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(Research Article)

Spatiotemporal Analysis of Jorgo Wato Forest Cover Changes, West Wallagga, Oromia, Ethiopia

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Abstract

A study was conducted in the Jorgo Wato forest, located in the West Wallagga zone and extending to the Buno Bedelle zone of Oromia National Regional State, with the objective of assessing the dynamics of forest cover change in the Jorgo Wato forest over the last three decades (1986–2016). 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 from Landsat TM, ETM+, and OLI/TIRS were used in this study. Support Vector Machines for supervised classification and post-classification were used for image classification, with results showing an overall accuracy of up to 99.49%, maximum producer's accuracies of up to 99.80, and User's accuracies of up to 100%, while the Kappa coefficient ranged between 96.98% and 99.17%. The result of the change analysis revealed that forests changed from 67.62% in 1986 to 74.77% in 2016, with an average rate of change of 20.13ha/year from 1986 to 2016, whereas farmland changed from 19.60% in 1986 to 12.28% in 2016, with a variation through 30 years and an average rate of change of -20.604ha/year from 1986-2016. Changes in forest cover increment have come from the expansion of coffee plantations and plantations of different tree species by the communities and by Oromia Forest and Wildlife Enterprise till now. Monoculture plantations cannot take the place of a natural forest and cannot support a lot of biodiversity, which is crucial for the management of natural resources. Future maintenance of the region's environmental equilibrium will require a method of combining both systems and concentrating more diverse species.

Keywords: Accuracy assessment; Change detection; Forest; Kappa coefficient; Image analysis; Satellite image

1. Introduction

The numerous tree species that predominate in forests make them significant resources. They are of considerable value to both rural and urban populations as a source of fuel, wood, and charcoal, as well as in terms of ecological and economic relevance in terms of preserving the delicate environment and boosting the national economy [1]. Additionally, it offers ecological, economic, social, and aesthetic benefits to humankind and other natural systems. It also influences climate through exchanges of energy, water, and atmospheric carbon dioxide [2]. Globally, forests occupy 3999Mha in 2015. This is equal to 0.6ha for each person on the earth, or 31% of the world's land area [3]. Broad conversion of forest cover has serious long-term environmental and social repercussions both worldwide and locally, including species extinction, habitat degradation, and global climate change. As the population grows, there is greater demand for resources like food, water, fuel, and so on, which puts great pressure on the environment [4]. Remote sensing application is a powerful method for surveying, mapping, and keeping track of earth resource availability. This technology works better when paired with GIS, which excels at handling, storing, and analyzing geographic and socioeconomic data.

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Because it offers a map-like representation of the Earth's surface that is spatially continuous, highly consistent, and accessible at a variety of geographical and temporal scales, remote sensing is an appealing source for thematic maps like those showing land cover. Remote sensing thematic mapping is often based on an image classification [9]. There are numerous uses for remote sensing in the areas of forestry, agriculture, and land use. Monitoring changes in forest cover requires the use of remote sensing and GIS technologies. Through the use of aerial photographs and satellite images interpretations in forest cover change detection analysis, for the generation of cover maps, and for inventory analysis, the potential of remote sensing and GIS in the field of forestry becomes established over a long period of time [10]. Multitemporal data are available for investigation of change detection. Due to the repeating coverage provided by the satellites at frequent intervals, satellite data has emerged as a key application in the identification of changes in forest cover [11]. According to [12], the process of detecting changes in an object's or phenomenon's state involves looking at photographs taken at several points in time. Around 44% of the world's forest land is found in tropical nations, followed by 8% in subtropical, 26% in temperate, and 22% in boreal nations. The rate of net worldwide deforestation has decreased by more than 50% during the past 25 years [3]. Ethiopia's forest cover in 2015 was 12,499 hectares [13]. From 167.5Mha in 1990 to 277.9Mha in 2015, the world's planted forest area expanded, with the rate of growth differing by region and climate zone. By the year of 2015 saw the planting of 277.9Mha of new forests, of which 56% are in the temperate zone, 15% are boreal, 20% are tropical, and 9% are subtropical [14]. Reduced pressure on forests as a result of economic expansion, shrinking rural populations, or higher agricultural productivity are a few of the factors leading to net gains in forest area, as are effective policies targeted at increasing forest area [15].

