Remote Sensing based multi-temporal land cover classification and change detection in northwestern Ethiopia

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Abstract
Spatiotemporal change analysis of semiarid regions is vital for understanding major threats to the ecosystem. This study examines land use and land cover (LULC) changes using multitemporal satellite imagery for the period 1972–2010. Supervised classification algorithm using support vector machines (SVM) was employed to monitor LULC transformations. A cross-tabulation matrix was used to assess the total change of land categories based on net change and swap change. The major land use change in this dynamic region were conversion of about 52 % woodlands to intensive land uses such as cropland in the period 1972 - 2010. The net change of woodland accounts for over 61 % and net-gain of cropland and grassland were about 53 % and 9 % respectively. Based on the socio-ecological field survey expansion of croplands, population pressure as well as overharvesting of trees, respectively, are major drivers of change. This significant change in land use is mainly due to accelerated human impact and subsequent agricultural land expansion. The result of this study provides a vital monitoring basis for continuous investigations of changes in the natural vegetation of semiarid environments.

Keywords: Semi-arid, Landsat Imagery, support vector machines (SVM), persistence, net change, swap change.

Introduction
Forests, grasslands and woodlands have been lost worldwide with conversion to cropland [Lambin et al., 2003; Slayback et al., 2003; Kindu et al., 2013] which significantly disrupts the natural vegetation of the ecosystem. Human activities are considered as the main driving forces for affecting and changing ecological ecosystems [Vitousek, 1994], understanding these changes would help for monitoring ecosystem responses to environmental change [Wang et al., 2009]. Studies of land use and land cover (LULC) change dynamics and the identification of respective driving forces have played a significant role in research into global environmental changes [Lambin et al., 1999; Huang et al., 2008]. In addition, LULC change investigations identify and describe the process of environmental changes and drivers of change that contribute in hindering sustainable development. These changes
have induced a broad scale of impacts on critical environmental processes including energy balance, water cycle, and biogeochemical processes [Heistermann et al., 2006; Huang et al., 2008]. The change in environment is attributed to population growth, economic development, trade and migration among the socioeconomic factors, which contribute to land use changes [Goklany, 1996]. Consequently, significant change in natural systems has resulted in the deterioration of ecosystems and increase of negative patterns of air quality [Pielke et al., 2002; Kalnay and Cai, 2003; Opdam and Wascher, 2004]. Changes in the environment are affecting the functioning of ecosystems, which subsequently leads to increased emission of greenhouse gases from soils, such as CO$_2$ and methane [IPCC, 2007]. Analysis of earth observation data has increased understanding of these change processes that serves to solicit solutions of respective social, economic and environmental problems [Lu et al., 2004]. Surveys solely based on fieldwork make land use mapping time consuming, labor intensive, costly and do not allow neither for full-coverage nor for a periodical monitoring of dynamic changes of the environment in suitable time intervals. Moreover, land use maps produced from such surveys become outdated and are of reduced efficiency in the face of increasing dynamics of changes of the environment. The availability of satellite imagery has enabled to better understand and address continuous LULC change processes over time. Satellite imagery has the potential for providing spatial and temporal consistent data for studies on monitoring changes in atmospheric, oceanic, forest fragmentation, landscapes changes and other types of land use transitions [Fichera et al., 2012; Carranza et al., 2014]. The Landsat series of satellites are among the longest continuous record of satellite-based earth observation, which significantly supports the monitoring of environmental changes [Chander et al., 2009]. Various studies demonstrate the capability of Landsat imagery for monitoring long term environmental changes in dry lands [Qin et al., 2006; Karnieli et al., 2008; Abd El-Kawy et al., 2011; Vanderpost et al., 2011]. LULC change assessment illustrates modifications in the condition of important features over time [Singh, 1989; Yeh et al., 1996]. It evaluates the extent of changes in land degradation and desertification [Adamo and Crews-Meyer, 2006; Gao and Liu, 2010], in deforestation [Renó et al., 2011], in habitat fragmentation as well as biodiversity loss [Lung et al., 2012; Carranza et al., 2014] and urban expansion [Fichera et al., 2012; Mertes et al., 2015] for better understanding and sustainable environmental management. Despite their significant contribution to both economic and ecological services, dry forests are currently under severe threats both from anthropogenic and natural calamities [Lemenih et al., 2012; Carranza et al., 2014]. Agriculture, resettlements expansion, fire, population growth and climatic variation are among the factors that significantly contributing to the decline in size and fragmentation of the dry forests [Eshete et al., 2005; Lemenih et al., 2012]. Several of these studies attempted to link the loss in dry forests with human activities but lacks in estimating the spatial extent of the declining woody resources and the major driving forces. In addition, the extent and severity of land use transition on the ecosystem of the surrounding arid environment is not well studied. During some periods of the high dry seasons, there is cloud of haze on the borders of Sudan and northwestern Ethiopia which may be rooted from the degradation of the natural wood vegetation of the region. The present study assessed land cover transition using SVM classification algorithms and relate them to major contributing factors that influence land cover transitions. The SVM classification model works well in spectrally complex land cover categories for better classification results [Tuia and Camps-Valls, 2011] and understanding of the significant
transitions in land cover. In this study multitemporal Landsat imagery covering the period of 1972-2010 were used to quantify dynamics in land degradation and comprehensive statistical assessment in a semiarid landscape using SVM classification algorithms.

