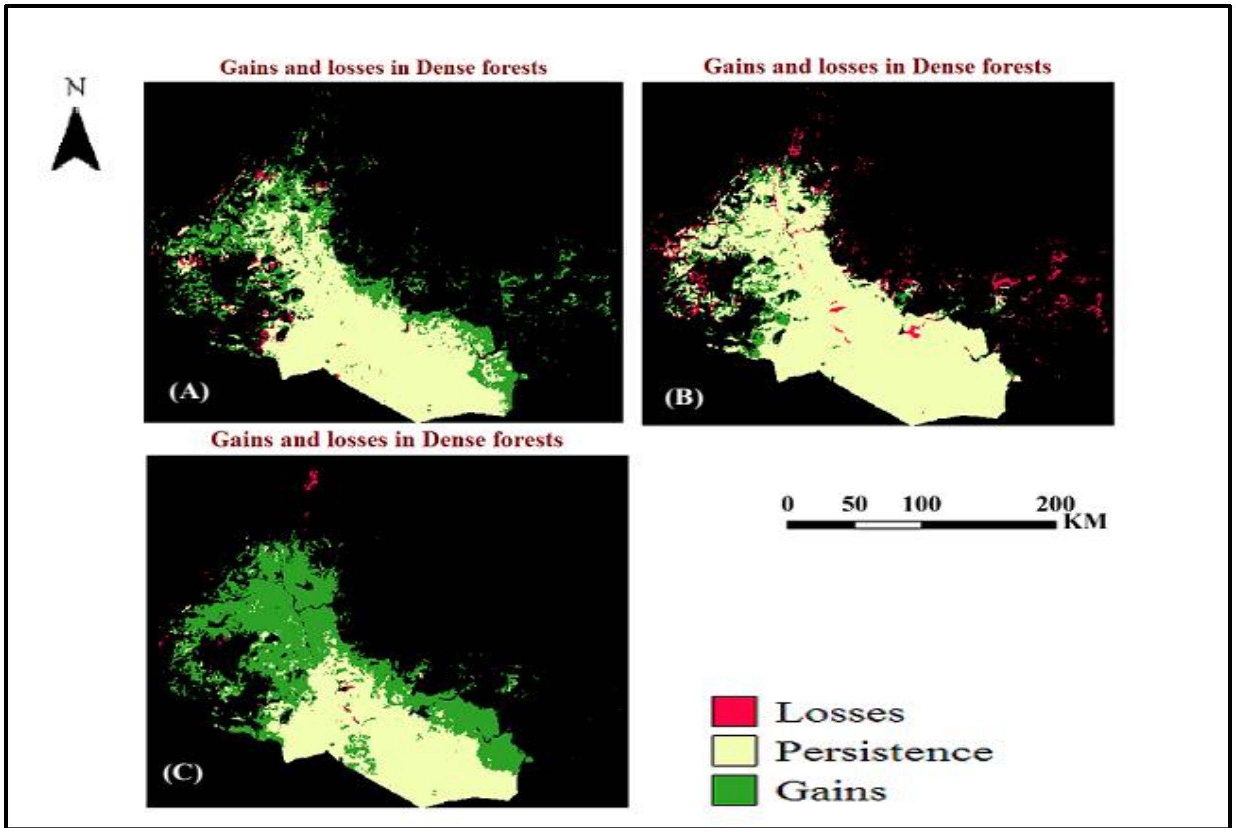

Figure 5. Map showing areas of gains (increase in size), losses (reduction in size) and persistence (area with no change in size) between A) 1995-2006, B) 2006-2016 and C) 1986-2016.
Source: Author.

2017). A study undertaken in Jimma city by Chalachew et al. (2015) shows that, plantation forest was increased from 599.32ha (6.22%) in 1984 to 1754.91ha (14.67%) in 2004 with a change rate of +66% (+155.59 ha) from 1984 to 2004 while other vegetation‟s decreased from 3.19% (307.49 ha) in 1984 to 2.12% (252.09 ha) in 2004 with a change rates of -55.395 ha (- 18%).

Payn et al. (2015) expressed that, the reasons for contributing net increases in forest area includes reduced pressure on forests as a result of economic growth, declining rural populations or improved agricultural productivity and effective policies aimed at expanding forest area (FAO, 2016a). In the study area, according to the information obtained from an expert, elders/key informants and community leaders, degraded lands were converted into plantation activities like coffee shade species and other plantation of exotic tree species by communities and Oromia Forest and Wildlife Enterprise (OFWE). Forests have sometimes re-established naturally when deforestation pressures have improved (FAO, 2016a). ‘'Replacement of natural forest by plantation forest is a major change in land use land cover changes dynamics‟ (Chalachew et al., 2015).

CONCLUSION AND RECOMMENDATION

The study revealed that a broader change and dynamics of land cover has been associated with broader range of impacts on the terrestrial resources of the area within 30 years during 1986- 2016. Much of the area has been changed. Forest cover of the study area has been increased due to mass plantation activities done by campaign of the local community since demarcation of the forest area, by Oromia Forest and Wildlife Enterprise and expansion of coffee plantation rather than agricultural production. Farmlands and others, and sparse forests and shrubs land cover have been converted to coffee plantations and other exotic tree plantations; results increment of forest and tree coverage of the area. Large patches of the native (natural) vegetation‟s have been converted and modified to coffee plantation and exotic tree species (*Eucalyptus species, Pinus patula and Cupressus lusitanica)* plantations. The expansion of fast growing exotic species such as *Cupressus lusitanica, Eucalyptus species, Gravillea robusta* and *Pinus patula* were observed during field assessment. Monoculture plantation cannot replace the natural forest and do not give home for many biodiversity which is important to natural resource management. A means of integrating both systems and focusing more diverse species will be needed in the future for maintaining the environmental equilibriums of the area.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

ACKNOWLEDGMENTS

The authors are grateful and thankful to Oromia Agricultural Research Institute (IQQO) for sponsoring and giving the opportunity to study at Jimma University College of Agriculture and Veterinary Medicine and appreciate Haro Sabu Agricultural Research Center staffs, especially Addisu Hailu, Ayalew Sida, Wegene Negesa and Firezer Girmaye for the accommodations; they have provided during fieldwork/data collection.

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