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Drivers of Land Use-Land Cover Changes in the Central Rift Valley of Ethiopia

(Pemacu Kegunaan Tanah - Perubahan Liputan Tanah di Lembah Rekahan Tengah Ethiopia)

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ABSTRACT

Land use-land cover change (LULCC) is driven by the interplay of forcing factors that act at global, regional, and local levels. Previous studies investigated mainly the basic socioeconomic drivers of LULCC. However, these studies less considered climate change vulnerability as a potential driver. Hence, this study is aimed to assess LULCC drivers in more fragile and dynamic landscapes of the East African Rift Valley region for the period of 1986-2016. We used a combination of Remote Sensing, Geographic Information System, logistic regression, and descriptive statistics to quantify and analyze the data. Image analysis results indicated that during the overall study period (1986-2016), grass/grazing land, agricultural land, and bare land have increased by 124%, 42%, and 34% respectively, whereas scattered acacia woodland, bush/shrubland, and swampy/marshy land have declined by 52%, 50%, and 31%, in that order. This image-derived change trend is in line with farmers' perceived results. The top most influential drivers of LULCC includes population growth (95%), fuelwood extraction (93%), agricultural land expansion (92%), charcoal making (92%), climate change/recurrent drought (79%), and overgrazing (71%) in descending order of percentage of respondents. Education level and age of farmers significantly ($p<0.05$) affected their perception towards less perceived drivers. Hence, in order to reduce the adverse socio-environmental impacts of spectacular LULCC in the region, policy and decision makers need to take into account such principal drivers, particularly population growth and climate change.

Keywords: Central Rift Valley; driver; Ethiopia; land use-land cover change; perception

ABSTRAK

Kegunaan tanah-perubahan litupan tanah (LULCC) didorong oleh interaksi faktor paksaan yang bertindak pada peringkat global, serantau dan tempatan. Kajian sebelum ini hanya mengkaji asas pacuan sosio-ekonomi LULCC. Walau bagaimanapun, kajian tersebut tidak menganggap kerentanan perubahan iklim sebagai pemacu berpotensi. Oleh itu, kajian ini bertujuan untuk menilai pemacu LULCC pada landskap yang lebih rapuh dan dinamik di rantau Lembah Rekahan Afrika Timur bagi tempoh 1986-2016. Kami menggunakan gabungan teknologi pengesanan jarak jauh, sistem maklumat geografi, regresi logistik dan statistik diskriptif untuk menentu dan menganalisis data. Keputusan imej analisis menunjukkan bahawa semasa tempoh kajian keseluruhan (1986-2016), rumput/ragut tanah, tanah pertanian dan tanah lapang telah meningkat masing-masing sebanyak 124%, 42% dan 34% manakala hutan kayu akasia, belukar/tanah semak dan tanah paya/rawang berselerak telah menurun sebanyak 52%, 50% dan 31%. Trend perubahan berasaskan imej ini adalah sejajar dengan keputusan yang dijangka oleh peladang. Pemacu LULCC paling berpengaruh termasuklah pertumbuhan populasi (95%), penyaringan kayu api (93%), pembesaran tanah pertanian (92%), pembuatan arang (92%), perubahan iklim/kemarau berulang (79%) dan ragutan melampau (71%) mengikut peratusan responden. Tahap pendidikan dan umur petani mempengaruhi persepsi mereka dengan ketara ($p<0.05$) terhadap pemacu yang kurang diamati. Oleh itu, untuk mengurangkan impak sosial alam sekitar LULCC pada rantau ini, dasar dan pembuat keputusan perlu mengambil kira pemacu utama tersebut, terutamanya pertumbuhan populasi dan perubahan iklim.

Kata kunci: Ethiopia; lembah rekahan tengah; pemacu; persepsi; perubahan kegunaan tanah-liputan tanah

INTRODUCTION

Land use-land cover change (LULCC) is driven by several interacting factors that act at global, regional, and local levels. These drivers are mainly originated from anthropogenic-induced activities (Harden 2014) even though natural factors, for instance, volcanic eruption, earthquake, landslide and climatological events also may contribute to substantial changes on planet earth. Anthropogenic-related drivers such as population growth (Geist et al. 2006; Meshesha et al. 2014), urbanization (d'Amour et al. 2017; Wang et al. 2016; Yirsaw et al. 2017), agricultural expansion (Ramankutty et al. 2006; Mustard et al. 2012), pasturing (Wassenaar et al. 2007), and global market forces (Lambin & Meyfroidt 2011; Lambin et al. 2003) are among the known drivers of LULCC. Besides such basic human-related drivers, recent studies indicated that climate change vulnerability has a significant forcing effect on LULCC (Biazin & Sterk 2013;

Kindu et al. 2015; Lambin et al. 2003; Reid et al. 2000; Zessner et al. 2017). This could be possible through its direct effect, for example, the effect of recurrent drought on land cover and crop productivity (Ravindranath & Sathaye 2002). Climate change could also indirectly affect LULCC by increasing the demand for more croplands and by forcing climate change vulnerable communities to adjust their land use choices in order to cope up with such changes (Messina et al. 2014; Zessner et al. 2017). This is particularly true in developing countries where agriculture is the backbone of the economy.

LULCC scientists advise that before any policy intervention, a thorough understanding of the complex set of immediate causes and indirect driving forces of LULCC is quite important in a given location (Geist & Lambin 2002; Harden 2014). For instance, Geist et al. (2006) pointed out the importance of two essential steps in any study of LULCC. That is first, identifying the change in the landscape, and second, attributing that change to some set of causative factors. Although LULCC drivers are recognized important globally, only a few studies integrated socioeconomic and climatic factors to investigate such change-cause relationships. In addition, LULCC drivers are markedly different in various time, landscape and region (Hassen & Assen 2018; Nzunda et al. 2013; Yirsaw et al. 2017). Hence, in regions like East Africa, where both LULCC and recurrent drought occurrence are the major environmental and livelihood challenges (Few et al. 2015), consideration of climate variability as a potential driver of LULCC has a paramount importance in contributing to limited previous scientific literature in this region.