**Study area**
The study area is located in semi-arid agro-climatic zone with a geographical location between 13°40’ N and 14°20’ N latitude and 36°27’ E and 37°32’ E longitude (Fig. 1). It covers an area of about 6,200 km² with an altitudinal range of 537 m to 1865 m above sea level. The average minimum annual temperature ranges between 22 °C to 28.7 °C while the mean maximum temperature ranges between 33 °C to 41.7 °C. Daytime temperatures are very high during the months of March to May with more than 44 °C. Mean annual rainfall ranges from about 450 mm to around 1100 mm (Fig. 2). The population of Kaftahumera has grown significantly from 48,690 in 1994 to over 110,000 in 2014 more than double in a period of two decades [CSA, 2014]. The woody vegetation of northwest Ethiopia is characterized by the association of Combretum-Terminalia and Acacia-Commiphora woodlands [WBISPP, 2004; Eshete et al., 2011] of which *B. papyrifera* is the most abundant tree species within the Combretum–Terminalia woodland. The current study area is a corridor of the Sudano-Sahelian Zone, which is known for its recurrent drought, high dust movement and low rainfall [Middleton, 1985].

![Figure 1 - Geographic location of the study area.](image-url)
Methods

Data

Landsat imagery

LULC change assessment and analysis are based on multitemporal cloud free Landsat imagery obtained on 29 November 1972, 29 November 1984, 29 November 2000 and 9 December 2010 (Tab. 1). Landsat imagery used for this study was acquired during the dry season and is freely available via the Landsat data archive of the United States Geological Survey (USGS: http://glovis.usgs.gov). These dates were selected based on some policy changes and availability of imagery.

Figure 2 - Climate graph of Kaftahumera, Ethiopia (Source: Ethiopian Institute of Agricultural Research, 2000 and National Meteorology Agency of Ethiopia, 2010).

Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM)

Digital elevation data of the SRTM DEM were obtained from http://earthexplorer.usgs.gov with a spatial resolution of 90 m and was used for the classification of geomorphological terrain features of Kaftahumera. SRTM provides digital elevation data with a near global coverage thus representing the most comprehensive high-resolution digital topographic database on a global level. The SRTM DEM data were transformed from geographic coordinates to Cartesian coordinates of the UTM projection system. DEM data were geometrically rectified to the UTM coordinate zone 37 North, Spheroid Clarke 1880, Datum Adindan. The 90 m resolution DEM data were resampled to 30 m pixels using a nearest neighbor algorithm. All DEM raster cells of Kaftahumera were classified into five elevation ranges (537-750 m, 750-1000 m, 1000-1250 m, 1250-1500 m and 1500-1865 m) in order to assess the magnitude of land use transitions in relation to elevation differences.
Landsat imagery pre-processing

