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Land use and land cover changes and the link to land degradation in Arsi Negele district, Central Rift Valley, Ethiopia

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ABSTRACT

Accurate information on land use and land cover change (LULCC) is critical for understanding the causes of change and for developing effective policies and strategies to slow and reverse land degradation. In Ethiopia, the speed and scale of LULCC has been accelerated in the last 3–4 decades of the 21st century. The objectives of this study were to assess: (i) the extent of LULCC and normalized difference vegetation index (NDVI) and the link to land degradation; (ii) the causes of LULCC and implication for climate change adaptation. Satellite images analysis was used to detect the change in area and vegetation index, and farmers' perception to see the magnitude of LULCC dynamics and causes of deforestation. Correlations were made between vegetation index with dry season rainfall and temperature. The analysis of confusion matrix of LULC classification showed 87% accuracy with Kappa coefficient of 0.84. In the period 1986–2016, agriculture and settlement areas have increased by 250% and 618%, respectively. On the other hand, forests and woodlands have decreased by 72% and 84%, respectively. These were also validated with the farmers' quantification results with similar trends. Different causes have played roles in the dynamics of LULCC. The results showed that vegetation dynamics vary both spatially and temporally against precipitation and temperature. This study informs the need to focus on halting deforestation and development of alternative energy sources. It further helps to design future land management directions, landscape based adaptation and rehabilitation strategies to be considered by policy makers.

1. Introduction

Land cover refers to the physical and biological cover over the surface of a land, while land use is the human use of a land for different activities. Land use and cover change (LULCC) is the term used for the human modification of the earth terrestrial surface as a result of the different human activities (FAO, 2016). Land degradation is the reduction or loss of the biological or economic productivity and complexity of land, reducing carbon storage in soil and vegetation, driving the loss of biodiversity and accelerating climate change (IUCN, 2015).

In Sub-Saharan countries, deforestation is accelerating with an alarming rate (Ouedraogo et al., 2010; Ahmed et al., 2016; Hamza and Iyela, 2012; FAO, 2016). The annual rate of deforestation in Africa was 1.6 million hectares yr^{-1} in 1990–2005 (FAO, 2012). Deforestation has historical background in the community cognition (Mekasha et al., 2014) and scientific bases in forest and climate sciences (Betts et al., 2008) as causes of climate change. LULCC can potentially affect regional and global climates by emitting or sequestering carbon and by altering the overall reflectance properties of the earth's surface (Houghton and Hackler, 2006). From local to global scales, land resources play critical roles in human livelihoods, as well as in ecosystem functioning and health (Chaudhary et al., 2016). To achieve these, understanding the condition and changes through time of land resources such as forests is important. Accurate information on LULCC is critical for understanding the causes of change and for developing effective policies and strategies to slow and reverse land degradation (Asfaw, 2014; Berhe, 2014; Girma and Hassan, 2014; Kindu et al., 2015; Kibret et al., 2016).

Globally, deforestation rate was 3 million hectares yr^{-1} in 1990–2000, and 6 million hectares yr^{-1} in 2000–2005 (FAO, 2012). This has implications to climate change and variability as well as to land degradation (IPCC et al., 2014; Ward et al., 2014; Stocker and Joos, 2015; Fischer and Knutti, 2015). For instance, deforestation induced an increase in mean temperature and the associated heat extremes and a decline in mean rainfall or rainfall frequency from local to global scales (Lawrence and Vandecar, 2015). LULCC can be associated

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with positive and/or negative outcomes on people and environment (Baumgartner et al., 2015; Mouri and Aisaki, 2015; Chaudhary et al., 2016; Kindu et al., 2016; Sonter et al., 2017). It was stated that LULCC has direct implications to achieve the sustainable development goals (SDGs) and to implement the actions required to combat climate change (FAO, 2016; Obersteiner et al., 2016; Meneses et al., 2017). And that is why studying LULCC is becoming important. Recognizing the causes of LULCC requires understanding of three key issues: how people make land-use decisions; how specific socio-environmental factors interact to influence these decisions, and how farmers perceived the changes; and finally, land use decisions are made and influenced by socio-environmental factors across a wide range of spatial scales, from household level decisions that influence local land use practices, to policies and economic forces that can alter land use regionally and even globally (Lambin and Geist, 2007).

Although LULCC and land degradation are not a new phenomena in Ethiopia, the speed and scale of the change, irrespective of the efforts done by different stakeholders on conservation actions, has been accelerated in the last 3–4 decades of the 21st century (Hailemariam et al., 2016). This is due to increasing population and the corresponding demand for agricultural expansion to feed the growing population (Rientjes et al., 2011; Wondie et al., 2016). Ethiopia resides in the list of African countries that have net loss in forest area and net gain in agricultural area in 2000–2010 (FAO, 2016). In the period 2000–2005, Ethiopia's forest and high woodland areas have changed by −9.4% and −4.3%, respectively (FAO, 2010).

Arsi Negele district is under dynamic pressure of deforestation which affects landscape functions (Amdie, 2007; Gebeyehu et al., 2015). It is vulnerable to climate change and variability feedbacks as well as to land degradations (Jansen et al., 2007). Halting deforestation can enhance ecosystem functionality and minimizes land degradation (IUCN, 2015). Land degradation increases the negative feedbacks of climate change and variability in the region and reduces adaptive capacity of smallholder farmers by retarding sustainable development. In addition, climate change and variability has an impact on the vegetation of a particular landscape and understanding the relationship and magnitude of change in vegetation with respect to climate variables is important for future landscape management decisions (Hiltner et al., 2016; Jennings and Harris, 2017). Previous studies in Ethiopia on LULCC (*e.g.* Ariti et al., 2015) have largely dealt with general changes, say in a district or watershed, but this particular study has dealt the changes across agro-ecologies to see the variation between them. This study has also dealt with time series trend analysis of dry season normalized difference vegetation index (NDVI) in relation to dry season temperature and rainfall which is hardly studied in Ethiopia in general and the study area in particular.