In Ethiopia, there are 11,527,000 hectares of other naturally regenerating forest and 972,000 ha of planted forest as of 2015 [3]. Forest gains occur through natural growth, planting, or purposeful seeding on non-forested land, such as afforestation, reforestation, or abandoned agricultural land, or through the implementation of forest policies that encourage tree planting in order to meet future needs for forest products and environmental protection [15]. There are roughly 80 National Priority Forest Areas in Ethiopia [5]. One of these is the Jorgo Wato forest, which is located in the West Wallagga zone of the Oromia Regional National State and extends to the Buno Bedelle zone of the Oromia Regional National State. It has a total area of roughly 8439.87 hectares (total area of designated forest area) [6]. However, the protection of these places from deforestation has not been successful due to encroachment to discover new land, mainly for agriculture, coffee plantations, and lack of legal status for these priority zones, among other reasons. Even though the Jorgo Wato forest is significant economically, hydrologically, and biologically on a regional and national level, the area is gravely threatened by the unsustainable exploitation of natural resources [7], [8]. The goal of the study was to evaluate the dynamics of the change in forest cover in the Jorgo Wato forest over the course of the last three decades (1986 to 2016).

2. Materials and Methods

2.1. Description of the Study Sites

The research was carried out in the Jorgo Wato Forest, which is part of Nole Kaba District of the West Wallagga Zone and extends to Mako district of Buno Bedelle Zone of the Oromia National Regional State (Fig. 1).