The imagery was processed using Environment for Visualizing Images (ENVI version 4.8) and ArcGIS 10 software packages. Due to the availability of reference data in 2000, Landsat TM 2000 image was geometrically rectified to the UTM coordinate zone 37 North, Spheroid Clarke 1880, Datum Adindan, using control points collected from topographic maps of the study area. An image to image registration was applied between MSS 1972, TM 1984 and TM 2010 imagery based on the TM 2000 reference image using the nearest neighbor algorithm. The root mean square error (RMSE) amounts between 0.3 to 0.5 pixels. All the four bands of MSS as well as bands 1-5 and 7 of TM imagery were used for extracting biophysical features. 450 stratified random reference samples and their attributes were collected in the field using handheld Garmin Oregon 450 GPS for ground-truthing and for accuracy assessment of classified imagery. Radiometric calibration and atmospheric correction were carried out to correct for changes in scene illumination, atmospheric and solar condition, viewing geometry, and instrument response characteristics [Pons and Solé-Sugrañes, 1994; Chander et al., 2009]. The calibration of Landsat imagery was performed based on the known solar geometry, and on the gain and bias values provided by the Landsat metadata. Five land cover classes were identified for classification and change detection assessment (Tab. 2).

Table 1 - Data used for land use/land cover change analysis.

| Imagery      | Path/row      | Acquisition date   |
|--------------|---------------|--------------------|
| Landsat MSS  | 183/50,183/51 | 29 November 1972  |
| Landsat TM   | 170/50,170/51 | 29 November 1984  |
| Landsat TM   | 170/50,170/51 | 29 November 2000  |
| Landsat TM   | 170/50,170/51 | 9 December 2010   |
| Topographic map | 1:50,000    | 1979               |

Image Classification

A multi-temporal classification approach using support vector machines (SVM) algorithm was used for mapping and land use transition assessment. SVM is a supervised classification method derived from statistical learning theory [Foody and Mathur, 2004]. SVM fit a linear hyperplane between two classes in a multi-dimensional feature space by maximizing the margin between training samples of the two classes [Foody and Mathur, 2004]. It separates the classes based on the optimal hyperplane, which maximizes the margin between the classes. SVM use kernel functions to transform training data into a higher dimensional feature space where linear separation is possible [Huang et al., 2002]. SVM implement the structural risk minimization principle, which attempts to minimize an upper bound on the generalization of error by striking a right balance between the training error and the capacity of the machine [Tripathi et al., 2006]. The risk of misclassification is minimized by maximizing the margin between the data points...
and the decision boundary.

Among the SVM kernels, the Gaussian radial basis function kernel (RBF) was selected for mapping and change detection assessment. RBF kernel requires setting of two parameters, the optimum Gaussian radial basis function ($\gamma$) that controls the kernel width and the regularization parameter ($C$) which controls the penalty of misclassification errors in order to handle non-separable classification problems [Huang et al., 2008]. In this study, the Library for Support Vector Machines (LIBSVM) program developed by Chang and Lin [2001] was used for classification. The model was parameterized based on the training samples of each land use type. A cross validation test was applied combining $\gamma$ and $C$ to obtain optimum values of these parameters for best classification outputs. We used a “one-against-one” approach, in which each class was compared to every other class individually for multi-class SVM classifications [Melgani and Bruzzone, 2004]. A classification accuracy assessment was performed using stratified random sampling representing the five land use classes. A confusion matrix was developed relying to the comparison of selected samples of classified imagery with respective ground sampling. In this process overall accuracy, producer and user accuracies and kappa coefficient were calculated for the time series of classification results [Congalton, 1991].

### Table 2 - Land cover classification scheme.

| Land cover class | Description |
|------------------|-------------|
| Woodland         | Woody plants with a canopy cover of more than 10% |
| Cropland         | Crop fields, parklands, fallows |
| Grassland        | Pasture lands, grass with scattered trees |
| Residential      | Cities, villages, roads |
| Waters           | Rivers, lakes, reservoirs, streams |

### Change detection matrix

Change detection analysis entails finding the type, amount and location of land use changes over time [Yeh et al., 1996]. Among the change detection approaches, post-classification comparison (PCC) was used for this study to identify changes in land cover. PCC is frequently employed for comparing data from different sources and dates [Yuan et al., 2005; Mundia and Aniya, 2006]. This approach is supportive in determining “from-to” changes in order to identify the transformations among the land cover classes [Jensen, 2005; Yuan et al., 2005]. PCC identifies changes by comparing independently classified multi-date imagery on a pixel-by-pixel basis using a change detection matrix [Yuan and Elvidge, 1998]. Any low degree of success depends upon the reliability of image classification [Fuller et al., 2003]. In this study, change detection assessment was applied to individual image classification outputs of the best performing SVM model in order to identify respective two-date change trajectories: 1972-1984, 1984-2000 and 2000-2010. MSS imagery was downscaled to 30 m pixel cell size in order to
provide spatial compatibility with TM imagery before performing the change trajectory analysis.