The objectives of this study were to assess: (i) the extent of LULCC and NDVI and the link to land degradation across agro-ecologies; (ii) the causes of LULCC and implication for climate change adaptation across agro-ecologies.

2. Materials and methods

2.1. The study area

The study was conducted in Arsi Negele district, Ethiopia, located between 7.15° and 7.75°N and 38.35–38.95°E. The annual temperature varies from 10° to 25 °C with annual rainfall between 500 and 1000 mm (Fig. 1). The altitude ranges from 1500 to 3000 masl. (lowland < 1600 m with semi-arid climate, midland 1600–2200 m with mild climate and highland > 2200 m with cold climate). The topography encompasses the central rift valley floor and extended to its eastern escarpment. Andosols and nitosols are the dominant soils types (Gebreslassie, 2014).

The lowland is dominated by agro-pastoral system; the potato-vegetable cultivation in lowland and midland; the maize-haricot bean in most of the midland and in some lowland; and barley-wheat cultivation in most of the highland and in some midland (MOA 2015). According to the Ethiopian Central Statistical Agency's (CSA) reports of the years 1994(c), 2005(p), 2007(c) and 2016(p), the total population of Arsi Negele district was 137,228; 198,307; 260,129 and 338,967 respectively (c and p indicating censuses and projections respectively). These reports showed that the population of the district has increased by more than double between 1994 and 2016.

2.2. Survey method

After reconnaissance survey, six kebeles (lowest administrative division in Ethiopia) representing Arsi Negele district (two each agro-ecologically representative adjacent kebeles) were selected. Samples of 355 households from the total households in the six kebeles (4257) were randomly selected for household survey based on normal distribution with confidence level of 95% and margin of error 5% followed by finite population correction (Israel, 1992; Bartlett et al., 2001). The kebeles are Mudi Arjo(n = 48) and Shalla Billa(n = 56) from lowland, Meko Odaa(n = 44) and Sirba Lenda(n = 59) from midland, Gode Duro (n = 108) and Meraro Hawilo(n = 40) from highland.

Three to five key informants per kebele were selected by snowball method (Bernard, 2006) by which the first was selected based on kebele officials' information, then he/she told us the second and the second told us the third and so on. Also three focus group discussions per kebele, encompassing 8–10 people per group, were formed including women, elders and youth. The household interview deal with gathering information on the biophysical and economic causes of LULCC and on trends of natural resource conditions. The focus group discussions and key informants interview deal on historical trends of forest landscapes, land degradation and on the magnitudes of LULCC. Assumed LULC classifications (consistent across agro-ecologies) were made by farmers based on their long-term perception on LULCC. Farmers have classified and defined the major LULC types in their own local context as follows.

*'Forest'***:** an area with natural mosaics, dense agroforestry, acacia woodlands and shrublands, state and private plantations of about a *timad* or more (*timad* is local land area measurement ≈0.25 ha).

*'Agricultural land'***:** all lands used for crop production by rain fed or irrigation. It includes parkland agroforestry.

*'Rangeland'***:** a land which is particularly open and covered by scattered tree fields with grasses for livestock grazing.

*'Habitation'***:** location occupied by individuals' houses and their homestead compound, towns, schools, roads, kebele offices, health centers and farmers' training centers.

Based on the assumed LULC classifications, FGDs participants have divided the relative proportions of each LULC using 100 objects which were assumed to represent the whole area of a kebele (100%) during a particular year. The relative proportion of each LULC in a kebele given by the six FGDs in each agro-ecology was summed up and divided by the number of FGDs to give the average relative proportion of an LULC per agro-ecology (Fig. 2).

2.3. Remote sensing method

Four hundred and forty-four ground control points were established using global positioning system (GPSMAP 78) at random locations of each LULC class to obtain historical LULC information of the landscapes based on key informants' knowledge of field observation (including photos) about LULC types and compare with observations obtained from satellite images in 2016. Based on Ethiopian national and FAO definitions (FDRE, 2016; FAO, 2016) and field data, the terrestrial LULC of the study sites in Arsi Negele district was categorized into seven different classes as described and defined below.

Forest: a land spanning at least 0.5 ha covered by trees, attaining a height of at least 2 m and a canopy cover of at least 20% or trees with the potential to reach these thresholds in situ in due course. It also