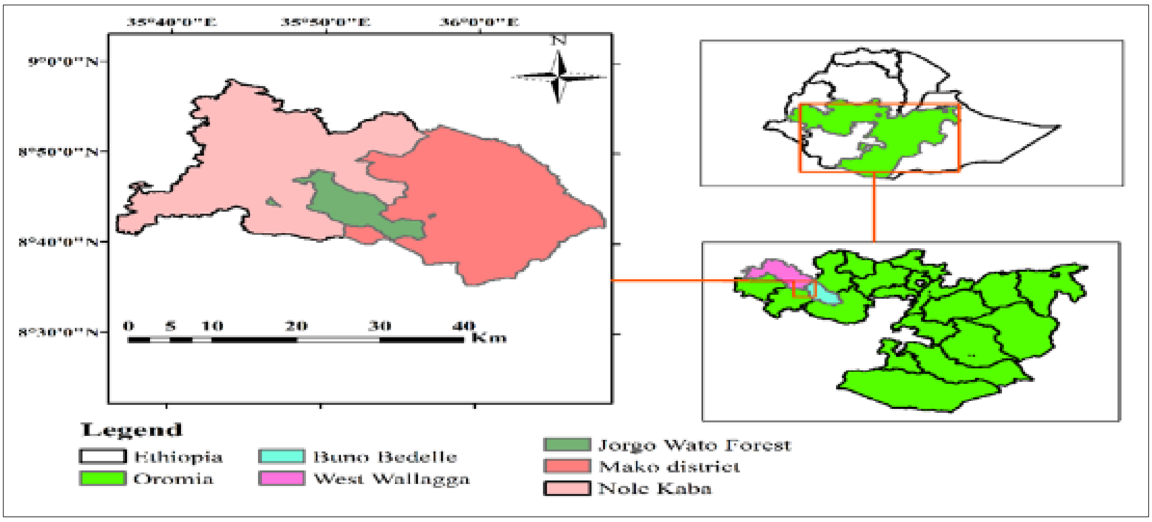

Figure 1 Location of Study Area Map

2.2. Sources, Methods, and Pre-Processing of Remote Sensing Data

Path 170 to row 54 of the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) satellites' imagery was used. From the USGS (United States Geological Survey) data portal, the images could be downloaded for free. The imagery that was used was all taken during the dry seasons, with little to no cloud cover, between the years 1986 and 2016, at intervals of about ten years. The chosen months of the year were ideal for getting clear photos, reducing misunderstanding between the spectral signatures of forest and non-forest green vegetation, such as crops and grasslands, and enhancing contrast between forest and non-forest land uses during dry seasons. Since rain-fed agriculture predominates in the region, dry seasons should see a greater spectral contrast between the forest and agricultural land. The entirety of Jorgo Wato's forest is covered by Row 54 and Path 170. Using ENVI version 5.1 software, all images underwent image pre-processing such as registration/geometric correction, atmospheric correction, and layer stacking [17]. Preprocessing techniques are used to enhance some aspects of the input image and improve the image data by suppressing undesired aberrations. Decision tree classifier employs a series of binary decisions to divide pixels into groups. It can do unsupervised classification without supplying training data or supervised classification in which you supply training data and define a classification method. With the use of Google Earth, supervised image classification techniques were used in this work to classify the images using ground facts (training regions). Using proportionate stratified random sampling, a total sample size of 4692, 2893, 7919, and 3068 pixels were obtained for the Landsat images from 1986, 1995, 2006, and 2016. Out of the total number of pixels gathered, 70% were utilized for classification and the remaining 30% were used to estimate accuracy.

One of the tools for supervised classification is the Support Vector Machine (SVM), which is used to determine the class that each pixel belongs to. The hierarchical, reduced resolution classification approach offered by ENVI's SVM enhances performance without noticeably diminishing outcomes. It works best when applied to environments with uniform features. The reduced resolution image and ROIs are used to train and operate the SVM classifier. From complex and noisy data, Support Vector Machine frequently produces good classification results. With a decision surface that optimizes the margin between the classes, it divides them. The pairwise classification approach is used by ENVI's SVM implementation for multiclass classification. In the time periods of 1986–1995, 1995–2006, and 2006–2016, change analyses and accuracy assessments were conducted. In order to conduct image classification, confusion matrix analysis, and change detection of the classified land cover class categories of the study area, regions of interest were defined and marked (Fig. 2).