The gain, loss, persistence, absolute value of net change, swap and total change were calculated for all the four classified imagery of each classes [Pontius et al., 2004; Braimoh, 2006]. Gain is the amount of a land use class i that added between time 1 and time 2 whereas loss is the amount of land use class j that is lost from time 1 to time 2. Persistence is the land use class that does not change from time 1 to time 2. Swap is the simultaneous loss and gain of a land use class in a landscape, which implied that a given area of a land use is lost at one location, while the same size is gained at a different location. Its analysis needs pairing each gained and lost pixels within a landscape [Braimoh, 2004; Pontius et al., 2004]. For a land use class j, amount of swap $s_j$ was calculated as:

\[ s_j = 2 \min(c_{j+} - c_{jj}, c_{+j} - c_{jj}) \]  \[1\]

where $s_j$ = amount of swap, $c_{j+}$ = Total column proportion of a land use class within the landscape, $c_{jj}$ = Persistence land use classes within the landscape, and $c_{+j}$ = Total row proportion of a land use class within the landscape.

The total change of a land use category was either the sum of the net change and the swap or the sum of the gains and losses. We also assessed the loss to persistence ratio ($l_p = \text{loss} / \text{persistence}$) which assesses the exposure of a land cover for a change, gain to persistence ratio ($g_p = \text{gain} / \text{persistence}$) which evaluates the gain of a land cover in comparison to its time 1 size, net change to persistence ratio ($n_p = \text{net change} / \text{persistence}$) [Braimoh, 2006].

**Socioeconomic data collection and analysis**

In order to understand LULC change dynamics, major drivers of changes were assessed using key informants. The key informants were identified from eight purposefully selected villages within the study area. Random sampling was used to select 78 households for individual interviews. A structured questionnaire was used for gathering socio-ecological information on specific land use transitions and main contributing factors. Descriptive statistics were employed to analyze the collected information.

**Results and discussion**

**Dynamics of LULC transition matrix**

Land cover classification based on Landsat imagery of 1972, 1984, 2000 and 2010 was assessed using an SVM supervised classification algorithm (Fig.3). The results showed the dynamics of spatial changes observed during a period of four decades. Confusion matrices were produced to signify class separation performance for 1972, 1984, 2000, and 2010 resulting in an overall accuracy of 84.4%, 92.0%, 90.6%, and 92.7% and Kappa values of 0.78, 0.90, 0.88, and 0.91 respectively. User’s and producer’s accuracies of individual classes also range from 70% to 100%.
Figure 3 - Land use and land cover (LULC) classification maps.

Table 3 presents the land cover transition matrix with the diagonals of each matrix indicating the proportion of land use classes that showed persistence from 1972 to 2010. The off-diagonal entries account for land uses that showed transitions from one category to other categories during the study period. Woodland, cropland and grassland are the dominant land use categories within the landscape during the study period. In 1972-1984, cropland occupied 13.05% of the landscape, expanding to the western part of the region. Woodlands are the major contributor (10.84%) to the newly emerging croplands. The decline in woodland is attributed to agricultural expansion and wood harvesting for charcoal and firewood. A socio-economic survey made by Lemenih et al. [2012] in one district of the northwestern arid region of Ethiopia has identified excessive wood harvesting and cropland expansion as the significant drivers of land use changes. During the period from 1984 to 2000, the cropland further expanded to 22.56% of the landscape. Woodland was the major contributor (14.60%) to the newly added cropland. During the period 2000 to 2010, the cropland area further stretched to 55.23% of the study region. Woodland is the major contributor (33.01%) for the newly emerged cropland. These significant increases in croplands contributed to major deforestation and woodland degradation coupled with rapid population growth and recurrent drought [Lemenih et al., 2012].
Table 3 - Land use/land cover transition matrices (%) (a) 1972 to 1984 (b) 1984 to 2000 (c) 2000 to 2010 and (d) 1972 to 2010.