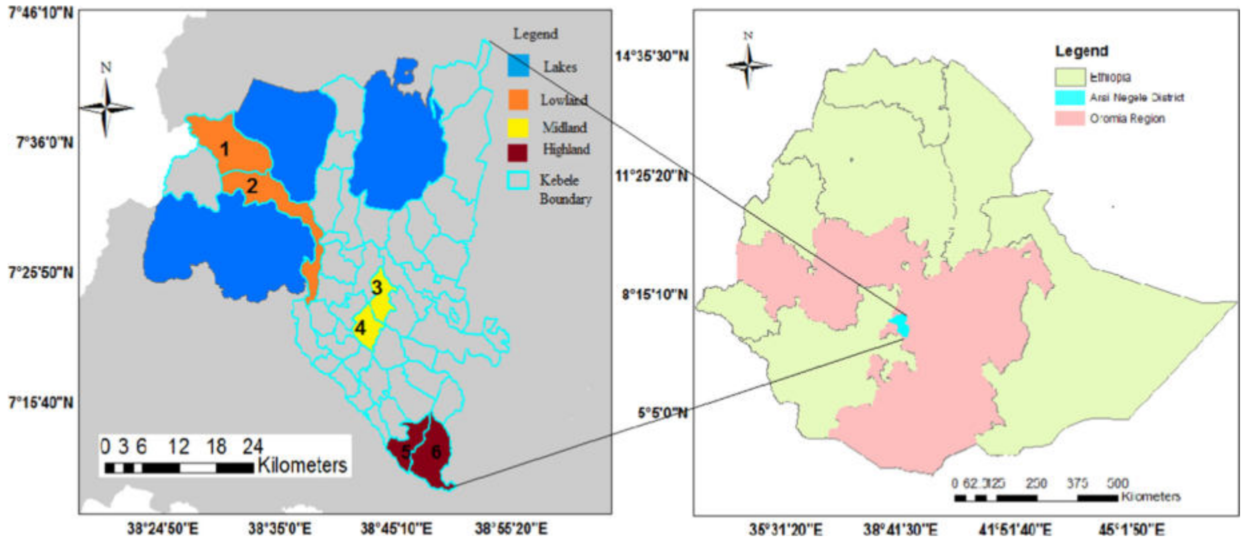

Fig. 1. Location map of the study area (**Kebeles**: 1 Mudi Arjo; 2 Shalla Billa; 3 Sirba Lenda; 4 Meraro Hawilo and 6 Gode Duro).

Fig. 2. Ways of LULCC quantification by focus group participants in their kebele.

Photos taken in Dec. 2015 in Arsi Negele district: lowland (top), midland (centre) and highland (bottom) agro-ecologies showing partial overviews of LULC

Photo 1.

includes mainly of eucalyptus woodlots exceeding 0.5 ha.

Crop land: arable and fallow land that grow annual crops or perennial crops on the small scale or commercial level by rain fed or irrigation schemes.

Woodland: a continuous stand of trees with a crown density of between 20% and 80%. Mature trees are usually single storied, although there may be layered under-stories of immature trees, and of bushes, shrubs and grasses/forbs. Maximum height of the canopy is generally not more than 20 m.

Grassland: land covered with the natural growth of *graminea* and herbaceous vegetation or a land sown with introduced grass and leguminous for the grazing of livestock.

Shrublands: land with shrubs/bushes canopy cover of 10% or combined cover of bush, and shrubs of 10%. Shrubs and bushes are woody perennial plants, 2 m in height at maturity in situ.

Bare land: land of limited ability to support life and in which less than one-third of the area covered by vegetation or other cover. It may be constituted by bare exposed rock, strip mines, quarries and gravel pits. In general, it is an area of thin soil, sand, or rocks.

Settlements and others: areas comprised of intensive use with much of the land covered by structures. Included in this category are towns, villages, strip developments along highways, transportation, power and communications facilities. It also includes foot paths and roads.

Pixel based supervised image classification was used and supplemented with field visit to help create training areas. Images of landsat TM (path/row 168/55) of spatial resolution 30 m (reflective) and 120 m (thermal) for January 1986; landsat ETM+ of spatial resolution 15 m (panchromatic), 30 m (reflective) and 60 m (thermal) for February 2000; and landsat-8 OLI (Operational Land Imager) sensor data for February 2016 were used for LULC classification. Landsat-8 OLI was used to deal with the data gaps of landsat ETM+ image products caused by the failure of scan line corrector of satellite on May 1, 2003. The images were corrected for geometric and atmospheric errors using earth resources data analysis system (ERDAS) imagine 2010 software. In case they might have a different spatial reference system, the images were projected to WGS84 Zone 37 N grid of the UTM projection. Field data collection using GPS and Google earth visualization were used for classification accuracy assessment. Final maps were prepared in ArcGIS 10 software. User's accuracy and producer's accuracy were calculated for the reference and classified data. The confusion matrix was performed to calculate total accuracy (the ratio of the sum of correctly classified elements along the diagonal to total number of pixels included in the assessment process) and Kappa coefficient (ratio of the difference between the correctly classified pixels and total number of

Table 1
Confusion matrix of LULC classification (number of pixels).

Classified data	Reference data							Total	User's Accuracy (%)
	F	WL	SL	GL	CL	BL	OS		
Forest (F)	**22**	2	0	1	0	0	0	25	88
Woodland (WL)	0	**95**	0	13	3	1	0	112	85
Shrub land (SL)	0	2	**63**	3	2	0	0	70	90
Grass land (GL)	0	0	1	**38**	1	1	1	42	91
Crop land (CL)	6	4	1	4	**90**	1	0	106	85
Bare land (BL)	0	0	2	1	0	**30**	2	35	86
Settlement & others(OS)	1	2	1	1	1	0	**48**	54	89
Total	29	105	68	61	97	33	51	444	
Producer's accuracy (%)	76	91	93	62	93	91	94		**87**
	F	WL	SL	GL	CL	BL	OS	Total	k
Agreement	22	95	63	38	90	30	48	386	**0.84**
Random	1.63	26.5	10.74	5.77	23.18	2.62	6.61	77	

pixels in the random classifications (classifications by chance) to the difference between the total number of pixels included in the assessment method and total number of pixels in the random classifications) (Cohen, 1960).

In addition, satellite data for normalized difference vegetation index (NDVI) analysis was used to correlate with climate dynamics with respect to temporal and spatial changes (Sisay and Burka (2016). Dry season (1–2 months after the end of rain season) cloud-free images downloaded from the US Geological Survey website were used for NDVI analysis for the months of November, December and January (1984/85, 1994/95, 1998/99, 2004/05, 2009/10 and 2013/14). As in the LULCC analysis, landsat images for the years before 2001 and landsat OLI for the years after that were used. The temporal variations were observed within three months timescale and the spatial variations were observed across the study sites representing lowland, midland and highland agro-ecologies.