Though variation in results exists, previous studies in Ethiopia documented that LULCC is mainly driven by the interplay of socioeconomic, policy/institutional and technological, and cultural factors. These include population pressure, agricultural expansion, poverty, deforestation for fuelwood and charcoal, access to markets, poverty, and weak management (Ariti et al. 2015; Bewket & Abebe 2013; Biazin and Sterk 2013; Kindu et al. 2015; Reid et al. 2000). However, studies that considered climate variability as a potential driver of LULCC are very scanty in Ethiopia. In addition, LULCC drivers are local specific, hence, instead of generalization of results, detail local scale analysis is very important to devise appropriate local measures. This is particularly true for the Central Rift Valley (CRV) of Ethiopia, where a tremendous LULCC has occurred over the last three decades. Hence, this study is intended to: compare observed LULCC results with perceived results; identify major underlying driving forces and proximate causes of LULCC; and identify socioeconomic determinants of farmers' perception towards LULCC drivers by integrating Remote Sensing, GIS, socioeconomic and climatic datasets. Such a combined study of anthropogenic and climatic-induced LULCC drivers helps to reduce the subsequent adverse socio-environmental effects and to devise appropriate policy intervention.

MATERIALS AND METHODS

THE STUDY AREA

The Central Rift Valley is situated about 170 km south of the capital city, Addis Ababa, Ethiopia. This study is mainly focused on the Ziway-Shala sub-basin which is specifically located within the limits of 38°20'-38°50' east longitude and 7°20'-8°00' north latitude (Figure 1). According to JICA (2012), it covers approximately an area of about 13,401 km^2. The CRV is topographically known for its extended depression zone with steep peripheral faults along its edges and surrounded by eastern and western highlands (JICA 2012). It is part of the Main Ethiopian Rift system which in turn belongs to the Great East African Rift system.

The climate of the CRV varies noticeably with season and altitude (Jansen et al. 2007). It is semi-arid in the rift floor and humid to sub-humid in the highlands. According to data from National Meteorological Agency, Ziway Station, the mean annual rainfall is about 739 mm while the mean minimum and maximum annual temperatures are 14°C and 27°C, respectively, in the areas of rift floor. Rainfall in CRV is extremely unpredictable which is one of the main constraints to agricultural production in the region (Jansen et al. 2007).

The dominant land use-land cover (LULC) types of the study area include open woodland, cultivated land, water body, and grazing land. The natural vegetation mainly comprises of open woodland and shrub/bushlands. The CRV catchment encompasses four major interconnected lakes (Figure 1) on its rift floor namely: Ziway, Langano, Abijata, and Shala, which together form a complex network of a closed hydrological system (Ayenew 2007; Hengsdijk & Jansen 2006).

The population of CRV has shown an accelerated growth rate of about 3% over the last three decades (Scholten 2007). The average family size is about seven in a rural area. According to data from Central Statistical Agency, the total population of the three districts in CRV, namely: Dugda, Adami Tulu-Jido Kombolcha and Arsi Negele, has grown by 42% and 86% in 2007 and 2016, respectively, from its value in 1994 (CSA 1994, 2007). Even though the rural-urban migration in search of employment become increased in recent years, about 85% of the population is still living in a rural area (CSA 2007).

LAND USE-LAND COVER DATA SOURCES AND PROCESSING

Both primary and secondary sources were used to generate the data used in this study. For historical and recent LULCC mapping and detection of 1986, 2000, and 2016, cloud-free Landsat5 Thematic Mapper (TM), Landsat7 Enhanced Thematic Mapper Plus (ETM$^+$), and Landsat8 Operational Land Imager (OLI) imageries were respectively used. These imageries were obtained from the Global Land Cover Facility (GLCF) online imagery portal of the United States Geological Survey (USGS) database archive (http://glovis.usgs.gov). Satellite imagery from the same season of the year (January to February) was used to minimize

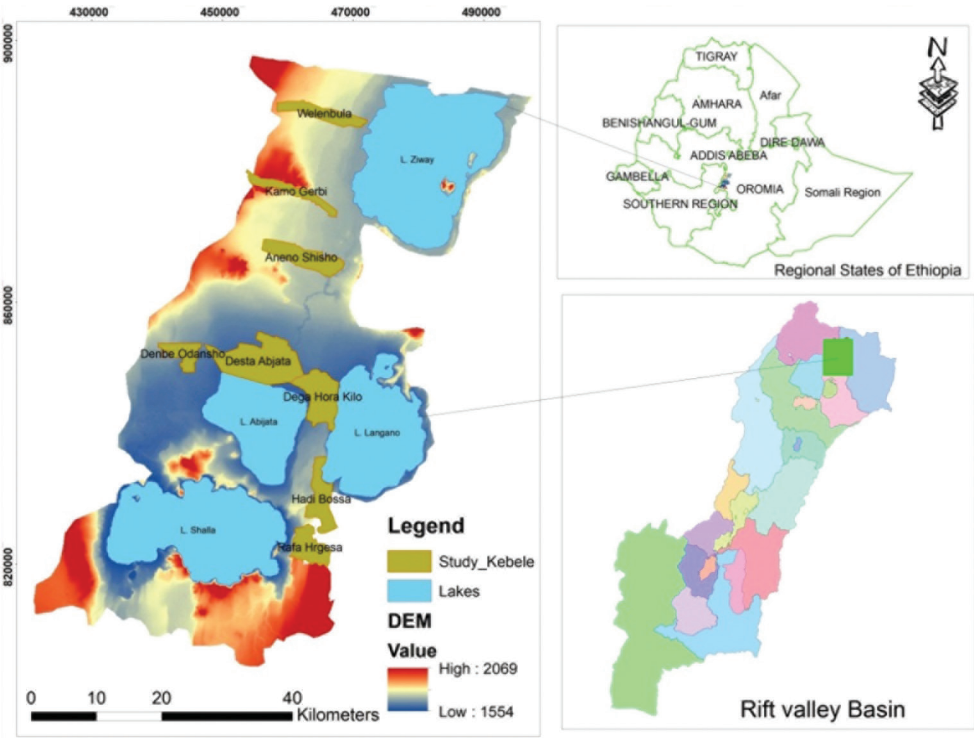

FIGURE 1. Location map of the study site

discrepancies in reflectance caused by seasonal vegetation fluxes and sun angle differences. Additional data like Ground Control Points (GCP), Google Earth Service, topographic map, and administration map of the study area were used for boundary delineation, navigation purpose, support in ground truthing/validation, and training site establishment for digital classification. A stratified random sampling method was used to collect about 60 GCPS per LULC class.