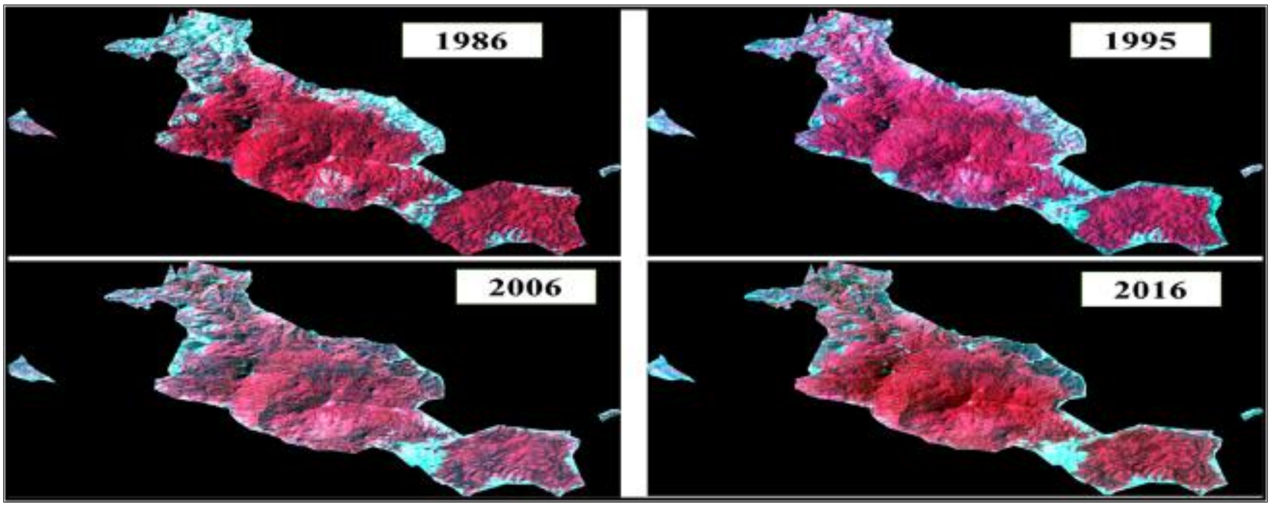

Figure 2 Identified Regions of Interest from Satellite Images from 1986 to 2016

3. Results and Discussion

3.1. Classification and Accuracy Assessment

Each land cover type category, each of the classified image, and each user's accuracy were evaluated together with overall accuracy, the Kappa coefficient, and the produce's and user's accuracy (Table 1 and Fig. 3).

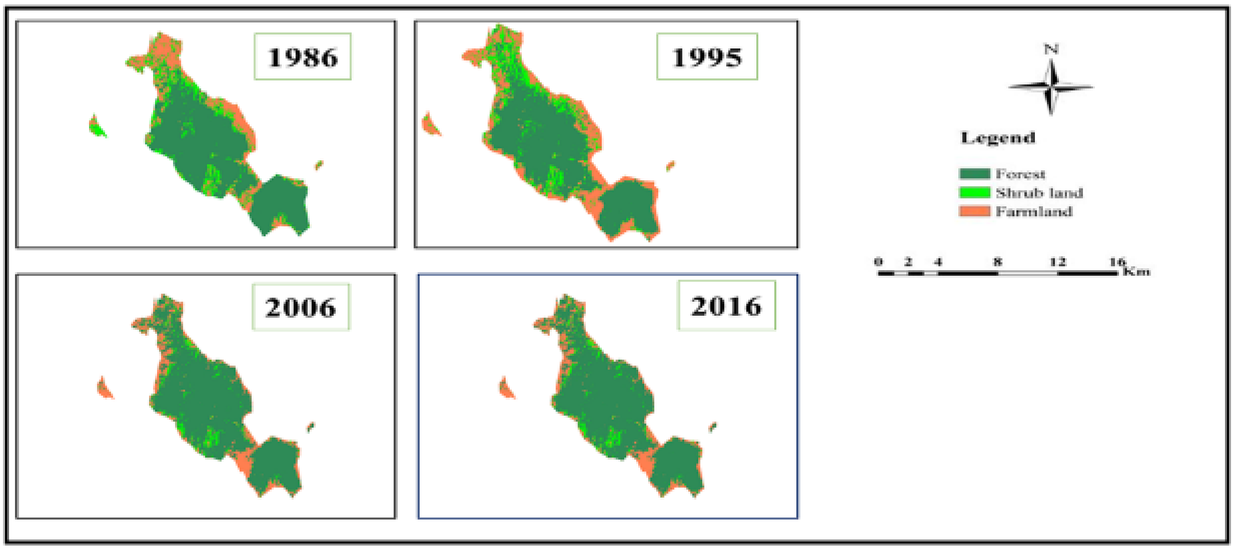

Figure 3 Classified satellite images of 1986, 1995, 2006 and 2016

Overall classification accuracy was 99.49%, 98.76%, 99.01%, and 98.99% during 1986, 1995, 2006, and 2016; the corresponding kappa coefficients were 99.17%, 96.98%, 97.50%, and 97.89% (Table 1). This finding is in line with [18], who claimed that the kappa coefficient (K) values ranged from 0 (total disagreement) to 1. When K is less than 0.4 (40%) or is between 0.4 (40%) and 0.75 (75%) or is greater than 0.75 (75%) then there is a poor agreement, good agreement, or excellent agreement, respectively.