The average NDVI values were derived for each study site for the dry period. The analysis was done using the radiometric indices tool of Quantum GIS version 2.18 software. The input image is a layer-stacked image, which has the red and near infrared spectral bands. The bands were defined regarding to the layer stack. Then, NDVI was chosen at 'available radiometric indices' section to enable determination of the NDVI. This process has been run for each temporal source image data. Then, the output raster data were imported to the ArcGIS environment to derive group statistics values of NDVI for each study site. Zonal statistics tool was employed to estimate average NDVI values of the highland, lowland and midland agro-ecologies across the temporal regimes (Zhu, 2016). Dry season satellite images have the advantage that perennial vegetation cover like forests, shrublands, woodlands, and most of the undergrowth vegetations including grassland and crop lands are distinctly distinguished. The various LULC types are better interpreted during dry season than other periods of the year. Furthermore, the effects of cloud on feature identification in satellite images are minimal during dry season.

Rainfall and temperature data for the months of November, December and January were obtained from the national Metrological Agency of Ethiopia (grid stations for each agro-ecology: see Mekonnen et al., 2017 that showed cyclical variations in rainfall tends) for the years indicated and correlate it with the respective NDVI data.

2.4. Data analysis

Mixed methods of qualitative and quantitative analyses were employed (survey and remote sensing) by which the combination of these methods may provide a better result than what each of these methods can do independently. GIS was used to produce the LULCC and NDVI maps and descriptive statistics to describe the change detection in the magnitudes of each LULC in the form of graphs and tables. Pearson's correlation was used to analyze the relationship between NDVI data and average monthly temperature and precipitation. In addition, multinominal logistic regression (MNLR) model was used to see the correlation of each cause of deforestation with agro-ecology expressed by Logit (y) $= \ln(p/1-p) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon_i$. **Where**: y is rate of presence of a cause of deforestation in an agro-ecology (dummy: yes or no); β_0 is the constant or the intercept of y; $\beta_1, \beta_2, \ldots \beta_n$ are regression coefficients to be estimated; $x_1, x_2, \ldots x_n$ are causes of deforestation; p is the predicted probability of having a cause of deforestation in lowland or highland agro-ecology with the reference category of midland agro-ecology, $1-p$ is the predicted probability of not having a cause of deforestation in lowland or highland agro-ecology with the reference category of midland agro-ecology; $(p/1-p)$ is the odds ratio; 1, 2, 3, …n is number of observations; and ε_i is error term of the ith cause of deforestation.

3. Results

Taking the 2016 classification as a basis, the results showed a confusion matrix of LULC classification with 87% accuracy and Kappa coefficient 0.84. These indicate a very good agreement between the reality and the classification results. User's accuracies range from 85% each for crop land and woodland to 91% for grassland. On the other hand, producer's accuracies range from 62% for grassland to 94% for settlements and other land uses. Correct classifications are placed along the matrix diagonal (Table 1).

3.1. Land use and land cover dynamics

The results indicated that there was a dynamics of LULCC in both the three agro-ecologies, either in positive or negative trends. Based on the satellite image analysis, the LULCC in 1986–2016 (Fig. 3A-C, 4a-d and Table 2) have shown the following trends: (i) forest area showed declined trend in all study sites. In 2000–2016, however, forest area has increased from almost nil to 2.5 ha in the midland and from 973.14 ha to 1090.30 ha in the highland. This was clearly validated during the ground truth assessments that the increase might be due to an extensive plantation by individual farmers. Nonetheless, this increment did not compensate the overall decline in 1980s and 1990s; (ii) woodland area showed declined trend in all study sites, but with highest decline in lowland study site; (iii) shrub land area showed declined trend in midland and increased trend in lowland and highland study sites; (iv) grass land area showed declined trend in lowland and highland study sites and increased trend in midland; (v) crop land area showed increased trend in all study sites with the highest increase in lowland and lowest in midland sites; (vi) bare land area showed increased trend in all study sites with the highest increase in lowland and lowest in highland; and (vii) settlement and other areas showed increased trend