Landsat images were pre-processed using Erdas Imagine Software version 2014 for geometric and atmospheric corrections using 30 m by 30 m ASTER Global Digital Elevation Model (AST-GDEM) of the study area, and the commonly used dark subtraction technique respectively (Jensen 1996). Each image was geo-rectified to Universal Transverse Mercator (UTM) WGS 1984 Zone 37 North coordinates using GCPs collected during the fieldwork (Hall et al. 1991; Wijedasa et al. 2012). A first-order affine transformation and nearest-neighbor resampling method were applied for LULC classification (Jensen 1996), resulting in a root mean square error (RMSE) below 15 m for all Landsat images. The procedure involved radiometric rectification of the 1986 and 2000 images to the 2016 image, followed by a tasseled cap orthogonal transformation of the original six bands in each image into three new dimensional spaces, corresponding to soil brightness, green vegetation and moisture indices (Hall et al. 1991; Zhang et al. 2002). Ground-truthing Global Positioning System (GPS) points recorded in the field were used for training of the 2016 imagery, to determine the LULC classes during the image classification process, and to assess the accuracy of the classification.

HOUSEHOLD SOCIOECONOMIC SURVEY AND SAMPLING

Primary data on household socioeconomic characteristics and perception on historical LULCC extent and drivers were gathered by the *in-situ* formal face-to-face household survey and focus group and key informant discussions. A questionnaire with semi-structured type was established to facilitate the survey. The first fieldwork was conducted from April to June 2017 and the second from September to October 2017. Important secondary socioeconomic and biophysical data was obtained from concerned governmental organizations like Rift Valley Lakes Basin Authority, *Woreda* (District) Agricultural Office and *Kebele* (Village, the lowest administrative unit in Ethiopia) Administrative Offices. In addition, climate and population data were obtained from the National Meteorological Agency and the Central Statistical Agency, respectively.

The household survey was conducted in two consecutive Districts found in CRV namely: Arsi Negele and Adami Tulu-Jido Kombolcha, which were selected based on agroecology and vulnerability to drought and LULCC in recent decades. This is based on prior information obtained from agricultural experts, development agents (medium level agricultural experts working at Village level), and District and Village administrative personnel. From these Districts, representative Villages were purposively selected based on access to market and infrastructure, drought vulnerability and experiences in using adaptation measures like irrigation to cope up with LULCC and drought. Accordingly, five Villages from Adami Tulu-Jido Kombolcha District namely: Welenbula, Kamo Gerbi, Aneno Shisho, Desta Abjata, and Denebe Odansho, and three Villages from Arsi Negele District namely: Dega Hora Kilo, Hadi Bossa, and Rafa Hargesa, were selected for household interviews and focus group discussions (Figure 1). The households interviewed were selected randomly from each Village considering age, sex, wealth status, and literacy. A total of 297 household heads were interviewed with an average of about 37 households per Village. In addition, at least one focus group discussion and an interview with one elder key informant were conducted per Village. A checklist of open-ended questions was used to guide the group and key informant discussions. Further discussions were also made with development agents working at Village level and experts at District level.

DATA ANALYSIS

Data were analyzed by using a combination of techniques including Remote Sensing, Geographic Information System-based processing, logistic regressions, and descriptive statistics. The LULC classification was done by employing a supervised maximum likelihood algorithm classification approach which is generally recognized as the popular classifier technique (Booth & Oldfield 1989; Hogland et al. 2013; Richards 2013). The supervised classification approach requires prior knowledge of the target area to set training sites and use of spectral information contained in individual pixels to generate LULC classes. According to Lillesand et al. (2014), the maximum likelihood method has a strong advantage because of its use of a well-developed probability theory though it has also drawbacks in certain circumstances. Accordingly, we classified the LULC categories of the study area into dense and scattered acacia woodlands, grass/grazing land, agricultural land, shrub/bush land, water body, marsh/swampy area, and bare land. The operational definition of each LULC category based on modified version of Anderson land use and cover scheme levels I and II (Anderson 1976), topographic maps, Google Earth, and the author's knowledge of the study area is as given in Bekele et al. (2018).

LULC classification accuracy assessment was done using an error or confusion matrix developed from a separate set of points randomly generated using a stratified random sampling approach to determine the precision of the classified image (Congalton & Green 2008; Jensen 1996). It is also essential for post-classification change detection analysis (Liu & Zhou 2004). The reference points were transferred to a GIS software program; in which they were overlaid with the classified images. A field check was made to test the accuracy of the reference points. The accuracy of a classification was assessed by comparing the classification with some reference data that was believed to reflect the correct LULC classes accurately. The overall accuracy was measured by counting the number of pixels classified consistently in the satellite image and on the ground and dividing this by the total number of sample pixels in each class (Congalton & Green 2008). Accordingly, we obtained an overall classification accuracy of at least 90% for the reference years of 1986, 2000, and 2016 which is adequate to continue the classification process.

A post-classification comparison (PCC) was done to refine previously classified images using ArcMap 10.3.1 software[R] (Jensen 1996; Lu et al. 2004). This was done by comparison of independently produced classified images, by properly coding the classification results of time 1 and time 2, from which a change map that indicates a complete matrix of change was produced (Singh 1989). Actual change was obtained by a direct comparison between the classified image from time 1 with that obtained for time 2 and results described by LULCC in a hectare and percentage. The percentage change of a given LULC type between two periods was calculated by using a general equation as in (1).

$$\Delta Lj = \frac{C_{+j} - C_{j+}}{C_{j+}} \times 100\% \quad (1)$$

where ΔL_j is the change (%) for a single LULC type; C_{+j} is the column total of grid cells for category j; and C_{j+} is the row total of grid cells for category j.