Table 1 Accuracy Assessment by year (in percent)

Land cover classes	1986		1995		2006		2016	
	Prod.	**User's**	**Prod.**	**User's**	**Prod.**	**User's**	**Prod.**	**User's**
Forest	99.44	99.28	99.63	98.88	99.71	99.26	99.71	99.18
Shrub land	92.44	93.53	89.22	94.95	87.13	90.85	95.55	94.78
Farmland	99.80	100.00	99.43	99.81	98.98	99.76	98.15	99.87
Overall accuracy (%)	**99.49**		**98.76**		**99.01**		**98.99**	
Kappa coefficient (%)	**99.17**		**96.98**		**97.50**		**97.89**	

3.2. Land Cover in 1986, 1995, 2006, and 2016

In 1986, the largest percentage of an area was made up of forest (67.62%), followed by farmland (19.60%) and shrub land (12.78%). In 1995, farm land and shrub land increased while forest decreased. According to Table 2, the percentage of forests increased from 77.56% in 2006 to 74.77% in 2016.

Table 2 Area coverage and percentage statistics of land cover class from 1986 to 2016

Land cover classes	1986		1995		2006		2016	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Forest	5708.97	67.62	5058.00	59.91	6551.10	77.56	6312.87	74.77
Shrub land	1078.92	12.78	1124.91	13.32	458.93	5.43	1093.14	12.95
Farmland	1654.74	19.60	2259.72	26.77	1436.04	17.00	1036.62	12.28
Total	**8442.63**	**100.00**	**8442.63**	**100.00**	**8446.07**	**99.99**	**8442.63**	**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

3.3. Forest Cover Change Analysis

Using comparisons between previous and later periods, the land cover change between 1986 and 1995, 1995 and 2006, 2006 and 2016 and 1986 to 2016 was quantified. Two decades' worth of land cover maps in the study area were subjected to change analysis using LCM methods, and the results revealed significant changes in all land cover class categories across the study periods. Farmland and shrub land experienced the greatest changes between the time periods of 1986 and 1995 (Table 3). In contrast to the latter, the former rose by 45.99ha (a mean rate of 5.11ha/yr) to reach 1078.92 ha. Forest cover decreased by -650.97 ha, with a rate of decline for the time period estimated to be -72.33 ha/yr. While farmland and shrub land decreased to -665.98 (-60.54ha/yr) and -823.68 (-74.88ha/yr), respectively, during the 1995–2006 study period, the forest rose by 1493.1ha with an average change rate of 135.74ha/yr (Table 3). Over the years 1995–2006, forests showed a net increase of 59.91% in change. This shows that there is a significant rate of conversion of farmland and shrub land to forest (Table 3). According to Table 3, between 2006 and 2016, shrub land rose (634.21 ha), whereas forest and farmland decreased (-238.23 ha and -399.42 ha, respectively). When the entire study period is taken into account, a significant rise in the amount of forest has been seen, going from 5708.97ha (67.62%) in 1986 to 6312.87ha (74.77%) in 2016, with a variation of 603.9ha (20.13ha/yr) over a 30-year period. While the amount of farmland decreased during the sequence of 30 years, from 1654.74 ha (19.60%) in 1986 to 1036.62 ha (12.28%) in 2016 (Table 3), a change of -618.12 ha (-20.604 ha/yr).

Table 3 Extent of land cover classes change in 1986-1995, 1995-2006, 2006-2016 and 1986-2016 years image data