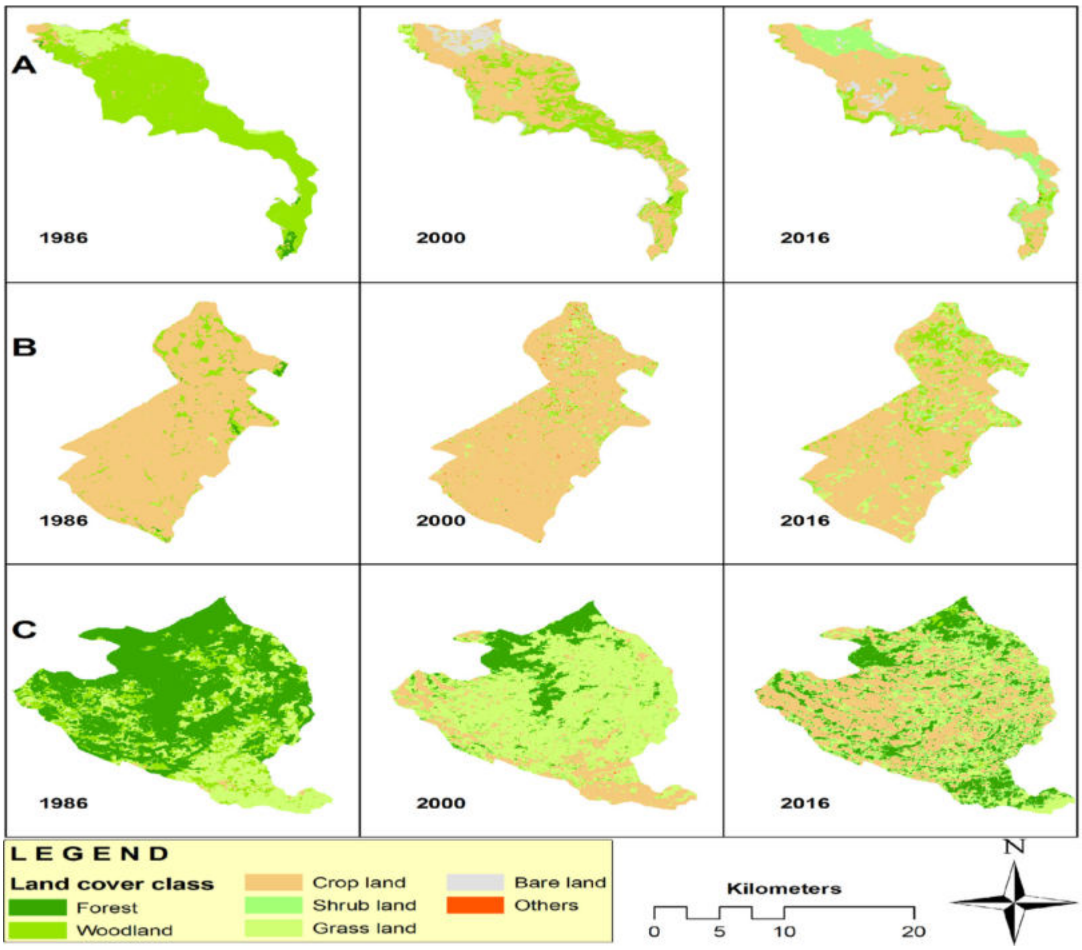

Fig. 3. LULC maps of the study sites in lowland (A), midland (B) and highland (C) of Arsi Negele District for the years 1986, 2000 and 2016.

in all study sites with the highest increase in highland and lowest in midland.

In the period 1985–2015, according to farmers' perception on their assumed LULC classification, the relative 'forest' cover has declined by 68.2%, 68.6% and 60.6% in the study sites of lowland, midland and highland agro-ecologies, respectively. In the same period, agriculture has increased by 221%, 182% and 211% in the respective agro-ecologies. These were also validated with the remote sensing section results with similar trends. Focus group participants pointed out that, the major LULC changes were forest/woodland to farmland conversion,

Table 2
Extent of LULC and the rate of change across agro-ecologies in study sites of Arsi Negele district, Ethiopia.

Agro-ecology	Year	LULC (ha)							
		Forest	Woodland	Crop land	Shrub land	Grass land	Bare land	Settlement & others	Total
Lowland	1986	200.00	10,981.78	1000.00	139.10	1476.43	418.47	7.37	14,223.15
	2000	9.89	3617.64	6732.67	1143.83	1500.20	1169.33	49.57	14,223.15
	2016	2.35	1431.66	7875.80	2866.57	656.83	1319.67	70.28	14,223.15
	Δ2016–1986	***− 197.65***	***− 9550.12***	***6875.80***	***2727.47***	***− 819.60***	***901.20***	***62.91***	***0.00***
	ΔPercent	**− 98.83**	**− 86.96**	**687.58**	**1960.80**	**− 55.51**	**215.36**	**853.60**	**0.00**
Midland	1986	54.16	1000.00	2547.05	559.36	84.80	0.00	5.04	4250.41
	2000	0.48	551.12	2756.21	206.32	594.01	108.99	33.28	4250.41
	2016	2.50	500.94	2548.34	401.57	731.89	11.17	54.00	4250.41
	Δ2016–1986	***− 51.66***	***− 499.06***	***1.29***	***− 157.79***	***647.09***	***11.17***	***48.96***	***0.00***
	ΔPercent	**− 95.38**	**− 49.91**	**0.05**	**− 28.21**	**763.09**	**0.00**	**971.43**	**0.00**
Highland	1986	3630.19	1005.16	76.11	430.00	1893.44	0.00	61.00	7095.90
	2000	973.14	525.35	1349.98	937.90	3201.44	0.09	108.01	7095.90
	2016	1090.30	93.57	2264.97	1478.79	1765.26	3.00	400.00	7095.90
	Δ2016–1986	***− 2539.89***	***− 911.59***	***2188.87***	***1048.79***	***− 128.18***	***3.00***	***339.00***	***0.00***
	ΔPercent	**− 69.97**	**− 90.69**	**2876.01**	**243.90**	**− 6.77**	**0.00**	**555.74**	**0.00**
Overall	1986	3884.35	12,986.94	3623.16	1128.46	3454.66	418.47	73.41	25,569.46
	2000	983.51	4694.11	10,838.86	2288.05	5295.65	1278.41	190.86	25,569.46
	2016	1095.16	2026.17	12,689.11	4746.93	3153.98	1333.84	524.28	25,569.46
	Δ2016–1986	***− 2789.19***	***− 10,960.77***	***9065.95***	***3618.47***	***− 300.68***	***915.37***	***450.87***	***0.00***
	ΔPercent	**− 71.81**	**− 84.40**	**250.22**	**320.66**	**− 8.70**	**218.74**	**614.18**	**0.00**

Table 3
Parameter estimates of MNLR for the causes of deforestation.