| (a) 1972-1984 | Woodland | Cropland | Grassland | Water | Residential | Total 1972 | Loss  |
|-----------|----------|----------|-----------|-------|-------------|-----------|-------|
| Woodland  | 76.55    | 10.84    | 4.64      | 0.00  | 0.00        | 92.03     | 15.48 |
| Cropland  | 0.62     | 1.39     | 0.45      | 0.02  | 0.00        | 2.47      | 1.08  |
| Grassland | 2.74     | 0.80     | 1.85      | 0.01  | 0.00        | 5.40      | 3.55  |
| Water     | 0.00     | 0.02     | 0.01      | 0.06  | 0.00        | 0.09      | 0.03  |
| Residential| 0.00    | 0.00     | 0.00      | 0.00  | 0.00        | 0.00      | 0.00  |
| Total 1984| 79.91    | 13.05    | 6.94      | 0.09  | 0.00        | 100       | 20.14 |
| Gain      | 3.36     | 11.65    | 5.09      | 0.03  | 0.00        | 20.14     |       |

| (b) 1984-2000 | Woodland | Cropland | Grassland | Water | Residential | Total 1984 | Loss  |
|------------|----------|----------|-----------|-------|-------------|------------|-------|
| Woodland  | 59.91    | 14.60    | 5.38      | 0.01  | 0.00        | 79.91      | 20.00 |
| Cropland  | 4.86     | 7.53     | 0.65      | 0.00  | 0.00        | 13.05      | 5.52  |
| Grassland | 2.45     | 0.42     | 4.05      | 0.03  | 0.00        | 6.94       | 2.90  |
| Water     | 0.01     | 0.00     | 0.01      | 0.07  | 0.00        | 0.09       | 0.02  |
| Residential| 0.00    | 0.00     | 0.00      | 0.00  | 0.00        | 0.01       | 0.00  |
| Total 2000| 67.24    | 22.56    | 10.08     | 0.11  | 0.01        | 100        | 28.43 |
| Gain      | 7.32     | 15.03    | 6.04      | 0.04  | 0.01        | 28.43      |       |

| (c) 2000-2010 | Woodland | Cropland | Grassland | Water | Residential | Total 2000 | Loss  |
|---------------|----------|----------|-----------|-------|-------------|------------|-------|
| Woodland      | 26.96    | 33.01    | 7.26      | 0.01  | 0.01        | 67.24      | 40.28 |
| Cropland      | 1.85     | 20.11    | 0.59      | 0.00  | 0.00        | 22.56      | 2.45  |
| Grassland     | 1.81     | 2.09     | 6.15      | 0.01  | 0.01        | 10.08      | 3.93  |
| Water         | 0.00     | 0.01     | 0.01      | 0.08  | 0.01        | 0.11       | 0.03  |
| Residential   | 0.00     | 0.00     | 0.00      | 0.00  | 0.01        | 0.01       | 0.00  |
| Total 2010    | 30.62    | 55.23    | 14.01     | 0.10  | 0.05        | 100        | 46.69 |
| Gain          | 3.66     | 35.11    | 7.85      | 0.02  | 0.04        | 46.69      |       |

| (d) 1972-2010 | Woodland | Cropland | Grassland | Water | Residential | Total 1972 | Loss  |
|---------------|----------|----------|-----------|-------|-------------|------------|-------|
| Woodland      | 29.68    | 51.96    | 10.35     | 0.01  | 0.03        | 92.03      | 62.35 |
| Cropland      | 0.12     | 1.63     | 0.71      | 0.01  | 0.01        | 2.48       | 0.85  |
| Grassland     | 0.82     | 1.63     | 2.95      | 0.00  | 0.00        | 5.40       | 2.45  |
| Water         | 0.00     | 0.01     | 0.01      | 0.08  | 0.00        | 0.10       | 0.02  |
| Residential   | 0.00     | 0.00     | 0.00      | 0.00  | 0.00        | 0.00       | 0.00  |
| Total 2010    | 30.62    | 55.23    | 14.01     | 0.10  | 0.05        | 100        | 65.66 |
| Gain          | 0.94     | 53.60    | 11.06     | 0.02  | 0.05        | 65.66      |       |

In the period 1972 to 2010 woodland had the highest loss, 62.35% of the total land cover, and cropland had the highest gain of 53.60% of the land cover (Fig. 4). The cross-tabulation matrices show that the most prominent transition from 1972 to 2010 is a conversion from woodland to cropland, which accounts for 51.96 % of the landscape. Different studies also showed an increase in area of cropland in other parts of the country [Reid et al., 2000; Garedew et al. 2009; Lemenih et al., 2012; Kindu et al., 2013] and globally [Lambin et al., 2003; Hanafi and Jauffret, 2008]. The rapid vegetation removal has exposed the topsoil to
wind and water erosion processes. A cloud of dust, which is likely to result from the removal of vegetation cover, is common over the northwestern drylands and can be aggravated by the influence of the observed vegetation loss and an increase in the frequency of droughts. The degradation of woodlands is contributing to the loss of carbon from both wood biomass and soil, which can lead to land degradation and reduction in ecosystem services [Alam et al., 2013; Carranza et al., 2014].