Farmers' perception of LULCC drivers is determined by household socioeconomic characteristics (e.g. level of education, age, gender, size of family, land holding size, income, policy and institutional change or access to market and infrastructure), which were collected during a household survey. The major socioeconomic determinants of farmers' perception to less perceived LULCC drivers were identified by applying a Binary Logistic Regression analysis method at the household level using SPSS statistical package, version 22. The perception of a particular LULCC driver as a driver is a dependent (response) variable whose response is expected to be binary (i.e. yes/no) in this study. On the other hand, household socioeconomic characteristics are the independent (explanatory) variables expressed by a mixture of discrete and continuous variables (Kindu et al. 2015; Lesschen et al. 2005). Hence, to examine the relationship between the perceptions (responses) and the different socioeconomic (explanatory) variables, a binary logistic regression method is a preferable statistical method when the response variable is binary (Kindu et al. 2015; Nzunda et al. 2013).

The logistic regression function at a household level, which estimates the probability of the independent variables on the dependent variable, is given by (2) as in Kindu et al. (2015) and Lesschen et al. (2005).

$$\text{Logit}(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \ldots + \beta_n X_n \quad (2)$$

where Y is the response variable implying the probability that Y = 1; α is the interception; $\beta_1 \ldots \beta_n$ is the coefficients of the associated explanatory variables, and $X_1 \ldots X_n$ is the explanatory variables.

Results and Discussion

COMPARISON OF PERCEIVED AND OBSERVED LAND USE-LAND COVER CHANGES

The results indicated that rural farmers of the study area are well aware of and have a good perception of historic LULCC (Table 1). Majority of the respondents perceived that they observed significant changes in LULC during last three decades. For instance, more than 90% of interviewee perceived that they observed the decline in both dense and scattered acacia woodlands, grasslands and water body; and observed an increase in the cultivated land over the last three decades. In addition, about 89% of respondents witnessed an increase in the bare land, whereas only very few respondents perceived no change for acacia woodlands, water body, and barren lands during the same period.

In line to households' perceived results, observed result of LULCC analysis using satellite imagery and GIS processing confirmed similar change trends except for the trend of few LULC classes. Figure 2 shows the spatiotemporal pattern of LULCC for 1986, 2000 and 2016 while Table 2 and Figure 3 summarize the LULC proportion and the change trends for each class and study period. Waterbody covered the largest area proportion of the landscape during all the study periods while scattered acacia woodland, which was the second in terms of area proportion in both 1986 and 2000, declined by about half of its area percentage in 2016 (11%). On the other hand, grazing land which was only 11% in 1986, has shown a substantial increment and took the second position in terms of area percentage in 2016 (25%). The variation in view of farmers from that of the image-derived observed trend for grazing land (Table 1) could be due to the fact that farmers usually perceive the trend from their own holding size decrease for grazing land (at the household level), while the observed image analysis result quantifies the change at the landscape level. For instance, farmers did not consider the area added to grazing land as a result of ecological succession along water retreat areas of Lake Abijata shore (Bekele et al. 2018).

LULC classes in the study area have experienced significant net gains and losses at the landscape level during the study period. For instance, during the first phase of the study period (1986-2000), agricultural land and dense acacia woodland have increased by 39% and 23%, whereas bare land and bush/shrub land have declined by 39% and 27%, respectively. On the other hand, during the second phase of the study period (2000-2016), grazing land and bare land have increased by 164% and 121%, whereas scattered acacia woodland, bush/shrubland, and dense acacia woodland have declined by 54%, 32%, and 27%, respectively. Bush/shrub land, swampy/marshy land and water body have declined, whereas agricultural land has increased throughout both study periods. Agricultural land had increased with a substantial rate until 2000, after which it showed only slight increment. This is simply due to the absence of more woodlands/bush lands for conversion

TABLE 1. Farmers' LULCC perception in CRV of Ethiopia (n=297)

Perception category	Respondents (%)				
	Dense/scattered acacia woodland	Grass/grazing land	Agricultural land	Waterbody	Bare land
Increase	0.00	6.00	96.80	0.00	88.89
Decrease	95.60	94.00	3.20	90.20	7.07
No change	4.40	0.00	0.00	9.80	4.04

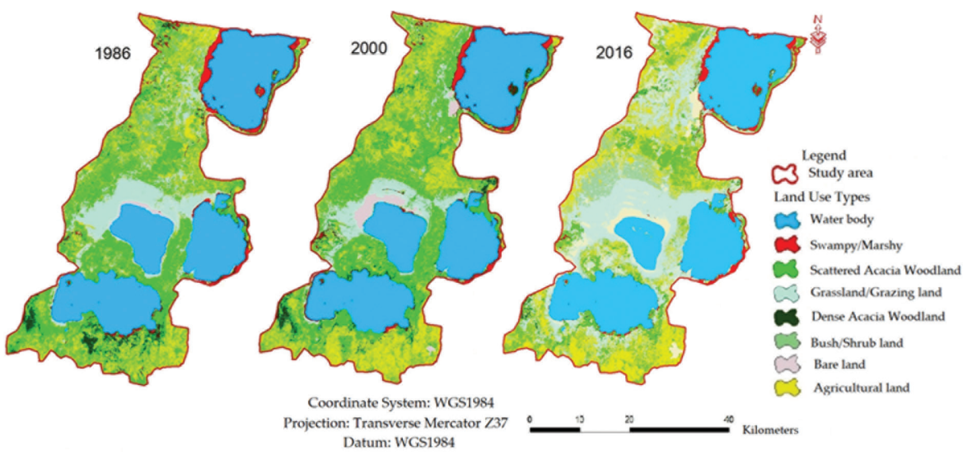

FIGURE 2. Land use-land cover maps for 1986, 2000 and 2016

TABLE 2. LULC distribution and changes (area, ha and %) in CRV of Ethiopia

LULC class	1986		2000		2016		LULC change (%)		
	ha	%	ha	%	ha	%	1986-2000	2000-2016	1986-2016
Agricultural land	45005.5	13.9	62740.2	19.4	64085.9	19.9	+39.4	+2.1	+42.4
Scattered acacia wood land	73838.3	22.9	77351.7	24.0	35759.9	11.1	+4.8	-53.8	-51.6
Bare land	12246.2	3.8	7428.1	2.3	16414.2	5.1	-39.3	+121.0	+34.0
Bush/Shrub land	38428.5	11.9	28073.7	8.7	19117.5	5.9	-26.9	-31.9	-50.3
Dense acacia woodland	7997.1	2.5	9870.5	3.1	7197.1	2.2	+23.4	-27.1	-10.0
Grass /Grazing land	35693.8	11.1	30335.8	9.4	80106.7	24.8	-15.0	+164.1	+124.4
Swampy/Marshy land	9647.9	3.0	7671.1	2.4	6668.6	2.1	-20.5	-13.1	-30.9
Water body	99981.7	31.0	99367.9	30.8	93489.1	29.0	-0.6	-5.9	-6.5
Total	322839.0	100.0	322839.0	100.0	322839.0	100.0			