Variables	Agro-ecology[a]											
	Lowland vs. midland						Highland vs. Midland					
	B	se	Wald	df	Sig.	Exp(B)	B	se	Wald	df	Sig.	Exp(B)
Intercept	1.91	0.79	5.81	1	0.016		20.11	1213.2	0.00	1	0.987	
[Agri_expa = 0.00]	0.03	0.36	0.01	1	0.929	1.03	− 0.83	0.43	3.72	1	0.054	0.43
[Agri_expa = 1.00]	0[b]			0			0[b]			0		
[Fwood_coll = 0.00]	− 13.4	1066.2	0.00	1	0.990	0.00	2.11	1.10	3.65	1	0.056	8.22
[Fwood_coll = 1.00]	0[b]			0			0[b]			0		
[PopPr_Pov = 0.00]	0.39	0.42	0.87	1	0.352	1.48	− 0.81	0.39	4.17	1	**0.041**	0.45
[PopPr_Pov = 1.00]	0[b]			0			0[b]			0		
[Rang_expa = 0.00]	− 1.02	0.41	6.24	1	**0.013**	0.36	− 1.37	0.40	11.74	1	**0.001**	0.25
[Rang_expa = 1.00]	0[b]			0			0[b]			0		
[Illg_log = 0.00]	− 0.44	0.31	2.03	1	0.154	0.64	− 1.19	0.34	12.42	1	**0.000**	0.30
[Illg_log = 1.00]	0[b]			0			0[b]			0		
[Lack_Consr = 0.00]	− 1.37	0.61	5.11	1	**0.024**	0.25	− 1.55	0.63	5.98	1	**0.014**	0.21
[Lack_Consr = 1.00]	0[b]			0			0[b]			0		
[Drgt_Ffire = 0.00]	0.05	0.00		1		1.05	− 16.4	1213.2	0.00	1	0.989	0.00
[Drgt_Ffire = 1.00]	0[b]			0			0[b]			0		

Note: $R^2 = 0.25$ (Cox & Snell), 0.28 (Nagelkerke). Model X^2 (14) = 91.385, $p < 0.001$.
[a] The reference category is MAE. b. This parameter is set to zero because it is redundant.

fueled by population increase and market forces. In FGDs, it was mentioned that forest/woodland conversion has coping/adaptation outcomes in the short-term by increasing production, income and enhances food security. However, the outcomes will lead to maladaptation in the long-term by reducing soil fertility, decreasing biomass, and exacerbating shortage of fuelwood for the poor for subsistence and income source, decreasing water quality and quantity and loss of biodiversity. On the other hand, conversion of farmland to forest (e.g. plantations, secondary forest) has maladaptation outcomes in the short-term leading to shortage of food grain and enhanced food insecurity. Nonetheless, it will have adaptation outcomes in the long-term, thereby increases biomass and biodiversity; improves soil fertility, water quality and quantity and ameliorates micro-climate.

3.2. Vegetation Index analysis

The analysis showed that NDVI varies both spatially and temporally in the study sites. The average dry season NDVI in the highland study site has decreased from 0.455 in 1984/85–0.215 in 2013/14. In the midland and lowland study sites, the average NDVI show relative increase from 0.103 to 0.146 and from 0.071 to 0.123, respectively. This might be due to an extensive plantation by smallholder farmers in the midland and vegetation rehabilitation works in the lowland that lead to vegetation greenness. In the years of observation (1984/85, 1994/95, 1998/99, 2004/05, 2009/10 and 2013/14), the lowest NDVI value of −0.116 was recorded in 1999 for the lowland study site and the highest in 1985 for the highland study site. In general, the NDVI showed decreased trend from 1985 to 2014 in the study sites with similar trend in the decline of forest and woodland cover (which contributes the largest share for NDVI values) as indicated in the LULCC analysis.

3.2.1. Mean monthly rainfall and NDVI

The average NDVI in the study sites was positively correlated with November mean monthly rainfall. The correlation are (r = 0.692; p = 0.127), (r = 0.788; p = 0.062) and (r = 0.346; p = 0.502) for the lowland, midland and highland study sites, respectively. For the December mean monthly rainfall, the mean NDVI is negatively correlated in the lowland (r = -0.179; p = 0.734) and midland (r = -0.34; p = 0.51), while positively correlated in the highland (r = 0.136; p = 0.797). The NDVI has shown similar relationship for the mean January rainfall, with correlations (r = -0.571; p = 0.236), (r = -0.439; p = 0.383) and (r = 0.043; p = 0.936) in the lowland, midland and highland agro-ecologies, respectively.

3.2.2. Mean monthly temperature and NDVI

The average NDVI value of the dry period in the lowland study sites has shown positive correlation with the mean monthly temperatures of the months of November (r = 0.311; p = 0.548), December (r = 0.746; p = 0.089) and January (r = 0.752; p = 0.085). It has shown similar relationship in the midland: November (r = 0.568; p = 0.240), December (r = 0.603; p = 0.205) and January (r = 0.680; p = 0.137). The relationship between average NDVI and mean monthly temperature has been reversed in the case of highland study site. The correlation were (r = -0.711; p = 0.113), (r = -0.641; p = 0.171) and (r = -0.757; p = 0.081) for the mean monthly temperatures of November, December and January, respectively.