Land cover classes	**1995**		**1986**		**Change (ha)**	**Average rate of change (ha)**
	Area (ha)	**%**	**Area (ha)**	**%**		
Forest	5058.00	59.91	5708.97	67.62	-650.97	-72.33
Shrub land	1124.91	13.32	1078.92	12.78	45.99	5.11
Farmland	2259.72	26.77	1654.74	19.60	604.98	67.22
Total	**8442.63**	**100.00**	**8442.63**	**100.00**		
Land cover classes	**2006**		**1995**		**Change (ha)**	**Average rate of change (ha)**
	Area (ha)	**%**	**Area (ha)**	**%**		
Forest	6551.10	77.56	5058.00	59.91	1493.1	135.74
Shrub land	458.93	5.43	1124.91	13.32	-665.98	-60.54
Farmland	1436.04	17.00	2259.72	26.77	-823.68	-74.88
Total	**8446.07**	**99.99**	**8442.63**	**100.00**		
Land cover classes	2016		2006		Change (ha)	Average rate of change (ha)
	Area (ha)	**%**	**Area (ha)**	**%**		
Forest	6312.87	74.77	6551.10	77.56	-238.23	23.823
Shrub land	1093.14	12.95	458.93	5.43	634.21	63.421
Farmland	1036.62	12.28	1436.04	17.00	-399.42	-39.942
Total	**8442.63**	**100.00**	**8446.07**	**99.99**		
Land cover classes	**2016**		**1986**		**Change (ha)**	**Average rate of change (ha)**
	Area (ha)	**%**	**Area (ha)**	**%**		
Forest	6312.87	74.77	5708.97	67.62	603.9	20.13
Shrub land	1093.14	12.95	1078.92	12.78	14.22	0.474
Farmland	1036.62	12.28	1654.74	19.60	-618.12	-20.604
Total	**8442.63**	**100.00**	**8442.63**	**100.00**		

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

According to change detection from 1986 to 1995, farm land replaced forest and shrub land by 645.93ha (32.21%) and 419.13ha (20.91%), respectively (Table 4; Fig. 4). A total of 30.15% and 20.42% of farmland and shrub land, respectively, were converted to forests. However, between the years 1986 and 2016 (Table 4; Fig. 4), 16.70% of farmland was converted to shrub land. In Table 4 and Table 5, as well as in Fig. 4, conversions of various land cover classifications between forest, shrub land, and farmland were listed. During the intervals from 1986 to 2016 (Table 5; Fig. 5), the forest had the greatest gains, whereas the farmland experienced the greatest losses. Between 1986 and 2016 (Fig. 5), farm land (1095.48ha) and shrub land (664.02ha) were the two major contributors to forest increment. This shows that forest cover has dramatically grown, whereas farmland and shrub land have decreased.

Table 4 Change detection of the image data for the years 1986-1995, 1995-2006, 2006-2016, and 1986-2016

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 %
Forest	Shrub land	311.04	15.51	70.29	3.34	356.94	27.73	287.73	12.31
	Farmland	645.93	32.21	52.38	2.49	183.96	14.29	290.70	12.43
Shrub land	Forest	168.93	8.42	733.14	34.80	154.80	12.03	477.36	20.42
	Farmland	419.13	20.91	174.78	8.30	18.99	1.48	186.66	7.98
Farmland	Forest	137.07	6.84	914.40	43.4	115.56	8.98	704.97	30.15
	Shrub land	323.01	16.11	161.55	7.67	456.75	35.49	390.51	16.70
Total		**2005.11**	**100.00**	**2106.54**	**100.00**	**1287.00**	**100.00**	**2337.93**	**99.99**

Table 5 Gains and losses in hectares by categories between 1986 and 1995, 1995 and 2006, 2006 and 2016, and 1986 and 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)
Forest	306.00	956.97	1651.32	122.76	270.99	544.68	1182.33	578.43
Shrub land	634.05	588.06	232.56	908.55	818.73	174.51	678.24	664.02
Farmland	1065.06	460.08	248.85	1097.28	219.33	594.00	477.36	1095.48