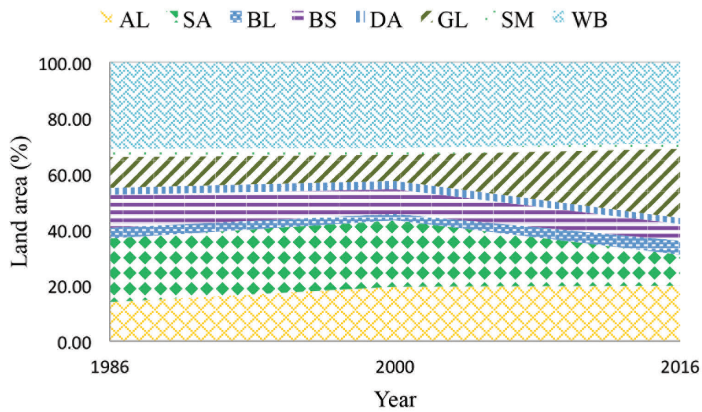

FIGURE 3. Trends in LULC classes of the study area from 1986-2016 (area in %): Years in the horizontal axis indicates maps used to construct this timeline. AL=agricultural land, SA=scattered acacia woodland, BL=bare land, BS=bush/shrub land, DA=dense acacia woodland, GL=grass/grazing land, SM=swampy/marshy land, and WB=water body

to continue the process of cropland expansion. During the overall study period (1986-2016), grass/grazing land, agricultural land, and bare land have increased by 124%, 42% and 34%, whereas scattered acacia woodland, bush/shrubland, and swampy/marshy land have declined by 52%, 50%, and 31%, in that order. This indicates grazing land experienced the highest area gain, whereas scattered acacia woodland experienced the highest area loss during the study period.

Table 3 shows the spatiotemporal change matrix (from-to) occurred for each LULC class at the class level. During the overall study period, grazing land mainly gained from scattered acacia woodland (7%) and agricultural land (3%) while agricultural land mainly gained from scattered acacia woodland (6%) and bush/shrubland (5%). This indicates both agricultural land and grazing land expansion mainly targeted the acacia woodland of the region for their gains. The increase in barren land was mainly due to gain from lake retreat areas and degradation of scattered acacia woodland and grazing land. On the other hand, during the same period, scattered acacia woodland mainly loses to grazing land (7%) and agricultural land (6%) while the decline in bush/shrubland was mainly due to its loss to agricultural land (5%) and grazing land (3%). Swampy/marshy land also has lost the most considerable portion of its area to grazing land during this period.

In agreement with the results of this study, earlier studies in the region (Ariti et al. 2015; Biazin & Sterk 2013; Garedew et al. 2009; Kindu et al. 2013; Meshesha et al. 2012; Temesgen et al. 2013) and studies elsewhere in the country (Hailemariam et al. 2016; Reid et al. 2000; Tefera 2011; Zeleke & Hurni 2001; Zewdie & Csaplovics 2016) also particularly indicated a decline in the acacia woodlands/forests and an increase in agricultural land in recent decades. The gain in agricultural land is mainly associated with the continual expansion of cropland with population growth, as population growth is the primary driver of LULCC in developing countries (Ariti et al. 2015; Braimoh 2006; Garedew et al. 2009; Meshesha et al. 2012). Similarly, the loss in acacia woodland and shrubland in the region is most likely due to continual deforestation for cropland expansion, charcoal making, and wood extraction and partly due to recent investment expansion in the region (Bekele et al. 2018; Molla 2015; Temesgen et al. 2013). On the other hand, the gain in grazing land is mainly due to land transition from lake retreat areas around the shore of Lake Abijata, that gradually shifted to grass/grazing land through ecological succession (Biazin & Sterk 2013;

TABLE 3. LULCC matrix for three LULC maps (1986, 2000 and 2016) (area in %)

1986	2000							
	AL	SA	BL	BS	DA	GL	SM	WB
Agricultural land (AL)	6.75	3.90	0.16	2.05	0.10	0.96	0.01	0.00
Scattered acacia wood land (SA)	4.73	11.58	0.22	3.34	1.53	1.37	0.10	0.00
Bare land (BL)	0.78	0.91	0.43	0.37	0.08	1.13	0.09	0.01
Bush/Shrub land (BS)	5.55	3.75	0.20	1.88	0.09	0.43	0.01	0.00
Dense acacia woodland (DA)	0.28	0.61	0.02	0.57	0.85	0.01	0.14	0.00
Grass/Grazing land (GL)	1.25	2.87	1.25	0.22	0.03	5.42	0.02	0.01
Swampy/Marshy land (SM)	0.08	0.33	0.03	0.26	0.38	0.07	1.73	0.10
Water body (WB)	0.00	0.02	0.00	0.00	0.01	0.00	0.28	30.66
2000	**2016**							
	AL	SA	BL	BS	DA	GL	SM	WB
Agricultural land (AL)	9.52	3.30	0.78	1.83	0.12	3.87	0.02	0.00
Scattered acacia woodland (SA)	5.68	4.48	1.00	3.18	0.69	8.64	0.27	0.01
Bare land (BL)	0.06	0.03	0.69	0.00	0.01	1.51	0.00	0.00
Bush/Shrub land (BS)	3.37	2.11	0.16	0.41	0.28	2.32	0.03	0.00
Dense acacia woodland (DA)	0.30	0.79	0.11	0.03	0.92	0.67	0.23	0.00
Grass/Grazing land (GL)	0.86	0.23	1.06	0.47	0.04	6.73	0.01	0.00
Swampy/Marshy land (SM)	0.05	0.13	0.11	0.00	0.15	0.39	1.35	0.18
Water body (WB)	0.00	0.01	1.17	0.00	0.01	0.69	0.14	28.76
1986	**2016**							
	AL	SA	BL	BS	DA	GL	SM	WB
Agricultural land (AL)	6.15	2.42	0.62	1.20	0.17	3.35	0.03	0.00
Scattered acacia woodland (SA)	6.26	5.15	0.97	2.55	1.06	6.69	0.20	0.00
Bare land (BL)	0.56	0.28	0.59	0.08	0.04	2.21	0.04	0.00
Bush/Shrub land (BS)	5.05	1.97	0.58	1.20	0.13	2.94	0.03	0.00
Dense acacia woodland (DA)	0.63	0.55	0.06	0.05	0.50	0.56	0.12	0.00
Grass/Grazing land (GL)	1.03	0.43	0.96	0.82	0.04	7.76	0.02	0.00
Swampy/Marshy land (SM)	0.17	0.26	0.09	0.01	0.28	0.57	1.44	0.16
Water body (WB)	0.00	0.01	1.22	0.00	0.02	0.74	0.18	28.80