3.3. Causes of deforestation and resource conditions

The MNLR analysis showed that, taking the midland agro-ecology (MAE) as the reference category, the relative log odds of being a cause of deforestation in lowland agro-ecology (LAE) will increase by 0.03 if agricultural expansion is a cause of deforestation [*agri_expa = 1.00*] to agricultural expansion is not a cause of deforestation [*agri_expa = 0.00*]. The relative risk ratio for LAE that agricultural expansion is not a cause of deforestation is 1.03. The relative log odds of being a cause of deforestation in highland agro-ecology (HAE) will decrease by 0.83 if agricultural expansion is a cause of deforestation [*agri_expa = 1.00*] to agricultural expansion is not a cause of deforestation [*agri_expa = 0.00*). The relative risk ratio for HAE that agricultural expansion is not a cause of deforestation is 0.43. The relative risk ratio for LAE that fuelwood collection is not a cause of deforestation is negligible. It's the same for drought and forest fire for HAE (see Table 3 for similar interpretation of the other variables).

More than 90% of the respondents in all agro-ecologies have perceived that forest, soil, water and biodiversity resources have declined from their past capital in the study sites. It was explained in FGDs that the impacts of resource depletion have resulted in land degradation and the lessening of the adaptive capacity of the socio-ecological system and make it vulnerable to climate change and variability.

4. Discussion

The results have indicated enormous LULCCs across the three agro-

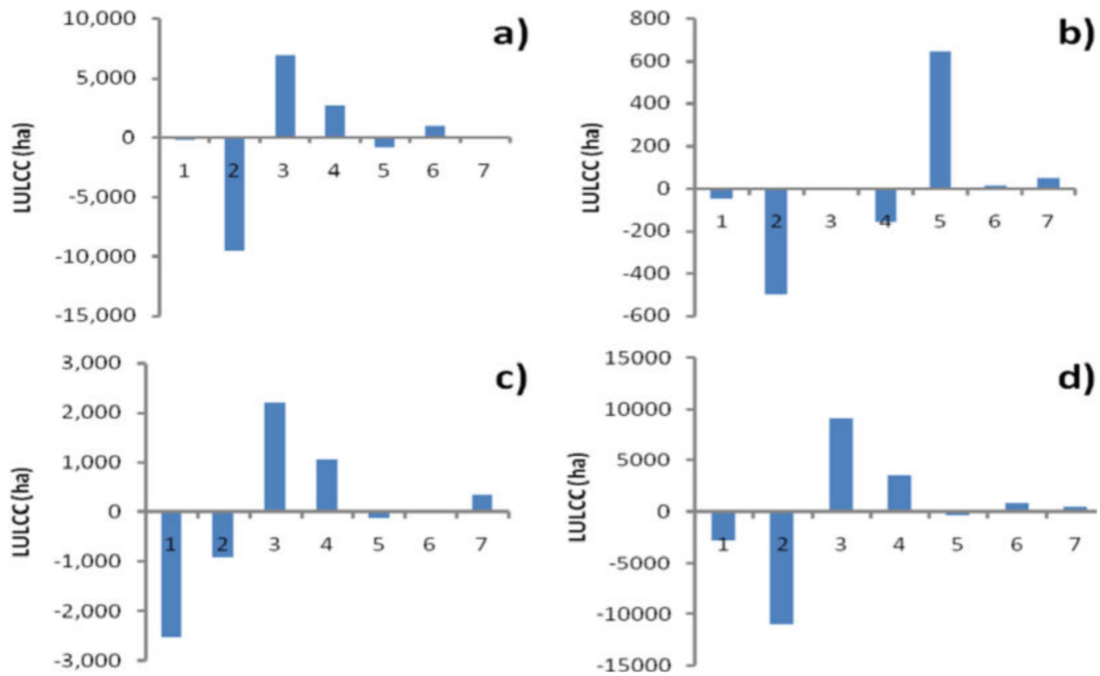

Fig. 4. : Magnitudes of LULCC between 1986 and 2016 in selected sites of Arsi Negele district in lowland (a), midland (b), highland (c) and overall (d) (1 = forest; 2 = woodland; 3 = crop land; 4 = shrub land; 5 = grass land; 6 = Bare land and 7 = settlements and others).

ecologies of Arsi Negele district. Seven major causes those are responsible for these changes, among which crop cultivation, fuelwood collection, population increase and poverty, have been identified by farmers. Classification accuracies of more than 85% show that satellite image analyses were effectively used to analyze LULCC across the different agro-ecologies. In aggregate, forest, woodland and grassland areas have shown a declined trend between 1986 and 2016, while crop land, shrub land, bare land, settlement and other areas have shown an increasing trend (Fig. 4d). Although with different magnitudes, the trends were more or less similar to the aggregate results across agro-ecologies except that shrub land area has declined and grassland area has increased in the midland (Fig. 4b).

As indicated in this study as well as other studies (*e.g.*, Shiferaw, 2011; Gashaw et al., 2014; Ariti et al., 2015; Bekele et al., 2015; Jaleta et al., 2016; Kleemann et al., 2017), crop land area has shown highly increased expansion at the expense of forest/woodland decline. Moreover, the perception in the decline (-) of forest, water, soil and biodiversity resources by more than 90% of the farmers shows how severe land resource degradations in the study sites are. These also impact ecosystem services (Kindu et al., 2015). The timescale analysis of NDVI also shows a general declined trend in vegetation in the study sites. Although the relationships between NDVI and temperature, NDVI and rainfall are insignificant ($p > 0.05$) in the study sites, they are better proxies to indicate that LULCC could be triggered by climate variables. In other words, climate factors in Arsi Negele district are less responsible for the changes in LULC and NDVI. This was also indicated by no tallies given by farmers for drought and forest fire as a cause of deforestation in the lowland and midland, and fewer tallies in the highland. This again remind us to rethink that the major causes of LULCC in Arsi Negele district are agricultural expansion, fuelwood collection, overgrazing, settlement expansion, resource depletions, population pressure and poverty (varies across agro-ecologies).