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

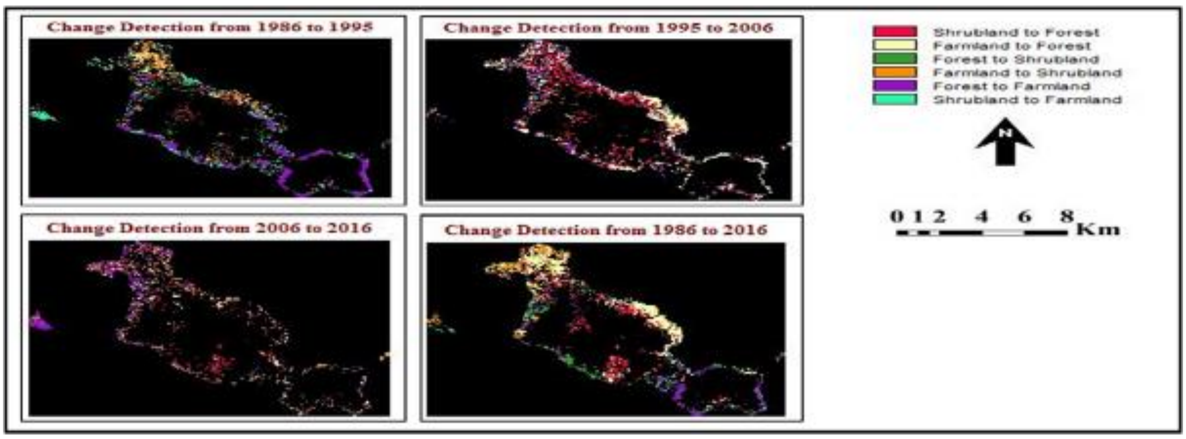

Figure 4 Map of Detection of land cover class changes from 1986 to 1995, 1995 to 2006, 2006 to 2016, and 1986 to 2016

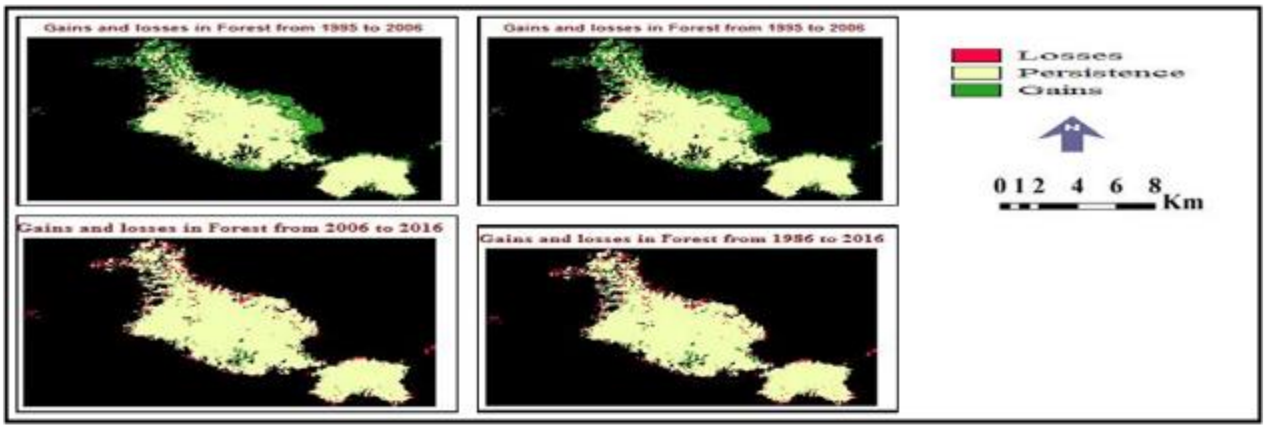

Figure 5 Maps from 1995 to 2006, 2006 to 2016, and 1986 to 2016 illustrate growth (increase in size), decline (decrease in size), and persistence (region with no change in size)