Temesgen et al. 2013). The other probable reason for the increase in grazing land could be land degradation and shift from acacia woodlands due to pressure from common free overgrazing (Meshesha et al. 2012), charcoal making and wood extraction (Garedew et al. 2009) in CRV and other parts of the country. Additionally, fallow and abandon croplands were classified as grazing land which also contributed to its area gain.

LAND USE-LAND COVER CHANGE DRIVERS

Based on farmers' perception, experts' opinion and personal field verification, a wide range of influential drivers contributed to a triggered LULCC, were identified in the study area. These drivers are well recognized by the majority of the rural farmers of the study area. As elaborated by Geist and Lambin (2002, 2001), these drivers fall within the broader classes of social, economic, environmental, policy/institutional and technological factors. Accordingly, population growth, fuelwood extraction and charcoal making, agricultural land expansion, recurrent drought, and overgrazing are the topmost perceived, and significant drivers of LULCC identified in the CRV of Ethiopia (Figure 4).

POPULATION GROWTH

About 95% of respondent farmers mentioned high population growth as the main underlying (root) driving force of LULCC in CRV (Figure 4). Projected population data of 1986, 2000 and 2016 for two districts in the study area, namely Arsi Negele and Adami Tulu-Jido Kombolcha, also indicated that there had been a sharp growth in population over the last three decades (Figure 5). The population has

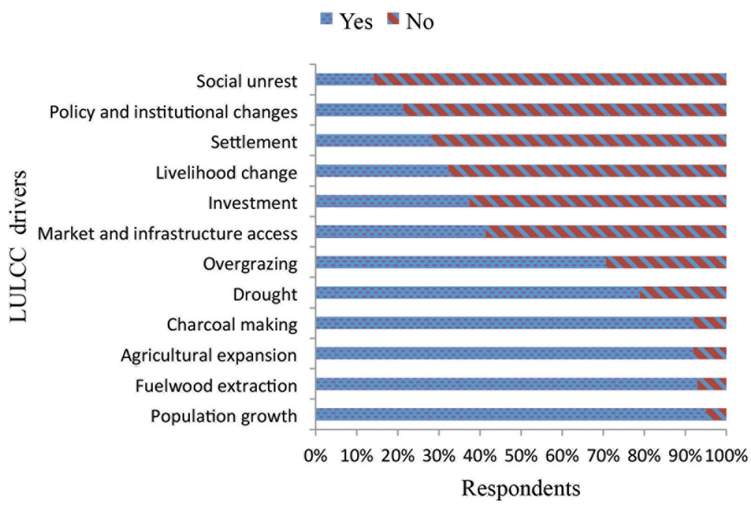

FIGURE 4. LULCC drivers as perceived by rural households (%) in CRV of Ethiopia (n=297)

increased by more than 235% of its figure in 1986 with an average annual growth rate of 3% (CSA 2007, 1994). This indicates that the population of the study area has been increased by more than three-fold during the last three decades. The other study by Meshesha et al. (2012) also pointed out that in 2008, the population in CRV has increased by about 4.5 times its value in 1965. As per the information obtained from District administrative officials, due to such high population growth and hence high unemployment rate, rural-urban migration is currently very high in the region. It is obvious that population growth as the underlying force can directly or indirectly accelerate the action of other drivers on LULC (Geist et al. 2006).

Ethiopia ranks second in the size of the population in the African continent next to Nigeria, with a projected population of more than 93 million in 2017 and an annual growth rate of 2.26% (CSA 2007). The rapid population growth, particularly in the study region, might be partly due to the polygamous cultural tradition of the farming community of the area (Biazin & Sterk 2013; Garedew et al. 2009; Kindu et al. 2015). In addition, despite an effort made by the Ministry of Health to encourage family planning in the country, the family size per household remained high, particularly in rural areas.

FUELWOOD EXTRACTION AND CHARCOAL MAKING

Next to population growth, fuelwood extraction and charcoal making are the major proximate causes of LULCC which were perceived by about 93% and 92% of respondents respectively (Figure 4). Key informants (elders) and focus groups also mentioned that access to electricity is almost none in the rural area, and hence as a result of this charcoal making and fuelwood extraction are the key factors contributed to the depletion of acacia woodland forests of the region, which was otherwise the dominant land cover class thirty years ago.