The results from satellite image analysis and farmers' perceptions of LULCC showed that, forest and woodland cover have been declined in the last three decades in the study sites. This was also complemented by the NDVI analysis showed by vegetation decline. This might show that the legitimate interests of local agricultural development and sustaining livelihoods are at the costs of the legitimate concerns over the losses of certain ecosystem functions and land degradation. This will impede the sustainable use of land for development and enhances land degradation (Nkonya et al., 2012; Pfaff et al., 2013) and increases greenhouse gas emission (Bellassen et al., 2008). The average dry season NDVI and climate parameters (temperature and precipitation) and their relationships were found to vary across agro-ecologies (Fig. 5a-f). The influences of rainfall and temperature on vegetation were also emphasized by farmers that the increase in temperature and decline of rainfall in recent time were due to deforestation (Mekonnen et al., 2017). In support of this, the studies by Lawrence and Vandecar (2015) as well as Zoungrana et al. (2015) have found that, air passing over dense tropical forests produced at least twice as much rainfall as air passing over areas with little vegetation. Similarly, a comparative analysis between NDVI and EVI in the Southwest of Burkina Faso, showed significant and strong positive correlation with the amount of rainfall (Zoungrana et al., 2015). The dynamic changes in LULC as showed by satellite image analysis and farmers' perception and decline of vegetation as showed by NDVI analysis indicate the overall land degradation in the study sites. LULCC and the consequent climate change feedbacks are among the driving forces of land degradation (Higginbottom and Symeonakis, 2014; Yengoh et al., 2014; Li et al., 2015). By considering the average dry season NDVI values over the years as a better proxy for vegetation degradation, the results showed higher vegetation degradation in the lowland and midland agro-ecologies than in the highland. This is also related to the decline of biomass productivity (e.g. Le et al., 2016) and affects the livelihoods of the people in the study sites and reduces their adaptation to climate change.

5. Conclusions

The results showed that LULCC dynamics are more pronounced in the lowland and highland agro-ecologies of Arsi Negele district. Paramount negative trends were observed in the forest and woodland areas and higher positive trend in crop land and settlement areas. Varying across agro-ecologies, these dynamic changes are mainly caused by increased demand of land for crop cultivation to feed the growing populations, and collection of fuelwood for household energy consumption and for market. As the decline of forests and woodlands

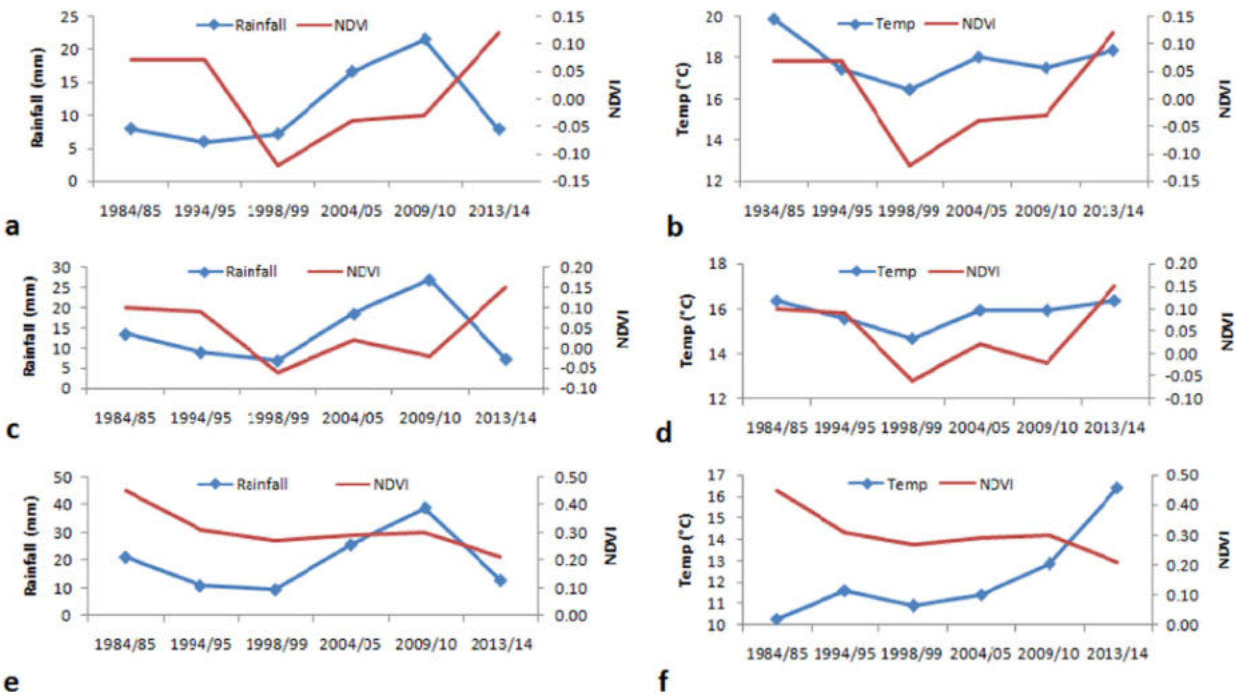

Fig. 5. : Dry season NDVI and its relationship with temperature and rainfall across agro-ecologies (lowland a & b, midland c & d, and highland e & f).

rises, so does the risk of land degradation with a knock-on effect on people that depend on them. Therefore, this study informs the need to focus on halting deforestation in order to stop further land expansion into forests and woodlands; development of alternative energy sources. It further helps to design future land management directions, landscape based adaptation and rehabilitation strategies to be considered by policy makers.

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Conflict of interest

The authors declare that there is no conflict of interest.

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