Table 4 indicates the values for gain, loss, total change, swap and net change for each LULC class. The land use categories that experienced the highest gains were cropland (53.60%) and Grassland (11.06%) in the period 1972-2010. The largest losses in the same period were observed for woodland (62.35%). The total net decline of woodland is at 61.41%, while the total long-term net increase in cropland (i.e., from 1972 to 2010) reaches 53% consuming the dry forest of the region. The grassland has shown high levels of swap (4.90%) compared to other land use classes.

The analysis of the amount of cropland gain compared to its loss is 63.06, which is the highest indicating cropland has gained 63 times compared to its loss. This is a significant gain of cropland from other land use categories. Gain in grassland is from woodland and abandoned cropland. Changes in woodland, cropland and grassland shows both swap and net change. Water and residential do not show significant change in swap and net change which indicates a minimal transition of both land covers within the landscape. The landscape change (gain and loss) increased from 20.14 % in 1972 to 1984 to 65.67 % in 1972 to 2010 showing a significant transition within the landscape. The dryforests of northwestern Ethiopia are known for their gum and resin production but currently faced significant threats which leads to loss of these and other ecosystem services of the dry forests. Studies on the financial returns of dryforests and major croplands of the region have shown a comparable financial benefit of the dryforests than converting them to croplands [Dejene et al., 2013].
Table 4 - LULC change within the landscape in 1972 and 2010 (%).

| Land cover  | Total 1972 | Total 2010 | Persistence | Gain | Loss | Total change | Swap | Absolute value of net change |
|-------------|------------|------------|-------------|------|------|--------------|------|------------------------------|
| Woodland    | 92.03      | 30.62      | 29.68       | 0.94 | 62.35| 63.29        | 1.88 | 61.41                        |
| Cropland    | 2.48       | 55.23      | 1.63        | 53.60| 0.85 | 54.45        | 1.70 | 52.75                        |
| Grassland   | 5.40       | 14.01      | 2.95        | 11.06| 2.45 | 13.51        | 4.90 | 8.61                         |
| Water       | 0.10       | 0.10       | 0.08        | 0.02 | 0.02 | 0.04         | 0.04 | 0.00                         |
| Residential | 0.00       | 0.05       | 0.00        | 0.05 | 0.00 | 0.05         | 0.00 | 0.05                         |
| Total       | 100.00     | 100.00     | 34.34       | 65.67| 65.67| 65.67        | 4.26 | 61.41                        |

The main spatial distribution of land use transitions exhibited within the landscape is shown in Figure 5. The spatial extents of the land cover types and the land use transition rates varied significantly over different periods. The majority of these changes concerns the conversion of woodlands to other land use types. The land use change has a considerable effect on vegetation distribution and on the natural ecosystems of the region.

Table 5 shows the trends in the annual mean change rates of land covers. A rapid reduction in woodland cover and a sharp increase in cropland took place from 1972 to 2010 within the landscape. The highest annual rate of woodland reduction occurred during the period 2000 to 2010 (-36.62%). On the other hand, 3.27% of average annual rate of increase in cropland observed from 2000 to 2010. Higher demand and price of oil crop, namely sesame, in the world market induced conversion of dryforests and expansion of croplands [Lemenih et al., 2007; Dejene et al., 2013].