Coupled with the lack of access to alternative energy sources, for example, rural electrification, fuelwood extraction and charcoal making are the potential drivers of LULCC in Ethiopia. Studies show that as of 2010, about 89% of energy source in the country dependents on biomass-based sources mainly firewood, charcoal, crop residue, and cow dung (Damte et al. 2012; Girma 2016). According to

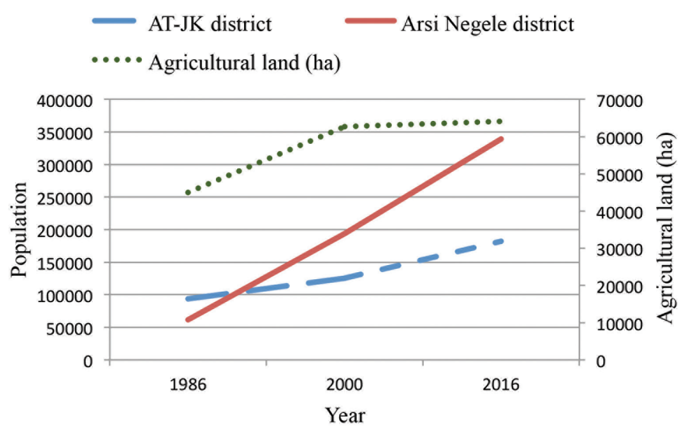

FIGURE 5. Population and agricultural land trend (1986-2016) in CRV: AT-JK= Adami Tulu-Jido Kombolcha District

Meshesha et al. (2012), biomass-based energy consumption has increased by about 81% from 1975 to 2000 in CRV following population growth. Charcoal making is further favored by the proximity and accessibility of the CRV to big charcoal market centers like Addis Ababa and other regional towns like Adama, Shashamane, and Hawassa. In addition, due to its high calorific value, the acacia trees are the most chosen trees for charcoal production in Ethiopia (Bahru et al. 2012) and Kenya (Oduor et al. 2012). Furthermore, due to recurrent drought and hence low income and food insecurity problem in recent years, rural farmers of the study area use charcoal and firewood market as a substitute source of income, which is taken as the adaptation mechanism to overcome such critical periods (Kindu et al. 2015). Previous studies in Ethiopia also mentioned charcoal making and fuelwood extraction as a key factors for the decline of acacia woodlands in the country (Ariti et al. 2015; Garedew et al. 2009; Molla 2015; Zewdie & Csaplovics 2016), whereas study in West Africa pointed timber logging as the main proximate cause for woodland decline in Ghana (Braimoh 2006), which is inconsistent with our result.

AGRICULTURAL LAND EXPANSION

According to information from households (92%), focus groups and key informants, an increase in population from time to time has led to reduced rural farmland holding size and subsistent farming. This, in turn, led to subsequent agricultural land expansion to feed the ever-growing demand for more cultivable lands, which is another driver of LULCC (Figure 4). Parallel to population growth, the other probable reason contributing for agricultural land expansion is that recently the CRV lakes region has been taken as one of the key potential agricultural investment zones by the Ethiopian government due to its proximity to Addis Ababa and accessible lake water resources for irrigation. This can be evidenced by the fast growth of small-holder and large-scale mechanized (horticulture and floriculture) irrigated farms around the CRV lakes (de Putter et al. 2012; Hengsdijk & Jansen 2006; Jansen et al. 2007). Such expansion in agricultural investment is partly driven by global market forces and subsequent government policy changes to attract foreign direct investment. Previous studies also mentioned population growth and subsequent agricultural land expansion as a major driver of rapid LULC dynamics in Ethiopia (Bewket & Abebe 2013; Dessie & Kleman 2007; Temesgen et al. 2018). Other studies in developing countries, where the economy is directly dependent on natural resource, similarly reported population growth and resultant cropland expansion as important drivers of LULCC (Ahmed et al. 2016; Braimoh 2006; Messina et al. 2014).

DROUGHT-VULNERABILITY AND OVERGRAZING

Recurrent drought occurrence and overgrazing are the other factors perceived by about 79% and 71% of respondent farmers respectively as immediate causes of LULCC (Figure 4). Key informants and focus groups also mentioned that they observed an increase in diurnal temperature and a more erratic rainfall distribution (late onset, early set-off, frequent dry spells and unusual floods due to increased intensity in few periods) in recent ten years. Cumulative rainfall distribution for the growing season (June to September) at Ziway Meteorological Station also indicates that there existed a high inter-annual variation (180-680mm) during the recent ten years (2007-2016) (Figure 6).

It is known that human-induced LULCC, particularly intensive agriculture, plays a significant role in influencing regional climate change. By reverse, climate change governs agricultural land use practice besides socioeconomic drivers (Ahmed et al. 2016; Reid et al. 2000). For example, studies show that climate change plays a significant role in driving LULCC in the Eastern Horn of Africa (Few et al. 2015) in general and in the CRV region of Ethiopia (Biazin & Sterk 2013) in particular. The CRV is one of the drought-

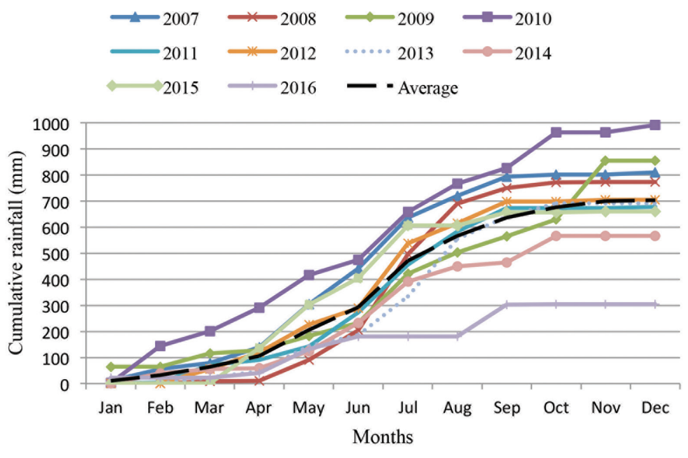

FIGURE 6. Cumulative rainfall for recent ten years (2007-2016) at Ziway Meteorological Station (Source: National Meteorological Agency)

vulnerable areas in the country (Jansen et al. 2007). The detailed study about how climate change vulnerability could affect farmers' historical land use change will be considered by the forthcoming paper by the authors.

Overgrazing is the other important forcing driver of LULCC especially contributing to land degradation, expansion of bare lands and drying of swampy areas and water bodies in the study area (Meshesha et al. 2012; Muzein 2006). For example, according to Meshesha et al. (2012), the number and density of livestock in CRV has increased by about 22 fold in 2008 from its value in 1965. Overgrazing which refers to grazing of land beyond its carrying capacity can affect the land by both deteriorating soil physical structures and by removing vegetation coverage which exposes the soil to erosion and excessive drying and expands barren lands (Azarnivand et al. 2010). In Ethiopia, the long-lived tradition of free-grazing in almost all parts of the country coupled with a huge number of cattle especially in pastoral and agropastoral areas remains the main potential cause of massive land degradation in the country.