Various scholars have outlined the causes of the intermittent increases in forest cover in Ethiopia and other regions of the world in general. Afforestation, reforestation [15], vegetation rehabilitation mechanisms of an area enclosure [19], conversion of agricultural land to forest may be the result of natural forest expansion or tree planting, as well as forest policies [15]. Forest gains occur through these methods as well as through planting or purposeful seeding of non-forested land. It is true that since the designation of the Jorgo Wato forest, everyone in the study area must have the right to participate in plantation operations in a cluster form of youthful group, women's group, and elder group. Farmland and shrub land were lost as the amount of forest cover increased. This is produced by the expansion of coffee plantations, the preservation of existing native tree species, and the expansion of plantations for other exotic tree species (Table 4; Table 5; Fig. 5). Currently, Oromia Forest and Wildlife Enterprise (OFWE) manages Jorgo Wato forest, and each year, over 100,000 seedlings are planted there [6]. Additionally, according to responses from FGDs, every person who lives nearby Jorgo Wato forest must have planted something on 2% of their own private properties.

According to replies from elders/key informants and FGDs, the majority of planted tree species provided coffee shades for the neighborhood communities surrounding the forest. Visual observations made during research times revealed that majority of the area's lands were covered with coffee plantations beneath the top layer of tree cover. Due to the value of trees as coffee shade, the area's forest cover increases on a larger scale. Ethiopia's remaining forest pieces have been rapidly transformed in recent years into coffee plantations, arable fields, and plantations [20]. Following community-led plantation campaigns that began during the Dergue regime's (1974–1991) rule, the study area's forest cover increased. The results of the current study, however, show that among the several land cover classifications, forest land cover dominated (Table 4). This increase in forest cover may have been brought about by large-scale plantations of exotic tree species, the preservation of native tree species already present, the expansion of coffee plantation activities, the emigration or destruction of local communities residing near or close to forested areas, the expansion of plantation land (collected from the communities), and restrictions on livestock and human entry (starting from the periods of delineation time) in order to collect wood and other forest products. Strong restrictions on livestock encroachment, fire control, and firewood collecting have an impact on vegetation regeneration [21]. In Jimma City, plantation forests increased from 599.32ha (6.22%) in 1984 to 1754.91ha (14.67%) in 2004 with a change rate of +66% (+155.59ha) from 1984 to 2004, while other vegetation decreased from 3.19% (307.49ha) in 1984 to 2.12% (252.09ha) in 2004 with a change rate of -55.395ha (-18%) [22]. According to [14; 15], factors that contribute to net gains in forest area include decreased pressure on forests brought on by economic expansion, a decline in rural population, increased agricultural production, and successful policies aiming at increasing forest area. These factors lead to an increase in forest cover. According to information from an expert, elders/key informants, and community leaders, degraded areas were turned into plantation operations in the study area by communities and OFWE, including the planting of exotic tree species and coffee shade species [6; 16]. When deforestation pressures have decreased, forests have occasionally regrown organically [6; 15]. "Replacing natural forest with plantation forest is a major change in land use, changing dynamics of the land cover" [22].

4. Conclusion and Recommendation

According to the study, a wider shift and dynamic of land cover has been linked to a wider range of consequences on the region's terrestrial resources during the course of 30 years, from 1986 to 2016. Due to the local communities' and OFWE's campaign of big plantation activities and the expansion of coffee plantations rather than agricultural production, a significant portion of the territory has changed and the forest cover of the area has expanded. Coffee plantations and other exotic tree plantations have replaced farmland and shrub land, increasing the area's forest and tree cover. Exotic tree species (*Eucalyptus species, Pinus patula*, and *Cupressus lusitanica*) and coffee plantations have replaced large areas of the native environment. During the field survey, it was possible to see the spread of fast-growing exotic species such as *Cupressus lusitanica, Eucalyptus* species, *Gravillea robusta*, and *Pinus patula*. Monoculture plantations cannot take the place of a natural forest and cannot support a lot of biodiversity, which is crucial for the management of natural resources. Future maintenance of the region's environmental equilibrium will require a method of combining both systems and concentrating more diverse species.

Compliance with ethical standards

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Disclosure of conflict of interest

The author declares no conflict of interest.

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