Table 5 - LULC change per class and annual rate of change (%).

| Land cover  | Percentage change (trend) | Annual rate of change (%) |
|-------------|---------------------------|---------------------------|
|             | 1972-1984 | 1984-2000 | 2000-2010 | 1972-1984 | 1984-2000 | 2000-2010 |
| Woodland    | -12.12   | -12.67   | -36.62   | -0.87     | -0.91     | -3.66     |
| Cropland    | 10.57    | 9.51     | 32.67    | 0.76      | 0.68      | 3.27      |
| Grassland   | 1.54     | 3.14     | 3.92     | 0.11      | 0.22      | 0.39      |
| Residential | 0.01     | 0.02     | 0.03     | 0.00      | 0.00      | 0.01      |
| Water       | 0.00     | 0.02     | -0.01    | 0.00      | 0.00      | 0.00      |

**Persistence of land uses**

During the study period, major land use classes have shown a significant transition like most parts of the country [Reid et al., 2000; Garedew et al., 2009; Tsegaye et al., 2010] and other dry land areas [Lambin et al., 2003; Hanafi and Jauffret, 2008]. The land cover transition is higher for woodland, cropland and grassland within the landscape. The amount of persistence, percentage of unaffected landscape, was 34.34% between 1972 - 2010. The study area has shown transitions on about 66% of the landscape.

The loss to a persistence ratio ($l_p$) assesses the exposure of a land cover for transition [Braimoh, 2006]. As the value of $l_p$ is higher than one, the land cover is exposed to changes to other land cover classes than persist. All land use classes except woodland has an $l_p$ value of lower than 1. Woodland has $l_p$ value of 2.10 indicating a higher vulnerability to lose than persist. Other land uses with values lower than one has a lower tendency of transition to other land uses (Tab. 6).
Table 6 - Gain to persistence (g_p), loss to persistence (l_p) and net change to persistence (n_p) ratios of land covers in the period 1972 and 2010.

| Land cover | g_p   | l_p   | n_p   |
|------------|-------|-------|-------|
| Woodland   | 0.03  | 2.10  | -2.07 |
| Cropland   | 32.88 | 0.52  | 32.36 |
| Grassland  | 3.75  | 0.83  | 2.92  |
| Water      | 0.25  | 0.25  | 0.00  |
| Residential| 0.00  | 0.00  | 0.00  |

The gain to persistence ratio (g_p) values higher than one indicate a greater chance of a land use to gain compared to their persistence [Braimoh, 2006]. Cropland (32.88) and grassland (3.75) have the highest g_p ratio indicating more gain than persistence. The g_p of woodland is almost zero, indicating the gain of woodland is insignificant compared to its persistence during the whole study period.

The net change to persistence ratio (n_p) of cropland is higher (32.36) indicating the net gain of cropland is 32 times higher than its persistence. The net loss of woodland (-2.07) is more than doubled to its persistence within the landscape. Grassland (2.92) also got a net gain of about three fold of its persistence during the study period. The net change to persistence is closer to zero for water and residential land uses indicating that they had a lower tendency to change.

Figure 5 - Spatial distribution of LULC change from 1972 to 2010 (WL: Woodland, CL: Cropland, GL: Grassland).
Distribution of land use changes along an elevation gradient
Overlaying the LULC map with the DEM reveals that the areas with elevations below 1000 m asl cover about 82% of the study area (Fig. 6 and Tab. 7). Land use transition process and extent vary considerably across altitudinal ranges. The most significant change in woodlands occurred in the areas with lower altitude within a range of 537 m to 750 m where 88.47% of the woodlands was lost since 1972 (2409.16 km²) to 2010 (277.68 km²). A significant increase in cropland is also exhibited in the same altitudinal range from 1972 (145.44 km²) to 2010 (2096.01 km²). The remaining woodland areas which are located at elevations below 1250 m have also experienced expansion of settlements and cropland. Loss of woodland cover exposes soils to wind and water erosion which leads to land degradation.

![Figure 6 - Land use distribution along an elevation gradient.](image)

Drivers of LULC changes
According to the respondents of the socio-ecological field survey (Tab. 8), most significant factors that contributed to the loss of vegetation cover were bushfire, agricultural land expansion, resettlement and overharvesting of trees. 64.9%, 78.4%, 78.4%, 94.6% and 94.7% of the respondents agree that overgrazing, bushfire, cropping extension, settlement expansion and overharvesting of trees respectively are the major causes of loss of tree cover. Bushfire is both natural and human induced and damages both properties of settlers and the woodlands. The natural occurrence of fire is linked to the dry climatic conditions of the region in which the dry biomass acts as a fuel. In addition, humans also set fire to clear the debris of their agricultural plots in which the fire escapes into the woodlands. According to the respondents, increase in human activities mainly agricultural expansion, collection of firewood and of construction wood and increase in population size significantly contributed to overutilization of the natural vegetation. Similar studies in northwestern Ethiopia and other semiarid regions also identified resettlement as major deriving factor for causing significant pressure on natural resources [Hanafi and Jauffret, 2008; Lemenih et al., 2012].
Table 7 - Classification of 2010 LULC categories of Kaftahumera overlaying the digital elevation model (DEM) acquired by the Shuttle Radar Topography Mission (SRTM).