POLICY AND INSTITUTIONAL CHANGES AND ACCESS TO MARKET AND INFRASTRUCTURES

Social unrest, policy and institutional changes, settlement, livelihood change, investment expansion, and access to market and infrastructure are the drivers of LULCC less perceived by respondent farmers (Figure 4). The logistic regression for selected less perceived drivers (policy and institutional change and access to market and infrastructure) at the household level is given in Table 4. There are seven determinant socioeconomic (explanatory) variables used in the analysis. Unfortunately, only level of education (p=0.04) and age (p=0.001) of the respondent (household head) positively and significantly affected the low perception of inhabitants on policy and institutional change as a driver of LULCC (Table 4(a)). Similarly, respondents' less perception of market and infrastructure access as a driver of LUCC was affected significantly (p=0.001) and positively by both education level and age of the farmer (Table 4(b)). This implies uneducated and younger farmers are less conscious about market access and institutional change as drivers of LULCC than either educated or older farmers. All the remaining socioeconomic variables namely: gender, number of families, size of land holding, income, and distance to nearest market center didn't significantly affect farmers' awareness towards both institutional and policy change, and market and infrastructure access as a driver of LULCC.

Though less perceived by interviewee farmers, studies show that policy and institutional changes (Biazin & Sterk 2013; Hassen & Assen 2018), settlement, access to market and infrastructure (Kindu et al. 2015), livelihood change, and investment expansion (Temesgen et al. 2018) are also other important drivers of LULCC in Ethiopia. For instance, the 1974 government change has followed by radical land use policy reforms in Ethiopian history in which land held by the monarchic system for centuries had been handed over

TABLE 4. Logistic regression results at household level for less perceived drivers (n=297): (a) Institutional and policy change, and (b) market and infrastructure access in CRV

Independent variables	**β**	S.E.	Wald	df	Sig.	Exp(**β**)	95% C.I. for Exp(**β**)	
							Lower	Upper
(a) Institutional and policy change as a driver								
Sex	-1.83	1.14	0.00	1.00	0.99	0.16	0.00	18.11
Age	0.28**	0.07	15.52	1.00	0.00	1.32	1.15	1.52
Education level	0.18*	0.09	3.73	1.00	0.04	0.83	0.69	1.00
Family size	-0.39	0.34	1.38	1.00	0.24	0.67	0.35	1.30
Land holding size	2.12	1.92	1.22	1.00	0.27	0.12	0.00	5.17
Income	0.44	0.41	1.18	1.00	0.28	1.56	0.70	3.47
Distance to nearest market	0.40	0.47	0.70	1.00	0.40	1.49	0.59	3.75
Constant	-2.14*	2.80	1.26	1.00	0.03	0.00		
R^2	0.49							
(b) Market and infrastructure access as a driver								
Sex	-0.01	1.24	0.00	1.00	0.99	1.01	0.09	11.60
Age	0.09**	0.03	11.10	1.00	0.00	0.91	0.87	0.96
Education level	0.61**	0.12	25.89	1.00	0.00	1.84	1.46	2.33
Family size	-0.13	0.12	1.36	1.00	0.24	0.87	0.70	1.10
Land holding size	0.11	0.22	0.24	1.00	0.63	1.11	0.73	1.70
Income	0.01	0.01	0.29	1.00	0.59	0.99	0.97	1.02
Distance to nearest market	0.03	0.06	0.26	1.00	0.61	1.03	0.91	1.17
Constant	-2.55*	1.92	1.77	1.00	0.04	.078		
R^2	0.42							

β = coefficient of explanatory variable, S.E. = standard error, df = degree of freedom, C.I. = confidence interval, R^2 statistically significant at $^*p$<0.05 and $^{**}p$<0.001. ROC (relative operation curve) = 83.8 % (a) and 89.9% (b) to peasants ('land to tillers') through 1975 proclamation for the first time in Ethiopian (Nega et al. 2003). This was followed by massive settlement (villagization) program in 1979 which in turn led to extensive clearance of previously natural forest covered areas and subsequent expansion of plantation forest and cultivated land in the country (Nega et al. 2003). The next government change in 1991 was also followed by subsequent policy changes that favored significant investment and infrastructural expansion in the country which also further accelerated LULCC (Nega et al. 2003).

CONCLUSION

This study tried to integrate Remote Sensing, GIS, climate data and socioeconomic survey to investigate LULC dynamics and its drivers in CRV of Ethiopia for the last three decades. Based on the results, it can be concluded that a rapid LULCC has occurred in the region. This change was driven by the interplay of socioeconomic, policy/institutional and natural factors like climate change. Majority of interviewee farmers also witnessed that they observed significant changes in LULC during last three decades. Accordingly, respondents have perceived the decline in both dense and scattered acacia woodlands, grazing land and water body; and observed an increase in agricultural land and bare lands during their life. This perceived result is in line with the observed result of satellite image analysis. Population growth is found to be the root (underlying) driving force behind rapid LULCC in CRV. Population growth also directly affected the driving effect of other factors. Next, fuelwood extraction, agricultural expansion, charcoal making, recurrent drought, and overgrazing are the top most influential drivers in their decreasing order of percentage of perceived farmers. This indicates that climate change/drought becomes one of the potential drivers of LULCC in climate change vulnerable regions like East Africa in recent decades.

In general, LULCC continued a major environmental and livelihood challenge in East Africa. These rapid LULC dynamics are driven by continued population growth as a root driving force. Hence, future land use policies at local, national and regional level need to consider such driving forces, particularly population growth, into account in order to maintain the fragile landscapes of the CRV while devising alternative household income generating sectors, for instance, improving access to off-farm employment opportunities. Besides, climate change vulnerability plays a significant role in shaping farmers' historical land use change and hence, it is important to devise strategies that strengthen the adaptation capacity of farmers.

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