| Elevation classification (m) | Area (km²) | % of total | Dominant LULC types, respectively |
|-----------------------------|------------|------------|----------------------------------|
| 537-750                     | 2761.24    | 44.70      | Woodland, agriculture, grassland and settlement |
| 750-1000                    | 2295.53    | 37.16      | Woodland, agriculture and grassland |
| 1000-1250                   | 786.65     | 12.73      | Woodland, agriculture and grassland |
| 1250 -1500                  | 215.20     | 3.48       | Woodland and agriculture          |
| 1500-1865                   | 118.60     | 1.92       | Woodland and agriculture          |
| Total study area            | 6177.22    | 100        |                                   |

Population growth associated with cropland expansion, human induced fire and inappropriate use of forest resources are the main drivers of the observed woodland loss [Lemenih et al., 2007; Lemenih et al., 2012]. The cropland expansion is marked by a sustained growth in population, increasing agricultural investments, a rise in oil crop price and a sharp increase in agricultural employment [Dejene et al., 2013]. For instance in 2011 the investment attracted more than 200,000 casual labourers in search of employment [http: //www.dppc.gov.et. accessed on18 April 2011]. As the region is semi-arid, the combination of overgrazing, drought, human population growth and agricultural expansion played a significant role in aggravating degradation of the natural vegetation and soil conditions. Over the last forty years woodlands have steadily declined in size and human actions have established the basis for an increase of wind erosion and the subsequent emergence of more and more drifting dust clouds originating from northwestern Ethiopia.

Table 8 - Perceptions of local people about the causes of the land use/cover change (%).

| Causes                      | Disagree | Not sure | Agree   |
|-----------------------------|----------|----------|---------|
| Bush fire                   | 10.8     | 10.8     | 78.4    |
| Cropping extension          | 8.1      | 13.5     | 78.4    |
| Overgrazing                 | 13.5     | 21.6     | 64.9    |
| Settlement                  | 2.7      | 2.7      | 94.6    |
| Over harvesting of trees    | 0.0      | 5.3      | 94.7    |

Conclusion
LULC change detection evaluates spatiotemporal change patterns and identifies the quantitative dimension of transitions within a landscape. This study examines the LULC changes of the semi-arid regions of Kaftahumera using multitemporal satellite imagery for the period 1972-2010 that provides current and historical LULC conditions. Supervised classification algorithm using SVM algorithm was employed to monitor LULC transformations. A cross-tabulation matrix was used to assess the total change of land categories based on net change and swap. Over the study period, there is a significant
changes in LULC, as evidenced by a sharp increase in cropland of about 53% and a net loss of over 61% of woodland within the landscape. The period 2000-2010 has shown a sharp increase of cropland and a sharp decline of woodland areas. Changes in economic growth and human activities contributed to an overuse of existing natural resources, which resulted in significant variations in the spatiotemporal patterns of land use changes with respect to specific altitudinal ranges. The dominant changes are exhibited in areas with elevations below 1000 m with a loss of 74% of woodlands from 1972 to 2010. Human activities, such as agriculture and settlement expansion, severely influenced the drylands by modifying the landscape and diminishing its natural ecosystem. Over the last forty years the woodlands have steadily declined in size and have been replaced by croplands. The combination of overgrazing, population growth and agricultural expansion contributed to the degradation of the woodlands of the region. The human impacts have prepared the stage for an increase of dust clouds originating from northwestern Ethiopia. The disturbance of the respective woodland ecosystem is closely related to the occurrence of significant land use transformation within the region. This change may result in an irreversible loss of biodiversity and in the depletion of ecological services provided by the natural environment. The results of this study quantify dynamics of land cover change and point towards appropriate action to implement sustainable use of the ecosystem. In the face of increasing population size and consequent need for intensifying exploitation of resources, it is vital to maintain a balance of sustainable utilization. Thus, it is crucial to further develop and enhance methods of periodical monitoring and assessment of LULC change in order to evaluate the environmental influences on semi-arid ecosystems that are increasingly affected by human impact.

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